Remote Sensing–Driven Hydrodynamic Modeling in Data-Scarce Regions: Integrating ICESat-2, Sentinel-2, SWOT and Re-analysis Models for Coastal Monitoring

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ABSTRACT

Hydrodynamic models in coastal and estuarine systems are typically constrained by sparse bathymetry, boundary, and validation data, especially in regions where field campaigns are costly or impractical. Here we develop and test a fully satellite-driven framework for hydrodynamic modeling in South Africa's Langebaan Lagoon without using any local in situ measurements. Bathymetry is derived by training multispectral Sentinel-2 reflectance against ICESat-2 ATL24 photon-derived depths using an XGBoost model optimized with Bayesian search. The final satellite-derived bathymetry reproduces independent ATL24 points with RMSE = 0.45 m and R^2 = 0.97. This bathymetry was used in a depth-averaged Delft3D Flexible Mesh model driven at the open boundary by TPXO tidal harmonics and by ERA5 winds. We validate modeled water surface elevation against 16 SWOT low-rate (250 m, unsmoothed) passes in 2023. SWOT–model comparisons yield an overall RMSE of 0.11 m and R^2 = 0.61, with typical point differences $<$0.10 m ($\sim$7% of the 1.5 m tidal range), and showed consistent spatial gradients in water level from the offshore boundary, through Saldanha Bay, and into the lagoon. At the offshore boundary, TPXO and SWOT sea surface heights agree closely (R^2 = 0.86). A simple phase adjustment of $\sim$26,min between TPXO and SWOT lowers the RMSE from 0.18,m to 0.11,m, showing that phase offset accounts for some of the discrepancy, with additional errors likely linked to non-tidal signals. Our results demonstrate that combining passive optical, photon-counting LiDAR, radar interferometry, and global tidal/atmospheric models enables robust, transferrable hydrodynamic modeling in data-scarce coastal systems, offering a cost-effective pathway for monitoring.

1 INTRODUCTION

Coastal and estuarine systems are dynamic, largely driven by the constant motion of water. The meeting of tides, waves, and river inflows drives salinity gradients, sediment transport, and flooding and drying, which together shape water quality, habitat characteristics, function and distribution, as well as productivity of these environments. Understanding these dynamics is fundamental for predicting how ecosystems respond to change as human pressures and climate change impacts intensify. Such changes can include shifts in habitat distribution, salinity regimes, sediment transport pathways, carbon storage, sea level rise and eventually changes in wetland stability (Kirwan and Mudd, 2012; Kirwan and Megonigal, 2013; Spencer et al., 2016; Schuerch et al., 2018; Payandeh et al., 2022). A well-calibrated hydrodynamic model forms the foundation for simulating sediment movement, morphology, and even ecosystem responses to changes in water levels, salinity, and sediment dynamics (Brush and Harris, 2010; Ganju et al., 2016). Yet, the accuracy of such models depends strongly on the availability of reliable field data for bathymetry, boundary conditions, and validation. In practice, collecting these data in coastal wetlands, deltas, or estuaries is difficult. Field campaigns can be costly, constrained by permits and at the mercy of weather or access. Such challenges explain why many of the world's coastal environments remain only sparsely mapped and monitored (Båmstedt and Brugel, 2017; Mohseni et al., 2022; Vargas-Yáñez et al., 2025).

Recent advancements in satellite remote sensing and global reanalysis products now offer promising alternatives to traditional field-based monitoring, particularly in data-scarce and difficult to access coastal environments. High-resolution multispectral imagery from Sentinel-2 has enabled the routine estimation of bathymetry through aquatic optical remote sensing and wave kinematics techniques, with reported accuracies typically around Root Mean Square Error (RMSE) of $\leq$ 1.5 m and a mean absolute error of $\sim$ 0.1 – 0.2 m in optically clear, non-turbid and shallow waters (e.g., Pacheco et al., 2015; Chénier et al., 2018; Traganos et al., 2018; Najar et al., 2022). Meanwhile, ICESat-2 laser altimetry has been shown to provide robust elevation "seed points" for calibrating passive satellite-derived bathymetry workflows, enabling operational and spatially efficient bathymetric mapping (e.g., Babbel et al., 2021; Le et al., 2024; Corcoran et al., 2024; Jung et al., 2025). Complementing these remote observations are global tidal models such as TPXO, which assimilate satellite altimetry, with tidal elevation and current fields that are commonly used to force coastal model boundaries (e.g., Stammer et al., 2014; Yang et al., 2020). On the atmospheric side, the ERA5 reanalysis supplies hourly wind and pressure fields that have been shown to improve wave and surge simulations compared with earlier reanalysis products (Dullaart et al., 2020). Finally, the Surface Water and Ocean Topography (SWOT) mission provides two-dimensional maps of water surface elevation with sub-kilometer resolution over coastal oceans and estuaries, allowing direct comparison of model and SWOT-measured water levels and improving calibration and validation of hydrodynamic models (**?**NASA/PO.DAAC, 2025). Together, these freely available datasets form a practical toolkit to initialize, force, and validate coastal hydrodynamic models reducing reliance on costly field campaigns while covering a larger area and longer time span than would otherwise be feasible.

Despite these advancements, most existing applications of remote sensing driven hydrodynamic modeling still require some degree of in situ data for calibration or validation, such as tide gauge records, measured bathymetry, or meteorological observations to, for example, supply tide gauge time series for calibration and verification, initialize seed depths for satellite derived bathymetry, or provide wind forcing inputs (Babbel et al., 2021; Williams and Esteves, 2017). This dependency limits their transferability to truly data-scarce regions, where logistical constraints or resource limitations prevent sustained ground-based monitoring (Ashphaq et al., 2021; Williams and Esteves, 2017).

In sub-Saharan and South African contexts, estuarine and lagoon systems are frequently characterized as data limited, and recent syntheses highlight both the ecological importance of these systems and the relative scarcity of long-term observational records needed for modeling and management (Van Niekerk et al., 2022; Whitfield et al., 2012). Langebaan Lagoon (Figure 11) is one such system: a shallow, microtidal lagoon of high conservation value, protected within South Africa's West Coast National Park and designated as a Ramsar site (Hanekom et al., 2009). Coastal lagoons are estimated to occur along only 13% of the extent of the world's coastlines, and most extensively along 18% of the African coastline (Badcock and Barnes, 1981). Lagoons form important breeding and nursery habitats for fin and shellfish, serving poor communities with food (Miththapala, 2013). Anthropogenic impacts, such as coastal development and industry, as well as increasing temperatures and evapotranspiration associated with climate change, can negatively impact the function of these systems through increased sedimentation (Essel et al., 2019), rendering coastal lagoons vulnerable. These pressures are acutely relevant in the coupled Saldanha Bay–Langebaan Lagoon system. The development of, and continuous dredging operations at, the Saldanha Bay port, together with ongoing and increasing residential development along the coast (Krug, 1999; Du Toit et al., 2022), have raised concerns about the hydrodynamics and sedimentation in the bay that is shared with the Langebaan Lagoon mouth. Changes in bathymetry between 1957 and 1977 showed accumulation of sediments at the Langebaan Lagoon mouth, whereas erosion occurred in other parts of the bay (Henrico and Bezuidenhout, 2020). The Langebaan Lagoon hosts one of the endangered submerged aquatic species, *Zostera capensis*, that occurs only in 62 estuaries of South Africa (Raw et al., 2023), and protection of these habitats is therefore crucial. Continuous monitoring of the bathymetry of both the bay and the Langebaan Lagoon, to better characterise possible natural inter- and intra-annual variations relative to those resulting from anthropogenic events and their impacts on ecosystems and species, is highly recommended. Against this backdrop, Langebaan Lagoon is an ideal testbed for examining whether a fully satellite-driven modeling workflow can be used where conventional observations are sparse or absent.

To overcome the limitations of conventional approaches, this study develops a fully satellite-driven framework for hydrodynamic modeling in coastal lagoons where field data are limited or unavailable. The workflow combines satellite-derived bathymetry, generated through a machine-learning approach using ICESat-2 and Sentinel-2 data, with a two-dimensional Delft3D Flexible Mesh model forced by global tidal and atmospheric reanalysis products. Model calibration and validation are carried out using spaceborne sea surface height observations, eliminating the need for local gauges or survey campaigns. By applying this framework to South Africa's Langebaan Lagoon, we demonstrate its capability to reproduce key hydrodynamic processes in a microtidal, data-scarce environment. The objectives are to (1) evaluate the feasibility of generating reliable bathymetry without in situ depth measurements, and (2) to assess the performance of a hydrodynamic model initialized, forced, and validated entirely from spaceborne and global products. While this study focuses on a single test case, the workflow is general and could be transferred to other coastal systems, especially where access, safety, or cost makes field measurements impractical.

2 METHODS

2.1 Bathymetry Estimation

Bathymetry was estimated by training multispectral surface reflectance from Sentinel-2 with photon-derived elevations from ICESat-2 ATL24 products (Parrish et al., 2025). The ATL24 product provides along-track bathymetric retrievals (referenced to EGM08) by detecting photons that penetrate the water column and return from the seabed. These elevations are derived from ICESat-2 L2A Global Geolocated Photon Data (ATL03) and are already refraction-corrected. Figure 2 shows two examples of ATL24 tracks across the lagoon. Depths along the track show intertidal and subtidal flats, with tidal channels clearly resolved. Deeper tidal channels appear as darker green meandering features in Sentinel-2 imagery, and reach depths of up to –8 m (referenced to EGM08), while brighter sandy lagoon floors in intertidal and

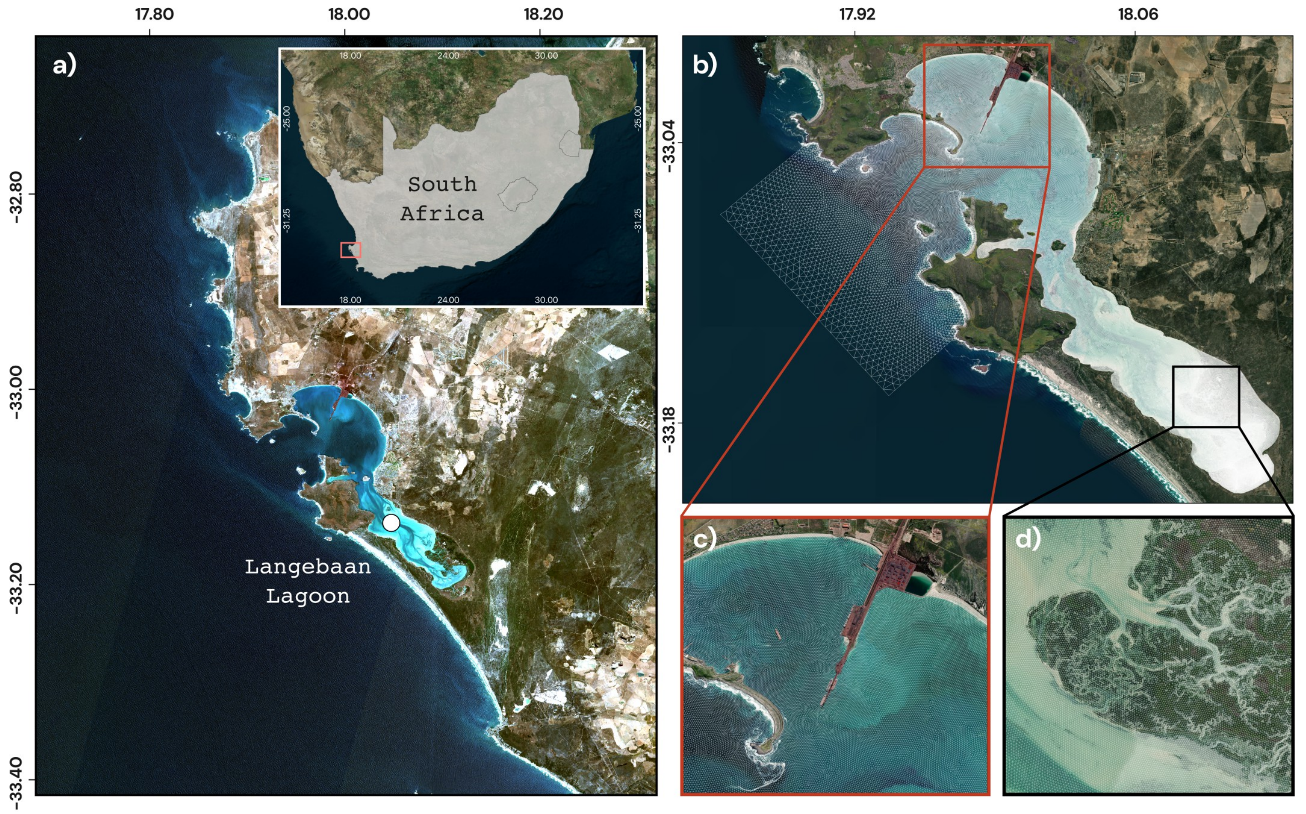

Figure 1. Spatial context and computational mesh. (a) The location of Langebaan Lagoon on the western margin of South Africa, highlighted within the red box. (b, c and d) The Delft3D Flexible Mesh grid applied in this study.

subtidal areas correspond to shallower depths between –3 and –1 m. In total, 17 ICESat-2 tracks were used in this study. Most crossed the lagoon itself, while several extended into Saldanha Bay and the adjacent offshore area. Figure 3 shows the location of all ICESAT-2 ground tracks that were used to train the model.

Sentinel-2 provides multispectral imagery at 10–20 m spatial resolution, which captures optical variations in the water column that can be related to depth. Sentinel-2 imagery allowed us to train a predictive model capable of extending point-based ICESat-2 depths across the full lagoon and bay. For model training, we focused on bands and ratios that have been shown to correlate well with bathymetry (Casal et al., 2019; Caballero and Stumpf, 2020; Wei et al., 2020). Specifically, we used the blue, green and red band ratios, the Normalized Difference Water Index (NDWI), and individual reflectance values from the red-edge bands (Table 1). These predictors provide a balance between the sensitivity to water depth and reduced influence of atmospheric and surface effects.

Sentinel-2 images were processed using the Acolite application (Vanhellemont and Ruddick, 2016) to correct for atmospheric effects and remove sun glint. Acolite was used because of its robust handling of coastal and turbid waters. Particularly the Dark Spectrum Fitting (DSF) method was applied (Vanhellemont and Ruddick, 2018), which estimates atmospheric path reflectance directly from darker pixels and effectively reduces adjacency and surface reflection errors. Acolite also allows for integrated sun glint correction, simplifying preprocessing. ICESat-2 ATL24 points were filtered based on quality flags and clarity indicators, then co-located with Sentinel-2 pixels to match reflectance and depth values. This produced a paired dataset of depth and reflectance values, which formed the input for model training. ATL24 bathymetry points

Table 1. Sentinel-2 predictors used to derive bathymetry. Band designations and central wavelengths are from the Sentinel-2 MSI sensor specifications.

Predictor	Description	Central Wavelength (nm)
B2/B3	Ratio of Blue to Green	490 / 560
B2/B4	Ratio of Blue to Red	490 / 665
B3/B8	Ratio of Green to NIR	560 / 842
B4/B8	Ratio of Red to NIR	665 / 842
NDWI	Normalized Difference Water Index	(Green–NIR) / (Green+NIR)
B5	Red-edge 1	705
B6	Red-edge 2	740
B7	Red-edge 3	783

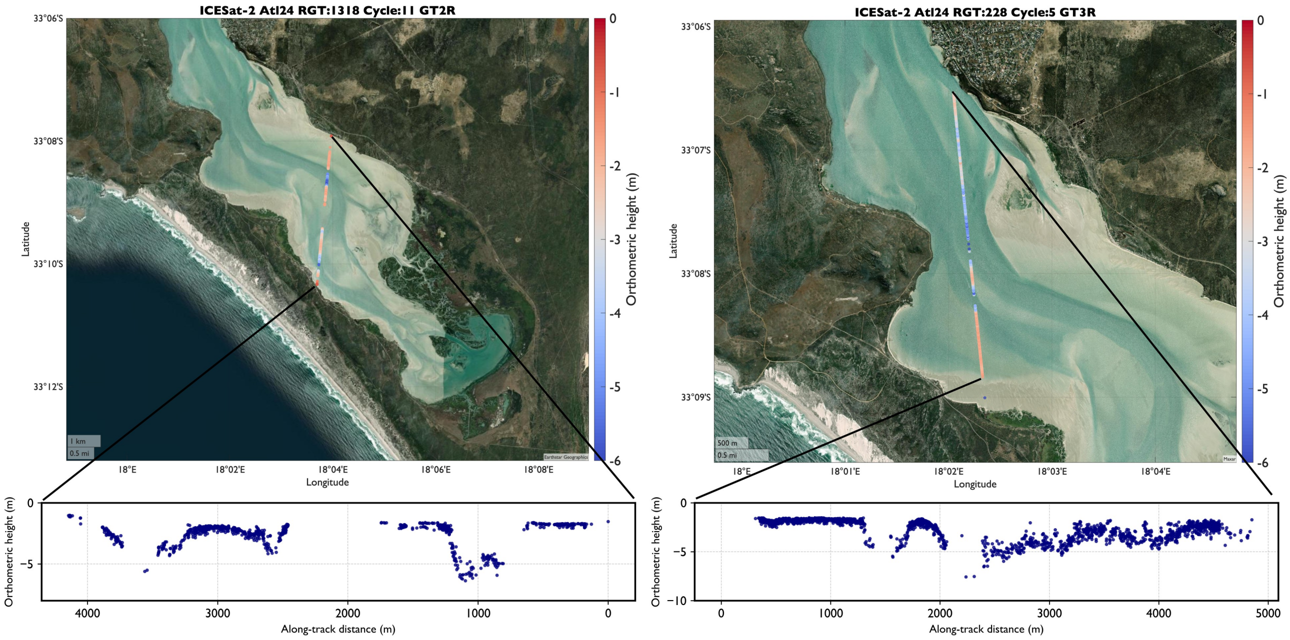

Figure 2. Examples of ICESat-2 ATL24 bathymetry elevations (referenced to EGM08). Each panel is labeled with the corresponding Reference Ground Track (RGT) number, cycle number, and laser beam identifier

were divided into independent training and validation sets using ICESat-2 track as the grouping variable: approximately 80% of ATL24 points (14 tracks) used for training and and the remaining 20% (3 tracks) reserved for validation. Entire tracks were assigned either to the training or validation set, reducing spatial autocorrelation between training and validation samples and ensuring an unbiased evaluation. The validation tracks were selected to span the full range of environmental settings in the study area, one in deep offshore waters, one within the bay, and one in the shallow lagoon (Figure 3).

Several machine learning models were tested to predict bathymetry from reflectance, including Random Forest, Random Forest with Bayesian optimization, XGBoost, and XGBoost with Bayesian optimization. For the models without Bayesian optimization, the hyperparameters were adjusted manually based on iterative trial-and-error rather than through an automated search. In the Random Forest models, the number of trees, maximum tree depth, and the minimum number of samples required to split a node were varied. In the XGBoost models, different combinations of learning rate, maximum tree depth, and subsampling ratio were tested.Bayesian optimization was then applied to both models to automatically search for the

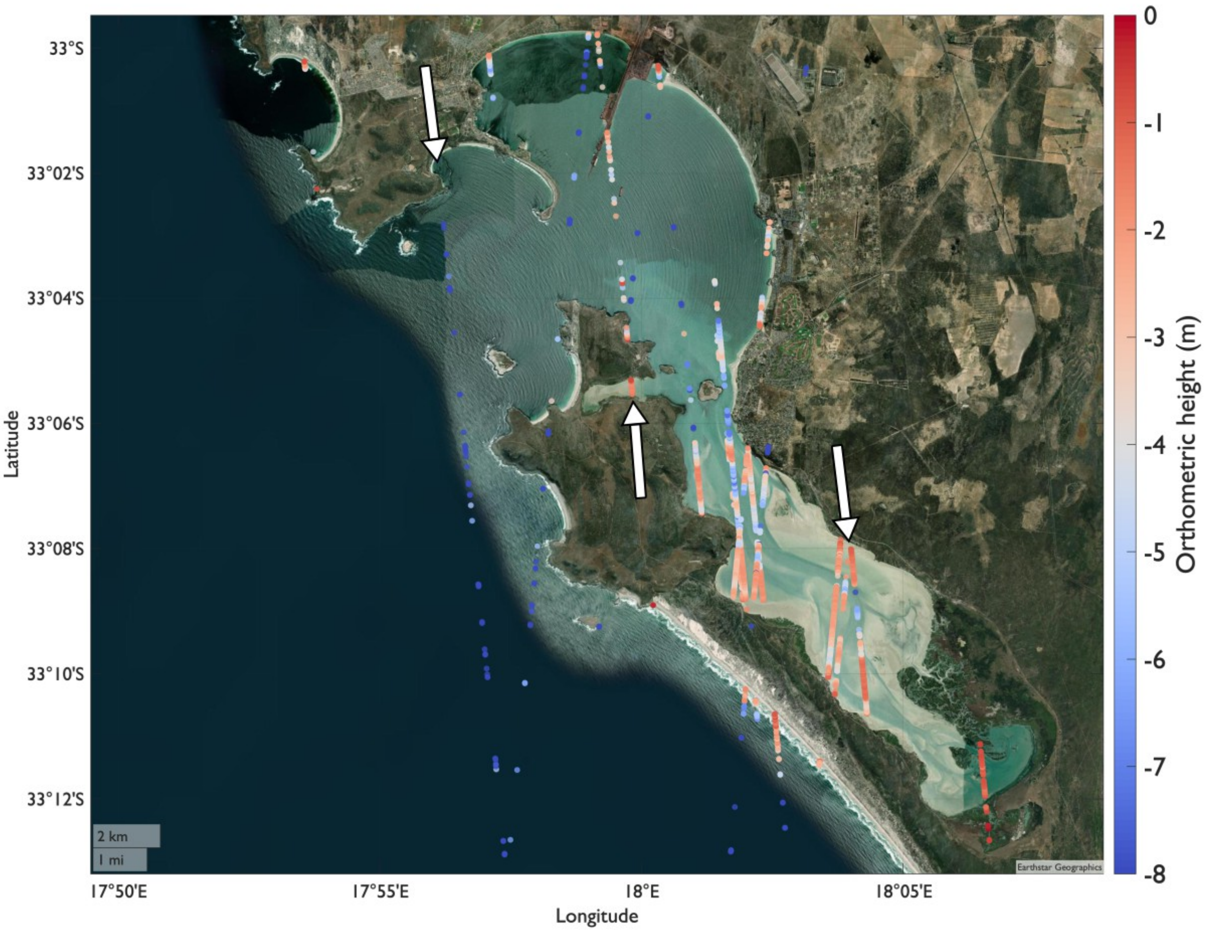

Figure 3. All ICESat-2 ATL24 bathymetry tracks (referenced to EGM08) used in this study to drive bathymetry. Tracks indicated by arrows (∼20% of all points) were reserved for validation, while the remaining tracks were used for model training.

best parameters. Performance was evaluated using the validation set. Reflectance from the first Sentinel-2 image was used to select the best-performing machine-learning model (Figure 4). Once the optimal model was identified, it was applied to the remaining 15 Sentinel-2 scenes to generate additional depth estimates. Bathymetry derived from each of these scenes was then validated independently against ATL24 points

Among all models, XGBoost with Bayesian optimization showed the best performance with an RMSE of 0.45 m and R^2 of 0.97, and was therefore selected as the final models to derive bathymetry (Figure 4). Validation of the individual bathymetries demonstrated that the model remained consistently accurate across scenes with varying wave conditions, supporting the robustness of the final averaged product (Table 2). Across these 16 images, validation RMSE values ranged from 0.36 to 0.57 m, with corresponding R^2 values between 0.95 and 0.98, and an overall average RMSE of 0.46 m and R^2 of 0.97.

During model development, a recurring challenge was interference from surface waves, which introduced noise into the predicted bathymetry. Band ratios helped to reduce these effects, but to further minimize wave related interferenceThe resulting depth maps were subsequently averaged to reduce wave-related

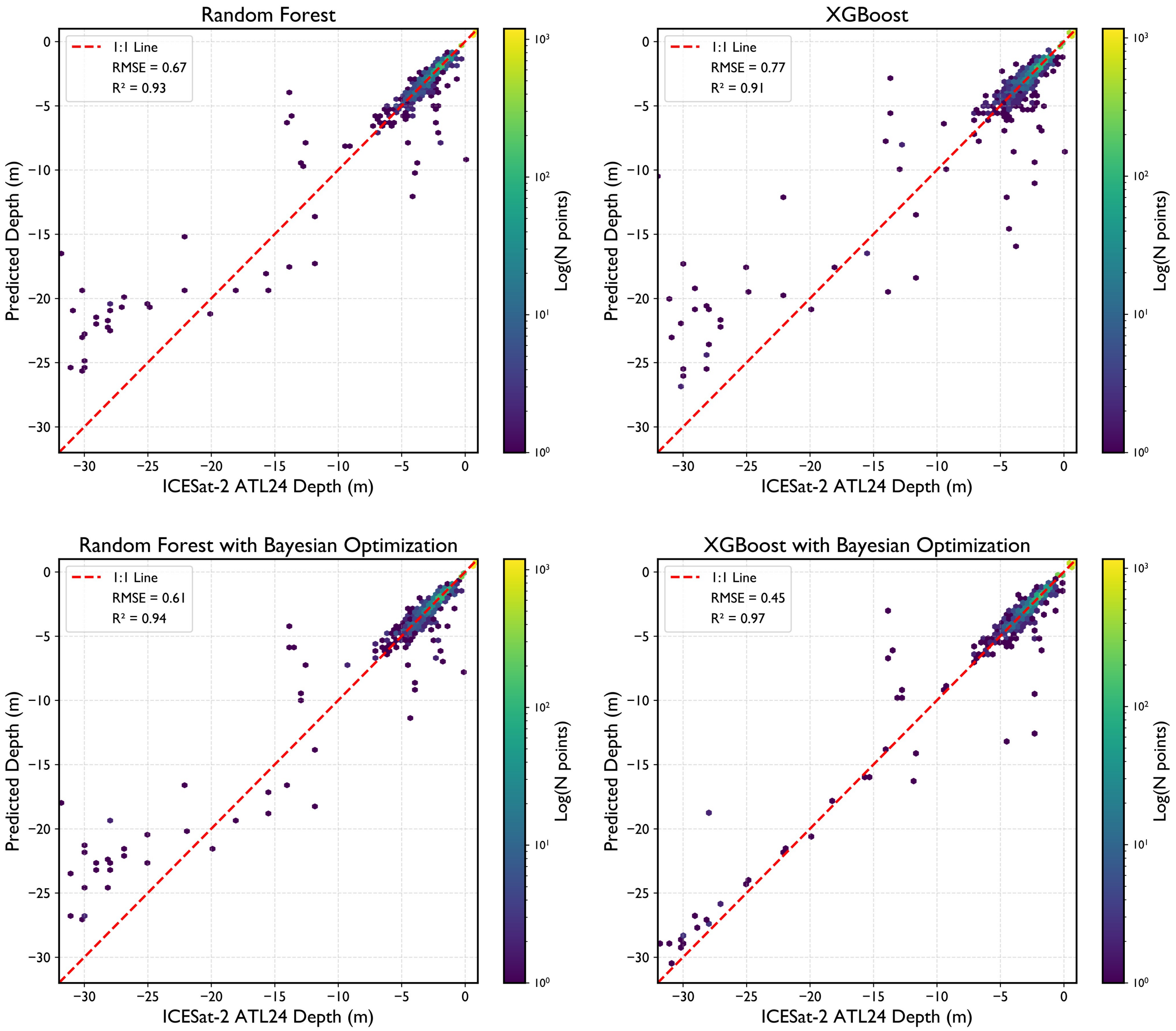

Figure 4. Comparison of model performance for bathymetry prediction using different machine learning approaches: Random Forest, Random Forest with Bayesian optimization, XGBoost, and XGBoost with Bayesian optimization. Performance was evaluated on an independent validation set, showing that XGBoost with Bayesian optimization achieved the best performance.

noise and produce the final bathymetry product. Finally, a Gaussian filter with a 3×3 spatial window was applied to the averaged bathymetry grid to further suppress high frequency noise and improve the spatial continuity of depth estimates. The final processed bathymetry is shown in Figure 5.

2.2 Hydrodynamic Model Setup

A two-dimensional, depth-averaged hydrodynamic model of Langebaan Lagoon was developed using the Delft3D Flexible Mesh Suite (Delft3D FM). Delft3D FM is a finite volume modeling system that solves the unsteady, nonlinear shallow water equations on an unstructured grid, making it well suited for estuarine and coastal environments with irregular geometries and complex bathymetry (Deltares, 2021). Unlike structured grids, the unstructured approach allows flexible refinement in areas of interest while maintaining

Table 2. Bathymetry validation for each Sentinel-2 image using the XGBoost model optimized with Bayesian search. Modeled depths are compared against independent ATL24 validation points.

Image	RMSE (m)	R^2
Image 1	0.45	0.97
Image 2	0.47	0.97
Image 3	0.44	0.97
Image 4	0.42	0.97
Image 5	0.54	0.96
Image 6	0.43	0.97
Image 7	0.41	0.97
Image 8	0.44	0.97
Image 9	0.45	0.97
Image 10	0.46	0.97
Image 11	0.49	0.96
Image 12	0.47	0.97
Image 13	0.36	0.98
Image 14	0.55	0.95
Image 15	0.57	0.95
Image 16	0.42	0.97
Average	**0.46**	**0.97**

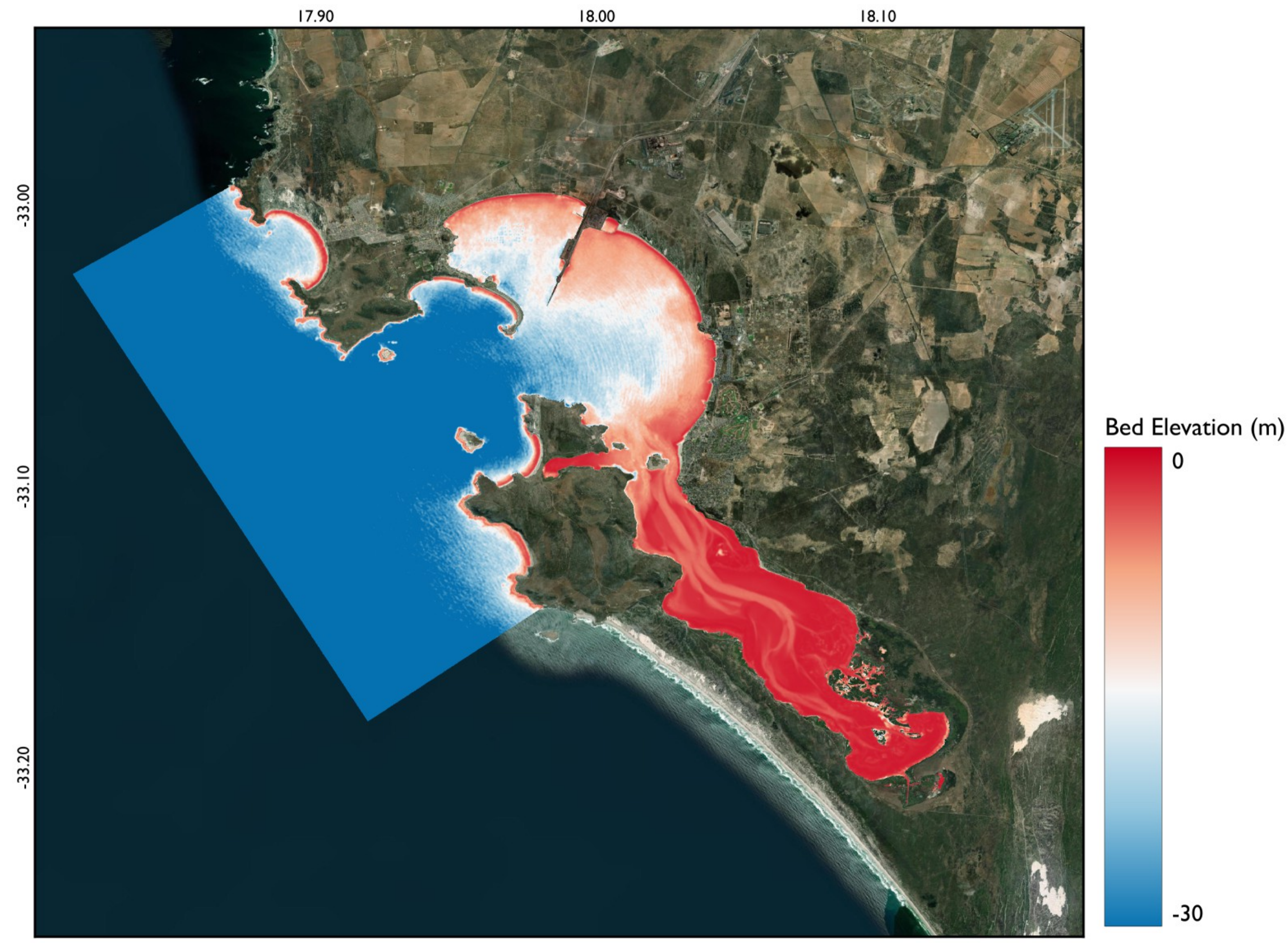

Figure 5. Final satellite-derived bathymetry for Langebaan Lagoon and Saldanha Bay. Depths represent the averaged prediction from 16 cloud-free Sentinel-2 scenes after training on ICESat-2 ATL24 points.

Table 3. Tidal harmonic constituents used to force the offshore boundary. Amplitudes (m) and phases (degrees) were taken from TPXO.

Constituent	Amplitude (m)	Phase (deg)
M2	0.506	34.0
S2	0.218	52.7
N2	0.109	26.9
K2	0.063	50.1
K1	0.055	105.6
SA	0.032	328.0
MU2	0.018	5.1
O1	0.016	234.9
NU2	0.016	31.8
2N2	0.016	15.5
P1	0.015	109.3
L2	0.013	25.9

efficiency in less dynamic regions. The unstructured grid was developed using Aquaveo's Surface Water Modeling System (SMS) (Zundel, 2000). Mesh resolution was intentionally varied to capture landscape complexity while maintaining computational efficiency. Higher-resolution triangular elements ($\sim$10 m) were applied within the lagoon's tidal channels, intertidal flats, and constricted inlets to ensure accurate representation of flow pathways. Coarser elements (40–200 m) were used in Saldanha Bay and offshore areas, where topographic complexity is lower. This gradation balanced model accuracy with computational efficiency. Islands were removed from the computational mesh. Prior to simulation, the mesh was checked for smoothness, orthogonality and other quality checks to meet accepted numerical standards. The final mesh comprised 171,182 nodes and 339,119 elements (Figure 1).

Open boundary conditions were imposed along the offshore edge of the domain using tidal amplitudes and phases taken from the TPXO global tidal model (Egbert and Erofeeva, 2002). As an additional check, we later compared TPXO reconstructed water levels against SWOT observations at the offshore boundary and found that they generally agreed well, which increases confidence in using TPXO as the tidal driver (Section 4.2).Twelve dominant tidal constituents were extracted from TPXO and applied to the eastern offshore boundary. Nodal corrections in Delft3d FM were set to be updated and applied to the tidal constituents every 24 hours. The tidal signal in the study area is predominantly semidiurnal, with M2 being the largest driver, followed by S2 and N2. Their amplitudes are 0.50 m, 0.21 m and 0.10 m, respectively, indicating a clear semidiurnal dominance with smaller diurnal modulation from constituents such as K1 and O1 and P1. The full list of constituents, amplitudes and phases used at the boundary is given in Table 2. In addition to prescribing tidal forcing along the eastern offshore boundary, Neumann (free outflow) conditions were applied at the northern and southern offshore boundaries to allow unrestricted water exchange. Hourly wind forcing was taken from the ERA5 reanalysis and applied to the model as surface forcing. Wind stress was calculated in the model using the drag coefficient formula of Large and Pond (1981), and the resulting stresses were applied as surface momentum fluxes in Delft3D-FM. ERA5 was chosen for its hourly temporal resolution, global coverage, and a horizontal grid spacing of 0.25°, which provides consistent, gap-free atmospheric fields appropriate for forcing models in data-scarce regions (Hersbach et al., 2020).

2.3 SWOT Data Processing

To evaluate model performance, we made use of observations from the NASA Surface Water and Ocean Topography (SWOT) mission. SWOT carries the Ka-band Radar Interferometer (KaRIn), which provides wide swath measurements of water surface heights over both the ocean and inland water bodies. The mission produces two main data streams tailored for different science communities: a high-rate (HR) stream for rivers and lakes, and a low-rate (LR) stream designed primarily for oceanography. Ideally, the HR products would have been the best fit for a semi-enclosed coastal system like Langebaan Lagoon, because of their finer resolution and suitability for smaller water bodies. However, HR data are only downlinked to selected target areas and no HR coverage was available for Langebaan Lagoon during the study period. For this reason, we relied on the LR products, specifically the Level-2 (L2) LR Sea Surface Height (SSH) data, which are continuously available globally, including over coastal zones.

Sixteen SWOT pass acquisitions intersecting the Langebaan Lagoon domain were downloaded from the PO.DAAC archive and processed (Christensen, 2025). For each pass we used the SWOT Level-2 Low Rate SSH Expert (SWOT_L2_LR_SSH_Expert_2.0) and Unsmoothed (SWOT_L2_LR_SSH_Unsmoothed_2.0) products (version C). The Expert file, provided on a 2 km swath-aligned grid with correction fields and diagnostic metadata, and the Unsmoothed file, which contains the native KaRIn measurements at roughly 250 m sampling and about 500 m resolution. Our final comparisons with the hydrodynamic model relied solely on the Unsmoothed SSH at approximately 250 m sampling, as this dataset preserves the finer spatial variability needed for lagoon-scale evaluation. The expert files played several supporting roles. First, we used the Expert quality flags and diagnostic fields to screen poor measurements and to identify reliable observations in each pass. Second, the expert files provide crossover correction fields at the regular 2 km grid; these corrections were interpolated onto the Unsmoothed sampling to remove the large-scale cross-track trends that otherwise dominate LR SSH. The resulting Unsmoothed arrays contained the original ssh_karin_2 values corrected with interpolated crossover height corrections (height_cor_xover). We then computed water surface elevation for every valid Unsmoothed point using a geoid derived from a GTX file (EGM08). Geoid heights were interpolated from NOAA VDatum GTX grids and sampled to the SWOT coordinates following the GTX specification (NOAA National Ocean Service, n.d.). These geoid values were then subtracted from the KaRIn SSH, after applying the crossover corrections, to produce the water surface elevation used in model comparisons. For clarity, the water surface elevation (WSE) computed from the Unsmoothed L2 product in our workflow is:

$$\mathrm{WSE} = ssh_{\mathrm{karin\_2}} + height\_cor\_xover - geoid_{\mathrm{GTX}} \tag{1}$$

where ssh_karin_2 is the Unsmoothed KaRIn SSH field, height_cor_xover is the crossover correction interpolated from the matching Expert file, and geoidGTX is the external geoid height sampled from the GTX grid (referenced to EGM08). We also examined the auxiliary tidal correction fields provided in the SWOT L2 Expert product, including the solid Earth tide, load tide, and pole tide terms. Across all passes and within the Langebaan Lagoon domain, these corrections were consistently small, with magnitudes on the order of 10^{-3} m. This is several orders of magnitude smaller than the tidal range in the area ($\sim$ 1.5 m), so their contribution to the total water surface elevation is negligible.

After computing WSE for each pass, we applied a set of quality-control steps. First, we used the interferometric total coherence as the primary quality flag and retained only pixels with coherence $\geq$ 0.8. Coherence provides a direct measure of phase stability between the two KaRIn antennas, so low-coherence pixels are more likely to be noise-dominated and yield unreliable heights. In addition, we masked land and near-coast pixels where SWOT retrievals are known to be less reliable, and discarded extreme outliers. The cleaned Unsmoothed WSE fields were saved as NetCDF outputs for each pass, and these per-pass Unsmoothed products (16 in total for 2023) formed the observational dataset used in model comparisons. Because HR products were not available for this area during the study period, working with the Unsmoothed LR files and leveraging Expert corrections was the most direct way to get higher-resolution, geoid-referenced WSE maps for lagoon-scale validation.

3 HYDRODYNAMIC MODEL PERFORMANCE

To evaluate model performance, we compared modeled water surface elevation with SWOT observations for 16 passes over Langebaan Lagoon during the 2023 simulation period. For each pass, we interpolated the model results from the unstructured mesh onto the corresponding SWOT grid coordinates so that the comparison was spatially consistent. This made it straightforward to compare maps, time snapshots, and point by point statistics. Our sensitivity tests showed that the model was most sensitive to bottom roughness. We used the Chézy friction formulation (Chézy, 1775) and tuned the Chézy coefficient by iterating model runs and comparing to SWOT. After trying a range of values we found that a Chézy coefficient of 57 $m^{1/2}/s$ produced the best overall agreement with the SWOT observations, so that value was used in the final simulations.

Figure 6 shows three example comparisons between model and SWOT for different acquisition dates. For the September 1 overpass, the spatial pattern was consistent between the model and SWOT. Water levels in the offshore area were about -0.2 to -0.4 meter and the southeast end of the lagoon fell to roughly -0.9 meter in both datasets. On November 24 the bay showed higher water levels, roughly 0.3 to 0.4 meter in Saldanha Bay, with lower values near the southeast lagoon around -0.1 meter. SWOT reported slightly higher elevations in the bay, up to 0.5 meter, whereas the model peaked near 0.3 meters. For the December 15 pass, the model showed water levels of about -0.3 to -0.2 meters in the bay and higher values toward the southeast lagoon near zero meter. SWOT captured the same pattern but with slightly higher values in the lagoon, up to about 0.1 meters. We also show scatter plots for these three passes and computed standard metrics to quantify agreement. The RMSEs were 0.07 m, 0.07 m and 0.05 m, and the corresponding R-squared values were 0.64, 0.53 and 0.54 for September 1, November 24 and December 15, respectively. Taken together, these results indicate that the model reproduces the main spatial patterns and timing seen by SWOT and performs well for lagoon-scale validation. Figure 7 shows the scatter plot of collocated model versus SWOT water surface elevations for all 16 passes. The scatter showed a clear relationship between the two datasets. The overall statistics were $R^2 = 0.61$ and RMSE = 0.11 m across all passes. The model explained most of the observed variance in the offshore area, inside the bay and at the lagoon. Typical average point differences were of the order of less than 10 centimeters, which was small ($\sim$7%) relative to the system tidal range ($\sim$1.5 m).

4 DISCUSSION

4.1 Bathymetry uncertainties

Bathymetry derived from ICESat-2 ATL24 and Sentinel-2 inevitably has non-negligible uncertainty. Early validation studies of ICESat-2 bathymetry showed typical errors on the order of a few tenths of a centimeter to about a meter depending on return quality and local conditions (Parrish et al., 2019, 2025), so ATL24 cannot be treated as a perfect ground truth set at this location. Machine-learning approaches that combine ATL24 seed points with Sentinel-2 reflectance have proven effective at extending along-track depths into full maps, and recent studies reported satellite derived bathymetry errors typically in the 1 m ± 0.5 m range for comparable coastal environments, with a few examples reaching lower RMSEs when seed points were abundant and water clarity was high (Xu et al., 2023). In the case of the Langebaan Lagoon's

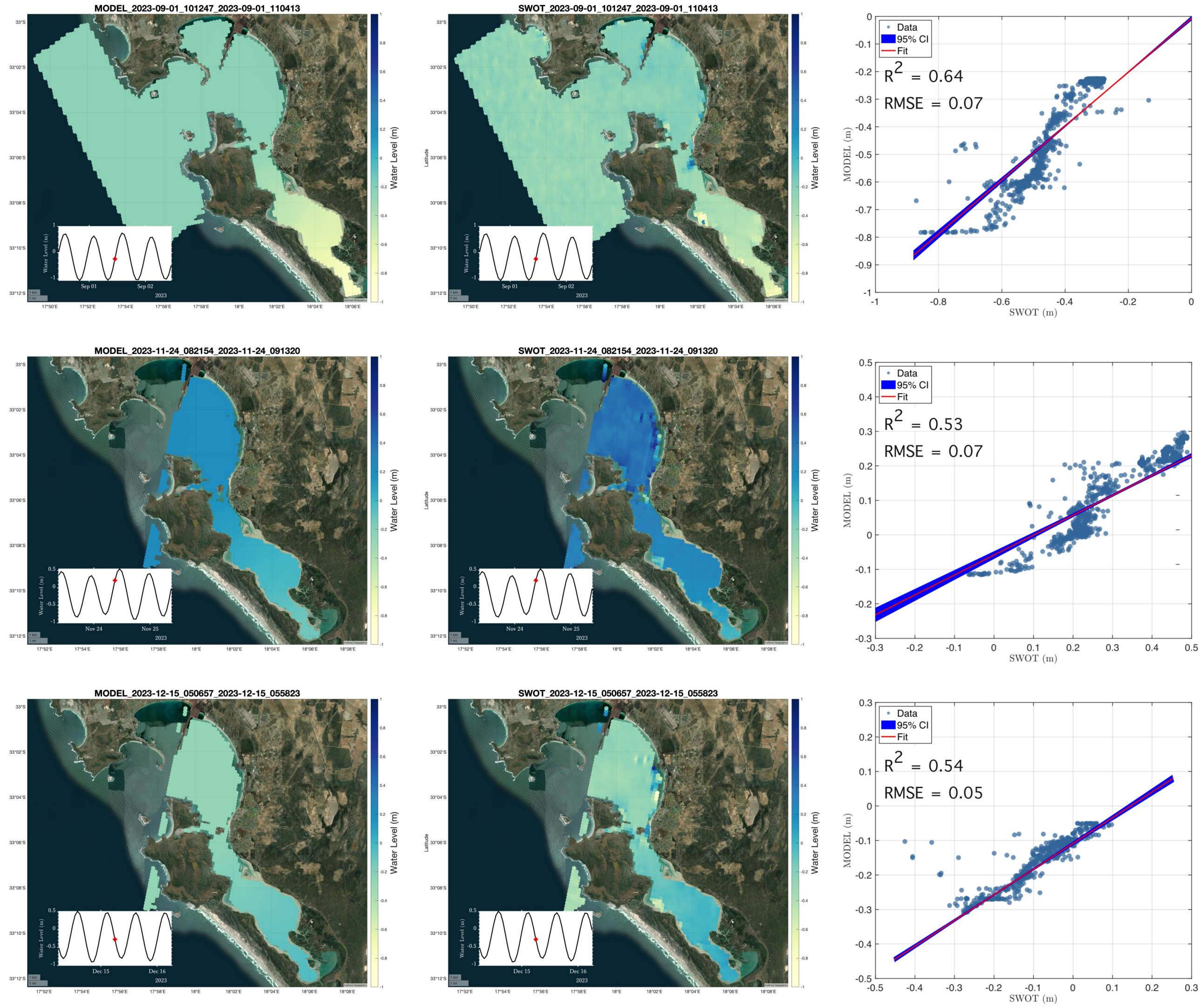

Figure 6. Comparison of modeled water surface elevation and SWOT observations for three acquisitions over Langebaan Lagoon. Maps show spatial patterns from the model (left) and SWOT (center), with corresponding scatter plots (right). Results are shown for September 1, November 24, and December 15, 2023 passes. Scatter plots include regression fits and performance metrics (RMSE and R^2)

analysis, the XGBoost model tuned with Bayesian optimization reproduced ATL24 itself with RMSE = 0.45 m and R^2 = 0.97, which is comparable but must be interpreted carefully: that error is relative to ATL24, not to independent sonar or Light Detection and Radar (LiDAR) surveys.

Depths in the Langebaan Lagoon ranges from near 1 m on tidal flats to about 40 m offshore according to regional charts and local studies of Saldanha Bay (Du Toit et al., 2022), so a fixed vertical error of a few decimeters has very different meaning across the lagoon. It is negligible in deep channels but potentially large relative to intertidal flats and shallow channels, where a 0.45 m error is a large fraction of depth. In addition, optical limits and turbidity remain a hard constraint: Sentinel-2-based bathymetry loses sensitivity as water clarity decreases and as depths approach the optical penetration limit, and several evaluation studies have shown rapidly increasing errors in turbid or deep zones (e.g., Wei et al., 2024). Therefore, our deeper offshore (∼35–40 m) areas are at the edge of optical penetration, while shallow lagoon (¡8 m)

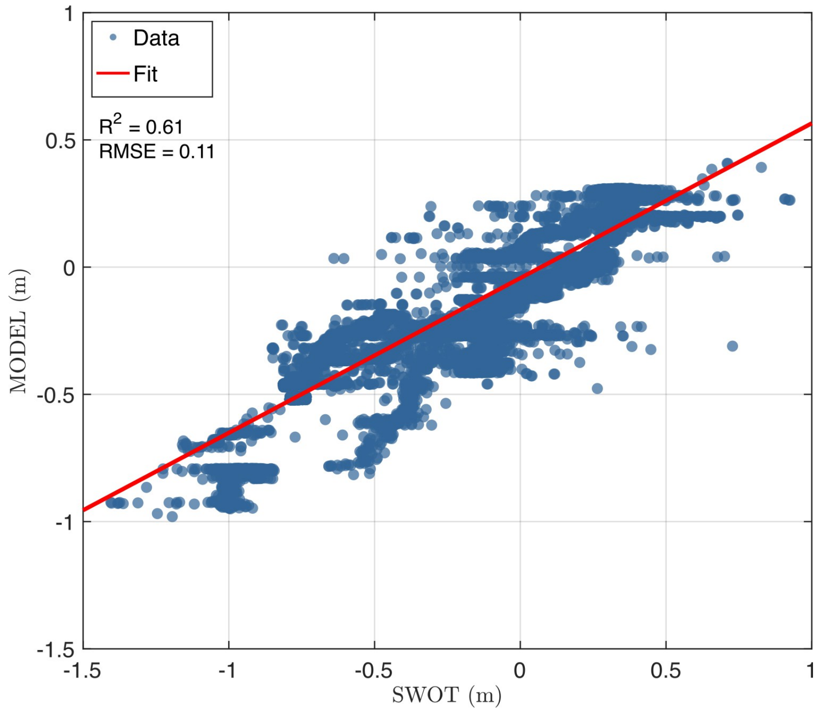

Figure 7. Scatter plot of collocated model versus SWOT water surface elevations for all 16 passes

zones are more reliably measured. However, in very shallow water ICESat-2 itself can underestimate depth when surface and bottom signals blur.

Uncertainty in the bathymetry translates directly into uncertainty in the hydrodynamic simulations. The modeling literature shows repeatedly that tidal amplitudes, phase propagation, local current speeds and inundation footprints are all sensitive to bathymetric detail; even modest vertical errors or smoothed small-scale features can change flow convergence, dissipation, and the local tidal prism (Cea and French, 2012). In our simulations, a 0.4–0.5 m typical bathymetry error (relative to ATL24) was small compared to the 30–40 m offshore depths but could produce sizeable relative changes in the shallow channels and flats where frictional effects matter most. Practically, this meant that some of the scatter against SWOT inside the lagoon could be traced to local depth mismatches rather than to fundamental failings of the hydrodynamic solver. It also explained why bottom friction tuning (the Chézy coefficient) had a strong leverage on fit metrics, i.e., calibration partly compensated for residual depth errors.

4.2 Boundary Condition Uncertainties

Global harmonic solutions such as TPXO are practical and easy to use as open boundary conditions because they give amplitudes and phases for the main tidal constituents everywhere and are widely validated against altimetry and tide gauges (Egbert and Erofeeva, 2002; Stammer et al., 2014). At the same time, several studies have shown that global models lose accuracy close to complex coastlines and in shallow, semi-enclosed seas where local bathymetry and resonance effects matter (Stammer et al., 2014; Zaron and Elipot, 2020; Gregg et al., 2024). Typical errors reported in regional evaluations are on the order of a few to a few tens of centimeters for the dominant constituents, although the exact value depends on local geometry and the quality of coastal bathymetry used in the global inversion (Stammer et al., 2014; Zaron and Elipot, 2020).

In this study, the model open boundary was forced with TPXO tidal harmonics. That makes it important to check how TPXO and SWOT agreed at the offshore boundary, because the boundary, located about 7 km seaward of the bay mouth and about 17 km from the lagoon mouth, so the boundary was reasonably close to the region of interest and could therefore transmit any bias into the domain. To assess the agreement, we reconstructed a TPXO tidal time series at the boundary and overlaid the collocated SWOT height points (Figure 8). For most passes, the SWOT points fell close to the TPXO curve, indicating good agreement, but the December 14 pass was a clear outlier, showing 0.42 m lower water level than the TPXO reconstruction. For other passes, differences between SWOT and TPXO ranged from 0.03 to 0.2 m. A scatter plot of all paired TPXO and SWOT values is shown in Figure 9. The two datasets were well correlated with $R^2 = 0.86$, although the RMSE was about 0.18 m.

To check whether part of the mismatch came from a timing offset rather than amplitude errors, we also ran a simple lag–correlation analysis between SWOT and the hourly TPXO time series at the boundary (Figure 10). We interpolated TPXO sea surface height to the SWOT pass times while scanning lags from -10 to +10 hours in 1 minute steps. The correlation decreased smoothly from about 0.6 at -10 hours lags to a minimum of -.95 in about -6 hours and then increased smoothly to a maximum of 0.98 when TPXO was shifted by roughly +26 minutes relative to SWOT, and then declined again for larger positive lags. At this optimal lag the RMSE reached its minimum, about 0.11 m, compared with about 0.18 m at zero lag. This pattern indicates a small phase offset between TPXO and SWOT, with a modest residual mismatch that remains even after the timing is corrected. Overall, the analysis suggests that TPXO provides a physically coherent boundary tide, and that part of the SWOT–TPXO difference is attributable to timing while the remainder likely reflects amplitude differences or other non-tidal errors rather than a fundamental problem in TPXO's tidal shape.

Another factor to consider is that TPXO supplies only the astronomical tide signal and cannot represent subtidal or supertidal variations, baroclinic effects, or short lived meteorological surges unless those are adjusted at the boundary. A practical way to handle this is to set up a local model inside a larger regional one. The regional model can be forced by TPXO tides at its boundary and by winds at the surface, so it captures both tidal and non-tidal variations. The local model would then take its boundary from the regional one, which helps smooth out the remaining errors and gives a more realistic signal near the coast.

4.3 Using SWOT for Model Calibration and Validation

SWOT's unique advantage is its two-dimensional mapping of sea surface height, which provides dense, high resolution coverage across the land–ocean continuum, including estuaries and bays, that were previously data scarce. These data can improve calibration and validation of hydrodynamic models by filling in the spatial gaps between sparse tide gauges or in situ sensors. In particular, SWOT LR (Low-Rate) data delivers sea surface height on a 250 m grid with minimal smoothing (unsmoothed), which makes it well suited for model validation in shallow coastal areas. In our study we likewise used the Unsmoothed LR product (250 m resolution) to validate the model.

Recent field studies confirm that bias-corrected SWOT SSH (LR or HR) agrees closely with both gauges and model outputs in coastal systems. For example, Lichtman et al. (2025) evaluated SWOT LR in the hyper tidal Severn Estuary (UK) against water level gauges and found very low error: the bias corrected LR sea surface height had an RMSE of only $\sim$0.14 m from gauges, with a nearly 1:1 linear relationship. In another study, Hart-Davis et al. (2024) used SWOT Cal/Val orbit data data in the Bristol Channel (UK) and showed that the principal tidal amplitudes derived from SWOT matched gauge measurements to within $\sim$0.018–0.03 m (amplitude errors of $\sim$1.8–3.0 cm) and 1.75°–2.75° in phase. In a tropical estuary, Diouf

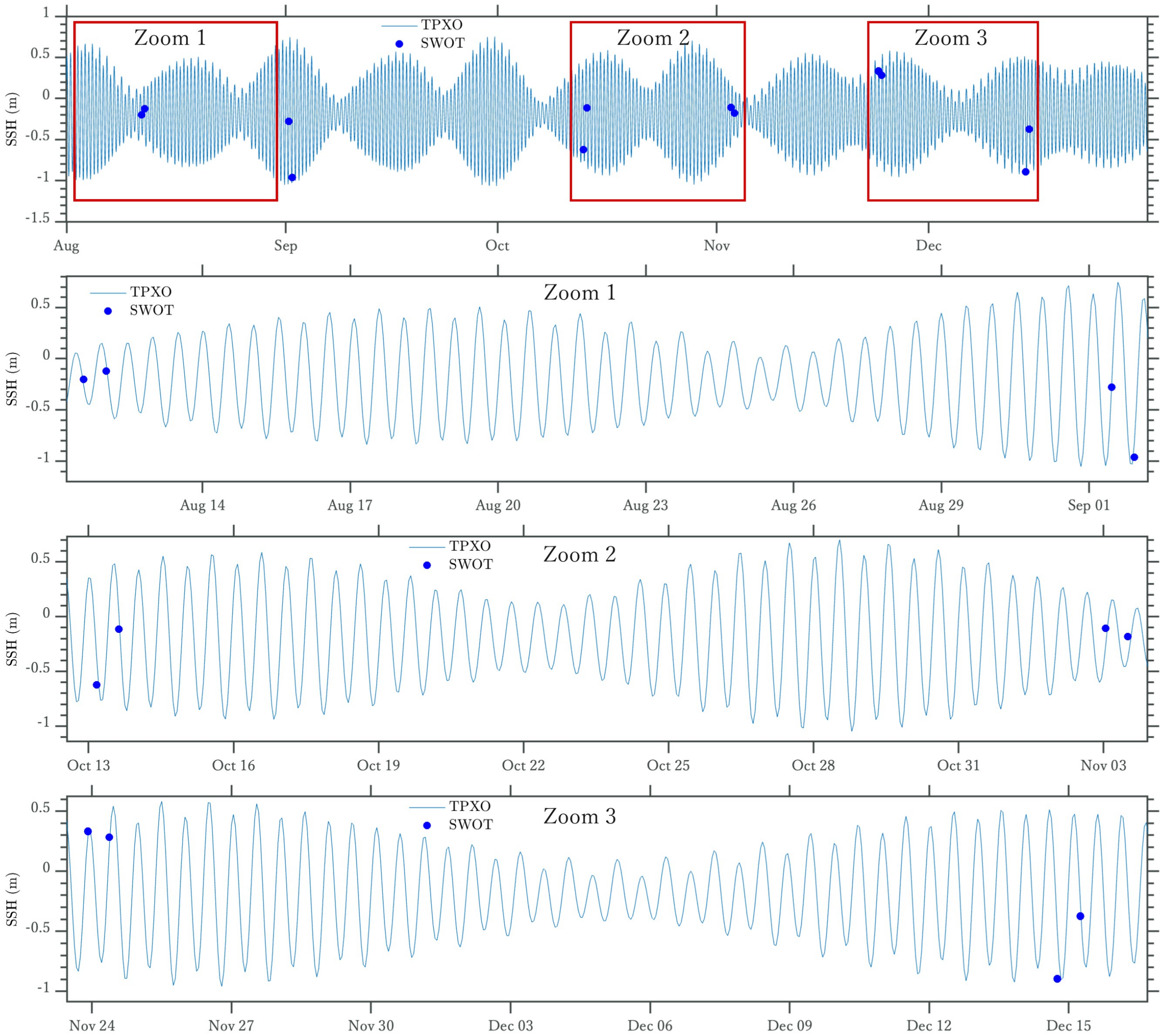

Figure 8. Comparison between TPXO-reconstructed sea surface height time series and SWOT sea surface heights for 16 passes along the model open boundary

et al. (2025) compared SWOT SSH (from high-rate (HR) pixel clouds) with a Delft3D hydrodynamic model in Senegal's Casamance Estuary: the SWOT data and model agreed very well in the main channel (correlation R $\sim$ 0.90, RMSE $\lesssim$ 0.25 m) but showed larger scatter in narrow side channels (R $\sim$ 0.42, RMSE up to $\sim$ 0.34 m). Likewise, Arildsen et al. (2025) used unsmoothed high-rate SWOT SSH in the Bristol Channel and found that the SWOT data captured the Severn tidal bore and associated waves with high accuracy, even in intertidal zones; they emphasize that minimal smoothing is required to preserve these fine features.

These results imply that SWOT LR altimetry, once properly bias-corrected, provides reliable validation of coastal models. In line with these studies, our own model comparison with SWOT showed close agreement: the LR SSH differences between the model and SWOT are on the order of a few decimeters and the regression slope is near unity. In other words, the metrics we obtain (correlation and RMSE) are comparable to those reported above. Table 3, summarizes several recent SWOT calibration/validation studies, the

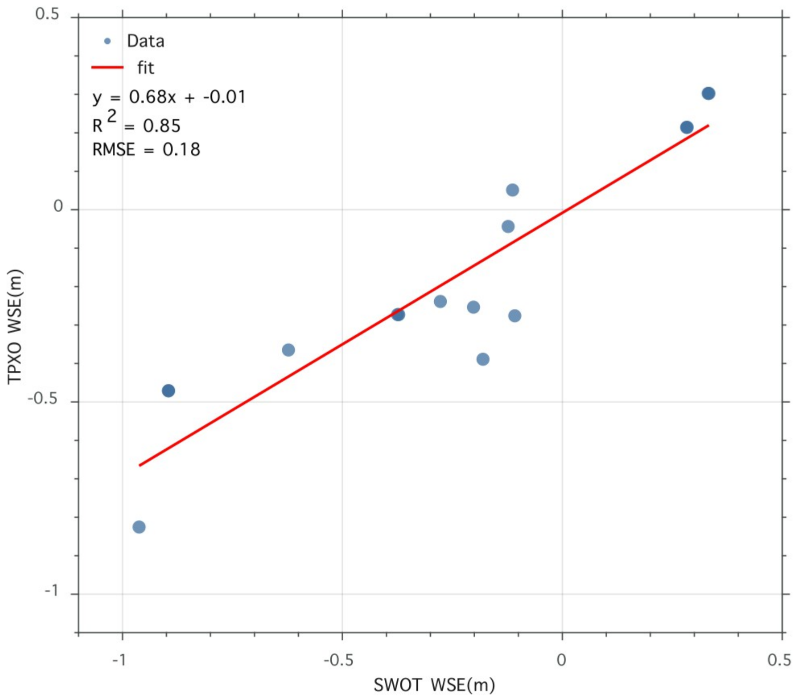

Figure 9. Scatter comparison between TPXO-reconstructed and SWOT observed sea surface heights at the model boundary for 16 satellite passes.

Table 4. Summary of selected studies using SWOT altimetry to calibrate or validate hydrodynamic models or tidal predictions. Domains range from open coast and estuaries to large rivers, and products include low-resolution (LR) and high-rate (HR) SWOT data. All report strong agreement between SWOT SSH and reference data, illustrating SWOT's utility for coastal model validation.

Study (ref)	Domain	SWOT Data	Compared To	Validation Metrics
Lichtman et al. (2025)	Severn Estuary, UK (hyper-tidal)	LR SSH (250 m, unsmoothed)	Tide gauges (water level)	RMSD $\approx$ 0.14 m; regression slope $\approx$ 0.99
Hart-Davis et al. (2024)	Bristol Channel and Great South Bay	HR SSH (KaRIn, 1-day Cal/Val)	Tide gauges (tidal analysis)	Tide amplitude error $\approx$ 0.018–0.03 m; phase error $\approx$ 1.8°–2.8°
Diouf et al. (2025)	Casamance Estuary, Senegal	HR SSH (pixel cloud)	Delft3D model	Main channel: $R \approx 0.90$, RMSE $<$ 0.25 m; Tributaries: $R \approx 0.42$, RMSE $\leq$ 0.34 m
Arildsen et al. (2025)	Severn River (Bristol Channel)	HR SSH (L2HR pixel cloud)	Two tide gauges	3.7 and 9.8 cm

environments they cover, the SWOT product used, and the key statistics (e.g., RMSE, correlation) that quantify model vs agreement with gauge observations. All of these studies that range from open ocean and tidal basins to estuaries, inland aquatic lacustrine systems and rivers, demonstrate the value of SWOT's 2D sea surface height for improving and validating hydrodynamic simulations in the coastal zone.

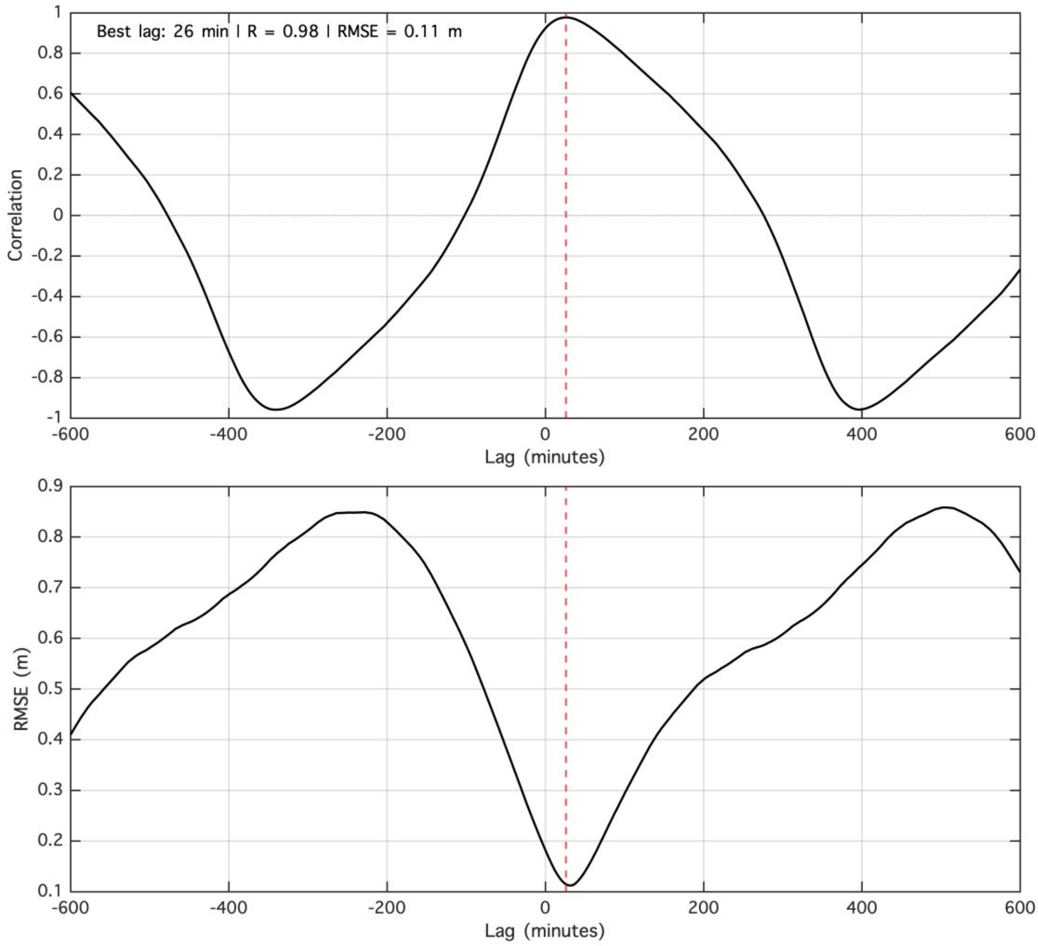

Figure 10. Cross-correlation analysis between SWOT and TPXO WSE time series at the offshore boundary. The upper panel shows the correlation coefficient as a function of temporal lag, and the lower panel shows the corresponding RMSE.

5 CONCLUSION

This study shows that it is possible to build and validate a hydrodynamic model in a coastal lagoon without using any local field measurements. By combining satellite bathymetry from ICESat-2 and Sentinel-2 with a machine-learning approach, we were able to derive a spatially continuous bathymetry map for the Langebaan Lagoon. The XGBoost model optimized with Bayesian optimization captured the bathymetric variability from offshore depths to shallow lagoon channels, matching independent ATL24 data with an RMSE of 0.45 m and an R^2 of 0.97. Using tidal harmonics from TPXO for the boundary and atmospheric forcing from ERA5, the model reproduced the water surface patterns inside the lagoon. Validation using SWOT water level observations confirmed that the model results were consistent with satellite measurements across 16 passes, with an overall RMSE of 0.11 meters and an R^2 of 0.61. SWOT's wide swath data allowed us to look beyond a single comparison point and instead evaluate spatial patterns across the entire lagoon. This greatly increases confidence in model performance, especially in places where in situ gauges are limited or do not exist. Although uncertainties remain, particularly from optical limitations in bathymetry and offsets between TPXO and SWOT at the boundary, the overall results demonstrate that remote sensing can support impressively accurate coastal hydrodynamic modeling in locations where direct measurements are not available. A key strength of this framework is that it integrates complementary remote sensing observations from passive optical sensors (Sentinel-2), spaceborne LiDAR (ICESat-2), and radar interferometry (SWOT), which reduces reliance on any single instrument and makes the approach more robust and transferrable.The approach presented here is therefore transferable to other data-scarce regions and offers a path toward cost-effective monitoring that does not depend on continuous field campaigns. With additional SWOT cycles and the release of more HR inland water level products, our method could be extended to narrower channels and more confined coastal systems, where finer spatial detail matters. Beyond water levels, the hydrodynamic model can be expanded into a coupled sediment/vegetation model, and future research can explore how satellite observations and global datasets can replace or supplement field inputs that such coupled models traditionally depend on.

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

ARP designed the study, developed the remote sensing–driven hydrodynamic modeling framework, processed ICESat-2, Sentinel-2, and SWOT datasets, performed model parametrization and simulations, and led the analysis and manuscript writing. MS supervised designing the study, the overall research, supported the conceptual development of the satellite-based modeling approach, supervised the SWOT, TPXO and ERA5 integeration into the model, and contributed to manuscript writing and revision. ADC and DJ provided technical insights on ICESat-2 data integration and contributed to methodological refinement and manuscript editing. HVD contributed local environmental expertise, contextual interpretation of South African wetland dynamics, and manuscript revision. AC contributed to SWOT data downloading, and manuscript revision.

All authors reviewed and approved the submitted version and agreed to be accountable for the content of this work.

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DATA AVAILABILITY STATEMENT

All datasets used in this study are publicly available. ICESat-2 ATL24 products were obtained from the NASA National Snow and Ice Data Center (NSIDC). Sentinel-2 multispectral imagery was accessed through the Copernicus Open Access Hub. SWOT water surface elevation data were acquired from the NASA PO.DAAC. ERA5 atmospheric reanalysis products were retrieved from the European Centre for Medium-Range Weather Forecasts (ECMWF) Climate Data Store. All data sources and access links are cited in the manuscript.

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