



SWOT-initialized reservoir operation forecasting: Validation in data-rich and application to data-limited regions

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Abstract. Challenges in reservoir operation are posed by the fact that reservoir release trajectories depend on both uncertain inflow forecasts and (in cases where in situ observations are not available) imperfect knowledge of the initial reservoir state. The recently launched (science data available since late 2023) Surface Water and Ocean Topography (SWOT) satellite provides global-scale reservoir water level and surface extent observations, creating new opportunities to constrain reservoir storage states for forecast initialization. Here we develop a SWOT-initialized reservoir operation forecasting framework and evaluate it both for two data-rich California reservoirs and a data-limited reservoir in Ethiopia. The operations framework combines SWOT-derived reservoir storage, monthly inflow forecasts, a reservoir operation model, and a downstream agricultural water demand-satisfaction assessment. Results from California reservoirs show that SWOT-derived storage provides useful initial conditions for seasonal reservoir operation forecasts (similar to those available based on in situ data), with water demand satisfaction approaching that obtained using in-situ storage initialization. The resulting storage and release forecasts capture the major seasonal dynamics. Although Ensemble Streamflow Prediction (ESP) (developed using historic observed reservoir inflows) generally provides more accurate inflow and reservoir-operation forecasts, a global reservoir inflow product (GloFAS) produced without local observations yields water demand satisfaction patterns that are broadly consistent with the in situ results. Application of the framework to the African reservoir (where essentially no in situ observations are available) demonstrates that, for the two years of SWOT data, nominal irrigation water demands are generally satisfied.

1. Introduction

Reservoirs play a critical role in water-resources management by regulating streamflow, which in turn assures the reliability of municipal and agricultural water supply, mitigates floods, and supports in-stream environments (Ahmad et al., 2014; Yan et al., 2024). In the western United States (WUS), reservoirs are particularly important because water availability is strongly seasonal, interannual variability is large, and droughts and atmospheric-river events can create rapid transitions between water scarcity and floods (Dettinger and Anderson, 2015; Spinti et al., 2023). Reservoir operators therefore rely on forecasts of future inflow, storage, and release over time scales ranging from days to seasons (e.g., Kim et al., 2022; McGuire et al., 2006; Özdoğan-Sarıkoç et al., 2023; Sushanth et al., 2023). Such forecasts can inform reservoir release planning, drought preparedness, flood control, and water allocation decisions (Delaney et al., 2020; Zanutto et al., 2025), but their usefulness depends on the quality of reservoir inflow and storage forecasts.

Reservoir storage forecast errors arise from two primary sources. The first is uncertainty in future inflow, which reflects uncertainty in meteorological forcing, runoff generation, snowmelt, and upstream flow conditions



(Rahmanifard and Gates, 2024). The second (important in cases where in situ data are not available) is uncertainty in the initial reservoir storage state, which constrains the subsequent storage and release trajectory (Tian et al., 2022). Initial-storage errors can dominate storage forecasts at short lead times, whereas accumulated inflow uncertainty dominates as forecast lead time increases (Yang et al., 2021; Zhao et al., 2011). A useful reservoir forecasting system must therefore distinguish the contribution of initialization error from the contribution of inflow forecast error and evaluate how both propagate into operationally relevant release forecasts.

In the developed world, reservoir stage (water level) usually is measured with in situ stage recorders. In combination with bathymetric surveys, the stage information is used to produce stage-storage relationships, so real-time or near real-time stage measurements can be converted to storage. Under these conditions, the largest source of storage errors are errors in bathymetry, which generally increase over time due to reservoir sedimentation. Alternatively (and of special importance in transboundary rivers where in situ stage information may not be available to downstream water users) satellite remote sensing provides an opportunity to estimate reservoir storage (e.g., Sentinel-1: Torres et al., 2012; Sentinel-2: Drusch et al., 2012; SWOT: Biancamaria et al., 2016). The recently launched Surface Water and Ocean Topography (SWOT) mission (data available from mid-2023 on) represents a major advance in satellite hydrology by providing, for the first time, spatially extensive and simultaneous observations of reservoir water-surface elevation (WSE) and surface extent, enabling consistent estimation of storage and storage changes for lakes and reservoirs in data-sparse regions (Fu et al., 2024). As we have shown in previous work (Ma et al., 2026) SWOT observations can produce reservoir storage estimates with useful accuracy for medium and large reservoirs.

Existing studies have advanced satellite-based reservoir storage estimation (e.g., Gao et al., 2012; Ma et al., 2026), streamflow forecasting (e.g., Maddu et al., 2022; Yang et al., 2019), and state updating in reservoir systems (e.g., Iglesias et al., 2013; Zhang et al., 2021). Nevertheless, most satellite-reservoir studies emphasize historical monitoring or storage reconstruction rather than reservoir-operation forecasts. In addition, storage accuracy alone does not establish whether a forecast is useful for water management: inflow (forecast) errors strongly affect reservoir storage forecasts, and reservoir releases (which determine whether downstream water demands are likely to be met) are strongly affected by reservoir storage errors which in turn are depending on inflow forecasts. A remaining need is therefore to connect satellite-derived storage initialization with seasonal inflow forecasts, reservoir operation modeling, and demand-oriented evaluation in a single transferable workflow.

Here, we address the above need by developing a SWOT-initialized reservoir operation forecasting framework, which we initially apply to two data-rich WUS reservoir systems, and then to a data-poor reservoir in the Ethiopian Highlands. In the data-rich WUS cases, monthly forecasts are made on regular forecast dates (e.g., the first of each month) rather than only on SWOT overpass dates. For each forecast date, we propagate the most recent SWOT-derived storage to the next forecast date with observed inflows using the Hanasaki reservoir operation model (Hanasaki et al., 2006). The resulting storage serves as the SWOT-based initial condition. Future inflows come from two seasonal forecasting approaches: locally derived Ensemble Streamflow Prediction (ESP) and the globally available Global Flood Awareness System (GloFAS) seasonal forecasts. The Hanasaki model converts these inflow scenarios into storage and release forecasts, which we evaluate relative to observations and downstream water-use demands.

The WUS reservoirs provide a controlled evaluation environment given that in-situ storage, inflow, and release observations are available for comparison. Our broader purpose, however, is transfer the methods to data-limited settings in which satellite storage and global inflow forecasts may be available even when continuous (in situ) reservoir observations are not. This study is organized around one overarching question: can SWOT-derived reservoir storage enable reservoir operation forecasting that informs downstream water-management decisions, especially in regions with limited in-situ observations? We address this question through four linked components: the accuracy of SWOT-based initialization, the performance of seasonal inflow forecasts, the propagation of those



85 uncertainties into storage and reservoir releases, and the ability of forecasted releases to meet agricultural water
86 demands (which is the primary water use in all three case studies).

87 2. Study Areas

88 2.1 Data-rich validation reservoirs: BUL and DNP

89 We first evaluate our water management framework at two well-observed reservoirs in the WUS: New Bullards Bar
90 Reservoir (BUL; Figure 1a) and Don Pedro Reservoir (DNP; Figure 1b). Both reservoirs drain the west slopes of
91 California's Sierra Nevada (see Figure X) and have sufficiently complete in-situ storage, inflow, and reservoir
92 release records to evaluate our reservoir storage and release forecast framework. The contrasting reservoir storage
93 capacities and operating settings across the three sites provide complementary validation cases for assessing the
94 forecasting framework.

95 BUL is located on the North Yuba River and has a maximum storage capacity of approximately 1,192 million m³
96 (Mm³). DNP is located on the Tuolumne River and is substantially larger, with a maximum storage capacity of
97 approximately 2,504 Mm³ (Ma et al., 2026). During the SWOT analysis period, both reservoirs reached more than
98 95% of their reported maximum storage capacities and exhibited pronounced seasonal filling and drawdown. These
99 conditions provide observations spanning reservoir filling, near-full storage, and drawdown and therefore support
100 evaluation of both initialization error and inflow-driven forecast error. We calculated reservoir storage-to-inflow
101 ratios from the in situ maximum storage capacity and mean annual inflow for each reservoir. Although the ratios
102 vary among reservoirs, all are well below 1.0, indicating limited interannual storage memory and suggesting that
103 reservoir operations are dominated by within-year rather than over-year regulation.

104 Because extensive in situ observations are available for BUL and DNP, they are used to evaluate the SWOT-
105 informed reservoir forecasting framework before its transfer to the data-limited setting. The DNP and BUL in-situ
106 records allow the SWOT-based initial storage state to be compared with observed-storage on each forecast issue date
107 and permit evaluation of forecasted inflow, storage, and release. This controlled validation is necessary before
108 applying the framework where equivalent observations are sparse.

109

110 2.2 Data-limited application: Tendaho Reservoir

111 Tendaho Irrigation Reservoir in the Lower Awash Basin, Ethiopia (Figure 1c), is used to demonstrate transfer of the
112 validated workflow to a data-limited setting. Tendaho is an irrigation-focused reservoir for which continuous storage
113 observations, detailed release records, and operating-rule information are more limited than for the WUS reservoirs.
114 At the same time, SWOT observations, historical inflow information, and project-scale irrigation-demand estimates
115 are available. Tendaho is therefore treated as a transfer application rather than as an equally data-rich validation
116 experiment.

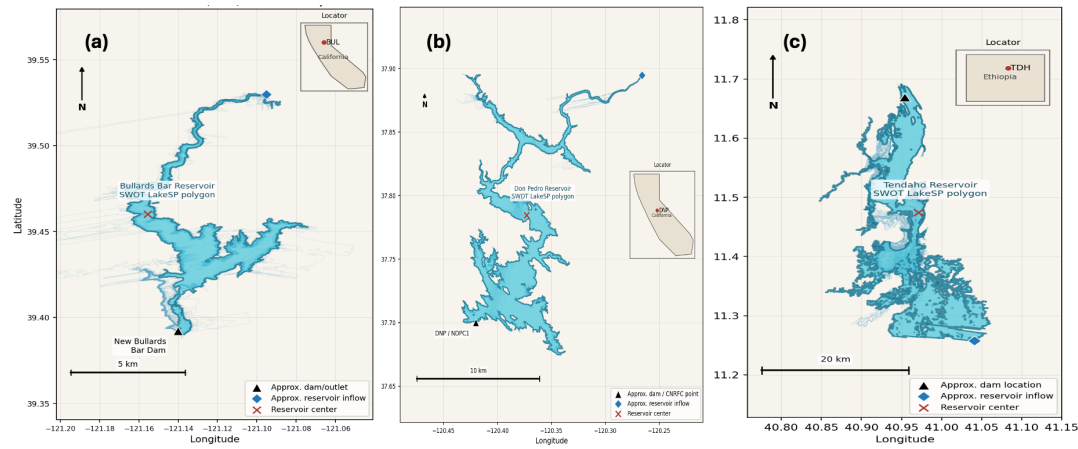


Figure 1. Study reservoirs and associated SWOT LakeSP (lake single pass) polygons: (a) New Bullards Bar Reservoir, California, USA; (b) Don Pedro Reservoir, California, USA; and (c) Tendaho Reservoir, Ethiopia. Symbols indicate the approximate dam/outlet location, reservoir inflow location, and reservoir center. Insets show the regional location of each reservoir.

3 Data

Our analysis combines four categories of data: SWOT observations of reservoir water-surface elevation and area; in-situ reservoir observations (BUL and DNP only) used for validation; seasonal reservoir inflow forecasts; and reservoir attributes and agricultural water-demand information used for reservoir modeling and demand-satisfaction assessment. The western U.S. reservoirs BUL and DNP provide relatively complete observational benchmarks, whereas the Tendaho application relies primarily on SWOT observations, globally available reservoir inflow forecasts, and limited historical and project-level information.

3.1 SWOT LakeSP observations

The SWOT Level 2 Lake Single-Pass Vector Data Product, Version D (LakeSP) product (NASA/JPL PO.DAAC, 2026) provides reservoir water-surface elevation (WSE) and surface area. We derived reservoir storage by adapting the reference-based framework of Ma et al. (2026). For each reservoir, we selected the maximum quality-controlled WSE observed during the SWOT science phase (August 2023–present) as the reference WSE and assumed that it represented the full-capacity condition. We used the corresponding reference storage in lieu of the reported design maximum storage capacity (e.g., from the Global Reservoir and Dam Database (GRanD)). We then estimated storage for each quality-controlled SWOT observation by calculating the storage change relative to this reference point from the difference between the observed and reference WSEs, multiplied by the corresponding SWOT surface area, and adding this change to the reference storage. Unlike the approach in Ma et al. (2026), this method does not require a paired in situ WSE–storage observation and therefore facilitates application in data-limited regions where reservoir observations are sparse or unavailable.

Following Ma et al. (2026), we excluded SWOT observations with insufficient reservoir spatial coverage or degraded quality. For each retained overpass, we estimated reservoir storage relative to a reservoir-specific reference WSE–storage pair using the quality-controlled SWOT-observed WSE and the corresponding SWOT-observed surface area from the SWOT LakeSP product. We used the observed surface area together with the change in WSE



to estimate the storage change from the reference condition (defined by pairing the maximum quality-controlled SWOT WSE observed during the science phase with the reported maximum storage capacity of each reservoir). No SWOT-based storage estimate was produced for overpasses that failed the quality-control criteria. We then used the resulting irregularly spaced (in time) storage estimates as satellite-derived initialization anchors, as described in Section 4.3.

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153 3.2 In situ reservoir observations

In situ observations provide the benchmark for our WUS validation experiments. We obtained daily or near-daily WSE, storage, inflow, and release records from the Yuba Water Agency for New Bullards Bar Reservoir (BUL) and from the U.S. Bureau of Reclamation (USBR) for Don Pedro Reservoir (DNP) (Ma et al., 2026). The reference storage values used to evaluate SWOT-derived storage are distinct from the daily in situ storage records used to construct the observed-storage initialization benchmark and to evaluate storage and release simulations from the Hanasaki reservoir model. We also used the in situ inflow records to evaluate the seasonal inflow forecasts.

We expressed all reservoir storage values as absolute storage so that SWOT-derived, propagated, simulated, and observed storage states (see Section 3.1) can be compared directly. In so doing, the underlying assumption is that each reservoir approached its reported maximum storage capacity during the SWOT observation period. This assumption appears reasonable for the two California reservoirs because water years 2024 and 2025 were relatively wet and both reservoirs reached near-capacity conditions during this period.

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166 3.3 Seasonal inflow forecasts

We used two seasonal inflow forecast data sets for the WUS reservoirs. Ensemble streamflow prediction (ESP; Day, 1985) essentially resamples hydrometeorological conditions from the historic past to produce streamflow ensembles that are initialized with hydrologic storage (soil moisture and snow water equivalent) on each forecast date. In our case, we used the Noah-MP (Niu et al., 2011) hydrologic model, which we calibrated using historical hydrometeorological data including observed reservoir inflows for BUL and DNP to produce ESP forecasts. In addition, we used The Global Flood Awareness System (GloFAS) ensemble forecasts produced by ECMWF. GloFAS provides consistent seasonal streamflow forecasts initialized at regular monthly intervals (Alfieri et al., 2013; Emerton et al., 2018). We bias corrected the GloFAS inflow forecasts using correction relationships derived from historical GloFAS simulations and corresponding in situ inflow observations (see Figure S1 and Figure S2 in section S1).

For Tendaho, the only inflow forecasts available to us were from GloFAS (ESP was not feasible as we lacked the historical hydrometeorological data that it requires). We corrected systematic bias using historical in-situ inflow observations from the period 1970-2000, and we applied the resulting corrections to the seasonal GloFAS forecasts for the SWOT period (no streamflow observations were available during the SWOT period).

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182 3.4 Reservoir attributes and agricultural water-demand data

Reservoir-specific inputs include maximum storage capacity, elevation-storage information, mean annual inflow, and the demand characteristics required by the reservoir operation model. We fixed these attributes during the paired initialization and inflow-forecast experiments so that differences in forecast performance can be attributed to the initial storage source and inflow forecast source.



For BUL, we estimated mean annual downstream agricultural demand from California Department of Water Resources (DWR) county-level agricultural applied water estimates for Yuba County for water years 1998–2020 (California Department of Water Resources, 2024 a,b,c,d). For DNP, we estimated downstream agricultural demand from DWR WUEData Aggregated Farm-Gate Delivery records for Turlock Irrigation District (TID) and Modesto Irrigation District (MID) (California Department of Water Resources, n.d.; <https://wuedata.water.ca.gov/>). MID reports monthly farm-gate deliveries, whereas TID reports bimonthly deliveries; the bimonthly TID values were split evenly across the two months. Historical demand profiles were calculated from 2012–2023 TID+MID farm-gate deliveries.

We then allocated the annual totals across months using Spatial CIMIS reference evapotranspiration fractions (California Department of Water Resources, n.d.), calculated as each month’s reference evapotranspiration divided by the annual total. This approach assumes that the seasonal distribution of irrigation demand follows atmospheric evaporative demand. We estimated a month-specific agricultural release fraction as the ratio of ET-distributed irrigation demand to historical mean monthly release. We multiplied forecasted total release by this fraction to obtain a proxy for agricultural water demand. For Tendaho, we distributed annual project-scale irrigation demand (Ministry of Irrigation and Lowland. (n.d.). Tendaho Dam and Irrigation Development Project) seasonally using normalized monthly net irrigation requirement values reported by Shonka and Gullie (2017).

4 Methods

4.1 Forecasting framework and experiment design

The forecasting framework consists of four linked steps (Figure 2). First, quality-controlled SWOT WSE and surface area observations are converted to reservoir storage. Second, the most recent SWOT-derived storage is propagated to each regular forecast issue date (10th of every month) and used to initialize the Hanasaki reservoir operation model (Hanasaki et al., 2006). Third, ESP and/or GloFAS seasonal inflow forecasts are used to simulate future storage and release. Fourth, forecasts are evaluated against available observations, and forecasted release is compared with agricultural demand using a demand-satisfaction ratio. For BUL and DNP, paired experiments combined either observed or SWOT-based storage initialization with either ESP or GloFAS inflow. Tendaho used the same workflow but with (only) SWOT initialization, bias-corrected GloFAS inflow, and literature-based irrigation demand.

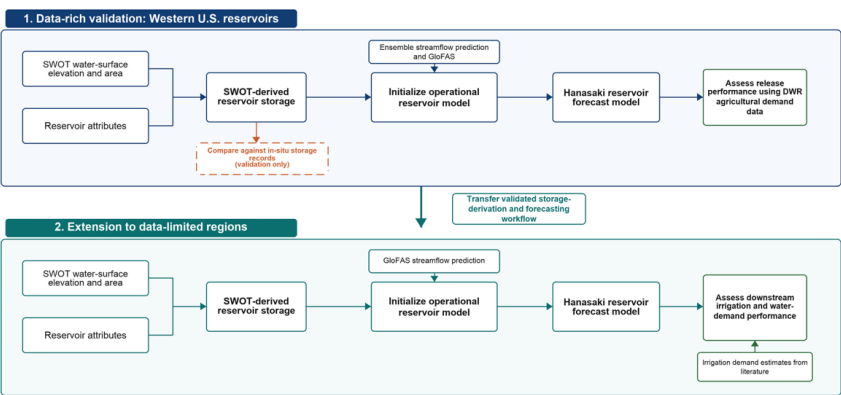


Figure 2. Conceptual framework for validating and transferring a SWOT-informed reservoir forecasting workflow from data-rich to data-limited regions.



218 4.2 Seasonal reservoir inflow forecasts

219 As noted above, we generated reservoir inflow forecasts at BUL and DNP using both ESP and GloFAS, and at
220 Tendaho using GloFASseasonal forecasts. ESP provides a locally configured ensemble of future inflow trajectories
221 by combining the modeled hydrologic state at each forecast issue date with meteorological forcing sequences
222 sampled from historical years. GloFAS provides globally consistent seasonal streamflow forecasts initialized at
223 regular monthly intervals, enabling reservoir inflow forecasting across regions worldwide, including basins where
224 locally configured forecasting systems are unavailable.

225 We generated ESP forecasts at BUL and DNO using the Noah-MP land-surface model (Niu et al., 2011) coupled
226 with the WRF-Hydro routing framework (Gochis et al., 2020). The model configuration follows the western U.S.
227 implementation described by Su et al., 2025 and Ma et al., 2026, including the land-surface parameterization,
228 routing-domain configuration, spatial resolution, and basin-specific setup used to simulate reservoir inflow. We
229 extracted simulated streamflow at the grid cells corresponding to the reservoir inflow locations and converted from
230 discharge to inflow volume for use in the reservoir operation simulations.

231 We obtained historical meteorological forcings for Noah-MP were from the 1-km continental United States forcing
232 dataset developed by Pan et al. (2025). The forcing variables include precipitation, near-surface air temperature,
233 surface pressure, downward shortwave radiation, downward longwave radiation, wind speed, and specific humidity.
234 The historical forcing record spans 1980 – current and is available at a temporal resolution of 1h. We used these
235 meteorological forcings to drive Noah-MP and WRF-Hydro for both the retrospective model simulations for water
236 years 2020 – 2022 (for spin up) and for the generation of ESP ensemble members during the forecast periods in
237 2024 and 2025 (see Section 3.3).

238 For each monthly forecast issue date, we first initialized the hydrologic model using the modeled land-surface and
239 routing states corresponding to that date. These states include soil moisture, snow water equivalent, groundwater or
240 subsurface storage, channel states, and other prognostic variables represented by the Noah-MP–WRF-Hydro system.
241 We then represented future meteorological uncertainty by replacing the unknown future forcings with
242 meteorological sequences drawn from individual historical years in the retrospective period 1980–2023. Each
243 historical forcing year is applied from the same forecast-date hydrologic state, producing one possible future inflow
244 trajectory. Therefore, for a given forecast cycle, all 44 ensemble members share the same initial hydrologic
245 conditions but differ in their subsequent meteorological forcing.

246 We used historical forcing sequences from 1980 to 2023 to generate 44 ESP ensemble members for each forecast
247 issue date. We initialized forecasts on 10th of each month and continued to the end of its water year (Sep 30th). We
248 aggregated the model outputs from the native 3-hourly to monthly inflow volumes. We summarized each ESP
249 ensemble using the ensemble mean, the interquartile range, and the 2nd–98th percentile range to represent forecast
250 uncertainty. We then used the same ESP inflow ensemble to force the reservoir operation model for the alternative
251 storage-initialization experiments. Specifically, we initialized reservoir simulations using either observed in-situ
252 storage or SWOT-derived storage, while the inflow ensemble and reservoir-model configuration were held constant.
253 This design allows the effect of initial-storage uncertainty to be evaluated separately from uncertainty in the future
254 inflow forecast.

255 We obtained GloFAS seasonal streamflow forecasts from version 4.0 of the GloFAS seasonal forecasting system
256 (Joint Research Centre and Copernicus Emergency Management Service, 2020). As for ESP, we initialized forecasts
257 on the 10th of each month. The GloFAS ensembles each contain 51 ensemble members and extend to a maximum
258 lead time of ~7 months. We extracted streamflow from the GloFAS grid cell located at or immediately upstream of
259 each reservoir inflow location. Where necessary, we converted discharge to reservoir inflow volume and aggregated
260 to the same temporal resolution used for the ESP forecasts.



For BUL and DNP, we first compared ESP and GloFAS forecasts with observed reservoir inflow. We then passed the two inflow products through the same reservoir operation model (Hanasaki) using identical reservoir parameters and storage-initialization alternatives. Because we held the forecast issue dates, reservoir-model configuration, and initial-condition experiments constant, differences in simulated storage, release, and demand-satisfaction performance can be attributed primarily to differences in inflow forecast quality.

For Tendaho Reservoir, an equivalent locally configured Noah-MP–WRF–Hydro ESP system was not available. GloFAS therefore provides the sole seasonal reservoir inflow forecast. We corrected systematic bias in GloFAS inflow using available historical in-situ inflow observations from 1980 to 2000. We based the bias-correction method on monthly means using the historical overlap period before being applied to the seasonal GloFAS forecasts. We then used the bias-corrected GloFAS ensemble to drive the same reservoir operation model applied in the western U.S. experiments. This configuration allowed the forecasting workflow to be transferred to a data-limited setting using SWOT-derived storage, a globally available seasonal inflow product, and limited historical information.

4.3 SWOT-based reservoir-storage initialization

The key methodological step in our forecast system is construction of a SWOT-based storage initial condition at each regular monthly forecast issue date, T_0 , which we took as the 10th of each month. Because SWOT overpass dates generally do not coincide with T_0 , we identified the latest valid SWOT-derived storage observation before T_0 and propagated forward with the reservoir operation model using ESP and GloFAS simulated inflow over the intervening period. The resulting state is referred to as the SWOT-initialized storage at T_0 .

We compared two initial-condition experiments for the WUS reservoirs. The benchmark experiment uses observed in-situ storage at T_0 , whereas the satellite-based experiment uses the propagated SWOT-derived storage at the same date. Both experiments use identical future inflow ensembles and identical parameters for the reservoir model. Their difference quantifies the effect of replacing contemporaneous in-situ storage with the SWOT-based initial state, including any error introduced while propagating the latest SWOT observation to T_0 .

This approach preserves a regular operational forecast schedule rather than restricting forecasts to SWOT overpass dates and is consistent with the monthly initialization schedule of GloFAS. Initialization effects are expected to be strongest near T_0 , whereas accumulated inflow uncertainty becomes increasingly important with lead time; however, reservoir storage memory may allow initial-state effects to persist.

4.4 Hanasaki reservoir operation model

We simulated reservoir storage and release with the Hanasaki reservoir operation model (Hanasaki et al., 2008). For each ensemble member, the model applies the reservoir water balance and operating rules to propagate the initialized storage under the forecast inflow trajectory. Reservoir-specific storage capacity, elevation-storage information, mean annual inflow, and demand or release characteristics are supplied where available, while the general model structure was unchanged across BUL, DNP, and Tendaho.

For each WUS forecast cycle, we ran the model for four combinations: observed-storage initialization with ESP inflow, SWOT-based initialization with ESP inflow, observed-storage initialization with GloFAS inflow, and SWOT-based initialization with GloFAS inflow. We simulated each ensemble member independently and summarized the resulting storage and release trajectories across members. Forecasts are issued monthly and continue through the available forecast horizon, up to the end of the water year where possible.



302 This factorial design separates the influence of the initial storage source from that of the inflow forecast source. At
303 Tendaho, we applied the same model sequence using SWOT initialization and bias-corrected GloFAS inflow, with
304 results interpreted in light of the more limited observational record.

305

306 **4.5 Forecast evaluation and agricultural demand-satisfaction assessment**

307 We evaluated forecast performance at the various inflow, storage, release, and agricultural-demand levels. We
308 compared Inflow forecasts with observed inflow by issue date and lead time. We evaluated storage forecasts relative
309 to observed storage Paired simulations quantify the effect of replacing observed-storage initialization with SWOT-
310 based initialization. We compared release forecasts with observed release where available. We assessed Water-
311 management relevance by directly comparing forecast-implied agricultural water supply with estimated monthly
312 agricultural demand. Forecasted supply below the demand estimate indicates a potential unmet-demand condition,
313 whereas supply above demand indicates that the estimated agricultural requirement could be met under the
314 forecasted release scenario.

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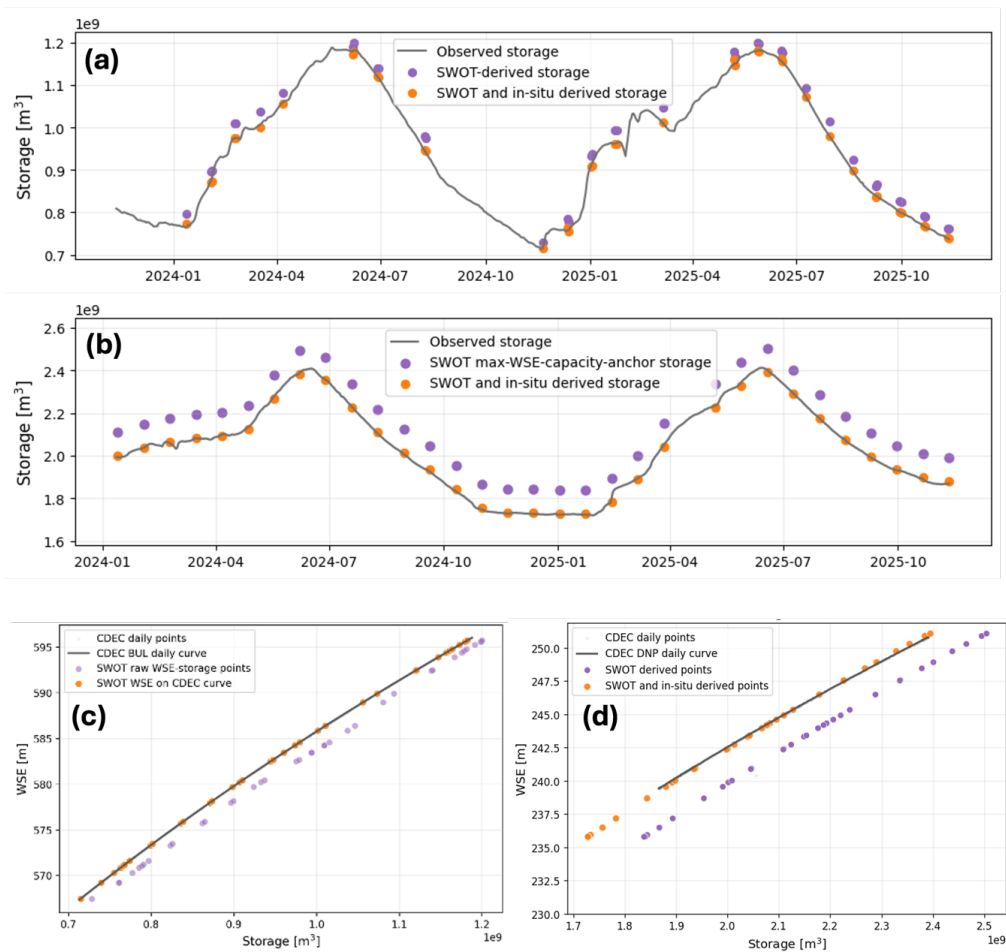
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336 **5 Results**
337 **5.1 SWOT-based reservoir storage initialization**



339 **Figure 3. Comparison of SWOT-derived and in-situ reservoir storage and elevation-storage relationships for New**
340 **Bullards Bar and Don Pedro reservoirs. Panels (a) and (b) show observed storage, storage derived directly from**
341 **SWOT observations, and storage estimated by combining SWOT and in-situ information for New Bullards Bar and**
342 **Don Pedro, respectively. Panels (c) and (d) compare the water-surface elevation-storage relationships for New**
343 **Bullards Bar Reservoir (BUL) and Don Pedro Reservoir (DNP), respectively, using agency records, SWOT-derived**
344 **observations, and combined SWOT-in-situ reference points.**

345
346 Figure 3 compares the storage time series derived from SWOT with the in-situ storage records for BUL and DNP.
347 For BUL, the combined SWOT-in-situ storage estimates closely follow the observed seasonal filling and
348 drawdown, including the two spring refill periods and subsequent summer declines. The directly SWOT-derived
349 estimates show somewhat greater scatter, but they generally preserve the timing and magnitude of the observed
350 seasonal cycle. The mean absolute difference between the combined estimates and the observed record is 25.1
351 million m3, compared with 3.5 million m3 for the direct SWOT estimates.



352 For DNP, the maximum-WSE capacity anchor (defined by pairing the maximum quality-controlled SWOT-observed
353 WSE during the science phase with the reservoir's reported design maximum storage capacity) produces a persistent
354 positive storage offset relative to the observed record, whereas the combined SWOT-in-situ estimates more closely
355 reproduce the observed seasonal variation. The corresponding elevation-storage comparisons in Figures 3c and 3d
356 show that the combined reference points align more closely with the agency curves than the unadjusted SWOT-
357 derived points.

358 Across the two reservoirs, the SWOT-only storage estimates capture 98.5% of the observed seasonal storage range at
359 BUL and 98.2% at DNP. Agreement is strongest under filling/refill conditions and weakest under drawdown
360 conditions. The larger persistent offset at DNP likely reflects the fact that the reservoir reached only 95.3% of its
361 reported maximum storage capacity during the SWOT science phase, based on the in-situ record. Consequently, the
362 maximum SWOT-observed WSE does not represent the true full-pool elevation and provides an imperfect upper
363 anchor for the elevation-storage relationship. For reservoirs that do not approach full capacity during the satellite
364 record, additional reservoir information, such as in-situ WSE and storage observations, an independently established
365 elevation-storage curve, or reliable design information linking full-pool elevation to maximum storage capacity,
366 may be necessary to derive accurate absolute storage estimates. In data-limited regions, SWOT-derived storage may
367 be more reliable for reservoirs with high inflow-to-capacity ratios, such as BUL, because their higher turnover
368 increases the likelihood that the satellite record captures near-full conditions and therefore provides a more
369 representative upper elevation-storage anchor. More generally, storage estimates may also improve as the SWOT
370 observational record lengthens, because a longer record increases the probability of observing reservoir states closer
371 to full capacity.

372 Overall, the storage comparison establishes that SWOT observations contain sufficient information to track the
373 seasonal reservoir state, but it also shows that reservoir-specific elevation-storage anchoring remains an important
374 source of systematic error. The influence of these biases on forecast initialization and subsequent storage predictions
375 is examined in the following section (section 5.3).

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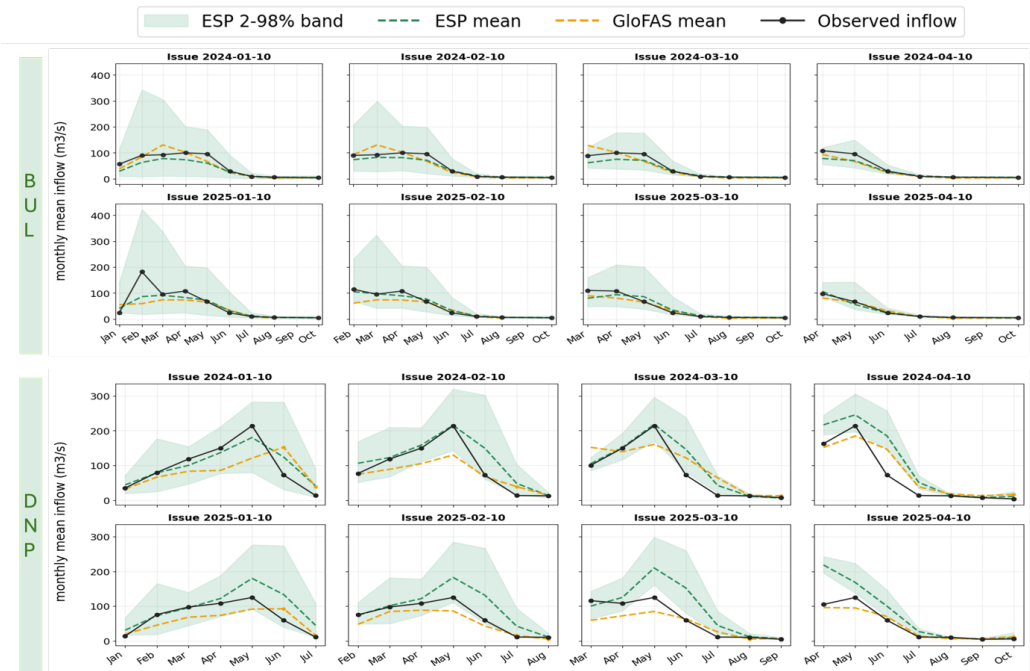
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390 **5.2 Seasonal reservoir inflow forecasts**



391
392 **Figure 4. Seasonal reservoir inflow forecasts from ESP and GloFAS for New Bullards Bar Reservoir (BUL) and**
393 **Pedro Reservoir (DNP) across monthly forecast issue dates.**

394
395 Figure 4 compares ESP and GloFAS inflow forecasts with observed reservoir inflow across monthly issue dates.
396 Both forecast systems reproduce the broad seasonal transition from winter–spring high flows to low summer inflows
397 at BUL and DNP. Forecast spread is largest during the high-flow and snowmelt periods and narrows as observed
398 inflow approaches zero later in the water year.

399 For BUL, ESP generally follows the observed seasonal trajectory more closely during the early- and mid-season
400 forecast cycles, whereas GloFAS shows larger departures during several high-flow months. For DNP, both products
401 capture the timing of the spring inflow peak, but the magnitude of the peak and the subsequent decline vary among
402 issue dates. Across all cycles, the mean normalized inflow error is 0.22 for ESP and 0.26 for GloFAS at BUL, and
403 0.23 and 0.38, respectively, at DNP.

404 A cycle-by-cycle comparison shows that ESP has the smaller inflow error in 4 of 8 BUL forecast cycles and 8 of 8
405 DNP cycles. The advantage is concentrated in the winter–spring high-flow season, when the magnitude and timing
406 of snowmelt and storm-driven inflows exert the greatest control on the seasonal water balance. During the low-flow
407 summer period, the absolute difference between ESP and GloFAS decreases because observed inflow approaches
408 zero; consequently, smaller summer errors should not necessarily be interpreted as greater forecast skill. A detailed
409 comparison of the May–August forecast cycles is provided in Figures S3 and S4 (section S2) for BUL and DNP,
410 respectively.

411 The ensemble range expands most rapidly over the first two lead months at BUL and over the first four to five lead
412 months at DNP, then contracts as members converge toward low summer inflow. Across all lead times, median



absolute inflow error decreases from 17.8 m³/s at leads of 0-30 days to 4.0 m³/s at leads longer than 90 days for ESP, compared with 25.6 and 3.2 m³/s for GloFAS. This decline reflects the transition into low-flow summer conditions rather than an improvement in long-lead forecast skill.

Taken together, the inflow results indicate that the locally configured ESP system provides the more accurate forcing during hydrologically active periods, while GloFAS retains the broad seasonal signal and therefore provides a viable global alternative where a local ESP implementation is unavailable.

5.3 Reservoir storage forecasts

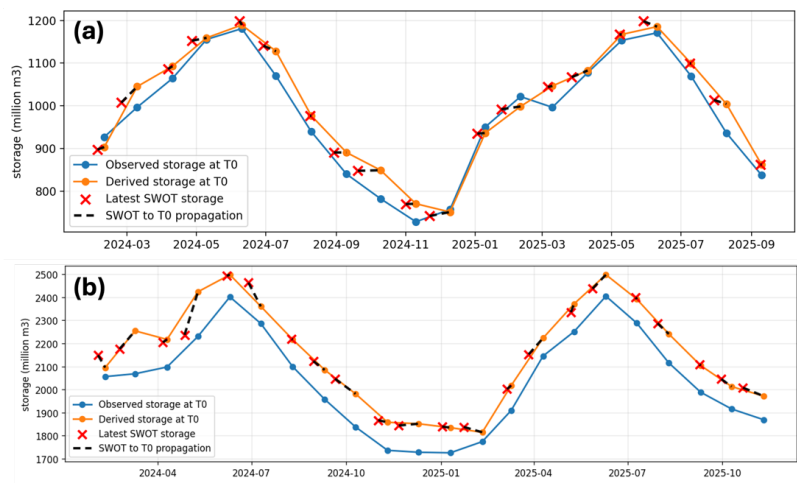


Figure 5. Comparison of observed and SWOT-based reservoir storage at monthly forecast issue dates for New Bullards Bar Reservoir (a; BUL) and Don Pedro Reservoir (b; DNP). Blue circles indicate observed (in situ) storage at the forecast initialization date (T0), red crosses indicate the latest available SWOT-derived storage observations before T0, black dashed lines show their propagation to T0, and orange circles indicate the resulting propagated SWOT-based storage estimates at T0. The propagation procedure is described in Section 4.3.

Figure 5 evaluates the storage state used at each monthly forecast issue date. At BUL, the propagated SWOT-based storage generally follows the observed storage at T0 and reproduces the seasonal refill and drawdown pattern, although small positive and negative deviations occur among issue dates. The mean absolute initialization difference is 62.4 million m³.

At DNP, the propagated SWOT-based storage is consistently higher than the observed storage over most of the study period, reflecting the positive offset in the SWOT-derived storage relation shown in Figure 3. Despite this bias, the propagated initialization retains the observed timing of seasonal storage changes. The corresponding mean initialization bias is 110.8 million m³.

The contrast between BUL and DNP illustrates the reservoir-specific persistence of initialization error. At BUL, the sign of the initialization difference changes among issue dates, and the mean signed difference remains modest (+30.5 million m³, or +3.1% of mean observed T0 storage). At DNP, the difference is consistently positive, with a mean bias of +110.8 million m³ (5.4%). The initialization error remains above 25 million m³ for 22 consecutive issue dates at DNP, consistent with the persistent offset in the elevation-storage relationship.



Despite these differences, the propagated SWOT state captures the phase of the seasonal storage cycle at every issue date. Thus, the principal limitation of the satellite-based initialization is the magnitude of storage rather than the timing of reservoir filling and drawdown.

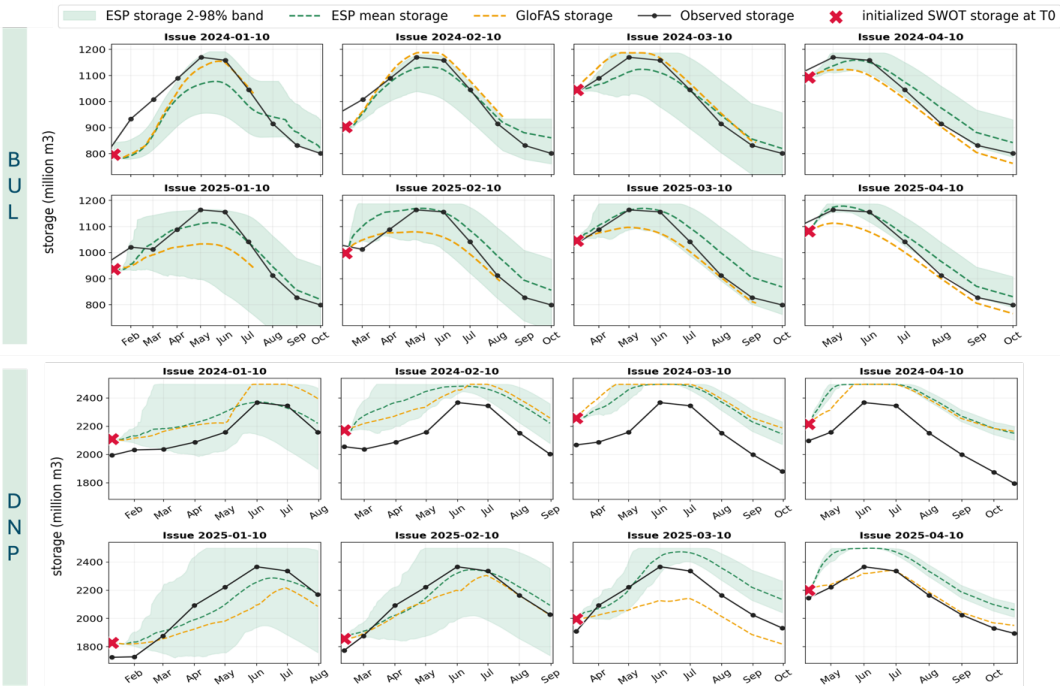


Figure 6. Comparison of ESP- and GloFAS-driven reservoir storage forecasts initialized with SWOT-based storage in comparison with observed (in situ) storage for New Bullards Bar Reservoir (BUL) and Don Pedro Reservoir (DNP) in 2024 and 2025. Black solid lines with circles represent observed storage, orange dashed lines represent forecasts driven by ESP inflows, green dashed lines represent forecasts driven by GloFAS seasonal inflows, green shading indicates the GloFAS forecast uncertainty range, and red crosses identify the SWOT-based initial storage at each forecast issue date. Each panel corresponds to an individual monthly forecast issue date.

The storage forecasts in Figure 6 show that both inflow products reproduce the principal seasonal pattern of spring filling followed by summer drawdown. For BUL, ESP-driven forecasts generally remain closer to the observed trajectory during the refill period, while the GloFAS-driven forecasts show larger departures for several forecast cycles. Differences between the two forecast products become smaller during the late-summer drawdown, when inflow is low, and reservoir storage declines more steadily.

For DNP, ESP-driven forecasts capture the seasonal rise and peak more consistently across the displayed years, whereas GloFAS-driven forecasts show greater underestimation during refill and larger spread among forecast cycles. However, both products reproduce the timing of the summer storage decline. Across all issue dates, the mean storage MAE is 42 million m³ for ESP and 80 million m³ for GloFAS at BUL, and 142 and 143 million m³, respectively, at DNP.



The effect of inflow forecast source becomes more pronounced as forecast lead increases. At short leads of 0–30 days, storage trajectories initialized from the same state remain relatively similar, whereas after 90 days the separation between ESP- and GloFAS-driven forecasts increases to an average of 99 million m³ at BUL and 105 million m³ at DNP. This pattern indicates a transition from initial-condition control near the issue date to accumulated inflow control later in the forecast horizon.

Interannual differences are also evident, with larger errors in 2024 than in 2025 at DNP, particularly during the 2024 refill season, when forecast inflow errors accumulate rapidly. Conversely, during the late-summer drawdown, the reservoir trajectories become smoother and the spread among inflow-driven forecasts decreases.

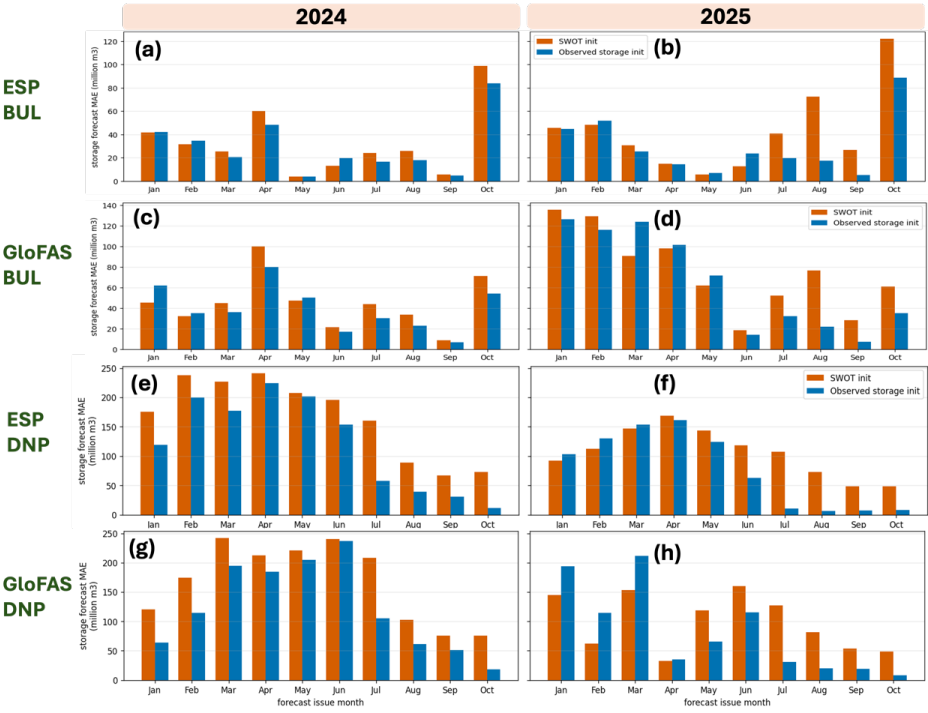


Figure 7. Monthly reservoir storage forecast errors under SWOT-based and observed-storage initialization for BUL and DNP using ESP and GloFAS inflow forecasts in 2024 and 2025.

Figure 7 compares monthly storage forecast errors obtained using SWOT-based and observed-storage initialization. At BUL, the two initialization approaches generally produce comparable storage MAEs, although observed-storage initialization yields lower errors for most issue months. Differences are relatively small for many forecast cycles, indicating that the propagated SWOT storage at T₀ is often close to the observed initial state. Larger discrepancies occur for several late-season issue dates, most notably August 2025 under the GloFAS forecasts, when the SWOT-initialized error substantially exceeds that obtained using observed storage.

At DNP, the influence of the initialization source is larger and more persistent. SWOT-based initialization generally produces higher storage MAEs than observed-storage initialization across both ESP- and GloFAS-driven forecasts, consistent with the positive bias in SWOT-derived storage identified in Figures 3 and 5. The difference is particularly evident for several issue months in 2024 and early 2025. Nevertheless, the magnitude of the forecast



error also varies substantially between ESP and GloFAS, showing that inflow forecast uncertainty remains an important contributor to total storage error. Averaged across all forecast cycles, replacing observed storage with SWOT-based initialization changes storage MAE by approximately 19.5% for BUL and 34.3% for DNP.

Across the complete set of monthly issue dates, SWOT-based initialization produces lower storage MAE than observed-storage initialization in 20 of the 80 experiments and higher MAE in 60 experiments. Thus, although observed-storage initialization generally provides the more accurate benchmark, SWOT-based initialization remains comparable for a meaningful subset of forecast cycles. Its performance is strongest when the satellite-derived initial state is close to the observed storage, whereas persistent bias in the SWOT estimate, as at DNP, degrades forecast accuracy across successive issue dates.

The relative contributions of initialization and inflow uncertainty also vary with forecast lead time. Near T0, the difference between paired initialization experiments is approximately 40 million m³, whereas the difference between ESP- and GloFAS-driven forecasts is approximately 5 million m³. At lead times longer than 60 days, the difference associated with the inflow product increases to approximately 30 million m³ and exceeds the initialization contribution in about 70% of the experiments. These results indicate that initial-storage uncertainty is most influential early in the forecast, while inflow uncertainty increasingly controls storage accuracy at longer seasonal lead times.

Overall, Figures 5–7 demonstrate that SWOT-derived storage can provide a practical alternative to contemporaneous in situ storage for forecast initialization, particularly when the satellite-derived storage has little systematic bias. However, the contrast between BUL and DNP shows that persistent bias in the SWOT-derived initial state can propagate through multiple forecast cycles. At longer lead times and during periods of substantial inflow, the accuracy of the seasonal inflow forecast becomes the dominant control on storage prediction performance.

5.4 Forecasted agricultural water supply relative to estimated demand

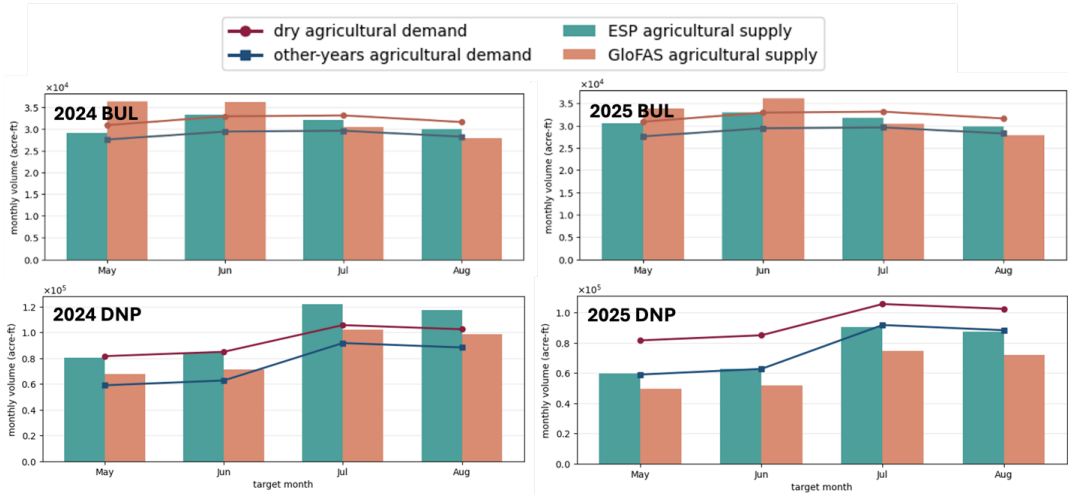


Figure 8. May–August agricultural water-supply derived from monthly initialized reservoir simulations forced by ESP and GloFAS inflow forecasts, compared with irrigation-demand estimates for other (all) years and dry years. Dry years are defined as the five driest water years during the agriculture record period (water year 1980–2020 for BUL; year 2012–2023 for DNP).



Figure 8 compares forecast-implied agricultural water supply with the estimated monthly demand benchmarks. Across the displayed May–August target months, ESP generally produces higher agricultural supply estimates than GloFAS. In panels (a) and (b), both products are near or above the other-years demand benchmark in most months, while neither product consistently reaches the higher dry-year demand benchmark.

In panels (c) and (d), the contrast between the inflow products is larger. ESP-derived supply is generally closer to, or exceeds, the corresponding demand estimates, whereas GloFAS-derived supply falls below demand in several months, especially during July and August. These comparisons indicate that conclusions about potential demand satisfaction depend on both the seasonal inflow forecast and the assumed hydrologic-year demand scenario. The average supply–demand difference is approximately +10,000 acre-ft for ESP and –6,000 acre-ft for GloFAS.

The comparison also reveals a clear interannual contrast. Forecast-implied agricultural supply is higher in 2024 than in 2025 for both inflow products, with the largest year-to-year decrease occurring in May. Under the other-years demand benchmark, forecasted supply is at or above demand in 13 of the 16 displayed month–year combinations for ESP and 7 of 16 combinations for GloFAS. Under the dry-year benchmark, the corresponding counts decrease to 8 and 7, respectively.

Differences attributable to storage initialization are smaller than those attributable to the inflow product in all 8 of the displayed target months. The mean absolute difference between supply estimates generated from SWOT- and observed-storage initialization is approximately 6,000 acre-ft, compared with an ESP–GloFAS difference of approximately 19,000 acre-ft. This indicates that agricultural supply estimates are relatively robust to the use of SWOT-based initialization, supporting its reliability for reservoir-based supply assessment.

Potential supply–demand mismatches are concentrated in July–August, when irrigation demand remains elevated, but forecast-implied reservoir inflow and release begin to decline. In contrast, supply above the estimated demand during May–June should be interpreted as excess forecast-implied release availability rather than as additional realized agricultural use. The results therefore describe the capacity of forecasted releases to meet the demand benchmark, not actual farm-level water deliveries.

Overall, the management assessment is sensitive to both the selected inflow forecast and the assumed demand scenario. ESP-driven simulations more frequently meet the estimated demand benchmarks, whereas the lower GloFAS-driven supply in several months produces a more conservative indication of potential demand satisfaction.



5.5 Application of the Validated Workflow in a Data-Limited Region: Tendaho Reservoir

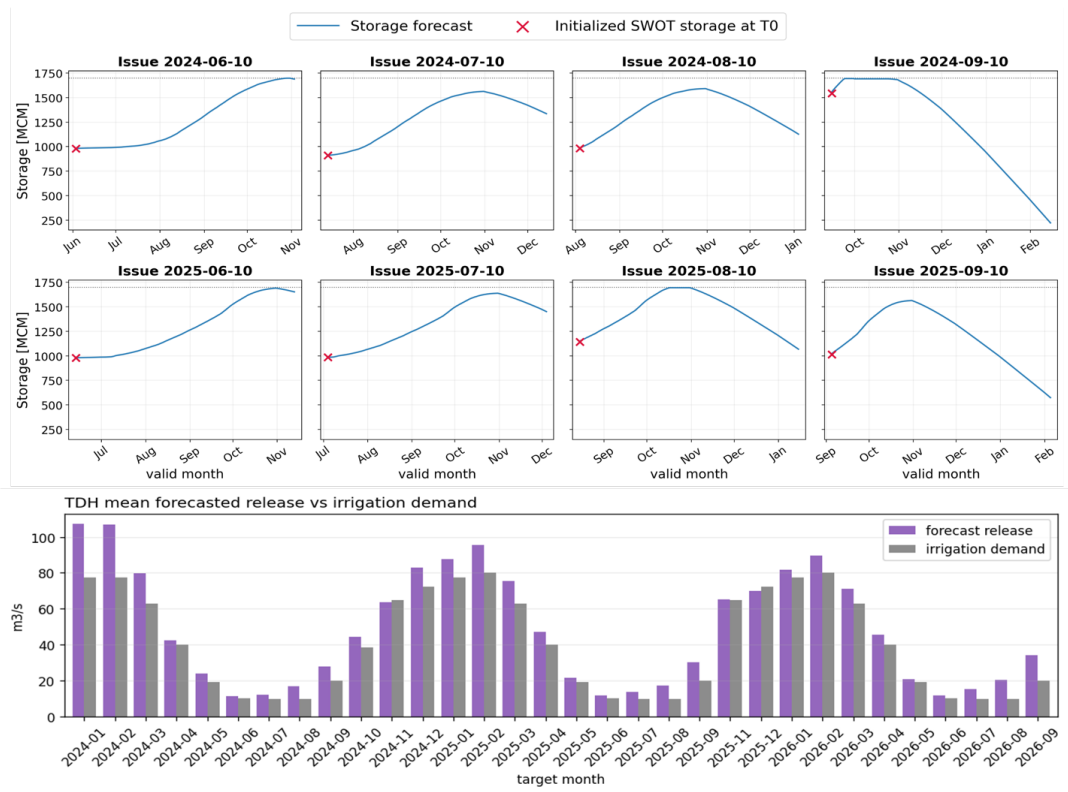


Figure 9. GloFAS-driven seasonal reservoir forecasts for Tendaho Reservoir. The upper panels show forecast storage trajectories initialized with SWOT-derived storage at T0 for eight issue months in 2024 and 2025, while the lower panel compares monthly mean forecast release with estimated irrigation demand.

Figure 9 shows the transferred workflow for Tendaho Reservoir using SWOT-derived initial storage and bias-corrected GloFAS inflow. The SWOT-observed WSE and corresponding derived storage time series used to characterize reservoir storage conditions are shown in Figure S5 in section S3. The upper panels present storage forecasts initialized at eight issue dates during 2024 and 2025. The forecast trajectories generally show seasonal storage accumulation followed by drawdown, although the timing and magnitude of the maximum storage vary among issue dates. Across the eight forecasts, simulated peak storage ranges from approximately 1,550 to 1,700 MCM, while the lowest end-of-forecast storage is approximately 200 MCM for the September 2024 initialization.

The monthly comparison indicates that mean forecast release is generally sufficient to meet the estimated irrigation demand. Across the 33 target months from January 2024 through September 2026, forecast release exceeds demand in approximately 30 months, falls below demand in two months, and is approximately equal to demand in one month. Potential shortfalls are limited primarily to November 2024 and November 2025, with the largest monthly



deficit occurring in November 2025 at approximately $3 \text{ m}^3 \text{ s}^{-1}$. In contrast, the largest positive release–demand differences occur in January and February 2024 and are approximately $30 \text{ m}^3 \text{ s}^{-1}$.

The seasonal release pattern broadly follows the prescribed irrigation–demand cycle, with the largest forecast releases generally occurring during November–February and the smallest during May–July. During months when forecast release exceeds demand, the mean positive difference is approximately $9\text{--}10 \text{ m}^3 \text{ s}^{-1}$, whereas the average shortfall during below–demand months is approximately $2 \text{ m}^3 \text{ s}^{-1}$. These results suggest that the modeled reservoir can satisfy the prescribed irrigation demand during most months, although small potential deficits may occur under particular combinations of storage, inflow, and seasonal demand.

Because continuous observed release and reservoir–specific operating–rule information are unavailable, these results should be interpreted as a demonstration of potential irrigation supply conditions rather than a direct validation of operational performance. Relative to the western U.S. cases, the Tendaho application relies more heavily on globally available and approximate inputs, including SWOT–derived initial storage, bias–corrected GloFAS inflow, generalized reservoir operating rules, and literature–based irrigation demand.

Despite these limitations, the Tendaho application preserves the same physical sequence identified in the validation reservoirs: satellite observations constrain the initial storage state, seasonal inflow forecasts determine the subsequent storage evolution, and the reservoir model translates these trajectories into a management–relevant comparison with irrigation demand. The results therefore demonstrate the potential utility of the framework for diagnosing seasonal irrigation supply conditions in regions where continuous operational observations are unavailable.

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6. Conclusions

We developed and evaluated a SWOT–initialized reservoir–operation forecasting framework that combines SWOT–based satellite–derived reservoir storage, seasonal inflow forecasts, reservoir–operation modeling, and agricultural water–demand assessment. We first evaluated the framework at two data–rich California reservoirs and then transitioned it to Tendaho Reservoir in Ethiopia to demonstrate its applicability in a data–limited setting.

Our results show that SWOT–derived storage can provide a practical alternative to in situ storage observations for reservoir operation at the forecast initialization date. At both California reservoirs, the SWOT–based initial states captured the timing of seasonal filling and drawdown. However, forecast performance depended strongly on the accuracy of the reservoir–specific elevation–storage relationship. Where the SWOT–derived storage contained little systematic bias, as at BUL, forecasts initialized with SWOT storage were often comparable to those initialized with observed storage. In contrast, the persistent positive storage offset at DNP propagated into subsequent forecasts and increased storage forecast errors across multiple issue dates.

The paired initialization and inflow experiment also clarified how forecast uncertainty changes with lead time. Initial–storage uncertainty had its largest influence near the forecast issue date, whereas differences associated with ESP (which requires a local history of in situ reservoir inflows) and GloFAS (available globally) inflow forecasts became increasingly important as lead time increased. This transition indicates that improvements in satellite–based reservoir–state estimation are especially valuable for short–lead forecasts, while seasonal forecast performance increasingly depends on the accuracy of future inflow estimates, which remain dependent on in situ data.

Application to Tendaho Reservoir demonstrates the potential of combining SWOT–derived storage with bias–corrected global inflow forecasts to assess agricultural water availability where continuous reservoir observations are unavailable. The framework therefore provides a transferable approach for identifying periods of potential water shortage and evaluating demand satisfaction in data–limited regions. Nevertheless, the Tendaho results should be interpreted as a demonstration rather than a fully validated forecast application because continuous observations of storage, release, and operating rules were unavailable during the SWOT period.



Overall, the study shows that satellite observations can extend reservoir-operation forecasting beyond well-monitored systems. Continued improvements in elevation–storage relationships, longer SWOT observational records, inflow bias correction, and representation of reservoir operating rules will further enhance the reliability and operational value of our framework.

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