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A First Look at River Discharge Estimation From SWOT Satellite Observations

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Special Collection:
Science from the Surface Water and Ocean Topography Satellite Mission

Key Points:

- The Surface Water and Ocean Topography (SWOT) satellite mission offers simultaneous and synoptic estimates of river discharge and other hydrological variables globally
- Results show that SWOT can track discharge dynamics without gauge information, with correct magnitude in some cases but with bias in others
- SWOT has the potential to provide valuable insights into global river discharge estimation, with implications for hydrologic science

Supporting Information:

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

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Abstract The Surface Water and Ocean Topography (SWOT) satellite has the potential to transform global hydrologic science by offering simultaneous and synoptic estimates of river discharge and other hydraulic variables. Discharge is estimated from SWOT observations of water surface elevation, width, and slope. A first assessment using just the highest quality SWOT measurements, over the first 15 months (March 2023–July 2024) of the mission evaluated at 65 gauged reaches shows results consistent with pre-launch expectations. SWOT estimates track discharge dynamics without relying on any gauge information: median correlation is 0.73, with a correlation interquartile range of 0.51–0.89. SWOT estimates capture discharge magnitude correctly in some cases but are biased (median bias is 50%) in others. There are already a total of 11,274 ungauged global locations with highest quality SWOT measurements where SWOT discharge is expected to accurately track discharge variations: this value will increase as SWOT data record length grows, algorithms are refined and SWOT measurements are reprocessed. This first look indicates that SWOT discharge is performing as expected for SWOT data that achieve performance requirements, providing observed information on discharge variations in ungauged basins globally.

Plain Language Summary River discharge is the volume of water passing a location on a river over a given interval of time. This quantity determines how much water and energy are available for humans,

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ecosystems, and sedimentary processes and is therefore essential knowledge for understanding, monitoring, and managing water movement and storage. Global knowledge of river discharge is limited by the sparsity of on-the-ground measurements, especially in countries without active monitoring programs or difficult to access sites, resulting in the vast majority of the world's rivers being unmeasured. The Surface Water and Ocean Topography (SWOT) satellite could revolutionize how we understand global water availability by providing comprehensive data on river flow and related variables without the need for ground-based measurements. In this study, we share the first estimates of river discharge from SWOT observations during the first 15 months of the mission. Our initial assessment indicates that it is in fact possible to effectively monitor river discharge from space, and correlations of SWOT discharge estimates with ground measurements range from moderate to strong. Despite unavoidable limitations in our study's river selection, these preliminary results suggest that SWOT holds promise for estimating river discharge as SWOT collects more data and its measurements become more accurate with time.

1. Introduction

River discharge plays a unique role in the water cycle, as it integrates the different hydrological processes of an entire basin. Therefore, river discharge estimation is essential for understanding and monitoring water fluxes and stores while also providing key information for managing water resources and risks. Although river gauges are an invaluable source of discharge data and have helped shape hydrologic science, they have inherent limitations due to their sparse spatial coverage and decreasing availability caused by practical, economic or political reasons (Gleason & Hamdan, 2017; Krabbenhoft et al., 2022). These limitations can be partially alleviated by complementing gauge measurements with remote sensing observations, particularly in ungauged basins or areas where gauges are sparse (Gleason & Durand, 2020).

Remote sensing offers a potentially viable strategy for estimating river discharge over large areas in a systematic and consistent manner (Van Dijk et al., 2016). Compared to establishing and maintaining an extensive ground-based measurement network for large rivers, remote sensing can be cost-effective as it provides more spatially extensive observations, especially over inaccessible regions, ensuring a baseline level of regular monitoring and data collection everywhere. While remote sensing will not remove the need for in situ discharge measurements, it can complement the existing gauging network. Many approaches have been developed to estimate river discharge from remotely sensed observations, all of which have historically required calibration with ground data or models. For example, several studies developed rating curves between in situ discharge and satellite-derived variables to estimate discharge at particular locations (e.g., Smith et al., 1996; Tarpanelli & Domeneghetti, 2021). These variables include river width (e.g., Feng et al., 2021), elevation (e.g., Getirana & Peters-Lidard, 2013; Paris et al., 2016), and slope (e.g., Paris et al., 2016). Alternative approaches have combined satellite observations with modeling and data assimilation to derive river discharge estimates (e.g., Ishitsuka et al., 2021; Pujol et al., 2020; Tourian et al., 2017). The overall objective of many of these studies was the estimation of discharge solely from satellite observations (Gleason & Smith, 2014), but very few studies have successfully estimated river discharge without in situ data (Brinkerhoff et al., 2020; Feng et al., 2021; Gleason & Smith, 2014; Gleason et al., 2014; Lin et al., 2023) and these have limited accuracy in many contexts. These approaches primarily use optical satellites to derive river width, and this is limited by uncertainties in the observations, clouds, river morphologies that preclude width changes, and underdeveloped estimation algorithms (Tarpanelli et al., 2021).

The Surface Water and Ocean Topography (SWOT) satellite mission, launched in December 2022, is a collaboration between the United States (NASA) and French (CNES) space agencies with the additional participation of the UK and Canadian space agencies. SWOT uses two Synthetic Aperture Radar antennas to provide the first-ever two-dimensional, high-resolution measurements of the elevation, extent and storage changes of land surface water bodies including rivers, lakes, and wetlands. These measurements of water surface elevation (WSE) and inundation alone have long been recognized as potentially revolutionizing our approach to monitoring and quantifying surface water (Alsdorf et al., 2007) and first results suggest that the SWOT mission can meet and even exceed its science requirements in some cases (Fu et al., 2024).

While these results are transformative, SWOT holds promise for estimating ungauged river discharge which can be considered the "holy grail of scientific hydrology" (Beven, 2006). A relatively extensive body of work has

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assessed and evaluated the potential of different methodologies to estimate river discharge from synthetic SWOT observations, starting with Andreadis et al. (2007) who assimilated water elevation observations into a hydrodynamic model to estimate discharge over a single river reach. Many of these approaches have focused on data assimilation (Gejadze et al., 2022; Larnier & Monnier, 2023; Revel et al., 2021) while other approaches have considered how to improve SWOT discharge temporal resolution via interpolation (e.g., Paiva et al., 2015). As the requirements for the SWOT mission include a river discharge data product, a set of algorithms with operational potential was developed. These algorithms form the core of "Confluence," an operational purpose-built cloud-based software platform that combines SWOT observations and ancillary data to create estimates of SWOT discharge globally, and pulls in situ discharge from global water agencies public repositories to assess SWOT discharge accuracy for each run (Durand et al., 2023). Preliminary assessments of these algorithms suggested SWOT-like observations could yield discharge with bias dominating the error when compared to gauges (Durand et al., 2016; Frasson et al., 2021, 2023). Fundamentally, the bias arises because the SWOT algorithms attempt to solve the ill-posed "mass conserved flow law inversion" problem (Larnier et al., 2021) by regularizing using a prior information for example, on mean annual flow. SWOT discharge algorithms improve over the prior estimates, but errors in prior estimates generally translate to error in SWOT discharge (Frasson et al., 2021). Thus, SWOT discharge bias results from bias in estimates of prior information used to drive the algorithms.

Here, we present the first SWOT discharge results from the initial 15 months of the mission. We evaluate discharge estimated only using SWOT measurements that are not subject to known anomalies in data SWOT processing: SWOT is an experimental mission and its river data products are continuously improving, but quality filtering is needed using SWOT's self-reported quality flags. Thus, SWOT data are aggressively filtered, reducing sample sizes, but increasing confidence in examining SWOT measurements that meet performance requirements. Nonetheless, SWOT discharge is estimated without any in situ gauge information making the validation results applicable to the problem of estimating discharge in ungauged basins. In addition to this initial validation of SWOT discharge, we provide an estimate of the extent of global locations expected to have accurate SWOT discharge estimates. Overall, our aim here is to assess whether or not SWOT discharge estimates meet pre-launch expectations, viz. accurately tracking discharge variations measured at in situ gauges (Durand et al., 2023).

2. Estimating River Discharge

River discharge estimation from SWOT leverages the unique capability of the satellite to simultaneously observe river WSE, width, and slope (Durand et al., 2023). SWOT observes these characteristics over a set of predefined river reaches (Altenau et al., 2021). The WSE, width and slope performance requirements are 10 cm, 15% of true width, and 1.7 cm/km for a nominal 10 km reach, and it is required to measure rivers wider than 100 m, with a goal of measuring rivers as narrow as 50 m (JPL, 2018). Each of these river reaches is approximately 10 km in length, to ensure adequate precision of reach-averaged observations (Rodríguez et al., 2020). Data at the native spatial resolution (varying across the swath but approximately 25 m on average) of the SWOT radar are averaged over each river to compute WSE and width measurements at "nodes," 200 m increments along river centerlines. The node measurements are used in turn to compute reach averaged estimates of WSE, width, and slope (Frasson et al., 2017), which are significantly more precise than the corresponding node-based estimates.

In this study, we exclusively use Version C of the "River Single-Pass" data product (JPL, 2020) for the SWOT measurements. While the minimum SWOT-observed river width for accurate discharge estimation is an open question (Fu et al., 2024) preliminary SWOT calibration and validation studies have demonstrated accurate WSE measurements for rivers at least as narrow as 80 m (Stuurman, 2024) so we examine river widths greater than 80 m in this study. From launch until July 2023, the SWOT satellite was in a 1-day exact repeat orbit in order to facilitate calibration and validation activities with non-global coverage. From July 2023 until present, SWOT has been in its nominal 21-day repeat orbit that measures nearly all rivers globally with the number of observations being dependent on latitude and swath geometry; there are approximately two observations every 21 days for most mid-latitude rivers. Here we processed all SWOT data from both the 1-day repeat calibration/validation and the 21-day repeat science orbits, creating river discharge estimates for SWOT spanning from 30 March 2023 to 21 July 2024, based on data available at the time Confluence was run. The period spans 479 days, or approximately 23 SWOT cycles, and thus most reaches would have approximately 45 SWOT overpasses during the Science Orbit.

At the core of discharge estimation from SWOT observations is the application of flow laws that relate its observables to discharge, and a set of algorithms to estimate unobserved parameters. One such flow law is the modified Gauckler-Manning-Strickler equation, transformed as described by Larnier et al. (2021) and Durand et al. (2023), which computes discharge as a function of hydraulic quantities observed by SWOT (WSE, river width, and river slope) and flow law parameters that are unobserved (resistance coefficient, hydraulic radius, etc.). The flow law parameters are computed using SWOT observations and a set of six algorithms with a priori information such as mean annual flow derived from global models (Durand et al., 2023). The discharge estimates are obtained from the so-called "unconstrained" branch of Confluence, which does not use any gauge measurements to calibrate the SWOT algorithms in any way. Even though there are different discharge estimation algorithms, here we compare gauge measurements with the SWOT "consensus" discharge, which is computed as a simple median across the available discharge estimates from the individual algorithms. An example of SWOT measurements and the consensus discharge estimate is shown in Figure S1 in Supporting Information S1.

To meaningfully assess SWOT discharge accuracy, we must take the data quality of SWOT observations into account using the associated flags of the data product (JPL, 2024). In this initial study we select and analyze only the "highest quality" SWOT measurements of WSE, width and slope by filtering out observations flagged as anomalous (JPL, 2020). Note that the SWOT data quality is expected to improve as processing algorithms are refined, so the scale and scope of what data are "highest quality" rapidly changes and we expect to be different when this article goes to print. As one example, we examine only SWOT measurements where the reach falls between 15 and 60 km of the spacecraft ground track: by design, SWOT will still produce a measurement when a reach falls outside that range, but the data are expected to be inaccurate and thus are flagged (JPL, 2024). We additionally filter statistical outliers identified in the time series of WSE, width and slope (details on these filters described in Text S1 in Supporting Information S1) resulting in a set of SWOT observations that meet the mission's performance requirements (JPL, 2018).

Even for the highest quality SWOT data used in this study, variability in discharge estimate accuracy is still a function of some aspects of the SWOT observations and how they are used in Confluence to estimate discharge. Hence, we stratify discharge performance based on two aspects of SWOT observations and discharge algorithm design. In SWOT nomenclature, a river reach is "completely observed" if reach-averaged WSE, width and slope observations pass all data quality filters. On the other hand, a reach is "conditionally observed" if a subset of nodes pass the data filtering but reach-averaged observations did not. As some of the SWOT discharge algorithms operate on node data, while others are driven by the reach-averaged observations the former will still produce a discharge estimate even for a "conditionally observed" river reach. Furthermore, we expect that SWOT discharge accuracy will vary with "hydraulic consistency" of the observations. That is, we leverage the fact that WSE and width must be positively correlated due to basic physical and geomorphic constraints on river bed geometry (Durand et al., 2024) making time series where WSE and width are negatively correlated "inconsistent." Negative correlations is a simple but effective way to flag physically implausible behavior, as even for rivers with steep banks width would remain effectively constant with changes in WSE. Therefore, we assess the performance of SWOT discharge by stratifying observations into "completely observed" reaches and ones that are "hydraulically consistent."

Gauge discharge measurements, acquired from water monitoring agencies globally, are computed by measuring water level and predicting discharge based on a rating curve. Studies have shown that such streamgauge observations are themselves subject to an uncertainty of at least 10% and often far greater (Coxon et al., 2015; Kiang et al., 2018), but are the best independent reference to assess SWOT discharge. Uncertainty in the SWOT-estimated discharge arises from errors in the SWOT observations (WSE, width and slope), as well as flow law approximations and assumptions (Frasson et al., 2023). These errors contribute to both random and systematic errors, the latter of which manifests as bias in the time series of SWOT discharge estimates. In pre-launch studies SWOT discharge was expected to track discharge variations with bias present in some cases (Durand et al., 2016; Frasson et al., 2023). As we are using the "unconstrained" SWOT discharge estimates here with a relatively short time series we expect that the bias will be larger than what future versions of SWOT discharge will have but the dynamics of observed discharge will still be captured.

3. Synoptic River Discharge

One of the most important aspects of SWOT is the ability to produce spatially continuous and consistent estimates of river discharge globally, complementing existing in situ gauge networks (Pavelsky et al., 2014) and facilitating the comprehensive understanding of river behavior and hydraulics across reaches (Carr et al., 2019; Li

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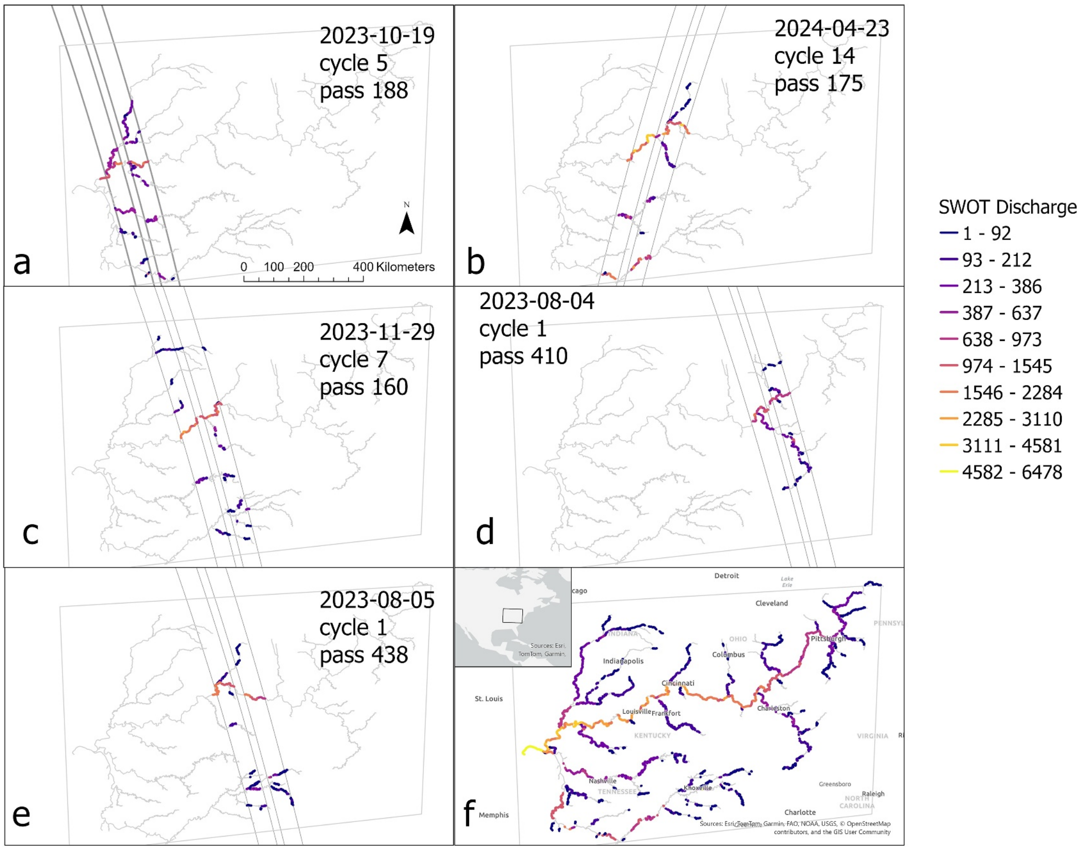

Figure 1. Examples of Surface Water and Ocean Topography discharge (in m^3/s) estimates (including conditionally observed reaches) for five satellite overpasses (a–e) and the average of all passes during the science orbit (21 July 2023–21 July 2024, s (f) are shown for 654 reaches across the Ohio River basin, USA. Mean discharge in panel (f) spans from 6,478 with a median value of 197.09 and a standard deviation of 972.6 (11 outliers with discharge 10,000 m^3/s) are not shown). The inlay in panel (f) shows the study area outline.

et al., 2022). Spatially distributed discharge can significantly enhance hydrologic modeling, as calibration against such distributed observations can improve a model's reliability and predictive capabilities (Pan & Wood, 2013). Moreover, spatially dense observations of discharge can aid in the better representation of lateral inflows, withdrawals and surface storage effects on river discharge that would otherwise be challenging to capture accurately (Papa et al., 2008). These synoptic discharge observations also have implications for many other purposes as they play a vital role in evaluating habitat availability for fish (Wegscheider et al., 2024), assessing pollution levels in rivers (Chidamba et al., 2016), estimating sediment transport (Segura & Pitlick, 2015), quantifying the thermal budget of rivers (King et al., 2020), monitoring river plumes (Osadchiev et al., 2020), and understanding surface-groundwater interactions (Anibas et al., 2012).

Figure 1 showcases the spatial and temporal aspects of SWOT discharge estimates with synoptic scale maps showing discharge for five different satellite overpasses, and the average of all overpasses within the study period in the Ohio River basin, USA. The figure includes discharge derived from SWOT measurements where reaches were conditionally observed. Each discharge measurement represents the instantaneous discharge at the satellite overpass time over a subset of river reaches in the domain. The pass from cycle 14, on 23 April 2024 (Figure 1b), shows higher flows on the mainstem Ohio than on the overpasses from the autumn, which is expected given that flows throughout the Ohio River basin tends to be higher in spring than in fall. The geolocation and timing of SWOT overpasses combine with river planform and timing of floodwave propagation to dictate "hydraulic visibility" of each river (Garambois et al., 2016) and the ability of the satellite to map floodwave spatiotemporal dynamics (Durand et al., 2010). For example, pass 181 (Figure 1e) is oriented along the downstream Wabash River, observing approximately 400 km of distance along the river centerline. In contrast, pass 160 is perpendicular with the upstream Wabash, and observes only approximately 200 km of river. The map of average

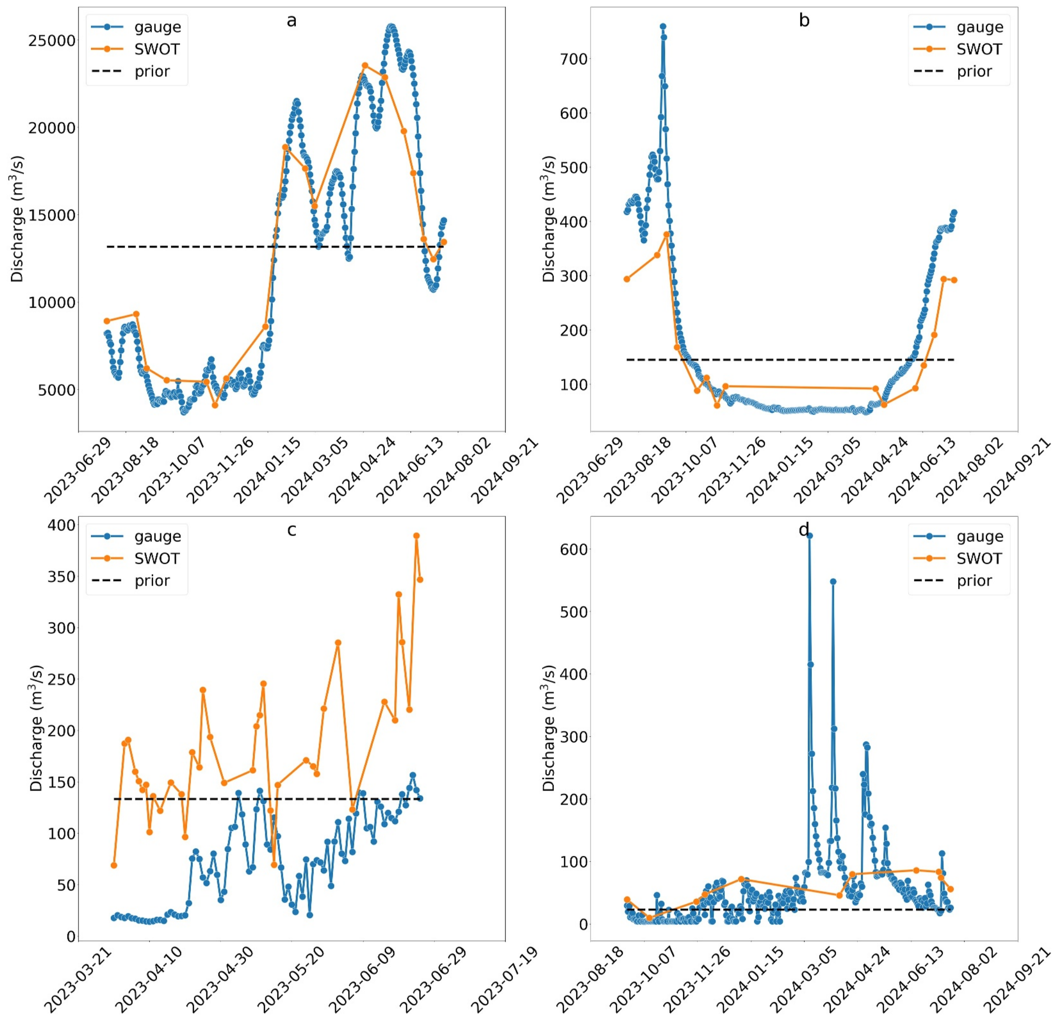

Figure 2. Hydrographs comparing Surface Water and Ocean Topography (SWOT) discharge with in situ discharge for four reaches, representing a wide range of SWOT performance: (a) reach 74210000201, the Mississippi River near Baton Rouge, Louisiana, United States; (b) reach 81130400021, the Kenai River near Soldotna, Alaska, United States; (c) reach 21602400201, the Le Drac River near Grenoble, France; and (d) reach 23229000561, the Loire River near Saint-Victor sur Loire, France. The prior estimate (dashed line) is computed from global models as described in Durand et al. (2023).

discharge (Figure 1f) shows values ranging from 1 m^3/s in the headwaters to 6,480 m^3/s at the Ohio River outlet where it flows into the Mississippi River. These variations are realistic as assessed by in situ gauges in the basin, presenting a spatially coherent view of average flow estimated by SWOT across the river network.

4. Preliminary Validation

The preliminary analysis presented herein shows that this early version of SWOT discharge meets pre-launch expectations by tracking gauge discharge variations for the highest quality SWOT data where and when reaches are completely observed. Figure 2 shows SWOT and gauge hydrographs for four reaches selected to illustrate the range of SWOT discharge performance. SWOT accurately tracks the Mississippi River near Baton Rouge, USA (Figure 2a) capturing both river discharge dynamics and magnitude (r = 0.965, normalized bias = 1.9%). Similarly, SWOT resolves discharge variations on the Kenai River near Sodotna, USA, (r = 0.97), but with a bias of 27% (Figure 2b, Pre-launch studies found that bias is most often due to bias in the prior (Frasson et al., 2021), which was −41% for this reach, rather than other factors such as the scale discrepancy between 10 km reaches and streamgauges (Durand et al., 2024; Rodríguez et al., 2020). Note the gap present here is due to SWOT data that are flagged as ice-impacted in the SWOT product. This level of performance, and a modest improvement in the prior bias, is well within expectations laid out prior to launch (Durand et al., 2023).

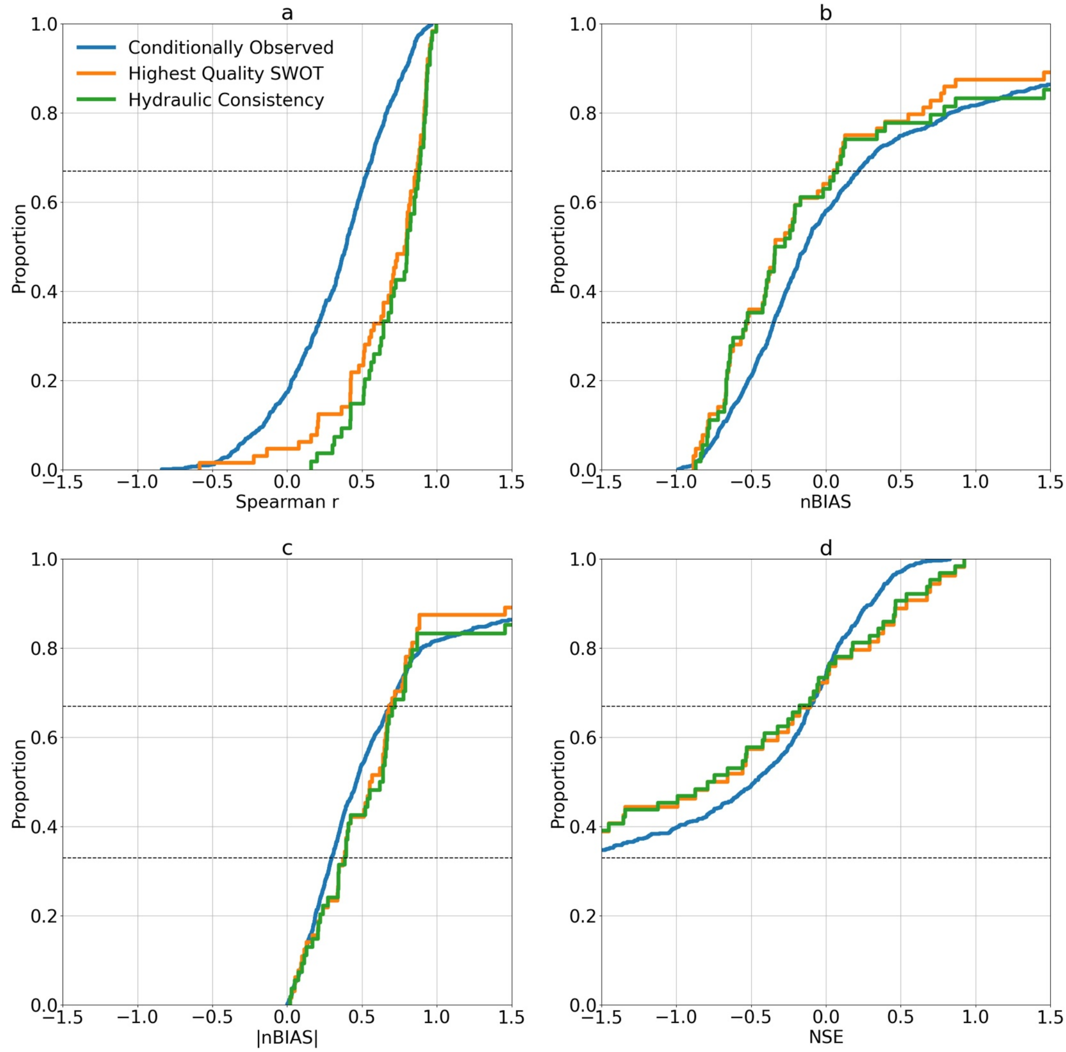

Figure 3. Performance statistics for the three categories of Surface Water and Ocean Topography (SWOT) discharge estimates are shown, including (a) the "conditionally observed reaches" (n = 827), (b) the "highest quality SWOT data" (n = 65), and (c) the "hydraulic consistency" requirement additionally imposed on the "highest quality SWOT data" (n = 54). Four measures of performance are shown: Spearman r, normalized bias, absolute value of normalized bias and Nash-Sutcliffe efficiency. The data are shown as empirical cumulative distribution functions. The x-axes are truncated at 1.5 and −1.5. The dashed lines correspond to the 33rd and 67th percentile.

SWOT also captures discharge variations on the Le Drac River near Grenoble, ($r = 0.65$) but SWOT estimates are much larger (162%) than the gauge (Figure 2c). We expect bias in SWOT discharge to drop as the length of SWOT time series increases, and other improvements (e.g., "basin scale" algorithm designed to estimate mean flow across river networks) are deployed in the near future (Durand et al., 2023). Moreover, SWOT discharge appears to overestimate the "flashiness" of the Le Drac, but still capturing the direction of the changes in discharge. This river reach is only 80 m wide, the very minimum value for which performance is assessed for this study, and such anomalies may be more common for narrower rivers. SWOT discharge does not meaningfully track the gauge on the Loire River near Saint-Victor sur Loire ($r = 0.2$), and bias is substantial (87%, Figure 2d) which presumably can be attributed to unflagged problems with the SWOT observations.

Across all "completely observed" reaches that had at least 10 valid observations after filters have been applied, we find that SWOT discharge estimates generally track gauge discharge quite well, but are subject to bias. Figure 3 shows performance for discharge estimated in order of least filtered ("conditionally observed") to most filters applied ("completely observed" and hydraulically consistent). Discharge performance for "conditionally observed" reaches shown in Figure 3a indicates two major differences compared with "completely observed" reaches. First, there are a total of 827 gauged reaches with at least 10 observations in this run, over an order of magnitude more than when we require reaches to be completely observed. This may be explained by considering that there are on average 50 nodes in each 10 km reach. The algorithms that produce discharge with only node data may be driven by one or two node observations, therefore it is far more likely that a small number of nodes pass the filters compared to the observations for the entire reach. Second, these observations for "conditionally observed" reaches are far less likely to track discharge variations. The median Spearman correlation is 0.39, approximately half the value, if we require, reaches to be completely observed. The lower correlation can be explained by considering that in most cases when a reach observation of WSE, width and slope has cleared all filters intended to isolate highest quality SWOT data, then most of the nodes within a reach are observed and are of good quality.

On the other hand, the median Spearman *r* is 0.73 and the interquartile range is 0.5–0.89 for reaches that were "completely observed" (Figure 3b), showing that SWOT discharge captures gauge variations well in most cases of those 65 river reaches. The median of the absolute value of the bias is 56%, which is larger than predicted in pre-launch studies (Durand et al., 2023), and can be explained by two factors, both of which point to expected future improvements in SWOT discharge. First, bias in SWOT discharge is (to first order) controlled by the bias in prior estimates of mean annual flow, and that prior bias in this study (62%) was larger than observed seen in pre-launch studies (Frasson et al., 2021, 50%). This is expected to improve with both the increasing length of SWOT timeseries, and algorithm changes designed at improving these prior estimates. Second, the expected SWOT discharge error level was computed assuming basin-scale algorithms that integrate information across river basins, shown by Durand et al. (2023) to reduce bias by approximately 10% (i.e., from 40% to 30% in that study), but not run in this study due to technical challenges. SWOT algorithms improved over the prior estimates of mean discharge for most reaches, and as technical issues are resolved we expect that future SWOT discharge will improve. The median Nash-Sutcliffe values are negative, which is attributable to the large bias present. The spatial locations of these reaches are shown in Figure S2 in Supporting Information S1.

Discharge performance for reaches exhibiting "hydraulic consistency" (Figure 3c) shows further improvement over the "completely observed reaches" (Figure 3a). There are a total of 54 reaches satisfying the consistency criterion and having at least 10 good observations. The median Spearman correlation improves to 0.8, compared with 0.73 for reaches requiring only complete observation and the inter-quartile range is 0.62–0.92.

We have focused discussion on bias and correlation separately, in order to highlight the various factors controlling SWOT discharge performance, namely the flow law parameter error, and the SWOT observation error (Durand et al., 2023). Metrics such as Nash-Sutcliffe efficiency (NSE) and normalized RMSE make it hard to disentangle that information as they lump together systematic and random errors. Although they are helpful for comparison to other studies they can be distracting for this initial look at SWOT discharge. Figure 3d shows that median NSE values are negative for all three filtering approaches, showing the dominance of bias on the NSE statistic. Furthermore, Figure S7 in Supporting Information S1 shows normalized RMSE with conditionally observed reaches having higher error, similar to the Spearman *r* results.

Figures S5 and S6 in Supporting Information S1 explore the effect of river width on Spearman *r* and normalized bias, respectively, across the conditionally observed, highest quality, and hydraulic consistency groups. In general, wider rivers have higher correlation and lower bias. This dependence on river size is minimal in conditionally observed reaches, but is prominent in the highest quality and hydraulically consistent groups. Median bias is reduced from 0.72 to 0.64, and 0.34 for river widths less than 100 m, between 100 and 200 m, and above 200 m, respectively, for the hydraulically consistent reaches. The effect is less pronounced for correlation, but in general, larger rivers do exhibit both lower bias and higher correlation.

Using the entire SWOT data archive accessed on 24 October 2024, 11,389 reaches globally meet the criteria to be considered highest quality SWOT data, and this should have accuracies comparable to Figure 3b, of which 115 are gauged. That is, SWOT is likely able to track discharge variations accurately for 11,274 ungauged reaches. Moreover, we expect this number to increase as the SWOT mission lengthens, which we further discuss in the following section. These results are an important benchmark to improve upon for future efforts of the SWOT Science Team Discharge Algorithm Working Group in coming years.

5. Outlook

This study presents a first look at river discharge generated from SWOT observations. The value of these observations is not limited to the estimation of discharge but likely extends to many other applications such as floods (Frasson et al., 2019) and carbon emissions (Brinkerhoff et al., 2022). Following many years of synthetic data studies (e.g., Andreadis et al., 2007; Frasson et al., 2023), we demonstrate that it is indeed feasible to estimate river discharge from actual SWOT observations, and we show an initial validation of the retrievals against in situ measurements. This study shows that SWOT discharge tracks discharge variations as expected, but has a higher bias than predicted in pre-launch studies; discharge bias is higher than expected for reasons that are explainable and are expected to improve in the future (Durand et al., 2023). For instance, Lin et al. (2023) published discharge estimates applicable to truly ungauged basins using Landsat to derive river widths and then discharge with an algorithm almost 10 years in development at that point. They showed median r values of 0.3 and 0.8 at over 3,000 gauges using static and monthly discharge priors, respectively. They also showed positive NSE results in about 25% and 50% of gauges for these same priors. SWOT discharge has achieved relatively similar accuracy "out of the box" without any time or scope for algorithm modification. Indeed, the results presented here represent an early benchmark which is expected to be surpassed as SWOT data quality and discharge algorithms improve and SWOT data times series continues to grow in length. Furthermore, future studies will leverage additional SWOT discharge algorithms: gauge-constrained estimates of SWOT discharge and basin-scale discharge algorithms (Durand et al., 2023) which should improve the accuracy of the results shown here mostly due to reduction in the estimation bias. Despite these caveats, it appears that SWOT is able to estimate discharge across a range of rivers, for highly variable flow conditions both in terms of dynamics and magnitude without any gauge information.

These initial validation results show that SWOT accurately tracks discharge variations for select reaches, but even these 11,289 select reaches represent more locations than in situ river discharge databases. For a point of comparison, we find that there are a total of 2,393 gauges in the Global Runoff Data Center with measurements within the past 2 years, and in water agencies that make their data available publicly for rivers wider than 80 m. These agencies include the U.S. Geological Survey in the United States, EAU in France, WSC and MELCCFP in Canada, DEFRA in the UK, DGA in Chile, Hidroweb in Brazil, ABOM in Australia, DWA in South Africa, and MLIT in Japan. Figure S3 in Supporting Information S1 compares the spatial distribution of the 11,289 select reaches where SWOT is expected to perform well with available gauges. SWOT measures discharge at lower precision and temporal resolution than gauges, and its records extend back only to launch: SWOT will never replace stream gauges. SWOT and stream gauges are complementary, with SWOT increasing discharge estimate coverage by an order of magnitude, spanning thousands of ungauged basins.

The uncertainties associated with these discharge estimates need to be carefully considered when using the data for scientific analysis and applications, particularly in the context of uncertainties in gauge streamflow (Horner et al., 2018; Kiang et al., 2018). Nonetheless, the SWOT mission's ability to estimate streamflow and its variations represents a significant advancement in the observation of global river discharge, particularly for relatively large rivers and in regions currently lacking in situ gauging infrastructure.

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Data Availability Statement

The data utilized in this study are derived from SWOT data products, and particularly the Level 2 River Single-Pass Vector Data Product available at the NASA Physical Oceanography Distributed Active Archive Center (PODAAC, https://podaac.jpl.nasa.gov/SWOT) (SWOT, 2024) and at the CNES Hydroweb next repository at https://hydroweb.next.theia-land.fr/. These data products are distributed in compliance with FAIR requirements. The software used to generate the discharge estimates, including the Confluence framework and individual algorithms, are available at https://github.com/SWOT-Confluence. The discharge estimates from SWOT used in this study are available at https://podaac.jpl.nasa.gov/dataset/SWOT_L4_DAWG_SOS_DISCHARGE (SWOT Discharge Algorithm Working Group, 2023).

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