

# Wide-Swath Altimetry over Rivers Reveals Natural and Regulated Seasonality Patterns Globally

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## Article

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# Wide-Swath Altimetry over Rivers Reveals Natural and Regulated Seasonality Patterns Globally

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# 1 Abstract

The seasonal pulse of rivers migrates across the planet, shaped by atmospheric circulation, basin memory and human control, with river discharge carrying this movement along valley corridors globally. Three years of the Surface Water and Ocean Topography (SWOT) mission global discharge product reveal these dynamics, their reorganization by climate teleconnections, and disruption by regulation. Seasonal activation emerges and evolves through the year: tropical activation reaches +64% above the annual mean in the northern Amazon and monsoon activation +52% in the Ganges in 2024. These patterns are undersampled by sparse and transboundary in-situ networks; SWOT’s dense sampling reveals a misrepresentation of basin dynamics of up to 27%. The SWOT period spans the transition from the strong 2023 El Niño to neutral and La Niña conditions in 2025, when seasonal discharge shifts by roughly twice its typical year-to-year variation in the northern Amazon–Orinoco system, while the strengthening 2025 La Niña drives the Congo down by about four-fifths of a typical year’s variation. SWOT further exposes where regulation breaks seasonal regimes: the Grand Ethiopian Renaissance Dam delays the Blue Nile by 2.8 months and dampens it by 46%, while the Aswan High Dam shifts the downstream Nile by 6 months and dampens it by 59%. SWOT thus opens a new view of the global river network, following water movement as it emerges, shifts, and is interrupted across continents.

# 2 Main

The world’s rivers record how environmental processes shape continental water movement. Climatic forcing, ocean-atmosphere variability, basin-scale hydrology and human water management are integrated in river discharge, a key hydraulic and hydrological variable describing the volume of water transported through river channels. Recognized as an essential climate variable [1], river discharge provides a diagnostic of how large-scale environmental signals propagate through continental hydrological systems. Despite its importance, it has historically been difficult to observe consistently at a global scale. In situ gauges provide accurate measurements, but they remain unevenly distributed and are often sparse in remote or politically sensitive regions [2–7].

The Surface Water and Ocean Topography (SWOT) mission represents a major advance in inland-water observation from space [8]. Its wide-swath Ka-band radar interferometer provides two-dimensional measurements of water surface elevation and surface extent [8, 9]. Each overpass captures water surface elevation, width, and slope along extended portions of river networks, allowing the discharge to be estimated with dedicated mission algorithms [10, 11]. The first global SWOT discharge product was released in 2026 [12, 13]. It includes an ensemble estimate from six operational algorithms developed within the SWOT hydrology community. Among them, SIC4DVar shows some of the strongest performance [14–17], with successful retrievals across a large fraction of river reaches. Here, we focus on the SIC4DVar discharge product, hereafter referred to as SWOT discharge.

Validation against the in-situ SWOT Validation Set (SVS) (Methods-5.5) shows consistent performance across diverse river conditions. The median absolute normalized bias is 0.25, with a 32nd-68th percentile range of 0.14-0.45, confirming that bias remains an important error component linked partly to prior information [13, 18]. In contrast, the median Pearson correlation is 0.86, with a 32nd-68th percentile range of 0.68-0.94, indicating strong skill in capturing discharge dynamics and timing across diverse river systems. Additional metrics are shown in the Supplementary Fig. S1, and full validation is provided by [13, 14]. Here, we focus on characterizing river dynamics, including their timing, relative variability and spatial organization; residual absolute bias therefore has limited impact on the analysis. We use the first three years of SWOT discharge to quantify how climate variability and human regulation reshape the timing, strength and continuity of continental water movement. SWOT now reveals a moving global architecture of flow: seasonal activation sweeping across continents with atmospheric circulation, basin-wide anomalies reorganizing through climate mode transitions, and dams delaying, damping or fragmenting these signals along managed corridors.

## 2.1 Global Active River Regimes

SWOT discharge enables tracking of the spatiotemporal evolution of seasonally active river regimes as they emerge, migrate, and decay across the globe. Using the seasonal discharge ratio, defined as the ratio between seasonal mean discharge and the mean discharge over the study period, (see Methods-5.6), we map and quantify the seasonal activation of discharge across the global network at the reach scale (Fig. 1 and S2). Here, seasonal activation describes how strongly river flow rises above, or falls below, its mean state during a given season. This provides an observation-based view of how large-scale atmospheric circulation translates into coherent river responses across continents [19].

The 2023-2025 sequence reveals a planetary-scale redistribution of river activity, supported by contemporaneous gauging stations (Figs. 1-(a)-(e), S2 and S4). In DJF 2023/24, activation concentrates in the austral tropics and winter storm-track regions. Southern-hemisphere activation is visible as austral-summer rainfall feeds tropical basins, while the Congo shows an early +37%, marking the first phase of its dual peak flow (Fig. S10). Meanwhile, western Europe responds to North Atlantic winter circulation, with the Loire and Danube at +31% and +44% for SWOT, compared to +49% and +56% for SVS (Fig. S4). AMJ 2024 shows a clear hemispheric snowmelt transition, as high-latitude rivers across North America and Eurasia activate strongly when accumulated winter snow is released into river networks, with the Ob at +52% and the Thelon reaching +91% for SWOT and +86% for SVS. Meanwhile, the wet-season signal reorganizes across the tropics as convection and the Inter-Tropical Convergence Zone (ITCZ) shift northward. This suppresses activation in equatorial Africa and strengthens the South American response, where delayed routing maintains discharge across the downstream network, with the northern Amazon at +64% in SWOT and +74% in SVS [20, 21]. By JAS, the active front has moved into the monsoon domain, with activation across South Asia: the Ganges at +52% and the Brahmaputra +61%. This contrasts with strong suppression during DJF and AMJ, when several monsoon

basins remain well below their annual mean, the Irrawaddy showing -71% for SWOT and -77% for SVS in DJF. Meanwhile, the tropical rain belt continues its northward migration, the northern Amazon strengthening to +71% for SWOT and +85% for SVS. In SON 2025, the Asian monsoon decays while activity shifts toward the African monsoon domain. The Niger reaches +36% and the northern Congo branch +35%, marking the second phase of the Congo response as the tropical rain belt migrates southward across equatorial Africa (Fig. S10).

Comparison with in situ discharge supports the seasonal activation patterns derived from SWOT (Figure 1-(f-g)). The direction of activation agrees between SVS and SWOT in most basin-season cases, generally exceeding 80% and reaching near-complete agreement in JAS-SON 2024. Amplitude agreement is lower, with most cases in the good-to-moderate ranges. While part of this discrepancy reflects biases in SWOT discharge and uncertainties in the in situ records themselves, differences also occur during seasons with pronounced spatial heterogeneity, when the limited number of available stations cannot represent the full basin-scale organization. This difference exposes a key limitation of gauge-based basin representations: stations are often sparse and clustered in accessible, populated regions with governments that share data, leaving large parts of the network unseen, especially in transboundary basins.

This representativeness effect is isolated by comparing station-sampled against network-wide activation (Fig. 1-(h-j), S4 and S5). Mean station-sampled ratio differences remain limited, below  $\pm 11\%$ , whereas network-wide differences are larger, reaching about +25% in DJF 2024 and falling to about -21% and -27% in JAS and SON 2025. The strongest differences occur during seasons with spatially organized activation, including JAS monsoon activation across South and Southeast Asia, SON redistribution toward equatorial Africa and weakening South American basins, and DJF austral-summer activation in tropical basins such as the Amazon and Congo. These differences concentrate in poorly gauged or unevenly sampled basins. Several examples illustrate this pattern (Figure S6). In basin 44, JAS 2023 gauges sample the western, strongly activated part of the network, whereas SWOT reveals a less uniform response. In basin 61, JAS 2023 shows a strong response in the ungauged Orinoco against suppressed activation in gauged locations. In the Amazon, DJF 2024/25 gauges emphasize the activated southern and eastern network, while SWOT also resolves the contrasting northern and southern response. In the Niger, SWOT reveals that DJF 2024 activation is confined to limited reaches, so one gauge station cannot represent the wider basin. These cases show that SWOT provides the spatially complete view needed to interpret seasonal river dynamics across large, heterogeneous and often transboundary basins.

## 2.2 Global Signature of Climate Oscillations

With three years of SWOT in orbit, inter-annual variability can be examined against large-scale climate teleconnections using discharge. Large-scale climate modes have been extensively characterized from atmospheric and oceanic observations, yet how their signals are transferred through land-surface processes into river discharge, and how these responses vary across basins, remains poorly constrained as globally dense observation-based discharge have been lacking. The SWOT period coincides with a

reorganization of tropical Pacific conditions (El Niño–Southern Oscillation (ENSO)): El Niño developed during 2023 and peaked in DJF 2023/24 before weakening into neutral conditions by AMJ 2024. Neutral conditions prevailed through most of 2024/25, before La Niña strengthens in SON 2025 and persisted through DJF 2025/26 [22]. This sequence gives SWOT a unique window on global river discharge reorganization across ENSO phases (Fig. 2 and S7).

Discharge Z-scores measure how far each basin departs from its expected seasonal state, in units of a typical year’s variation (standard deviations, STDs) (Methods-5.6). During the developing El Niño in JAS 2023, South Asian activity weakened, with the Indian subcontinent only about half a typical year’s variation above normal (+0.56 STDs) against nearly a full one (+0.9) in JAS 2024/2025. This reflects a weaker monsoon season and the reduced surface-water availability reported across several major basins in 2023 [23]. The Nile was near its seasonal norm in JAS 2023 (-0.07) versus +0.57/+0.67 in 2024/2025, indicating reduced variability [24]. Across South America, El Niño peaked in SON 2023, with the Amazon and Orinoco-Guianas basins falling to -0.77 and -0.29. This matches the exceptional 2023 Amazon drought, reported from mid-2023 onward, when low rainfall and high temperatures drove river levels to their lowest in over a century [25, 26]. River-level minima reported in October [27] coincide with the strongest negative SON anomalies observed by SWOT. In contrast, southern Pacific South America reached +0.87/+0.71 in JAS/SON, consistent with the 2023 coastal El Niño and its anomalous warming and intense rainfall along the Peruvian coast [28].

During the DJF 2023/24 El Niño peak, the tropical South American wet season stayed weak: the Amazon was near-neutral (+0.05), whereas the Orinoco–Guianas deficit deepened to -0.89. Meanwhile, equatorial Africa turned above-normal, with the Congo at +0.75, and Western Europe rose to about +0.45, reflecting active Euro-Atlantic storm-track activity and positive North Atlantic Oscillation-like conditions [29, 30]. As El Niño weakened through 2024/2025, the dominant signal reversed toward wetter tropical South America, consistent with enhanced convection under neutral-to-weak-La-Niña conditions [31, 32]. The Amazon reached +0.40 in AMJ 2025, and strong reach-scale anomalies (Fig. S8) over La Plata during 2024 reflect with the severe May floods in Rio Grande do Sul and Porto Alegre [33]. By AMJ 2025, the northern Amazon swung from -0.64 in SON 2023 to +1.42, and the southern Amazon from -0.79 in SON 2024 to +0.45, reversals of nearly two typical years’ variation that highlight the contrasting hydrological expressions of the ENSO transition. By late 2025, as La Niña strengthened, Africa showed the largest winter shifts: the Congo fell from +0.75 in DJF 2023/24 to -0.07 in DJF 2025/26, North Africa rose from +0.10 to +1.27, and Mediterranean Europe increased to +0.5. This extreme North African anomaly reflects the exceptional winter rainfall and flooding in early 2026, tied to repeated atmospheric rivers and a southward-displaced North Atlantic jet [34].

SWOT thus allowed the transition from El Niño to La Niña to be followed directly through its imprint on major river basins. Relative to neutral conditions, El Niño reduced Amazon basin discharge by about 1.3 times its typical interannual variation, and by nearly two times in its northern sector, while weakening the monsoon-season response by about one-third over the Indian subcontinent and two-thirds over the Nile.

As La Niña developed, the dominant anomalies shifted toward Africa, with the Congo changing by about four-fifths of its typical interannual variation relative to the El Niño peak and North Africa by more than one full interannual variation. SWOT also shows how these large-scale phases combine with regional circulation events, including enhanced Atlantic storm-track activity over Europe during El Niño and atmospheric-river episodes over North Africa during La Niña.

The results are consistent with responses reported in focused basin-scale studies, supporting the robustness of the SWOT signal. The fundamental advance, however, is that these responses can now be observed and quantified as a spatially complete global system, extending beyond the gauged network to reveal how seasonal regimes and ENSO-driven anomalies emerge, propagate, amplify or weaken across entire river networks with unprecedented spatial detail. Building this observational record of how individual basins respond to successive climate anomalies provides a basis for anticipating their hydrological response as comparable large-scale forcings develop in the future.

### 2.3 Regulation of Seasonal Patterns

Seasonal regimes are not always transferred naturally through river networks. In regulated basins, the seasonal pulse produced by climate forcing can be intercepted by reservoirs, delayed by storage, and damped by hydropower or irrigation releases [35]. The set of rivers in Fig. 3 illustrates examples of highly seasonal rivers in which dams and reservoirs introduce discontinuities in the timing, amplitude, and coherence of discharge, reshaping the seasonal signal as it moves downstream. Such dynamics remain difficult to resolve with gauges alone, particularly in transboundary, regulated or ungauged basins where in situ discharge observations are sparse or not openly accessible. SWOT provides a new opportunity to observe these alterations directly from space. This is particularly important since such dynamics are often absent or simplified in global hydrological models, which tend to smooth reservoir effects and miss the local breaks and phase shifts that define regulated seasonal regimes [36].

The Nile provides the clearest example of a seasonal regime reorganized by storage. Along the Blue Nile-Main Nile pathway, the flood pulse generated in the Ethiopian Highlands is initially strong, with high monthly discharge ratios during JAS. This signal is intercepted by the Grand Ethiopian Renaissance Dam (GERD), the large hydropower reservoir on the Blue Nile in Ethiopia, during the recent filling and early operation period captured by SWOT [37–39]. Since 2023, monthly patterns suggest evolving release behavior downstream of GERD. Lag-corrected metrics quantify this transformation (see Methods-3): the downstream signal is delayed by 2.8 months, damped by 46%, and retains only moderate coherence with the upstream signal ( $C^*=0.61$ ). Farther downstream, both Nile pathways converge toward the dominant control of the Aswan High Dam, where the seasonal signal is shifted by 6 months, damped by 59%, and weakly coherent ( $C^*=0.36$ ). These results are consistent with the known role of Aswan in suppressing the natural Nile flood and redistributing flow for irrigation and hydropower [40–42]. The White Nile pathway adds an important contrast: its more buffered seasonal signal is partly re-amplified after confluence with

the more seasonal Blue Nile, emphasizing that regulation must be interpreted together with tributary mixing [43].

Other regulated rivers show different forms of alteration. In the Zambezi, the Kariba and Cahora Bassa dams impose long storage delays of 4.2 and 6 months, respectively, with weak coherence ( $C^*=0.26$  and  $0.20$ ), consistent with strong reservoir control of the middle and lower Zambezi [44]. In the Mekong, the monsoon pulse remains visible, but the upper cascade reorganizes its timing and amplitude: the Xiaowan-Nuozhadu reach shows a 1.8-month delay, 17% damping and reduced coherence ( $C^*=0.49$ ) [45–47]. In Brazil, Sobradinho strongly alters the São Francisco, with a 4.5-month delay, 78% damping and low coherence ( $C^*=0.38$ ), while Tucuruí on the Tocantins preserves timing but strongly reduces amplitude, with 75% damping and high coherence ( $C^*=0.88$ ) [48, 49]. Finally, the Yellow River illustrates an even more complex human-shaped seasonal pulse: the Qingtongxia-regulated reach shows a 3.2-month delay, 37% damping and moderate coherence ( $C^*=0.64$ ), while downstream reservoir operations further modify the timing and structure of flow [50, 51]. These observation-based diagnostics show that SWOT can expose how reservoirs reshape seasonal river dynamics and provide information needed to represent regulated rivers more realistically in global models.

### 3 Outlook

A directly observed global record of river discharge changes the scale at which river dynamics can be understood. SWOT provides the hydrologic community, for the first time, with globally consistent observation-based discharge estimates across connected river networks, including ungauged and transboundary regions that could previously be examined only through sparse gauges or model simulations. In just three years, the record already resolves seasonal activation migrating with atmospheric circulation, inter-annual anomalies tracking ENSO transitions that shift seasonal discharge by 0.3 to 1.3 times its typical year-to-year variation across major basins, and regulation that delays or severs these signals along managed corridors, offsetting them by up to six months and damping their amplitude by as much as 78%. These estimates remain bounded by SWOT’s spatial coverage, its accuracy in challenging settings and revisit sampling; limitations that synergies with other Earth-observation missions can help mitigate. As the record lengthens, SWOT will turn this first global view into a reference for detecting how continental water movement shifts under climate variability, basin memory, and expanding human control.

### 4 Data and code availability

This study uses SWOT discharge product, produced by the SIC4DVAR discharge algorithm using the SWOT version D RiverSP products available at PO.DAAC (<https://doi.org/10.5067/SWOT-RIVERSP-2.0>) and Hydroweb.next ([https://hydroweb.next.theia-land.fr/?pid=SWOT\\_L2\\_HR\\_RIVERSP\\_REACH](https://hydroweb.next.theia-land.fr/?pid=SWOT_L2_HR_RIVERSP_REACH)). SIC4DVar codes are available at <https://github.com/SWOT-Confluence/sic4dvar>. Validation dataset is available at <https://doi.org/10.18419/DARUS-5843>.

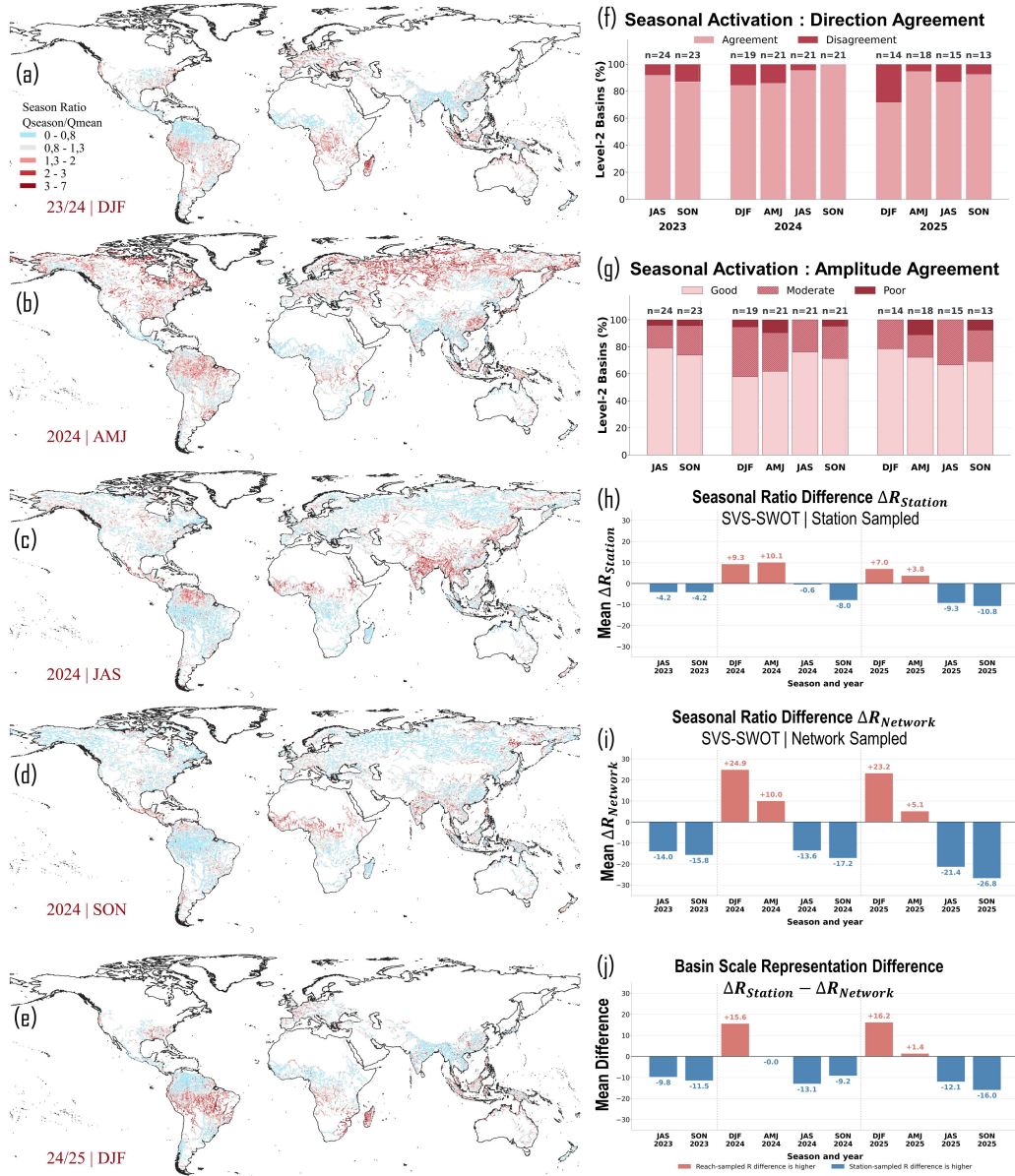


**Fig. 1** Seasonal activation and validation of discharge ratios. Panels (a-e) reach-scale seasonal discharge ratios derived from SWOT during 2023-2025. Panels (f-g) agreement between SWOT and SVS in the direction and amplitude of seasonal activation at the level-2 basin scale. Panels (h-j) seasonal ratio differences between station sampled and network sampled activation, aggregated over all basins for each season.

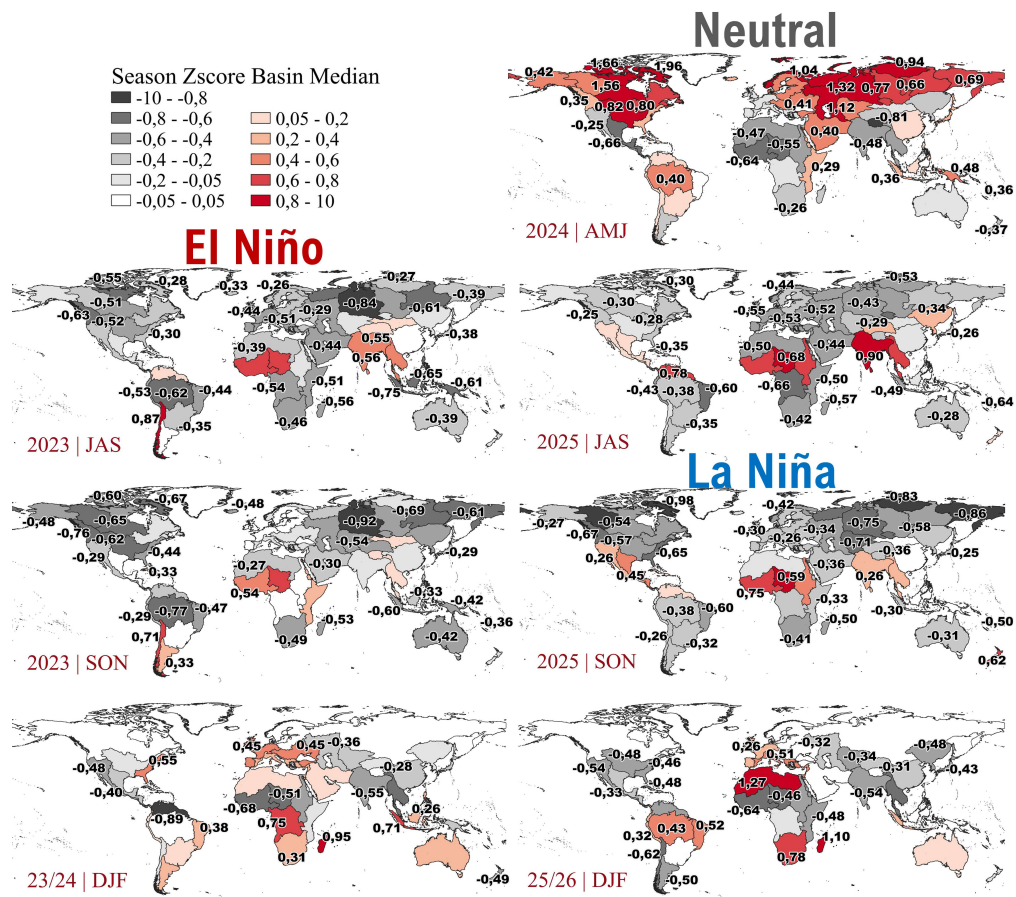


**Fig. 2** Standardized seasonal discharge anomalies (Z-score) derived from discharge across the development and peak of the 2023/24 El Niño, the subsequent neutral phase, and the emergence of the 2025/26 La Niña.

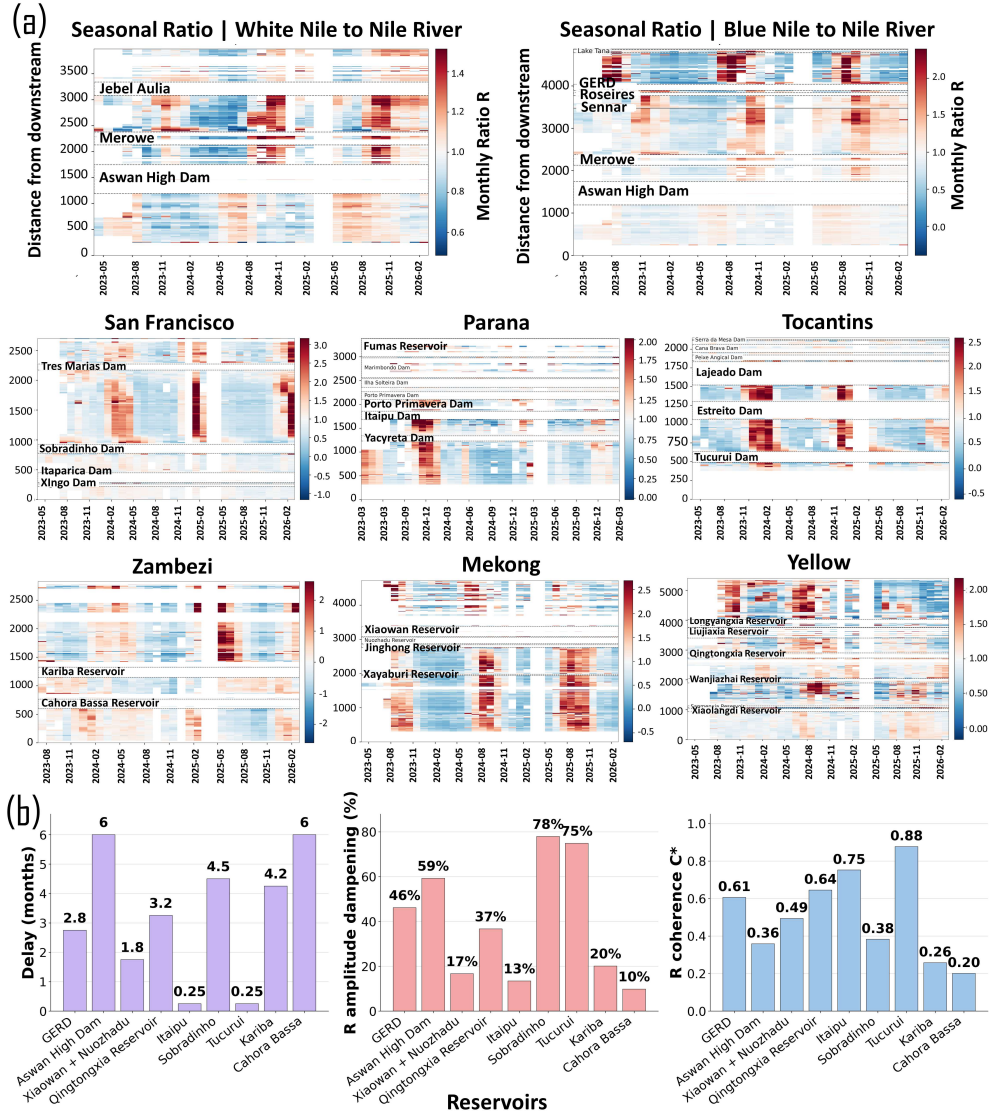


**Fig. 3** Reservoir-induced alteration of seasonal discharge regimes. (a) Hovmöller diagrams of monthly discharge ratio along regulated river corridors. The horizontal axis represents time, and the vertical axis represents longitudinal distance along the river pathway. Dashed horizontal lines mark major reservoirs/dams. (b) Estimated delay, amplitude damping and lag-adjusted coherence across selected reservoirs.

## 5 Methods

### 5.1 SWOT Measurements: Water Surface Elevation, Width and Slope

The river discharge estimates derived from SWOT rely on hydraulic quantities measured by the Level-2 River Single Pass (RiverSP) product [52]. This product provides simultaneous observations of water surface elevation (WSE), river width, and water surface slope, which form the basis for satellite-based discharge estimation. The RiverSP data are distributed at two spatial scales: nodes and reaches. Node-level measurements represent localized observations of WSE and river width derived from aggregated radar pixels spaced approximately every 200 m along the mapped river centerline. These node observations are subsequently aggregated to produce reach-scale quantities by averaging measurements over predefined river segments with a typical length of about 10 km. The reach definitions follow the segmentation of the SWOT River Database (SWORD) [53], which provides the global river network framework used for SWOT inland water products.

The present study uses the RiverSP Version D dataset, which spans SWOT observations from the start of the Calibration and Validation (Cal/Val) phase onward and covers both reprocessed and forward-processed data. Version D integrates data generated through two processing streams. The first stream, PGD0, corresponds to reprocessed observations collected between March 30, 2023, and April 27, 2025. The second stream, PID0, contains forward-processed observations acquired from April 28, 2025 onward. Version D supersedes the earlier Version C products and incorporates updated processing algorithms, calibration parameters, and geophysical models. It also uses SWORD v17b [53] and the updated Version D processing baseline for RiverSP products, providing the most recent SWOT river observations used in this study. Additional details on the processing chain and product characteristics can be found in the SWOT User Handbook [54].

### 5.2 SWOT Measurements Filtering

Prior to discharge estimation, SWOT observations are subjected to a series of pre-filtering procedures designed to remove unreliable measurements and ensure the consistency of hydraulic variables used in the discharge algorithms. The configuration used here is implemented within the Confluence pre-diagnostics module [55]. The filtering procedure first imposes acquisition geometry constraints on the SWOT observations. Only measurements located within a cross-track distance between 10000m and 60000m from the satellite ground track are retained, and observations flagged as ice or partial ice are removed. Additional constraints are applied to the physical characteristics of the river reaches. Specifically, reaches shorter than 5000m or narrower than 60m are excluded. These thresholds are determined using information derived from both the raw SWOT observations and the SWORD river database. Beyond these geometric criteria, several data quality conditions are also enforced. The filtering requires a minimum dark fraction of 0.6, a minimum observed reach fraction of 0.4, and at least 10 valid pixels per node. To further identify anomalous measurements, a Tukey

outlier detection method is applied to the water surface elevation, river width, and water surface slope variables.

Quality control information is provided through bitwise quality flags defined at both the reach and node levels. Individual quality attributes are categorized into four classes: good, suspect, degraded, and bad. In this study, two composite bitwise indicators are constructed to retain only reliable measurements: the reach-level flag `reach_q.b` (507510784) and the node-level flag `node_q.b` (532680192). These composite flags are computed by summing the relevant bitwise indicators while excluding measurements classified as degraded or bad. The filtering procedures are applied independently at the reach and node levels within the Confluence framework. A comprehensive description of the filtering strategy and the definition of individual quality attributes is provided in the SWOT L2 RiverSP Product Description Document [56].

### 5.3 SWOT Discharge

River discharge within the SWOT mission is estimated using a set of six algorithms developed by the SWOT Discharge Algorithms Working Group specifically for the mission. These algorithms use the hydraulic variables derived from the RiverSP products at both node and reach scales together with ancillary river information from SWORD. Discharge estimates are produced at the reach scale, corresponding to predefined river segments with an average length of approximately 10 km.

Most algorithms rely on formulations derived from the Gauckler–Manning–Strickler equation [57, 58], which relates discharge to hydraulic quantities observable by SWOT, including water surface elevation, river width, and water surface slope. The flow-law parameters required by this formulation, such as the hydraulic resistance coefficient and hydraulic radius, are not directly observable. They are estimated within the discharge estimation algorithms. The operational framework includes three algorithms operating at the reach scale: MetroMan [59], MOMMA [10], and SAD [60]—and three algorithms operating at the node scale: NeoBAM [61, 62], HiVDi [58, 63], and SIC4DVar [15, 17]. All algorithms are executed globally within the Confluence computational framework [55], which enables consistent large-scale processing of SWOT observations.

The discharge estimation is performed in a reanalysis mode, meaning that the algorithms use the complete set of available SWOT observations since launch within a consistent reprocessed dataset. In addition to discharge, the algorithms estimate key flow law parameters (FLPs), including the reference cross-sectional area  $A_0$  and the Manning friction coefficient  $n$ . These parameters, together with SWOT-derived cross-sectional hypsometric curves, are subsequently used in the forward processing of the future Level-2 discharge product. The resulting reanalysis discharge estimates constitute the Level-4 discharge product. A consensus discharge estimate is obtained by computing the median ensemble of the six algorithm outputs for each SWOT overpass and each SWORD reach.

Discharge estimation within the SWOT framework incorporates prior information on the mean river discharge derived from global hydrological modeling systems. In the current product, the prior mean discharge is derived from two independent global

datasets: GRADES-HydroDL [64] and  $\delta$ HBV2 [65]. When both datasets provide estimates for a given river reach, the prior discharge is defined as the average of the two values; otherwise, the available dataset is used individually.

#### 5.4 SWOT Discharge: SIC4DVar Discharge Estimation

In this study, discharge is estimated using SIC4DVar, which is the discharge estimation module of the broader SICFLOW processing chain. SICFLOW derives river hydraulic variables from SWOT observations through three main steps. First, a densification stage is applied to improve the quality as well as the spatial and temporal consistency of SWOT WSE and river width observations. Using the SWOT hydraulic catalogue of observed river profiles, this step reconstructs missing or filtered observations of WSE and width through an explicit Bayesian approach. Second, the densified node-scale observations of WSE and width are used to estimate the shape of the active river bathymetry along the river network. This step provides, for each node, the cross-sectional geometry of the active portion of the river, defined as the region experiencing wetting and drying during the SWOT observation period. Third, SIC4DVar uses the resulting hydraulic geometry together with the densified SWOT observations to estimate discharge.

Two versions of SIC4DVar have been developed. The full-cost version, SIC4DVar-FC, combines a Saint-Venant hydrodynamic model with a hybrid Bayesian–variational data assimilation framework and is primarily intended for basin-scale applications. The low-cost version, SIC4DVar-LC, referred to as SIC4DVar in the Main Text for simplicity, is designed for global application within the SWOT operational framework. It is implemented in the Confluence platform and contributes to the production of the official global SWOT discharge product. This low-cost version is used in the present study.

SIC4DVar-LC relates discharge to hydraulic quantities observed or derived from SWOT. It is based on an integrated form of the Gauckler–Manning–Strickler relation, in which discharge depends on the hydraulic characteristics of the flowing cross-section, the water-surface slope along the reach, and channel friction. Because SWOT does not directly observe river-bed elevation or channel friction, these quantities are estimated through an inverse Bayesian framework, combining the physical hydraulic relation with prior information. Discharge priors are provided by global hydrological models, while the posterior discharge distribution integrates the range of plausible river bed, friction values and discharge states. In the low-cost configuration, the likelihood term is set to unity, substantially reducing computational requirements while retaining the Bayesian treatment of parameter uncertainty and enabling global-scale application. The complete SIC4DVar formulation and its validation are described in [14].

#### 5.5 SWOT discharge Validation Set (SVS)

The SWOT discharge Validation Set (SVS; version 1.0.0) includes 3,643 river gauging stations worldwide [66]. The validation stations were compiled from 13 national and international hydrological data providers, including the National Water and Sanitation Agency (ANA), the French public water information service (EAU), the Swiss

Federal Office for the Environment (BAFU), the Australian Bureau of Meteorology (ABOM), the Department of Water and Sanitation of South Africa (DWS), the UK Department for Environment, Food & Rural Affairs (DEFRA), the Global Runoff Data Centre (GRDC), the Canadian National Water Data Archive (HYDAT), the Québec Ministry of the Environment, the Fight Against Climate Change, Wildlife and Parks (MEFCCWP), the Japanese Water Information System (MLIT), the Swedish Meteorological and Hydrological Institute (SMHI), the U.S. Geological Survey (USGS), and the German Federal Waterways and Shipping Administration (WSV). A complete list of stations and data sources is provided in Table S1 in the Supplementary Material.

Gauge discharge time series were filtered to retain only finite, non-negative values and were aggregated to monthly means to match the temporal scale of the SWOT discharge analysis. The comparison was restricted to months for which both SVS and SWOT discharges were available, and station-reach pairs were retained only when at least six common valid months were present. To avoid unstable estimates from very low-flow or weakly seasonal records, only stations with a coefficient of variation of at least 0.25 in both the SVS and SWOT discharge time series were retained. This filtering resulted in a subset of 1,996 stations used for validation.

Performance metrics against the SVS include normalized bias (nbias), Pearson correlation (R), and Nash-Sutcliffe Efficiency (NSE) coefficient.

## 5.6 Discharge Seasonality Metrics

To characterize the seasonal dynamics of river discharge, two complementary metrics are derived from the SWOT-SIC4DVar discharge time series: seasonal activation and standardized anomalies. These metrics allow the identification of dominant seasonal regimes as well as departures from the typical annual cycle.

### 5.6.1 Season Discharge Ratio

To identify periods of strong seasonal activation, a seasonal discharge ratio is computed by comparing discharge during a given seasonal window to the annual mean discharge:

$$R_{\text{season}} = \frac{Q_{\text{season}}}{Q_{\text{mean}}} \quad (1)$$

where  $Q_{\text{season}}$  represents the mean discharge over a selected seasonal period and  $Q_{\text{mean}}$  is the mean discharge over the entire observation period. Values greater than one indicate periods of enhanced discharge relative to the annual average, highlighting the activation of seasonal hydrological regimes.

### 5.6.2 Standardized Seasonal Anomaly (Z-score)

To identify regions where seasonal discharge deviates from its typical variability, a standardized anomaly is computed as:

$$Z = \frac{Q_{\text{season}} - Q_{\text{mean}}}{\sigma_Q} \quad (2)$$

where  $Q_{season}$  is the mean discharge during the seasonal window,  $Q_{mean}$  is the mean discharge over the entire observation period, and  $\sigma_Q$  is the standard deviation of the discharge time series. Positive Z-score values indicate stronger-than-usual seasonal activation, while negative values indicate reduced discharge relative to the seasonal norm.

## 5.7 Regulated rivers: delay, amplitude damping and coherence

To quantify how reservoirs modify seasonal discharge signals, three lag-corrected regulation metrics are computed between upstream and downstream river segments: delay, amplitude damping, and coherence. For each reservoir or reservoir cascade, monthly discharge-ratio time series are first extracted for the segment upstream of the control structure and for the segment downstream of it. These are denoted  $R_u(t)$  and  $R_d(t)$ , respectively, where  $R$  is the monthly discharge ratio relative to the local annual mean.

The regulation delay is estimated from standardized segment anomalies so that the lag detection is controlled by the timing of the seasonal signal rather than by differences in amplitude. For each segment, the monthly ratio is standardized as:

$$Z_u(t) = \frac{R_u(t) - \mu_{R_u}}{\sigma_{R_u}}, \quad Z_d(t) = \frac{R_d(t) - \mu_{R_d}}{\sigma_{R_d}} \quad (3)$$

where  $\mu_R$  and  $\sigma_R$  are the mean and standard deviation of the monthly discharge-ratio time series. The downstream signal is then shifted relative to the upstream signal over a set of candidate lags  $\tau$ , ranging from 0 to 6 months. For each lag, the lagged correlation is computed as:

$$C(\tau) = \text{corr}(Z_u(t), Z_d(t + \tau)) \quad (4)$$

The regulation delay  $\tau^*$  is defined as the lag that provides the strongest coherent downstream response to the upstream seasonal signal. When several lags provide similar correlations, the earliest strong local maximum is retained to avoid selecting later seasonal harmonics. This delay represents the phase shift introduced by storage and managed releases.

After the delay is identified, amplitude damping and coherence are computed using the original monthly discharge ratios, centered around the annual mean:

$$r_u(t) = R_u(t) - 1, \quad r_d(t) = R_d(t) - 1 \quad (5)$$

The upstream and downstream signals are aligned using the selected delay  $\tau^*$ . The seasonal amplitude of each signal is then estimated using the 10th-90th percentile range, which is less sensitive to outliers than a maximum-minimum range:

$$A_u = P_{90}(r_u(t)) - P_{10}(r_u(t)) \quad (6)$$

$$A_d = P_{90}(r_d(t + \tau^*)) - P_{10}(r_d(t + \tau^*)) \quad (7)$$

Amplitude damping is defined as:

$$D_A = 1 - \frac{A_d}{A_u} \quad (8)$$

and is expressed as a percentage. Positive values indicate that the downstream seasonal signal is damped relative to the upstream signal, whereas negative values indicate downstream amplification or re-activation, for example through tributary inputs or managed releases.

The lag-corrected coherence is finally computed as:

$$C^* = \text{corr}(r_u(t), r_d(t + \tau^*)) \quad (9)$$

This metric measures whether the downstream seasonal signal preserves the shape of the upstream signal once the delay has been accounted for. High values of  $C^*$  indicate that the seasonal pulse is mainly delayed and/or damped but remains coherent, whereas low values indicate a stronger reorganization of the seasonal signal. Together,  $\tau^*$ ,  $D_A$ , and  $C^*$  separate three distinct effects of regulation: the delay of seasonal propagation, the attenuation of seasonal amplitude, and the loss of upstream-downstream coherence.

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## Author contributions

H.O. conceptualized and performed the study. I.G., P.O.M. and H.O. developed the SICFLOW/SIC4DVar algorithms and its operational global versions in Confluence. D.Q., C.C. and I.R. contributed to its implementation and product generation. C.C. has contributed to the filtering configuration. The SWOT SVS dataset collection and matching have been performed by P.S. and M.J.T. The Confluence platform was built and run by C.G. and M.D. SICFLOW algorithm development and operational implementation was discussed and funded by N.P., D.L., and S.P.L. Distribution of SWOT products through CNES Hydroweb portal was performed by C.E. H.O. wrote the original draft. T.P., A.C., P.B., C.D., J.W. and J.W. provided several valuable improvements to the draft. All authors discussed the results, commented on, and approved the final paper.

**Supplementary information.**

## SWOT SIC4DVar Performance

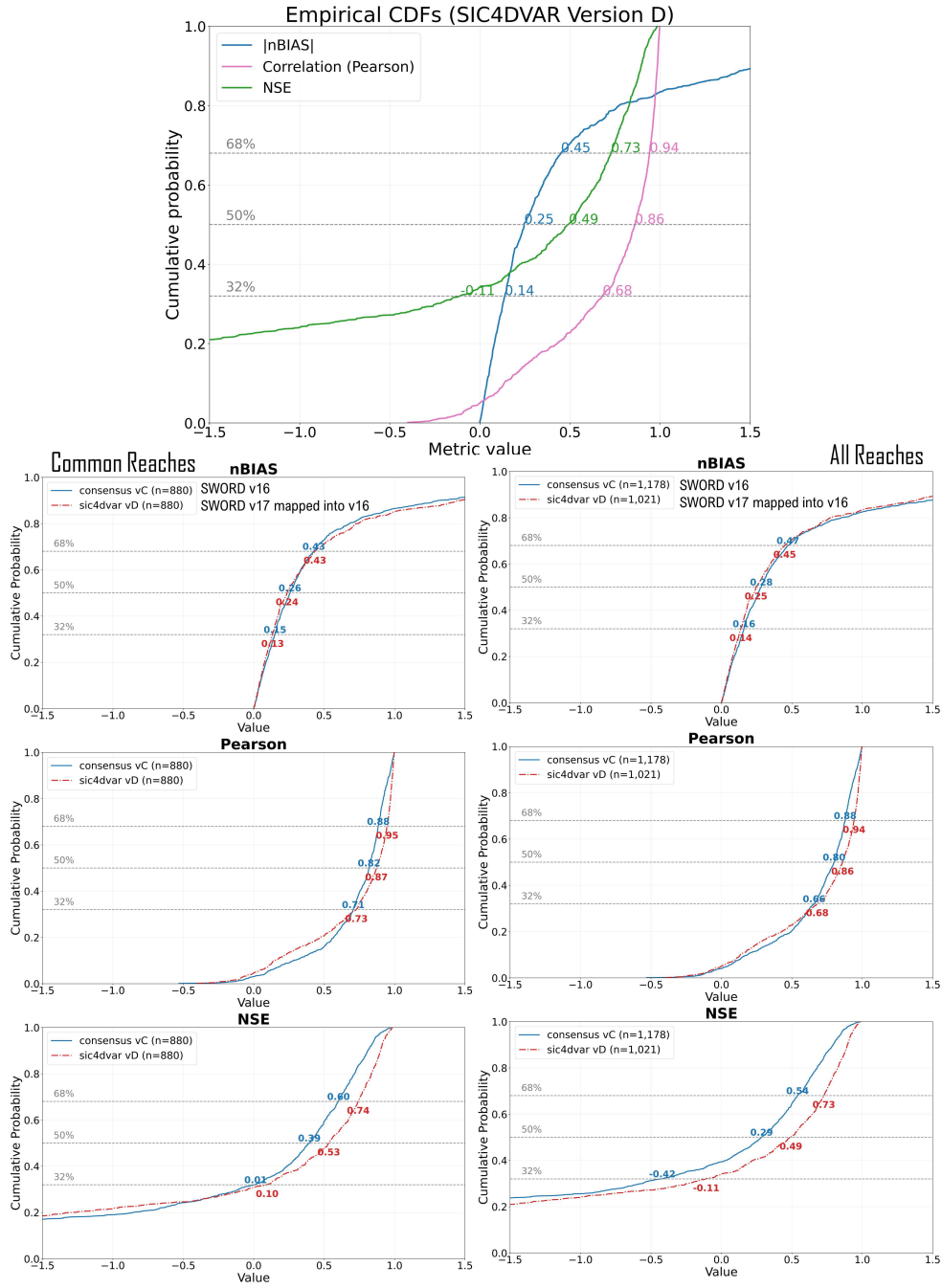


**Fig. S1** Empirical cumulative distributions of SIC4DVar Version D (SWORD v17) performance against SVS discharge. The upper panel summarizes absolute normalized bias (nBIAS), Pearson correlation and Nash–Sutcliffe efficiency (NSE) with the 32nd, 50th and 68th percentiles indicated. Lower panels compare the publicly released Version C consensus (SWORD v16) and SIC4DVar Version D (SWORD v17 mapped into v16) over common validation reaches (left) and their respective full validation samples (right). The Version D consensus product had not yet been released at the time of the study.

## Active Regimes

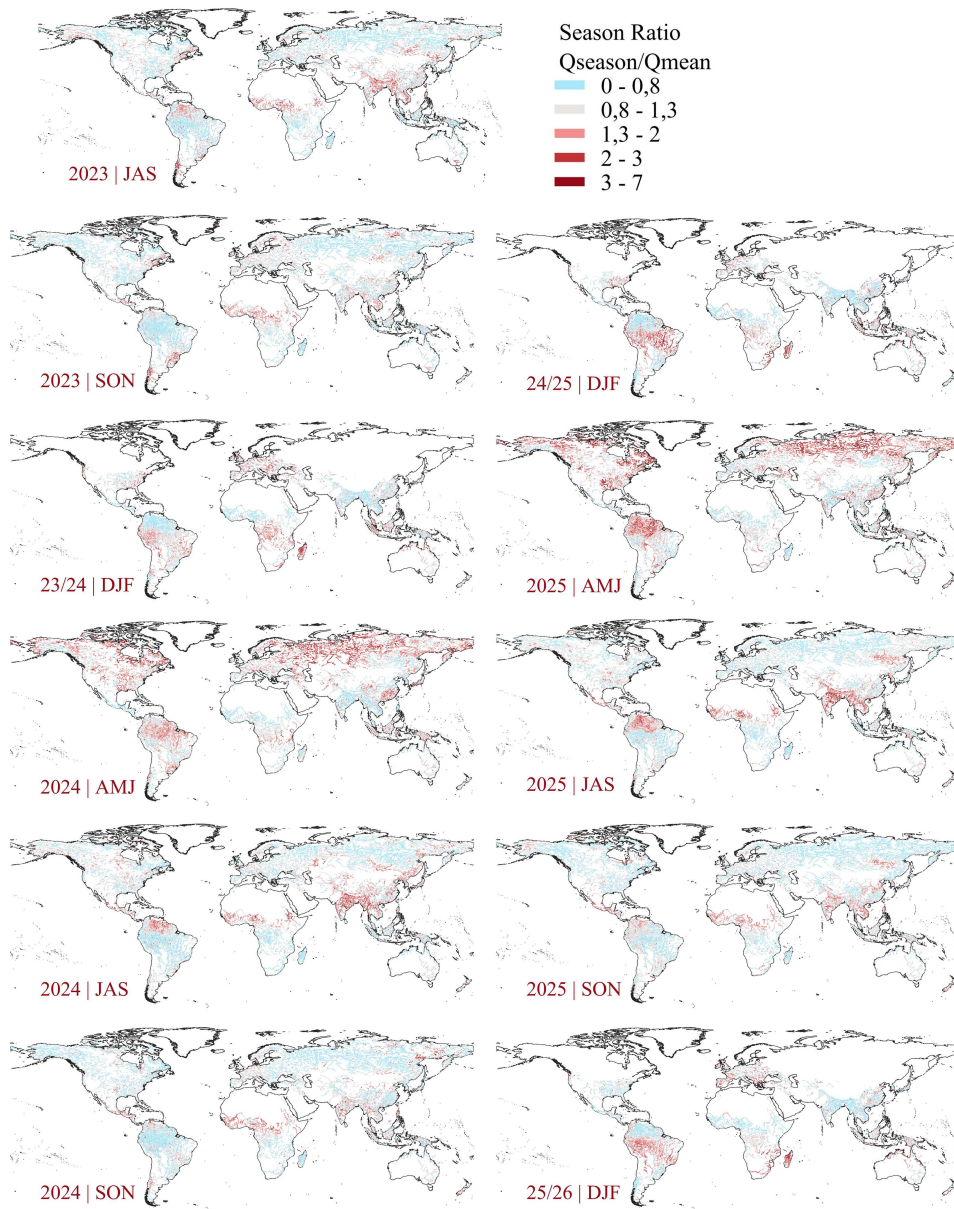


**Fig. S2** Seasonal discharge ratio ( $R$ ) derived from SWOT-SIC4DVar discharge for March 2023 to February 2026. Anomalies greater than 1 indicate higher seasonal activation relative to the average discharge, while values less than 1 indicate lower seasonal activation relative to the average discharge.

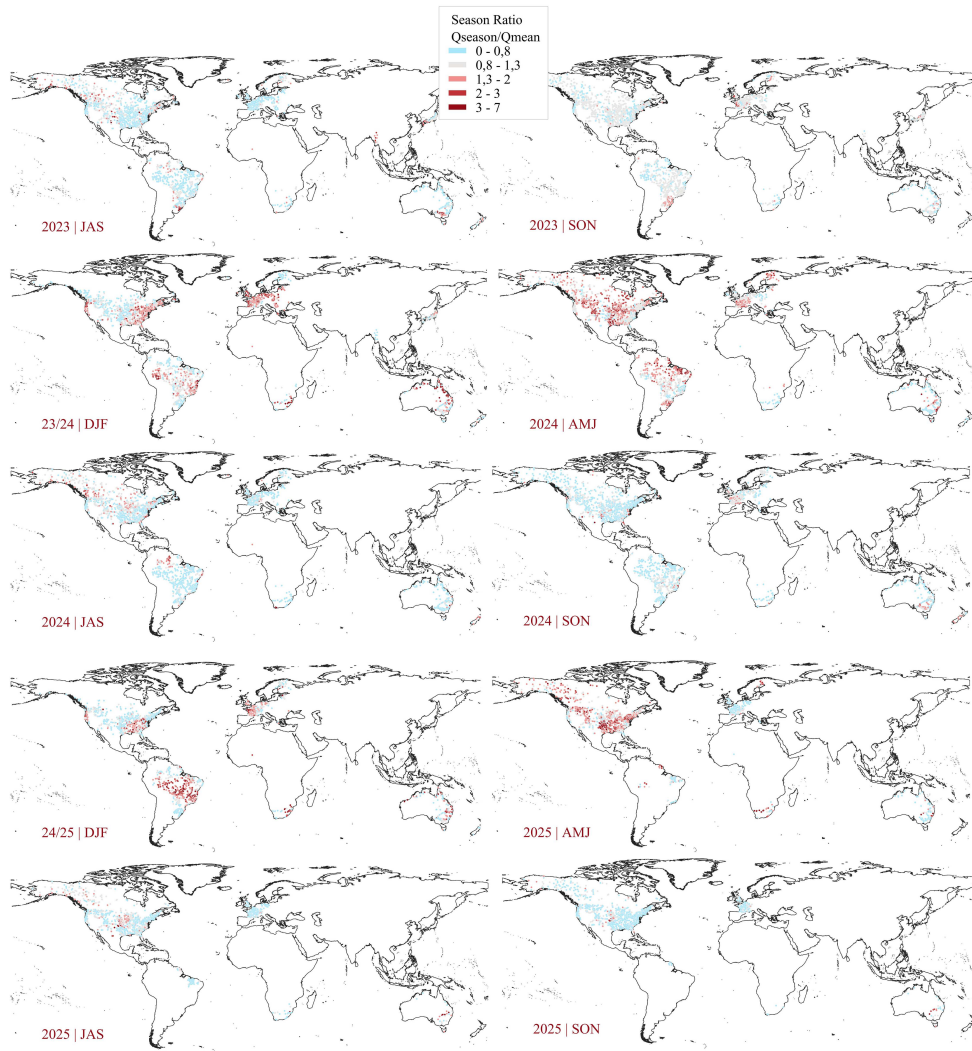


**Fig. S3** Seasonal discharge ratio ( $R$ ) derived from in-situ SVS discharge for March 2023 to December 2025. Anomalies greater than 1 indicate higher seasonal activation relative to the average discharge, while values less than 1 indicate lower seasonal activation relative to the average discharge.

## Seasonal Activation | Station-Sampled

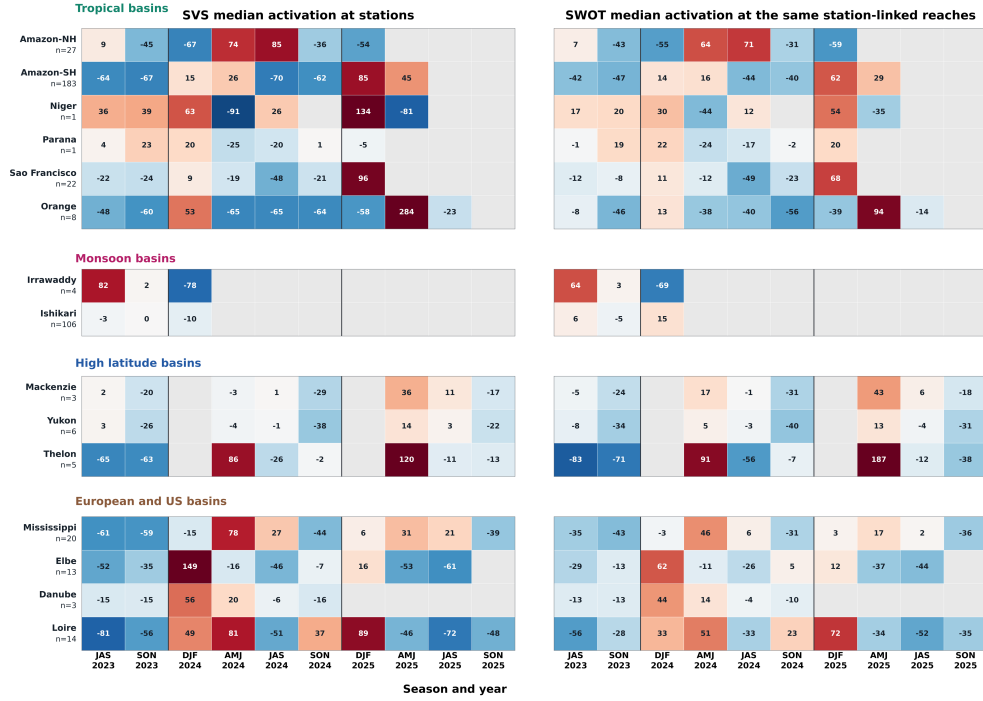


**Fig. S4** Station-sampled comparison of seasonal activation. Median seasonal discharge anomalies from in situ observations at validation stations (left) and SWOT-SIC4DVar estimates over the corresponding station-linked reaches (right). Values are expressed as percentages relative to the mean discharge; n indicates the number of stations.

## Seasonal Activation | Network-Sampled

### Tropical basins

|                        |     |     |     |     |     |     |     |     |     |     |     |
|------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Amazon-NH<br>n=1699    | 2   | -40 | -48 | 29  | 15  | -35 | -43 | 78  | 41  | -6  | -38 |
| Amazon-SH<br>n=12808   | -36 | -45 | 7   | 19  | -38 | -45 | 26  | 22  | -23 | -22 | 28  |
| Orinoco<br>n=162       | 51  | -12 | -64 | -9  | 66  | -9  | -57 | 39  | 85  | 34  | -49 |
| Congo-NH<br>n=1572     | 7   | 40  | 3   | -22 | -4  | 35  | -29 | -26 | 0   | 22  | -26 |
| Congo-SH<br>n=3180     | -28 | -8  | 37  | 5   | -33 | -15 | 12  | -3  | -30 | -16 | 5   |
| Niger<br>n=355         | 3   | 18  | -5  | -44 | 3   | 36  | 4   | -35 | 10  | 29  | 3   |
| Betsiboka<br>n=32      | -56 | -49 | 68  | -21 | -45 | -53 | 51  | -40 | -56 | -44 | 134 |
| Parana<br>n=143        | -10 | 23  | 23  | -9  | -31 | -30 | 1   | -10 | -20 | -7  | 0   |
| Sao Francisco<br>n=170 | -8  | -11 | 26  | -1  | -44 | -23 | 66  | -30 | -43 | -42 | 69  |
| Orange<br>n=159        | -42 | -37 | 15  | -35 | -49 | -48 | -35 | 76  | -18 | -24 | 76  |

### Monsoon basins

|                      |     |     |     |     |    |     |     |     |     |     |     |
|----------------------|-----|-----|-----|-----|----|-----|-----|-----|-----|-----|-----|
| Ganges<br>n=158      | 46  | 12  | -26 | -45 | 52 | 25  | -26 | -39 | 73  | 45  | -19 |
| Brahmaputra<br>n=110 | 70  | -4  | -57 | -6  | 61 | -2  | -59 | 29  | 45  | 6   | -62 |
| Indus<br>n=225       | 16  | -7  | -26 | -5  | 30 | -2  | -25 | 3   | 33  | 6   | -17 |
| Mekong<br>n=182      | 42  | 12  | -62 | -51 | 83 | 34  | -59 | -28 | 97  | 62  | -43 |
| Irrawaddy<br>n=105   | 67  | 8   | -71 | -38 | 98 | 6   | -75 | 8   | 78  | 14  | -72 |
| Ishikari<br>n=507    | -22 | -14 | -14 | 12  | 6  | -10 | -27 | 10  | -13 | -13 | -26 |

### High latitude basins

|                    |     |     |  |     |     |     |  |     |     |     |  |
|--------------------|-----|-----|--|-----|-----|-----|--|-----|-----|-----|--|
| Mackenzie<br>n=119 | -3  | -24 |  | -10 | -11 | -32 |  | 40  | 5   | -26 |  |
| Yukon<br>n=264     | -8  | -26 |  | 20  | -7  | -27 |  | 17  | -6  | -14 |  |
| Ob<br>n=473        | -48 | -64 |  | 52  | 4   | -44 |  | 54  | -22 | -47 |  |
| Yenisei<br>n=204   | -30 | -42 |  | 76  | -30 | -38 |  | 67  | -31 | -35 |  |
| Lena<br>n=464      | -32 | -44 |  | 33  | -48 | -49 |  | 65  | -6  | -26 |  |
| Thelon<br>n=841    | -52 | -39 |  | 114 | -19 | -18 |  | 117 | -14 | -36 |  |

### European and US basins

|                      |             |             |             |             |             |             |             |             |             |             |             |
|----------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Mississippi<br>n=257 | -36         | -42         | -4          | 62          | 1           | -26         | 6           | 43          | 2           | -38         | -43         |
| Elbe<br>n=123        | -18         | -5          | 49          | -1          | -15         | 12          | 11          | -16         | -15         | -14         | -11         |
| Danube<br>n=157      | -6          | -5          | 42          | 27          | -8          | -4          | -21         | -13         | -22         | -28         | -5          |
| Loire<br>n=64        | -57         | -32         | 31          | 39          | -35         | 5           | 49          | -35         | -49         | -30         | 61          |
|                      | JAS<br>2023 | SON<br>2023 | DJF<br>2024 | AMJ<br>2024 | JAS<br>2024 | SON<br>2024 | DJF<br>2025 | AMJ<br>2025 | JAS<br>2025 | SON<br>2025 | DJF<br>2026 |

Season and year



**Fig. S5** Network-sampled seasonal activation across selected river basins. Cells show the median seasonal discharge anomaly, expressed as a percentage relative to the mean discharge, across all SWOT-observed reaches within each basin. Basins are grouped by dominant hydroclimatic regime, and n indicates the number of sampled reaches.

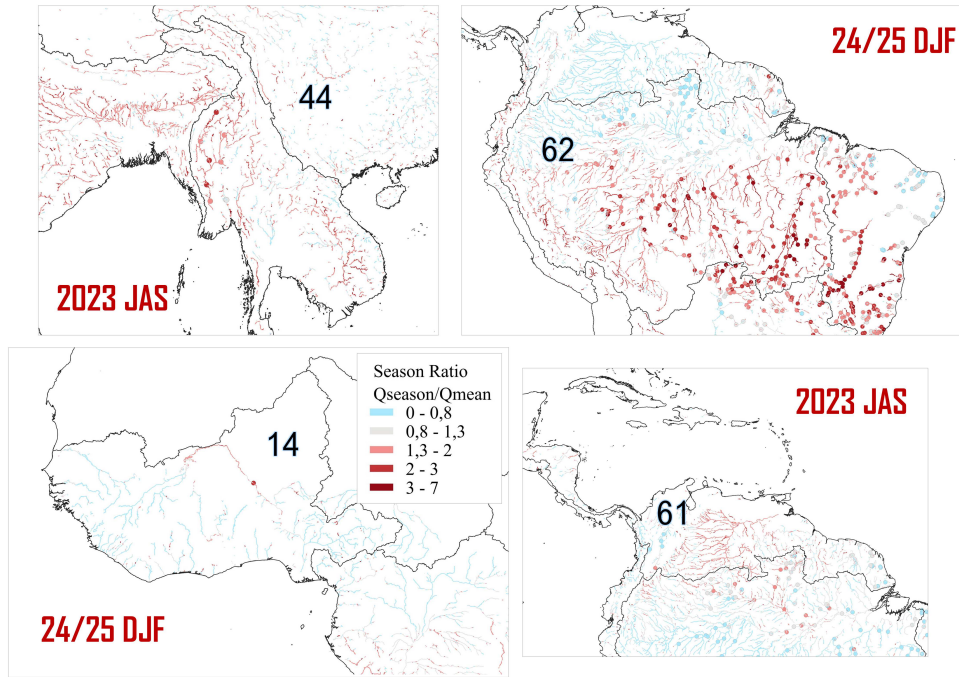


**Fig. S6** Spatial heterogeneity of seasonal activation within selected level-2 basins. Reach-scale seasonal discharge ratios are shown for basins 44 and 61 in JAS 2023, basin 83 in AMJ 2024, and basins 14 and 62 in DJF 2024/25. Values above and below one indicate locally enhanced and suppressed discharge, illustrating spatial variability that may not be represented by a limited number of stations.

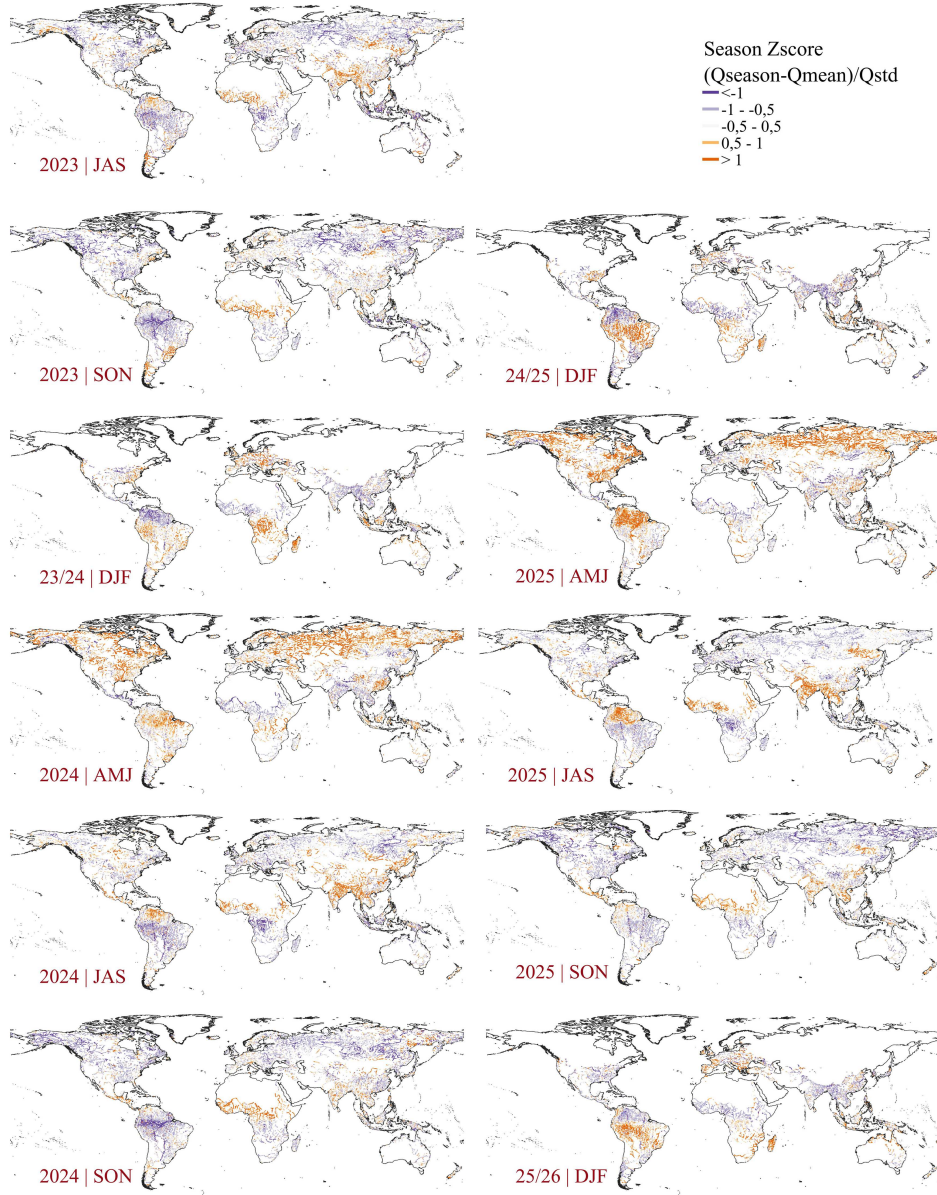


**Fig. S7** Standardized seasonal anomaly (Z) derived from SWOT-SIC4DVar discharge for March 2023 to February 2026. Positive anomalies indicate stronger-than-usual seasonal activation, while negative anomalies indicate reduced-than-usual seasonal activation.

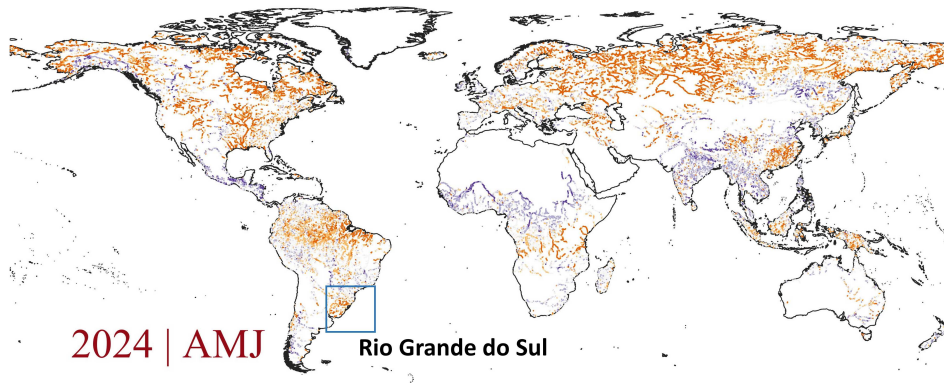


**Fig. S8** Global reach-scale standardized discharge anomalies during AMJ 2024 derived from SWOT-SIC4DVar estimates. The box highlights the strong positive anomalies across Rio Grande do Sul during the May 2024 flood period.

## Natural and Regulated Signatures

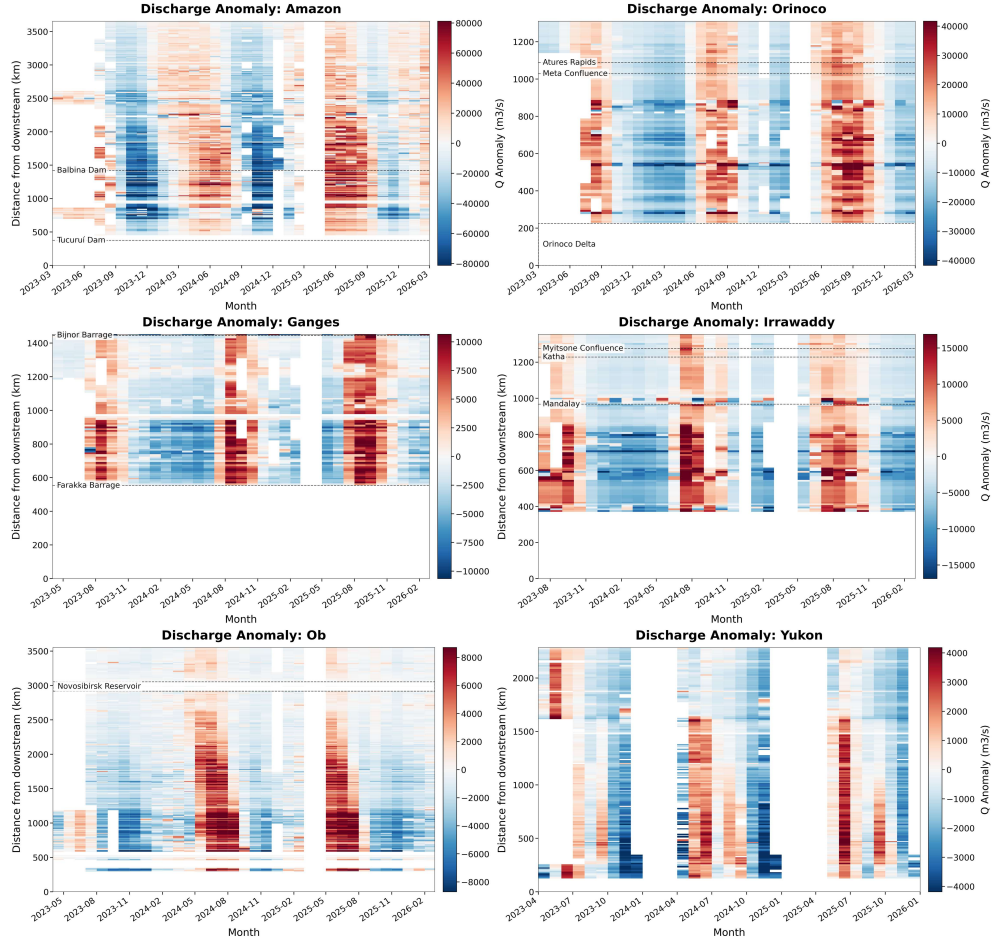


**Fig. S9** Hovmöller diagrams of discharge anomaly (top,  $m^3s^{-1}$ ) and relative discharge anomaly (bottom, %) along the River mainstream, derived from SWOT-SIC4DVar estimates. The horizontal axis represents time, and the vertical axis represents distance from the outlet.

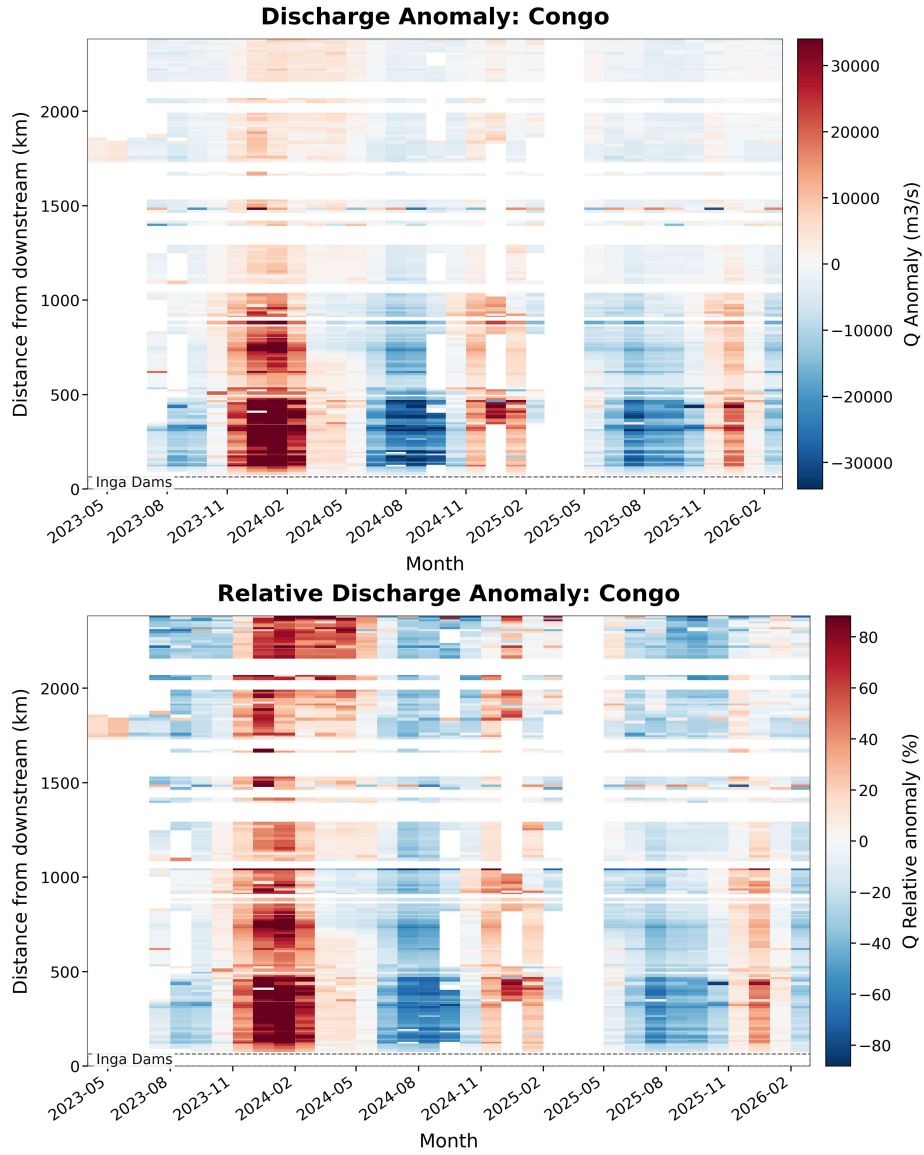


**Fig. S10** Hovmöller diagrams of discharge anomaly (top,  $m^3s^{-1}$ ) and relative discharge anomaly (bottom, %) along the Congo River mainstream, derived from SWOT-SIC4DVar estimates. The horizontal axis represents time, and the vertical axis represents distance from the outlet.

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