

Assessing the Impact of Freshwater Fluxes from Major

Rivers Quantifying freshwater fluxes from Major rivers and assessing their impact on the Atlantic Ocean

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Abstract. This study evaluates the impact of [riverine](#) freshwater fluxes on the Atlantic Ocean. The river discharge has been estimated at the outlet of 18 major rivers flowing into the Atlantic by solving the water mass balance equation at the river basin scale. In this approach, water storage changes are evaluated with satellite gravimetry measurements. In contrast, atmospheric fluxes (i.e., precipitation, evapotranspiration) are assessed with atmospheric reanalyses, in situ measurements from a global network of rain gauges, or a global hydrological model. The river discharge estimated with the water mass balance is consistent with independent river gauge measurements across all South American rivers, in particular the Amazon, where the annual and monthly climatology can be estimated with an error of less than 5 % when compared with in situ measurements. Larger discrepancies are observed for other basins, likely due to uncertainties in the precipitation and evapotranspiration fluxes. When climatological estimates of the river discharge are replaced by the water mass balance approach in ocean model simulations, a decrease in the sea surface salinity bias is observed at the outlet of the Amazon and across the whole Atlantic. The water mass balance approach can bring new observational constraints on freshwater fluxes flowing from the continent to the ocean, but is not universally reliable due to potential biases in atmospheric flux estimates. When combined with in situ measurements or hydrological model predictions, the water mass balance approach can enhance freshwater flux quantification, leading to improved ocean model simulations near major river outlets. In particular, the enhanced river runoff dataset significantly reduces salinity biases, with associated changes in ~~reduced~~-vertical stratification, ~~enhanced~~-upper ocean circulation, and [basin scale](#) meridional transports.

1 Introduction

Freshwater fluxes play a critical role in shaping ocean dynamics, primarily by inducing regional density variations through changes in salinity. ~~These freshwater~~[Freshwater](#) inputs, originating from river discharge, precipitation, and ice melt, influence upper-ocean stratification, circulation, and air-sea interactions. In regions such as the eastern tropical North Atlantic, freshwater fluxes drive seasonal and interannual variability in sea surface salinity (SSS), modulating the upper-ocean buoyancy balance and affecting ocean-atmosphere coupling (Thouvenin-Masson et al., 2024). On a broader scale, major river systems such as the Amazon have

34 been shown to affect global thermohaline circulation, heat distribution, and atmospheric convection (Huang and Mehta, 2010;
35 Jahfer et al., 2017).

36

37 In addition to salinity regulation, freshwater fluxes contribute to ocean mass redistribution, influencing both regional and global
38 sea level. Mass anomalies caused by land-to-ocean water ~~exchanges~~[fluxes](#) propagate rapidly—within ~10 days—across ocean
39 basins through barotropic waves (Dobslaw and Thomas, 2007). Changes in terrestrial water storage, driven by natural variability
40 and anthropogenic activities, have been linked to sea level changes ranging from a few millimeters to several centimeters on time
41 scales from days to decades (Cáceres et al., 2020; Hamlington et al., 2020; Pfeffer et al., 2022). As the global hydrological cycle
42 intensifies with climate change (Fournier et al., 2023), understanding the variability of these fluxes becomes essential for accurate
43 ocean state estimation and climate prediction.

44

45 Despite their importance, freshwater fluxes are often poorly represented in ocean models. Many operational systems and reanalyses
46 (e.g., (Storto et al., 2019)) rely on climatological or highly simplified river discharge datasets, which fail to capture the temporal
47 variability and long-term trends critical for accurate simulation of ocean salinity, circulation, and sea level. This limitation affects
48 not only the realism of ocean simulations but also the fidelity of coupled atmosphere-ocean models used for climate forecasting
49 (Sausen et al., 1994). Incorporating more realistic, time-varying freshwater inputs has been shown to improve both regional sea
50 level simulations and the representation of key climate signals (Tajouri et al., 2024).

51

52 Traditional estimates of river discharge rely heavily on in situ stream gauges, which suffer from uneven spatial coverage and are
53 often located far upstream from river mouths (Dai and Trenberth, 2002). Additionally, access to gauge data is restricted in many
54 regions due to institutional, political, and economic constraints. These limitations hamper efforts to consistently quantify freshwater
55 fluxes into the ocean at global scales.

56

57 Satellite gravimetry offers a promising alternative. Observations from the GRACE (Tapley et al., 2004) and GRACE-FO (Landerer
58 et al., 2020) missions enable monitoring of large-scale water mass redistribution across the Earth system. By combining satellite-
59 derived terrestrial water storage anomalies with vertical atmospheric fluxes—precipitation and evapotranspiration—from
60 reanalyses or land surface models, river discharge can be estimated using the Water Mass Balance (WMB) approach. This method
61 has been used to estimate monthly and seasonal freshwater fluxes from river basins to continental scales, showing critical sensitivity
62 to the choice of atmospheric reanalyses used to estimate vertical fluxes (Syed et al., 2005, 2009). Validation efforts in the Amazon
63 basin have demonstrated good agreement between WMB-derived river discharges and in situ measurements at Óbidos, both in
64 terms of seasonal variability and long-term trends (Chen et al., 2020). Importantly, this approach can also help identify biases in
65 atmospheric flux estimates—especially evapotranspiration—that affect freshwater balance accuracy.

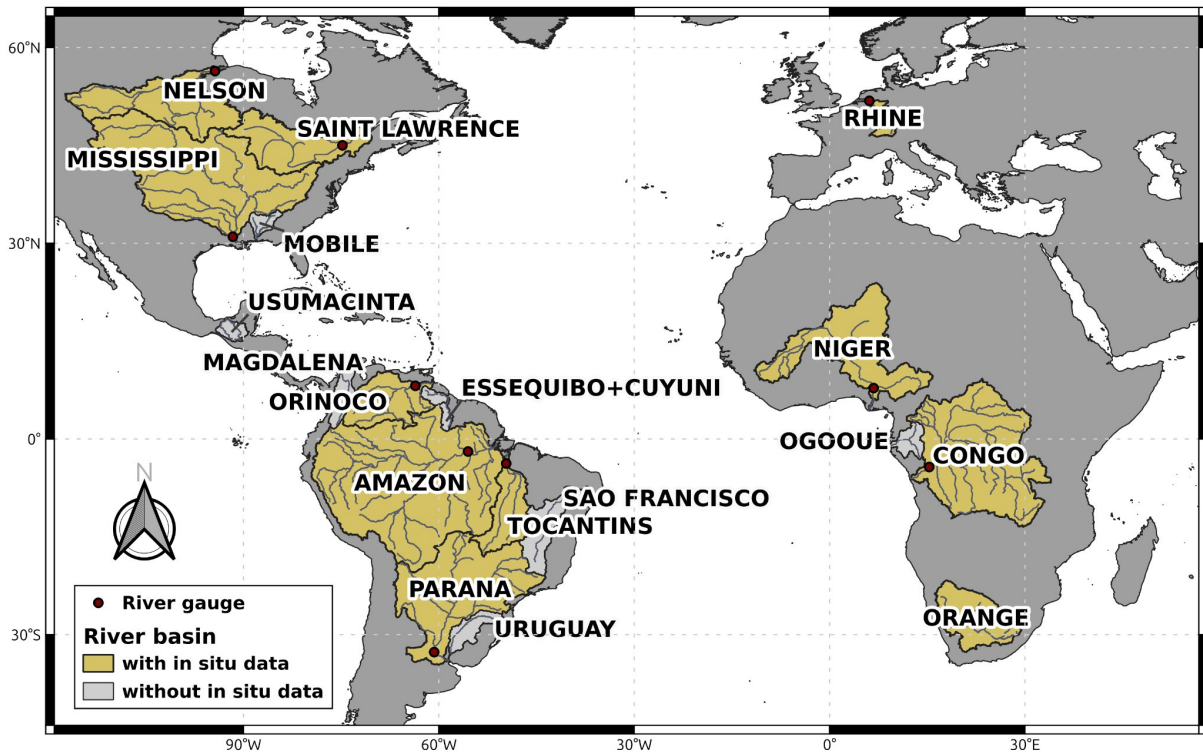
66

67 In this study, we apply the WMB approach to estimate river discharge from 18 major river basins draining into the Atlantic Ocean.
68 These estimates are validated against available in situ river gauge data. The WMB-derived discharges are then used as freshwater
69 forcing in ocean model simulations. Simulated sea surface salinity is compared to ~~independent verifying data, such as the~~ EN4
70 objective analyses-, to evaluate the accuracy of the approach [versus independent observations](#), and to assess the impact of land-to-
71 ocean freshwater fluxes on the Atlantic Ocean at seasonal to interannual timescales.

72 **2 Data and Methods**

73 **2.1 Study area**

74 The objective of this study is to assess the impact of freshwater fluxes on the Atlantic Ocean by estimating river discharge using
75 the Water Mass Balance (WMB) approach. This method combines satellite gravimetry data from the GRACE and GRACE-FO
76 missions with atmospheric or land surface reanalyses to quantify river discharge.
77



78
79 **Figure 1: Map of the 18 selected rivers with their associated catchment areas. The yellow areas represent river basins**
80 **where in situ data have been used for quality assessment, with the locations displayed of the river gauges shown as red dots.**
81 **Light grey areas represent river basins where no in situ measurements were available over the observation period (January**
82 **2003 - December 2020).**

83
84 To ensure a comprehensive coverage of all major rivers discharging into the Atlantic Ocean, all rivers with an average discharge
85 exceeding 2,000 m³/s were initially identified using data from the HydroRIVERS database (Lehner and Grill, 2013). From this
86 preliminary selection, only the rivers with a catchment area larger than 100,000 km² were retained, in order to align with the spatial
87 resolution of GRACE and GRACE-FO measurements, which is approximately 300 × 300 km. This process resulted in the selection
88 of 18 river basins distributed across four continents—North and South America, Africa, and Europe—and encompassing a wide
89 range of climatic regimes in terms of precipitation and temperature (Fig. 1). [The largest river to be excluded \(in terms of discharge\)](#)
90 [is the Rio Atrato, with an average long-term discharge of 3768 m³/s \(Lehner and Grill, 2013\).](#)

91
92 The main characteristics of the selected basins are summarized in Table 1. River names and outlet locations are taken from the
93 HydroRIVERS database (Lehner and Grill, 2013). Notably, the Essequibo and Cuyuni Rivers were combined due to their shared
94 outlet. Although the Orange River has an average discharge below the 2,000 m³/s threshold (~300 m³/s), it was included in the

95 final selection due to its extensive catchment area, which ensures compatibility with the spatial resolution of satellite gravimetry
96 data. The basin areas are extracted from the Major River Basin database (GRDC, 2020).

97

River Name	Latitude of the river outlet	Longitude of the river outlet	Basin area (km ²)	Mean discharge at outlet (m ³ /s)	In_situ measurements	Mean precipitation (m/years)
Amazon	-0.67	-51.10	5965894	205604	GRDC	2.38
Congo	-6.07	12.48	3705225	39637	HyBAM	1.44
Orinoco	8.58	-60.98	941419	37053	HyBAM	2.47
Mississippi	29.19	-89.28	3240620	21894	GRDC	0.85
Parana	-33.93	-58.54	2646513	18311	GRDC	1.28
Saint-Lawrence	46.80	-71.21	1053299	12344	GRDC	1.03
Tocantins	-2.20	-49.41	772469	11408	Dai&Trenberth	1.57
Magdalena	11.02	-74.79	260737	7248	-	3.38
Niger	4.41	6.06	2122995	6859	GRDC	0.55
Uruguay	-32.93	-58.11	266134	6423	-	1.68
Ogooue	-1.00	8.92	215213	4805	-	1.83
Cuyuni and Essequibo	6.45	-58.59	154857	3935	-	2.17
Usumacinta	18.56	-92.67	127388	3583	-	1.80
Nelson	56.93	-92.75	1106520	2750	GRDC	0.62
Sao Francisco	-10.46	-36.42	637202	2697	GRDC	0.75
Rhine	51.96	4.16	163122	2451	GRDC	1.07
Mobile	30.70	-88.04	112528	2100	-	1.29
Orange	-28.60	16.47	977322	310	GRDC	0.37

98 **Table 1: Selected basins characteristics. River outlet coordinates are given in degrees. Mean discharge at the outlet**
99 **corresponds to the long-term average discharge from the Hydro Rivers dataset. The mean precipitation corresponds to**
100 **ERA5 precipitations averaged over the basin area during the 2002—2019 period.**

101 2.2 In- Situ Measurements of the River Discharge

102 The Global Runoff Data Centre (GRDC) Data Download Portal offers the most comprehensive, quality-controlled database of
103 river discharge observations, comprising daily and monthly time series from over 10,800 gauging stations along approximately
104 7,000 rivers worldwide (Federal Institute of Hydrology, 2024). The database incorporates various in situ measurement techniques
105 as described by (Dobriyal et al., 2017). Typically, manual discharge measurements are collected at different river stages using

devices such as current meters, Acoustic Doppler Current Profilers (ADCPs), or other flow-measuring instruments. For each stage (water level), the corresponding discharge is recorded. A rating curve—often modeled as a power-law function—is then fitted to these data, enabling continuous estimation of river discharge from continuously monitored stage values. However, this method carries inherent uncertainties, typically around 15%, and is both time-consuming and labor-intensive (Créteaux et al., 2016). Establishing and maintaining in situ gauging stations is therefore costly, which limits their deployment primarily to main river stems, resulting in sparse coverage and limited data availability for remote rivers and tributaries. Moreover, the number of active gauges in the GRDC database has significantly declined since the 1980s, with only 14% remaining active by 2020 (Elmi et al., 2024). For example, just 2,200 stations have reported discharge data beyond 2015. While some stations provide daily data, others report only monthly values.

To enhance the coverage, the GRDC database has been complemented by the HYBAM (HYdro-géochimie du Bassin Amazonien) project (Catalogue – Hybam, 2025), which provides monthly in situ discharge measurements using the ADCP method (Dobriyal et al., 2017) for 17 stations located in South America and the Congo Basin.

In order to avoid gaps in the Tocantins dataset from GRDC, discharge estimates from (Dai, 2017) have been used as reference. In situ measurements were acquired at the Tuvcurui station located the closest to the river mouth. Temporal gaps are filled with data from nearby gauges if available and otherwise with a regression based on a hydrological model. Additional corrections are detailed in (Dai et al., 2009).

Combining the GRDC, HYBAM and Dai&Trenberth datasets, in situ discharge measurements were available for 11 out of the 18 selected rivers since 2000 (Fig. 2). The Magdalena, Usumacinta, Essequibo, Cuyuni, São Francisco, Uruguay, and Ogooué rivers were not sampled since 2000. The Orange River had the longest observation period, lasting 90 years until today, while the Niger River had only 13 years of intermittent data since 2002. Among the 11 rivers sampled with in situ observations, the Orange, Rhine, Nelson, Saint Lawrence, Paraná, Orinoco, Congo, and Amazon rivers all benefited from long, continuous discharge records spanning over the 16 years of the period covered by the WMB approach using GPCC precipitation and ISBA-CTRIP evapotranspiration.

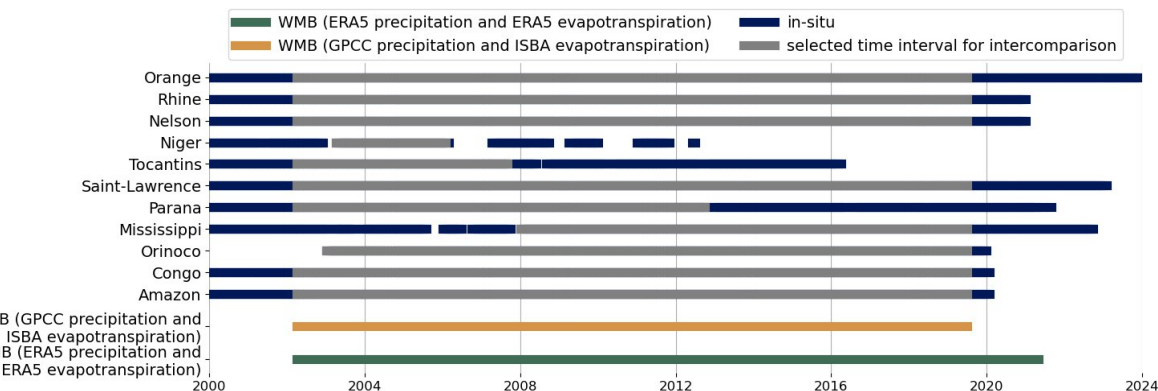


Figure 2: Availability of river discharge measurements through time. Blue lines represent periods with available in situ discharge data. Grey lines indicate the longest continuous interval with monthly in situ data, used for comparison with WMB results. The orange line shows the time span covered by the WMB approach using GPCC precipitation and ISBA evapotranspiration, bounded by the launch of the GRACE satellites (start) and the availability of the ISBA-CTRIP model (end). The green line shows the WMB time span based on ERA5 precipitation and evapotranspiration.

139 2.3 The Water Mass Balance Approach

140 The river discharge can be estimated using the water mass balance equation, expressed as:

$$\frac{dS}{dt} = P - ET - R \quad (1)$$

141 where dS/dt are the changes in land water storage in time, P the precipitation, ET the evapotranspiration and R the river discharge.

142
143 Terrestrial Water Storage (TWS) anomalies have been estimated from April 2002 to August 2023 at monthly timescales and with
144 a spatial resolution of 1 degree using an ensemble of GRACE and GRACE-FO solutions derived from (Blazquez et al., 2018). The
145 GRACE and GRACE-FO ensemble comprises 120 solutions, allowing the estimation of uncertainties associated with different
146 processing strategies and geophysical corrections needed for hydrological applications. The ensemble is based on coefficients of
147 the Earth's gravitational potential anomalies estimated by five centers (CNES, CSR, JPL, GFZ, ITSG). A large variety of post-
148 processing corrections are applied to the ensemble, including two models of the geocentre motions (Lemoine and Reinquin, 2017;
149 Sun et al., 2016), three models of the oblateness (C20) of the Earth (Cheng et al., 2013; Lemoine and Reinquin, 2017; Loomis et
150 al., 2019), and two [GIA](#) Glacial Isostatic Adjustment (GIA) models (Caron et al., 2018; Peltier et al., 2018). To reduce the
151 anisotropic noise, ~~decorrelation filters, called DDK~~ [denoising and decorrelation kernel \(DDK\)](#) filters (Kusche et al., 2009), are
152 applied to GRACE solutions, using two different orders (DDK3 and DDK6) corresponding to different levels of filtering. The
153 ensemble of 120 solutions results from combining these five processing centers, two geocenter models, three oblateness models,
154 two GIA corrections, and two filters.

155
156 The monthly TWS anomalies are then averaged at river basin scale. To compute the first derivative of TWS changes (dS/dt), the
157 GRACE and GRACE-FO time series need to be processed in order to fill data gaps ranging from 1 (satellite operations) to 11 (time
158 gap between the two missions) months. In our dynamic interpolation, we first remove the seasonal terms (annual and semi-annual
159 sinusoids) and linear trends estimated by least squares adjustments, we then use linear interpolation to reconstruct residual TWS
160 times series at the start of each month, and finally we add the seasonal terms and linear trends back to the reconstructed TWS time
161 series. The first derivative of TWS changes (dS/dt) can then be computed as the difference between two consecutive TWS
162 estimates. As noted by (Chen et al., 2020), it is important to interpolate terrestrial water storage (TWS) anomalies to the start of
163 each month. This ensures that the differentiation between consecutive months yields a first-order estimate of TWS changes that is
164 consistent with precipitation and evapotranspiration data averaged over calendar months.

165
166 The precipitation (P) is averaged by calendar month and by basin, using the GPCC observational product (Schneider et al., 2015)
167 spanning over 1980-2022 or with the ERA5 reanalysis (Hersbach et al., 2020) spanning over 1980-today. The mean
168 evapotranspiration is estimated with the ERA5 reanalysis spanning over 1980-today, or with the ISBA-CTRIP hydrological model
169 (Decharme et al., 2019) spanning over 1979-2019. Two combinations of river discharge (R) are then calculated based on the
170 difference between the net precipitation ($P-ET$) and the first derivative of terrestrial water storage changes (dS/dt) for each river
171 basin. The first combination uses ERA5 precipitation and evapotranspiration and will be referred to hereafter as WMB1. [It should
172 be noted that the ERA5 water budget is not globally closed, with precipitation exceeding evaporation and spurious variability
173 associated with changes in the assimilation system \(Hersbach et al., 2020; Mayer et al., 2021\). At the river-basin scale considered
174 here, ERA5 budget residuals are considerably smaller than in previous reanalyses \(Mayer et al., 2021\), but any remaining regional
175 bias of net freshwater maps directly onto the WMB discharge estimates and contributes to its errors.](#) The second uses GPCC

precipitation together with ISBA-CTRIP evapotranspiration and will be referred to hereafter as WMB2. It may be noted that the ISBA-CTRIP hydrological model is forced with GPCC precipitation, ensuring consistency at the model scale, between the atmospheric fluxes considered.—The combination using ERA5 atmospheric fluxes spans over the full GRACE and GRACE-FO observation period considered in this study (i.e. April 2002 to May 2021), while the combination using GPCC and ISBA-CTRIP spans over April 2002 until July 2019.

2.4 Performance Metrics¶

The WMB approach is evaluated using several performance metrics: percent bias (PBias) for the temporal mean, the correlation coefficient (R), the variability ratio (γ), and the modified Kling-Gupta Efficiency (KGE'). The R score is Pearson's correlation coefficient, ranging between -1 (perfect anti-correlation), and +1 (perfect correlation) highlights the strength of the linear relationship between two datasets. The proportional bias corresponds to the sum of the differences between the predicted and observed values, normalized by the average of observed values. It ranges between -∞ and +∞, 0 corresponding to no bias. It is computed as follows: ¶

$$PBias = \frac{\sum_{i=1}^N (P_i - O_i)}{\sum_{i=1}^N O_i} \quad (2)¶$$

Where P_i refers to a predicted value at time i , and O_i to the reference value at the same timestep. The variability ratio is computed as follows: $\gamma = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o}$ with σ_s the standard deviation of the predicted values and σ_o the standard deviation of the reference data. ¶

The modified Kling-Gupta Efficiency index (KGE') balances correlation, bias, and variability and is widely used in hydrological studies as a goodness-of-fit criterion. It was proposed by (Kling et al., 2012) as an updated version of the original KGE metric (Gupta et al., 2009) ranging between -∞ and 1, where 1 indicates the perfect fit. ¶

$$KGE' = 1 - \sqrt{(R - 1)^2 + (PBias - 1)^2 + (\gamma - 1)^2} \quad (3)¶$$

¶

2.5 Ocean Model Simulations

To assess the impact of river discharge estimates on ocean model simulations, this study employs the NEMO ocean model (version 4.0.7, (Madec et al., 2017)), which includes the sea-ice dynamic and thermodynamic model SI³. The model is configured on the ORCA1 grid, featuring a horizontal resolution of 1°, with ~~enhanced-resolution~~1/3° meridional resolution enhancement in the tropical ~~regions~~belt, and 75 vertical depth levels with partial steps (Bernard et al., 2006). The surface boundary conditions are computed using the CORE bulk formulas (Large and Yeager, 2009), implemented via the AEROBULK package (Brodeau et al., 2017). Meteorological forcing data are derived from the ECMWF ERA5 atmospheric reanalysis (Hersbach et al., 2020) at hourly frequency. The model setup is the same as the CIGAR reanalysis (Storto and Yang, 2024). It incorporates a 3-band RGB scheme for net shortwave radiation, with extinction coefficients based on a monthly climatology of chlorophyll. Vertical mixing is parameterized using the TKE scheme (Gaspar et al., 1990), and tracers and momentum are diffused using Laplacian and bi-Laplacian operators, respectively.

¶

Experiment¶ □	Type□	River forcing□	Rivers modified□	P and ET used□	Time resolution□
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REF	Control	Monthly climatology of Dai and Trenberth (2002), as compiled by Bourdalle-Badie and Tréguier (2006)	None (reference)	-	Monthly climatology
J5	Control	JRA55-do daily runoff (Tsujino et al., 2018), from the CaMa-Flood routing of JRA-55 land-surface runoff, calibrated to the Dai et al. (2009) discharges	All rivers, globally	-	Daily, interannually varying
A1	WMB1, all Atlantic rivers	WMB1 discharge at the outlet of the 18 rivers of Table 1; REF climatology elsewhere	18	ERA5/ERA5	Monthly, interannually varying
A2	WMB2, all Atlantic rivers	WMB2 discharge at the outlet of the 18 rivers of Table 1; REF climatology elsewhere	18	GPCC/ISBA	Monthly, interannually varying
S1	WMB1, high-confidence rivers	WMB1 discharge for the Amazon, Orinoco and Tocantins only; REF climatology elsewhere	3	ERA5/ERA5	Monthly, interannually varying
S2	WMB2, high-confidence rivers	WMB2 discharge for the Amazon, Orinoco and Tocantins only; REF climatology elsewhere	3	GPCC/ISBA	Monthly, interannually varying

Table 2: List of the ocean model experiments. All simulations share the same NEMO 4.0.7–SI3 ORCA1 configuration, ERA5 atmospheric forcing, initial conditions from the CIGAR reanalysis, and cover the period January 2003 - December 2020.

¶

The experiments we present do not include any data assimilation or bias correction. This approach allows us to evaluate the impact of the river discharge dataset without any interplay with observations. The experiments cover the period from January 2003 to December 2020 and are all initialized from the same initial conditions, taken from the CIGAR reanalysis.

We configured several experiments to assess the impact of different river discharge inputs on ocean modeling, summarized in Table 2. The reference experiment (REF) uses the standard NEMO monthly climatology of river discharge from the (Dai and

Trenberth, 2002) dataset, as compiled by (Bourdalle-Badie and Treguier, 2006). A second experiment (J5) uses daily varying runoff from the JRA-55-do dataset (Tsujino et al., 2018), based on a bias-corrected land component of the JRA-55 atmospheric reanalysis (using ERA5 as atmospheric forcing as all the other experiments). Although also JRA-55-do relies on an atmospheric reanalyses, its approach is intrinsically different from our WMB data: the JRA55-do runoff is produced by a river routing model forced by JRA-55 land-surface runoff, whose input is adjusted to match the Dai et al. (2009) estimates, with no information from satellite gravimetry.

In addition, we conducted four experiments that incorporate Water Mass Balance (WMB)-derived discharge estimates in place of the monthly climatology for the Atlantic Ocean. Experiments A1 and A2 replace the discharge climatology with WMB estimates for all 18 major rivers listed in Table 1. A1 uses precipitation and evapotranspiration from GPCC and ISBA, respectively the ECMWF ERA5 reanalysis (WMB1), while A2 uses both fields from the ECMWF ERA5 reanalysis GPCC and ISBA (WMB2), respectively. Experiments S1 and S2 focus on isolating the impact of the Amazon, Orinoco, and Tocantins rivers, which show high-confidence results under the WMB approach. In these experiments, WMB estimates are used only for those three rivers, while discharge from all other rivers follows the reference climatology. As with A1/A2, S1 uses GPCC and ISBA, while S2 uses ERA5.

To adopt the WMB-derived dataset in the NEMO simulations, the 18 major river basins have been remapped onto the NEMO ORCA1 grid through conservative remapping, using the local spread of the runoff within the coastlines of the pertinence of each river drainage basin, proportional in area to the monthly climatology of (Bourdalle-Badie and Treguier, 2006) ERA5 while S2 uses GPCC and ISBA..

The WMB provides a single discharge time series at the mouth of each of the 18 rivers, whereas NEMO requires runoff to be prescribed as a freshwater flux on ocean grid points. To adopt the WMB-derived dataset in the NEMO simulations, for each of the 18 rivers, we retained this spatial distribution unchanged from the climatology of Bourdalle-Badie and Tréguier (2006), and rescaled it at every month so that the runoff integrated over the corresponding grid points equals the WMB discharge, thus conserving the total freshwater volume delivered to the ocean; runoff at all other grid points is left at its climatological value. Note also that river runoff in the ocean simulations is all injected at the sea surface (first model level).

3 Quantification of freshwater fluxes over 18 major rivers

3.1. Comparison of river discharge estimates at the Obidos station

The Amazon River has a mean discharge more than four times greater than that of the next largest river flowing into the Atlantic—the Congo River (Table 1). Accurately estimating the Amazon River discharge is therefore crucial for assessing the impact of freshwater fluxes on the ocean. This assessment is carried out by comparing river discharge estimated with the WMB approach to in situ measurements at the Óbidios gauging station, located approximately 500 km upstream of the Amazon delta (Fig. 3). To ensure consistency between the WMB-derived and observed discharge, TWS anomalies, precipitation (P), and evapotranspiration (ET) were averaged over the station drainage area, as defined by the Global Runoff Data Centre (GRDC).

Overall, excellent agreement can be observed between the WMB estimates and in situ measurements acquired at the Obidos gauge, with Pearson’s correlation coefficient reaching 0.87 when ERA5 is used to constrain atmospheric fluxes (WMB1) and 0.88 when GPCC and ISBA-CTrip are used (WMB2) (Fig. 3). When excluding the strong seasonal cycle, the WMB discharge still

exhibits good agreement with the GRDC reference, with Pearson's correlation coefficient of 0.45 for WMB1 and 0.47 for WMB2. The average river discharge ($1.734 \times 10^5 \text{ m}^3/\text{s}$) is well captured by the WMB approach, with a difference of only +2 % in WMB1 and -3% in WMB2.

Differences between both WMB approaches appear in their ability to retrieve the seasonal cycle amplitude. While excellent agreement (+ 5%) with in situ data is retrieved in WMB1, more significant discrepancies occur in WMB2, leading to an overestimation of the annual cycle of the river discharge by 46% when compared with in situ data.— The differences between WMB1 and WMB2 arise from differences in the estimated net precipitation, primarily due to lower mean, higher noise and greater variability in ISBA evapotranspiration, including at annual timescales, when compared with ERA5 (Fig. A1). The phase of the seasonal cycle is also well captured by the WMB approach. The months of the highest and lowest discharge are May and November, both for in situ measurements and the WMB1 approach. By comparison, the highest discharge is two months late when comparing WMB2 to in situ measurements.

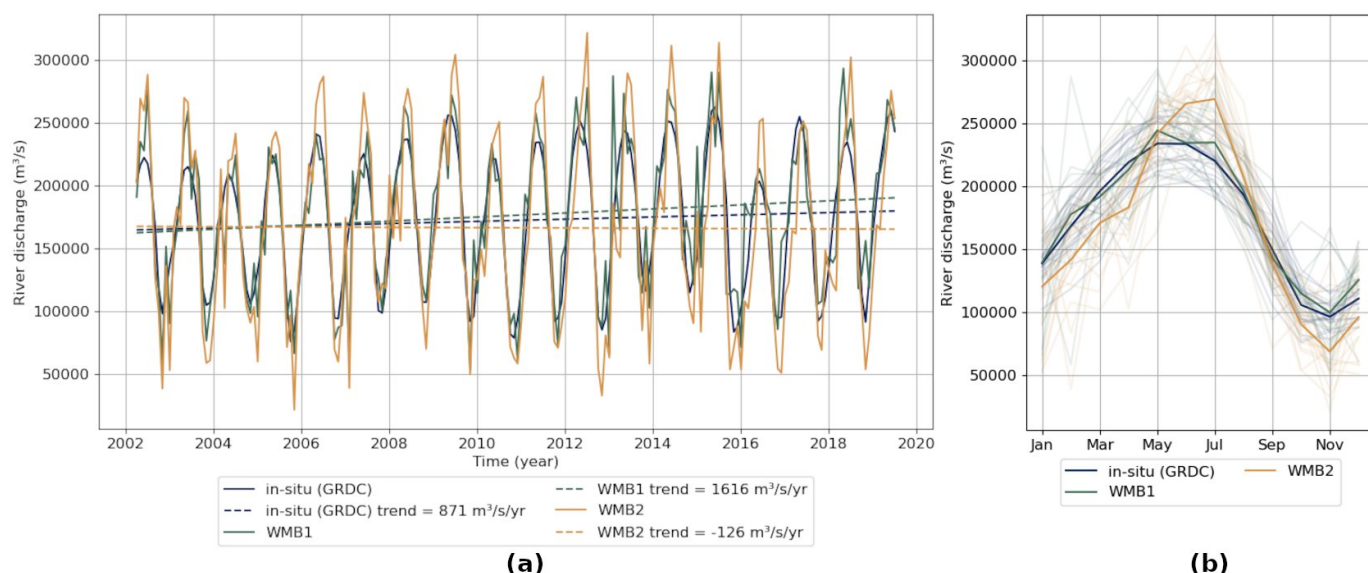


Figure 3: Discharge values at Obidos-Linografo station on the Amazon. In situ measurements are taken from the GRDC dataset, WMB1 refers to estimates from the WMB approach using ERA5 for precipitation and evapotranspiration. WMB2 refers to the WMB approach using GPCC for precipitation and ISBA for evapotranspiration. (a) displays monthly discharge values as solid lines, and the corresponding decadal trends as dashed lines. (b) shows seasonal cycles, with the solid line representing the mean seasonal cycle for each dataset.

Linear trends have also been computed by ordinary least square adjustment over April 2002—December 2019. A small decadal trend of $871 \text{ m}^3/\text{s}/\text{yr}$ is observed in in-situ river discharge measurements, overestimated with WMB1 and underestimated with WMB2. It may however be noted that this trend is not significant in regard with the annual and interannual variability of the Amazon discharge, and these values are likely to change a lot depending on the observation period considered. Linear trends shown in Fig. 3a were calculated and found to be statistically insignificant. Both WMB approaches exhibit stronger high frequency variability compared to in situ measurements with extreme events more marked with WMB2 than WMB1.

The Overall, the WMB approach is further evaluated using several performance metrics: percent bias (PBias) for the temporal mean, the correlation coefficient (R), the variability ratio (using ERA5 data (WMB1) shows excellent agreement with in situ measurements, yielding a KGE' score of 0.84. In contrast, using GPCC precipitation and ISBA-CTrip evapotranspiration

(WMB2) results in more pronounced discrepancies—both in the annual cycle and higher-frequency variations—leading to a lower KGE' score of 0.53. These results confirm the reliability of the WMB approach for estimating Amazon River discharge but highlight the sensitivity of the method to the choice of datasets used to estimate vertical atmospheric fluxes as shown previously γ), and the modified Kling-Gupta Efficiency (KGE'). The R score is Pearson's correlation coefficient, ranging between -1 (perfect anti-correlation), and +1 (perfect correlation) highlights the strength of the linear relationship between two datasets. The proportional bias corresponds to the sum of the differences between the predicted and observed values, normalized by the average of observed values. It ranges between $-\infty$ and $+\infty$, 0 corresponding to no bias. It is computed as follows: ¶

$$PBias = \frac{\sum_{i=1}^N (P_i - O_i)}{\sum_{i=1}^N O_i} \quad (2) ¶$$

Where P_i refers to a predicted value at time i , and O_i to the reference value at the same timestep. The variability ratio is computed as follows: $\gamma = \frac{\sigma_s / \sigma_o}{\sigma_o / \sigma_s}$ with σ_s the standard deviation of the predicted values and σ_o the standard deviation of the reference data. ¶

The modified Kling-Gupta Efficiency index (KGE') balances correlation, bias, and variability and is widely used in hydrological studies as a goodness-of-fit criterion. It was proposed by (KlingChen et al., 2012) as an updated version of the original KGE metric (Gupta et al., 2009) ranging between $-\infty$ and 1, where 1 indicates the perfect fit. ¶

2020)). Biases in net precipitation (P-E), in particular, directly affect the accuracy of discharge estimates. The differences between WMB1 and WMB2 highlight the sensitivity to atmospheric forcing, as precipitation and evapotranspiration are derived using substantially different approaches, including reanalyses, in situ observations, and hydrological models. Although only three sources are considered (ERA5, GPCC, and ISBA-CTrip), their methodological diversity likely provides a realistic representation of the dispersion among atmospheric flux estimates. Thus, the spread between WMB1 and WMB2 provides a meaningful indication of the uncertainty associated with the choice of atmospheric forcing, consistent with the findings of Lehmann et al. (2022) demonstrating that ERA5-Land generally performs well for water-budget closure, but shows larger

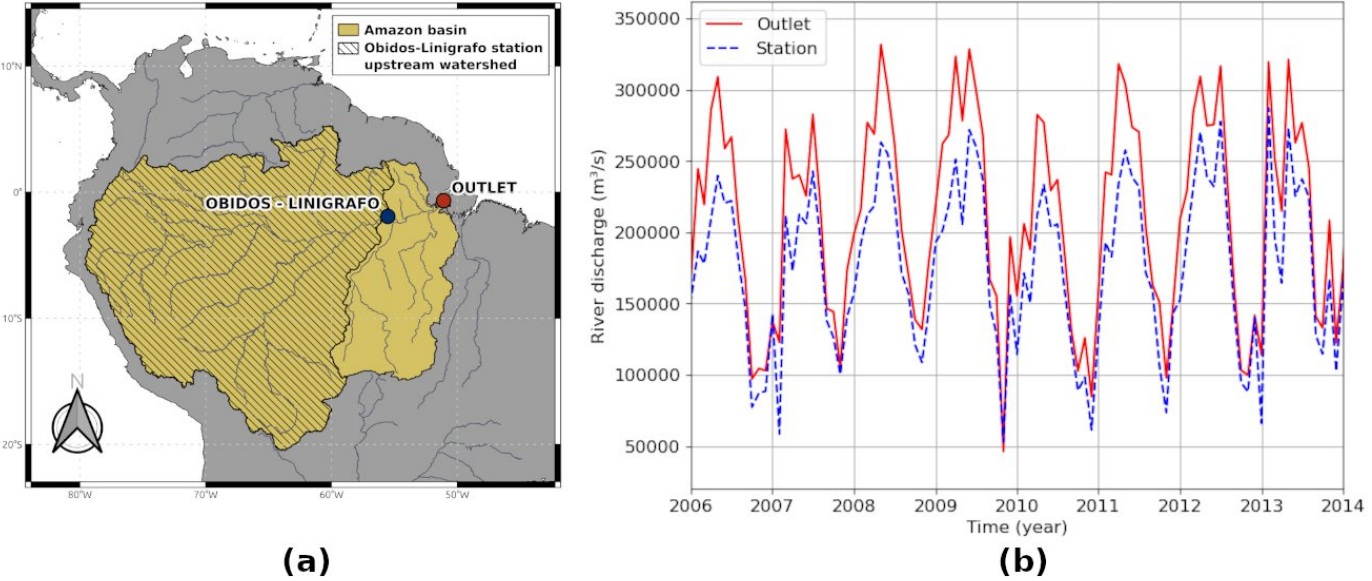
$$KGE' = 1 - \sqrt{(R-1)^2 + (PBias-1)^2 + (\gamma-1)^2} \quad (3) ¶$$

¶ Overall, the WMB approach using ERA5 data (WMB1) shows excellent agreement with in situ measurements, yielding a KGE' score of 0.84. In contrast, using GPCC precipitation and ISBA-CTrip evapotranspiration (WMB2) results in more pronounced discrepancies—both in the annual cycle and higher-frequency variations—leading to a lower KGE' score of 0.53. These results confirm the reliability of the WMB approach for estimating Amazon River discharge and highlight the sensitivity of the method to the choice of datasets used to estimate vertical atmospheric fluxes as shown previously by (Chen et al., 2020)). Biases in net precipitation (P-E), in particular, directly affect the accuracy of discharge estimates.

3.2. Sensitivity of the river discharge to the distance of the gauging station to the outlet

River discharge estimates based on in situ measurements can underestimate the total freshwater flux entering the ocean when gauging stations are located far upstream from the river mouth, as they capture only a portion of the full basin's drainage area. This is the case for the Óbidos station, located approximately 500 km upstream of the Amazon Delta (Fig. 4a). The Water Mass Balance (WMB) approach enables discharge estimation over any drainage area large enough to be resolved by GRACE and GRACE-FO satellite observations. In this study, we compare discharge estimates for the entire Amazon Basin and the Óbidos drainage area using the WMB method, driven by ERA5 atmospheric fluxes—a configuration shown to provide accurate results at Óbidos.

321 The Óbidos drainage area is approximately 22% smaller than the entire Amazon River Basin, excluding several major tributaries
 322 such as the Tapajós, Xingu, and Jari (Fig. 4a). As a result, the mean river discharge at Óbidos is 15% lower than at the river mouth.
 323 Similarly, the amplitude of the annual discharge cycle is underestimated by 20% when using data from Óbidos instead of the full
 324 basin. Peak flow—defined as the maximum discharge—also shows an underestimation of 15% at Óbidos compared to the river
 325 outlet. These discrepancies are substantial and must be considered when assessing the influence of Amazonian freshwater fluxes
 326 on the Atlantic Ocean. For context, a 10% underestimation in the Amazon’s mean discharge is equivalent to omitting the entire
 327 flow of the Mississippi River (Table 1).
 328



329
 330 **Figure 4: Comparison between discharge values at the Obidos-Linografo station located furthest downstream of the Amazon and at the**
 331 **river outlet. Figure (a) shows the location of the Obidos-Linografo station as a blue dot and the river outlet as a red dot. The complete**
 332 **river basin is represented in yellow, and the hatched area corresponds to the Obidos-Linografo station upstream watershed. Figure (b)**
 333 **displays estimated discharge values using the WMB approach with ERA5 precipitation and evapotranspiration data. The red curve**
 334 **represents the estimation at the outlet location (using the whole river basin), and the blue curve represents the estimation at the Obidos-**
 335 **Linografo station (using the station’s upstream watershed).**
 336

337 3.3. WMB discharge estimated for 18 major rivers flowing into the Atlantic

338 River discharge was estimated at the outlet of each of the 18 selected rivers (Fig.-1) using the Water Mass Balance (WMB)
 339 approach, driven by two combinations of vertical atmospheric fluxes: ERA5 reanalysis (WMB1), and GPCC precipitation with
 340 ISBA evapotranspiration (WMB2) (Table 2). The results show significant discrepancies in both mean discharge and seasonal
 341 variability depending on the dataset used to represent atmospheric fluxes.

342
 343 The largest difference in mean discharge was observed for the Congo River, where WMB2 yielded a discharge of 58,537 m³/s,
 344 compared to 27,801 m³/s with WMB1—representing a 53% difference. For smaller rivers, relative differences are even more
 345 pronounced. In the Niger River, the choice of dataset results in a 74% difference, while the Magdalena River shows an 87%
 346 difference. In extreme cases, such as the São Francisco River, the WMB method produced a negative mean discharge when forced
 347 with GPCC and ISBA, clearly highlighting the method’s failure to capture river discharge. These discrepancies stem from excessive

348 noise or biases in one or more components of the WMB equation and emphasize the method's sensitivity to the quality of regional
 349 atmospheric data.

350

351 The largest difference in seasonal discharge amplitude was found in the Amazon River, where the seasonal variation amplitude is
 352 overestimated larger by 56,844 m³/s, or 31% in WMB2 compared to WMB1. Significant differences in seasonal variability were
 353 also found between WMB2 and WMB1 for other rivers, such as the Orinoco: 19,506 m³/s (55% of WMB1 amplitude), Mississippi:
 354 13,982 m³/s (48%), and Nelson: 10,909 m³/s (134%) Rivers. Such discrepancies underscore the limitations of the WMB method,
 355 which is highly sensitive to uncertainties in atmospheric forcing. Improving the accuracy of net precipitation estimates (P – E) at
 356 regional scales would directly enhance the reliability of WMB-based discharge estimates.

357

358 The discharge estimates from the WMB approach are generally lower than the Dai and Trenberth (2002) climatology used in the
 359 REF experiment. WMB1 and WMB2 discharges are lower than the reference climatology for 13 out of 18 rivers. The total
 360 freshwater fluxes are reduced by 28% in WMB1 and 22% in WMB2 compared to the REF experiment. However, no general pattern
 361 emerges regarding the comparison of seasonal discharge amplitudes.[¶]

362 ¶

363 While the WMB method is sensitive to the choice of atmospheric forcing data, it offers the significant advantage of enhanced
 364 spatial coverage. Specifically, it enables discharge estimates at the outlets of all 18 rivers—whereas in situ gauging stations exist
 365 for only 11, and usually not at the river mouths (e.g., Óbidos). Relying solely on these limited observations would lead to an
 366 underestimation of the total mean freshwater flux by 21% with respect to the total flux estimated at the outlets, and an
 367 underestimation of the seasonal amplitude by 27% (Fig.-5). This estimate is based on river discharge values resulting from the
 368 WMB1 approach, considering (i) the full drainage area of all 18 river basins and (ii) the drainage areas corresponding to the 11
 369 gauging stations located closest to the river mouths (Fig.-1).

370

River name	WMB1		WMB2		<u>Dai & Trenberth</u> [□]	
	Mean discharge (m ³ /s)	Annual amplitude (m ³ /s)	Mean discharge (m ³ /s)	Annual amplitude (m ³ /s)	<u>Mean discharge (m³/s)</u> [□]	<u>Annual amplitude (m³/s)</u> [□]
Amazon	208968	180925	203757	237769	<u>282119</u> [□]	<u>244293</u> [□]
Congo	27801	36903	58537	32961	<u>45360</u> [□]	<u>26880</u> [□]
Orinoco	35054	35381	34393	54887	<u>15912</u> [□]	<u>32438</u> [□]
Mississippi	16054	29418	11430	43400	<u>10976</u> [□]	<u>12161</u> [□]
Parana	18856	23922	20076	22907	<u>6685</u> [□]	<u>2576</u> [□]
Saint-Lawrence	12533	11206	8674	19803	<u>28746</u> [□]	<u>23241</u> [□]
Tocantins	10114	30338	14569	22634	<u>2384</u> [□]	<u>5969</u> [□]

Magdalena	19068	11642	10179	10973	15866□	11852□
Niger	3349	29246	13084	31139	18711□	23050□
Uruguay	4403	5232	4372	4997	6685□	2576□
Ogooue	4248	6635	5228	9623	16066□	11783□
Cuyuni and Essequibo	2537	5111	2592	6786	23297□	34512□
Usumacinta	3078	7952	4418	10809	7182□	10802□
Nelson	3085	8117	2359	19026	8182□	7906□
Sao Francisco	-1334	7127	3056	9996	5472□	5393□
Rhine	2442	1898	1524	2353	4845□	2931□
Mobile	1540	2631	1276	2599	12997□	14779□
Orange	16	3935	1103	4479	5449□	5035□
Total	371811	184358	400627	314353	516932□	253895□

Table 2: Water Mass Balance discharge estimates at river outlets, using the and climatology from Dai & Trenberth at river outlets, where no in situ measurements are available. The water mass balance approach forced with ERA5 (WMB1) or GPCC and ISBA (WMB2) atmospheric fluxes **are being used**. Mean seasonal amplitude refers to the difference in discharge between the maximum and minimum value in the mean seasonal cycle. Both the seasonal amplitude and the mean discharge are computed over the 2002—2019 period. The “Total” row refers to the sum of each river time series.

River discharge estimates derived from the WMB approach are subject to significant uncertainties, as evidenced by the large variability associated with the choice of atmospheric forcing data. ~~To further evaluate the method's performance, the river discharge was estimated using the WMB approach over the drainage areas of the 11 selected gauging stations and compared with~~ ~~As no reference discharge measurements are available at the river's outlets, the method's performance is further evaluated over the drainage areas of the 11 selected gauging stations. River discharge estimated using the WMB approach was compared with the~~ ~~corresponding~~ in situ measurements. The resulting mean and annual discharge amplitudes are listed in Table 3. The amplitude and mean discharge are computed over the longest uninterrupted common interval between the in situ, WMB1 and WMB2 time series. These statistics can therefore not be directly compared between rivers. The “Total” row refers to the sum WMB1 and WMB2 time series over the 11 stations during the 2002—2019 period. As the in situ measurements' time coverage is not consistent between rivers, no total value is provided.

River name	Mean discharge ($\text{kg}/\text{m}^3/\text{s}$)			Annual amplitude ($\text{kg}/\text{m}^3/\text{s}$)		
	In situ	WMB1	WMB2	In situ	WMB1	WMB2

Amazon	173434	177495	167785	137590	144549	200581
Congo	39665	27509	57450	25295	35430	30675
Orinoco	33520	30677	30410	65020	31631	49123
Mississippi	21618	16164	9601	21229	25800	38895
Parana	17178	17939	19668	3202	36766	42817
Saint-Lawrence	7345	7409	5005	1501	4643	19098
Tocantins	10068	9616	13996	18965	32664	32820
Niger	5630	1564	10995	12360	31940	30045
Nelson	3891	3105	2326	1120	7716	18433
Rhine	2080	2442	1524	1456	1898	2353
Orange	124	-32	845	213	5587	5519
Total	-	293559	320295	-	133767	266507

Table 3: Intercomparison of the mean and annual discharge values estimated at the selected gauging stations with in situ measurements and with the water mass balance approached forced with ERA5 (WMB1) or GPCC and ISBA (WMB2) atmospheric fluxes. The “Total” row refers to the sum of each river time series.

The largest errors in the mean discharge are obtained for the Congo river which is overestimated [relative to the in situ observations](#) by 17 784 m³/s (+ 45%) in WMB2 and underestimated by 12 156 m³/s (-31%) in WMB1. The errors in the mean discharge are generally higher with WMB2, though there are no systematic biases: for some rivers the mean discharge is overestimated (e.g. Congo, Parana, Tocantins, Niger and Orange) and for some others it is underestimated (e.g. Amazon, Orinoco, Mississippi, Saint Lawrence, Nelson, Rhine). The absolute and relative amplitude of the errors is also variable depending on the river selected. In WMB1, the relative error on the mean river discharge is under 15% for 5 out of 11 rivers, namely the Amazon, Orinoco, Parana, Tocantins and Saint-Lawrence.

Similarly, for the annual cycle, WMB2 generally results in larger deviations from in situ measurements compared to WMB1. The most pronounced errors in the mean annual amplitude occur for the Amazon (+62,991 m³/s, or +46% relative to in situ) and the Parana (+39,615 m³/s, or +1237%) in WMB2. Notable errors are also observed in WMB1, particularly for the Congo (-33,308 m³/s, or -51%), Paraná (+33,564 m³/s, or +1048%) and Niger (+19,580 m³/s, or 158%) Rivers. The error in the annual amplitude of river discharge remains below 15% for only the Amazon, and only when using ERA5 forcing. Once again, no systematic bias is apparent, as both the magnitude and direction of the errors vary depending on the river and the atmospheric dataset used.

The WMB approach is further evaluated using the PBias for the temporal mean, the correlation coefficient (R), the variability ratio (γ), and the modified Kling-Gupta Efficiency (KGE'). All metric values are provided in Table [A1 B1](#) of the Appendix, while PBias and R are illustrated in Fig. [65](#).

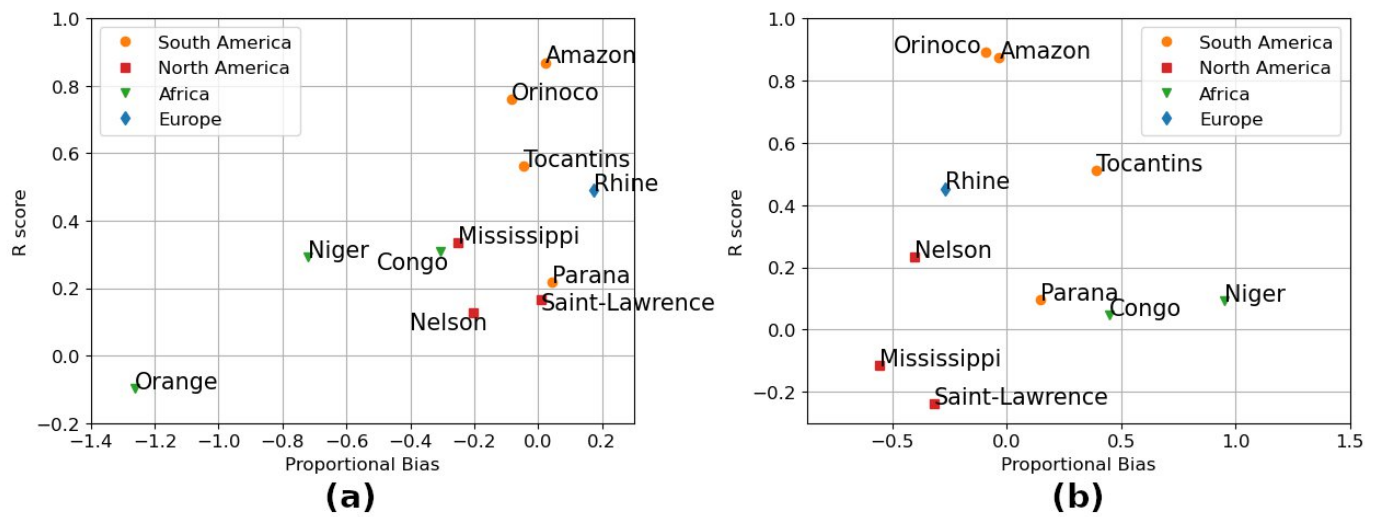


Figure 5: Quality metrics computed at the selected in situ stations by comparing WMB estimates to in situ measurements taken as reference. Figure (a) shows scores for WMB estimates with ERA5 precipitation and ERA5 evapotranspiration. Figure (b) shows scores for WMB estimates with GPCC precipitation and ISBA evapotranspiration. Results for the Orange River are outside of the figure's range with a proportional bias value of 5.80 and an R-score of -0.25.

The WMB approach yields reasonable performance for South American rivers—particularly the Amazon—when forced with ERA5 atmospheric fluxes, as indicated by PBias values close to zero and R scores above 0.5. In contrast, results are more variable and generally less satisfactory for rivers in Africa and North America. Both WMB configurations struggle to capture the mean discharge of African rivers: values are typically underestimated in WMB1 (ranging from -31% to -112%) and overestimated in WMB2 (ranging from +45% to +580%). Overall, the correlation (R score) is higher when using ERA5 than GPCC-ISBA for 8 out of the 11 rivers analyzed.

The variability ratio highlights the substantial high-frequency noise present in the WMB estimates compared to other metrics (PBias, R Score, KGE'). Although the WMB approach generally captures the mean discharge adequately, its high-frequency variability is considerably greater than that observed in in situ data. Across both atmospheric datasets, the median variability ratio is 2.2 for WMB1 and 1.9 for WMB2.

4 Impact of freshwater fluxes on the Atlantic

In this section, we summarize the results of the impact of the river discharge datasets on the ocean model simulations described in Section 2.4, focusing primarily on salinity fields and then on derived diagnostics.

[Figure 7](#)[Fig. 6](#) illustrates the spatial distribution of differences in the mean absolute error (MAE) in sea surface salinity (SSS) across the different model configurations, compared to the EN4 observational dataset (Good et al., 2013). [The Note that EN4 is an optimal interpolation analysis whose coverage on continental shelves and in coastal river-plume regions is sparse, so the metrics presented below are indicative of large-scale improvements rather than of precise plume structure itself. Nonetheless, the comparison provides insight into the systematic deviations introduced by each river discharge dataset and highlights the effectiveness of the new WMB-derived river discharge dataset.](#)

440 The REF experiment, based on the (Dai and Trenberth, 2002) climatology, exhibits significant deviations in regions influenced by
441 major river discharges, particularly in the Amazon plume and along the West African coast ([shown in the bottom right panel](#)). The
442 JRA55-do-driven experiment (J5) displays a somewhat reduced MAE compared to REF, suggesting that its daily varying runoff
443 better captures temporal variability but still lacks improvements in [key regionsmany areas](#).

444
445 The A1 and A2 experiments demonstrate a distinct improvement in MAE, particularly in the western tropical Atlantic and along
446 the equatorial current systems, where freshwater input plays a crucial role in stratification and circulation e.g., (Foltz et al., 2019;
447 Pailler et al., 1999). Both show overall lower MAE values, whose reduction is significant in many regions and [the Atlantic basin](#)
448 [mean equals -0.080.07](#) psu and [-0.070.08](#) psu for A1 and A2, [being around -0.04 psu for both S1 and S2, andrespectively. For both](#)
449 [S1 and S2 the mean reduction is -0.04 psu](#), indicating that using the WMB estimates only for the Amazon, Orinoco, and Tocantins
450 leads to about half of the bias reduction compared to the full WMB dataset. [In some few localized areas \(e.g., some areas in the](#)
451 [Gulf of Guinea\), the MAE shows slight increase with the use of A1 or A2, difficult to attribute unambiguously, but likely due to](#)
452 [the suboptimal spatial distribution, unchanged from the climatology of Bourdalle-Badie and Tréguier \(2006\).](#)

453
454 This implies that the WMB-derived runoff improves the representation of freshwater input into the ocean [model](#). The improved
455 consistency with EN4 data suggests that the WMB dataset corrects for biases present in the climatological approach, particularly
456 in regions with high seasonal and interannual variability in discharge. In particular, from the sea surface salinity mean difference
457 of A1 or A2 minus REF (Fig. 6), it appears that both systematically [decrease the North Atlantic wide freshwater input, resulting](#)
458 [in an increase in sea surface salinity, whose patterns resembleincrease sea surface salinity, obviously due to a decrease the North](#)
459 [Atlantic-wide freshwater input, with patterns resembling](#) those of the MAE reduction. There exist only a few areas where the
460 enhanced dataset reduces the surface salinity, confined in the South Atlantic. The differences between the WMB approach using
461 [GPCC+ISBA or the ERA5 reanalysisERA5 or GPCC/ISBA](#) are generally small, and relevant only locally, e.g., in the South-
462 western African coasts (corresponding to the Congo river mouth). [The largest local changes occur in the Gulf of St. Lawrence and](#)
463 [off the Congo mouth, where the semi-enclosed geometry and the narrow plumes amplify the salinity response to a given runoff](#)
464 [perturbation; in these regions, our discharge estimates depart most from the climatology \(St. Lawrence\) or are most sensitive to](#)
465 [the atmospheric forcing dataset \(Congo\).](#)

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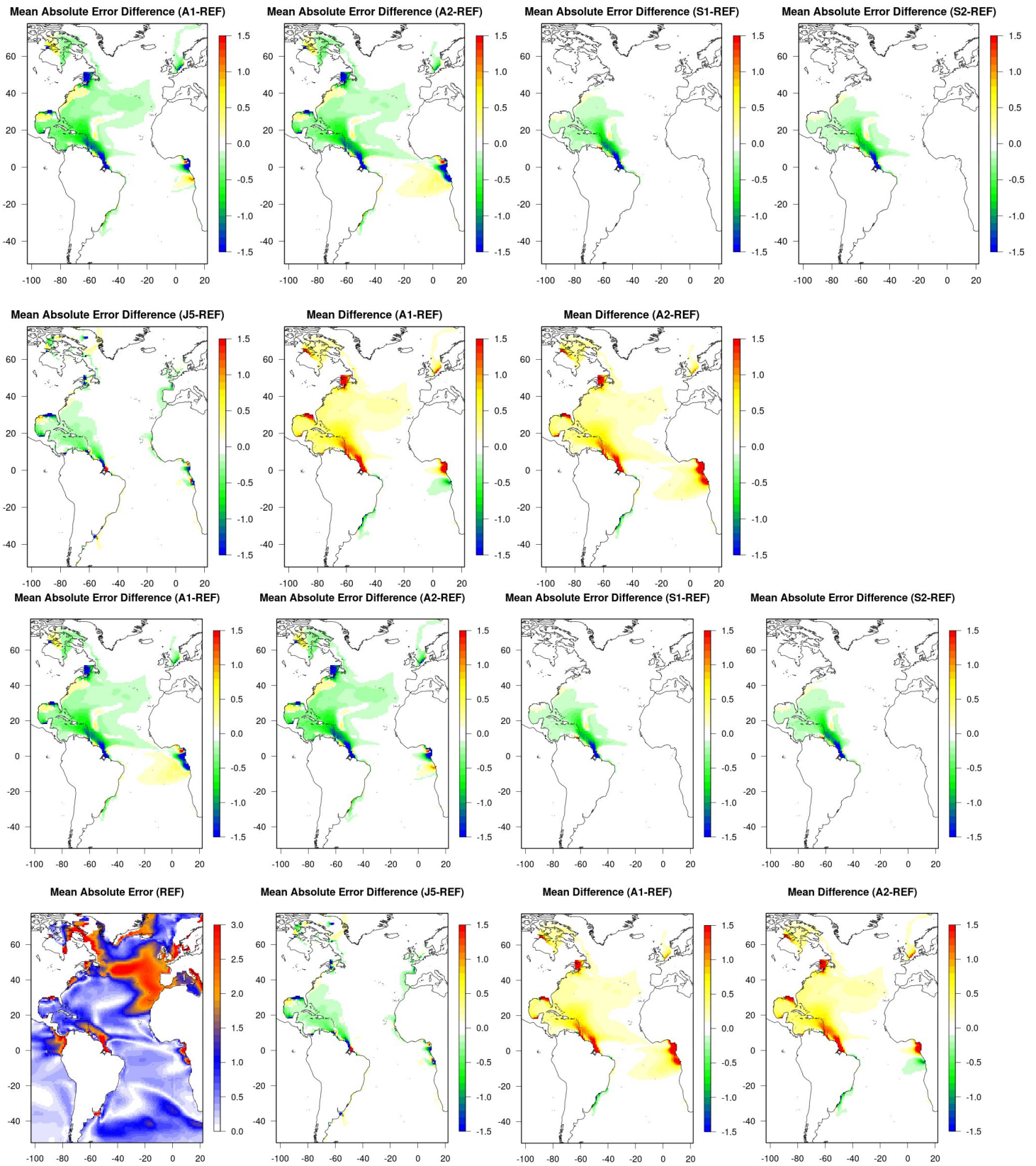
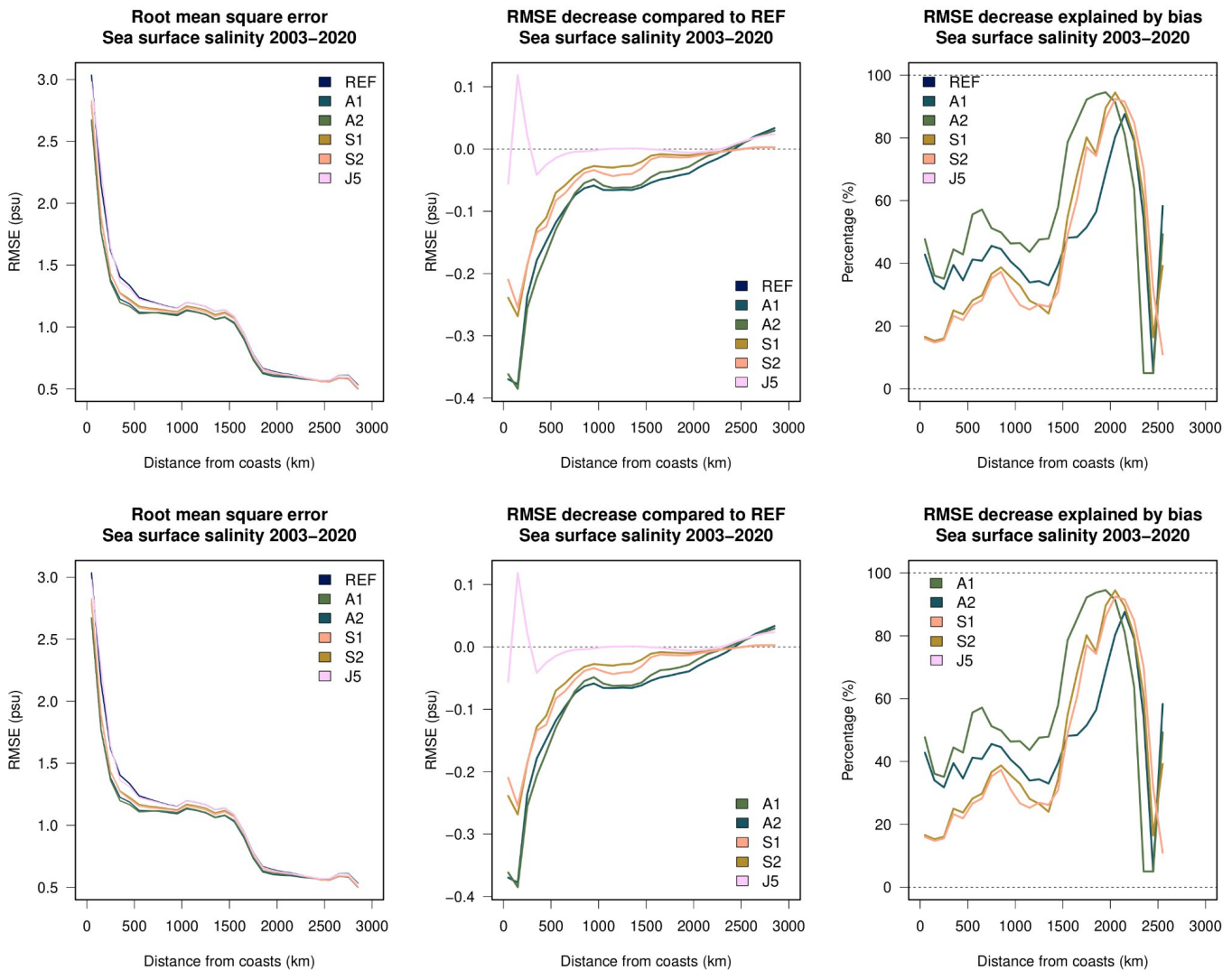


Figure 6: Differences in sea surface salinity mean absolute error (MAE) between the experiments described in the text (A1, A2, S1, S2, J5) and REF. The MAE is computed versus EN4 objective analyses of salinity (Good et al., 2013). Negative values indicate a reduction of MAE compared to REF. Panel f, g: Difference in the mean absolute error (MAE) of sea surface salinity between each experiment (A1, A2, S1, S2, J5) and REF, i.e. $MAE(\text{experiment vs. EN4}) - MAE(\text{REF vs. EN4})$, computed against EN4 objective analyses of salinity (Good et al., 2013). Negative values therefore indicate an error reduction with respect to REF. Panel e: MAE from the REF experiment; Panel g, h: time-mean difference of SSS between A1 or A2 and REF. The period is 2003-2020. Units are psu.

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Figure 7 evaluates the root mean square error (RMSE) of salinity [versus EN4 salinity analyses](#), as a function of distance from the coast, providing a quantitative assessment of how well the model represents coastal-to-offshore salinity gradients and how far into the open ocean the changes in runoff expand. The REF experiment consistently shows higher RMSE values close to the coast, indicative of the limitations of the monthly climatology in capturing realistic freshwater inputs, combined with its inherent variability therein. On the contrary, the J5 experiment exhibits only moderate improvements [near the coastline, likely due to the inclusion of time-varying runoff, although the skill score rapidly worsens close to the coastline, while exhibiting negative and then rather neutral scores](#) towards the open ocean. The A1 and A2 configurations equally demonstrate a notable reduction in RMSE, particularly within the first few hundred kilometers from the coast, indicating a more accurate representation of riverine freshwater distribution. The S1 and S2 experiments confirm localized RMSE reductions, supporting the necessity of accurate basin-scale freshwater modeling around, notably, the Amazon River mouth.



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Figure 7: RMSE metrics (2003-2020) as a function of the distance to coast in the North Atlantic Ocean. From left to right: RMSE of the experiments; their RMSE decrease compared to REF; the percentage of RMSE reduction explained by bias reduction.

The RMSE decomposition into systematic (bias-driven) and non-systematic errors (right panel of Fig. 7) [is performed considering that \$RMSE^2 = BIAS^2 + STDEV^2\$, where STDEV is the standard deviation of model minus observations, and the \$100 \cdot \(BIAS^2 /\$](#)

493 RMSE²) represents the percent of score (improvement) explained by the bias correction. This diagnostic highlights that a
494 significant portion of RMSE reduction in the ALL-experimentA1 and A2experiments is associated with bias corrections rather
495 than random error reductions. The high percentage of RMSE decrease explained by bias correction suggests that climatological
496 runoff datasets introduced systematic deviations in modeled salinity fields, which the WMB dataset effectively mitigates.

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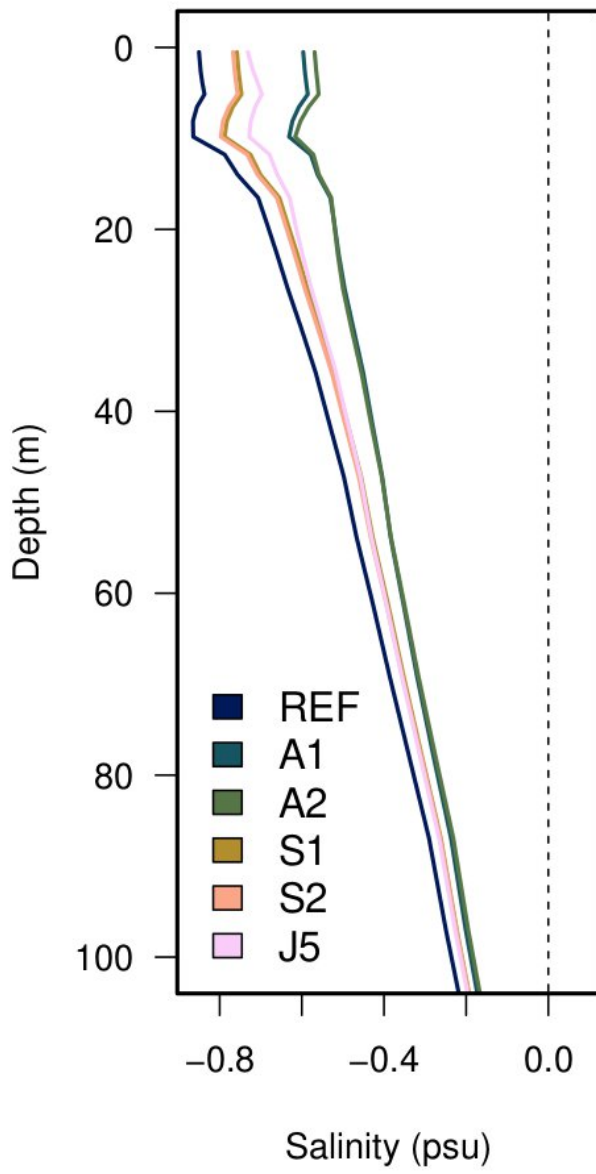
498 In Fig. 8, we show profiles of Bias and RMSE versus in situ salinity profiles for the gridpoints closer than 500km to the shoreline.
499 This figure provides an assessment of the vertical structure of salinity biases and RMSE compared to EN4 data (Good et al., 2013),
500 offering insights into how different runoff configurations affect subsurface salinity distribution. The REF experiment shows a
501 pronounced fresh bias in the upper layers. The J5 experiment partially reduces surface bias but still exhibits deviations at
502 intermediate depths; while S1, S2 provide an intermediate solution, A1 and A2 significantly reduce the fresh bias in the surface
503 layer, bringing salinity profiles closer to observations, with improvements extending into the subsurface layers, namely extending
504 to ~100m depth. The overall RMSE reduction in the top 100 m of depth is equal to ~~41%, 40~~10%, 11%, 5%, 5%, and 5%, for A1,
505 A2, S1, S2 and J5, respectively, suggesting that the joint use of GPCC+ and ISBA slightly outperforms the use of land freshwater
506 fluxes from ERA5. A2 (WMB2) marginally outperforms A1 (WMB1), contrasting with the discharge validation metrics, where
507 WMB1 scores better against the gauges than WMB2. However, it should be noted that the differences between A1 and A2
508 validation metrics are very small; additionally, the fact that the salinity response to a runoff perturbation is nonlinear, being
509 modulated by plume spreading, stratification and vertical mixing, and that not all 18 rivers have verifying discharge data, likely
510 explain the apparent inconsistency.

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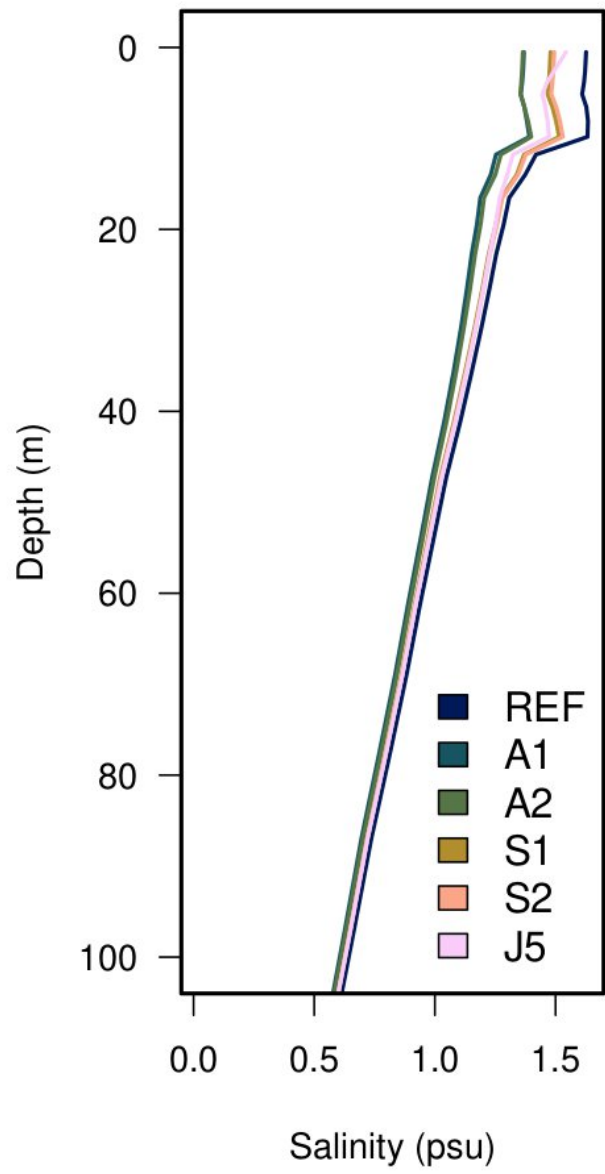
512 The largest RMSE values are concentrated in the upper ocean (halocline), where riverine freshwater influences are most
513 pronounced. The A1 and A2 experiments reduce RMSE not only at the surface but also at intermediate depths, suggesting a more
514 realistic penetration of freshwater input into the ocean interior. The systematic error reduction across depths indicates that the
515 positive impact of the WMB dataset penetrates through the upper ocean, potentially leading to a more physically consistent
516 representation of vertical stratification. Slight improvements were also found in sea surface temperature, with a reduction of MAE
517 of the order of 0.1°C or less; however, changes in SST are not statistically significant and are not shown, ~~although recent studies~~
518 ~~outline possible mechanisms of the changes of coastal stratification on the SST (Aroucha et al., 2025. Recent studies show that~~
519 ~~riverine freshwater can affect coastal SST, either through a halosteric modification of the sea surface height gradient and the~~
520 ~~associated geostrophic advection, as found for the Congo plume by Aroucha et al. (2025), or through the inhibition of vertical~~
521 ~~mixing and upwelling by the enhanced near-surface stratification, as found for the Niger plume by Topé et al. (2023).~~

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Salinity Bias



Salinity RMSE



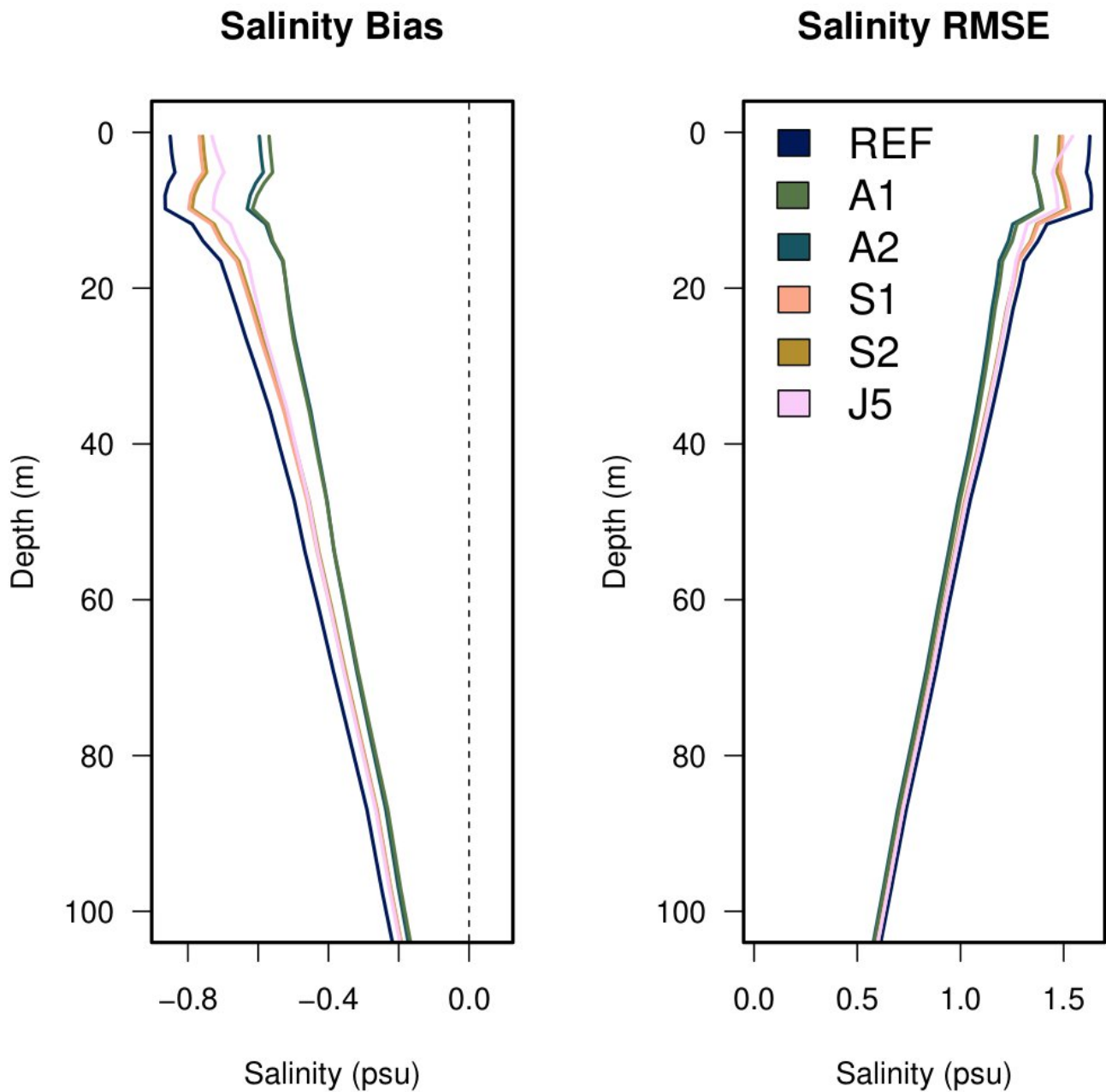


Figure 8: Salinity bias and RMSE profiles for the experiments presented in the text, calculated against EN4 objective analyses of salinity (Good et al., 2013), for the period 2003-2020. Only gridpoints closer than 500km to the shoreline are used.

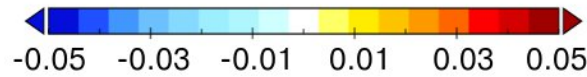
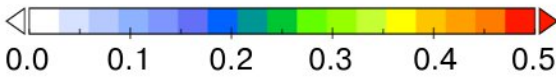
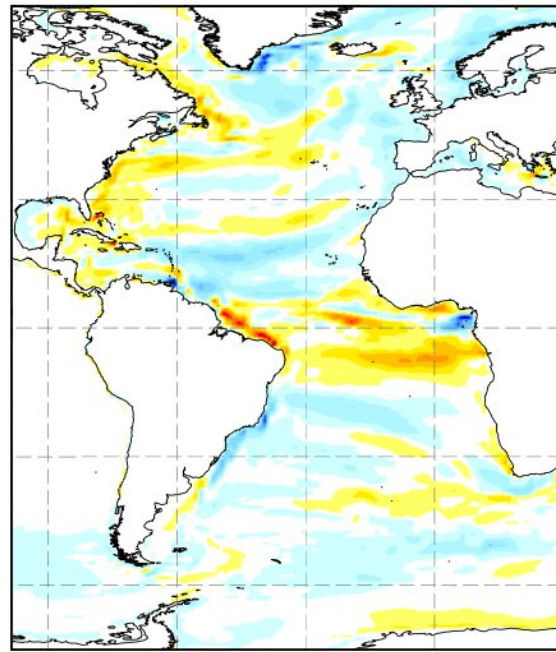
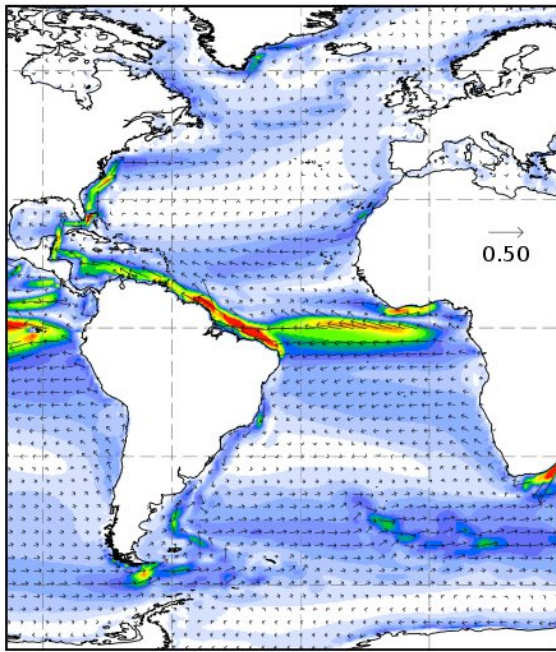
The introduction of the WMB-derived river discharge dataset leads to an increase in salinity compared to the REF experiment, especially in the Amazon plume and other freshwater-influenced regions. This modification affects ocean stratification and upper-ocean mixing, and subsequently impacts large-scale circulation and meridional transport. In [A1, increased sea surface salinity and weaker stratification enhance vertical mixing, which A2, the reduced freshwater input weakens the near-surface haline stratification in the plume, so that vertical mixing](#) redistributes momentum [across over](#) a deeper ocean layer. This [leads to a reduction in upper-ocean results in reduced surface](#) current speeds; downstream of the Amazon [River discharge and other river mouths, counteracting enhanced circulation upstream. This is visible in Fig. 9, which shows the mean current speed for ALL \(left panel\) and the mean difference between ALL and REF \(right panel\) and Orinoco mouths, along the coastal pathway towards the Caribbean, and in a](#)

535 [compensating intensification at the river mouths and in the equatorial band \(Fig. 9, central panel\). The S2-REF difference \(Fig. 9,](#)
536 [right panel\) reproduces the same dipole with comparable amplitude but confined to the western tropical Atlantic, showing that](#)
537 [these changes are driven by the Amazon, Orinoco and Tocantins discharge; on the contrary, the broader basin-scale response,](#)
538 [namely the intensification of the eastward flow at the latitudes of the North Equatorial Counter Current \(NECC\) and the weakening](#)
539 [over the subtropical North Atlantic, requires the full 18-river dataset. Same results as A2 and S2 hold for the A1 and S1](#)
540 [experiments. A comparable halosteric control of coastal currents by river plumes has been reported for the Niger \(Alory et al.,](#)
541 [2021; Topé et al., 2023\) and Congo rivers \(Aroucha et al., 2025\).](#)

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543 ¶

Sea surface current speed

Current speed difference (A1-REF)



Mean sea surface currents (A2)

Current Speed Difference (A2-REF)

Current Speed Difference (S2-REF)

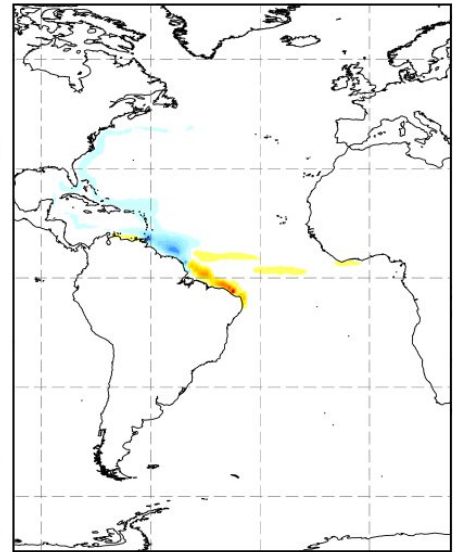
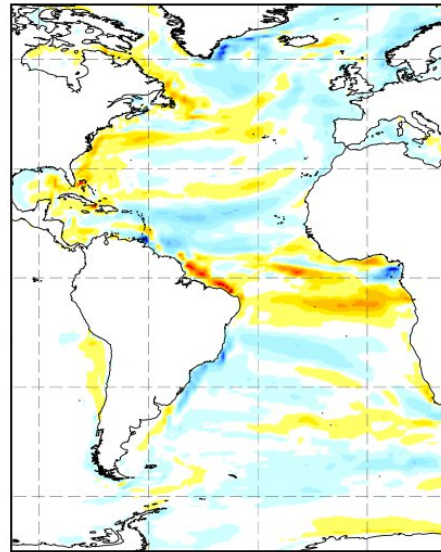
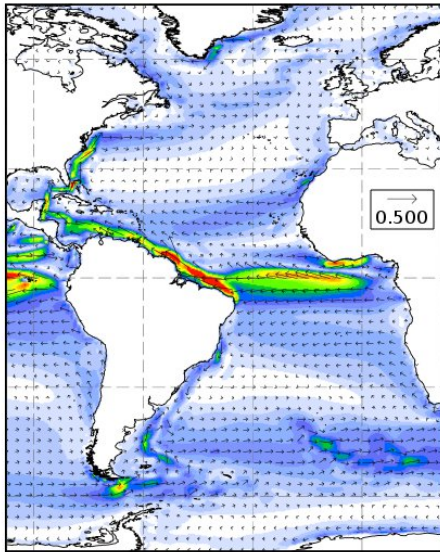
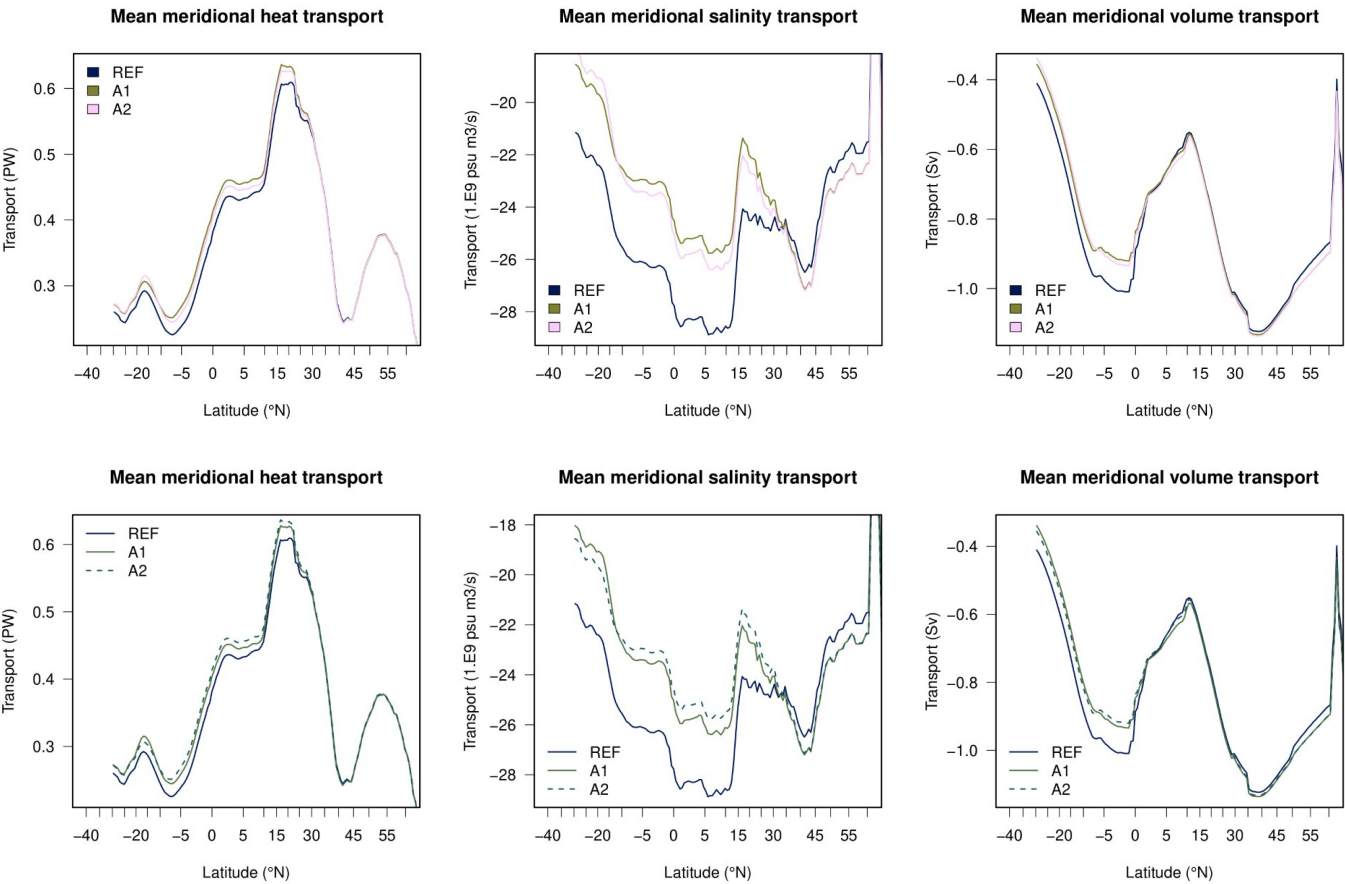


Figure 9: Mean sea surface current in the North Atlantic Ocean for A1A2 (left panel) and difference between A1 in current speed between A2 and REF (central panel) and between S2 and REF (right panel), over the period 2003–2020. Units are m s^{-1} .

Additionally, the reduced freshwater input in A1 and A2 weakens the horizontal density gradients, possibly causing more direct northward transport along the coast and reducing the strength of the North Brazil Current retroflexion, and enhancing the interaction with the North Equatorial Countercurrent (NECC)NECC, which transports water eastward towards the Atlantic cold tongue, as in general less freshwater-driven stratification allows for larger net meridional exchanges.

These mechanisms are indeed associated with an increase of meridional transports in the South and Equatorial Atlantic (up to about 15°N) and a slight decrease of transports north of 15°N, visible in Fig. 10. Although relatively small in absolute numbers, modifications to the riverine inputs consistently modify the meridional redistribution of mass, heat, and freshwater across the Atlantic Ocean. No significant impact is found on the thermohaline overturning circulation (not shown), although the relative shortness of the experiments, imposed by gravimeter data availability, may conceal the impact of the freshwater on low-frequency thermohaline circulation.

560



561

562 **Figure 10: Meridional volume, heat, and salinity transports across the Atlantic Ocean, for the A1, A2, and REF experiments over the**
563 **2003-2020 period.**

564 **5 Conclusions and Perspectives**

565 Freshwater fluxes play a crucial role in the ocean salinity, circulation, and sea level variability, and yet are often poorly represented
566 in general ocean circulation models. This study uses the Water Mass Balance (WMB) approach, combining satellite gravimetry
567 and atmospheric data, to estimate river discharge. The comparison of the WMB approach to in situ measurements has shown
568 mitigated potential for estimating freshwater discharge into the Atlantic Ocean.

569

570 For the Amazon River—the largest contributor of freshwater to the Atlantic—the WMB method closely reproduces in situ
571 measurements at the Óbidos station, capturing both seasonal and long-term trends with a high correlation coefficient ($R \approx 0.88$)
572 and a Kling-Gupta Efficiency (KGE') score of 0.84. Importantly, the WMB approach enables discharge estimation at the river

573 outlet and captures full basin contributions more accurately than upstream gauges like Óbidos, avoiding substantial underestimation
574 of freshwater fluxes.

575

576 At a broader scale, the WMB method enabled freshwater flux estimation across 18 major Atlantic-draining river basins,
577 demonstrating good spatial coverage and strong agreement with in situ data for several South American rivers. ERA5 atmospheric
578 forcing consistently outperformed the GPCC–ISBA combination [in the comparison with river gauges](#), with lower mean biases and
579 better correlation across most basins.

580

581 However, strong regional limitations persist: the WMB method performs less reliably over African and North American rivers,
582 where biases in atmospheric reanalyses can lead to significant errors in both mean discharge and seasonal amplitude. Additionally,
583 WMB river discharge estimates exhibited exaggerated high-frequency variability, especially when using GPCC–ISBA forcing,
584 reflecting noise sensitivity and uncertainty in net precipitation estimates.

585

586 ~~Despite these limitations in the WMB approach~~[At the ocean-basin scale](#), the improved salinity representation in the A1 and A2
587 experiments indicates that freshwater processes are better captured. Using all Atlantic river drainage basin data, RMSE is reduced
588 near the coast, confirming that the WMB dataset improves the representation of riverine freshwater dispersal. Bias correction is
589 the dominant factor in RMSE reduction, reinforcing the systematic improvements provided by the new dataset. Furthermore, the
590 WMB-derived dataset improves salinity biases not only at the surface but also at depth, enhancing the realism of ocean stratification
591 (see also, e.g., (Aroucha et al., 2025)). The use of GPCC+ISBA freshwater fluxes in the WMB formulation slightly outperforms
592 the use of the ERA5 fluxes, with an RMSE reduction of 11% and 10%, respectively, compared to using the climatological runoff.
593 Furthermore, the adoption of only three high-confidence river discharge estimates (Amazon, Orinoco, and Tocantis) leads to about
594 half of the error reduction compared to the full 18-river dataset.

595

596 Given that ocean salinity affects density stratification and mixing, these improvements have downstream impacts on ocean
597 circulation, thermocline structure, and regional climate variability. We have shown in particular the associated changes in reduced
598 vertical stratification, enhanced upper ocean circulation, and [basin-scale](#) meridional transports. These findings highlight the
599 importance of accurate river discharge datasets, aligning with previous studies emphasizing the role of riverine inputs in shaping
600 upper-ocean dynamics ((Chandanpurkar et al., 2022; Feng et al., 2021)). The improved salinity representation has implications for
601 ocean circulation, stratification, climate modeling, and biogeochemical cycles, reinforcing the need for continued refinement of
602 freshwater flux datasets.

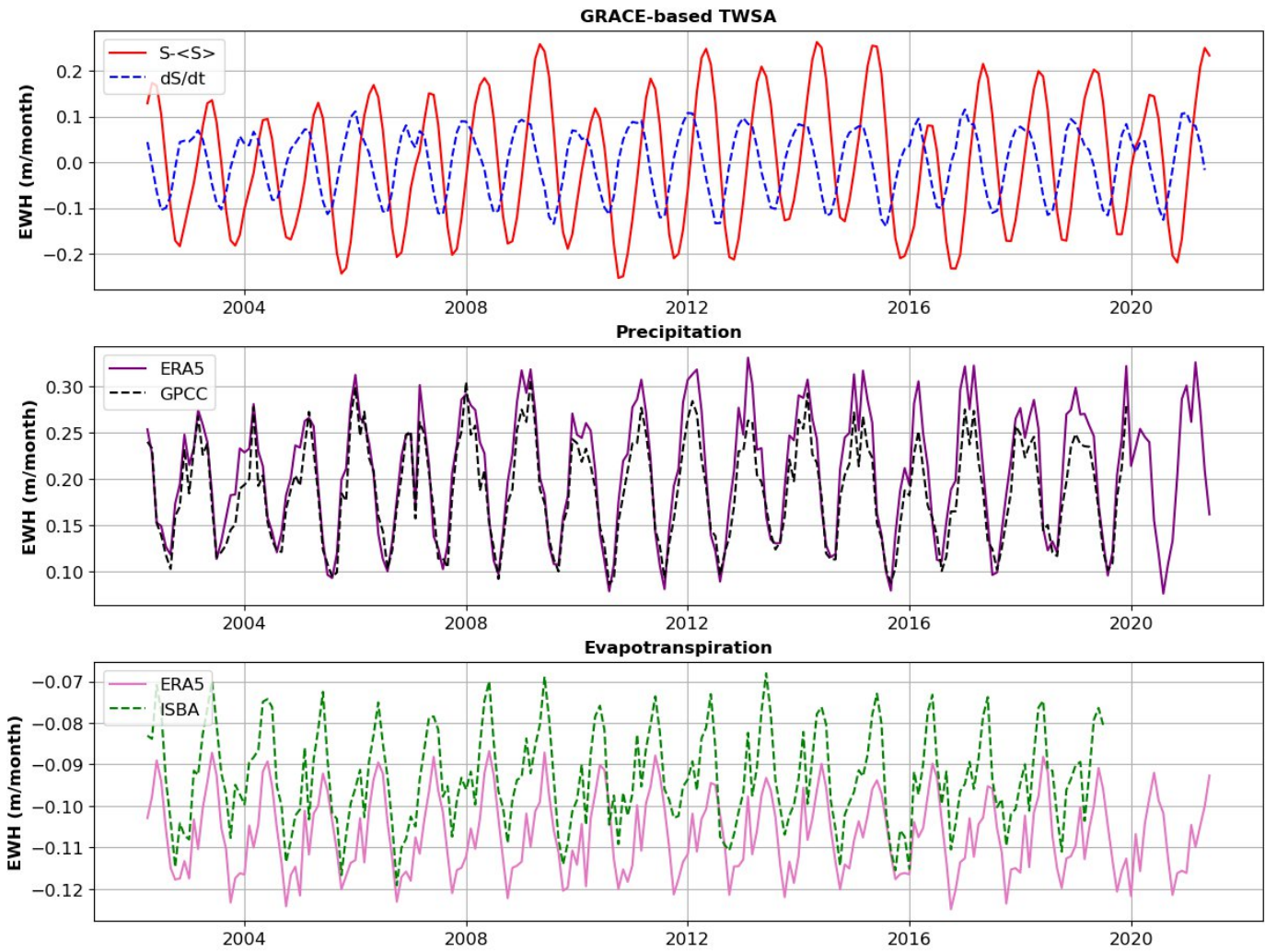
603 ¶

604 [The performance of the WMB approach differs between the river-basin and ocean-basin scales. At the river-basin scale, the use of](#)
605 [the ERA5 reanalysis to estimate atmospheric fluxes generally provides slightly better performance in river discharge estimation,](#)
606 [whereas at the ocean-basin scale, the GPCC minus ISBA freshwater fluxes yield lower RMSEs when evaluated against surface](#)
607 [salinity observations, although differences between the experiments using the two datasets are very small. This scale dependence](#)
608 [may arise because local and regional biases in atmospheric forcing can partially compensate when integrated over an entire ocean](#)
609 [basin. Consequently, a reanalysis may provide a more accurate representation of net precipitation at the regional scale while](#)
610 [performing differently when its associated freshwater flux is evaluated in an ocean model against Atlantic surface salinity. In other](#)
611 [words, a freshwater flux can be locally accurate while still resulting in a biased integrated freshwater input to the Atlantic Ocean.](#)

612

613 In summary, the WMB approach, particularly when constrained with ERA5 atmospheric data, is a promising tool for improving
614 ocean model forcing in regions lacking dense hydrological monitoring. Nevertheless, its accuracy is highly dependent on the
615 quality of atmospheric flux inputs and remains limited by coarse spatial resolution and noise, especially in smaller or poorly
616 monitored basins. Continued improvement in satellite data integration and regional flux estimation is essential to enhance its
617 robustness across diverse hydrological settings. Artificial intelligence techniques could further enhance performance by integrating
618 in situ measurements with the WMB approach to better identify sources of bias and error. Significant improvements are anticipated
619 with future NGGM (Next Generation Gravity Mission) and MAGIC (Mass change And Geosciences International Constellation)
620 satellite gravity missions, aiming at delivering higher spatial and temporal resolution, reduced uncertainties, and lower data latency
621 in gravity field observations. [Although distinct from the WMB approach, it is worth noting the potential of the Surface Water and
622 Ocean Topography \(SWOT\) mission, with preliminary results showing the mission's ability to estimate streamflow and its
623 variations in large, ungauged river systems where in situ infrastructure is unavailable \(Andreadis et al., 2025\).](#)
624 ¶

625 [Appendix A¶](#)



626
627 ¶

628 **Appendix A** **Figure A1: Decomposition of the Water Mass Balance equation for WMB1 and WMB2 at the Obidos station. The monthly**
629 **time series are expressed as Equivalent Water Height in m/month over the station drainage area. From top to bottom: total water storage**
630 **anomaly and first time derivative from GRACE, precipitation from ERA5 and GPCC, evapotranspiration from ERA5 and ISBA.**
631

632 **Appendix B**

Metric	R (correlation)		γ (Variability ratio)		PBias		KGE'	
Atmospheric dataset	WMB1	WMB2	WMB1	WMB2	WMB1	WMB2	WMB1	WMB2
Amazon	0.87	0.88	1.08	1.45	0.02	-0.03	0.84	0.53
Congo	0.31	0.05	3.41	1.37	-0.31	0.45	-1.52	-0.12
Orinoco	0.76	0.89	0.66	0.89	-0.08	-0.09	0.57	0.82
Mississippi	0.33	-0.11	2.20	3.92	-0.25	-0.56	-0.40	-2.17
Parana	0.22	0.10	6.80	6.21	0.04	0.14	-4.85	-4.29
Saint-Lawrence	0.17	-0.24	6.30	13.23	0.01	-0.32	-4.37	-11.30
Tocantins	0.56	0.51	2.03	1.17	-0.04	0.39	-0.12	0.35
Niger	0.29	0.09	9.05	1.24	-0.72	0.95	-7.11	-0.34
Nelson	0.13	0.23	7.22	11.68	-0.20	-0.40	-5.28	-9.72
Rhine	0.49	0.45	2.03	3.07	0.17	-0.27	-0.16	-1.16
Orange	-0.10	-0.25	-55.52	1.89	-1.26	5.80	-55.54	-5.00

633 **Table A1 B1: Several dimensionless quality metrics computed at the selected in situ stations by comparing WMB estimates to in situ**
634 **measurements taken as reference.**

635

636 **Data availability**

637 Discharge time series estimated with the Water Mass Balance approach (WMB1 and WMB2) at the outlet for each river are
638 available online at: <https://doi.org/10.5281/zenodo.17589359>

639 **Author contribution**

640 LK, TV, JP, CSz, GG and CSi collected and curated the input data to the discharge estimates. LK, TV, JP and CSz produced the
641 discharge timeseries. AS and CY performed the impact analysis on the ocean model. The manuscript was primarily written by LK,
642 TV, JP and AS, with contributions and comments from the other coauthors.

643 **Competing interests**

644 The authors declare that they have no conflict of interest.

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649

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