

Key Points:

- Closed ensemble variance decomposition of raw time series includes a new term accounting for ensemble variance of the long term time mean
- Fully time varying rivers and Greenland fluxes induce an indirect response in internal thermosteric variance in the Kuroshio region
- River runoff variability increases halosteric forced interannual variance in the maritime continent and in the tropical South Atlantic

Supporting Information:

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

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Impact of Fully Time-Varying Freshwater Fluxes From Greenland and Rivers on Externally Forced and Internal Sea Level Variability

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Abstract In forced ocean general circulation models (OGCMs), regional sea-level interannual variability arises from internal ocean dynamics and external forcings, among which freshwater fluxes from Greenland and rivers are typically prescribed as a seasonal climatology rather than with their full variability. This study examines the impact of fully time-varying rivers and Greenland fluxes on forced and internal sea-level variability over 1980–2018, using ensemble-based sensitivity experiments of an eddy-permitting OGCM. We introduce an improved, closed ensemble variance decomposition by adding a biased variance term which accounts for ensemble variance in the long-term time mean. The impact of continental freshwater fluxes variability on sea-level variance is highest in the tropical South Atlantic, the maritime continent, and the Kuroshio region. The first two regions are mainly impacted by rivers, primarily through a forced halosteric response, occurring over the full ocean depth in the tropical South Atlantic and mostly over the first 50 m in the maritime continent. In the Kuroshio region, sea-level variance is impacted by both rivers and Greenland through an internally driven response of thermosteric origin. The biased variance enables to correctly evaluate the sources of halosteric sea-level variability in that region as it reveals that its long-term variability is not well resolved by our experiment length. These results emphasize the need for accurately representing time-varying freshwater fluxes in OGCMs to better capture sea-level variability, and the value of the newly closed decomposition for correctly attributing changes in internal variance of any variable, especially in regions of high variability and for short-timescale experiments.

Plain Language Summary In forced ocean models, regional sea level interannual variability has two contributions: the “forced” variability, caused by external factors impacting ocean properties, and the “internal” variability, which happens naturally from non-linear ocean dynamics. Among external factors, freshwater fluxes from Greenland and rivers fluctuate over various timescales. Yet, most models only use a repeated seasonal cycle for these inputs. This study looks at how using fully time-varying river runoff and Greenland discharge affects regional sea level interannual variations over 1980–2018. It compares three sets of simulations: one with fully varying Greenland and river fluxes, one with a repeated seasonal cycle for rivers, and one with a repeated seasonal cycle for both. In the tropical south Atlantic and maritime continent, sea level fluctuations are sensitive to river runoff variability, with a forced response primarily due to salinity variations. These variations occur over the full depth in the former and mostly over the first 50 m in the latter. In the Kuroshio region, sea level variations are impacted by both rivers and Greenland variability, with temperature and salinity changes driven by internal dynamics. These findings highlight the importance of including time-varying freshwater fluxes in forced ocean models to better represent regional sea level interannual variability.

1. Introduction

Understanding the causes of regional sea level variability is of great importance to societies, as it would help to better adapt to future sea level rise. The drivers of regional sea level variability are numerous and act on a variety of spatial and temporal scales. On interannual timescales, the main drivers of regional sea level variability are steric and dynamic sea level change (itself driven by oceanic advection and diffusion, and local heat, freshwater, and momentum flux forcing), ice sheets and glaciers melting, land water storage change, and solid Earth deformation (Hamlington et al., 2020).

The causes of regional sea level variability can be categorized as external or internal to the ocean. External drivers are the external processes that affect the ocean and modify its properties (e.g., freshwater exchange with the

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cryosphere, hydrosphere, and atmosphere; heat exchange with the atmosphere; wind momentum flux). In contrast, internal variability arises spontaneously within the ocean due to ocean dynamics, even in the absence of variability in the forcing (Eady, 1949; Holland, 1978; Salmon, 1998).

Among the external drivers, continental freshwater fluxes from the melting of the Greenland ice sheet and river runoff are important contributors to regional sea level variability (Brunnabend et al., 2015; Piecuch & Wadehra, 2020). These two sources of freshwater to the ocean are of particular interest because they present recent modifications associated with climate change. The latter disrupts the hydrological cycle, affecting river runoff (Durand et al., 2019), and also induces global warming, leading to accelerated melting in Greenland (Mouginot et al., 2019; Otosaka et al., 2023). The contribution of the full time-variability of Greenland melting and of river runoff to regional sea level variability has not been studied in as much detail (Chandanpurkar et al., 2022; Stolzenberger et al., 2022), and always separately, overlooking their possible combined effect on regional sea level change. In addition, part of the interannual to decadal sea level variability also arises in models as internally driven, especially in regions of high mesoscale activity (Berloff & McWilliams, 1999; Colin de Verdière & Huck, 1999; Sérazin et al., 2015). It is therefore important to be able to establish precisely whether modeled sea level interannual variability is externally forced or internally driven.

In this study, we characterize the effects of fully time-varying Greenland and rivers freshwater fluxes, in combination and separately, on regional sea level variability on interannual timescales over the 1980–2018 period. To this end, we use forced ocean simulations that combine a sensitivity approach based on Tajouri et al. (2024), which allows us to isolate the effects of temporal variability in freshwater forcing, and an ensemble-simulation approach. The latter allows us to attribute the response in sea level variability to being forced or internally driven (after some key assumptions that will be fully explicit). In recent work, a similar ensemble modeling approach has been used to disentangle the sea level variability forced by the atmosphere and internally driven at interannual (Carret et al., 2021; Close et al., 2020) and decadal (Llovel et al., 2018) time scales, but it has not yet been applied to separate the sea level variability forced by continental freshwater fluxes from internally driven variability. Our ensemble variance decomposition framework builds upon previous studies (Carret et al., 2021; Jamet et al., 2019; Leroux et al., 2018) and introduces a term accounting for ensemble variance of the long term time mean signal, which we call biased variance. We show that, specifically for short-term period averaging, this approach is crucial in order to derive a closed variance budget of ensemble time series that is free of any time preprocessing. We address the following questions:

1. In which areas is the biased variance contribution to internal variance significant, and how does it evolve with period's length?
2. What is the impact of fully time-varying Greenland and worldwide rivers freshwater fluxes on the forced and internal parts of the interannual sea level variability, as well as its halosteric, thermosteric, and manometric components?

The paper is organized as follows: in Section 2 we describe the modeling strategy, the ensemble variance decomposition framework, and the methodology for computing the annual sea level and its components from the simulations. In Section 3, we characterize the interannual variability of sea level and its components within the reference ensemble (forced using a repeated seasonal cycle for continental freshwater fluxes globally). We focus on the contributions of forced and internal variability and how the internal variance is influenced by the length of the time period considered. In Section 4, we evaluate the impact of fully time-varying continental freshwater fluxes on the sea level variability (and its components). We finally discuss the broader implications of the results, examine the study's limitations, and conclude in Section 5.

2. Methods

2.1. Description of the Model Simulations

The setup used for the sensitivity experiments is the same as that described in Tajouri et al. (2024) and is summarized here. The model configuration is based on NEMO (Nucleus for European Modeling of the Ocean) v.4.0.6, with 0.25° horizontal resolution and 75 vertical levels. The simulations are global and fully coupled with the sea ice model SI3 (Vancoppenolle et al., 2023), and include icebergs. The model is forced by the Japanese 55-year atmospheric reanalysis (JRA-55) at a 3-hr resolution (Kobayashi et al., 2015) using the National Center for Atmospheric Research (NCAR) bulk formulas (Large & Yeager, 2004). The model uses a non-linear free surface

and a z^* coordinate approach, which means that the thickness of each vertical level varies at each time step. No sea surface salinity relaxation is applied to our ensemble simulations following the same strategy as in Tajouri et al. (2024). A thorough description of the configuration of the model is archived on Zenodo (Molines & Leroux, 2024).

We use three ensemble simulations of 10 members each named ES, EGR, and ER covering the period 1980–2018. *E* stands for Ensemble, *S* for Seasonal, *G* for Greenland, and *R* for Rivers. The ensemble ES is first created using a restart file from 31 December 1974, which originates from a single simulation that was spun-up over a 17-year period. To create the initial spread, the methodology of Bessi eres et al. (2017) was used, which we briefly describe here. To generate the ensemble dispersion, a stochastic version of the equation of state is used for year 1975 (Brankart, 2013) in each member, and is then switched off for the rest of the ensemble hindcast (from 1976 to 2018). Therefore each member of the ES ensemble is unique due to this perturbation strategy applied for 1 year. From 1976, the 10 members are integrated and forced by the same continental and atmospheric conditions. To obtain the same atmospheric fluxes, the fluxes are first computed for each member and then the ensemble mean of the fluxes is applied to each member to each ice free grid cell (the grid cells covered by sea ice are forced using their own individual fluxes for each member from the SI3 model and are masked out in this study). Only heat and evaporation fluxes are concerned, momentum fluxes are kept individual for each member, using the current feedback parameterization (Renault et al., 2020). This ensemble averaging flux procedure is done online, leading to a coupling of the ensemble individual members (i.e., the ensemble members are linked together by the ensemble-mean surface flux). This strategy is meant to reduce artificial damping of ocean surface variability by prescribed atmospheric conditions. Second, to generate the EGR and ER ensembles, restart files from each of the 10 ES members at 31 December 1979 were used. Each of the 10 members of the EGR and ER ensembles is then integrated until 2018, using the same continental and atmospheric conditions for ice free grid cells within each ensemble, following the method applied to ES. The creation of the three ensembles is illustrated in a schematic (Figure S1 in Supporting Information S1).

The three ensembles only differ in the temporal variability of the continental freshwater forcing used for Greenland's discharge and river runoff (the fluxes from Antarctica do not vary between simulations). ES is the ensemble of reference and corresponds to all continental freshwater fluxes set as seasonal (i.e., a seasonal cycle repeated every year). The EGR ensemble corresponds to all continental freshwater fluxes set as fully varying (except Antarctica). We thus interpret the difference EGR–ES as the combined impact of fully varying Greenland discharge and river runoff (referred to as Gr + Riv hereafter). It will serve as a benchmark comparison in Section 4. To further analyze the separated impacts of Greenland and river runoff on the total signal, we have run the ensemble ER, which corresponds to all river runoff set as fully varying but Greenland's discharge set as seasonal. We thus interpret the difference ER–ES as the isolated impact of fully varying river runoff (referred to as RIVERS hereafter). Finally, due to limitation in computational resources, we were not able to produce the ensemble EG, which would correspond to Greenland's discharge set as fully varying but river runoff set as seasonal. Instead, we will estimate the impact of fully varying Greenland discharge as a residual through the difference EGR–ER (referred to as GREENLAND hereafter). Note however that this approach assumes the system responds to different forcings through a linear combination, a condition which might not always be met (Jamet et al., 2020).

The fully varying and seasonal freshwater fluxes used to force our sensitivity ensemble simulations were derived from three data sets. For river runoff, we use the ISBA-CTRIP land surface model-reanalysis over the 1979–2019 period providing daily data (Decharme et al., 2019). The daily seasonal cycle of river runoff was computed over the 1979–2019 period. Mouginot et al. (2019) provided the fully varying Greenland mass loss monthly data over the 1972–2018 period. The monthly seasonal cycle of Greenland's discharge was estimated over the 1950–1972 period, corresponding to the period prior to Greenland's current intense melting trend (Mouginot et al., 2019). For Antarctica, the annual calving and basal melt rates estimates for each ice shelf were derived from Rignot et al. (2013).

River runoff and Greenland discharge are implemented differently. River runoff is spread over the top 10 m of the ocean. Greenland ice sheet freshwater fluxes come from multiple sources. The surface runoff from land terminating glaciers is treated as river runoff. The subglacial runoff from marine terminating glaciers is routed to the NEMO coastal wet cell nearest to the mouth of the 262 fjords of the data set –which are not resolved by the model– and then spread between the surface and the fjord's sill depth. Calving from tide water glaciers is

translated to the model fjord's mouth. Melting of icebergs in fjords is represented by converting 50% of the iceberg mass to liquid discharge at the first model sea-point (Enderlin et al., 2016), and treated together with subglacial runoff. This value was chosen to account for the high uncertainty of iceberg melt in fjords (Benn et al., 2017; Moon et al., 2018; Straneo et al., 2013). The remaining 50% are kept to feed as calving source the explicit iceberg representation (using the Lagrangian iceberg model of Marsh et al. (2015)).

2.2. Ensemble Variance Decomposition

The following ensemble variance decomposition approach is used to decompose the total variance. It corresponds to two terms: the forced variance and the internal variance, the latter being composed of the intrinsic and the biased variance.

Let's define our variable of interest for a given member i of a given ensemble as $f_i(t) = \langle f \rangle(t) + f'_i(t)$, where $\langle f \rangle(t) = \frac{1}{N} \sum_{i=1}^N f_i(t)$ represents the ensemble mean, with N the number of members, i the member index, t the time, and f'_i the anomaly with respect to the ensemble mean. The time-variance of $f_i(t)$ is:

$$\sigma^2(f_i(t)) = \overline{(f_i(t) - \overline{f_i(t)})^2} = \overline{f_i^{*2}(t)}, \quad (1)$$

where the overbar indicates the time averaging operator $\left(\bar{x} = \frac{1}{T} \sum_{t=1}^T x\right)$, and $f_i^{*}(t)$ the anomaly with respect to the temporal mean. Note that the time-variance operator σ^2 has been developed with T the total number of time points of the signal. Thus, Equation 1 corresponds to a biased variance estimator, which is necessary for the following derivation.

We then expand Equation 1 following $\overline{(x - \bar{x})^2} = \bar{x}^2 - \bar{x}^2$, which leads to

$$\sigma^2(f_i(t)) = \overline{(\langle f \rangle(t) + f'_i(t))^2} - \left(\overline{\langle f \rangle(t) + f'_i(t)}\right)^2 \quad (2)$$

where f has been decomposed into an ensemble mean and a perturbation contribution.

Expanding the squares and rearranging the terms leads to:

$$\sigma^2(f_i(t)) = \underbrace{\overline{\langle f \rangle^2(t)} - \overline{\langle f \rangle(t)}^2}_{\sigma^2(\langle f \rangle)} + \underbrace{\overline{f_i'^2(t)} - \overline{f'_i(t)}^2}_{\sigma^2(f'_i)} + 2 \underbrace{\left(\overline{\langle f \rangle(t) f'_i(t)} - \overline{\langle f \rangle(t)} \overline{f'_i(t)}\right)}_{I(\langle f \rangle, f'_i)}. \quad (3)$$

This provides a measure of time variance for an individual ensemble member, which is decomposed into an ensemble mean contribution ($\sigma^2(\langle f \rangle)$), an ensemble anomaly contribution ($\sigma^2(f'_i)$), and an interaction term ($I(\langle f \rangle, f'_i)$). Now, given that an ensemble provides several realizations of time variance decomposition, we are able to provide an ensemble mean estimate of time variance, the latter being usually referred to as the total variance. Hence, the total variance is defined in the temporal anomalies dimension. The ensemble mean of (3) leads to:

$$\langle \sigma^2(f_i(t)) \rangle = \sigma^2(\langle f \rangle) + \overline{\langle f_i'^2(t) \rangle} - \overline{\langle f'_i(t) \rangle^2} + 2 \overline{\langle \langle f \rangle(t) f'_i(t) \rangle - \overline{\langle f \rangle(t)} \overline{f'_i(t)}}. \quad (4)$$

Using the fact that the ensemble mean and the time mean operators commute and replacing $f'_i(t)$ by $f_i(t) - \langle f \rangle(t)$, the second term on the right hand side of (4) can be written as:

$$\overline{\langle f_i'^2(t) \rangle} = \overline{\langle (f_i(t) - \langle f \rangle(t))^2 \rangle} = \overline{\epsilon^2(f_i(t))} \quad (5)$$

where $\epsilon^2(x)$ is used to refer to the biased ensemble variance estimator.

The third term of (4) can be re-written using again $f'_i(t) = f_i(t) - \langle f \rangle(t)$, leading to an expression for the ensemble variance of the temporal means, that is

$$\langle \overline{f'_i(t)}^2 \rangle = \langle (\overline{f_i(t)} - \overline{\langle f \rangle(t)})^2 \rangle = \epsilon^2(\overline{f_i(t)}). \quad (6)$$

Finally, since the ensemble mean and the time mean operators commute, the last term on the right hand side of Equation 4 vanishes identically because $\langle f'_i(t) \rangle = 0$ by definition.

To summarize, we have an exact decomposition of the ensemble mean of the time variance of each ensemble member as the sum of the time variance of the ensemble mean (referred to as the forced variance), the time mean of the ensemble variance (referred to as the intrinsic variance), minus the ensemble variance of the time mean field (referred to as the biased variance), that is:

$$\underbrace{\langle \sigma^2(f_i(t)) \rangle}_{\text{Total}} = \underbrace{\sigma^2(\langle f_i(t) \rangle)}_{\text{Forced}} + \underbrace{\overline{\epsilon^2(f_i(t))} - \epsilon^2(\overline{f_i(t)})}_{\substack{\text{Intrinsic} \\ \text{Biased}}} \quad (7)$$

Internal = $\langle \sigma^2(f'_i(t)) \rangle = \epsilon^2(\overline{f_i^*(t)})$

The intrinsic variance is the counterpart of the total variance in the ensemble anomalies dimension. It corresponds to the impact of the full temporal variability of each member on the ensemble spread. As both the intrinsic and the biased variance terms quantify variations across ensemble members, we define the internal variance as Internal = Intrinsic – Biased. Therefore, the intrinsic variance is separated into a contribution of the time mean (i.e., background) state of each member (the biased variance) and a contribution of the temporal anomalies of each member (the internal variance). The internal variance can also be computed independently both in the temporal anomalies dimension as the ensemble mean of the time variance of the ensemble anomalies ($\langle \sigma^2(f'_i(t)) \rangle$), and in the ensemble anomalies dimension as the time mean of the ensemble variance of the temporal anomalies ($\overline{\epsilon^2(f_i^*(t))}$). Thus, the internal variance enables to link both dimensions and Equation 7 can be rewritten as:

$$\text{Internal} = \underbrace{\langle \sigma^2(f_i(t)) \rangle}_{\text{Total}} - \underbrace{\sigma^2(\langle f_i(t) \rangle)}_{\text{Forced}} = \underbrace{\overline{\epsilon^2(f_i(t))}}_{\text{Intrinsic}} - \underbrace{\epsilon^2(\overline{f_i(t)})}_{\text{Biased}} \quad (8)$$

$\langle \sigma^2(f'_i(t)) \rangle$

The decomposition of the total variance into the time variance of the ensemble mean and the ensemble mean of the time variance of the ensemble anomalies can be interpreted as the forced and internal components, respectively. However these terms are not independent. As the ocean is a nonlinear system, they can interact with each other. The ensemble variance decomposition approach is graphically presented in Figure 1.

The biased variance magnitude is particularly dependent on the length of the time period considered. An interesting property of this term is that, as the period considered becomes shorter, the biased variance compensates the intrinsic variance, so that the total variance on short timescales represents only the forced variance. Meanwhile, as the period considered becomes longer, the biased variance by definition will reflect the variance due to the longer time scales of variability of each member. What remains to be seen experimentally is how quickly the biased variance varies between these two extreme situations.

This ensemble variance decomposition does not assume any time processing and is more general than the one proposed by previous studies (Carret et al., 2021; Jamet et al., 2019; Leroux et al., 2018) as it includes the (potentially large) effects associated with long term time mean ensemble spread. In practice, the data will be prepared prior to analysis (see Section 2.4), but in a way to conserve long term trends and time mean signals which depend upon ensemble members, hence of an internal nature. We note, however, that for this decomposition to be

valid, the time and ensemble variance estimators must be expressed as $\sigma^2 = \frac{1}{T} \sum_{t=1}^T$ and $\epsilon^2 = \frac{1}{N} \sum_{i=1}^N$ respectively.

This introduces biases in the estimated time and ensemble variances of $\frac{T-1}{T}$ (2.6% in our case) and $\frac{N-1}{N}$ (10% in

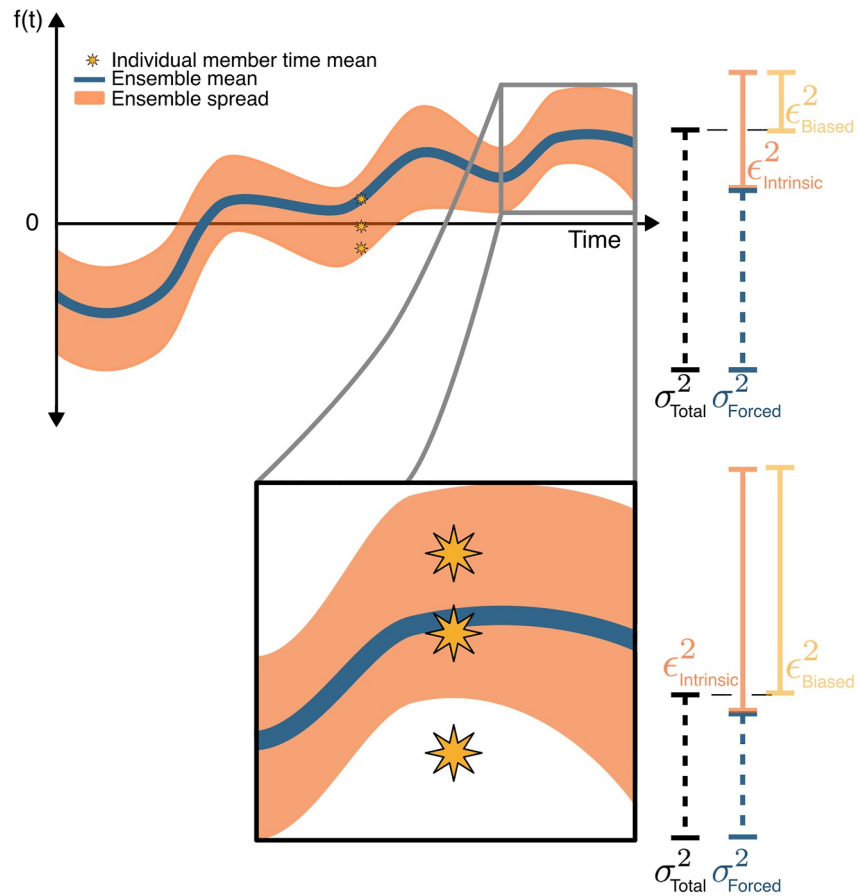


Figure 1. Schematic presenting the principle of the ensemble variance decomposition for a variable f for a given grid point. The thick blue curve represents the ensemble-mean ($\langle f_i(t) \rangle$), the orange shaded area the ensemble-spread at each time step ($\epsilon^2(f_i(t))$), and the yellow stars the individual member time-means ($\overline{f_i(t)}$)—only three are represented for readability. The forced variance (σ_{Forced}^2) is calculated as the time-variance of the ensemble mean, the intrinsic variance ($\epsilon_{\text{Intrinsic}}^2$) is calculated as the time-mean of the ensemble variances, and the biased variance ($\epsilon_{\text{Biased}}^2$) is calculated as the ensemble variance of the time means. On the right, the total, forced, intrinsic, and biased variances are represented using the black, blue, orange, and yellow lines respectively. Following Equation 7, we have $\sigma_{\text{Total}}^2 = \sigma_{\text{Forced}}^2 + \epsilon_{\text{Intrinsic}}^2 - \epsilon_{\text{Biased}}^2$, with σ_{Total}^2 the ensemble mean of the time variance of each ensemble member. The decomposition of the total variance varies with the length of the time series, with larger intrinsic and biased variances for short periods (bottom panel) compared to longer periods (top panel).

our case), respectively. For large ensembles run over a long time, these biases will be close to zero and thus negligible.

2.3. Sea Level Decomposition

To study the interannual sea level variability, the ensemble variance decomposition is applied on annual time series of simulated sea level anomalies and its steric, manometric, halosteric, and thermosteric components.

The simulated regional sea surface height (SSH, defined with respect to a surface of constant geopotential) can be decomposed into its density-driven (steric) and mass-driven (manometric) components following the equation (Gill & Niller, 1973):

$$\text{SSH} = \underbrace{-\frac{1}{\rho_0} \int_{-h}^0 \rho \, dz}_{\text{steric}} + \underbrace{\frac{P_b - P_a}{\rho_0 g}}_{\text{manometric}}, \quad (9)$$

where z is the vertical coordinate, h the ocean depth, P_a the sea-surface loading (such as atmospheric surface pressure and sea ice loading), ρ_0 the mean seawater density (1035 kg m^{-3} in NEMO), g the acceleration due to gravity, ρ the density, and P_b the bottom pressure. In our set of experiments, the sea-surface loading effect is not taken into account. Thus, the manometric component is computed as $\frac{P_b}{\rho_0 g}$ using annual outputs. The steric sea level can be further decomposed into its temperature (thermosteric) and salinity (halosteric) contributions.

Steric (SSH_ρ), halosteric (SSH_S), and thermosteric (SSH_θ) sea level components, are computed offline at a monthly frequency for several depth ranges (from the surface to 50, 100, 300, 700, and 2,000 m) and for the full-depth of the water column as follows:

$$\text{SSH}_\rho = -\frac{1}{\rho_0} \int_{-z}^0 (\rho(T, S, p) - \rho_{\text{ref}}(p)) dz, \quad (10)$$

$$\text{SSH}_\theta = -\frac{1}{\rho_0} \int_{-z}^0 (\rho(T, \bar{S}, p) - \rho_{\text{ref}}(p)) dz, \quad (11)$$

$$\text{SSH}_S = -\frac{1}{\rho_0} \int_{-z}^0 (\rho(\bar{T}, S, p) - \rho_{\text{ref}}(p)) dz, \quad (12)$$

where z is depth, ρ_{ref} is a reference density profile calculated for $T = 0^\circ\text{C}$ and $S_A = 35.16504 \text{ g kg}^{-1}$ with the Thermodynamic Equation Of Seawater - 2010 (TEOS-10) and depending only on the hydrostatic pressure p (IOC, SCOR and IAPSO, 2010), and the overbars indicate the climatological-mean for each month over the 1980–2018 period. We then average the monthly fields to obtain the yearly steric, halosteric, and thermosteric sea level components.

2.4. Sea Level Anomaly Computation

Prior to analysis, a necessary correction is applied to the simulated SSH annual time series. As the NEMO model is based on the Boussinesq approximation—conserving volume rather than mass and introducing spurious extra terms—the global mean steric sea level is not explicitly represented during the integration of the simulation (Greatbatch, 1994). Therefore, a global mean SSH time series must be subtracted from each member. To account for this, the individual global mean SSH time series for each member is first removed from every grid point following:

$$g_i^{\text{corr}}(t) = g_i(t) - \overline{g(t)}, \quad (13)$$

where $\overline{\cdot}$ is the globally weighted mean.

Second, at each grid point, we calculate Sea Level Anomalies (SLA) by subtracting the ensemble-mean of the time-mean SSH signal over the 1980–2018 period that is:

$$g_i^{\text{anom}}(t) = g_i^{\text{corr}}(t) - \langle \overline{g_i^{\text{corr}}(t)} \rangle. \quad (14)$$

Using the ensemble-mean time-mean, rather than the individual member time-mean, ensures that the variability of each member remains unchanged. We intentionally avoid removing any type of variability from the signal (e.g., linear trends) to preserve the original internal variability of the simulations (see Section 5 for further discussion). For consistency, we apply the same steps (i.e., (13) and (14)) to the manometric, steric, halosteric, and thermosteric sea level time series.

3. Decomposition of Sea Level Interannual Variance in the Reference Ensemble

Before exploring the impact of fully varying continental freshwater fluxes on sea level variance, we first characterize the variance of SLA and its components by performing the ensemble variance decomposition in the reference ensemble ES over the 1980–2018 period.

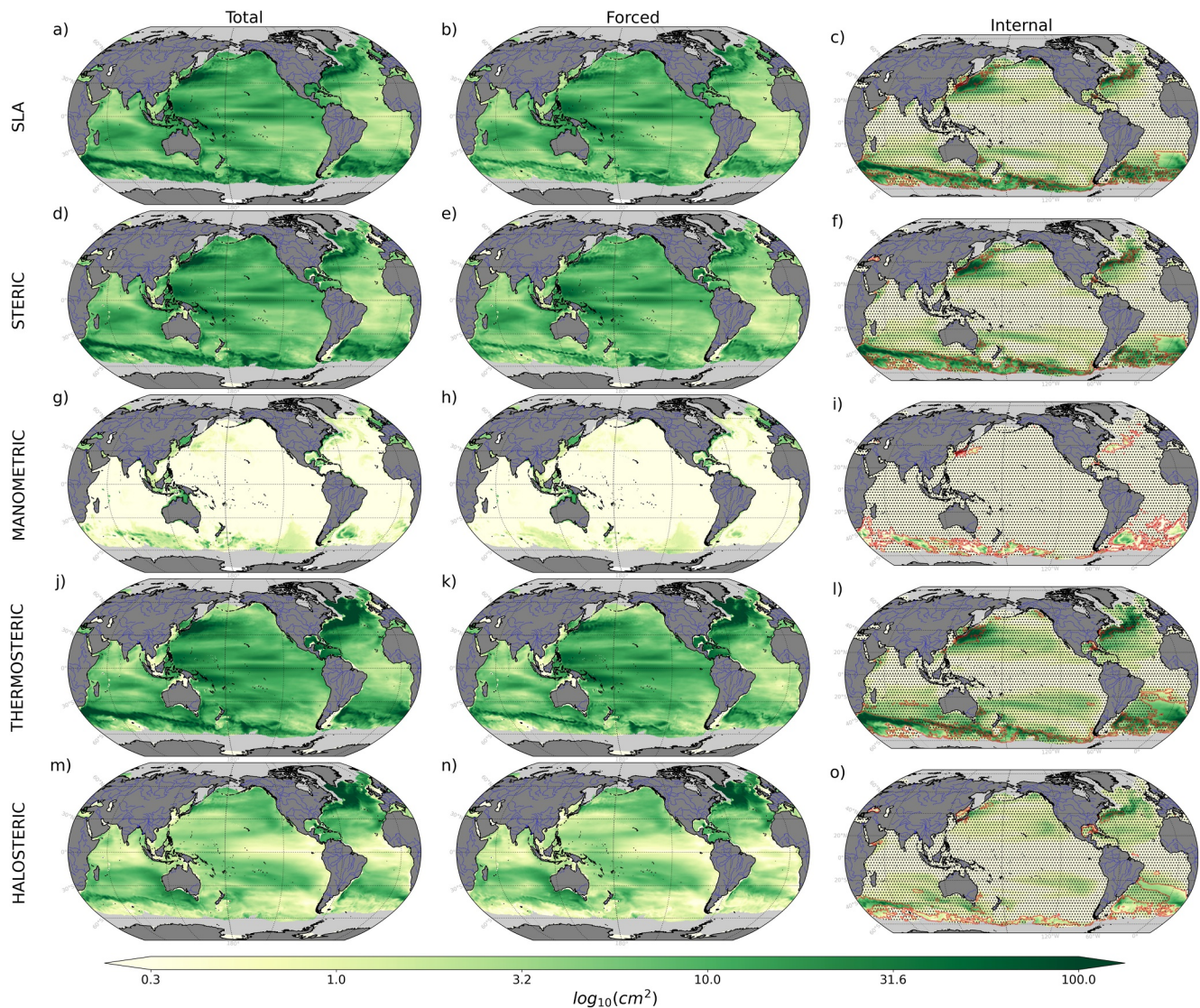


Figure 2. Total (first column), forced (second column), and internal (third column) variances (cm^2) of the SLA (a–c), the steric (d–f), the manometric (g–i), the thermosteric (j–l), and the halosteric (m–o) sea level components in ES over the period 1980–2018. The colorbar is in $\log_{10}$ scale. For panels in the third column the red contours indicate regions where the internal variance dominates over the forced variance (ratio forced/internal < 1) and the hatching indicate regions not corresponding to this criterion. The grid cells covered by sea ice are masked out in light gray.

3.1. Partitioning of Total Variance Into Forced and Internal Variances

Strong SLA total variance is found in the western boundary currents, the Antarctic Circumpolar Current (ACC), the equatorial Pacific, and the Indian Ocean between 5 and 30°S (Figure 2a). On the contrary, weak SLA total variance is found in the subtropical Atlantic and Pacific gyres, and in the Northern Indian Ocean. The SLA total variance is primarily attributed to the forced variance across most of the global ocean (89.7% of the total ocean area) (Figure 2b), while the internal variance is dominant in the Gulf Stream region, the Kuroshio region, the ACC, and the Agulhas leakage region (Figure 2c, red contoured regions indicate a forced/internal variance ratio < 1).

The SLA total variance is largely of steric origin over most of the globe except in shallow regions, the Argentinian basin, and the Mediterranean sea where the manometric variance dominates (Figures 2a–2d and 2g) in accordance with the literature (Forget & Ponte, 2015). Interestingly, the manometric total variance in the Argentinian basin presents strong forced and internal contributions (Figures 2h and 2i), the latter being due to the strong turbulent circulation present there (Mason et al., 2017). Note that manometric variance is the dominant mechanism of

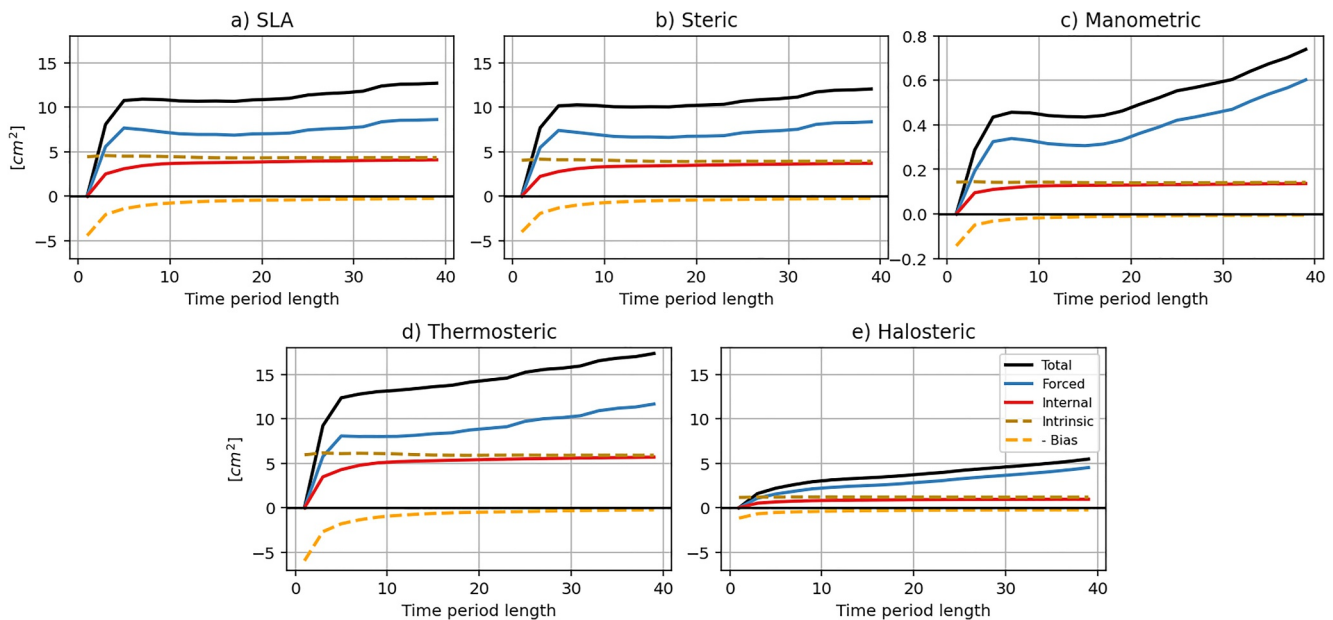


Figure 3. Globally weighted average of variance terms for SLA (a), steric (b), manometric (c), thermosteric (d), and halosteric (e) components in ES, plotted as a function of period length in years for periods computed as $[t_0 - \delta t : t_0 + \delta t]$ with $t_0 = 1999$ and $\delta t \in \{1, \dots, 19\} \subset \mathbb{N}$. Total, forced, internal, intrinsic, and biased variance are in black, blue, red, brown, and orange respectively. Note that the biased variance is plotted with a negative sign, and panel (c) has a different y-axis scale.

interannual sea level variance at high latitudes (Forget & Ponte, 2015), although we do not show it here because we did not include ice-covered regions in our analysis. Both manometric and steric variances are mostly driven by their forced component (Figures 2e and 2h) except in the Gulf Stream region, the Kuroshio region, the ACC, and the Agulhas leakage region where the internal variance dominates (Figures 2f and 2i). This distribution into forced and internal parts depends, among other things, on the model resolution. Our eddy-permitting $1/4^\circ$ -resolution probably results in an underestimation of internal variance, especially in eddy-active regions (Chassignet et al., 2020; Sérazin et al., 2018).

These results are very similar to the ones of Carret et al. (2021) who carried out a similar study (50-member ensemble based on NEMO v.3.5 ORCA025.L75 over the period 1993–2015). The similarity, despite our use of fewer members, gives us confidence that 10 members are sufficient to gain insight into the partitioning between forced and internally driven interannual sea level variability.

Here, we propose to extend these results in three directions: first, by accounting for long term time mean signals in the variance decomposition, which will be shown to be significant in some circumstances (Section 3.2); second, by accounting for fully time varying freshwater fluxes (Section 4); third, by decomposing the steric sea level variance into its halosteric and thermosteric components (Figure 2), which we now discuss.

The steric total variance is principally driven by the thermosteric component over most of the globe except in the North Atlantic, the North Pacific, and shallow coastal zones where the halosteric variance is also substantial (Figures 2d–2j and 2m). Notably, in the Gulf Stream region and the subpolar North Atlantic, the thermosteric and halosteric total variances exceed the steric total variance, suggesting covariability and mutual compensation. This aligns with Durack et al. (2014) and references therein who showed that thermosteric expansion (warming) is partially offset by halosteric contraction (enhanced salinity) in the North Atlantic, leading to a more spatially uniform total steric change. Overall, the thermosteric and halosteric sea level total variances are mostly forced, except in the Gulf Stream region, the Kuroshio region, the ACC, and the Agulhas leakage region, where the internal variance prevails (Figures 2k, 2l, 2n, and 2o).

3.2. Contribution of Long Term Time Mean Signals

To understand the time dependence of the biased variance term, and hence of the ensemble variance decomposition, we analyze the globally averaged decomposition for the SLA and its components as a function of period

length in years defined as $[t_0 - \delta t; t_0 + \delta t]$, with $t_0 = 1999$ and $\delta t \in \{1, \dots, 19\} \subset \mathbb{N}$ (Figure 3). For SLA, the globally averaged total, forced, and internal variances increase similarly with period length, rising sharply from 1-year to 5-year periods, then more gradually up to the 39-year period (Figure 3a black, blue, and orange curves). This suggests that the global partitioning of SLA total variance is only weakly sensitive to period length, with roughly two-thirds attributed to forced variance and one-third to internal variance. A similar pattern holds for the steric component, but not for other components, where forced variance continues to rise and does not reach a plateau by the end of the simulations. For all variables, intrinsic variance changes very little with period length, indicating that the ensemble spread has saturated. However, period length affects how internal variance is partitioned between intrinsic and biased variances. At short periods, biased variance dominates. As period length increases, biased variance decreases exponentially, and intrinsic variance becomes dominant. The period length required for this transition varies by variable: it is similar for globally averaged SLA, steric, manometric, and thermosteric components (3 years), but longer for the halosteric component (5 years). The period length at which internal variance transitions from being dominated by biased variance to being dominated by intrinsic variance may serve as an indicator of the dominant timescale of variability. Overall, this analysis shows that the decomposition of global internal variance depends on period length, with biased variance contributing substantially for periods shorter than 10 years across all variables.

Internal variance –and its intrinsic and biased components– is not spatially homogeneous (Figure 2). The spatial patterns of intrinsic and biased variances closely resemble that of the internal variance (not shown). Having established the global average behavior, we now assess the time dependence of this decomposition at the local scale. To do so, we compare the biased variance contribution to internal variance of SLA and its components over two contrasting periods: 1980–2018 (39 years), when the global biased contribution is minor, and 1998–2000 (3 years), when it is more substantial (Figure 4).

The SLA, steric, and thermosteric components show similar regional changes when the period is shortened from 39 to 3 years: the area where biased variance exceeds 10% of internal variance increases from 16.7%, 19.9%, and 10.4%, respectively, for the 39-year period (Figures 4a, 4c and 4g) to virtually the entire ocean for the 3-year period (Figures 4b, 4d and 4f). Additionally, for the 3-year period, biased variance exceeds 50% of internal variance over 34.4%, 37.5%, and 39.4% of the ocean area, respectively (Figures 4b, 4d and 4h). The most time-dependent regions –defined as the ocean regions where the biased variance exceeds 10% for the 39-year period and 50% for the 3-year period– include the equatorial Atlantic and Indian Oceans, the northern Australian marginal seas, the European continental shelf, the central North Pacific, the Japan and East China Seas, and the subpolar North Atlantic. Conversely, the manometric component shows the weakest time dependence, with biased variance exceeding 50% of internal variance over only 13.7% of the ocean area during the 3-year period, primarily in marginal seas.

In stark contrast, the halosteric component exhibits the greatest sensitivity to period length among all sea level components (Figures 4i and 4j). For the 3-year period, biased variance contributes over 50% of internal variance over 70.2% of the ocean (about twice the SLA case) and drops to 3% for the 39-year period (against 0% for the SLA). Notably, the halosteric biased variance contribution remains the highest among sea level components even for the 39-year period, exceeding 10% of internal variance over 36.1% of the ocean (namely in the Southern Ocean and the western Pacific Ocean between 20 and 40°N) –again, about twice that of SLA. This result indicates that halosteric sea level variability operates on longer timescales than other components in most regions. Therefore, the contribution of biased variance to internal variance is highly dependent on location and sea level component. For the longest period analyzed (39 years), this contribution is non-negligible (i.e., exceeding 10%) and affects between 6.7% and 36.1% of the ocean area, depending on the sea level component.

To summarize, the SLA interannual variability in ES is mostly forced globally, except in regions of high mesoscale activity (western boundary currents, the ACC, and the Agulhas leakage region), where internal variance dominates. The SLA variability is largely of thermosteric origin across most of the globe. The new term of the ensemble variance decomposition, the biased variance, significantly contributes to internal variance, depending on location, period length (particularly for periods shorter than 10 years), and variable of interest. In the next section, we explore the impact of fully time-varying continental freshwater fluxes from Greenland and rivers on the ensemble variance decomposition.

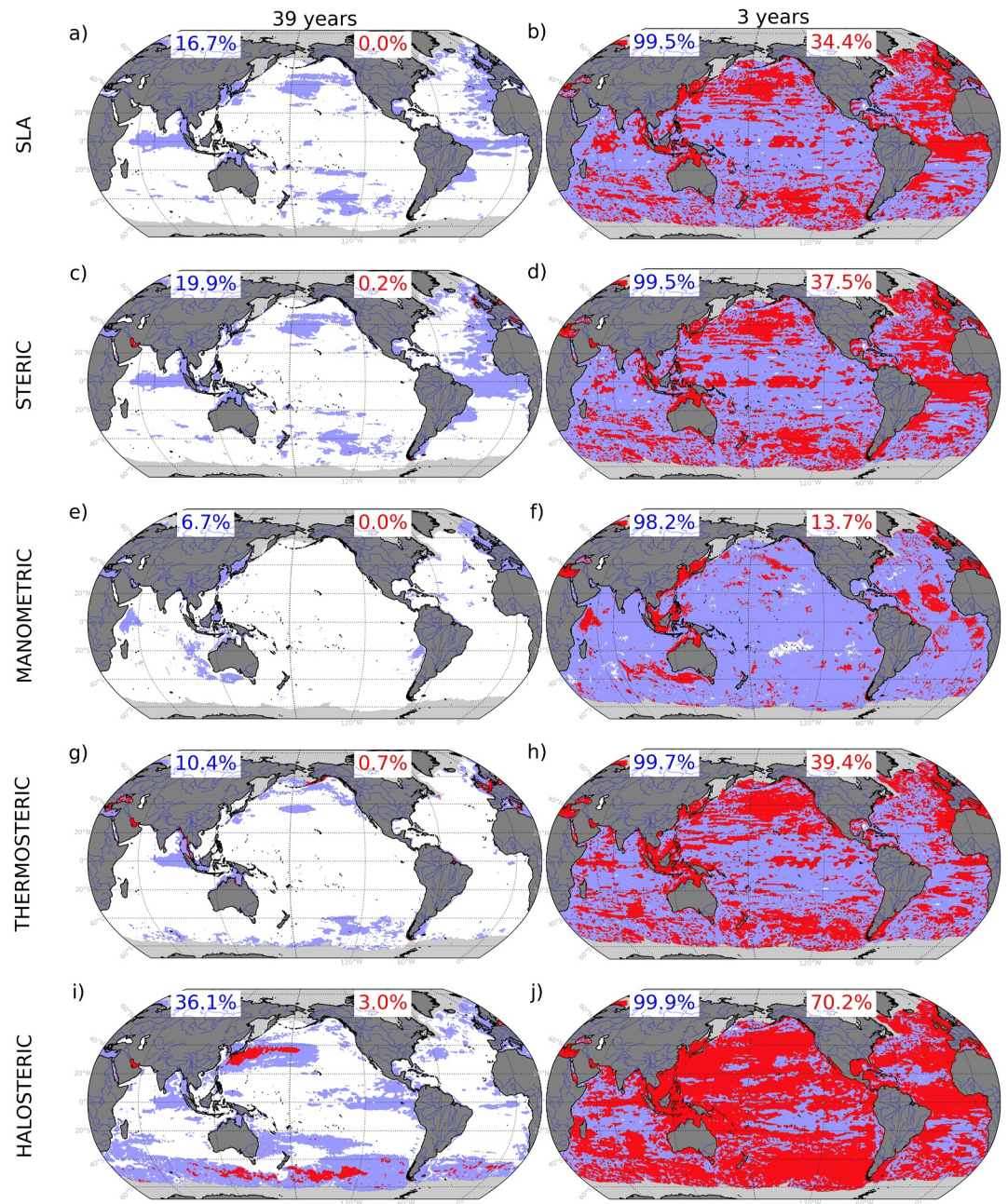


Figure 4. Biased variance contributing more than 10% (50%) to internal variance—calculated as the ratio of biased variance to intrinsic variance—is highlighted in blue (red) for the SLA (a–b), steric (c–d), manometric (e–f), thermosteric (g–h), and halosteric (i–j) components in ES. The first column corresponds to the 1980–2018 period (39 years), and the second column to the 1998–2000 period (3 years). The percentages on each panel indicate the proportion of the global ocean area where the biased variance contribution to the internal variance exceeds 10% (blue) or 50% (red).

4. Impact of Fully Time-Varying Freshwater Fluxes on Sea Level Variance

We now turn our interest to the response of the SLA variance to fully time varying freshwater fluxes. As described in Section 2, fully varying freshwater fluxes are imposed as source terms on ocean boundaries, and are common to all members within a given ensemble. Hence, changes from seasonal to fully varying freshwater fluxes are expected to imprint into the forced component of the SLA variance. However, as will be shown, changes in forcing do also induce changes in the internal variability of the ocean in strongly eddying regions.

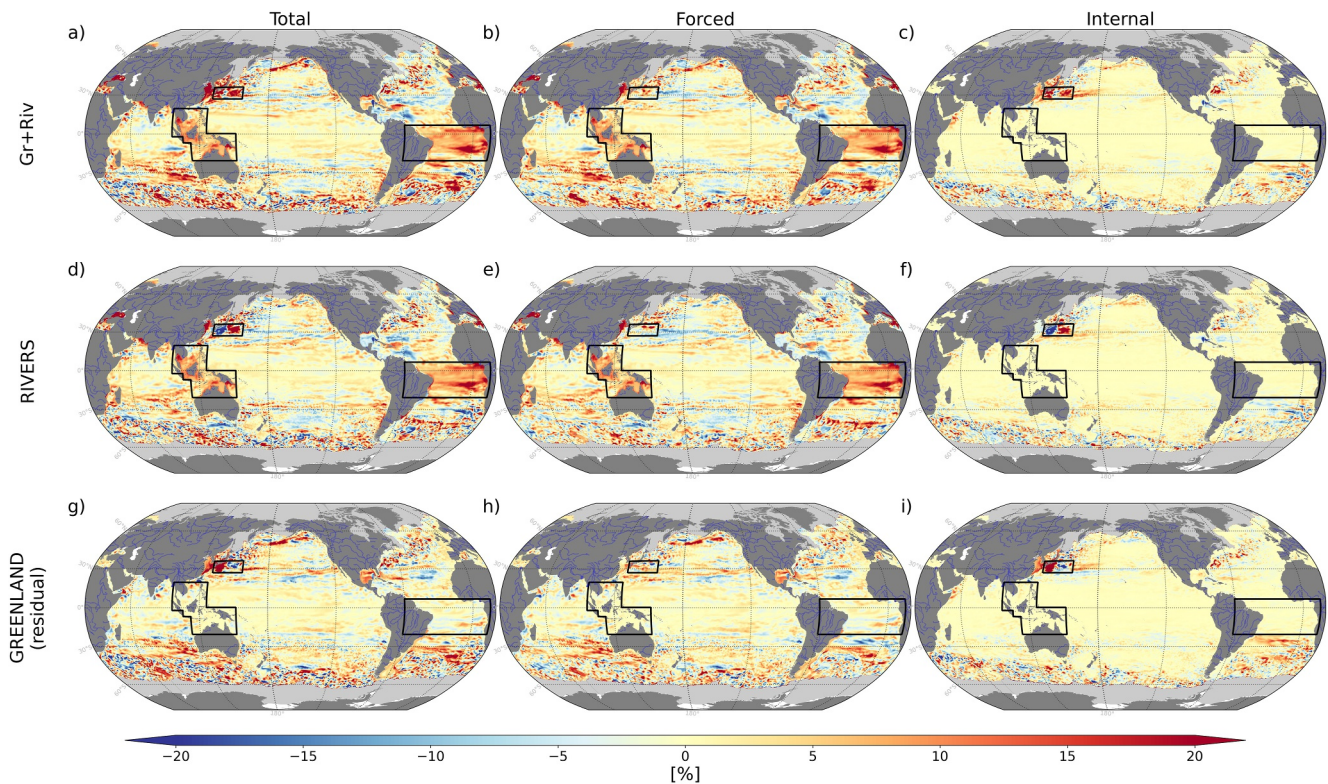


Figure 5. Impact of fully time-varying freshwater fluxes from Greenland and rivers (a–c), from rivers (d–f), and from Greenland (g–i) over the 1980–2018 period on total (first column), forced (second column), and internal (third column) SLA variances in ES. The variance sensitivities are expressed as percentages relative to the SLA total variance in ES (e.g., panel (i) corresponds to $100 \times \text{VAR}_{\text{internal}}^{\text{ES}} / \text{VAR}_{\text{total}}^{\text{ES}}$), maintaining the relationship: total = forced + internal. For each column we have Gr + Riv – RIVERS = GREENLAND. The black boxes indicate the regions of interest: the tropical South Atlantic, the Maritime Continent, and the Kuroshio region.

4.1. Impact on the SLA Total Variance Decomposition

The impact of fully varying freshwater fluxes from Greenland and rivers on SLA total variance decomposition into forced and internal contributions is shown on Figure 5 as percentages relative to the SLA total variance in ES. In Gr + Riv, the SLA total variance is particularly impacted in three regions outlined by boxes in Figure 5a: the tropical South Atlantic ocean (SA box), the maritime continent (MC box), and the Kuroshio region, where the average impact is 5.53%, 4.02%, and 9.73%, respectively.

In the SA and MC boxes, the impact on the Gr + Riv SLA total variance arises from the response of the forced variance (Figure 5b). Furthermore, examining the impact of river runoff variability alone reveals that the response of forced variance in Gr + Riv is primarily due to fluctuating river runoff, with an average impact of 5.60% in the SA box and 3.80% in the MC box (Figure 5e). This is expected as the SA and MC boxes encompass regions with a high density of rivers, including some of the world's highest-discharge rivers in the Atlantic box, and the mouths of the Mekong and Purari-Kikori-Fly rivers (southeast of Papua New Guinea) in the MC box (Figure 5e).

Although changes in forcing are expected to imprint into the forced component of the SLA variance, this is not the case in strongly eddying regions and particularly in the Kuroshio box where the sensitivity of the Gr + Riv SLA total variance mainly imprints in the internal component (amounting to 77.8% of the SLA total variance change on average in the box) (Figure 5c). An evaluation of the robustness of this response is given in the supplementary information S2. This is because the mean and turbulent circulations interact, with the latter drawing energy from the former (e.g., Hochet et al., 2022). Consequently, changes in freshwater flux forcing can also modify the turbulent circulation. The Gr + Riv SLA internal response in the Kuroshio box involves a response to RIVERS displaying a strong dipole, with a large variance drop in the western part of the box and a large variance rise in the eastern part (Figure 5f). By mirror effect, the SLA internal variance in GREENLAND in the Kuroshio box (computed as a residual, cf. Section 2.1) also forms a dipole but with opposite signs and smaller amplitude on the

eastern side (Figure 5i). Given its compensatory effect, validating this new result on the impact of fully varying Greenland discharge, would require a dedicated ensemble of simulations EG (cf. Section 2.1).

Thus, the impact of fully time varying freshwater fluxes from Greenland and rivers on SLA interannual variance consists of two distinct responses on which we will focus in the following sections: (a) a response in forced variance to river runoff variability in the SA and MC boxes, and (b) a response in internal variance to fluctuations in both river runoff and Greenland discharge in the Kuroshio box.

4.2. The Response of Sea Level Forced Variance to Fully Varying River Runoff

The aim of this section is to identify which sea level component and depth range drive the SLA forced variance response to river runoff fluctuations in the SA and MC boxes. As the SLA forced variance response is relatively homogeneous within each box (Figure 5e), we first average the SLA and its components over each box before performing the ensemble variance decomposition.

4.2.1. The Tropical South Atlantic Ocean Box

Comparing ES and ER, we find that the spatially averaged SLA total variance increases by 13% when considering river runoff variability, driven by an increase in forced variance (Figure 6a), in agreement with Figure 5. Furthermore, this increase is primarily driven by the steric forced variance which rises by 11% in ER compared to ES. The thermosteric forced variance decreases by 13.73%, while the halosteric forced variance increases by 65.14% (Figure 6a), suggesting that the forced halosteric component is responsible for the SLA variance increase in the SA box in RIVERS.

To determine at which depths the forced variance response occurs, we perform the ensemble variance decomposition of the box-averaged steric, thermosteric, and halosteric components across increasing depth ranges: 0–50, 0–100, 0–300, 0–700, 0–2,000 m, and 0–bottom (Figures 6b–6d). The steric forced variance increases for all depth ranges when considering river runoff variability (Figure 6b), with maximum sensitivities observed in the 0–100 m and 0–300 m ranges, where the ES forced variance rises by 23.21% and 22.36%, respectively. In contrast, the thermosteric forced variance is lower in ER compared to ES across all depth ranges, with the largest decrease (10.28%) occurring in the 0–300 m range (Figure 6c). The evolution of the halosteric forced variance with depth between ES and ER shows a complex pattern (Figure 6d). It is smaller in ER than in ES for the depth ranges shallower than 700 m, with the largest decrease (41.17%) in the 0–300 m range. This decrease probably reflects the widespread variance reduction in the central and western parts of the box, although an increase in variance is also occurring near the western coast of Africa, in the gulf of Guinea, and the Angola Gyre (Figure S5 in Supporting Information S1). However, the halosteric forced variance is larger in ER than in ES for the 0–2000 m and 0–bottom depth ranges, with the largest increase (69.52%) in the 0–2000 m range. This increase in variance for the deeper ocean layers can be explained by the positive response spanning most the box (Figure S5 in Supporting Information S1). This suggest that river runoff variability can induce important salinity changes in the 700–2,000 m range in the SA box, potentially through circulation adjustments.

The responses of the forced variance in ocean layers from the surface to 700 m –thermosteric and halosteric components decreasing while the steric component increases– between ES and ER is unexpected (Figures 6b–6d). Further analysis of the forced variances response in RIVERS across various depth ranges (cf. Figure S3–S5 in Supporting Information S1) reveals that, unlike the SLA, the steric, thermosteric, and halosteric variances are not homogeneous across the box between the surface and 700 m, possibly explaining the unexpected response when first averaging over the box. In addition, for the ocean layers 0–300 m and 0–700 m, the spatial pattern of steric forced variance in RIVERS cannot be fully explained by the halosteric and thermosteric patterns. This suggests that the spatial co-variability of halosteric and thermosteric sea levels plays an important role in the steric sensitivity in RIVERS. This is in line with Ghoms, Mohamed, et al. (2024) who showed that halosteric and thermosteric trend patterns co-vary in opposite ways within the SA box.

The complex variation in halosteric forced variance between ES and ER over depth indicates that the entire water column must be considered to accurately estimate the halosteric response to river runoff variability in the SA box and thus of the SLA. A range of processes can explain how river runoff variability influences horizontal and vertical salinity and temperature changes in the SA box. We could cite cascading effects involving coastally trapped Kelvin waves propagation which play a key role in the observed and modeled SLA dynamics in the South

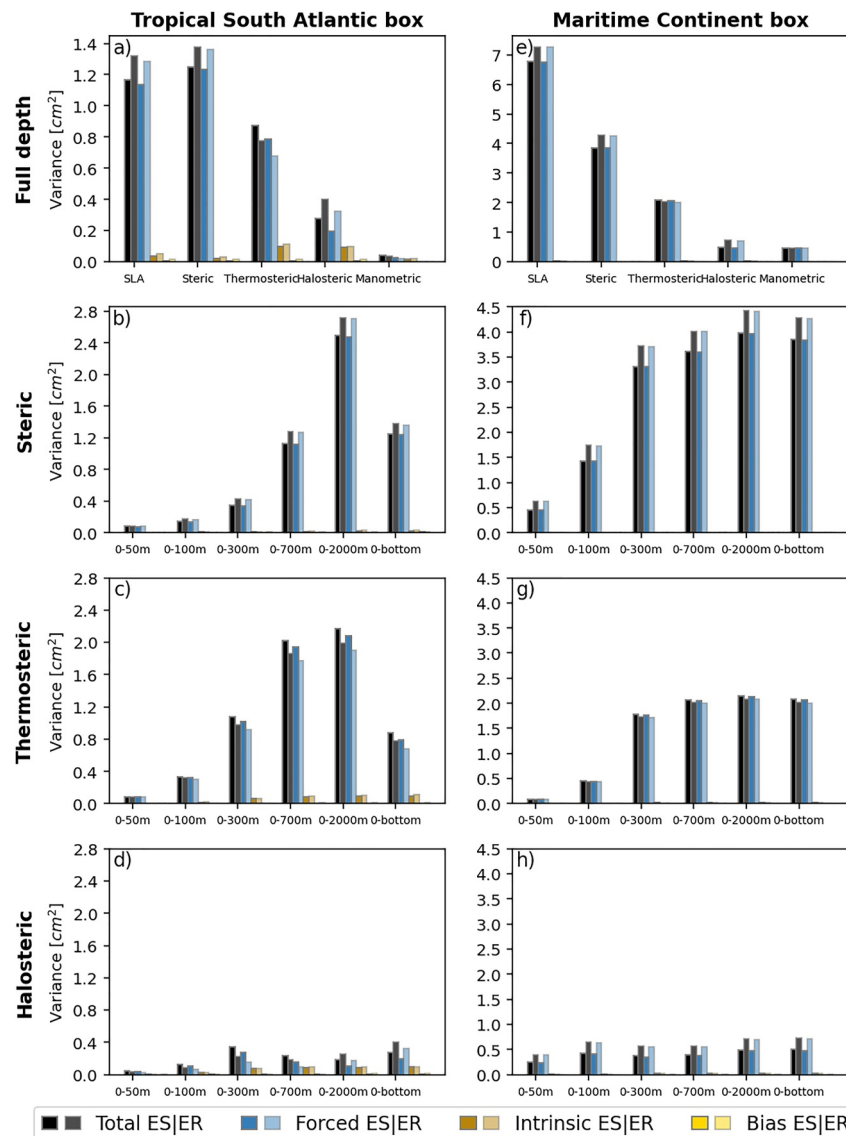


Figure 6. Ensemble variance decomposition over the 1980–2018 period of spatially averaged SLA, full-depth steric, thermosteric, halosteric, and manometric components over the tropical South Atlantic Ocean (a) and Maritime Continent (e). Panels (b–d, f–h) show the steric (b, f), thermosteric (c, g), and halosteric (d, h) variance decomposition across increasing depth ranges (0–50 m, 0–100 m, 0–300 m, 0–700 m, 0–2000 m, and 0–bottom) for the tropical South Atlantic Ocean (b)–(d) and Maritime Continent (f)–(h) boxes. Total, forced, intrinsic, and biased variances are shown in black, blue, orange, and yellow respectively. Dark colors represent ES, and light colors represent ER.

Atlantic (Bachèlery et al., 2020; Ghomsi, Raj, et al., 2024), vertical and horizontal shear and mixing (Suga & Talley, 1995), barrier layer formation and erosion (Mignot et al., 2007), modification of the Atlantic Antarctic Intermediate Water position, and air-sea interactions.

4.2.2. The Maritime Continent Box

Comparing ES and ER, the SLA total and forced variances each increase by 7.6% when considering river runoff variability, in line with Figure 5 (Figure 6e). This increase is primarily driven by the steric forced component which rises by 11.2% in ER compared to ES. The thermosteric forced variance decreases by 2.4% when considering river runoff variability, while the halosteric forced variance increases by 51.2%. Therefore, the increase in SLA forced variance in response to variable river runoff (Figure 5) is largely of halosteric origin in the MC box.

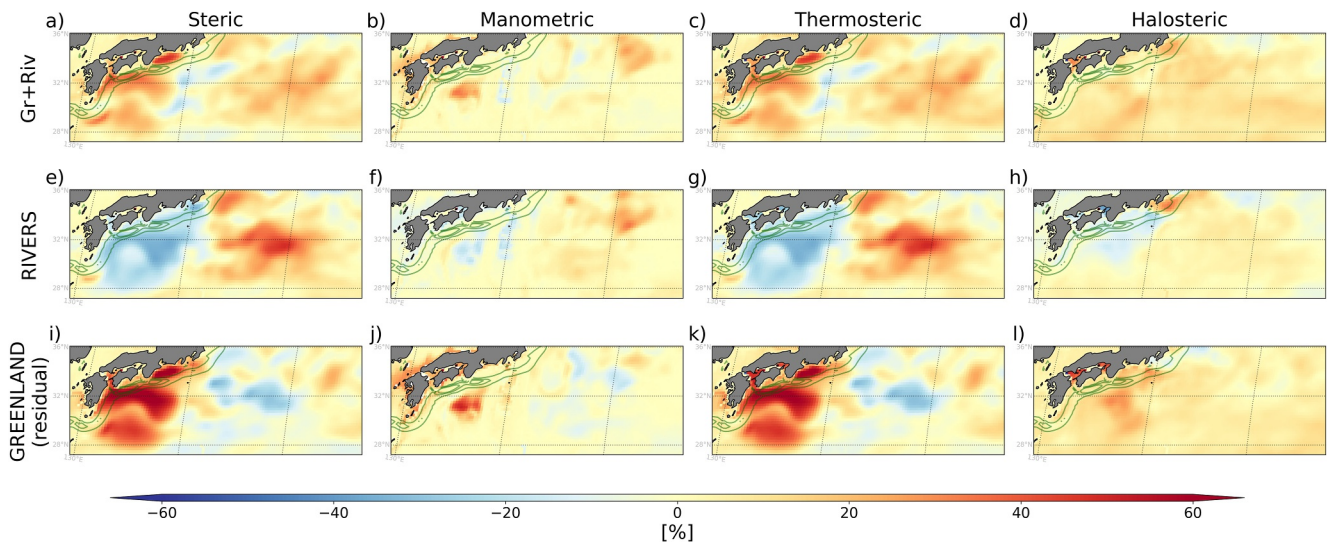


Figure 7. Sensitivity of the internal variance of the steric (a, e, i), manometric (b, f, j), thermosteric (c, g, k), and halosteric (d, h, l) components in ES to the fully time-varying freshwater fluxes from Greenland and rivers (a)–(d), from rivers (e)–(h), and from Greenland (i)–(l) over the 1980–2018 period in the Kuroshio box. The variance sensitivities are expressed as percentages relative to the SLA total variance in ES of each component (e.g., panel (i) corresponds to $100 \times \text{VAR}_{\text{internal}}^{\text{Steric EGR-ER}} / \text{VAR}_{\text{total}}^{\text{Steric ES}}$). The green contours are the ensemble mean of the surface Mean Kinetic Energy (MKE) in ES (0.1, 0.2, and 0.3 m² s⁻²). Note the change of the color-scale compared to Figure 5.

Comparing ES and ER across depth ranges, the gain in steric forced variance in response to variable river runoff is maximum in the upper 50 m (38.7%) and gradually decreases with greater depth ranges (Figure 6f). For the thermosteric sea level, the difference between the two ensembles is minimal (at most 2.7%) and varies very little with depth (Figure 6g). The gain in halosteric forced variance is highest over the upper 50 m (62.5%), and decreases slightly with increasing depth ranges (Figure 6h). Thus, the gain in SLA forced variance in response to river runoff variability is primarily of halosteric origin and occurs mainly within the upper 50 m of the ocean in consistency with the fact that river runoff is applied to the first 10 m and that 23% of the MC box ocean area is shallower than 50 m.

These results highlight the importance of the freshwater fluxes in setting the sea level variability in this region in accordance with Llovel and Lee (2015) who found a large halosteric contribution to sea level change associated with freshening in the upper 300 m in this region. Our results have implications for the Indonesian Throughflow modelization as river runoff can create a freshwater plug affecting dynamic height and pressure gradient along the Makassar Strait resulting in an inhibition of the southward flow of the Indonesian Throughflow, with consequences for the global ocean circulation (Gordon et al., 2003; Hu & Sprintall, 2016; Lee et al., 2019).

To summarize, the response in SLA forced variance to fluctuating river runoff in the SA and MC boxes is predominantly halosteric, with a slight thermosteric compensation. The changes occur over the whole water column in the SA box and within the first 50 m in the MC box.

4.3. The Response of Sea Level Internal Variance to Fully Varying Freshwater Fluxes in the Kuroshio Box

In the Kuroshio box, the response of SLA internal variance to fully varying river runoff and Greenland discharge (Figures 5c, 5f and 5i) indicates that a source of forced variance, here the continental freshwater fluxes forcing, can trigger a response in internal variance. The aims of this section are to determine which sea level component is responsible for the response in SLA internal variance to fully varying river runoff and Greenland discharge, and to further understand the internal response of SLA –and its components– by decomposing it into its intrinsic and biased contributions.

The response in internal variance to fully varying river runoff and Greenland discharge in the Kuroshio box varies between sea level components (Figure 7). The spatial patterns and magnitudes of the steric and thermosteric internal variance sensitivities in Gr + Riv, RIVERS, and GREENLAND resemble those of SLA internal variance, while the manometric and halosteric internal variance sensitivities are weaker but also positively correlated with

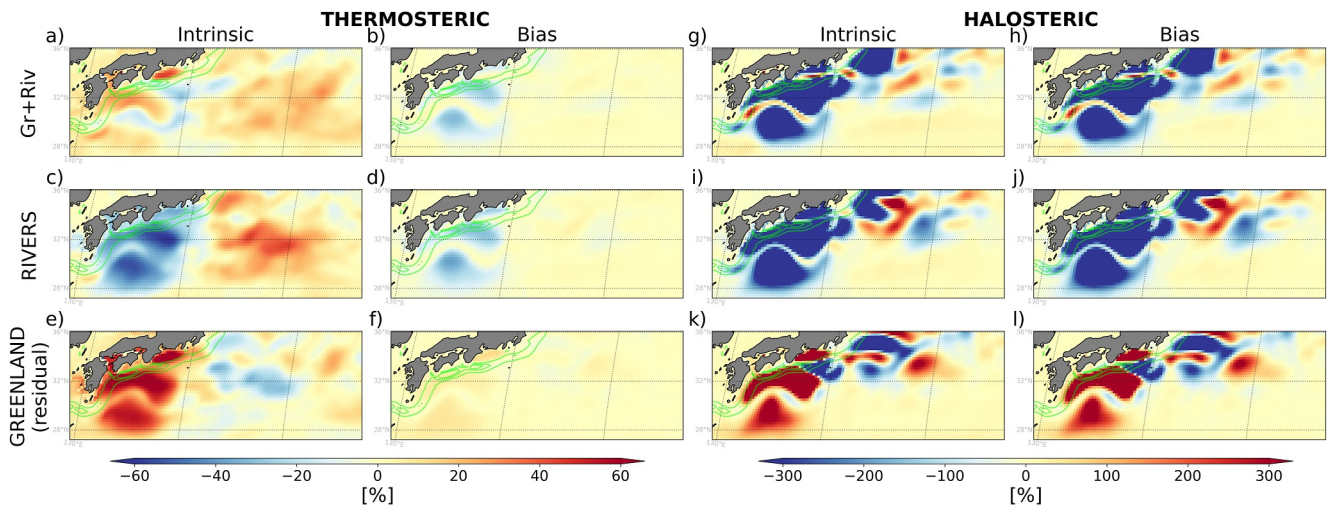


Figure 8. Panels a–f: Sensitivity of the thermosteric intrinsic (a, c, e) and biased variances (b, d, f) in ES to fully varying river runoff and Greenland discharge (a)–(b), rivers only (c)–(d), and Greenland only (e)–(f) over the 1980–2018 period in the Kuroshio box. The variances sensitivities are expressed as a percentage of the total thermosteric variance in ES. The difference of the two columns (Intrinsic – Biased) is equal to the thermosteric internal variance of Figure 7. Panels g–l: Same as a–f but for halosteric intrinsic (g, i, k) and biased (h, j, l) variances, expressed as a percentage of the total halosteric variance in ES. Green contours are identical to those in Figure 7.

the total term (Figure 7). This indicates that the response in SLA internal variance is primarily of thermosteric origin. It remains to be determined how the internal variance responses are partitioned into intrinsic and biased variances.

To that end, we decompose the internal responses of SLA and its components in Gr + Riv, RIVERS, and GREENLAND into their intrinsic and biased contributions (Figure 8). As expected, the spatial patterns and magnitudes of the thermosteric intrinsic and biased variance responses (Figures 8a–8f) resemble those of the SLA (not shown), indicating that the SLA intrinsic and biased variance responses originate principally from the thermosteric component. Overall, the response in thermosteric internal variance is mainly intrinsic (Figures 8a, 8c and 8e). The contribution of biased variance is asymmetric between the western part of the box, where it is relatively stronger, and the eastern part, where it is weaker (Figures 8b, 8d and 8f). The strong intrinsic and biased variances on the western side of the box in both ES (Figure 4) and as a response to fully varying freshwater fluxes (Figure 8) may be related to the interannual oscillations of the Kuroshio Current between the 2 possible paths south of Japan in the sensitivity ensembles: a large meander path (large southward meander around 137°E) and a non-meandering path flowing close to the coast of Japan (Yoshida, 1964). Observation-based and model-based studies further showed that the Kuroshio path variations were self-sustained, eddy-driven (Akitomo & Kurogi, 2001), wind-forced (Yang & Liang, 2019), and could be caused by baroclinic instabilities (Qiu & Miao, 2000). The transition among the Kuroshio paths is highly sensitive to the ocean state before the transition southeast of Kyushu (Aoki et al., 2020), possibly explaining the high sensitivity of this area in our sensitivity experiments. We conclude that the response in thermosteric (thus in SLA) internal variance to fluctuating freshwater fluxes is primarily intrinsic, with a secondary contribution from the biased variance on the western side of the box.

Remarkably, the halosteric intrinsic and biased variances are extremely sensitive in Gr + Riv, RIVERS, and GREENLAND (Figures 8g–8l, note the adjusted color scale) and exhibit similar spatial magnitude, nearly canceling each other and resulting in the small internal variance sensitivities shown in Figures 7d, 7h and 7l. Previous methods would have missed this compensation (e.g., Carret et al., 2021; Leroux et al., 2018), wrongly suggesting that halosteric internal variability is important in that region. Figure 4i shows that in the Kuroshio region the biased variance contribution is high in ES, meaning that the dominant timescales of halosteric variability are not resolved by the length of our experiments. The strong response in halosteric biased variance in Gr + Riv, RIVERS, and GREENLAND reveals that these longer time scales of variability are also strongly impacted by the freshwater flux forcing variability.

In summary, in the Kuroshio box, the thermosteric and halosteric sea level components can respond strongly to freshwater forcing variability. The strong SLA internal variance response to fluctuations in continental freshwater fluxes is mostly of thermosteric origin and is associated with very limited biased variance. The internal variability response in Gr + Riv appears to be a response to the combined effects of river runoff and Greenland discharge, which partly compensate for each other. The response in internal variance to Greenland discharge variability in the Kuroshio box is particularly noteworthy because it is both indirect and remote as it is very unlikely that water discharged around Greenland reaches the Kuroshio region given the simulation duration. This impact could occur via rapid adjustment involving waves traveling through the Arctic Ocean (Eisenman et al., 2024) and then the North Pacific Ocean. However, given the compensatory response of GREENLAND, independent simulations (ensemble EG, cf. Section 2.1) are required to confirm this result.

5. Summary and Conclusions

Temporal variations in freshwater fluxes from the Greenland Ice Sheet and rivers are represented in a forced, eddy-permitting global ocean general circulation model. We use sensitivity experiments, combined with an ensemble-based approach, to investigate the impact of the temporal variability of these freshwater sources—both individually and combined—on the interannual variability of regional sea level from 1980 to 2018. This approach allows us to decompose the impact into a forced response and an internally driven response.

Our ensemble variance decomposition is novel in that it avoids applying any temporal processing to individual members, thereby preserving the raw temporal and ensemble variability and allowing us to study all signal variability simultaneously. This approach results in a rigorously closed decomposition which includes a new term: the biased variance. This closed decomposition is well suited to our methodology as it has enabled us to demonstrate that the internal variance in the Kuroshio region is sensitive to the variability of continental freshwater forcing.

The biased term is crucial for understanding the variability simulated by an ensemble approach, as it separates intrinsic variability related to the time-mean state of each member (biased variance)—which can be interpreted as the “climate” shift reached by each member depending on the length of the period used to compute the time mean—from that related to the temporal anomalies with respect to the time-mean (internal variance) for any time period. In most modeling studies, long-term behavior is typically removed before variance analysis (e.g., Close et al., 2020; Jamet et al., 2019; Leroux et al., 2018). Our methodology retains this long-term behavior, which contains part of the system's physical variability (along with model drift), without compromising the rigor of the results. We showed that the significance of the biased variance term depends on the region, the sea level component, and the length of the period. It is especially crucial for periods shorter than 10 years, both regionally and globally, and can also be important locally over longer timescales, such as in the Kuroshio region (Figures 3, 4 and 8). Therefore, we argue that biased variance should be considered in studies focusing on regional sea level interannual variability using ensemble simulations.

The sensitivity of SLA total variance to fully varying river runoff and Greenland discharge is high in three regions: the tropical South Atlantic, the maritime continent, and the Kuroshio region. The first two regions are mainly impacted by river runoff variability, with a forced response primarily of halosteric origin, occurring over the full ocean depth in the SA box, and mostly over the first 50 m for the MC box (Figure 6). In contrast, the Kuroshio region is sensitive to both Greenland discharge and river runoff variability, involving an internally driven response of mostly thermosteric origin. The sensitivity of the Kuroshio region to Greenland discharge requires confirmation through independent simulations (ensemble EG, cf. Section 2.1). Two other notable responses are the increase in forced variance associated with Greenland discharge variability south of the Aleutian Islands and along the east coast of the United States, from the Mid-Atlantic Bight to the Gulf of Mexico (Figure 5b). The Aleutian Islands response arises from both thermosteric and halosteric contributions and occurs primarily between 100 and 300 m (cf. Figures S7–S10 in Supporting Information S1), indicating a direct influence of Greenland's discharge variability on this remote region through combined halosteric and thermosteric effects. Along the east coast of the United States, the response is both halosteric and thermosteric and extends throughout the full ocean depth, whereas in the Gulf of Mexico it is also of mixed halosteric and thermosteric origin but occurs mainly below 300 m down to the bottom (cf. Figures S11–S13 in Supporting Information S1). These responses are relevant for major coastal areas and may reflect AMOC variability. A detailed explanation of these responses is beyond the scope of the present study and is left for future investigation.

The significant impact of river runoff variability on forced sea level variability in the tropical South Atlantic and Maritime Continent boxes contrasts with its less extensive impact in other regions where river runoff is also intense. Although these disparities require additional analyses, looking at the impact of river runoff variability on forced sea surface salinity (SSS) variability (Figure S6 in Supporting Information S1) can inform us on its impact on the dispersion of the major river plumes globally. For most of the major river systems worldwide (e.g., the Ganges-Brahmaputra, Paraná, Mississippi, and Changjiang), the impact of river runoff variability on SSS variability remains largely confined to coastal areas. In contrast, for the Amazon, Niger, Congo, and rivers in the Maritime Continent region, this impact extends far from the coast into the open ocean. This pattern aligns with existing knowledge on the offshore transport of the latter river plumes by regional ocean circulation and wind stress (Chao et al., 2015; Coles et al., 2013; Hopkins et al., 2013; Kida et al., 2019; Martins & Stammer, 2022). A similar pattern is observed in the map showing the impact of river runoff variability on forced sea level variability (Figure 5e). For instance, in the subtropical North Atlantic, high forced SLA variability (−10% to +10%) in RIVERS corresponds well with high forced SSS variability in RIVERS, which is likely due to the Amazon river. Additionally, our finding of a low impact of Ganges-Brahmaputra runoff variability on SLA variability is consistent with Chandanpurkar et al. (2022), who conducted model sensitivity experiments comparing two simulations: one forced by daily JRA55-do discharge (Tsujino et al., 2018) and the other by its seasonal climatology. Their results showed that, while fully time-varying river discharge from the Ganges-Brahmaputra significantly affects SSS variability in the northern Bay of Bengal, it has little to no impact on sea surface height variability.

A limitation of this study is our model resolution which underestimates the SLA internal variability, especially in eddy-active regions (Chassignet et al., 2020; Sérazin et al., 2018). Model resolution also influences the simulated effects of varying Greenland discharge (Stolzenberger et al., 2022) and river runoff (Feng et al., 2021) on sea level, potentially affecting our sensitivity results. Another limitation is the number of members of the ensemble simulations which can lead to a poor separation of internal variability in some regions (Figure S2 in Supporting Information S1). In addition, without an independent method to estimate numerical drift in our simulations, we chose not to assume or remove any drift, as doing so could alter the total variance and the physical long-term variance. Model drift is likely similar across the three ensembles and should not affect the sensitivity results.

These results emphasize the importance of accurately representing the temporal variability of river runoff and Greenland discharge in forced ocean simulations to properly capture regional sea level interannual variability. This is supported by Tsujino et al. (2020) who showed improved seasonal and interannual sea level variability in the second phase of the Ocean Model Intercomparison Project (OMIP-2) –which includes fully varying freshwater fluxes from rivers, Greenland, and Antarctica (Tsujino et al., 2018)—compared to the first phase (OMIP-1), which used the Large and Yeager (2009) climatology and excluded ice sheets.

Finally, to better characterize and understand the interplay between forced and internal variability, a possible follow-up would be to carry out variance budget of the different constituents of SLA. Indeed, computing the variance budget of an advected variable g (e.g., temperature, salinity) is a means of quantifying locally the sources and sinks of g -variability and thus of better understanding the mechanisms behind this variability. This methodology has been used on several occasions (Arzel et al., 2006; Buckley et al., 2012; Hochet et al., 2015, 2020; Jamet et al., 2022; Sévellec et al., 2006, 2021) including for the study of seasonal and interannual variability of steric sea level (Hochet et al., 2023; Hochet, Llovel, et al., 2024) and for the study of interannual variability of salinity in the Arctic Ocean (Hochet, Lique, et al., 2024).

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

To reproduce the simulations, the model code (NEMO 4.0.6) can be downloaded at <https://svn-mirror.nemo-ocean.eu/NEMO/releases/r4.0/r4.0.6/>; the JRA-55 reanalysis is available at (Japan Meteorological Agency Japan, 2013); and a thorough description of the configuration of the model is available at (Molines & Leroux, 2024). The data and Jupyter notebooks used to produce our analyses can be found at (Tajouri, 2025a, 2025b) respectively.

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