



LFS-SEnDA: a global ocean forecast system with an efficient Sliding-Ensemble-based Data Assimilation scheme

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Abstract. This study develops an efficient Sliding-Ensemble-based Data Assimilation (SEnDA) scheme and integrates it into the LICOM Forecast System to establish LFS-SEnDA. In SEnDA, time-dependent sliding ensemble samples are used to represent temporally varying background-error covariance structures. Meanwhile, SEnDA has incorporated a parallel-friendly analysis procedure and an accelerated solver to improve computational efficiency. Compared with the conventional Ensemble
15 Optimal Interpolation scheme, SEnDA improves analysis quality, particularly in eddy-rich regions, and achieves about a 30-fold speedup in the analysis step. Within the IV-TT Class-4 assessment, LFS-SEnDA ranks among the leading candidate global ocean forecast systems and achieves the highest composite score based on sea surface temperature, sea level anomaly, upper-ocean temperature, and salinity over forecast days 1–6. At a 1-day lead time, LFS-SEnDA achieves global RMSEs of approximately 0.38 °C for sea surface temperature and 0.06 m for sea level anomaly. These results indicate that LFS-SEnDA
20 provides an efficient and scalable framework for improving multivariate ocean state estimation and global ocean forecasting.

1. Introduction

Global ocean forecast systems (GOFSS) enable monitoring, understanding, and prediction of the global ocean's state and evolution by integrating ocean observations, numerical models, and data assimilation. The resulting analyses and forecasts further support marine environmental prediction, climate monitoring, maritime safety, ecosystem management, and ocean-
25 related decision-making (Álvarez Fanjul et al., 2025; Bell et al., 2015). Ongoing ocean warming (Cheng et al., 2019; Levitus et al., 2012) and more frequent extreme ocean events (Holbrook et al., 2019; Oliver et al., 2018) are increasingly challenging the monitoring and early-warning capabilities of GOFSS. These growing demands underscore the urgent need for continued development of GOFSS.

Over the past few decades, GOFSS have advanced toward higher spatial resolution and improved predictive capability (Álvarez Fanjul et al., 2025; Bell et al., 2015; Storto et al., 2019). This progress has been enabled by the expansion of observing networks
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(Fujii et al., 2019) and continued improvements in numerical models (Griffies et al., 2016; Intergovernmental Panel On Climate Change (IPCC), 2023; Xie et al., 2025) and data assimilation methods (Carrassi et al., 2018; Moore et al., 2019). Most GOFSS have been implemented in operational eddy-resolving configurations, such as those developed by Mercator Ocean International (European Union-Copernicus Marine Service, 2016), the UK Met Office (Barbosa Aguiar et al., 2024; Blockley et al., 2014),
 35 and the Euro-Mediterranean Center on Climate Change (Masina et al., 2026; Storto and Masina, 2016). To operate at such high resolutions, both computational cost and forecast quality should be considered (Álvarez Fanjul et al., 2025). In fact, the data assimilation scheme plays a central role in balancing these requirements.

Among data assimilation schemes, three-dimensional variational (3DVar) approaches are widely used in operational GOFSS because of their stability and computational efficiency (Archer et al., 2022; Li et al., 2008), which make them suitable for high-
 40 resolution operational applications (Barton et al., 2021; Masina et al., 2026). However, variational systems depend on carefully designed and continuously refined background-error covariances. Ensemble-based data assimilation provides an alternative by estimating background-error covariances directly from ensemble samples, and has been adopted in some GOFSS (Brassington et al., 2023; Chen et al., 2025; European Union-Copernicus Marine Service, 2016; Lellouche et al., 2013; Smith et al., 2016; Sun et al., 2020; Zhang et al., 2023). Ensemble-based methods can represent flow-dependent background-error
 45 statistics, but they require repeated ensemble forecasts and are therefore computationally expensive for global eddy-resolving applications. To reduce this cost, several GOFSS (Chamberlain et al., 2021; Chen et al., 2025; European Union-Copernicus Marine Service, 2016; Smith et al., 2016) have adopted simplified approaches, such as the single evolutive extended Kalman (SEEK) filter and an ensemble optimal interpolation (EnOI)- type sample selection scheme (Oke et al., 2010). This strategy improves computational affordability and has been successfully applied in eddy-resolving ocean data assimilation (Castruccio
 50 et al., 2020), but it weakens the flow dependence of the background-error covariance. In general, accurately representing background-error covariances and maintaining computational efficiency have been two fundamental requirements in ocean data assimilation. This trade-off between analysis quality and computational cost lies at the heart of designing assimilation schemes for GOFSS.

To address the trade-off between efficiency and quality, this study develops a Sliding-Ensemble-based Data Assimilation
 55 system (SEnDA), which follows the general idea of EnOI by avoiding repeated ensemble forecasts. Here, SEnDA adopts a time-dependent sliding-ensemble sampling strategy to improve flow-dependent features using historical ensemble samples. In addition, a spread adjustment is introduced to reduce the risk of unrealistically large background spread associated with historical samples. To further improve computational efficiency, SEnDA combines the low-cost EnOI framework with a parallel-friendly analysis procedure and a fast Cholesky-decomposition solver. These designs allow SEnDA to provide an
 60 efficient and flexible assimilation framework for eddy-resolving operational GOFSS. We further incorporate SEnDA into the LICOM Forecast System (LFS), called LFS-SEnDA, to implement and assess this framework in an operational forecasting context. The results of LFS-SEnDA are evaluated against observations and the previous version of LFS (LFSv1.0; Liu et al., 2023; Zheng et al., 2023), which employed a simple nudging method for data assimilation. In this paper, we describe the design

and implementation of LFS-SEnDA, with particular emphasis on the SEnDA subsystem, and evaluate its computational efficiency, assimilation performance, and forecast skill.

2 LFS-SEnDA System and the Evaluation Methods

2.1 Description of LFS-SEnDA

LFS-SEnDA produces daily forecasts and outputs at a horizontal resolution of 0.1° , including sea surface height (SSH), three-dimensional temperature and salinity fields, and zonal and meridional current velocities. The system comprises three subsystems: the data collection subsystem, the data assimilation subsystem, and the forecast subsystem. The system workflow is illustrated in Fig. 1.

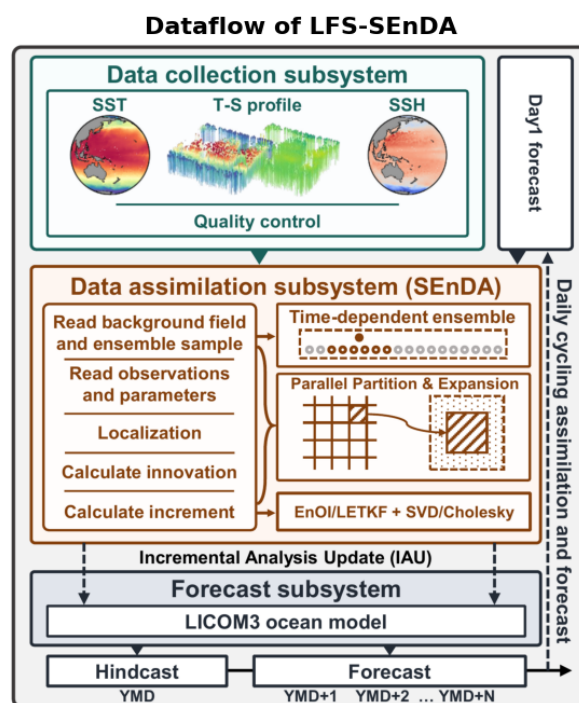


Figure 1. Schematic workflow of the LFS-SEnDA system.

In the LFS-SEnDA workflow, the data collection subsystem ingests raw observations including sea surface temperature, sea surface height anomalies, Argo profiles, atmospheric forcing fields, background fields, and initial fields. The background fields



and pre-processed observation data are transferred to the data assimilation subsystem. To strike a balance between computational cost and operational timeliness, we apply the data assimilation on a coarsened 0.25° global grid to derive the analysis increments (Barbosa Aguiar et al., 2024; Chen et al., 2025). Subsequently, these increments are gradually added into the forecast subsystem over a 24-hour window using the Incremental Analysis Update (IAU) technique (Bloom et al., 1996). This stage generates the ocean hindcast field and establishes the initial conditions for the subsequent forecast cycle.

2.1.1 Data collection subsystem

In this subsystem, for a given assimilation date, the system collects satellite-derived sea surface temperature (SST) and sea level anomaly (SLA) observations, subsurface temperature and salinity profiles, and atmospheric forcing fields. In both the operational forecasting scenario and the experiments presented in this study, only observations available up to the assimilation date are used. In near-real-time operations, if the current day's satellite observations are unavailable, data from the previous day are used as a fallback. Given the horizontal sparsity and uneven distribution of Argo observations, they are sampled from the period spanning the 15 days from the assimilation date backward to the assimilation date (Chen et al., 2025). Specifically, SST observations are derived from the OSTIA (Operational Sea Surface Temperature and Ice Analysis) product (European Union-Copernicus Marine Service, 2015), while SLA data are sourced from a multi-mission merged altimetry dataset (European Union-Copernicus Marine Service, 2017). Subsurface temperature and salinity profiles are obtained from the Argo. Atmospheric forcing fields are downloaded from the Global Forecast System (https://www.emc.ncep.noaa.gov/emc/pages/numerical_forecast_systems/gfs.php).

To prevent the over-concentration of profiles in localized areas, a spatial density constraint is applied, limiting the data to at most one Argo profile per 1° grid cell. In regions with extremely sparse Argo coverage, defined here as 2° grid cells containing no Argo observations, the system includes an extensible interface for assimilating reconstructed temperature and salinity profiles or reprocessed gridded temperature and salinity products, thereby providing supplementary observational constraints. Following data collection, all observations undergo preprocessing, including interpolation, quality control, and estimation of observation errors. Satellite observations are first interpolated onto a 0.25° grid to align with the data assimilation subsystem. For subsurface data, given the high vertical density of the original data, both Argo and reconstructed profiles are vertically thinned and interpolated onto model layers. Quality control is then performed by filtering data using physical range checks, deviations from the mean, and quality flags from the data sources.

The observation error is estimated according to the following formulation:

$$\varepsilon^2 = f(t)(\varepsilon_m^2 + k\varepsilon_r^2). \quad (1)$$

Here, $f(t)$ represents a temporal weighting function that quantifies the influence of temporal error on observation errors. Within the assimilation window, $f(t)$ varies linearly from 1 to 2 as a function of the observation's temporal location relative to the analysis time. The term ε_m denotes the measurement error. For SLA and SST, these values are provided directly within the observation products. In contrast, the measurement errors for temperature and salinity profiles are prescribed as 0.25°C



110 and 0.02 psu, respectively. The term ε_r represents the representation error, which is derived from the model's variance. The coefficient k is prescribed as a constant, with a default value of 1.

2.1.2 Data assimilation subsystem

Building on the EnOI framework, LFS-SEnDA introduces a time-dependent background error covariance through a sliding ensemble sampling scheme. Specifically, the assimilation ensemble is dynamically constructed from a 15-year historical
115 simulation of LICOM3 forced by JRA55-do atmospheric forcing (Lin et al., 2020), with samples selected according to the current assimilation date. For each year, 15 samples are extracted at 5-day intervals within a ± 35 -day window around the corresponding calendar date, resulting in a total ensemble size of 225. This sampling approach mitigates the excessive spread often associated with fully static ensembles while effectively reflecting large-scale circulation features and error correlation structures specific to the current date. This mechanism enhances the representativeness of the background error covariance
120 matrix without compromising computational efficiency. Similar dynamic sampling schemes have proven beneficial for improving assimilation accuracy (Toye et al., 2021).

To further constrain the excessive spread introduced by historical ensemble samples, two treatments are applied. First, the daily climatology of the ensemble samples is removed. Second, a spread-scaling factor is introduced to reduce the overly large subsurface spread associated with long-term historical sampling. This factor is calculated as the ratio of the mean standard
125 deviation of samples within individual years to the standard deviation computed across all historical samples. In addition, within the mixed layer, temperature and salinity increments that oppose the surface forcing and tend to destabilize stratification are truncated. This is done to prevent progressively stronger instability during cycled assimilation and forecasts.

The subsystem employs the Gaspari–Cohn function (Gaspari and Cohn, 1999) as the horizontal localization operator. The radius is dynamically adjusted with latitude using an offset cosine function, with smaller values applied at high latitudes to
130 match the varying dynamical Rossby radius and improve computational efficiency. Vertical localization is optional, with the system employing a density-based scheme (Xie and Zhu, 2010) to mitigate spurious vertical correlations in temperature and salinity. Furthermore, a specific adjustment is implemented for SLA assimilation. Since the SSH forecast from the LFS system is based on a volume-conserving model with a global mean SSH of zero, the global average of SLA observations is removed during assimilation. This observational mean is subsequently added back during post-processing to ensure consistent sea-level
135 representations with the observational references.

To enhance computational efficiency, the LFS-SEnDA subsystem employs a domain decomposition strategy based on a longitude-latitude grid. To minimize inter-processor communication during the observation-gathering phase, each sub-domain is extended by a predefined localization radius, ensuring that all necessary observations are locally accessible to each analysis cell (Fig. 1). Within this decomposed framework, the solution procedure is further optimized. In the conventional EnOI-like
140 formulation, the analysis increment δX is derived as:

$$\delta X = \alpha A A^T H^T (S S^T + R)^{-1} D'. \quad (2)$$



Here, A represents the ensemble anomaly matrix, H is the observation operator, S represents projection of the ensemble anomalies into the observation space, calculated as $S = HA$, R denotes the observation error covariance, D' is the innovation vector, α is a scaling coefficient used to modulate the magnitude of the analysis increment and is set to 1. The matrix inversion in Eq. (2) constitutes a major computational bottleneck, particularly when the number of assimilated observations is large. Improving the efficiency of this operation is therefore critical for high-resolution applications. Conventional implementations commonly employ singular value decomposition (SVD) to obtain a stable solution to the inverse problem (Evensen, 2004). However, because $SS^T + R$ is symmetric positive definite, the corresponding linear system can instead be solved using Cholesky decomposition. This avoids the more expensive SVD-based inversion and reduces the computational cost of this step by several tens of times (Golub and Van Loan, 2013).

Moreover, because the analysis is performed in parallel across local subdomains, spatial variations in the number of observations can lead to substantial computational load imbalance. To alleviate this problem, a Local Ensemble Transform Kalman Filter (LETKF) formulation is introduced, in which the analysis increment is computed as:

$$\delta X = A(\alpha(N - 1)I + S^T R^{-1} S)^{-1} S^T R^{-1} D'. \quad (3)$$

Here, α serves a similar function to that in Eq. (2) and is likewise set to 1, N denotes the ensemble size, and I is the identity matrix. Since the matrix inversion occurs in the ensemble subspace, the matrix dimension is determined solely by the ensemble size rather than the number of observations. This consistency across sub-domains ensures optimal load balancing and facilitates computational acceleration in parallel environments.

Table 1 compares the computational costs of different assimilation solution strategies under an identical model configuration.

The experiment replaces the SVD-based matrix inversion with a Cholesky-based solution called EnOI-o1 (optimized method 1), whereas the experiment computes the analysis increments following the LETKF analysis procedure called EnOI-o2 (optimized method 2). SEnDA incorporates both optimizations. The results show that introducing a LETKF-like local analysis scheme, combined with Cholesky decomposition, substantially improves assimilation efficiency, greatly reducing the fraction of total runtime spent on the analysis step. Using 1600 processes, the complete assimilation procedure takes approximately 7 min. Of this, the analysis step takes only about 30 s, corresponding to an approximately 30-fold speedup relative to the traditional EnOI solver (Table 1). This improvement considerably enhances the feasibility of extending the system toward higher-resolution configurations. Furthermore, this assimilation scheme has been implemented in kilometer-scale forecasting experiments on the Sunway OceanLight and China's New-generation Intelligent Supercomputer platforms, exhibiting both strong scalability and maintaining assimilation accuracy (Zhou et al., submitted).



Table 1. Computational efficiency of different analytical methods*

	EnOI	EnOI-o1	EnOI-o2	SEnDA
Analysis step wall-clock time	1142 s	139 s	45 s	32 s
Analysis step Speedup	1.0	8.2	25.4	35.7

* The assimilation experiment was conducted using an identical configuration with 1,600 parallel processes. The localization radii were set to 200 km for SST and SLA observations and 300 km for temperature and salinity profiles.

175 **2.1.3 Forecast subsystem**

The forecasting subsystem is primarily based on LASG/IAP Climate System Ocean Model Version 3 (LICOM3) (Li et al., 2020; Lin et al., 2020), which configures a horizontal grid of 3600×2302 cells with a meridional grid spacing of 11 km and an average zonal grid spacing of approximately 6.9 km (ranging from 11 km at the equator to 2.7 km around the Southern Ocean). Vertically, it employs η -coordinates with 55 levels, allocating 42 layers within the upper 1000 m. Additionally, a thermodynamic sea-ice model, CICE4 (Hunke and Lipscomb, 2010), is coupled with LICOM3 via a flux coupler (Craig et al., 2012). Data models are implemented for the other two components, namely the atmosphere and land; atmospheric variables and runoff are first read from their respective data models and then passed to the coupler. Every 6 hours, the coupler computes the surface momentum, heat, and freshwater fluxes by combining these inputs with the SST and surface ocean currents from LICOM3, as well as the sea-ice concentration from CICE4, and then distributes the updated fluxes back to each component. Upon receiving the assimilation increments, the subsystem gradually integrates them into the model over a 1-day window using the IAU method, thereby suppressing numerical shocks and ensuring forecast continuity. This procedure yields both the hindcast field for the current day and the initial conditions for the subsequent forecast phase. Ultimately, the subsystem collects background and forcing fields to run the simulation, with the forecast window dynamically determined by the specific forcing dataset—extending to 15 days, for instance, under GFS forcing.

190 **2.2 Experimental design**

To assess the assimilation performance and forecasting skill of LFS-SEnDA, three sets of experiments were conducted. To quantify the improvements in the analysis fields produced by the SEnDA assimilation scheme and assess their subsequent impacts on forecast skill, an assimilation sensitivity experiment (ExpA-Y) and a year-round forecast experiment (ExpF-Y) were conducted. A cycling data assimilation and forecast experiment (ExpF-C) was further performed to evaluate the system under a realistic operational configuration.



ExpA-Y aims to investigate the impact of ensemble sampling strategies on assimilation quality across various temporal scales and physical variables. A total of 36 assimilation cases were performed at 10-day intervals over a full annual cycle from October 2023 to September 2024, comparing two distinct sampling strategies. The static ensemble uses 120 samples, each consisting of the first day of each month over a 10-year historical period. To maintain a consistent ensemble size, the sliding ensemble employs a time-dependent set of 120 samples, extracted from a ± 30 -day sliding window centered on the assimilation date over the same 10-year period (12 samples per year). No-assimilation background fields are used as a control experiment to assess the effectiveness of data assimilation. Notably, neither vertical localization nor a reconstructed profile was applied during these assimilation experiments.

ExpF-Y uses the analysis fields generated by the SEnDA as initial conditions. This experiment evaluates the system's forecasting skill across various seasons. Similar to ExpA-Y, it comprises 36 cases initiated every 10 days from October 2023 to September 2024. Each case involves a 7-day forward integration to assess the error growth and prediction limits under different seasonal stratification and circulation regimes.

ExpF-C assesses the performance and stability of LFS-SEnDA under operational conditions. Starting from October 1, 2023, a continuous, cycling assimilation-forecast experiment was conducted. The system performed daily assimilation and forecasting for 36 consecutive days. This experiment focuses on the cumulative effect of daily updates and the system's ability to maintain dynamical stability and forecast accuracy during uninterrupted operational cycles.

2.3 Verification data and methods

For the assimilation experiments, validation was conducted using both the assimilated observations and the GLORYS12V1 reanalysis (Jean-Michel et al., 2021), the latter being used to calculate climatological temperature in eddy-rich regions. For the forecast experiments, the verification data were obtained from the IV-TT Class-4 product (Bell et al., 2015), which provides observation, climatology, and forecast data. The observation combines data from different sources over a single day and across the global domain. The climatology data is defined by the monthly Levitus climatology interpolated to the corresponding calendar day. In addition, forecast products from GLO12V4, FOAM, GIOPS, OceanMAPS, and GOFS-CMCC are included for intercomparison, with detailed information on these systems provided in Table 2. Beyond the assessment of LFS-SEnDA, forecasts produced by LFSv1.0 are also analyzed to quantify the performance improvements achieved in the new system.



Table 2. Basic configurations of the GOFs analyzed in the present study

Forecast System	Model	Assimilation	Horizontal Resolution	Vertical levels	References
LFS-SEnDA	LICOM3 + CICE4	SEnDA	1/10°	55	This study
LFSv1.0	LICOM3 + CICE4	Nudging	1/10°	55	(Liu et al., 2023)
FOAMv14.1	NEMO3.6 + CICE 5	NEMOVAR based on 3DVar	1/4°	75	(Blockley et al., 2014)
GLO12V4	NEMO3.6 + LIM3	SAM2 based on SEEK; 3DVar bias correction	1/12°	50	(European Union-Copernicus Marine Service, 2016)
GIOPsv3.4	NEMO3.6 + CICE4	SAM2 based on SEEK; 3DVar bias correction	1/4°	50	(Smith et al., 2016)
OceanMAPsv4.0_i	MOM5	hybrid-EnKF	1/10°	51	(Brassington et al., 2023)
GOFsv1.0.4	NEMO3.4 + LIM2	OceanVar based on 3DVar	1/16°	98	(Storto and Masina, 2016)

Under the IV-TT class-4 framework, five global-mean metrics are used to measure the system's performance and skill: bias, root mean squared error (RMSE), anomaly correlation (AC), persistence skill score (PSS), and climatological skill score (CSS).

225 The formulae are as follows.

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (F_i - O_i), \quad (4)$$

$$\text{RMSE}_X = \sqrt{\frac{1}{n} \sum_{i=1}^n (X_i - O_i)^2}, \quad (5)$$

$$\text{AC} = \frac{\sum_{i=1}^n (F_i - C_i)(O_i - C_i)}{\sqrt{\sum_{i=1}^n (F_i - C_i)^2} \sqrt{\sum_{i=1}^n (O_i - C_i)^2}}, \quad (6)$$

$$\text{PSS} = 1 - \frac{\text{RMSE}_F}{\text{RMSE}_p}, \quad (7)$$



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$$CSS = 1 - \frac{RMSE_F}{RMSE_C}. \quad (8)$$

F , O , C , and P represent the forecast, observation, climatology, and persistence. X in the formula of RMSE denotes each of F , C , and P . n is the total number of observations within one day. Because GLO12V4 forecast outputs are replaced by hindcast products after several days, the assessment presented here is based on its hindcast results. Consequently, GLO12V4 is also not included in the PSS and CSS calculations. To provide a comprehensive assessment of forecast performance, an composite score (COMPS) for a given forecasting system x is defined based on the RMSE of four variables, including SST, SLA, subsurface temperature (T), and salinity (S):

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$$COMPS^x = \frac{1}{4} \left(\sum_{i=1}^4 1 - \frac{RMSE_i^x}{RMSE_i^{ref}} \right), i \in \{SST, SLA, T, S\}. \quad (9)$$

Here, the overbar indicates the average RMSE over forecast lead times from day 1 to day 6, and $RMSE_i^{ref}$ denotes the largest RMSE among the assessed GOFs for variable i .

240 In the regional assessment, the ocean is divided into 9 regions, including a global domain and 8 ocean basins. The specific spatial boundaries of these regions are listed in Table A1.

To further evaluate the performance of mesoscale eddy forecasting, we first identify and track eddies. Specifically, SLA fields are scanned over a sequence of incremental thresholds to isolate cyclonic (CEs) and anticyclonic (AEs) eddies. The resulting closed contours are subjected to strict morphological constraints, including a circularity threshold of greater than 0.4, an aspect ratio of less than 3, and a radius range between 30 and 250 km. To handle nested structures, we designed a hierarchical spatial pruning strategy that considers geometric containment and allows single-core boundaries to expand, effectively preventing the over-merging of independent multi-cores. Finally, to evaluate forecast performance against observations, an optimal, one-to-one eddy matching is established within a spatial tolerance of 500 km.

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3. Results

250 3.1 Assimilation performance

A good analysis field is expected to maintain strong physical consistency and minimize forecasted errors relative to observations. By constructing a sliding ensemble, the background error covariance can better characterize spatial correlations. In the Indian Ocean, a region profoundly influenced by monsoon dynamics, static ensembles fail to capture seasonal variability (Fig. 2a) and instead yield largely isotropic correlation structures. In contrast, the time-dependent ensemble aligns the spatial correlations with the flow field, accurately reflecting distinct seasonal varying features (Fig. 2b, c). The advantages of this time-dependent approach extend beyond horizontal scales to the characterization of the ocean's vertical structure (Fig. 2d–f). Analysis increments derived from the sliding ensemble exhibit enhanced variability near the mixed layer, whereas those from

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static ensembles tend to be overly diffused throughout the water column (Fig. 2d). Specifically, while static increments fail to account for the temporal evolution of ocean stratification (Fig. 2e), the sliding ensemble effectively tracks changes in mixed layer depth (MLD), with the maximum increments closely following the temporal migration of the MLD (Fig. 2f). Such physically consistent increments are instrumental in reducing imbalance-induced adjustment processes during model integration (Smith and Haines, 2009).

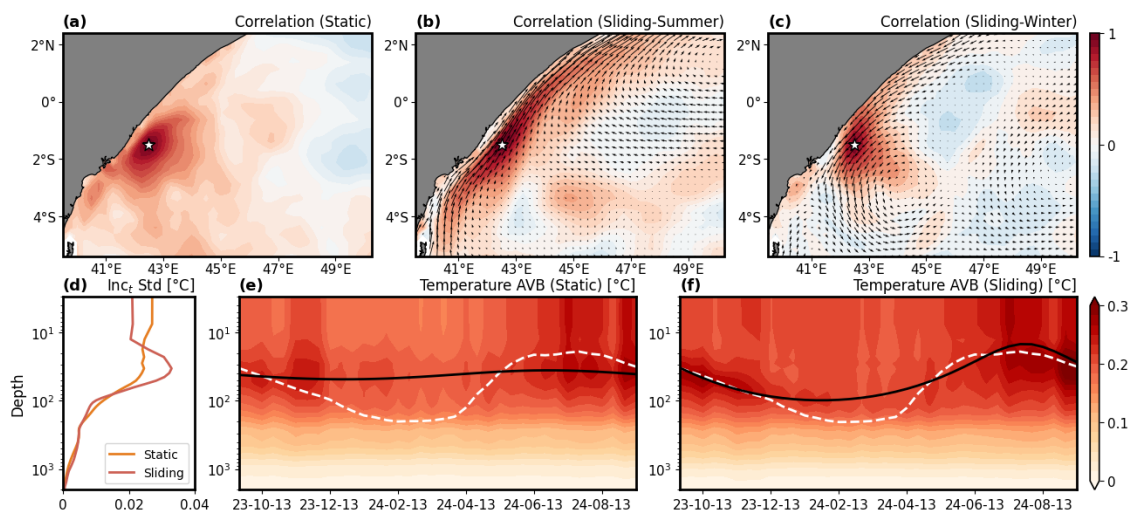


Figure 2. (a–c) Spatial correlation coefficients between the flow field at the star-marked reference location and those at other locations for the static samples and the sliding-window samples during summer and winter seasons, respectively. The asterisk is located at (42.5°E, 1.5°S). Black arrows in panels (b) and (c) represent the mean current velocity for the corresponding seasons. (d) Vertical distribution of the temporal standard deviation of temperature increments (°C). (e, f) Time–depth cross-sections of temperature increments in the Northern Hemisphere extratropics (20°N – 90°N) for the static and the sliding ensemble assimilation, respectively. The white dashed and black solid curves denote the mean mixed layer depth and the sine function fitted to the depth of maximum increments, respectively.

The advantages of capturing partially flow dependence are directly reflected in reduced error levels in the analysis fields. Compared to the static ensemble, the sliding-window approach yields a substantial reduction in the Mean Absolute Error (MAE) for SST and SLA, particularly within energetic current systems (Fig. 3a–f). Overall, the RMSEs of the analysis fields exhibit systematic improvements (Fig. 3g–j). Specifically, the mean RMSE of SST decreases by 8.4% (from 0.35 °C to 0.32 °C), while the SLA RMSE drops by 3.1% (from 0.069 m to 0.066 m). When the ensemble size is expanded to 225, the SLA RMSE can be further reduced to about 0.055m. Notably, these improvements are even more pronounced in high-uncertainty regions, such as eddy-rich and strong-current zones, where the RMSE decreases by 14.5% for SST (from 0.47 °C to 0.40 °C) and 5.5% for SLA (from 0.132 m to 0.124 m). Furthermore, error levels in subsurface temperature and salinity profiles are notably reduced in the upper ocean, indicating a more accurate vertical reconstruction of the water column.

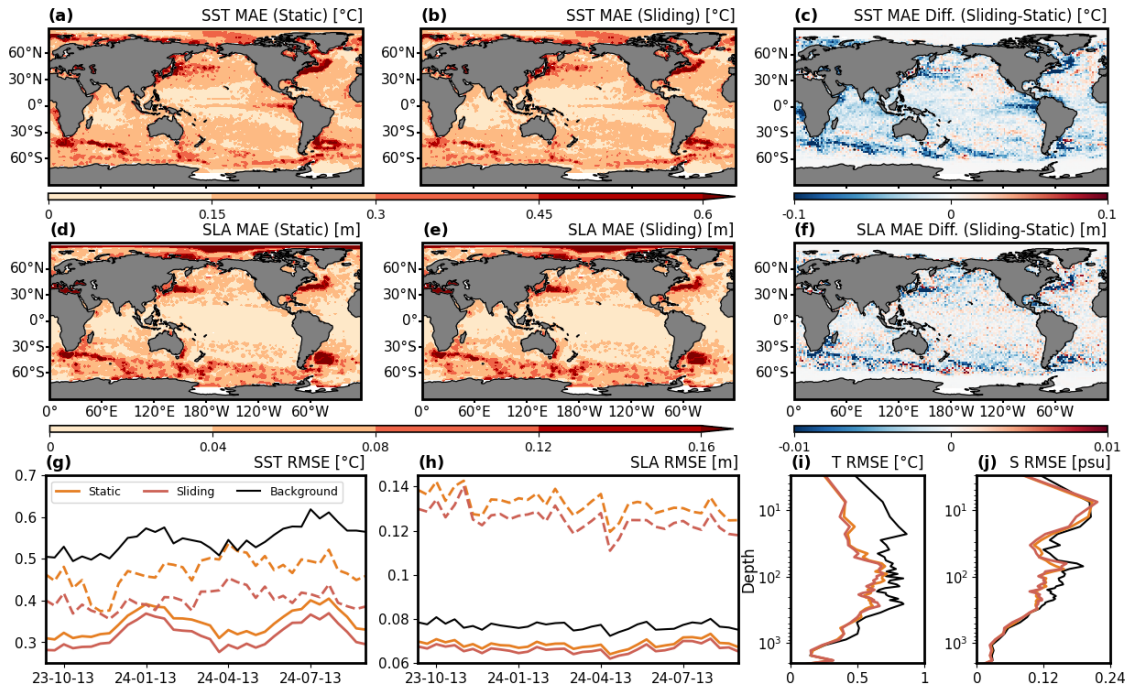


Figure 3. MAE of SST for (a) static and (b) sliding ensembles, and (c) their differences ($^{\circ}\text{C}$). (d-f) is the same as (a-c), but for SLA (m). (g) RMSE of background (black solid), static (orange solid), and sliding (red solid) analysis SST ($^{\circ}\text{C}$). Dashed lines represent the RMSEs in eddy-rich regions, defined as areas outside 5°S – 5°N where EKE exceeds one standard deviation (Ding et al., 2022), for the static (orange dashed) and sliding (red dashed) analysis SST ($^{\circ}\text{C}$). (h) is the same as (g), but for SLA (m). (i) and (j) are RMSEs for background (black solid), static (orange solid), and sliding (red solid) analysis of temperature ($^{\circ}\text{C}$) and salinity (psu), respectively.

3.2 Forecast performance

In general, LFS-SEnDA attains the highest COMPS among the analyzed systems for 1–6-day forecasts, highlighting its highly competitive forecasting capability (Fig. 4a). In terms of the mean RMSE averaged over days 1–6, LFS-SEnDA ranks second for SST, SLA, and temperature profiles, and third for salinity profiles (Fig. 4a). Furthermore, it demonstrates high fidelity in capturing both large-scale SST anomalies and SLA induced by mesoscale eddies, yielding forecast features that closely align with observed spatial patterns (Fig. 4b, c).

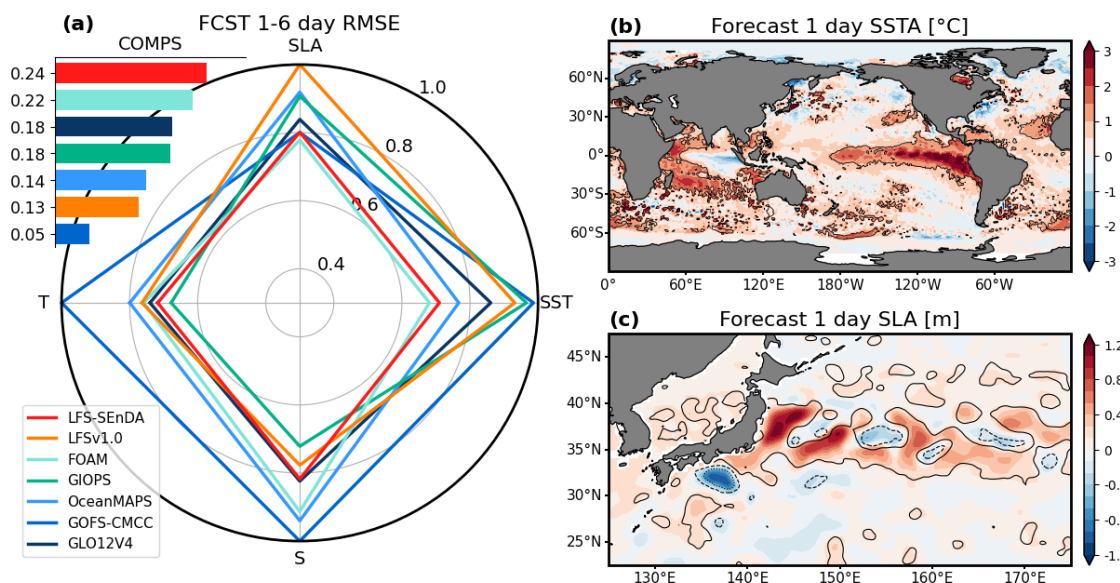


Figure 4. (a) The 1–6-day averaged RMSEs for SST, SLA, temperature (T), and salinity (S), normalized by the maximum RMSE (radar) and the COMPS (bar) across the assessed GOFs, including LFS-SEnDA (red), LFSv1.0 (orange), FOAM (cyan), GIOPS (green), OceanMAPS (light blue), GOFs-CMCC (dark blue), and GLO12V4 (dark steel blue). For GLO12V4, hindcast results are presented. (b) SSTA from the Day-1 forecast valid on 25 October 2023, overlaid with 1°C contours from the OSTIA. (c) SLA from the Day-1 forecast valid on 25 October 2023, overlaid with -0.4 (dotted), 0 (dashed) and 0.4 (solid) m contours from the multi-mission merged altimetry dataset.

3.2.1 SST and SLA performance

The SST and SLA forecast performance of LFS-SEnDA is assessed using bias, RMSE, and AC (Figs. 5 and 6). For SST, LFS-SEnDA exhibits a weak cold bias, with a day-1 mean bias of approximately -0.05 °C that gradually increases to about -0.20 °C by day 6. Despite this bias, LFS-SEnDA represents a clear improvement over LFSv1.0, with the day-1 cold bias reduced by about 0.07 °C. Consistent improvements are also evident in RMSE and AC. The day-1 SST RMSE is 0.38 °C and increases moderately to 0.57 °C by day 6, yielding a 1–6 day mean RMSE of 0.48 °C, which represents an average reduction of about 0.15 °C relative to LFSv1.0. Meanwhile, the AC of LFS-SEnDA exceeds 0.9 during the first three forecast days and remains above 0.85 through day 6, about 0.07 higher than that of LFSv1.0 at comparable lead times.

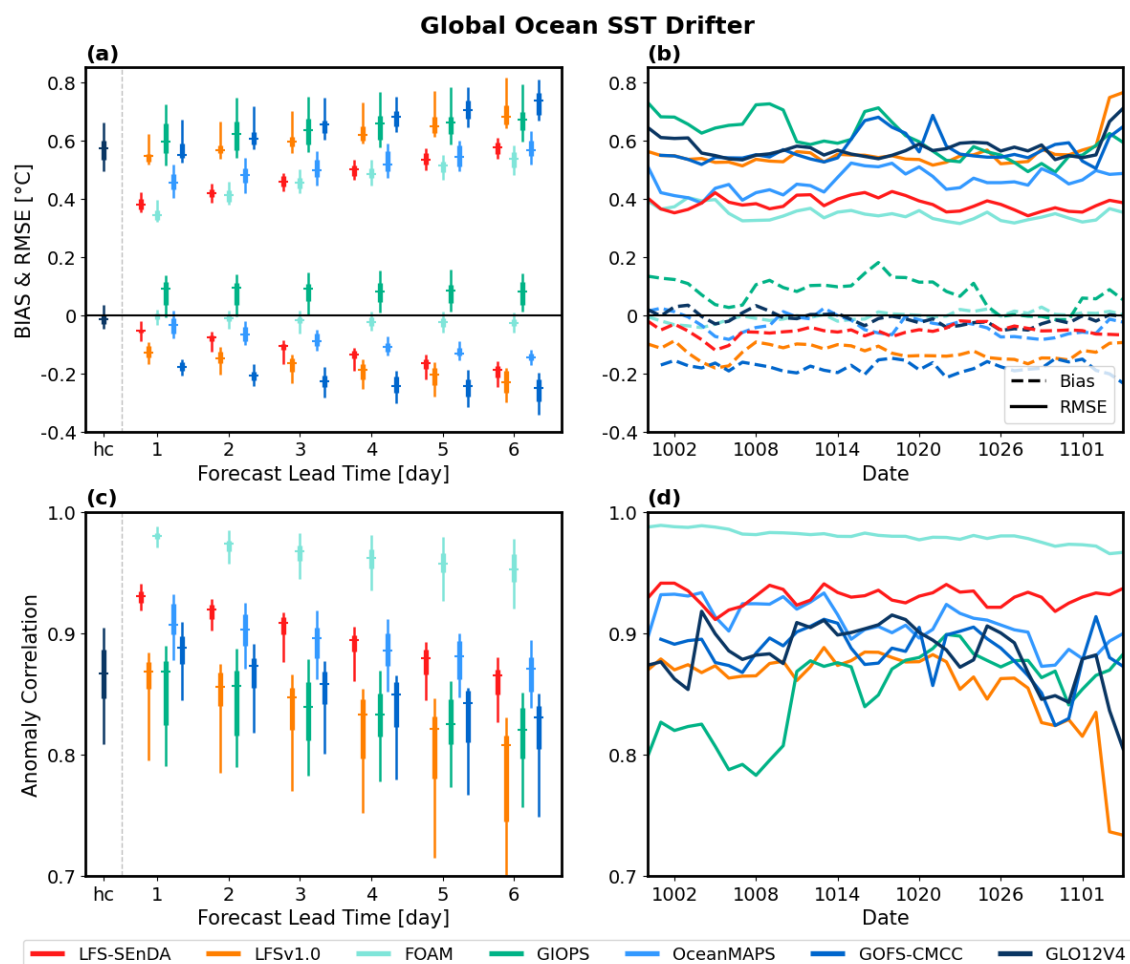


Figure 5. Assessment of forecast SST against in situ drifter observations based on ExpF-C. (a) Bias and RMSE of forecast SST (°C) as a function of forecast lead time. The boxes are the interquartile range and the 90th percentile. (b) Time series of day-1 forecast SST bias and RMSE (here, hindcast for GLO12V4). (c) AC of forecast SST as a function of forecast lead time. The boxes are the interquartile range and the 90th percentile. (d) Time series of day-1 forecast SST AC (here, hindcast for GLO12V4).

For SLA, LFS-SEnDA shows a small and stable bias across forecast lead times. Correspondingly, the SLA RMSE remains at a relatively low level, increasing slowly from about 0.06 m on the first forecast day to approximately 0.07 m by day 6. The 1–6 day mean RMSE is 0.066 m, about 0.017 m lower than that of LFSv1.0. The AC of SLA exceeds 0.80 on the first forecast day and gradually decreases to about 0.71 by day 6. Similar SST and SLA forecast behavior is obtained in ExpF-Y (Figs. S1 and S2). The experiment also reveals seasonal variations in forecast performance. SST forecasts tend to be less accurate during the boreal summer (June–August). In contrast, SLA shows weaker seasonal variability, but a systematic increase is observed during February–April across several systems. These seasonal variations in error may be associated with inaccuracies within the gridded SST and SLA observations (Fig. S3).

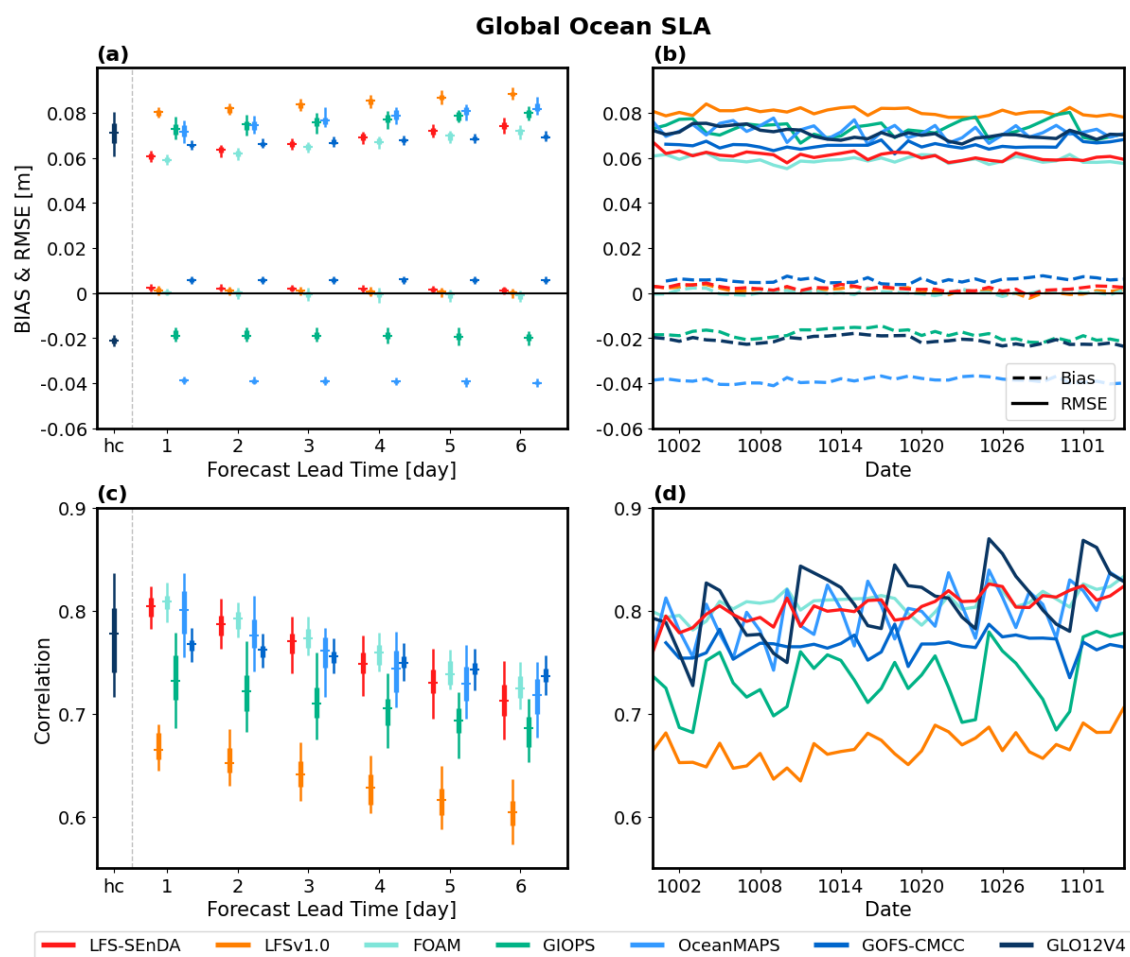


Figure 6. Same as Figure 5, but for SLA.

Compared with other GOFs, LFS-SEnDA demonstrates competitive performance for both SST and SLA. For SST, cold biases similar to those in LFS-SEnDA are also present in OceanMAPS and GOFS-CMCC. In terms of RMSE, LFS-SEnDA ranks second only to FOAM during the first three forecast days, with FOAM exhibiting a day-1 RMSE of about 0.35 °C, whereas the day-1 RMSEs of OceanMAPS, GOFS-CMCC, GLO12V4, and GIOPS all exceed 0.4 °C. During days 3–6, the SST RMSE of LFS-SEnDA increases and approaches that of OceanMAPS as the cold bias grows with lead time. For SLA, LFS-SEnDA achieves RMSE values comparable to those of FOAM during the first three forecast days, while both systems are surpassed by GOFS-CMCC at forecast days 5–6, as its SLA RMSE increases more slowly with lead time.



340 From the perspective of temporal evolution and forecast stability, LFS-SEnDA shows relatively consistent behavior across these metrics. During the cycling assimilation forecast period, both SST and SLA errors exhibit limited temporal variability. For SST, the RMSE remains below about 0.4 °C for most lead times, and the day-1 AC consistently exceeds 0.9. For SLA, the day-1 RMSE remains stable at approximately 0.06 m, with the corresponding AC consistently around 0.8. In contrast, all other GOFSSs analyzed here, except FOAM, exhibit larger temporal fluctuations in both RMSE and AC.

345 3.2.2 T-S profiles performance

The forecast performance of subsurface temperature and salinity from LFS-SEnDA and other GOFSSs is assessed (Fig. 7, Fig. S4). For temperature, LFS-SEnDA exhibits relatively small mean biases across forecast lead times, with a slight cold bias in the upper ocean (<100 m) and a weak warm bias at deeper layers. The RMSE increases modestly from about 0.62 on day 1 to around 0.72 on day 6. The 1–6 day mean RMSE is approximately 0.66, representing an average reduction of about 0.04 relative to LFSv1.0, with particularly notable improvements near the surface and at around 100 m depth. The mean temperature AC remains above 0.6 throughout the 1–6 day forecast period, showing an average increase of about 0.05 compared with LFSv1.0 and improvements across most vertical levels. For salinity, LFS-SEnDA shows slight degradation relative to LFSv1.0, mainly due to higher RMSE in near-surface and deeper layers. This deterioration may be related to the relatively small salinity spread in the ensemble samples, which limits the adjustment toward salinity observations during the multivariate analysis update.

355 Similarly, the results from ExpF-Y show a trade-off between subsurface temperature and salinity, with improved temperature forecasts but slightly degraded salinity performance, and limited predictive skill for both variables in the deeper ocean (Figs. S5 and S6).

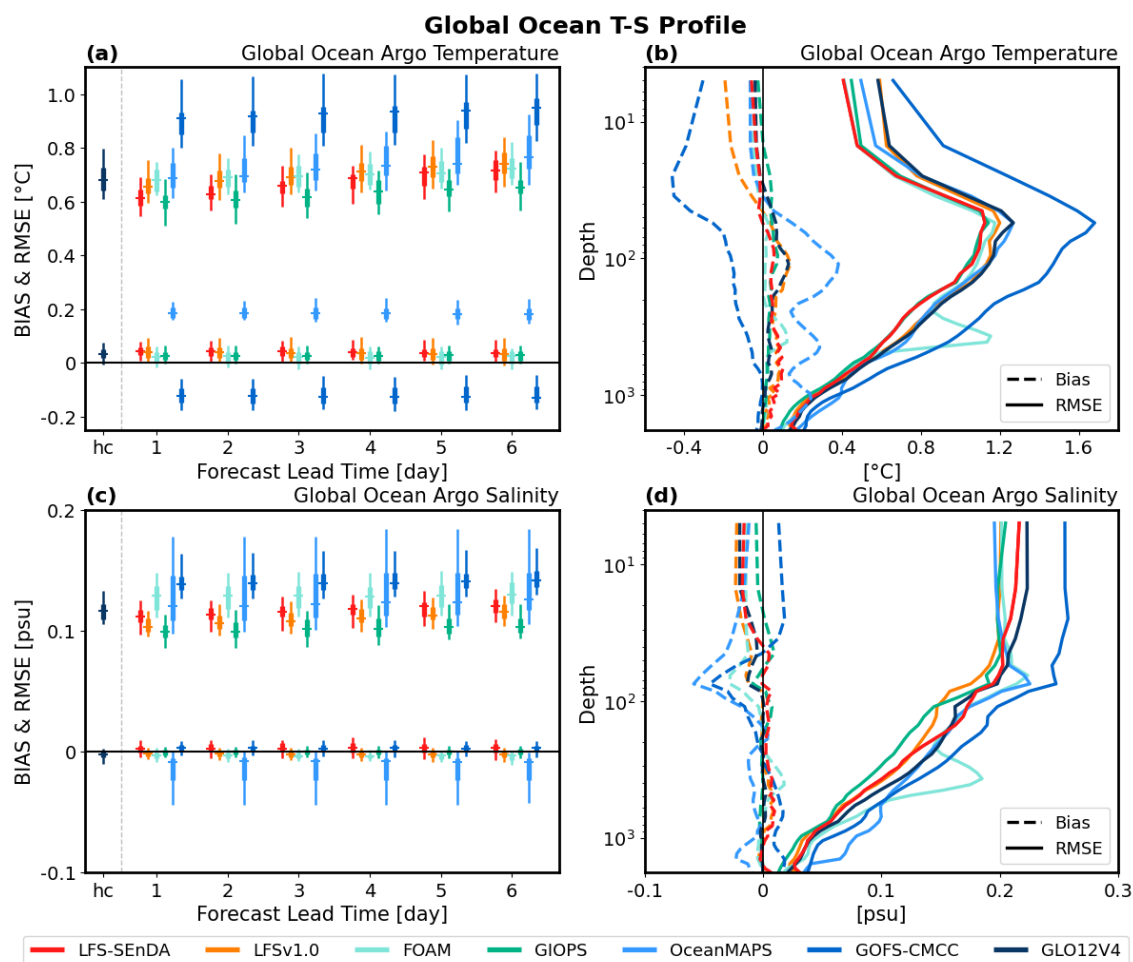


Figure 7. Assessment of forecast T-S profile against Argo observations based on ExpF-C. (a) Bias and RMSE of forecast temperature profiles (°C) as a function of forecast lead time. The boxes are the interquartile range and the 90th percentile. (b) Vertical distribution of bias (dashed) and RMSE (solid) for day-1 forecast temperature profiles (here, hindcast for GLO12V4). (c) and (d) are the same as (a) and (b), respectively, but for salinity (psu).

Compared with other GOFs, LFS-SEnDA demonstrates competitive performance in subsurface temperature and salinity. For temperature, the overall RMSE and AC of LFS-SEnDA rank second only to GIOPS among the analyzed systems. In addition, LFS-SEnDA shows particularly strong performance in the upper ocean, achieving the best performance among the assessed systems. Its performance is relatively weaker in deeper layers, which may be associated with the limited spread of the samples within the ensemble. For salinity, LFS-SEnDA exhibits overall moderate performance compared with the other systems. As with temperature, forecast performance is relatively good in the upper ocean but decreases in the deeper ocean, likely due to the same limitation associated with the ensemble's limited spread.

3.2.3 Forecast skill score

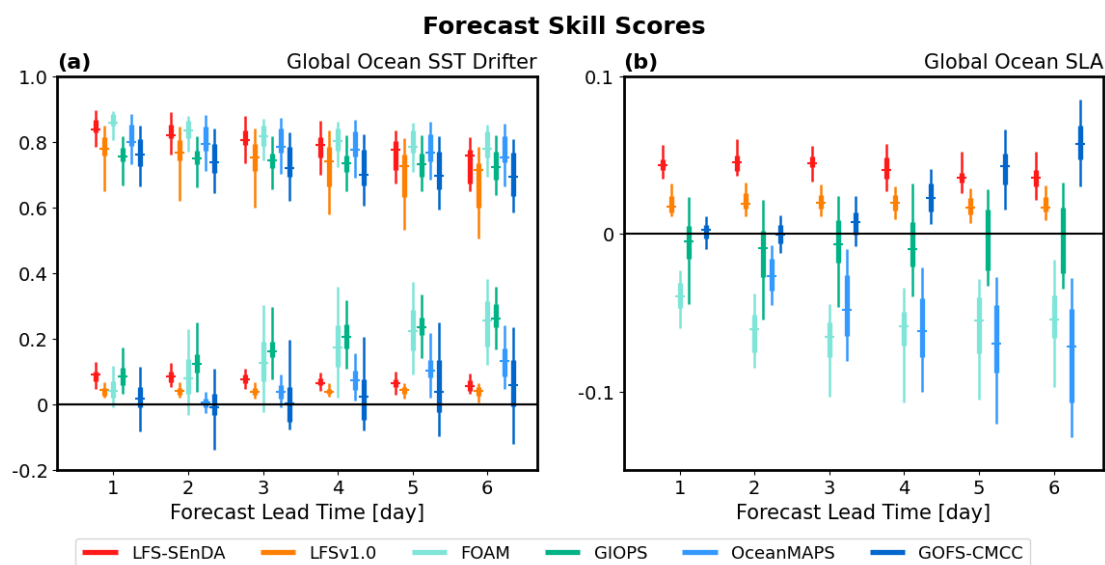
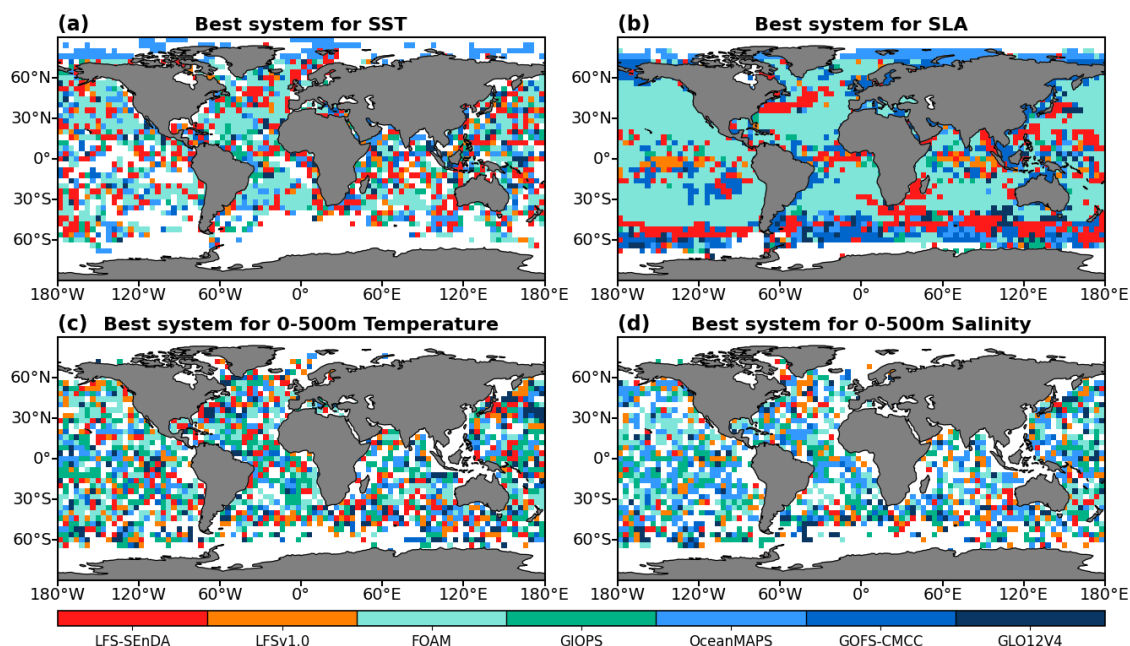


Figure 8. The forecast skill scores of the forecast SST (a) and SLA (b) as a function of lead time based on ExpF-C. (a) The upper and lower curves represent the Continuous Stratified Score (CSS) and Predictive Skill Score (PSS), respectively. (b) is only PSS for SLA.

The PSS quantifies forecast skill relative to a persistence forecast, indicating whether a new forecast under the cycling assimilation framework outperforms the previous forecast (Figs. 8 and S7). For SST, all analyzed GOFs, including LFS-SEnDA, exhibit consistently positive mean PSS across all lead times. Compared with LFSv1.0, LFS-SEnDA shows higher PSS values from day 1 to day 6. However, the PSS of LFS gradually decreases as lead time increases, likely due to its relatively large forecast bias. For SLA, LFS-SEnDA and LFSv1.0 are the only two systems among those analyzed that maintain positive mean PSS, with LFS-SEnDA showing more pronounced positive values. For subsurface variables, both LFS-SEnDA and LFSv1.0 generally maintain positive PSS for Argo temperature and salinity. In contrast, most of the other analyzed GOFs fail to sustain consistently positive PSS for subsurface temperature and salinity.

The CSS evaluates whether forecasts from the GOFs outperform a climatological reference (Figs. 8 and S7). For SST, LFS-SEnDA maintains relatively high CSS values, decreasing from about 0.85 on day 1 to around 0.74 by day 6. This represents an improvement of approximately 0.07 compared with LFSv1.0 and ranks second among the analyzed GOFs. For subsurface temperature and salinity, CSS values are generally smaller and even become negative in some systems. Nevertheless, LFS-SEnDA consistently maintains positive CSS. For temperature, the CSS of LFS-SEnDA is slightly higher than that of LFSv1.0, whereas for salinity it is marginally lower. Overall, the CSS results indicate that LFS-SEnDA provides forecasts that are consistently superior to the climatological baseline and exhibits competitive performance compared with the other GOFs.

3.2.4 Regional performance



395 **Figure 9. The best-performing forecast system based on ExpY-C. Binned maps indicating the forecast system with the lowest 1-day RMSE averaged within each 4° grid box for (a) SST, (b) SLA, as well as upper 500 m (c) temperature and (d) salinity. Here, hindcasts are used for GLO12V4.**

The regional comparison further reveals marked spatial heterogeneity in forecast skill among the analyzed GOFs (Figs. 9 and
 400 S8). The binned best-system maps indicate that no single system dominates globally across all variables, highlighting the regional dependence of forecast performance.

For SST, LFS-SEnDA is frequently identified as the best-performing system in dynamically active regions, including parts of
 western boundary current systems, the equatorial oceans, and the Southern Ocean, whereas FOAM shows more extensive
 advantages over several basin-interior regions (Fig. 9a). The basin-scale RMSE statistics further show that LFS-SEnDA
 405 maintains low SST errors across most basins, with particularly small errors in the tropical Atlantic, South Atlantic, South
 Pacific, and Australasia regions (Fig. S8a). Larger SST errors occur in the North Atlantic, North Pacific, and Indian Ocean,
 consistent with enhanced mesoscale variability and stronger air–sea coupling in these regions.

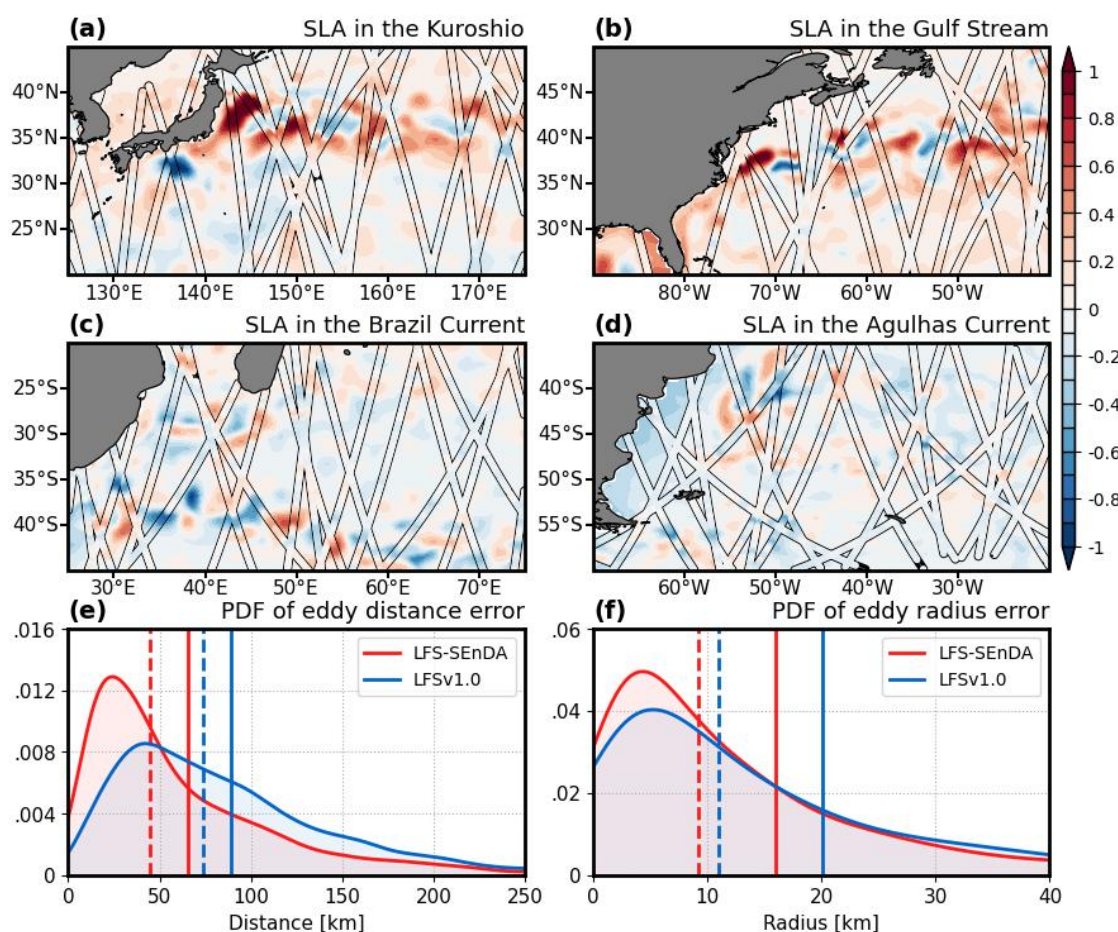


Figure 10. SLA (m) snapshots of the 1-day lead forecast in (a) the Kuroshio, (b) Gulf Stream, (c) Brazil Current, and (d) Agulhas Current regions on October 28, 2023. The ribbons represent the SLA of L3 along-track satellite data. The PDFs of (e) distance and (f) radius errors for matched eddy pairs across the four regions for LFS-SEnDA (red) and LFS v1.0 (blue). The solid and dashed lines represent the corresponding mean and median values.

For SLA, the regional advantage of LFS-SEnDA is also concentrated in eddy-rich regions, indicating an improved capability to represent sea-level variability under dynamically active conditions (Fig. 9b). To further verify this enhanced performance, a representative snapshot of the SLA on October 28, 2023, is presented (Fig. 10). In highly dynamic western boundary current regions—such as the Kuroshio, Gulf Stream, Brazil Current, and Agulhas Current—the spatial structures predicted by LFS-SEnDA exhibit remarkable fidelity, which closely resembles the along-track Level-3 satellite observations (Fig. 10). This superior forecasting skill is further substantiated by the characterization of mesoscale eddies. Quantitative detection and matching analysis reveal that the day-1 forecast from LFS-SEnDA achieves an average matching success rate exceeding 60%, a performance comparable to that of LFSv1.0 (Fig. S9). However, LFS-SEnDA significantly ($p < 0.001$) outperforms LFSv1.0,



reducing the average center distance displacement from 89.6 km to 65.6 km and the average radius discrepancy from 20.0 to 16.0 km among the matched eddy pairs (Fig. 10e, f).

425 In the basin-scale statistics, LFS-SEnDA generally ranks in the leading group among the systems compared (Fig. S8b). Nevertheless, SLA errors remain relatively large in the North Atlantic, South Atlantic, and Australasia regions, where energetic mesoscale variability accounts for a substantial portion of the basin area. This basin dependence indicates that eddy-rich regions remain challenging for SLA prediction across GOFs, even when the assimilation system improves the representation of dynamically active ocean states.

430 For temperatures above 500 m, LFS-SEnDA is identified as the best-performing system in a more limited number of regions, mainly near energetic current zones (Fig. 9c). In contrast, GIOPS exhibits broader advantages across many open-ocean regions. Nevertheless, the basin-scale RMSEs indicate that LFS-SEnDA generally remains among the better-performing systems, ranking near second globally and across several individual basins (Fig. S8c). The upper 500 m temperature RMSEs are relatively high in the North Atlantic, North Pacific, and tropical Pacific, where strong vertical stratification, active mesoscale

435 variability, and complex air–sea interactions may increase subsurface forecast uncertainty. For salinity in the upper 500 m, LFS-SEnDA generally performs at an intermediate level among the analyzed GOFs (Figs. 9d and S8d). Relatively large salinity RMSEs are found in the North Atlantic, tropical Atlantic, and tropical Pacific, which may be associated with uncertainties in the representation of freshwater processes, including sea-ice-related freshwater fluxes, river runoff, and precipitation–evaporation forcing.

440 **4. Conclusions and discussions**

This study develops the GOFs named LFS-SEnDA, which upgrades the data assimilation method from the LFSv1.0 framework by implementing an improved sliding ensemble assimilation method, referred to as SEnDA. By incorporating the sliding sampling strategy, the efficacy and physical coherence of the assimilation have been improved, providing a more reliable initial state for the forecast system and eliminating LFS's reliance on other forecast systems. In addition, the optimized analysis

445 procedure reduces the computational time of the analysis step by more than 30 times, supporting its potential application to future kilometre-scale GOFs.

Consequently, the forecast performance is improved relative to the previous version, LFSv1.0, which indicated the excellent performance of the data analysis method and its application. For forecasts at lead times of 1–6 days, the SST RMSE decreases from approximately 0.63 °C to 0.48 °C, with an AC of about 0.9. Similarly, the RMSE of SLA decreases from around 0.083

450 m to 0.066 m, with an AC of approximately 0.76. For temperature profiles, the mean RMSE is reduced from about 0.70 °C to 0.66 °C, while the corresponding AC generally remains above 0.6. Within the framework of the IV-TT Class 4 assessment system for ocean forecasting, LFS-SEnDA achieves the highest composite score among the participating operational systems.

Regional assessments further indicate that the system performs particularly well in dynamically active regions, such as western boundary current areas, where SST, SLA, and temperature profile forecasts show superior skill compared with other systems.

455 Despite these improvements, several aspects require further development. A systematic cold bias remains in SST, which may need to be corrected by improving or replacing the atmospheric forcing fields. Further analysis has shown that the assimilation and forecast improvements for temperature and salinity are also limited at greater depths, possibly due to insufficient ensemble spread in the subsurface ocean. Introducing a bias-correction scheme for temperature and salinity may help alleviate these systematic biases. Future development should also include sea-ice data assimilation to enhance prediction capability in polar
 460 regions, particularly in ice-ocean interaction regions.

Appendix A: IVTT class 4 ocean basin definitions

Table A1. IV-TT Class-4 ocean basin definitions

Name	Longitudes	Latitudes
Global Ocean	90°S~90°N	180°W~180°E
North Pacific	0~65°N	100°E~77°W
Tropical Pacific	20°S~20°N	90°E~70°W
South Pacific	60°S~0	100°E~70°W
North Atlantic	0~70°N	100°W~31°E
Tropical Atlantic	20°S~20°N	70°W~30°E
South Atlantic	60°S~0	70°W~30°E
Indian Ocean	40°S~31°N	20°E~120°E
Australasia	70°S~20°N	90°E~180°E



Code and data availability

465 The assimilation system and validation codes are publicly available under an open-source license through the Zenodo repository at <https://doi.org/10.5281/zenodo.21738114> (Zhou et al., 2026a). The assimilated SST data are available from https://data.marine.copernicus.eu/product/SST_GLO_SST_L4_NRT_OBSERVATIONS_010_001/description (European Union-Copernicus Marine Service, 2015). The assimilated SLA data are available from https://data.marine.copernicus.eu/product/SEALEVEL_GLO_PHY_L4_NRT_008_046/description (European Union-
470 Copernicus Marine Service, 2017). The assimilated Argo profile data are available from <https://data-argo.ifremer.fr> (Argo, 2026). The GLORYS12V1 reanalysis data used for validation are available at https://data.marine.copernicus.eu/product/GLOBAL_MULTIYEAR_PHY_001_030/description (Jean-Michel et al., 2021). The forecast data used for validation are publicly available under an open-source license via the Zenodo repository at <https://doi.org/10.5281/zenodo.21738114> (Zhou et al., 2026b).

475 Author contributions

Yanzhi Zhou developed the system, performed the experiments, conducted the analysis, and drafted the manuscript. Zipeng Yu assisted in the development of the system. Tao Zhang and Jiangfeng Yu provided valuable suggestions on system development. Maoxue Yu and Kai Xu contributed to the computational performance optimization of the system. Weipeng Zheng and Hailong Liu provided comments and revised the manuscript. Pengfei Lin conceptualized the research, acquired
480 funding, and revised the manuscript.

Competing interests

The authors declare there are no conflicts of interest for this manuscript.

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