Response to Referee #1 Comments

We are grateful to the reviewer for the helpful feedback. By taking these suggestions into account, we have revised the manuscript. At the same time, we have addressed all the comments here, point by point responses to the comments are listed in red.

Referee #1 Comments:

The paper describes a new sea-level dataset using observations from satellite altimetry, overall it is well written, and the quality meets the standards of ESSD. The sea-level community would applaud the release of this dataset, especially if it is updated routinely. Therefore, I would recommend it for publications.

Major comments:

Gridded sea level products, especially with global coverage, are essential for investigating sea level rise. The C3S product is a prominent dataset that is widely used by the community; the PolyU SLA data perform comparably to the C3S data, demonstrating its reliability, and potential applications. In particular, I believe that the PolyU data would contribute considerably to understanding the sea level rise along coast where the altimetry observations suffer from larger uncertainties; now we have more for further evaluations against tide gauges or other products.

Major suggestions:

Data processing: The mapping approach relies on the LSC method. Authors mentioned that the spatial distributions are important (lines 272-274). This raises a question from me, what if the distributions are uneven, how does it affect the spatial interpolation? More importantly, I concerned with the choice of parameters used in LSC, the relevant discussions on the effect of parameters on the final SLA are missing. Plus, authors claimed that the LSC is unbiased, what if the covariance matrix are not stable, do you consider regularizations? If so, I doubt the solutions are 'unbiased'. Finally, I am also curious that how do authors implement the LSC, i.e., you estimate the covariance matrix globally, or regions by regions, the latter would require less computation resources but more time, although I am not sure how this affects the final solutions. So please provide more details on the mapping approach.

Response: Thanks. A variety of methods can be used for data gridding and interpolation, including the Shepard method, continuous curvature tension splines, and the LSC method. Previous studies (Jin et al., 2011) have systematically compared these approaches and demonstrated that LSC exhibits superior applicability and stability when processing satellite altimetry data. In addition, LSC has been widely employed in the construction of mean sea surface (MSS) models and has been validated in numerous studies. Therefore, the LSC method is adopted in this study for data gridding.

Satellite altimetry observations are distributed along orbital tracks, and the fusion of multi-source datasets inevitably leads to spatially uneven data coverage. To mitigate the impact of this issue on interpolation results, efforts are made during the LSC gridding process to ensure a spatially uniform distribution of observations used for interpolation. Specifically, an "eight-quadrant search strategy" is implemented: for each grid point, an initial search radius (twice the grid spacing) is defined, and observations are selected within eight surrounding quadrants. If fewer than five observations are found in any quadrant, the search radius is progressively expanded until the requirement is met. If the radius exceeds approximately 300 km and the requirement is still not satisfied, all available observations within that quadrant are retained, and additional observations from neighboring quadrants are incorporated to ensure that the total number of observations used for interpolation reaches approximately 40. This strategy effectively alleviates the influence of spatially heterogeneous data distribution on the interpolation results.

In the LSC gridding procedure, the construction of the covariance function is a critical step, including both the covariance between observations and the cross-covariance between observations and prediction points. In this study, a second-order Markov covariance function is adopted, in which spatial correlation decays exponentially with increasing distance. The second-order Markov covariance function can be expressed as:

$$D(d) = D_0 \cdot \left(1 + d / \alpha\right) \cdot e^{-d/\alpha}$$

where d is the spherical distance between an observation and a grid point. D_0 represents the signal variance and describes the covariance amplitude at zero distance; it can be estimated from the sample variance of observations located around the grid point. α is the spatial correlation length, which controls the decay rate of the covariance with increasing distance. The value of α varies with latitude; it is typically 200–240 km in low latitudes, 100–120 km in mid-latitudes, and 60–100 km in high latitudes. In the LSC gridding interpolation process, the noise variance of observations is determined as the crossover difference accuracy after crossover adjustment, divided by $\sqrt{2}$ for each satellite mission. Owing to the stability of the adopted covariance model, no additional regularization is introduced in the computation. Further details on LSC can be found in Jordan (1972), Moritz (1978), Rapp and Bašić (1992), Jin et al. (2016), and Yuan et al. (2020, 2023).

Given the considerable computational cost associated with LSC, a regional block-wise strategy is further implemented to enhance computational efficiency. Specifically, the domain from 80°S to 60°N is divided into 20° × 20° blocks, while the region from 60°N to 80°N is partitioned into 24° × 20° blocks. This results in a total of 144 subregions, of which 141 contain valid SLA observations. LSC gridding is performed independently within each subregion, followed by a merging and integration step to reconstruct the global field. For grid lines located within overlapping areas between adjacent subregions, a weighted averaging scheme based on the associated error estimates is applied to ensure smooth transitions and spatial consistency. In this way, the proposed strategy significantly reduces computational demand while preserving the stability, continuity, and reliability of the final gridded results.

Comparison with C3S: Authors stated that the major (methodological) differences include the along-track data processing and crossover adjustments, and mapping approach. For instance, we can observe apparent differences from Figures 5 and 7, prominent regions include Kuroshio Current, Gulf Stream, and other dynamically active regions. But how much would two products differ over these regions, adding relevant time-series for comparison would help to understand.

Response: Thanks. We have revised the manuscript to include time-series comparisons at nine selected points located within dynamically active regions (e.g., the Kuroshio Extension, Gulf Stream Extension, Antarctic Circumpolar Current, etc.), where noticeable differences are observed in Figs. 5 and 7. The corresponding SLA time series and their differences between the PolyU and C3S products are now presented in Fig. 8, with the locations of these points indicated in Fig. 5 and their coordinates listed in Table 3.

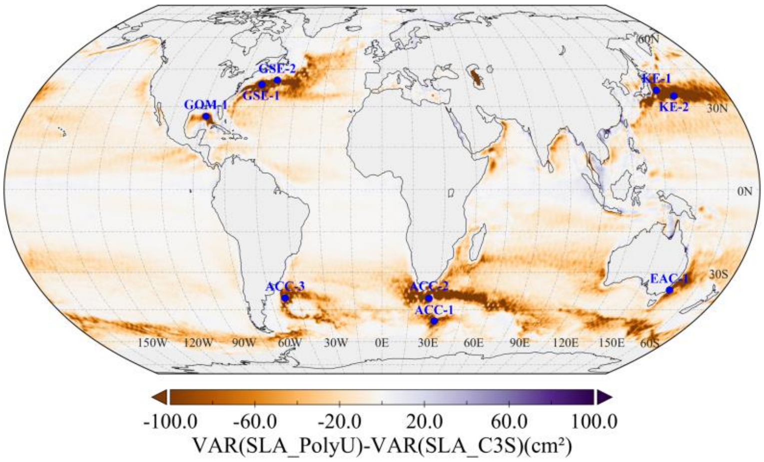

Figure 5. The spatial distribution of the SLA variance differences between the PolyU and C3S products over the January 1993–December 2024 period. Nine representative locations in dynamically active ocean regions, marked by blue dots, are selected for subsequent time-series comparisons.

Table 3. Geographic coordinates of the nine selected points in dynamically active ocean regions.

Region	Point Name	Longitude	Latitude
Antarctic Circumpolar Current	ACC-1	30.125	-49.875
	ACC-2	24.125	-39.125
	ACC-3	308.125	-40.125
East Australian Current	EAC-1	151.625	-36.125
Gulf of Mexico	GOM-1	272.125	26.125
Gulf Stream Extension	GSE-1	295.875	38.125
	GSE-2	303.875	40.125
Kuroshio Extension	KE-1	145.125	36.625
	KE-2	152.125	34.625

Figure 8 shows that, although these points are located in regions where the PolyU and C3S products exhibit relatively large differences in SLA variance and trends, the overall temporal evolution of the SLA time series from the two products remains generally consistent at each site, capturing the main characteristics of sea-level variability, including seasonal and interannual variations. From the difference time series (PolyU–C3S), the mean differences at most points are close to zero, and the variations fluctuate around zero, indicating the absence of a significant systematic bias between the two products. However, the STD of the differences varies considerably among stations, reflecting spatial differences in the consistency of variability amplitude between the two products. For example, some points (e.g., GSE-1 and KE-1) exhibit relatively large STDs, suggesting noticeable differences in short-term fluctuations or local variability, whereas others (e.g., ACC-1 and ACC-3) show smaller STDs, indicating better agreement between the two products. In addition, the variance information shown in the figure (Var and ΔVar) also indicates substantial regional differences in variance; however, these differences are mainly reflected in variability amplitude and do not alter the overall temporal evolution patterns of the two time series.

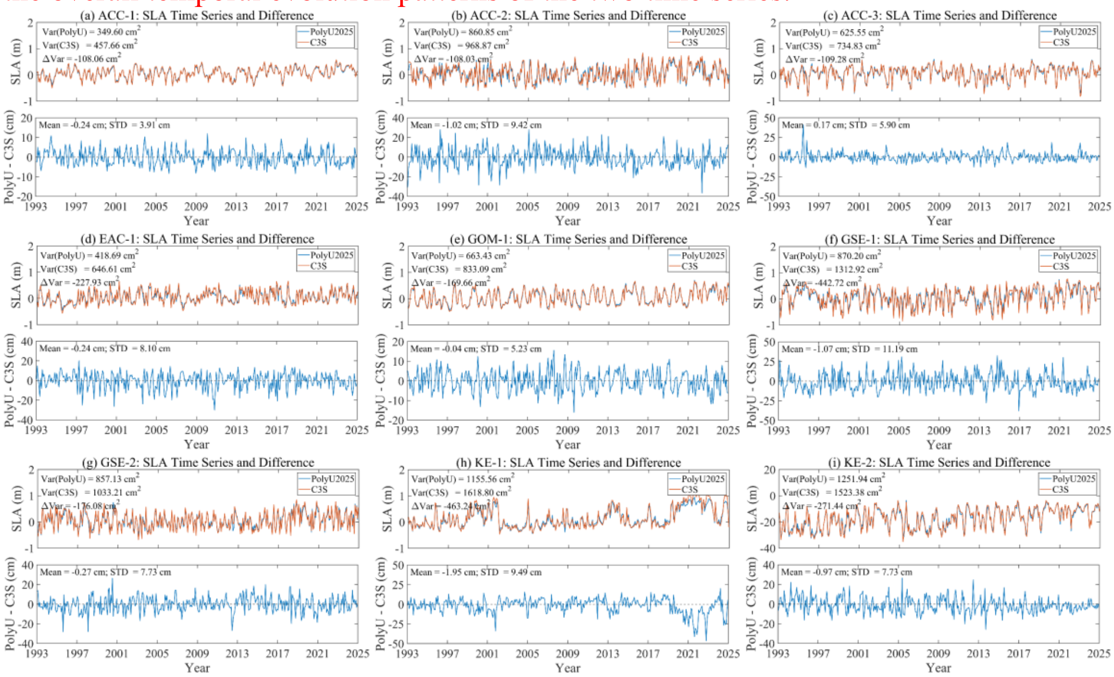

Figure 8. SLA time series and their differences between the PolyU and C3S gridded SLA products at nine selected points (locations shown in Fig. 5).

Comparison with TG: authors compared their data to TG observations, instead of selecting the nearest grid point, they considered the grid point that shows the strongest correlation. This is a good choice. But how do authors define the search radius, it is ambiguous (line 445, is it 1 degree or a specific distance, e.g., 50 km). It is also ambiguous how authors compare SLA to TG in Figure 8. Do you remove the linear trends? If not, I would suggest authors compare them after removal of the trends, or better also remove seasonal changes. Please show us examples for both the highest variance reduction and the lowest (i.e., add time series for SLA and TG to figure 8).

Response: Thanks. In this study, the search radius is defined as 1° around each TG location, following the approach of Sánchez-Román et al. (2023). Within this radius, the grid point whose SLA time series shows the highest correlation with the corresponding TG record is selected as the representative altimetric SLA for that station. Prior to computing the correlation, the linear trend and seasonal signals (annual and semi-annual components) are removed from both the TG and altimetric SLA time series to ensure that the selection is based on the consistency of temporal variability rather than long-term trends and seasonal cycles.

In Fig. 9 (previously Fig. 8 in the original manuscript), we compare the variance of the differences between the SLA time series from PolyU and C3S with respect to TG records, expressed as percentages relative to the variance of the TG time series. This metric is intended to assess the overall discrepancies, including contributions from trends, seasonal signals, and variability. Therefore, linear trends and seasonal signals were retained in the original analysis to ensure a consistent comparison of the overall differences between the two products relative to TG observations. This approach is consistent with that adopted in previous studies (e.g., Taburet et al., 2019). This has been clarified in the revised manuscript.

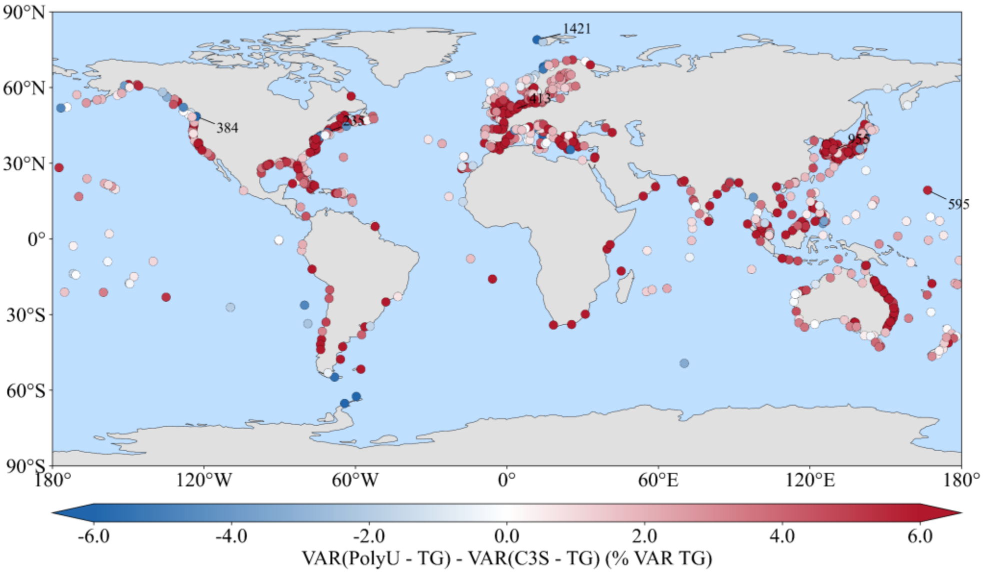

Figure 9. Difference of the variance between gridded products and TG successively using the PolyU and C3S gridded products. The statistic is expressed as a percentage of the variance of the TG observations. Numbers denote TG station identifiers from the PSMSL database, with a subset used for subsequent time-series analysis.

Based on the spatial distribution of the normalized residual-variance differences shown in Fig. 9, six representative TG stations (IDs: 235, 384, 413, 595, 955, and 1421) were selected for further analysis, and their locations are indicated in the Fig. 9. These stations were chosen from those with relatively complete observational records over the period from January 1993 to December 2024. Among them, stations 235, 384, and 1421 exhibit variance difference percentages of −5.96%, −15.33%, and −6.48%, respectively, corresponding to the largest negative values, whereas stations 413, 595, and 955 show values of 8.81%, 5.71%, and 7.56%, representing the largest positive values. These stations therefore capture the most pronounced positive and negative differences between the two gridded products relative to TG observations. Using these stations, a detailed comparison of the SLA time series from PolyU, C3S, and TG was performed (see Fig. 10). The time series shown in Fig. 10 have been detrended and deseasoned.

As illustrated in Fig. 10, both gridded SLA products show a high level of consistency with the TG time series after removing the linear trend and seasonal signals, with correlation coefficients generally exceeding 0.7, indicating good temporal agreement with TG observations. Despite this, these stations correspond to the extreme values of the variance difference percentage shown in Fig. 9, suggesting that, even when the temporal patterns are similar, noticeable differences remain in the variance difference percentage. At stations 235, 384, and 1421, PolyU shows higher correlation coefficients and STD values closer to those of TG, whereas at stations 413, 595, and 955, C3S shows higher correlation coefficients and STD values closer to TG. In addition, the STD values vary among stations, indicating that both PolyU and C3S exhibit deviations from TG as measured by STD, and that these deviations differ between the two products and across locations, even though both products maintain overall good agreement with TG observations.

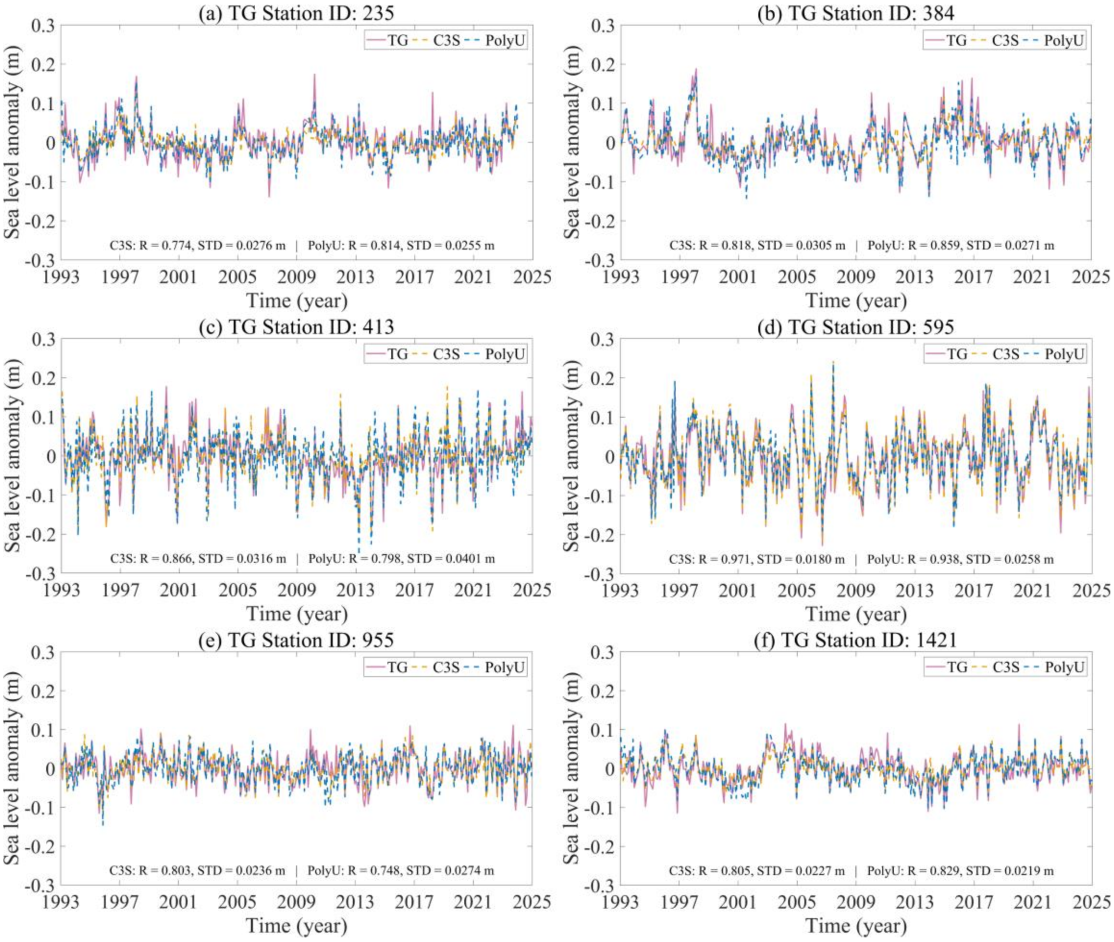

Figure 10. Comparison of detrended and deseasoned SLA time series from tide-gauge (TG), PolyU, and C3S products at selected stations identified in Fig. 9, with correlation coefficients (R) and standard deviations (STD) quantifying their agreement with the TG time series.

Minor suggestions:

Line 22, what do you mean 'a stable' characterization?

Response: Thanks. Here, we intended to convey that the PolyU2025 SLA provides sea-level trend and acceleration estimates that are as reliable as those derived from C3S. As shown in Fig. 6, the estimated global mean sea-level trends from PolyU2025 and C3S are 3.21 ± 0.28 mm yr^{-1} and 3.17 ± 0.31 mm yr^{-1}, respectively. In addition, the difference between the two-time series has a mean of 0.00 cm and a standard deviation of 0.16 cm, indicating a high level of agreement without detectable systematic bias. To avoid ambiguity, we have replaced “stable” with “robust” in the revised manuscript.

Line 36, ‘sea level’ missing a hyphen, please use the consistent typing style;

Response: Thanks. It has been addressed in the revised manuscript.

Line 46, global or near-global coverage?

Response: Thanks. We agree that “near-global coverage” is more accurate, and the text has been revised accordingly.

Line 55, what do you mean climate-scale? This term is cited multiple times, but I think it is ambiguous.

Response: Thanks. In this study, it refers to sea-level variability at decadal and longer time scales, including long-term trends and low-frequency variability. To improve clarity, we have revised the manuscript by replacing “climate-scale” with more explicit expressions such as “long-term sea-level change”.

Line 90, with plans for continuous updates, you mean you are committed to updating?

Response: Thanks. Yes, the gridded SLA product will be updated as new satellite altimetry data become available.

Line 145, do authors consider removal of the TG associated with large trends? Because these TG stations may also reflect local changes that cannot be captured by SA. That’s why I recommend authors to remove the trends before comparison.

Response: Thanks. We agree that TG records with large trends may reflect local changes that are not fully captured by SA. In this study, TG stations with large trends were not explicitly excluded. This is because TG data are primarily used to assess the consistency between the PolyU2025 SLA and the C3S product, rather than to independently analyze absolute sea-level trends. Prior to the comparison, a strict quality control procedure was applied to the TG data, including: (1) excluding stations with less than 10 years of data during the period from January 1993 to December 2024; (2) removing monthly values exceeding three times the standard deviation of each time series; and (3) retaining only stations with more than 90% valid data. These steps help reduce the influence of anomalous or unstable records. In addition, as the analysis is based on a large number of TG stations, the impact of local anomalous trends at individual stations on the overall consistency assessment is expected to be limited.

Line 158, what do you mean ‘SLA variable’

Response: Thanks. Here, “SLA variable” refers to the sea level anomaly (SLA). To avoid ambiguity, we have revised the text accordingly.

Line 164, why resampling reduces the measurement noise? In my experiences, use more data (especially their average) would reduce the noise.

Response: Thanks. We agree that, in general, using more observations or their averages can help reduce measurement noise. In this study, however, the purpose of the subsampling step is not simply to reduce the number of observations, but to be commensurate with the filtered signal, so that only as many points as needed to represent the remaining spectral content are retained, thereby avoiding the propagation of unresolved high-frequency noise into the gridding process. This approach is consistent with the DUACS/C3S processing framework, where along-track SLA data are low-pass filtered and then subsampled to be commensurate with the filtered signal, so that only the necessary observations are retained (Pujol et al., 2016; Taburet et al., 2019). The text has been revised accordingly.

Line 330, is there any evidence supporting the millimeter level uncertainty? How do you mean exactly, do the lone-term trends have a millimeter uncertainty?
Response: Thanks. The expression "millimeter level uncertainty" may have been unclear. In this context, it does not refer to the uncertainty of long-term trends. Instead, it refers to the magnitude of the monthly global-mean SLA differences between the PolyU and C3S products, which are generally within 0.5 cm. Such small values indicate that the differences between the two products are minimal at the global scale and that there is no systematic offset. To avoid ambiguity, we have revised the text accordingly.

Line 366, in studies 'focusing'
Response: Thanks. It has been addressed in the revised manuscript.

Line 375, several studies have suggested that sea level trend estimates should consider color noise (e.g., Mu et al., 2025; https://doi.org/10.1029/2025GL117434). Mu et al. (2025) did consider a AR(1) model, but they used yearly data. The monthly data should consider AR(3) or AR(5). I don't think this is a series issue, but authors should add more wordings, so readers can learn more.
Response: Thanks. We agree that the accurate estimation of sea-level trend uncertainty is influenced by multiple factors, including temporal correlation in the noise. Previous studies (e.g., Ablain et al., 2019; Guérou et al., 2023; Gobron et al., 2026) have provided comprehensive assessments of sea-level trend uncertainties by considering various sources of error and their temporal structures.

Ablain, M., Meyssignac, B., Zawadzki, L., Jugier, R., Ribes, A., Spada, G., Benveniste, J., Cazenave, A., and Picot, N.: Uncertainty in satellite estimates of global mean sea-level changes, trend and acceleration, Earth Syst. Sci. Data, 11, 1189–1202, https://doi.org/10.5194/essd-11-1189-2019, 2019.
Guérou, A., Meyssignac, B., Prandi, P., Ablain, M., Ribes, A., and Bignalet-Cazalet, F.: Current observed global mean sea level rise and acceleration estimated from satellite altimetry and the associated measurement uncertainty, Ocean Sci., 19, 431–451, https://doi.org/10.5194/os-19-431-2023, 2023.
Gobron, K., Hohensinn, R., Loizeau, X. et al. A Unified Framework for Trend Uncertainty Assessment in Climate Data Records: Demonstration on Global Mean Sea Level. Surv Geophys (2026). https://doi.org/10.1007/s10712-025-09922-7

We acknowledge that, for monthly data, higher-order autoregressive models (e.g., AR(3) or AR(5)) may better represent the temporal correlation of the noise compared to a simple AR(1) model. However, as noted, this is not a primary issue affecting the main conclusions of this study. The objective here is to provide a general and consistent estimate of trend uncertainty, rather than to fully characterize the detailed noise structure.

Following the reviewer's suggestion, we have added a brief clarification in the revised manuscript to better explain this aspect and to provide additional context for readers.

Line 460, in figure 8, I would suggest authors to add several examples of time series for comparison.

Response: Thanks. It has been addressed in the revised manuscript.

Line 480, what is this 'nested moving-average approach', any terminology for this method.

Response: Thanks. The term "nested moving-average approach" was used in the original manuscript to describe a simple temporal decomposition method in which moving averages with different window lengths are successively applied to separate variability at different time scales, and band-limited components are obtained through differencing. To improve clarity, we have revised the description in the manuscript to a more explicit expression, i.e., "a multi-scale decomposition based on successive moving averages," which better reflects the methodology and is easier for readers to understand.

Line 520, in figure 10, I would suggest authors to add histogram.

Response: Thanks. It has been addressed in the revised manuscript.

Line 580, in figure 12, it would be nice to show the average for those stations, may be along with their standard deviations.

Response: Thanks. It has been addressed in the revised manuscript.