



# 15 Years of Satellite, In-Situ and Reanalyzed Salinity Data: Insights into Sea Surface Salinity Trends, Variability, and Water Cycle Links

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**Abstract.** Sea Surface Salinity (SSS) trends and variability have been studied for long periods of time, using historical archives and Argo float data. Studies in the past have shown that the long-term (50+ years) salinity trend patterns reveal freshening in the climatological fresh region and an increase in salinity in the already salty region, indicating an intensification of the hydrological cycle. However, especially before the Argo period, the spatial and temporal distributions of SSS were sparse and uneven. As of 2025, 15 years of satellite-derived sea surface salinity data are available with unprecedented temporal and global coverage. This is an opportunity to revisit trends and variability in SSS and its link to the intensification of the ocean water cycle. This study looks at linear trends and variability from different SSS datasets for the period between 2011 and 2024 (satellite era). An intercomparison of the trends estimated from the different datasets found a general good agreement between statistically significant trends in all datasets, both in terms of sign of the trends and intensity. Significantly positive trends were found for the North and South Atlantic, the tropical Pacific, and west of Australia; while negative trends were found in the North Pacific, Eastern Indian Ocean and the South Pacific convergence zone, as well as in the regions of the Congo and Amazon River plumes. In general, the saltier regions were found to be trending positively, except for the South Pacific Convergence Zone and East of Australia; while the fresher regions are becoming fresher, except for the Western Pacific. These trends were compared with longer term trends from 1960 to the present. While the relatively short time span limits the detection of climatic signals, some of the trends found in the satellite era were consistent with the long-term trends, most notably an intensification of the interbasin contrasts, with a salting in the Atlantic and a freshening in the northern Pacific. A comparison with the long-term trends also helped to distinguish between interannual to decadal variability and anthropogenic trends, with some of the shorter-term trends in the tropical Pacific for instance being a consequence of the multiple multi-year La Niña events during the satellite period.



## 30 1 Introduction

Anthropogenic climate warming has been shown to intensify the global water cycle (e.g. Held and Soden, 2006; Douville et al., 2021). A warming climate increases the water-holding ability of the atmosphere, as per the Clausius-Clapeyron relation (Borger et al., 2022; Wan et al., 2024), which in turn enables more evaporation and potentially more precipitation. These variables are crucial to assess the intensification of the Earth water cycle, and possible increase in frequency and intensity of extreme events such as floods, droughts, and storms (e.g. O’Gorman, 2015; Gu et al., 2022). Yet, freshwater fluxes are challenging to measure reliably over the oceans and across long term time scales (Gulev et al., 2021). Hence, sea surface salinity (SSS) has been used as an indirect tracer of possible trends in freshwater cycle (Yu et al., 2020). The analysis of the SSS trends reveals the so-called “rich get richer” paradigm, i.e. dryer regions get dryer and wetter regions get wetter, that manifests at the ocean surface by saltier regions get saltier in historical dataset and future projection (IPCC, 2021). This underlines the importance of using SSS as a source of insight into long-term variations of the water cycle and the effects of climate change (Yu et al., 2020).

Salinity trends have been studied in the past, using in situ data consisting of different combinations of Argo and historical archives. Durack and Wijffels (2010) looked at trends in global ocean salinity for the period between 1950 and 2000. They found that the 50-yr linear surface salinity trend patterns follow the climatology patterns closely, highlighting a strengthening of the mean salinity pattern and an intensification of the hydrological cycle in a warmer world as expected by Solomon et al. (2007) and Held and Soden (2006). Terray et al. (2012) presented the linear SSS trends for 1970-2002 from in situ observations and projected trends in climate models (2011-2060). They found a significant freshening in the Pacific and a significant salting in the Atlantic, leading to an increase of the interbasin contrast. This result is consistent across papers that investigate salinity trends (e.g. Durack and Wijffels, 2010). Terray et al. (2012) also found that the trends in the Pacific and the increase in the interbasin contrast were different from those expected due only to internal variability, suggesting the emergence of an anthropogenic signal. Cheng et al. (2020) looked at the period between 1960 and 2017 using a new salinity dataset, for both the sea surface and averaged over the top 2000 m of the water column. They found that contrasts in the subsurface salinity have also increased, with an amplification of existing salinity patterns. They also highlighted that, because subsurface salinity is less affected by interannual variability and sampling error, this amplification signal is separate from natural variability (i.e. of anthropogenic origin). Gould and Cunningham (2021) extended the analysis of changes in surface salinity to almost 150 years, using data from the voyages of HMS Challenger and the HMS Gazelle in the 1870s. They found that the salinity pattern amplification seen for the period between the 1870s and 1950s was  $54 \pm 10\%$  lower than for the post-1950s period, which implies an acceleration of the amplification (and, consequently, of the hydrological cycle) for the post-1950s period.

Quite recently, SSS data based on a multivariate interpolation of in situ and satellite measurements – combining both sea surface salinity and temperature (SST) (also analyzed in the following) - were included in a linear inverse model to assess the global ocean empirical dynamical modes over the 1993-2018 period (Buongiorno Nardelli and Iudicone, 2025). The analysis has allowed to filter out the contributions associated with Pacific Decadal Oscillation (PDO) as well as to El Niño/La Niña



interannual signals, revealing the ocean response to long-term external forcing as the least-damped non-oscillating mode. The strongest salinity changes indicate a reduced flow from major rivers, recently linked to human activity (Gudmundsson et al., 2021), and a salinity decrease in the Intertropical Convergence Zone and Antarctic Circumpolar Current. Buongiorno Nardelli and Iudicone (2025) showed that notable salinification occurs in the tropical southern Atlantic, western Indian Oceans, extending to the South Atlantic Current and Agulhas Retroflexion. Compared to other studies, salinity trends along the US west coast (midlatitudes) and the subpolar North Atlantic show more complex dynamics than simple water cycle amplification. Prior to the development of the Argo autonomous profiling floats network in the early 2000s, in situ SSS data were sparsely collected in space and time. Bingham et al. (2002) looked at the distribution of SSS observations in a dataset combining the World Ocean Database 1998 (WOD98) and a thermosalinograph and bucket salinity database. They found that, for the period between 1874 and 1998, 27% of one-degree squares in the world ocean had no observations, while 70% had only 10 or fewer observations. At this time, the global large-scale time mean SSS field was known, but with almost unexplored interannual and decadal variations.

Since the early 2000s, there has been a large increase in near-surface and subsurface salinity data sampling at a global scale, with the deployment of around 3000 Argo floats in the global ocean, providing at least one salinity cast every 10 days in a three-degree cell in the top 2 km of the water column (Thierry et al., 2025).

Satellite measurements of sea surface salinity started only in 2010, with the launch of the Soil Moisture and Ocean Salinity (SMOS) satellite mission (Kerr et al., 2010). For the first time, global SSS measurements were obtained continuously every 3 days with about 43 km resolution with a synthetic aperture radiometer operating in L-Band frequency (Font et al., 2010). Another satellite L-Band radiometer, Aquarius, operated from mid-2011 to mid-2015 with an 80-150 km resolution and a 7-day global coverage (Lagerloef et al., 2008). Finally, the Soil Moisture Active Passive (SMAP) radiometer was launched in 2015 and has been providing SSS measurements with around 40 km resolution and 3-day global coverage (Entekhabi et al., 2010). Both SMOS and SMAP are still functioning, providing respectively more than 15 years and 10 years of SSS data, which opens the door to deepen the study of trends over recent years.

The novelty of the present study is that it focuses on the satellite era, a period when unprecedented temporal and spatial resolutions of observations allow for better monitoring of SSS variability and trends. Previously, only the paper of Olmedo et al. (2022) has focused on satellite SSS data for global trend analysis. However, this paper was published at a time when less than 10 years of satellite data was available and uses only 8 years of SMOS SSS data, retrieved using a different algorithm than the one used in this study. They found limited regions of statistically significant trends, which were not in good agreement with trends derived from in situ Argo data.

Therefore, there is still the question, on the one hand, if satellite data can produce similar SSS trends to the in-situ data, and on the other hand, what novelties the satellite data can bring in the study of trends. We aim to answer these questions in this paper. For this, we look at the trends in SSS from six different SSS datasets available in the Copernicus Marine database, for the last 15 years. They include satellite-only SSS datasets (SMOS-only), an optimal interpolation dataset that includes only in situ SSS (ISAS), a model reanalysis that assimilates only in situ SSS (Glorys, which also assimilates in situ and satellite SLA



and SST data) and products based on combinations of satellite and in situ SSS and SST observations (ARMOR3D, Multi Observation Global Ocean Sea Surface Salinity and SMOS/SMAP optimal interpolation). These datasets are detailed in the next section; the methods for computing the trends and their statistical significance are described in section 3; the results are presented in section 4. Because 15 years remains a short period of time for the computation of trends, in section 4 we complement the results with the long-term trends derived from a longer in situ derived product, the Institute of Atmospheric Physics (IAP) global ocean salinity gridded product. Finally, the conclusions are presented in section 5.

## 2 Data

The number of SSS products is increasing thanks to the advances in SSS from satellite observations. In this paper, we used SSS products yielded from different technologies: satellite-only, in situ-only, and a combination of both satellite and in situ data (also exploiting multivariate approaches). Table 1 summarizes the six SSS products analyzed in this work. It is important to note that among the included SSS products, some of them provide completely independent information about SSS temporal variability; for example, SMOS SSS (L3G product) is completely independent from any product using only in situ SSS measurements, such as ISAS or Glorys. At the same time, other products are not completely independent as they assimilate some of the same data. For instance, the SMOS/SMAP OI uses SMOS and ISAS data in their optimal interpolation, while the ARMOR3D uses the CNR SSS dataset in their upstream.

**Table 1: Products used in the study**

| Product ref. no. | Product ID and type                                                                    | Data access                                  | Documentation                                                                                                           |
|------------------|----------------------------------------------------------------------------------------|----------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|
| 1                | MULTIOBS_GLO_PHY_SSS_L3_MYNRT_015_014, [SMOS L3G], satellite observations              | EU Copernicus Marine Service Product (2024a) | Quality Information Document (QUID): Parracho et al. (2024)<br><br>Product User Manual (PUM): Tarot and Parracho (2024) |
| 2                | SMOS/SMAP OI<br>MULTIOBS_GLO_PHY_SSS_L4_MY_015_015, in-situ and satellite observations | EU Copernicus Marine Service Product (2024b) | QUID: Koldziejczyk (2024)<br><br>PUM: Tarot (2024)                                                                      |



|   |                                                                                                   |                                                                                        |                                                                                        |
|---|---------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|
| 3 | ISAS17, in situ data                                                                              | SEANOE,<br><a href="https://doi.org/10.17882/52367">https://doi.org/10.17882/52367</a> | Gaillard et al. (2016)<br><br>Kolodziejczyk et al. (2023)                              |
| 4 | MULTIOBS_GLO_PHY_TSUV_3D_MYNRT_015_012, [ARMOR3D], in-situ and satellite observations             | EU Copernicus Marine Service Product (2023a)                                           | QUID: Greiner et al. (2023)<br><br>PUM: Verbrugge (2023)                               |
| 5 | GLOBAL_MULTIYEAR_PHY_001_030, [Glorys], in situ data and numerical models                         | EU Copernicus Marine Service Product (2023b)                                           | QUID: Dréville et al. (2023)<br><br>PUM: Dréville et al. (2024)                        |
| 6 | MULTIOBS_GLO_PHY_S_SURFACE_MYNRT_015_013, [CNR], in-situ and satellite observations, includes SST | EU Copernicus Marine Service Product (2024c)                                           | QUID: Buongiorno Nardelli et al. (2024)<br><br>PUM : Buongiorno Nardelli et al. (2023) |

### 3 Methods

- 115 The trends were computed using the Theil-Sen method (Theil, 1950; Sen, 1968) on the monthly mean anomalies of each dataset. These anomalies were computed by removing the monthly climatology in each dataset (for the period 2011-2024) from the monthly mean data. The Theil-Sen method is a non-parametric statistic that computes the median slope of all the pairwise combinations of points. This method has been shown to be less sensitive to outliers in the data than the more commonly used least squares method (Parracho et al, 2018).
- 120 The significance of the trends was assessed using a modified Mann–Kendall test (Hamed and Rao, 1998), which is suitable for autocorrelated data. According to this test, a significant trend is a trend that is significantly different from 0 with 95% confidence.



## 4 Results

### 4.1 Intercomparison of results obtained from different Sea Surface Salinity global products

125 The global SSS trends are shown for the different products in Figure 1. The areas where the trends are not statistically significant are masked with stippling. The latitudes are restricted to between 50°S and 50°N because there are well known issues in satellite data related to sea-ice contamination and less sensitivity of the L-Band radiometric signal to SSS near the polar regions where SST is low (Reul et al. 2020, Xie et al. 2023) and there are fewer in situ data (Gabarró et al., 2023). In general, large areas of positive and negative statistically significant trends are found and are consistent across the different analysed SSS products. Slight differences are observed in the intensity of the trends, with slightly more intense trends found in SMOS L3G (product 1) and Glorys (product 5) data and slightly less intense trends in ISAS (e.g. in the North and South Atlantic, product 3). However, there are more regions of statistically significant trends in ISAS than in the other products, likely because the data is smoother. ISAS applies objective analysis with spatial and temporal smoothing to interpolate in-situ data, which reduces short-scale variability and results in a lower standard deviation. There are also differences between the products in smaller regions, such as river plumes (e.g. of the Amazon and Congo rivers) and areas of higher variability. In the SMOS L3G data, there are negative trends near the coast that are not present in the other datasets. Whether this could be related to a temporal evolution of the SMOS land-sea contamination (Kolodziejczyk et al. 2016) remains to be further studied. On the other hand, the trends in SMOS/SMAP OI (product 2) are close to those observed in ISAS, because the former uses ISAS data as upstream in the optimal interpolation. The ARMOR3D (product 4) and CNR (product 6) products also include in situ observations (and weight them differently considering characteristic temperature decorrelation scales), therefore their trends are also close to ISAS and SMOS/SMAP OI. Furthermore, since ARMOR3D uses the CNR product as an upstream, their patterns are very similar. Comparing two datasets that are completely independent in terms of temporal variabilities, SMOS L3G and Glorys, we find similar results, especially away from the coast, and in regions where trends are statistically significant.

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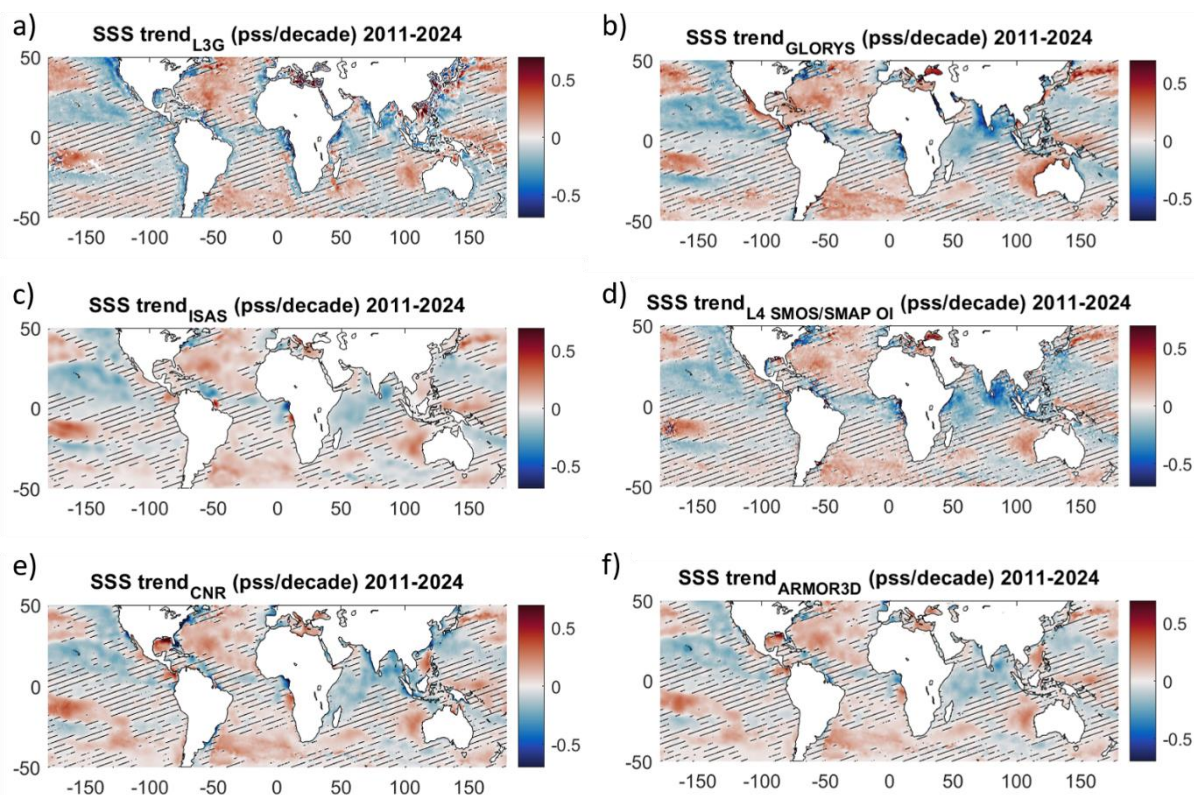
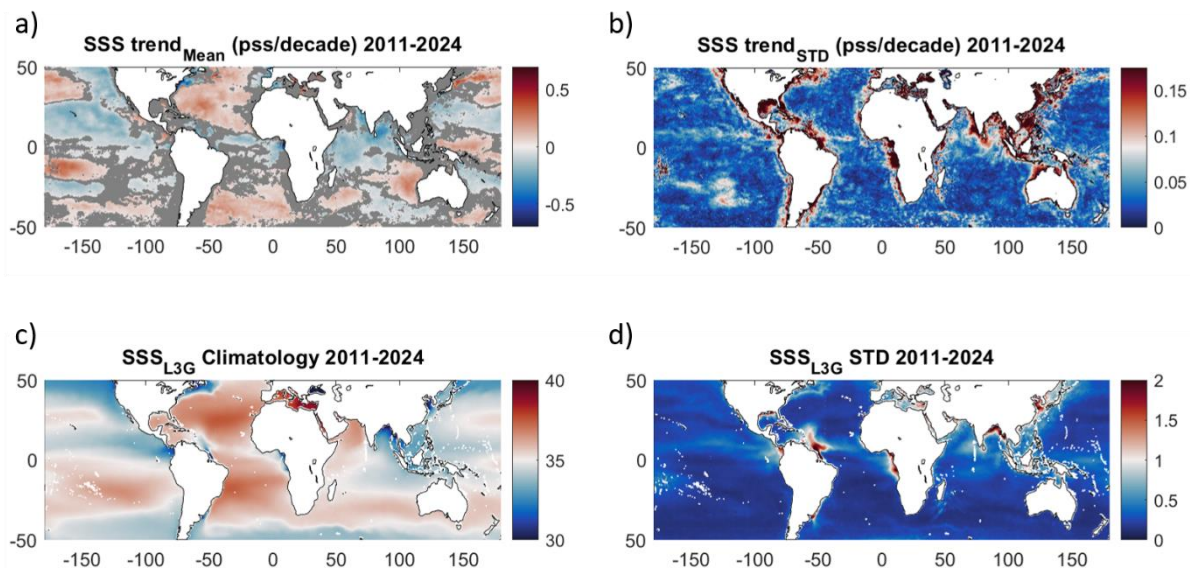


Figure 1: Linear trends (in pss per decade) in SSS computed using the Theil-Sen method for different SSS products: SMOS L3G (a), GLORYS (b), ISAS (c), SMOS/SMAP OI (d), CNR (e) and ARMOR3D (f). Regions where the trends are not statistically significant using the Mann-Kendall test are covered by stippling.





150 **Figure 2: Mean trend (a) and standard deviation of the trends (b) in the products 1-6. The mean trend is overlaid with grey stippling for the gridpoints where the standard deviation of the trends exceeds the mean of the trends. Climatology (c) and standard deviation of SSS (d) for the SMOS L3G dataset. The climatology and standard deviation maps for SMOS L3G are consistent with the results obtained from the other datasets in the study (not shown).**

Figure 2a and 2b, respectively, show the mean value and standard deviation (STD) of SSS trends obtained from the 6 product trends. The standard deviation (Figure 2b) provides information about the level of uncertainty of the estimated trends and the gridpoints where the standard deviation exceeds the trends were overlaid in white stippling over the mean trends in Fig. 2a. Some of the regions where we observe the biggest STD in the trends obtained using the six datasets (Figure 2b) correspond to river plumes. For instance, in the Amazon River plume, ISAS shows a small area of positive trends that is not observed in the other datasets, while ISAS, ARMOR3D and CNR show a positive trend in the Congo river plume that is negative in the observations-only datasets, SMOS and Glorys. These river plumes are also regions of higher standard deviation of the monthly SSS (shown for SMOS L3G in Figure 2d). Some of the regions of higher STD of the trends also correspond to regions where the radio frequency interferences (RFI) contaminate the L-band, affecting the SMOS data. This is a local effect especially seen around Samoa, Barbados, and the Guinea Gulf (Bonjean et al 2024). Finally, there are also differences close to the coast, where the SMOS L3G data has negative trends that are not observed in the other datasets. Aside from the regions mentioned above, the STD of the trends are about an order of magnitude smaller than the trends (under 0.05 pss/decade), which means that the trends derived by the different datasets are consistent with each other.

When maps of the mean salinity trends estimated from the 6 product's trends (Figure 2a) are compared to the SSS climatology (Figure 2c), we can see that some of the regions of higher salinity also have positive SSS trends, while regions of lower salinity correspond to regions of negative trends. This is observed in the North and South Atlantic, where positive trends correspond to salty regions, and in the North Pacific, where negative trends correspond to a lower salinity region. This agrees with the increase in inter-basin contrasts and the intensification of salinity patterns already described in the literature and expected in theory. Other regions where “salty gets saltier and fresh gets fresher” are Eastern Indian Ocean (where a fresh region of the east coast of India shows a freshening trend) and west of Australia (where an already saltier region has a positive SSS trend). Some regions, however, do not follow the intensification pattern. In the Southern Pacific Ocean there is a trend-dipole in a region of higher salinities, which closely resembles the patterns of SSS anomalies evolution observed and modelled during La Niña events (Figure 4 in Hasson et al. (2014)). In fact, during the period at study, there were three multi-year La Niña events (2010-2012, 2016-2018 and 2020-2023) which covered most of the investigated period and whose impact can be seen in the trends, that is negative SSS trend in the mid-latitudes in the Pacific and a positive SSS trend slightly south of the equator. Local deviations from simple water cycle amplification patterns are consistent with the results discussed in Buongiorno Nardelli and Iudicone (2025) and the trend dipole identified in the Southwestern Pacific matches almost perfectly with the patterns shown in their Figure S12, associated with the Central Pacific El Niño-Southern Oscillation mode. Both Pacific Decadal Oscillation (PDO) and El Niño Southern Oscillation (ENSO) modes can also explain the differences in the trends estimated for the Amazon plume during the different periods (and applying different techniques).



To do an exhaustive analysis of the results obtained from the different products, the SSS variability in regions with statistically significant SSS trends is analyzed further in the next subsection.

## 4.2 Regions of important changes of Sea Surface Salinity

The regions where the linear trends in SSS are significant were delimited by the boxes shown in red in Figure 3a. The monthly time series of average SSS anomalies in each box are shown in Figure 3b for the six different products and were used to compute the trends presented in Table 2, which shows the results for all products and regions. The trends' significance was tested, and non-significant trends are underlined.

The time-series of the SSS anomalies for the 8 regions, and for the 6 datasets show a general good agreement among them, with different products superposing well, even though some datasets are noisier (SMOS L3G and Glorys). Some exceptions are for example in 2024 when SMOS L3G separates from the rest of the time series for SASG; while CNR separates from the other time series in SALOMON in 2011 and EAUS in 2023 and ARMOR3D separates from the other time series at the end of 2023 in Salomon and SASG. In EIND, there is no SMOS L3G data from December 2023, due to RFI contamination in the region. In some cases, there is a clear interannual variability, such as in NPAC and SALOMON that can affect the result of the linear trend algorithm. Nevertheless, as indicated by the statistically significant trends obtained in these regions, the long-term change is more important than the interannual.

In general, according to Table 2, the trends are statistically significant in these boxes across all datasets. The only exception is EAUS in the ISAS, CNR and ARMOR3D datasets. Figure 4 shows the statistically significant trends by region and product. The results are consistent across different products, with statistically significant trends having the same sign and order of magnitude in most datasets, except for EIND, where the trends vary between -0.110 in ISAS and -0.262 in Glorys. Trends are more intense for SMOS L3G and Glorys for the SPURS, SPCZ and EAUS regions (and for Glorys in EIND), and lower for SMOS L3G in NPAC and SALOMON. Trends are higher in ISAS for SALOMON, and lower in SASG, where the trend obtained is very close to the value obtained for SMOS/SMAP OI. In general, results are consistent between SMOS/SMAP OI and ISAS (except for EIND), because ISAS is used to constrain the SMOS/SMAP OI. The similarities between CNR and ARMOR3D trends are also expected, because CNR data is used as upstream in ARMOR3D. However, it is important to note that even between the independent datasets, SMOS L3G and Glorys, there is a good agreement.

It is interesting to note that in the studied regions, the trends obtained for the climatological fresher regions are negative, but not all the trends of the climatological saltier regions are positive, with negative trends obtained in SPCZ and EAUS.

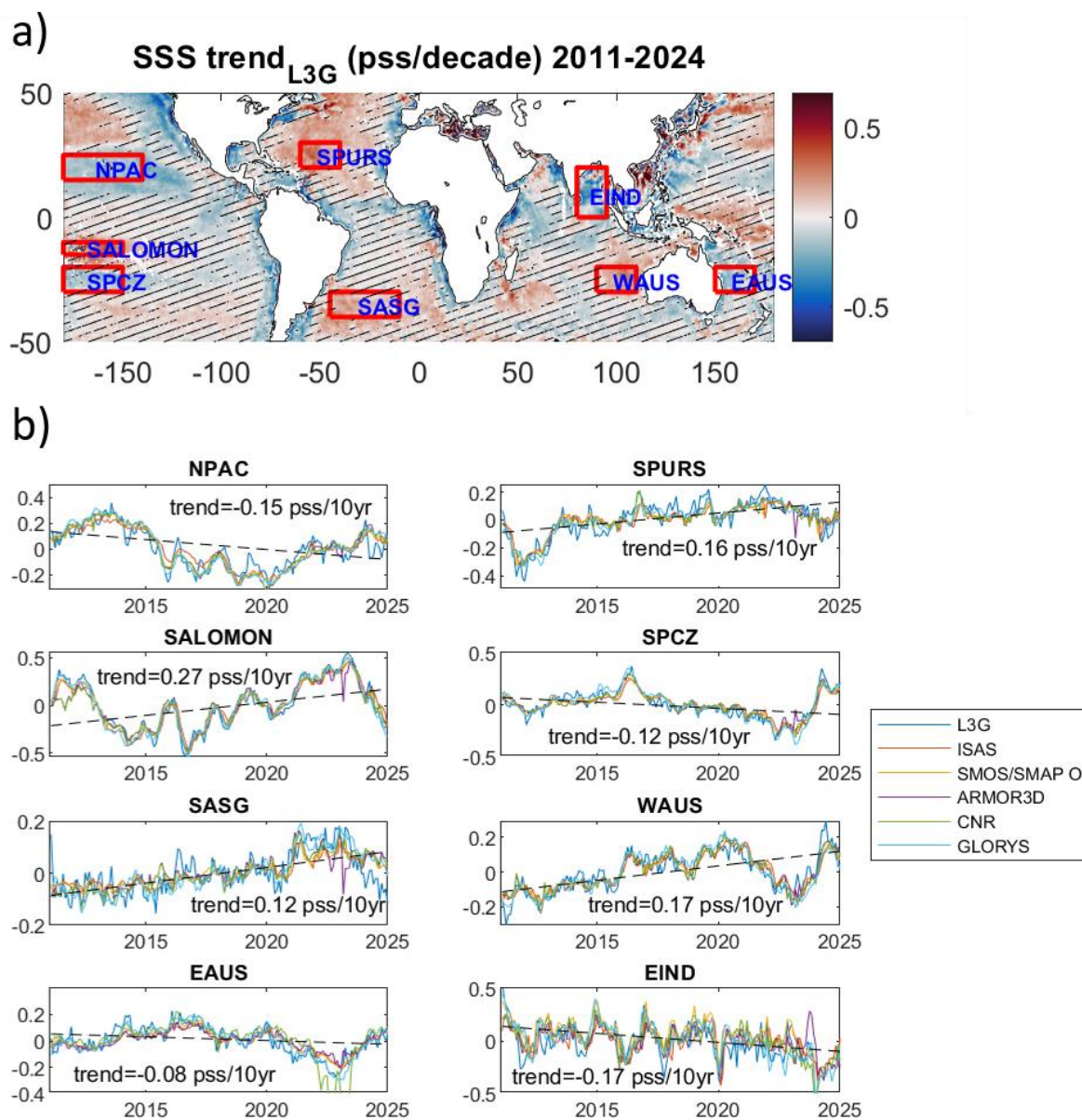
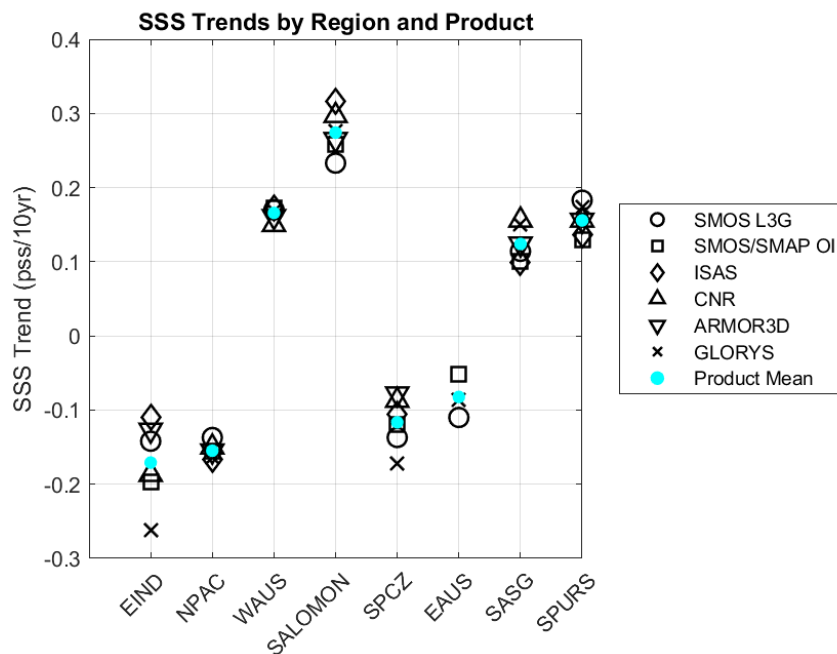


Figure 3: a) Regions selected to depict the mean SSS anomalies time series and their trends are defined by the red rectangles and correspond to the regions where the trends are significant in most of the products. b) Time series of the SSS anomalies averaged over the regions selected in a): NPAC stands for North Pacific, SPURS is the region of the Salinity Processes in the Upper Ocean Regional Study (Reverdin et al. 2015), SALOMON is the region covering the Solomon Islands, SPCZ stands for South Pacific Convergence Zone, SASG is South Atlantic Subtropical Gyre, WAUS stands for Western Australia, EAUS is Eastern Australia, EIND refers to Eastern India. The mean trend across all products for each region is represented by the dashed line and indicated in each box.



220 **Table 2: SSS linear trends computed using the Theil-Sen method in the analysed regions (in pss/10yr). Underlined values are NOT significant (p-value>0.05 in Mann-Kendall test).**

|         | SMOS L3G | SMOS/SMAP OI | ISAS   | CNR    | ARMOR3D | GLORYS |
|---------|----------|--------------|--------|--------|---------|--------|
| NPAC    | -0.137   | -0.156       | -0.167 | -0.150 | -0.155  | -0.164 |
| SPURS   | 0.183    | 0.129        | 0.136  | 0.156  | 0.156   | 0.174  |
| SALOMON | 0.233    | 0.258        | 0.316  | 0.297  | 0.265   | 0.276  |
| SPCZ    | -0.137   | -0.119       | -0.106 | -0.087 | -0.078  | -0.172 |
| SASG    | 0.114    | 0.101        | 0.099  | 0.156  | 0.124   | 0.150  |
| WAUS    | 0.170    | 0.173        | 0.173  | 0.150  | 0.161   | 0.168  |
| EAUS    | -0.110   | -0.051       | -0.043 | -0.028 | -0.02   | -0.086 |
| EIND    | -0.142   | -0.197       | -0.110 | -0.187 | -0.127  | -0.262 |

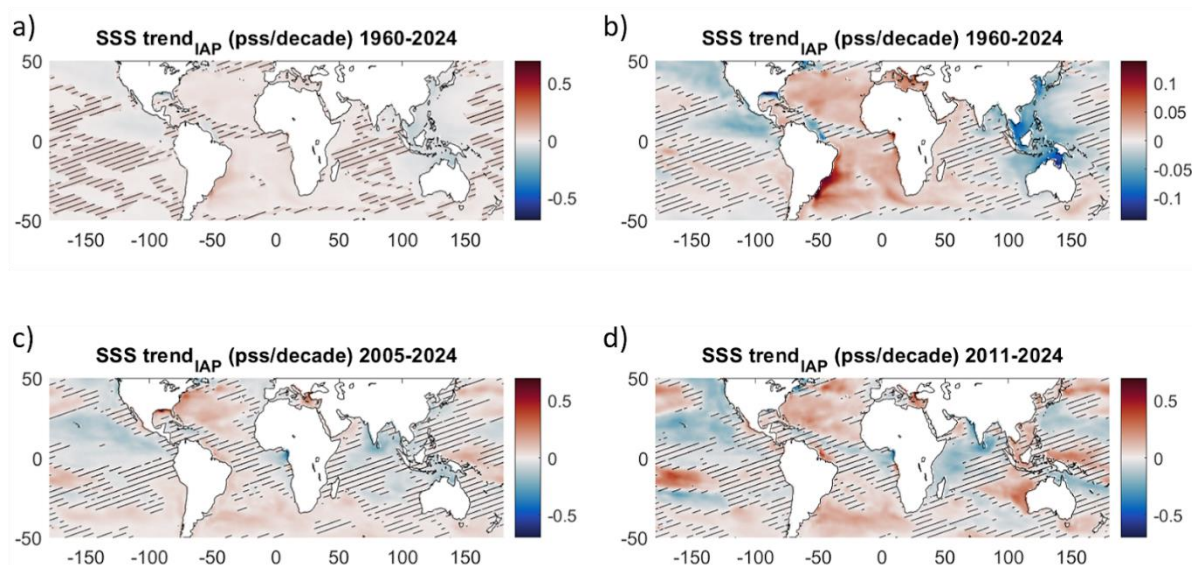


225 **Figure 4: SSS trends computed using the Theil-Sen method in the selected regions, shown in Fig. 3a (in pss/10yr) for all the data products, excluding the products where the trends are not statistically significant (p-value>0.05 in Mann-Kendall test). Regions are ordered according to their mean SSS in the regions, from the freshest region on the left to the saltiest region on the right. The light blue dot corresponds to the mean trend across all products.**



### 4.3 Comparison with long term SSS trends

To assess if the significant trends observed for the last 15 years are consistent with longer term trends, the Institute of Atmospheric Physics (IAP) global ocean salinity gridded product (Cheng, 2022), available from 1940 to present, was used. This monthly dataset has a  $1^\circ \times 1^\circ$  horizontal resolution, on 119 vertical levels, from 0 to 6000 m depth, and uses primarily bias-corrected in situ observations of CTD, Argo, Bottle, Glider, mooring etc. from the World Ocean Database (Cheng & Zhu 2016; Cheng et al. 2020). The trends and statistical significance were computed for the salinity at the first level (surface), for different time periods: 1960-2024 (the full period of the dataset was not used as data for 1940-1959 reportedly has a large uncertainty), 2005-2024 (the Argo period) and 2011-2024 (the satellite period). The results are shown in Figure 5.



**Figure 5: Linear trends computed using the Theil-Sen method for the IAP SSS product at different periods of time. The regions where the trends are not statistically significant according to the Mann-Kendal test are covered with stippling. The top panels a) and b) correspond to the trends for the 1960-2024 period. They show the same trends with different colorscales. The bottom panel includes the trends for the 2005-2024 (c) and 2011-2024 (d) periods. The colorscales in a), c) and d) are the same, for easier comparison of the order of magnitude of the trends for different time periods, while the colorscale in b) is adjusted to better visualize the less intense trends for 1960-2024.**

For the satellite period (2011-2024), the trends obtained in the IAP dataset are consistent with the ones obtained in the other datasets (compare Figure 2a with Figure 5d). The same regions of significant positive and negative trends were found. However, when the period is extended to the Argo period, the trends are less intense (by a factor of 2) and although most regions show a trend of the same sign, there are also some differences (e.g. west of Australia). For the longer 1960-2024 period,



the trends have an intensity that is even lower than the trends observed for the satellite period by a factor of 5. These results suggest an intensification of the SSS trends in the last 15 years or could also be due to the scarcity of observations in the pre-Argo period that lead the gridded observations to be too constrained by (and tend more towards) the climatology. In fact, the longer-term trends (Figures 5a and 5b) show a pattern very similar to the climatology shown in Figure 2c (as expected from the literature). In addition, trends in salinity are not linear (as seen in time series of Figure 3b), so when looking at such a short period as 15 years, some interannual and interdecadal variability may have an influence. Notably, the 2011-2023 period featured the strongest and longest La Niña events since 1980.

For example, Vinogradova and Ponte (2017) argued that between 1993 and 2010 changes in surface salinity did not follow the expected pattern of amplification of salinity contrasts, which they explained by the fact that anthropogenic hydrological signals take longer to emerge in the sea surface salinity compared the surface freshwater fluxes.

In fact, short-term trends can be very affected by internal variability, whereas long-term trends are slowly emerging. By comparing the trends obtained at different time scales we can begin to separate anthropogenic trends from natural variability. In this sense, Figure 5 highlights that the short-term trends show some regions that are consistent with the longer-term trends, most notably the increase in the interbasin contrast, with the increasing salinity trend in the North Atlantic and a decreasing salinity trend in the North Pacific. Short-term trends are also consistent with long-term trends in the salting South Atlantic and freshening Indian ocean off the coast of India. These results agree with an anthropogenic modification of the Hadley cell (Gulev et al. 2021; Pinho et al. 2021) and the long period of negative-phase Pacific Decadal Oscillation (PDO) in the years at study (Sun et al. 2022), as also suggested in Buongiorno Nardelli and Iudicone (2025). Other past studies (e.g. Wills et al 2018) have found it difficult to separate global warming from PDO and ENSO.

## 5 Conclusions

Whereas several papers have already examined long-term salinity trends using in-situ datasets, the novelty of this paper lies in the use of two independent sources of data to compute SSS trends over the past 15 years: products derived from up-to-date satellite data on one hand, and from up to date in situ data on the other hand. Satellite data offer spatial and temporal coverage of SSS that was previously unattainable, and the length of the satellite record is now becoming sufficient for deriving statistically significant trends. In this paper, we analyzed various products from different datasets and found consistent trends, even when comparing completely independent datasets such as SMOS L3G (a satellite-only dataset) and Glorys (which does not assimilate satellite SSS).

Past studies have shown that spatial patterns of salinity change over multiple decades generally resemble the average salinity fields. However, those earlier studies referred to the period from roughly 1950 to 2008 (i.e., the pre-Argo era), when observations were sparse. In contrast, our analysis covers the period from 2011 to the present and identifies several regions where the trends do not follow the pattern of the climatology. This suggests local deviations from simple water cycle amplification patterns. In fact, when comparing our results with a long-term dataset derived from a combination of in-situ data



and models, we found similar trends between the datasets over the last 15 years, but different trend patterns from the long-term trends. On the one hand, a comparison with the trends in this dataset for the Argo period (post-2005) found that the intensity of trends has increased in recent years (although there can also be Salinity sensors drift in the Argo data (Wong et al, 2020)). While, on the other hand, a comparison with the longer-term trends (1960 to present) allowed us to separate trends that are part of long-term trends (such as the positive trend in the North Atlantic, which is a common feature of all periods and products), from the trends resulting from natural variability (such as the positive and negative trend pattern found in the Tropical Pacific due to the predominance of weak to strong La Niña conditions during the study period). This study has shown that satellite, in situ and reanalysis SSS trends agree well (although longer records are still necessary to further minimize the influence of interannual and interdecadal variability), suggesting that these different SSS datasets could be used in the future to derive an SSS Ocean Monitoring Indicator.

### Data availability

The datasets used in this study are publicly available at the Copernicus Marine Service (as listed in Table 1).

ISAS data is available at SEANOE: <https://doi.org/10.17882/52367>

IAP data is available at: <http://www.ocean.iap.ac.cn/pages/dataService/dataService.html>

### Author contribution

A.C.P. wrote the manuscript with input from all co-authors and conducted the trend analysis, with assistance from P.Z. and M.S. All co-authors contributed to the conceptualization of the study and the development of the analysis method.

### Competing interests

The authors declare that they have no conflict of interest.

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