

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

Ana Claudia Parracho¹, Patricia Zunino², Michela Sammartino³, Jacqueline Boutin¹, Eric Greiner², Bruno Buongiorno Nardelli³, Nicolas Kolodziejczyk⁴

¹LOCEAN, Sorbonne Université, Paris, 75005, France

²Collecte Localisation Satellites (CLS), Ramonville-Saint-Agne, 31520, France

³National Research Council (CNR), Naples, ~~80133~~⁸⁰¹²⁴, Italy

⁴LOPS, Université de Bretagne Occidentale, Brest, 29280, France

10 *Correspondence to:* Ana Parracho (ana-claudia.parracho@locean.ipsl.fr)

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.

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 getting 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 showed that these Pacific trends and the increasing interbasin contrast cannot be explained by internal variability alone, indicating an emerging anthropogenic signal. ~~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) analyzed salinity changes from 1960 to 2017 using a new dataset, at both the surface and over the upper 2000 m. ~~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 probably of anthropogenic origin, rather than due to 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) (~~discussed further here~~~~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 ([Frankignoul et al., 2017](#)). 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 20 000 Argo floats in the global ocean. Over 4000 Argo floats are currently in operation~~~~around 3000 Argo floats in the global ocean, each~~ 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

95 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.

This raises two questions: whether satellite data can reproduce SSS trends seen in in situ data, and what new insights they provide. ~~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 ~~sevensix~~ different SSS datasets (mostly) 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 does not assimilate satellite SSS, 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 ~~isremains~~ 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.

110 2 Data

The number of SSS products is increasing thanks to the advances in satellite remote sensing of 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-seven~~ SSS products analyzed in this work, while Table 2 summarizes their input data, resolution and temporal coverage. Products 1-6 provide the core information used to derive trends over the last 15 years. It is important to note that among the included SSS products, some of them provide completely independent information about SSS temporal variability; for example, the interannual variability in SMOS SSS (~~L3G product~~) is completely independent from any product using only in situ SSS measurements, such as ISAS or ~~Glorys~~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.

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. The trends and statistical significance were computed for the salinity at the 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).

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) Product User Manual (PUM): Tarot and Parracho (2024)
2	SMOS/SMAP-01 MULTIOBS_GLO_PHY_SSS_L4_MY_015_015, in situ and satellite observations	EU Copernicus Marine Service Product (2024b)	QUID: Kolodziejczyk (2024) PUM: Tarot (2024)
3	ISAS17, in situ data	SEANOE, https://doi.org/10.17882/52367	Gaillard et al. (2016) 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) PUM: Verbrugge (2023)
5	GLOBAL_MULTIYEAR_PHY_001_030, [Glorys], in situ data and numerical models	EU Copernicus Marine Service Product (2023b)	QUID: Drévillon et al. (2023) PUM: Drévillon et al. (2024)

6	<u>MULTIOBS_GLO_PHY_S_SURFACE_MYNRT_015_013, [CNR], in situ and satellite observations, includes SST</u>	<u>EU Copernicus Marine Service Product (2024c)-</u>	<u>QUID:</u> <u>Buongiorno Nardelli et al. (2024)-</u> <u>PUM:</u> <u>Buongiorno Nardelli et al. (2023)</u>
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<u>Product ref. no. and abbreviation</u>	<u>Product ID and type</u>	<u>Data access</u>	<u>Documentation</u>
<u>1 - SMOS</u>	<u>CATDS-PDC L3OS 3G, satellite SSS observations only</u>	<u>SEXTANT, https://doi.org/10.12770/9c97fb5c-d7d5-4bc2-a5c7-57944026cd60</u>	<u>Boutin et al. (2018)</u> <u>Vergely et al. (2022)</u>
<u>2 - ISAS</u>	<u>ISAS17, in situ data</u>	<u>SEANOE, https://doi.org/10.17882/52367</u>	<u>Gaillard et al. (2016)</u> <u>Kolodziejczyk et al. (2023)</u>
<u>3 - GLORYS</u>	<u>GLOBAL MULTIYEAR PHY 001_030, in situ data and numerical models</u>	<u>EU Copernicus Marine Service Product (2023b)</u>	<u>QUID:</u> <u>Dréville et al. (2023)</u> <u>PUM:</u> <u>Dréville et al. (2024)</u>
<u>4 – SMOS/S MAP OI</u>	<u>MULTIOBS GLO PHY SSS L4 MY 015_015, in situ and satellite observations</u>	<u>EU Copernicus Marine Service Product (2024b)</u>	<u>QUID:</u> <u>Kolodziejczyk (2024)</u> <u>PUM: Tarot (2024)</u>
<u>5 - CNR</u>	<u>MULTIOBS GLO PHY S SURFACE M YNRT_015_013, in situ and satellite observations, includes SST</u>	<u>EU Copernicus Marine Service Product (2024c)</u>	<u>QUID:</u> <u>Buongiorno Nardelli et al. (2024)</u>

			<u>PUM : Buongiorno Nardelli et al. (2023)</u>
<u>6 – ARMOR3 D</u>	<u>MULTIOBS GLO PHY TSUV 3D MYN RT_015_012, in situ and satellite observations</u>	<u>EU Copernicus Marine Service Product (2023a)</u>	<u>QUID: Greiner et al. (2023)</u> <u>PUM: Verbrugge (2023)</u>
<u>7 - IAP</u>	<u>IAPs-v2, bias-corrected in situ observations</u>	<u>Ocean and Climate – Chinese Academy of Sciences</u> <u>http://www.ocean.iap.ac.cn/pages/dataService /dataService.html</u>	<u>Cheng et al. (2020)</u> <u>Cheng and Zhu (2016)</u>

Table 2: Input data, resolution and temporal coverage of the products used in the study.

<u>Product ref. no. and abbreviation</u>	<u>Input data</u>	<u>Resolution</u>	<u>Temporal coverage</u>
<u>1 - SMOS</u>	<u>SMOS SSS (CATDS L2Q Copernicus Marine Service datasets, Parracho et al. 2024)</u>	<u>1/4°</u>	<u>2010-present</u>
<u>2 - ISAS</u>	<u>In situ salinity profiles from Argo and Deep Argo floats and other in situ measurements, particularly where Argo sampling is sparse</u>	<u>1/2°</u>	<u>2002-present</u>
<u>3 - GLORYS</u>	<u>In situ salinity profiles (from EN4)</u>	<u>1/12°</u>	<u>1993-present</u>
<u>4 – SMOS/SMAP OI</u>	<u>Optimal interpolation of in situ observations (ISAS) and satellite (SMOS and SMAP) observation</u>	<u>1/4°</u>	<u>2010-present</u>
<u>5 - CNR</u>	<u>Multivariate optimal interpolation combining satellite salinity observations from SMOS and SMAP with in situ salinity measurements (Cora/Easycora Copernicus Marine</u>	<u>1/8°</u>	<u>1993-present</u>

	<u>Service datasets) and satellite OSTIA SST information</u>		
<u>6 – ARMOR3D</u>	<u>In situ observations (Argo profiling floats, XBT, CTD1 and moorings measurements) and satellite observations (the CNR product)</u>	<u>1/4°</u>	<u>1993-present</u>
<u>7 - IAP</u>	<u>Bias-corrected in situ observations of CTD, Argo, Bottle, Glider, mooring etc. from the World Ocean Database, plus data owned by the research group</u>	<u>1°</u>	<u>1940-present</u>

3 Methods

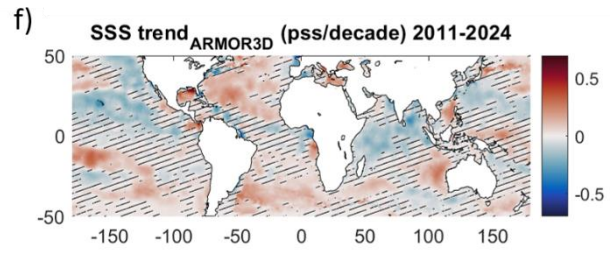
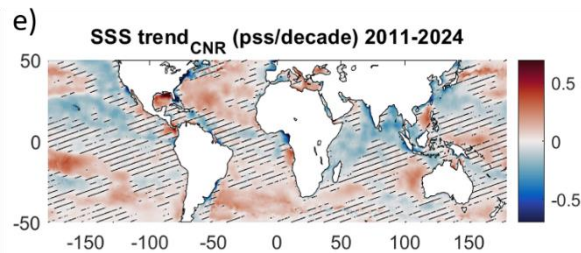
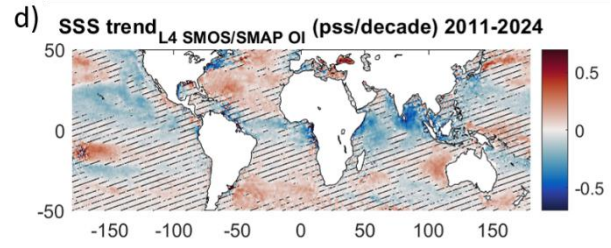
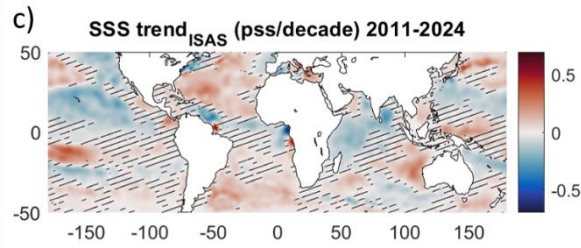
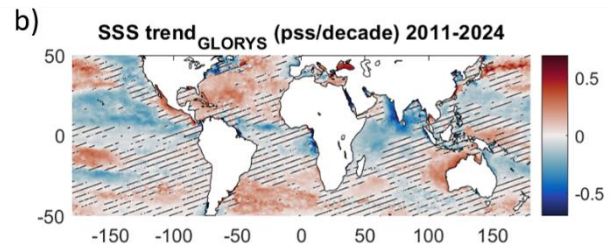
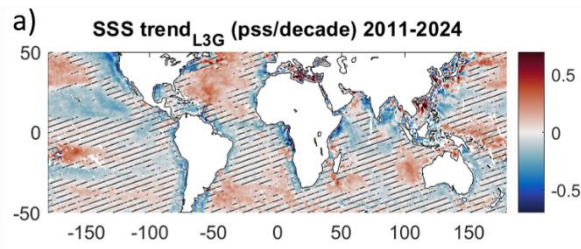
- 135 The trends were computed using the Theil-Sen method (Theil, 1950; Sen, 1968) on the monthly mean anomalies of each dataset. These anomalies were computed by removing the monthly climatology in each dataset (for the period 2011-2024) from the monthly mean data. The Theil-Sen method is a non-parametric 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).
- 140 The significance of the trends was assessed using a modified Mann–Kendall test (Hamed and Rao, 1998), which is suitable for autocorrelated data. A significant trend is one that differs from zero at 95% confidence.~~According to this test, a significant trend is a trend that is significantly different from 0 with 95% confidence.~~

4 Results

145 4.1 Intercomparison of results obtained from different Sea Surface Salinity global products

- 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 ~~lower~~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).
- 150 In general, large areas of positive and negative statistically significant trends are found, and are consistent across the different analysed SSS products. The agreement between the trends obtained with various products is particularly remarkable for

datasets that are independent, such as SMOS (product 1) and GLORYS (product 3). We find similar results for these two datasets, especially away from the coast, and in regions where trends are statistically significant. Besides, consistent trends between SMOS/SMAP OI (product 4) and ISAS (product 2) are found, which can be partly explained by the fact that ISAS is used to constrain the large scale variability of SMOS/SMAP OI. Some similarities between CNR (product 5) and ARMOR3D (product 6) trends are also expected, because CNR data is used as an upstream in ARMOR3D. -The ARMOR3D and CNR 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. Slight differences are observed in the intensity of the trends, with slightly more intense trends found in SMOS L3G (product 1) and GlorysGLORYS (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 which are areas of higher variability. In the SMOS L3G data, there are negative trends near the coast that are not present in the other datasets (e.g. in the Pacific near the coast of South America and in the Atlantic near the coast of South Africa). Whether this could be related to a temporal evolution of the SMOS land-sea contamination (Kolodziejczyk et al. 2016) remains to be further studied. Nevertheless, these negative trends appear on both ascending and descending SMOS passes (not shown) whereas SMOS land-sea contamination strongly varies between ascending and descending satellite passes. In addition, few in situ measurements are available near land and future studies would be needed to better assess trends there. 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.



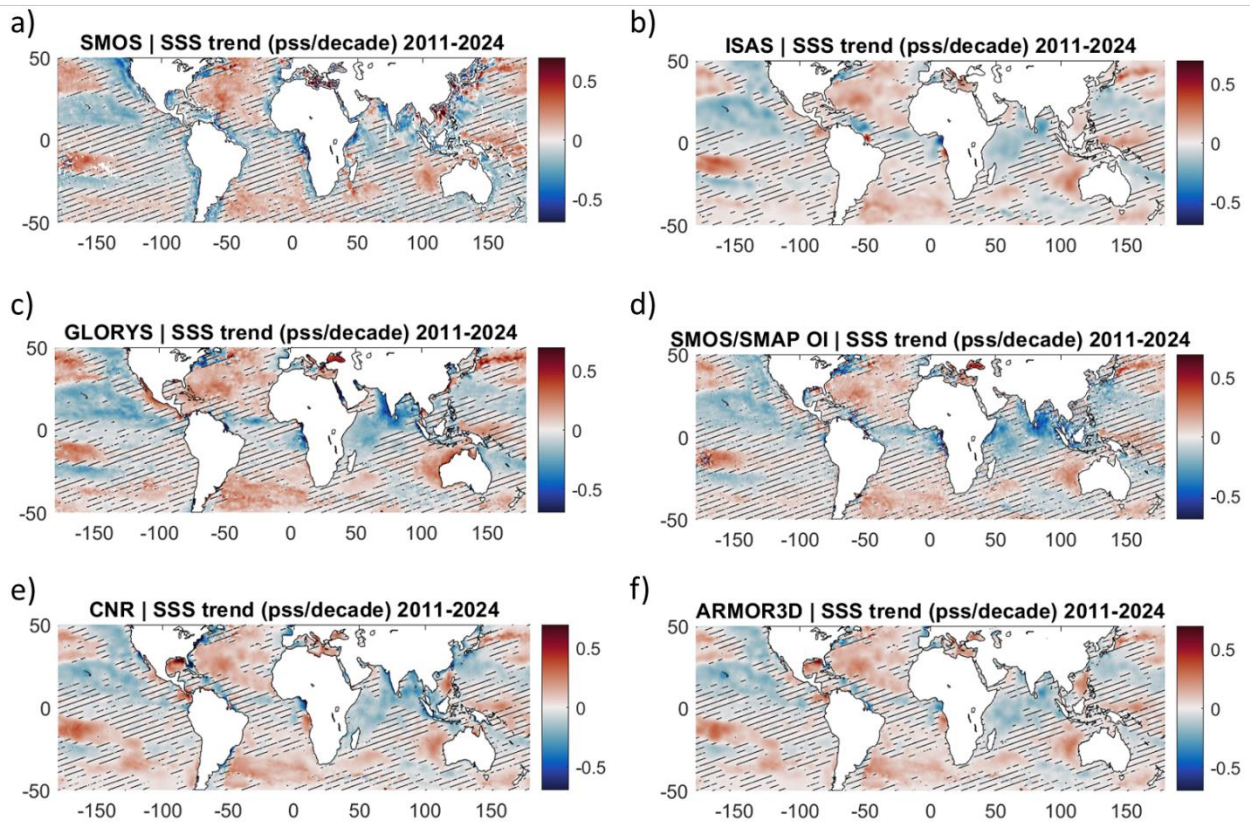


Figure 1: Linear trends (in pss per decade) in SSS computed using the Theil-Sen method for different SSS products: SMOS ~~L3G~~ (a), ~~GLORYS~~ISAS (b), ~~ISAS~~-GLORYS (c), SMOS/SMAP OI (d), CNR (e) and ARMOR3D (f). Regions where the trends are not statistically significant using the Mann-Kendall test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

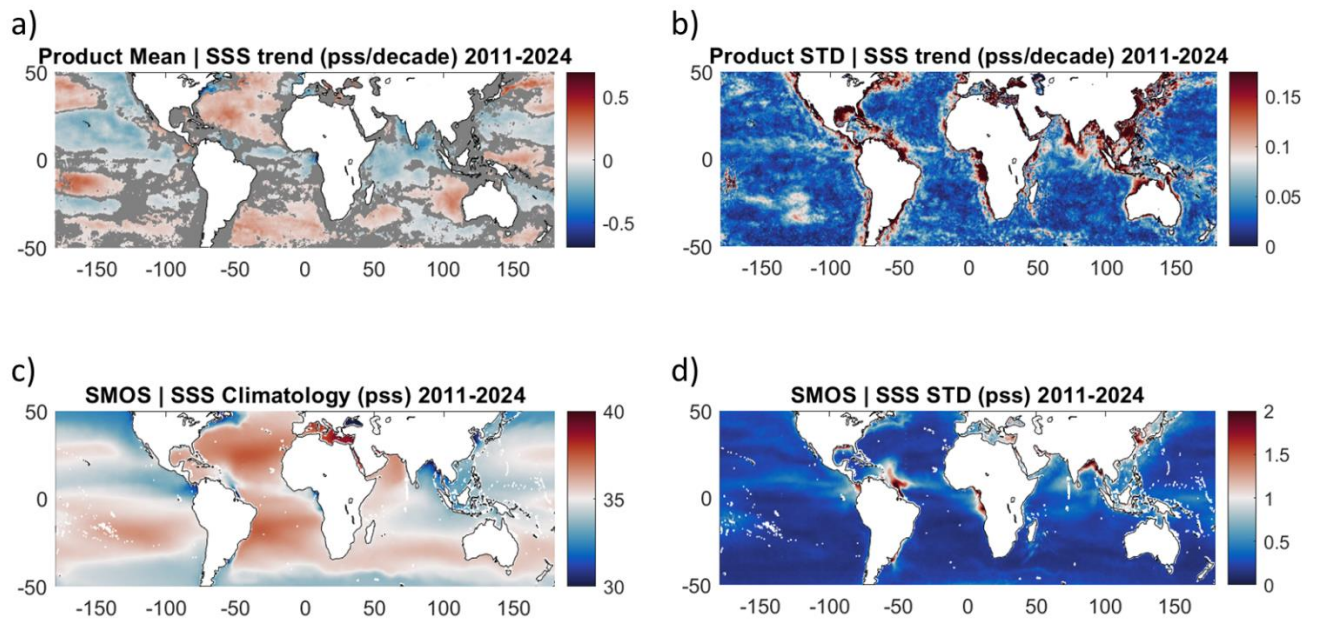
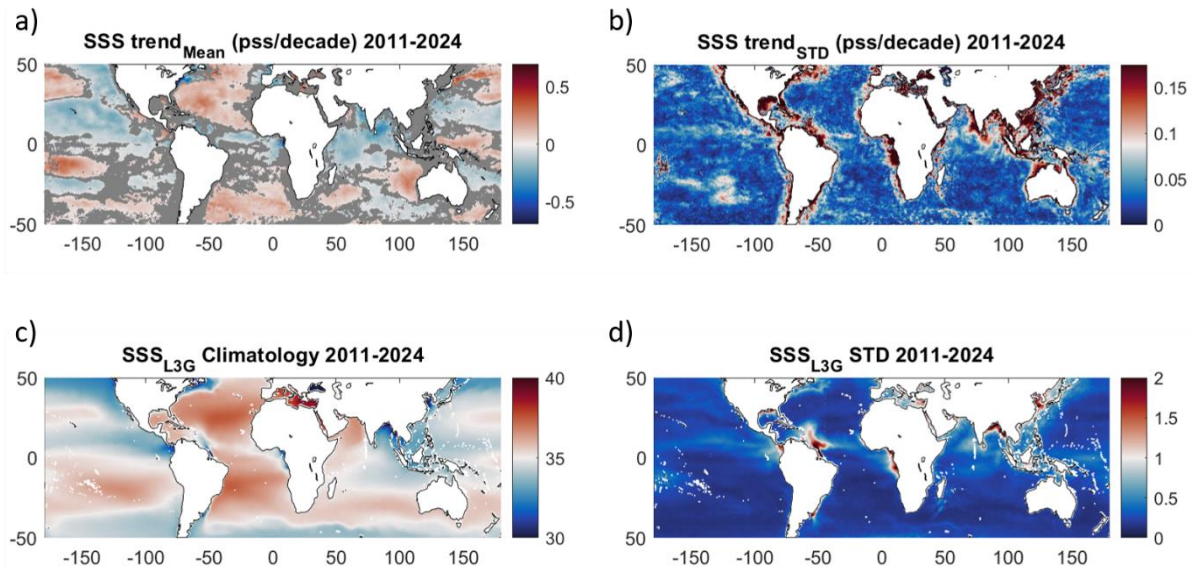


Figure 2: Mean trend (a) and standard deviation of the trends (b) in the products 1-6. The mean trend is overlaid with grey stippling for the gridpoints where the standard deviation of the trends exceeds the mean of the trends. Climatology (c) and standard deviation of SSS (d) for the SMOS **L3G**-dataset.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

In order to quantify the consistency between the trends derived from the different datasets, Figure 2a and 2b, respectively, show the mean value and standard deviation (STD) of SSS trends obtained from the 6 products were computed and are

presented in Figure 2a and 2b, respectively 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 ~~within white-grey~~ stippling over the mean trends in Fig. 2a. In general, 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. However, there are some exceptions. T~~Some of the regions where we observe~~ the biggest STD in the trends obtained using the six datasets (Figure 2b) corresponds to river plumes. For instance, in the Amazon River plume, ISAS shows a small area of positive trends (Figure 1b) 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~~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 radiometric signal, 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.~~

In order to assess if the observed statistically significant trends correspond to an intensification of salinity patterns, as described in the literature and expected in theory, the trends in Figure 2a were compared with the ~~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, we~~ can see that some of the regions of higher salinity (e.g. the North Atlantic) also have positive SSS trends, while regions of lower salinity (e.g. the North Pacific) correspond to regions of negative trends. This reveals an increase in inter-basin contrasts, ~~some of the regions of higher salinity also have positive SSS trends, while regions of lower salinity correspond to regions of negative trends. This agrees with the increase in inter basin contrasts and the intensification of salinity patterns already described in the literature and expected in theory. 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 ~~found in the Eastern~~ Indian Ocean east of India (where a fresh region ~~of the east coast of India~~ shows a freshening trend) and in the South Atlantic and west of Australia (where ~~an~~ already saltier regions ~~has have~~ 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 ~~salinitie~~salinity, 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 with a 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~~
225 ~~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, in Nardelli and
Iudicone (2025)).

To do an exhaustive analysis of the results obtained from the different products, the SSS variability in regions with statistically
230 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 most SSS products are significant were delimited by the boxes shown in red in Figure
3a (see the coordinates of the boxes in Table 3). 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 42 and Figure 4, which shows
235 the results for all products and regions. The trends' significance was tested, and non-significant trends are underlined.

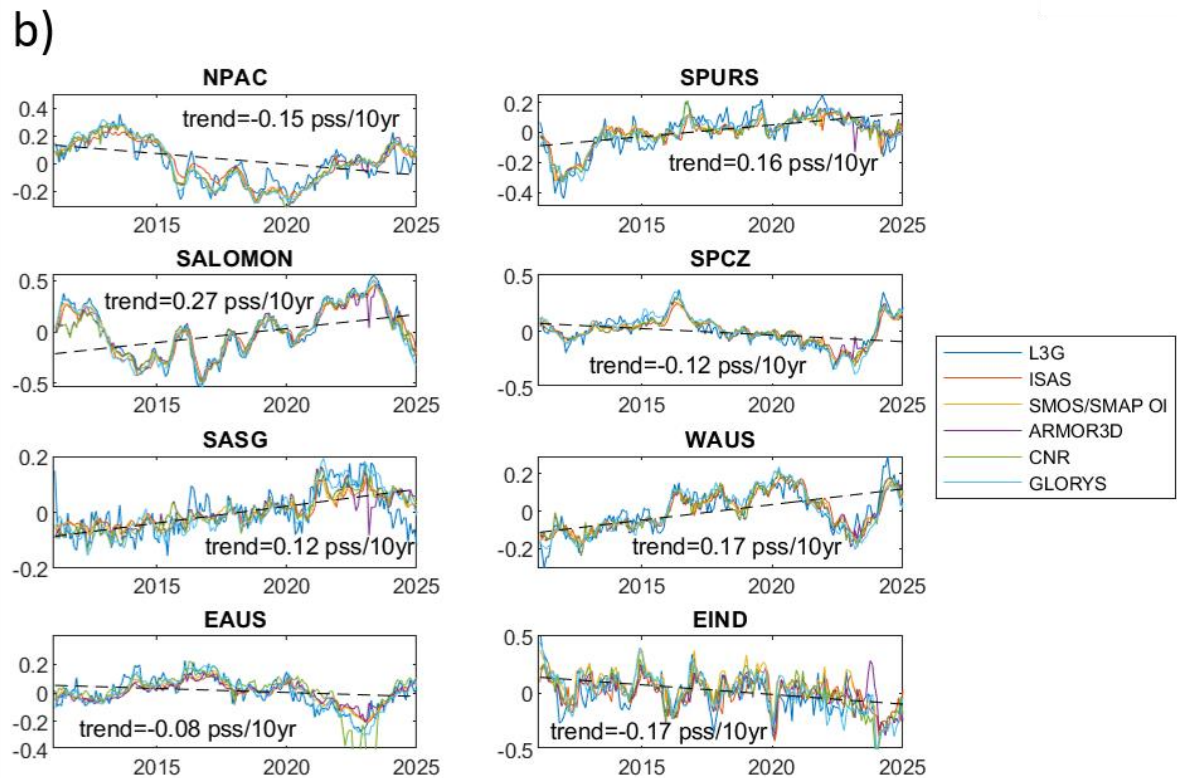
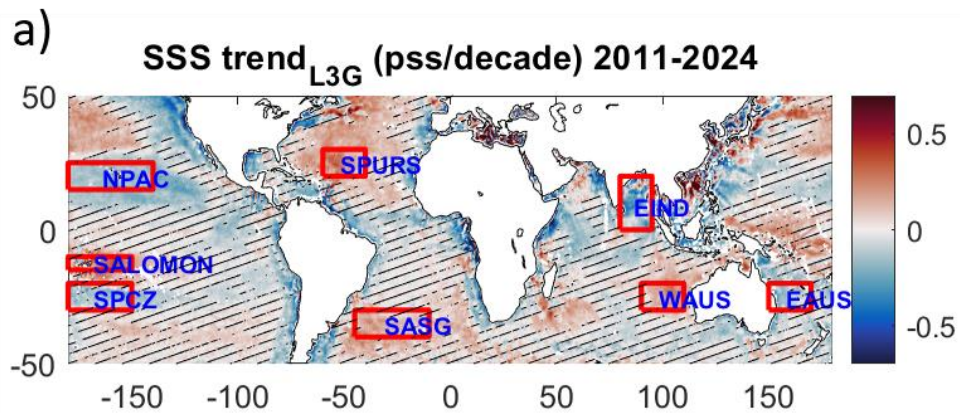
The time-series of the SSS anomalies ~~of the 6 datasets in each of the 8 regions for the 8 regions, and for the 6 datasets~~ show a
general good agreement among them, with different products superposing well (Figure 3b).

In spite of the general good agreement between SSS products, some differences are observed between the time series from the
various products (Figure 3b). even though On the one hand, some datasets ~~are noisier (SMOS L3G and Glorys)~~ show slightly
240 more variability in certain regions. For example, SMOS and GLORYS show higher variability in the eastern Indian Ocean,
where sparse in situ coverage coincides with strong coastal signals linked to river discharge and surface currents that are well
captured by SMOS (Akhil et al., 2020). Increased variability in these datasets is also found in stratified regions such as the
South Pacific near the South Pacific Convergence Zone (SPCZ), likely reflecting differences in SSS representation. Whereas
SMOS samples only the upper centimeter of the ocean and GLORYS represents an average over the top meter (effectively a
245 surface measure), the other datasets are more strongly influenced by deeper in situ observations. In addition, the 1/12° eddy-
resolving resolution of GLORYS in the tropics may amplify variability, even at low frequencies, compared to lower-resolution
or more strongly filtered products. Conversely, in the Solomon Islands region, the higher SMOS variability may also be related
to RFI contamination (Bonjean et al., 2024).

~~Some exceptions are for example~~ On the other hand, some of the datasets separate from the others at certain periods of time.
250 ~~For instance, in 2024 when SMOS L3G separates from the rest of the time series for SASG; while the~~ CNR time series separates
from the other ~~s~~ time series in the Solomon Islands SALOMON in 2011, -ARMOR3D, which assimilates the CNR data, also
follows this discrepancy (probably related to the number and treatment of in situ observations, and handling of background in
their processing chains). ~~and~~ In the East of Australia EAUS in the 2022-2023 period, - the higher weight given to in situ
observations in the CNR processing algorithm may enhance the representation of certain regional processes that are less evident
255 in the other datasets. In this context, the stronger negative SSS anomalies observed in CNR SSS in 2022–2023 may be
associated with precipitation variability affecting the western New Caledonia region and consequently the East of Australia

area in that period (Blunden et al. 2023), and ARMOR3D separates from the other time series at the end of February 2023 in the Solomon Islands, SALOMON, and SASC, the South Atlantic, the North Atlantic, and the Eastern Indian Ocean. This is because of anomalous data assimilated in the ARMOR3D near real time (NRT) data, which was used to complete the reprocessed time series, for the last two years of the period at study. In the Eastern Indian Ocean, EIND, there is no SMOS L3G or SMOS/SMAP OI data from December 2023, due to RFI contamination in the satellite data in the region. Finally, SMOS separates from the rest of the time series in the South Atlantic after 2024 for an unclear reason. For all the datasets, in some cases, regions, there is shown a clear interannual variability, such as in the North Pacific, NPAC, and the Solomon Islands, SALOMON, that can affect the result of the linear trend algorithm. Nevertheless, as indicated by the statistically significant trends obtained in these regions, indicate a robust the long-term change is more important than despite the interannual variability. In general, according to Table 4 and Figure 4, the trends are statistically significant in these boxes across all datasets, with the exception of East of Australia in the ISAS, CNR and ARMOR3D datasets, with statistically significant trends having the same sign and order of magnitude in most datasets. 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 the South Pacific and East of Australia. Finally, the Eastern Indian Ocean is the region where the trends vary the most from one product to another (between -0.110 pss/decade in ISAS and -0.262 pss/decade in GLORYS, Table 4).

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 SASC, 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.



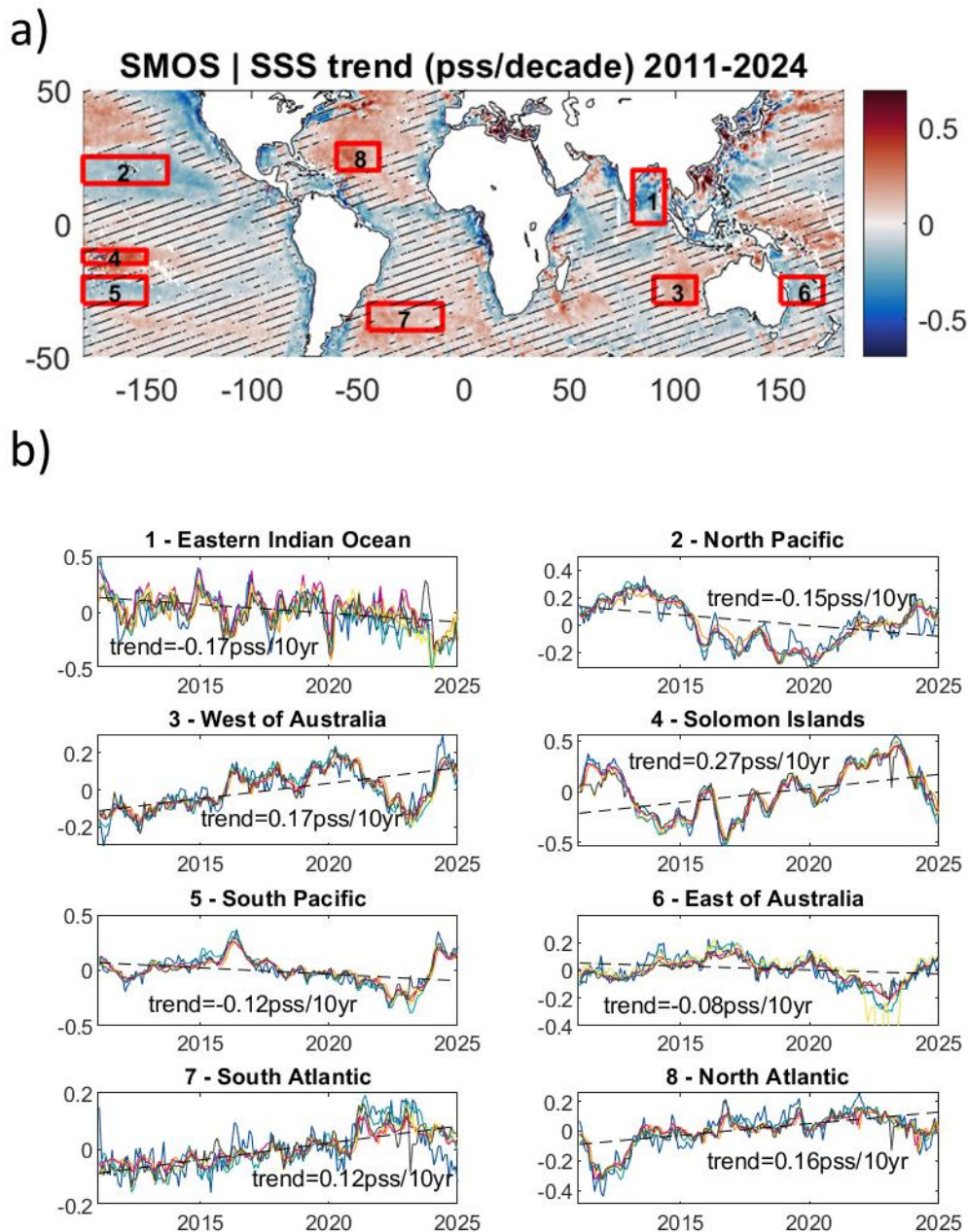


Figure 3: a) Regions selected to depict the mean SSS anomalies time series and their trends are defined by the red rectangles and correspond to the regions where the trends are significant in most of the products. Regions are ordered according to their mean SSS in the regions, from the freshest region (1) to the saltiest region (8). b) Time series of the SSS anomalies averaged over the regions selected in a): 1 is the Eastern Indian Ocean, 2 is the North Pacific, 3 corresponds to West of Australia, 4 to region of the Solomon Islands, 5 to South Pacific, 6 to South Atlantic and 8 to North Atlantic. 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,

295 ~~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.

Table 3: Coordinates of the red boxes defined in Figure 3a.

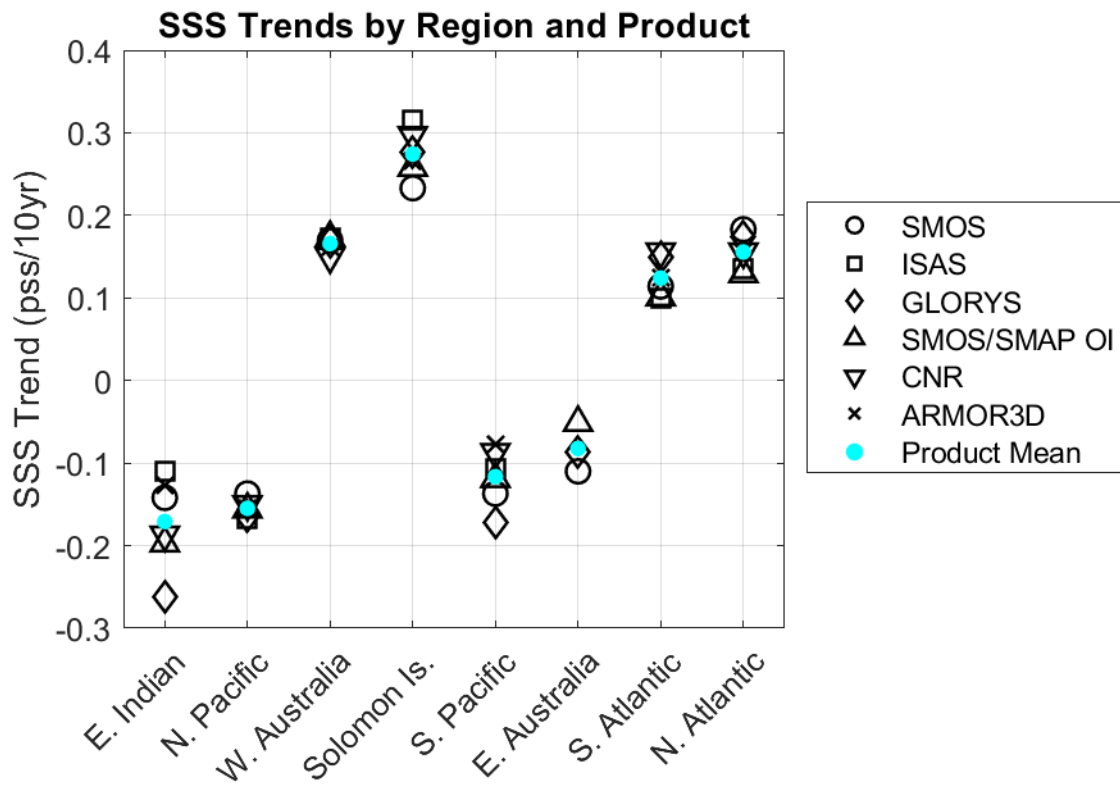
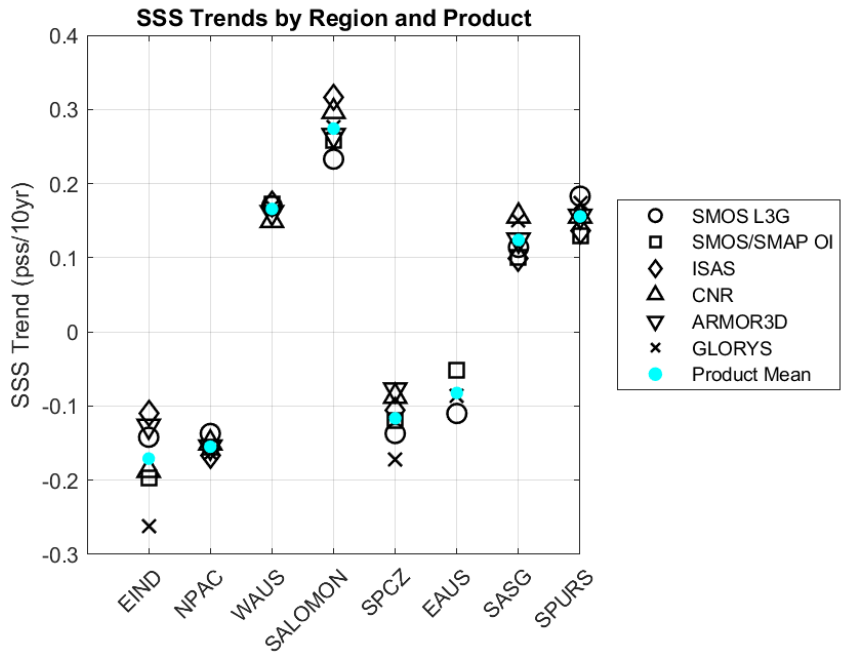
	<u>Minimum Latitude</u> (°N)	<u>Maximum Latitude</u> (°N)	<u>Minimum Longitude</u> (°E)	<u>Maximum Longitude</u> (°E)
<u>1- Eastern Indian Ocean</u>	<u>0</u>	<u>20</u>	<u>80</u>	<u>95</u>
<u>2 - North Pacific</u>	<u>15</u>	<u>25</u>	<u>-180</u>	<u>-140</u>
<u>3 - West of Australia</u>	<u>-30</u>	<u>-20</u>	<u>90</u>	<u>110</u>
<u>4 - Solomon Islands</u>	<u>-15</u>	<u>-10</u>	<u>-180</u>	<u>-150</u>
<u>5 - South Pacific</u>	<u>-30</u>	<u>-20</u>	<u>-180</u>	<u>-150</u>
<u>6 - East of Australia</u>	<u>-30</u>	<u>-20</u>	<u>150</u>	<u>170</u>
<u>7 - South Atlantic</u>	<u>-40</u>	<u>-30</u>	<u>-45</u>	<u>-10</u>
<u>8 - North Atlantic</u>	<u>20</u>	<u>30</u>	<u>-60</u>	<u>-40</u>

300 **Table 24:** 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	ISAS		SMOS/SMAP OI	CNR	ARMOR3D
Eastern Indian Ocean	-0.142	-0.110	-0.262	-0.197	-0.187	-0.127
North Pacific	-0.137	-0.167	-0.164	-0.156	-0.150	-0.155
West of Australia	0.170	0.173	0.168	0.173	0.150	0.161
Solomon Islands	0.233	0.316	0.276	0.258	0.297	0.265
South Pacific	-0.137	-0.106	-0.172	-0.119	-0.087	-0.078

<u>East of Australia</u>	<u>-0.110</u>	<u>-0.043</u>	<u>-0.086</u>	<u>-0.051</u>	<u>-0.028</u>	<u>-0.02</u>
<u>South Atlantic</u>	<u>0.114</u>	<u>0.099</u>	<u>0.150</u>	<u>0.101</u>	<u>0.156</u>	<u>0.124</u>
<u>North Atlantic</u>	<u>0.183</u>	<u>0.136</u>	<u>0.174</u>	<u>0.129</u>	<u>0.156</u>	<u>0.156</u>

	<u>SMOS</u>	<u>ISAS</u>	<u>GLORYS</u>	<u>SMOS/SMAP OI</u>	<u>CNR</u>	<u>ARMOR3D</u>
<u>1 - Eastern Indian Ocean</u>	<u>-0.142</u>	<u>-0.110</u>	<u>-0.262</u>	<u>-0.197</u>	<u>-0.187</u>	<u>-0.127</u>
<u>2 - North Pacific</u>	<u>-0.137</u>	<u>-0.167</u>	<u>-0.164</u>	<u>-0.156</u>	<u>-0.150</u>	<u>-0.155</u>
<u>3 - West of Australia</u>	<u>0.170</u>	<u>0.173</u>	<u>0.168</u>	<u>0.173</u>	<u>0.150</u>	<u>0.161</u>
<u>4 - Solomon Islands</u>	<u>0.233</u>	<u>0.316</u>	<u>0.276</u>	<u>0.258</u>	<u>0.297</u>	<u>0.265</u>
<u>5 - South Pacific</u>	<u>-0.137</u>	<u>-0.106</u>	<u>-0.172</u>	<u>-0.119</u>	<u>-0.087</u>	<u>-0.078</u>
<u>6 - East of Australia</u>	<u>-0.110</u>	<u>-0.043</u>	<u>-0.086</u>	<u>-0.051</u>	<u>-0.028</u>	<u>-0.02</u>
<u>7 - South Atlantic</u>	<u>0.114</u>	<u>0.099</u>	<u>0.150</u>	<u>0.101</u>	<u>0.156</u>	<u>0.124</u>
<u>8 - North Atlantic</u>	<u>0.183</u>	<u>0.136</u>	<u>0.174</u>	<u>0.129</u>	<u>0.156</u>	<u>0.156</u>



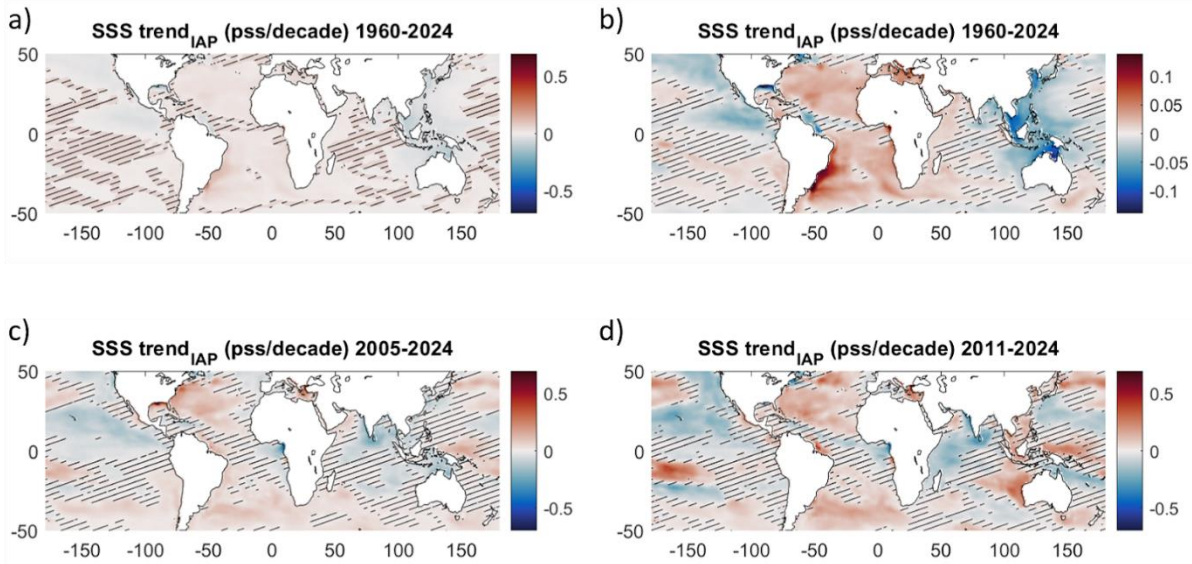
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Figure 4: SSS trends computed using the Theil-Sen method in the selected regions, shown in Fig. 3a (in pss/10yr) for all the data products, excluding the products where the trends are not statistically significant (p-value>0.05 in Mann-Kendall test). 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

315

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.



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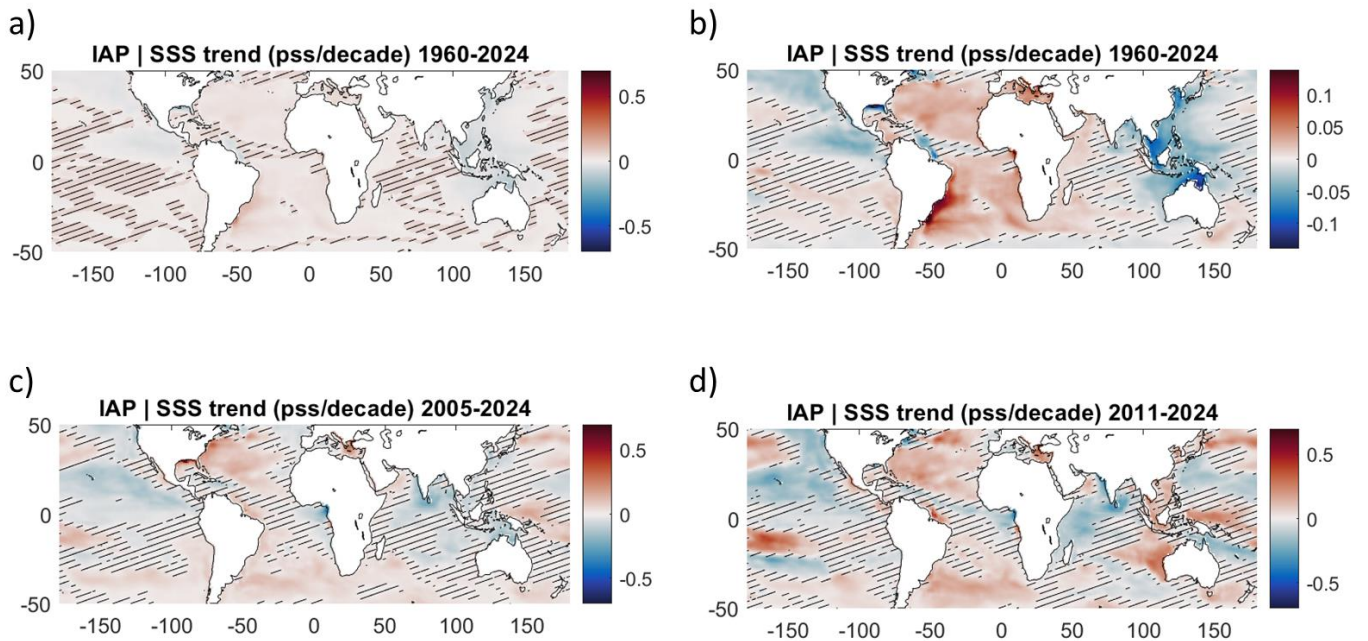


Figure 5: Linear trends in SSS computed using the Theil-Sen method for the IAP-SSS product at different periods of time. The regions where the trends are not statistically significant according to the Mann-Kendal test are covered with stippling. The top panels a) and b) correspond to the trends for the 1960-2024 period. They show the same trends with different colorscales. The bottom panel includes the trends for the 2005-2024⁴³ (c) and 2011-2024⁴³ (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.

The IAP product was used to assess if the results for the last 15 years are consistent with longer term trends. 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), and 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 as the sign of the trends estimated for the satellite period, 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. In fact, Moreover, the longer-term trends (Figures 5a and 5b) show a pattern very similar to the SSS climatology shown in Figure 2c (as expected from the literature). 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, when looking at such a short

340 ~~period as 15 years, interannual and interdecadal variability have a strong influence on the estimation of a linear trend (as seen in the time series of Figure 3b), and 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~~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
345 ~~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 in~~ some regions ~~that~~ are consistent with the longer-term
350 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 increasing salinity of the~~ 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
355 Iudicone (2025). Other past studies (e.g. Wills et al 2018) have also 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: up-to-date products derived from ~~up-~~
360 ~~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~~GLORYS (a
365 ~~model reanalysis which assimilates only in situ salinity which does not assimilate satellite SSS and other in situ and satellite parameters~~).

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
370 amplification patterns. This was also found, for example, by Vinogradova and Ponte (2017) for the period between 1993 and 2010, which they explained by the fact that anthropogenic hydrological signals take longer to emerge in the sea surface salinity

compared to the surface freshwater fluxes. Indeed, comparison of our results with a long-term dataset derived from a combination of in situ observations and model outputs reveals consistent trends between the datasets over the past 15 years; however, these patterns differ from the longer-term trends. 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~~ showed that the intensity of trends has increased in recent years (although there can also be ~~Salinity~~ 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 2011-2024 study period).

This study has shown that satellite, in situ and reanalysis SSS trends agree well in most regions (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).

SMOS data is available at SEXTANT: <https://doi.org/10.12770/9c97fb5c-d7d5-4bc2-a5c7-57944026cd60>

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.

References

Bingham, F. M., Howden, S. D., and Koblinsky, C. J.: Sea surface salinity measurements in the historical database, J. Geophys. Res.-Oceans, 107(C12), SRF-20, 2002.

Blunden, J., Boyer, T., and Bartow-Gillies, E., eds.: State of the climate in 2022, *Bull. Am. Meteorol. Soc.*, 104, S1–S501.,
 400 2023.

Bonjean, F., Boutin, J., Vergely, J. L., Richaume, P., and Sabia, R.: Recovery of SMOS salinity variability in RFI-contaminated regions, *IEEE T. Geosci. Remote Sens.*, 2024.

Boutin, J., Vergely, J.-L., Marchand, S., D'Amico, F., Hasson, A., Kolodziejczyk, N., Reul, N., Reverdin, G., and Vialard, J.:
 405 New SMOS sea surface salinity with reduced systematic errors and improved variability, *Remote Sens. Environ.*, 214, 115–
134, <https://doi.org/10.1016/j.rse.2018.05.022>, 2018.

Buongiorno Nardelli, B. and Sammartino, M.: EU Copernicus Marine Service Product User Manual for the Multi Observation Global Ocean Sea Surface Salinity and Sea Surface Density, MULTIOBS_GLO_PHY_S_SURFACE_MYNRT_015_013, issue 1.3, Mercator Ocean International, last access: 16 July 2025, 2023.

Buongiorno Nardelli, B. and Pisano, A. and Sammartino, M.: EU Copernicus Marine Service Quality Information Document
 410 for the Multi Observation Global Ocean Sea Surface Salinity and Sea Surface Density, MULTIOBS_GLO_PHY_S_SURFACE_MYNRT_015_013, issue 1.4, Mercator Ocean International, <https://documentation.marine.copernicus.eu/QUID/CMEMS-MOB-QUID-015-013.pdf>, last access: 16 July 2025, 2024.

Buongiorno Nardelli, B. and Iudicone, D.: A dynamical geography of observed trends in the global ocean, *Sci. Adv.*, 11(17), 3532, 2025.

415 Cheng, L.: IAP observational salinity gridded dataset at 0.25 resolution, *Inst. Atmos. Phys., Chin. Acad. Sci.*, 2022.

Cheng, L. and Zhu, J.: Benefits of CMIP5 multimodel ensemble in reconstructing historical ocean subsurface temperature variations, *J. Climate*, 29, 5393–5416, 2016.

Cheng, L., Trenberth, K. E., Gruber, N., Abraham, J. P., Fasullo, J. T., Li, G., Mann, M. E., Zhao, X., and Zhu, J.: Improved estimates of changes in upper ocean salinity and the hydrological cycle, *J. Climate*, 33, [https://doi.org/10.1175/JCLI-D-20-](https://doi.org/10.1175/JCLI-D-20-0366.1)
 420 [0366.1](https://doi.org/10.1175/JCLI-D-20-0366.1), 2020.

Douville, H., Raghavan, K., Renwick, J., Allan, R. P., Arias, P. A., Barlow, M., Cerezo-Mota, R., Cherchi, A., Gan, T. Y., Gergis, J., Jiang, D., Khan, A., Pokam Mba, W., Rosenfeld, D., Tierney, J., and Zolina, O.: Water Cycle Changes, in: *Climate Change 2021: The Physical Science Basis*, Cambridge Univ. Press, 1055–1210, <https://doi.org/10.1017/9781009157896.010>, 2021.

425 Drévillon, M., Lellouche, J.-M., Régnier, C., Garric, G., Bricaud, C., Hernandez, O., and Bourdallé-Badie, R.: EU Copernicus Marine Service Quality Information Document for the Global Ocean Physics Reanalysis, GLOBAL_REANALYSIS_PHY_001_030, issue 1.6, Mercator Ocean International, <https://documentation.marine.copernicus.eu/QUID/CMEMS-GLO-QUID-001-030.pdf>, last access: 16 July 2025, 2023.

Drévillon, M., Fernandez, E., and Lellouche, J.-M.: EU Copernicus Marine Service Product User Manual for the Global Ocean
 430 Physics Reanalysis, GLOBAL_REANALYSIS_PHY_001_030, issue 1.6, Mercator Ocean International, <https://documentation.marine.copernicus.eu/PUM/CMEMS-GLO-PUM-001-030.pdf>, last access: 16 July 2025, 2024.

- Durack, P. J. and Wijffels, S. E.: Fifty-year trends in global ocean salinities and their relationship to broad-scale warming, *J. Climate*, 23, 4342–4362, <https://doi.org/10.1175/2010JCLI3377.1>, 2010.
- Entekhabi, D., Njoku, E. G., O’Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., Entin, J. K., and Yueh, S.: The soil moisture active passive (SMAP) mission, *Proc. IEEE*, 98, 704–716, <https://doi.org/10.1109/JPROC.2010.2043918>, 2010.
- EU Copernicus Marine Service Product: Multi Observation Global Ocean 3D Temperature Salinity Height Geostrophic Current and MLD, Mercator Ocean International, <https://doi.org/10.48670/moi-00052>, 2023a.
- EU Copernicus Marine Service Product: Global Ocean Physics Reanalysis, Mercator Ocean International, <https://doi.org/10.48670/moi-00021>, 2023b.
- EU Copernicus Marine Service Product: SMOS CATDS Qualified (L2Q) Sea Surface Salinity product, Mercator Ocean International, <https://doi.org/10.1016/j.rse.2016.02.061>, 2024a.
- EU Copernicus Marine Service Product: SSS SMOS/SMAP L4 OI - LOPS-v2023, Mercator Ocean International, <https://doi.org/10.1175/JTECH-D-20-0093.1>, 2024b.
- EU Copernicus Marine Service Product: Multi Observation Global Ocean Sea Surface Salinity and Sea Surface Density, Mercator Ocean International, <https://doi.org/10.48670/moi-00051>, 2024c.
- Font, J., Camps, A., Borges, A., Martin-Neira, M., Boutin, J., Reul, N., Kerr, Y. H., Hahne, A., and Mecklenburg, S.: SMOS: The challenging sea surface salinity measurement from space, *Proc. IEEE*, 98(5), 649–665, <https://doi.org/10.1109/JPROC.2009.2033096>, 2010.
- Frankignoul, C., Gastineau, G., and Kwon, Y.-O.: Estimation of the SST response to anthropogenic and external forcing and its impact on the Atlantic multidecadal oscillation and the Pacific decadal oscillation, *J. Climate*, 30, 9871–9895, 2017.
- Gabarró, C., Hughes, N., Wilkinson, J., Bertino, L., Bracher, A., Diehl, T., Dierking, W., Gonzalez-Gambau, V., Lavergne, T., Madurell, T., Malnes, E., and Wagner, P. M.: Improving satellite-based monitoring of the polar regions: Identification of research and capacity gaps, *Front. Remote Sens.*, 4, 952091, 2023.
- Gaillard, F., Reynaud, T., Thierry, V., Kolodziejczyk, N., and von Schuckmann, K.: In-situ based reanalysis of the global ocean temperature and salinity with ISAS: variability of the heat content and steric height, *J. Climate*, 29(4), 1305–1323, <https://doi.org/10.1175/JCLI-D-15-0028.1>, 2016.
- Gould, W. J. and Cunningham, S. A.: Global-scale patterns of observed sea surface salinity intensified since the 1870s, *Earth Syst. Sci. Data*, 13, 2737–2760, <https://doi.org/10.5194/essd-13-2737-2021>, 2021.
- Greiner, E., Verbrugge, N., and Mulet, S., and Guinehut, S.: EU Copernicus Marine Service Quality Information Document for the Multi Observation Global Ocean 3D Temperature Salinity Height Geostrophic Current and MLD, MULTIOBS_GLO_PHY_TSUV_3D_MYNRT_015_012, issue 1.2, Mercator Ocean International, <https://documentation.marine.copernicus.eu/QUID/CMEMS-MOB-QUID-015-012.pdf>, last access: 16 July 2025, 2023.
- Greiner, E., Remy, E., Tranchant, B., and Legalloudec, O.: Data assimilation of Soil Moisture and Ocean Salinity (SMOS) observations into the Mercator Ocean operational system: focus on the El Niño 2015 event, *Ocean Sci.*, 15, 543–563, 2019.

- 465 Gu, L. and Yin, J. et al.: Intensification of global hydrological droughts under anthropogenic climate warming, *Water Resour. Res.*, 59(1), e2022WR032997, 2022.
- Gudmundsson, L., Boulange, J., Do, H. X., Gosling, S. N., Grillakis, M. G., Koutroulis, A. G., and Zhao, F.: Globally observed trends in mean and extreme river flow attributed to climate change, *Science*, 371, 1159–1162, 2021.
- Gulev, S. K., Thorne, P. W., Ahn, J., Dentener, F. J., Domingues, C. M., Gerland, S., and Vose, R. S.: Changing state of the
470 climate system, in: *Climate Change 2021: The Physical Science Basis, Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, 287–422, <https://doi.org/10.1017/9781009157896.004>, 2021.
- Hamed, K. H. and Rao, A. R.: A modified Mann-Kendall trend test for autocorrelated data, *J. Hydrol.*, 204(1–4), 182–196, 1998.
- 475 Hasson, A., Delcroix, T., Boutin, J., Dussin, R., and Ballabrera-Poy, J.: Analyzing the 2010–2011 La Niña signature in the tropical Pacific sea surface salinity using in situ data, SMOS observations, and a numerical simulation, *J. Geophys. Res.-Oceans*, 119(6), 3855–3867, <https://doi.org/10.1002/2014JC009864>, 2014.
- Held, I. M. and Soden, B. J.: Robust responses of the hydrological cycle to global warming, *J. Climate*, 19(21), 5686–5699, <https://doi.org/10.1175/JCLI3990.1>, 2006.
- 480 IPCC: *Climate Change 2021: The Physical Science Basis, Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by: Masson-Delmotte, V. et al., Cambridge Univ. Press, <https://doi.org/10.1017/9781009157896>, 2021.
- Kerr, Y. H., Waldteufel, P., Wigneron, J. P., Delwart, S., Cabot, F., Boutin, J., and Mecklenburg, S.: The SMOS mission: New tool for monitoring key elements of the global water cycle, *Proc. IEEE*, 98(5), 666–687,
485 <https://doi.org/10.1109/JPROC.2010.2043032>, 2010.
- Kolodziejczyk, N., Boutin, J., Vergely, J. L., Marchand, S., Martin, N., and Reverdin, G.: Mitigation of systematic errors in SMOS sea surface salinity, *Remote Sens. Environ.*, 180, 164–177, 2016.
- Kolodziejczyk, N., Prigent-Mazella, A., and Gaillard, F.: ISAS temperature, salinity, dissolved oxygen gridded fields, SEANOE, <https://doi.org/10.17882/52367>, 2023.
- 490 Kolodziejczyk, N.: EU Copernicus Marine Service Quality Information Document for the SSS SMOS/SMAP L4 OI - LOPS-v2023, `MULTIOBS_GLO_PHY_SSS_L4_MY_015_015`, issue 2.0, Mercator Ocean International, <https://documentation.marine.copernicus.eu/QUID/CMEMS-MOB-QUID-015-015.pdf>, last access: 16 July 2025, 2024.
- Lagerloef, G., Colomb, F. R., Le Vine, D., Wentz, F., Yueh, S., Ruf, C., Lilly, J., Gunn, J., Chao, Y. I., DeCharon, A., and Feldman, G.: The Aquarius/SAC-D mission: Designed to meet the salinity remote-sensing challenge, *Oceanography*, 21(1),
495 68–81, <https://doi.org/10.5670/oceanog.2008.77>, 2008.
- O’Gorman, P. A.: Precipitation extremes under climate change, *Curr. Clim. Change Rep.*, 1(2), 49–59, 2015.
- Olmedo, E., Turiel, A., González-Gambau, V., González-Haro, C., García-Espriu, A., Gabarró, C., and Scipal, K.: Increasing stratification as observed by satellite sea surface salinity measurements, *Sci. Rep.*, 12(1), 6279, 2022.

- Parracho, A. C., Bock, O., and Bastin, S.: Global IWV trends and variability in atmospheric reanalyses and GPS observations, *Atmos. Chem. Phys.*, 18(22), 16213–16237, 2018.
- Parracho, A., Boutin, J., and Tarot, S.: EU Copernicus Marine Service Quality Information Document for the SMOS CATDS Qualified (L2Q) Sea Surface Salinity product, MULTIOBS_GLO_PHY_SSS_L3_MYNRT_015_014, issue 2.0, Mercator Ocean International, <https://documentation.marine.copernicus.eu/QUID/CMEMS-MOB-QUID-015-014.pdf>, last access: 14 July 2025, 2024.
- Piepmeyer, J. R., Ruf, C. S., Yueh, S. H., Fore, A. G., Tang, W., Hayashi, A., and Freedman, A. P.: SMAP L-band microwave radiometer: Instrument design and first year on orbit, *IEEE T. Geosci. Remote Sens.*, 55(4), 1954–1966, <https://doi.org/10.1109/TGRS.2016.2631978>, 2017.
- Prevedi, M., Seager, R., and Kushnir, Y.: A canonical response of the hydrological cycle to global warming, *J. Climate*, 30(15), 6133–6149, <https://doi.org/10.1175/JCLI-D-16-0684.1>, 2017.
- Qin, X., Bower, A. S., Lozier, M. S., and Zou, S.: Measurements of ocean interbasin freshwater transport: Progress, challenges, and the path ahead, *Geophys. Res. Lett.*, 48(23), e2021GL094132, <https://doi.org/10.1029/2021GL094132>, 2021.
- Reul, N., Tenerelli, J., Boutin, J., Vergely, J. L., Marchand, S., and Quastel, M.: L-band sea surface salinity retrieval algorithm: Application to SMOS mission, *Remote Sens. Environ.*, 180, 89–100, <https://doi.org/10.1016/j.rse.2016.02.042>, 2016.
- Reverdin, G., Morisset, S., Boutin, J., and Martin, N.: Rain-induced variability of near sea-surface T and S from drifter data, *J. Geophys. Res.-Oceans*, 117(C2), C02032, <https://doi.org/10.1029/2011JC007569>, 2012.
- Reverdin, G., Martin, N., Boutin, J., Bellenger, H., Lee, T., and Reul, N.: Recent changes in the surface salinity of the tropical Atlantic Ocean, *Deep-Sea Res. Pt. I*, 130, 1–20, <https://doi.org/10.1016/j.dsr.2017.10.002>, 2017.
- Reverdin, G., Cravatte, S., Kestenare, E., Ghantous, M., Boutin, J., and Singh, A.: Near-surface salinity and temperature as seen by drifters in the tropical Pacific during SPURS-2, *Oceanography*, 33(2), 38–47, <https://doi.org/10.5670/oceanog.2020.203>, 2020.
- Reverdin, G., Quilfen, Y., Marié, L., Sutherland, G., and Kestenare, E.: Rain and wind variability above the tropical Atlantic Ocean inferred from satellite data and in situ observations, *J. Geophys. Res.-Oceans*, 127, e2021JC018025, <https://doi.org/10.1029/2021JC018025>, 2022.
- Rousset, C., Madec, G., Talandier, C., Bouillon, S., Bouttier, P.-A., and Vancoppenolle, M.: The Louvain-La-Neuve sea ice model LIM3.6: Global and regional capabilities, *Geosci. Model Dev.*, 8, 2991–3005, <https://doi.org/10.5194/gmd-8-2991-2015>, 2015.
- Roemmich, D., Church, J., Gilson, J., Monselesan, D., Sutton, P., and Wijffels, S.: Unabated planetary warming and its ocean structure since 2006, *Nat. Clim. Change*, 5(3), 240–245, <https://doi.org/10.1038/nclimate2513>, 2015.
- Roemmich, D., Church, J., Monselesan, D., Gilson, J., Sutton, P., and Wijffels, S.: Unabated planetary warming and its ocean structure since 2006, *Nat. Clim. Change*, 5, 240–245, <https://doi.org/10.1038/nclimate2513>, 2015.

- Rodell, M., Beaudoin, H. K., L'Ecuyer, T. S., Olson, W. S., Famiglietti, J. S., Houser, P. R., Adler, R., Bosilovich, M. G., Clayson, C. A., Chambers, D., and Robertson, F. R.: The observed state of the water cycle in the early twenty-first century, *J. Climate*, 28(21), 8289–8318, <https://doi.org/10.1175/JCLI-D-14-00555.1>, 2015.
- Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C. J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., and Entin, J. K.: The Global Land Data Assimilation System, *B. Am. Meteorol. Soc.*, 85(3), 381–394, <https://doi.org/10.1175/BAMS-85-3-381>, 2004.
- Rudnick, D. L., Wijffels, S. E., Riser, S. C., Katsumata, K., and Schmitt, R. W.: Observing the salinity of the ocean, *Annu. Rev. Mar. Sci.*, 7, 1–25, <https://doi.org/10.1146/annurev-marine-010814-015610>, 2015.
- Sallée, J. B., Shuckburgh, E., Bruneau, N., Meijers, A. J. S., Bracegirdle, T. J., Wang, Z., and Roy, T.: Assessment of Southern Ocean water mass circulation and characteristics in CMIP5 models: Historical bias and forcing response, *J. Geophys. Res.-Oceans*, 118(4), 1830–1844, <https://doi.org/10.1002/jgrc.20135>, 2013.
- Schanze, J. J., Schmitt, R. W., and Yu, L.: The global oceanic freshwater cycle: A state-of-the-art quantification, *J. Mar. Res.*, 69(3), 449–476, <https://doi.org/10.1357/002224011798765923>, 2011.
- Schmitt, R. W.: Salinity and the global water cycle, *Oceanography*, 21(1), 12–19, <https://doi.org/10.5670/oceanog.2008.63>, 2008.
- Schmitt, R. W.: The ocean's role in climate, *Oceanography*, 23(4), 14–19, <https://doi.org/10.5670/oceanog.2010.06>, 2010.
- Sen, P. K.: Estimates of the regression coefficient based on Kendall's tau, *J. Am. Stat. Assoc.*, 63, 1379–1389, 1968.
- Simmons, A. J., Willett, K. M., Jones, P. D., Thorne, P. W., and Dee, D. P.: Low-frequency variations in surface atmospheric humidity, temperature, and precipitation: Inferences from reanalyses and monthly gridded observational data sets, *J. Geophys. Res.-Atmos.*, 115, D01110, <https://doi.org/10.1029/2009JD012442>, 2010.
- Skliris, N., Marsh, R., Josey, S. A., Good, S. A., Liu, C., Allan, R. P., and Dai, A.: Salinity changes in the world ocean since 1950 in relation to changing surface freshwater fluxes, *Clim. Dyn.*, 43(3–4), 709–736, <https://doi.org/10.1007/s00382-014-2131-7>, 2014.
- Smith, D. M., Eade, R., and Pohlmann, H.: A comparison of full-field and anomaly initialization for seasonal climate prediction, *Clim. Dyn.*, 41, 3325–3338, <https://doi.org/10.1007/s00382-013-1883-5>, 2013.
- Song, Q., Wang, J., Xie, X., and Chen, J.: Changes in global terrestrial evapotranspiration during 1982–2010, *J. Geophys. Res.-Atmos.*, 118, 1–13, <https://doi.org/10.1002/jgrd.50422>, 2013.
- Stammer, D., Wunsch, C., and Ponte, R. M.: Space-time variability of ocean mass from GRACE: Global and regional patterns, *Geophys. Res. Lett.*, 35, L01605, <https://doi.org/10.1029/2007GL031002>, 2008.
- Steele, M., Morley, R., and Ermold, W.: PHC: A global ocean hydrography with a high-quality Arctic Ocean, *J. Climate*, 14, 2079–2087, [https://doi.org/10.1175/1520-0442\(2001\)014<2079:PAGOHW>2.0.CO;2](https://doi.org/10.1175/1520-0442(2001)014<2079:PAGOHW>2.0.CO;2), 2001.
- Stewart, A. L., and Thompson, L. A.: Surface water salinity changes in the North Atlantic Ocean, *J. Geophys. Res.*, 117, C04025, <https://doi.org/10.1029/2011JC007685>, 2012.

- Stroeve, J., Holland, M. M., Meier, W., Scambos, T., and Serreze, M.: Arctic sea ice decline: Faster than forecast, *Geophys. Res. Lett.*, 34, L09501, <https://doi.org/10.1029/2007GL029703>, 2007.
- Su, J., Hong, H., and Xu, Q.: Investigation of ocean salinity trends using Argo data, *J. Oceanogr.*, 72, 1–12, <https://doi.org/10.1007/s10872-015-0270-3>, 2016.
- Swart, N. C., and Fyfe, J. C.: Observed and simulated changes in the Southern Hemisphere surface westerly wind stress, *Geophys. Res. Lett.*, 39, L16711, <https://doi.org/10.1029/2012GL052810>, 2012.
- Talley, L. D.: *Descriptive physical oceanography: An introduction*, 6th Edn., Academic Press, Boston, 2011.
- Tarot, S.: EU Copernicus Marine Service Product User Manual for the SSS SMOS/SMAP L4 OI - LOPS-v2023, MULTIOBS GLO PHY SSS L4 MY 015 015, issue 2.0, Mercator Ocean International, <https://documentation.marine.copernicus.eu/PUM/CMEMS-MOB-PUM-015-015.pdf>, last access: 16 July 2025, 2024.
- Theil, H.: A rank-invariant method of linear and polynomial regression analysis, *Indag. Math.*, 12, 173, 1950.
- Trenberth, K. E., and Fasullo, J. T.: Tracking Earth's energy: From El Niño to global warming, *Surv. Geophys.*, 33, 413–426, <https://doi.org/10.1007/s10712-012-9184-0>, 2012.
- Tsimplis, M. N., and Shaw, A. G. P.: Sea level trends in the Mediterranean Sea from tide gauges, *Global Planet. Change*, 42, 311–322, <https://doi.org/10.1016/j.gloplacha.2004.07.002>, 2004.
- Vellinga, M., and Wood, R. A.: Impacts of thermohaline circulation shutdown in the twenty-first century, *Clim. Change*, 91, 43–63, <https://doi.org/10.1007/s10584-008-9447-5>, 2008.
- Verbrugge, N.: EU Copernicus Marine Service Product User Manual for the Multi Observation Global Ocean 3D Temperature Salinity Height Geostrophic Current and MLD, MULTIOBS GLO PHY TSUV 3D MYNRT 015 012, issue 1.2, Mercator Ocean International, <https://documentation.marine.copernicus.eu/PUM/CMEMS-MOB-PUM-015-012.pdf>, last access: 16 July 2025, 2023.
- Vergely, J.-L., Boutin, J., and Kolodziejczyk, N.: SMOS OS Level 3 and Level 4 algorithm theoretical basis document, ACRI-ST, <https://doi.org/10.13155/92266>, 2022.
- Vinogradova, N. T. and Ponte, R. M.: In search of fingerprints of the recent intensification of the ocean water cycle, *J. Clim.*, 30, 5513–5528, 2017.
- Vose, R. S., Applequist, S., Durre, I., Menne, M. J., and Gleason, B. E.: NOAA Global Historical Climatology Network – Daily (GHCN-Daily), Version 3, NOAA National Climatic Data Center, <https://doi.org/10.7289/V5D21VHZ>, 2014.
- Waliser, D. E., and Guan, B.: Intensity, propagation and symmetry characteristics of the MJO: Evidence from multiple observational datasets, *Clim. Dyn.*, 38, 2275–2291, <https://doi.org/10.1007/s00382-011-1065-9>, 2012.
- Wang, C., Lee, S.-K., and Enfield, D. B.: Atlantic warm pool variability and its association with the Atlantic meridional mode, *Geophys. Res. Lett.*, 33, L19704, <https://doi.org/10.1029/2006GL026642>, 2006.
- Wang, X., and Wang, L.: Changes in Arctic sea ice extent from satellite data, *J. Climate*, 27, 4253–4267, <https://doi.org/10.1175/JCLI-D-13-00360.1>, 2014.

- Wunsch, C., and Heimbach, P.: Bidecadal thermal changes in the abyssal ocean, *J. Phys. Oceanogr.*, 39, 574–588, <https://doi.org/10.1175/2008JPO3829.1>, 2009.
- Xu, Z., and Hu, D.: Trends of sea surface temperature in the South China Sea, *J. Ocean Univ. China*, 12, 765–773, <https://doi.org/10.1007/s11802-013-2176-5>, 2013.
- Yang, S., and Tung, K.-K.: Trends in Southern Hemisphere surface wind stress and implications for ocean circulation, *Geophys. Res. Lett.*, 40, 5219–5223, <https://doi.org/10.1002/grl.50960>, 2013.
- Zhang, R., and Delworth, T. L.: Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes, *Geophys. Res. Lett.*, 33, L17712, <https://doi.org/10.1029/2006GL026267>, 2006.
- Zhao, Z., and Wang, B.: Intraseasonal oscillation signals in the Indian Ocean SST, *J. Climate*, 25, 4357–4373, <https://doi.org/10.1175/JCLI-D-11-00346.1>, 2012.
- Zhou, L., Dickinson, R. E., Tian, Y., Fang, J., and Dai, Y.: Evidence for a significant urbanization effect on climate in China, *Proc. Natl. Acad. Sci. USA*, 101, 9540–9544, <https://doi.org/10.1073/pnas.0400008101>, 2004.
- Zhu, J., and Liang, S.: Characterization of MODIS Land Surface Temperature product over Northern China, *Remote Sens. Environ.*, 115, 2908–2919, <https://doi.org/10.1016/j.rse.2011.07.006>, 2011.
- Zveryaev, I. I.: Statistical characteristics of extreme precipitation events in the Moscow region, *Theor. Appl. Climatol.*, 123, 123–136, <https://doi.org/10.1007/s00704-014-1262-7>, 2016.
- Zwally, H. J., and Giovinetto, M. B.: Mass changes of the Greenland and Antarctic ice sheets and shelves and contributions to sea-level rise: 1992–2002, *J. Glaciol.*, 52, 626–638, <https://doi.org/10.3189/172756506781828566>, 2006.
- Zygmuntowski, M., Jungclaus, J., and Zanchettin, D.: Impact of volcanic eruptions on the North Atlantic Oscillation, *Clim. Past*, 13, 1419–1438, <https://doi.org/10.5194/cp-13-1419-2017>, 2017.
- Zwiers, F. W., and Zhang, X.: Anthropogenic influence on long return period daily temperature extremes in western North America, *J. Climate*, 24, 881–891, <https://doi.org/10.1175/2010JCLI3433.1>, 2011.
- Zorita, E., and von Storch, H.: The analog method as a simple statistical downscaling technique: Comparison with more complicated methods, *J. Climate*, 12, 2474–2489, [https://doi.org/10.1175/1520-0442\(1999\)012<2474:TAMASA>2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012<2474:TAMASA>2.0.CO;2), 1999.
- Zou, L., and Zhai, P.: Changes in frost days and their spatial distribution over China, *J. Geophys. Res.*, 112, D05111, <https://doi.org/10.1029/2006JD007251>, 2007.
- Zubair, L., and Ropelewski, C. F.: The relationship between sea surface temperature anomalies and precipitation in the tropical Pacific, *J. Climate*, 16, 3103–3121, [https://doi.org/10.1175/1520-0442\(2003\)016<3103:TRBSSTA>2.0.CO;2](https://doi.org/10.1175/1520-0442(2003)016<3103:TRBSSTA>2.0.CO;2), 2003.