A gridded sea surface salinity data set for the tropical Pacific with sample applications (1950–2008)

T. Delcroix, G. Alory, S. Cravatte, T. Corrège, M.J. McPhaden

1. Introduction

Sea Surface Salinity (SSS) has been recognized as an essential variable of the global observing system for climate (e.g., GCOS, 2004). Quantifying SSS changes in the open ocean is critical for monitoring climate variability and for understanding the related changes in heat, fresh water, momentum, and CO₂ fluxes between the ocean and the atmosphere. Given the importance of SSS, the purpose of this paper is to derive an unprecedented monthly gridded SSS product for the tropical Pacific Ocean, defined over a longitudinal range of 120°E–70°W; 30°N–30°S, with a grid resolution of 1° longitude, 1° latitude and 1 month, from 1950 to 2008. The product, together with its associated error field, is derived from an objective analysis of about 10 million validated SSS records, with most of the data originating from Voluntary Observing Ships, TAO/TRITON moorings and Argo profilers (during the most recent period). We expect this product to benefit studies in oceanography, meteorology and paleoceanography. As examples of applications, we analyse: (a) the seasonal and ENSO (El Niño Southern Oscillation) modes of observed SSS variability, (b) the ability of 23 coupled models used in the Intergovernmental Panel for Climate Change 4th Assessment Report (IPCC AR4) to simulate the mean SSS and these two time varying modes, and (c) the usefulness of the SSS product and of its associated error field in calibrating and validating the paleo-salinity time series. We anticipate improvements and regular updates to our product, as more SSS data become available from in situ networks and from the ongoing and near-future satellite-derived observations by SMOS (Soil Moisture and Ocean Salinity) and Aquarius.

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The rest of the paper is organized as follows. Section 2 describes the collected in situ SSS data, the data validation and the gridding procedure. Section 3 then illustrates a few examples of the usefulness of our SSS gridded product by: (a) describing the two main modes of observed SSS variability, (b) testing the ability of 23 climate models issued from the World Climate Research Program Coupled Model Intercomparison Project (WCRP CMIP3; Meehl et al., 2007) to simulate those modes, and (c) illustrating the complementarities of the in situ and paleo-salinity data for the analysis of long time series. Conclusions and discussion appear in Section 4.

2. Data collection, data processing, and gridding procedure

We gathered about 10 million records of near-surface (0–10 m) salinity data within 30°N–30°S and 120°E–70°W during 1950–2008, originating from several data bases and measurement techniques. Those records include: (a) surface samples collected from Voluntary Observing Ship (VOS) programs, obtained mainly from the French SSS Observation Service (SOS), (b) surface samples obtained from the World Ocean Data Base 2009 (WODB09), excluding data from the IRD (Institut de Recherche pour le Développement; formerly ORSTOM) already included in the French SOS data base, (c) thermosalinographs (TSGs) installed on board the VOS and French research vessels, again mainly obtained from the French SOS, (d) TSGs installed on TAO/TRITON moorings and on vessels servicing these moorings, (e) hydrocasts, STD, and CTD data collected during research cruises, mainly obtained from the WODB09 and augmented with data from archives at the Pacific Marine Environmental Laboratory (PMEL) and IRD, and (f) CTD data from Argo floats, obtained from the WODB09. The websites used for downloading these data are given in the Acknowledgement section.

Information on the 1950–2003 records, their origins, the time period they cover, the data sampling characteristics, the quality control procedures, their relative accuracy, and a way to blend the different data sets are described in Delcroix et al. (2005, 2007) and Cravatte et al. (2009). The post-2003 TSG data were validated with a new technique that specifically corrects instrumental drift with the help of daily salinity samples collected on board as well as with collocated Argo measurements when available (Alory et al., in preparation). As for Argo data obtained mostly from 2003, only salinity values with a ‘good’ quality code (QC = 1 in the original data base) were considered for our analysis.

As the near-surface salinity records we gathered were from different data bases, we first looked for duplicates based on identical salinity values and space–time locations: about 4.3% of the data was removed this way. Following Delcroix et al. (2005), we then eliminated about 1.4% of data through standard statistical tests, rejecting values based on 5, 4 and then 3.5 standard deviations computed in 5° longitude and 1° latitude boxes (ignoring data in the Banda Sea and in the Atlantic for near-boundary boxes). The 1° latitude by 1° longitude distributions of the number of 5-day bins, including at least one SSS observation, are shown for 1950–1969, 1970–1989, and 1990–2008, respectively, in Fig. 1a, b, and c, and the

Fig. 1. Spatial distribution of the number N of 5-day bins with SSS observations per 1° longitude by 1° latitude grid box for (a) 1950–1969, (b) 1970–1989, and (c) 1990–2008 time periods, respectively. The colour codes for N stretch from dark blue (N = 1) to dark red (N ≥ 241). The three heavy-lined 2° latitude by 20° longitude rectangles show the so-called ITCZ, warm pool and SPCZ boxes discussed in Section 3.
yearly evolution of observations of each data type is shown in Fig. 2. Some regions are well sampled (mainly the western half of the tropical Pacific), whereas other regions (like the southeastern Pacific or the central north Pacific) remain poorly sampled. The VOS TSG lines and TAO/TRITON moorings dominate the spatial patterns; we also note a small number of observations before the 1970s as well as a marked increase in VOS TSG, TAO/TRITON and Argo observations from 1985, 1988, and 1997, respectively.

Since we gathered near-surface (0–10 m) salinity values, the question then arises as to what a surface salinity measurement is. As noted by Delcroix et al. (2007) and Cravatte et al. (2009), near-surface salinity measurements collected from bucket and TSG from VOS at a given depth (that depend on the ship water intake in case of TSG) are probably representative of the 0–10 m averaged salinity since they are collected in the wake of ships steaming at 15–25 knots with drafts of 10–15 m. For all but the VOS data, value closest to 5 m depth alone was retained when more than one salinity value within 0–10 m was obtained at a given time and location. Moreover, a recent study indicates that the vertical salinity difference between 1 and 10 m is less than 0.05 in the tropics 90% of the time (Hénocq et al., 2010). Only the term SSS will be used hereafter.

To further filter out outliers and high frequency time–space variations, not considered here, we then computed medians of all SSS values within grid elements of 1° latitude by 1° longitude by 5 days. Following Cravatte et al. (2009), an optimal interpolation analysis (De Mey and Ménard, 1989) was then applied to the median data, to produce a gridded field at a resolution of x = 1° longitude, y = 1° latitude and t = 1 month. This method, applied to a 3D base (x, y, t), gives an optimal value of SSS at each grid point, by using surrounding data only. Around each grid point, only data included in the ellipsoid defined in dimensions by 2000 km of longitude, 500 km of latitude and 2 months are included in the analysis. These data are then mapped taking into account the spatial and temporal scales of the involved physics. The decorrelation scales used (1 month, 1600 km of longitude, 275 km of latitude), and the signal-to-noise ratio (S/N = 1) were deduced from Delcroix et al. (2005). The use of this S/N value requires the assumption that the instrumental errors are small relative to sampling errors. The gridded field was produced in two steps. In the first step, a first mean guess field was made by gridding all the SSS data using only spatial Gaussian weighting, without time consideration. The differences between this first guess and the data were then mapped using the interpolation method. In a second step, we used the mean monthly climatology of the gridded field as the guess field, and the differences between this second guess field and the data were then mapped again using the interpolation method.

It is noteworthy that the gridding method gives, in addition to the interpolated salinity, a normalized error (e) at each grid point allowing us to estimate the confidence we can place in the variability we observe. The normalized error (ranging from 0 to 1) is a percentage of the variance (σ²) of SSS anomalies relative to mean monthly climatology. Thus, SSS errors (in pss) can be expressed as δS = eṣσ. Given the gridding method used, an SSS value is equal to its mean monthly climatology, with e = 1, for grid points with no surrounding data. To ease interpretation of the normalized error, Fig. 3 shows the May 1997 error together with all the 5-day bins of the SSS data taken into account for estimation of the May 1997 SSS value. It indicates that the error is rather small (say less than 0.4) in the vicinity of SSS values collected along ship tracks and TAO moorings and within about ± 1 month. In contrast,
the error becomes rather large (say over 0.6) in the absence of nearby data in space or time, as seen north of 10°N along 120°W.

3. Key observed structures, model evaluation and paleoceanographic application

3.1. Observed structures

The 1950–2008 averaged SSS map (Fig. 4a) shows high-salinity regions located SE of French Polynesia and NW of the Hawaiian archipelago, near the centre of subtropical gyres, and low-salinity regions largely in the Inter Tropical and South Pacific Convergence Zones (ITCZ, SPCZ) and in the western and eastern warm pools, as described by numerous authors. This mean distribution of SSS tends to mirror the mean distribution of $E-P$ (Evaporation minus Precipitation), with the main differences between both fields reflecting the contribution of the mean oceanic circulation (Baumgartner and Reichel, 1975; Levitus, 1986; Delcroix and Hénin, 1991; Johnson et al., 2002). The corresponding standard deviation map (not shown) reveals that the maximum temporal variability ($>0.25$) appears under the ITCZ and SPCZ, in the far eastern equatorial Pacific (off Panama, Columbia, and Equator), and in the vicinity of the eastern edge of the western warm pool (5°S–5°S and 160°E–180°E). This pattern of variability mainly results from the cumulative effects of the seasonal and interannual (ENSO) variabilities, respectively, estimated by computing the first EOF on monthly mean climatology (Fig. 4b), and by regressing the 25-month Hanning filtered SSS time series lagged by 5 months onto Rayner et al. (2003) filtered NINO3.4 Sea Surface Temperature (SST) anomalies (Fig. 4c). This lag corresponds to the 25-month Hanning filtered SSS time series lagged by 5 months onto Rayner et al. (2003) filtered NINO3.4 Sea Surface Temperature (SST) anomalies (Fig. 4c). This lag corresponds to the first interannual EOF mode of SSS and that of SST in observations (see, Delcroix, 1998).

Fig. 4b shows that maximum changes at the seasonal time scale occur under the ITCZ and SPCZ. The normalized EOF seasonal time function (not shown here) indicates maximum SSS in April in the ITCZ, and in October in the SPCZ, consistent with the seasonal P regime as established in previous studies (e.g., Delcroix, 1998; Boyer and Levitus, 2002). Fig. 4c shows that maximum changes at the interannual (ENSO) time scale are located in the western equatorial Pacific (with a peak near Nauru island), in the SPCZ (with a peak near Fiji islands) and, with a lesser amplitude, east of the dateline along a band located slightly south of the mean ITCZ position, as well as within 5°–10°N west of 160°E. These patterns correspond closely to the ENSO-related EOF spatial patterns discussed by Delcroix (1998), though the confidence in these features is strengthened in the present analysis with the addition of 14 years’ new measurements. The maximal ENSO changes in SSS occur in the western half of tropical Pacific in contrast to SST where the maximum ENSO variability occurs in the east. Surface waters freshen in the western equatorial Pacific and become saltier in the south-western Pacific during El Niño and vice versa during the La Niña events. Earlier studies have shown these changes to be consistent with zonal advection and precipitation changes linked to the displacements of the warm pool and SPCZ (e.g., Delcroix and Picaut, 1998; Gouriou and Delcroix, 2002). These remarkable ENSO signatures in SSS should thus prove in models to be realistic at interannual time scales. Note that detailed SSS signatures of individual El Niño and La Niña events, as well as the relative impacts of Eastern and Central Pacific El Niño, are discussed in Singh et al. (submitted).

To further focus on the seasonal and ENSO variabilities, Fig. 5 shows the SSS times series in three typical 2° latitude by 20° longitude boxes: (a) box 1 under the ITCZ (9°–11°N; 140°–160°W), (b) box 2 in the warm pool (1°S–1°N; 160°E–180°E), and (c) box 3 under the SPCZ (10°–12°S; 170°E–170°W; see Fig. 1 for the box positions). Computation of the relative amplitude shows that changes at the seasonal time scale are dominant under the ITCZ, still of importance under the SPCZ, and are relatively weak in the warm pool, accounting for 68%, 20%, and 10% of the total variance with annual amplitude variations of about 0.3, 0.2, and 0.15, respectively. Interestingly, there is a well-marked and almost out-of-phase ENSO signal in the warm pool and SPCZ, with peak to peak variations of the order of 1.3 between El Niño and La Niña events. The apparent lack of variability prior to the mid-1970s when the data density was poor is reflected in large amplitude errors, indicating that the observed ENSO variability then cannot be trusted.

3.2. IPCC model evaluation

Climate models used for the assessment of future hydrological changes in the context of global warming must correctly reproduce the main modes of observed SSS variability if they are to be trusted.
As an example of model evaluation, we compare the observed versus simulated SSS derived from a set of 23 twentieth-century climate coupled models, which participated in phase 3 of the WCRP CMIP, used to prepare the 4th assessment report of the IPCC. Details of the models, hereafter identified by 23 capital letters from B to X, are summarized in Table 1. To benchmark their performance, we present a comparison between the geographical distribution of mean, seasonal and ENSO-related variabilities in SSS. The degree of correspondence between the observed and simulated SSS fields is assessed by computing a spatial correlation coefficient ($R$), spatial root mean square difference (RMSD), and the spatial standard deviations of the two fields ($s_{mod}$ and $s_{obs}$). The comparison is made only when the errors of the observed field are less than 0.6 (60% of the observed interannual SSS variance). The different time scales of the simulated SSS variability are extracted in the same way as with the observed SSS variability, as discussed above. The basic statistics are summarized in the Taylor diagrams (Taylor, 2001), as was done for other variables in earlier CMIP studies (e.g., Lambert and Boer, 2001). To ease interpretation of the Taylor diagrams, the performances of three (out of 23) CMIP3 climate models are also shown as maps in Fig. 4d, e, and f, for direct comparison with the observed features in Fig. 4a, b, and c. These three models were selected for their relatively good skill scores (see below); note that we excluded models D, E, H, and M in Table 1 in whose ocean–atmosphere coupling schemes water flux adjustments were applied. These water flux adjustments were typically made by adding spatially (and sometimes seasonally) varying fresh water fluxes to the ocean surface to minimize the climatological bias in salinity (Stouffer and Dickson, 1998; see also Section 8.2.7 in Randall et al., 2007).

3.2.1. Mean SSS

A visual comparison of Fig. 4a–d shows that the geographical distribution of the mean SSS is rather well captured by model N, with a qualitatively good distribution of the low and high-salinity regions. Notable differences however show up. For example, the simulated high-salinity waters of the south-east tropical Pacific are located excessively far to the east, the low-salinity waters under the eastern and western parts of the ITCZ are too fresh and low SSS under the SPCZ extends exceedingly far to the south-east. The Taylor diagram of the mean SSS for all models is shown in Fig. 6. There, the correlation coefficient ($R$) between the observed field and a modelled field is given by the azimuthal position of the small circle representing the model, the standard deviation of the observed ($s_{obs}$) or modelled ($s_{mod}$) fields is given by the radial distance from the origin, and the centred RMSD between the observed and modelled fields is given by the distance separating them, scaled with the green dashed circles. As an example, $R = 0.84$, $s_{mod} = 0.75$, and RMSD $= 0.4$ in model N, and $s_{obs} = 0.68$ in the observations. Excluding the D, E, H, and M models, fresh water flux corrected (see Table 1), Fig. 6 indicates that five models, K, L, N, O, P, behave similarly with $R \geq 0.7$, RMSD from 0.4 to 0.6, and $s_{mod}/s_{obs}$ in the order of 1. Differences in the geographical pattern of the mean SSS...
appear much larger in all the other models, with statistical skill ranging from 0.15 to 0.75 for $R$, 0.5 to 0.8 for RMSD, and 0.5 to 1.3 for $s_{mod}/s_{obs}$. Note, in addition, that the mean values of spatially averaged SSS of three out of the five 'best' models (i.e., N, O, and P) also best resemble the corresponding observed mean value (Fig. 6).

3.2.2. Seasonal variability

The spatial distribution of the seasonal variability in model I (Fig. 4e) compares quite well with observations (Fig. 4b) capturing the maximum amplitude in the ITCZ and SPCZ in phase opposition (a similar figure would hold in models B, L, Q, and R). However, there are differences in the location of the SPCZ and in the northwest tropical and far eastern equatorial Pacific variabilities. The Taylor diagram for the seasonal variability (Fig. 7) indicates that $R$ barely exceeds 0.7 (excluding the seasonally water-adjusted model H), and ranges within [0.5, 0.7] in most of the models. Also, most of the models overestimate the amplitude of the seasonal variability, with $s_{mod}/s_{obs}$ values typically within 1 and 2. A detailed examination of all model simulations reveals that these relatively poor scores probably reflect overly strong seasonal variations in the ITCZ and in the SPCZ; this occurrence, moreover, unrealistically stretches zonally over most of the basin. These features reflect a well-known deficiency in coupled models often described as the 'double-ITCZ' syndrome (e.g., Bellucci et al., 2010). Aside from this common bias, the phasing of the seasonal variability is rather well simulated in most models (Fig. 7).

3.2.3. ENSO variability

Based on spectral analysis of NINO3 or NINO3.4 SST anomalies, previous studies have shown that the dominant time scale of ENSO can range from 2 to 7 years in CMIP coupled models (Achuta Rao and Sperber, 2006; Guilyardi et al., 2009). To consistently capture the spatial SSS signature of ENSO in all models, whatever be their dominant ENSO time scales, we thus computed the regression of SSS anomalies onto the simulated NINO3.4 SST anomalies, with SSS lagging SST by 5 months, as seen in the observations. In a similar way, the SSS/SST lag has been estimated for models from a SSS EOF analysis and shows values close to observations for most models when the correlation is significant (Fig. 8). The spatial distribution of the ENSO signature in SSS in model O (Fig. 4f) compares reasonably well with the observed features (Fig. 4c). It shows negative SSS anomalies in the west in the equatorial band, and positive SSS anomalies in the SPCZ during El Niño, and vice versa during La Niña. Although model O is one of the 'best' models for simulation of the spatial patterns of ENSO-related SSS changes (see Fig. 8), the simulated changes are excessively strong ($s_{mod}/s_{obs}$ ~ 2), located too far to the west in the equatorial band. Also, in this model, changes

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**Table 1**

List of the models analyzed in this study, with CMIP3 Identification (ID).

<table>
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Acronyms in the Flux adjustment column stand for Heat (H), Water (W), Momentum (M), Monthly (Mo), and Annual (An).

a Except for water where icebergs occur.

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**Fig. 6.** Taylor diagram displaying the main statistics between the spatial distributions of observed (letter A) and modelled (letters B to X) mean SSS. The colour codes, scaled on the right vertical bar, represent the observed and modelled spatially averaged SSS. Details about models B–X are given in Table 1.
in the SPCZ tend to be located excessively far to the east unlike those seen in the observations. The Taylor diagram of all models shows that the ENSO-SSS varies vastly from one model to the other, with most $R$ values ranging from 0.2 to 0.6, RMSD from 0.03 to 0.1, and $\sigma_{\text{mod}}/\sigma_{\text{obs}}$ from 0.3 to as much as 4 (Fig. 8). The best $R$ ($\geq 0.6$) values are obtained from models N, O, and P (excluding the fresh water flux-corrected M model) that also ‘best’ simulate the observed ENSO signal in SST (van Oldenborgh et al., 2005). We verified that such a correspondence was not due to the way we estimated the ENSO-related signal in SSS (i.e., regressing the SSS field onto NINO3.4 SST and so taking the ENSO-SST as a reference). As an alternative approach, we computed the Taylor diagram of the first interannual EOF spatial pattern of the simulated SSS fields (figure not shown), and obtained similar results, as seen in Fig. 8. Besides, it is worth noting that models D and E, both are fresh water flux-adjusted but not on interannual time scales, also ‘adequately’ simulate the ENSO

Fig. 7. As in Fig. 6 but for the spatial distributions of the seasonal variability in SSS. The colour codes, scaled on the right vertical bar, represent the month of maximum seasonal SSS in the ITZ mean area.

Fig. 8. As in Fig. 6 but for the spatial distributions of the ENSO-related variability of SSS. The colour codes, scaled on the right vertical bar, represent the lag (in months) between the first interannual EOF SST and SSS time functions (with SST leading). Blank colours for some models indicate insignificant correlation between these two EOF time functions.
signature in SSS, with R in the order of 0.5–0.6, RMSD in the order of 0.05, $\sigma_{\text{resid}}/\sigma_{\text{obs}}$ near 1, and a lag similar to observations between the SST/SSS signals. In summary, large differences in modelled and observed ENSO-SSSs show up, suggesting that most of the present models can be improved upon to adequately represent the SS balance on interannual time scales.

3.3. Paleoceanographic application

Another important application of the SSS gridded data set is the calibration and validation of paleo-SSS tracers. These are being developed in various archives such as planktonic foraminifera and massive corals. The latter offers the possibility of accessing nearly 300 years of records. Stable isotopes and trace elements were measured following standard procedures. As for offering nearly 300 years of records. Stable isotopes and trace elements were measured following standard procedures. As for the precipitation/evaporation balance (like salinity, to a large part).

To reconstruct paleo-SSS, the combination of two tracers is needed. The stable oxygen isotopic composition of coral (designated as $\delta^{18}O_c$) is dependent upon temperature and the $\delta^{18}O$ of seawater (designated as $\delta^{18}O_{\text{sw}}$), which is itself a function of the precipitation/evaporation balance (like salinity, to a large part). Coupling $\delta^{18}O_c$ to an independent temperature tracer such as the Sr/Ca ratio theoretically allows one to calculate $\delta^{18}O_{\text{sw}}$ and hence to obtain paleo-SSS data.

To demonstrate the utility of the gridded SSS data set, we use yearly coral data from Rotuma island (12°29’S, 177°02’E; i.e., north of Fiji and slightly south the SPCZ box in Fig. 1) on the edge of the Western Pacific Warm Pool and under the SPCZ. The coral head was drilled in October 1998 and belongs to the genus Porites. A 3.37 m core was retrieved, slabbed, and X-rayed to establish a chronology. The coral started growing in 1710, potentially offering nearly 300 years of records. Stable isotopes and trace elements were measured following standard procedures. As for $\delta^{18}O_c$ measurements were made in triplicate and a standard deviation was calculated. The $\delta^{18}O_{\text{sw}}$ values of each year were calculated following Gagan et al. (1998). The comparison with the gridded SSS data, averaged over the box 11°13’S, 172°182 E, is shown in Fig. 9. Overall, the two records show a good correlation ($R=0.57$; see Table 2), and a calibration can be performed over the whole period covered by both data sets (i.e., 1958–1996; see Eq. (1) in Table 2). However, the length of the gridded data set is sufficient for performance of a calibration/validation exercise with the coral data, as recommended by Crowley et al. (1999). We tested different record lengths for the calibration period (i.e., 10, 15, and 20 years). In all cases, we obtained similar results with comparable correlation coefficients; hence we chose a calibration period of 10 years. So as to take full advantage of the SSS gridded data set, we calculated the correlation coefficient between SSS and $\delta^{18}O_{\text{sw}}$ in a 10-year sliding window. We found that R is highest (i.e., $R=0.96$; see Table 2) in the 1976–1985 window, which also corresponds to the period where the associated errors in SSS are the smallest (Fig. 10).

We then reconstructed SSS from our coral data using Eq. (2) (Table 2), and calculated the difference between the gridded SSS and the reconstructed SSS (here termed “residual”). The absolute value of this residual was then compared to the gridded SSS error (averaged over the box), in conjunction with the standard deviation in the $\delta^{18}O_c$ measurements (Fig. 10). Mean residual values and correlation coefficients between gridded and reconstructed SSSs were also calculated before and after the validation period (Table 2).

Our results indicate that $\delta^{18}O_{\text{sw}}$ is a relatively good tracer of SSS at least since about 1975. Prior to 1975, the correlation between the

Table 2
Summary of statistics for the calibration and validation periods. R is the correlation coefficient between $\delta^{18}O_{\text{sw}}$ and gridded SSS during the calibration period, and between gridded and reconstructed SSS during the validation period. The mean residual is the average of the absolute values of the difference between gridded and reconstructed SSS. Equations are those from the ordinary least square regression between $\delta^{18}O_{\text{sw}}$ and gridded SSS.

<table>
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<th>Years</th>
<th>R</th>
<th>Mean residual</th>
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<td>1958–1996</td>
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<td>0.21</td>
<td>$\delta^{18}O_{\text{sw}} = -17.11 + 0.503 \times \text{SSS}$ (1)</td>
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<td>0.96</td>
<td>0.05</td>
<td>$\delta^{18}O_{\text{sw}} = -20.04 + 0.584 \times \text{SSS}$ (2)</td>
</tr>
<tr>
<td>Validation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1986–1996</td>
<td>0.75</td>
<td>0.13</td>
<td>Using (2)</td>
</tr>
<tr>
<td>1958–1975</td>
<td>0.27</td>
<td>0.34</td>
<td>Using (2)</td>
</tr>
<tr>
<td>1958–1975+1986–1996</td>
<td>0.53</td>
<td>0.26</td>
<td>Using (2)</td>
</tr>
</tbody>
</table>

![Fig. 9. Time series of $\delta^{18}O_{\text{sw}}$ extracted from a Rotuma Porites coral (blue) and of gridded SSS (red: box: 11°–13°S, 172°–182°E). The limit between the calibration and validation periods is shown.](image-url)
reconstructed and gridded SSS degrades for various reasons. The error in the gridded SSS increases, indicating a paucity of data in the box considered here. However, it should be noted that the highest residuals are also associated with the highest standard deviations in the measured \( \delta^{18}O \) (about 1968, see Fig. 10), and that residuals decrease in the oldest part of the records where standard deviations are low.

This comparison of the gridded SSS data with a paleo SSS tracer extracted from a coral clearly shows the value of the gridded data set for calibration and validation of paleo-tracers. Importantly, it also reveals that both the error associated with the gridded field and the error in the measured \( \delta^{18}O \) must be considered carefully when interpreting the results. Contrary to common practice in paleoceanography, where calibration is carried out on the most recent portion of a record, we choose the subset of data with the lowest associated errors to perform the calibration (in our case, the 1976–1985 period). This work also suggests the possibility of using coral data to fill space/time gaps in the gridded instrumental data set.

4. Conclusion and discussion

Past and recent published analyses of SSS changes have proven to be extremely valuable for improvement of our understanding of climate changes at different time/space scales. Having recognized the importance of SSS and the need for an interannual gridded product, we derived an unprecedented gridded data set for the tropical Pacific (30°N–30°S), with a resolution of 1° latitude by 1° longitude by 1 month for 1950–2008, together with its error field. We are confident that this data set will be a useful complement to models of the WCRP CMIP3, and (c) illustrated the usefulness of the some clues on how these modes are simulated in 23 coupled models of the double-ITCZ problem (Dai, 2006; Lin, 2007; de Szeoke and Xie, 2008; Randall et al., 2007), and/or their poor representation of ocean dynamical processes that affect the SSS. This speculation remains to be elucidated. In the mean time, whatever causes the relatively poor skill scores, our results suggest that only about 2–5 models are at present ‘best’ suited for simulating the SSS.

The tropical Pacific gridded data set we derived—although unique, given its time/space resolution and the covered time period—is clearly a first step and, as such, should be treated as an experimental product. We acknowledge that numerous possible improvements and updates have to be addressed in the future, as more in situ and remotely sensed data become available. To name a few, improvements could include: (a) a refinement of decorrelation time and space scales, (b) the consideration of the prevalence of El Niño or La Niña periods that have been shown to modify these scales (Delcroix et al., 2005), (c) the use of weighting factors when combining observations originating from different platforms with different accuracies, including coral proxy data that could also be used to improve spatial and temporal coverage, (d) in general, the testing of more sophisticated optimal interpolation techniques (e.g., Ballabrera-Poy et al., 2003), and (e) the development of approaches to merge near-surface in situ and skin satellite measurements, in the near future, taking advantage of the experience gained from a similar merging of SST observations (Reynolds et al., 2002).

To expand on our study, we believe it is critical to pursue the collection of SSS observations from the complementary in situ platforms, to learn how one can take advantage of observations derived from the recent (SMOS; Kerr et al., 2001) and future (Aquarius; Lagerloef et al., 2008) satellites, and to strengthen the interest of modellers in SSS variability. The electronic version of our SSS gridded field and the associated error field are (will be) available.
from the web site of the French SOS (http://www.legos.obs-mip.fr/en/observations/ss/).

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References


