An empirical parameterization for the salinity of subsurface water entrained into the ocean mixed layer (S_e) in the tropical Pacific

Rong-Hua Zhang, Antonio J. Busalacchi, Raghuram G. Murtugudde, Phillip A. Arkin, and Joaquim Ballabrera-Poy

Earth System Science Interdisciplinary Center (ESSIC), University of Maryland, College Park, Maryland, USA

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[1] An empirical parameterization for $\boldsymbol{S_e}$ is proposed and tested in an intermediate ocean model (IOM) of the Tropical Pacific Ocean. An inverse modeling approach is first adopted to estimate S_e from a sea surface salinity (SSS) anomaly (SSSA) model using observed in-situ SSS measurements, simulated upper ocean currents, and freshwater flux (evaporation minus precipitation, E-P) data. A relationship between S_e and sea level (SL) anomalies is then obtained by utilizing an empirical orthogonal function (EOF) technique. This empirical scheme is able to estimate S_e anomalies reasonably well in the equatorial Pacific Ocean and can be used to parameterize S_e fields in terms of SL anomalies for use in SSSA calculations. An optimized S_e parameterization naturally leads to a balanced depiction of the subsurface effect on SSS variability in association with entrainment and vertical mixing. As a result, SSSA simulations can be potentially improved in the Tropical Pacific.
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1. Introduction

[2] Understanding the ocean's role in climate has been getting increased attention in recent years. Many of the previous studies have focused on temperature fields and air-sea interaction associated with surface heat fluxes. Indeed, modeling of sea surface temperature (SST) variability in the tropical Pacific has made remarkable progress, leading to skillful predictions of El Niño-Southern Oscillation (ENSO) with 6 to 12 month lead-times [e.g., *Zebiak and Cane*, 1987, hereinafter referred to as ZC87; *Zhang et al.*, 2003].

[3] Ocean salinity is another key variable in the interactions between the Earth's water cycle, ocean circulation and climate. Recent data analyses and modeling studies indicate that salinity can play an active role in maintaining the Pacific climate and its low-frequency variability through its effect on the horizontal pressure gradients, the stratification, the equatorial thermocline, the tropical dynamics and ENSO [e.g., *Delcroix and Hénin*, 1991; *Vialard and Delecluse*, 1998; *Murtugudde and Busalacchi*, 1998; *Maes*, 2000; *Ballabrera-Poy et al.*, 2002]. At present, salinity and its variability are not simulated realistically by ocean models [e.g., *Lagerloef*, 2002]. In particular, SSSA simulations in the tropical Pacific Ocean still remain inadequate for climate studies, with relatively large systematic errors in most state-of-the-art models; errors in the coupling between the pycnocline, salinity entrainment and SSS variability continue to plague ocean models from the intermediate class to ocean general circulation models (OGCMs).

[4] Intermediate models of SST have played a very important role in the development of our physical understanding of ENSO. One obvious advantage of such an intermediate approach is that only perturbations fields are calculated explicitly, whereas the mean climate is specified directly from observations. At present, this class of models remains competitive with more complex OGCMs and offers great promise for further advancing seasonal-to-interannual climate prediction such as ENSO forecasts [e.g., ZC87; *Zhang et al.*, 2003]. Taking advantage of the intermediate SST modeling approach, we have developed a similar intermediate method to advance SSS modeling in the Tropical Pacific [e.g., *Zhang et al.*, 2003, 2005].

2. An Intermediate SSS Anomaly (SSSA) Model

[5] The governing equation determining the evolution of interannual SSS variability in the surface mixed layer can be written as:

$$
\begin{aligned}
\frac{\partial S'}{\partial t} = & -u'\frac{\partial \overline{S}}{\partial x} - (\overline{u}+u')\frac{\partial S'}{\partial x} - v'\frac{\partial \overline{S}}{\partial y} - (\overline{v}+v')\frac{\partial S'}{\partial y} \\
& - \{(\overline{w}+w')M(-\overline{w}-w') - \overline{w}M(-\overline{w})\}\frac{(\overline{S_e}-\overline{S})}{H} \\
& - (\overline{w}+w')M(-\overline{w}-w')\frac{(S'_e-S')}{H} + \frac{K_h}{H}\nabla_h(H\nabla_h S') \\
& + \frac{2K_v}{H(H+H_2)}(S'_e-S') + \frac{1}{H}\{(\overline{E}-\overline{P})S' + (E'-P')\overline{S} \\
& + (E'-P')S'\}
\end{aligned}
$$

Here, S' and S'_e are anomalies of SSS and the salinity of subsurface water at the base of the mixed layer; H is the depth of the mixed layer; ($H + H_2$) is a constant (125 meter); M(x) is the Heaviside step function; E and P are evaporation and precipitation, respectively; $\overline{S}$ and $\overline{S}_e$ (defined as the salinity at the base of the surface mixed layer) are the prescribed seasonally varying mean SSS and S_e from the World Database 2001 (see http://www.nodc.noaa.gov/OC5/WOA01/pr_woa01.html) [*Levitus et al.*, 2005]; and other variables are conventional. As expressed, the local rate of SSS change (tendency) is controlled by horizontal advection, entrainment (the M(x) terms), anomalous fresh water flux, horizontal diffusion and vertical mixing, respectively.

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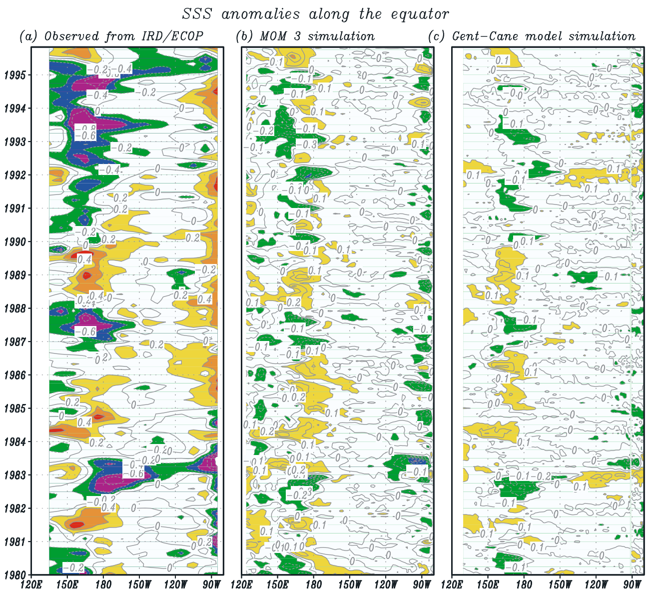

Figure 1. SSS anomalies along the equator for the period 1980–1995, (a) observed from the Institut de Recherche pour le Developpement IRD/ECOP, France, simulated from (b) a level OGCM (MOM 3) and (c) a layer OGCM (The Gent-Cane model), respectively. Note that the contour interval is 0.2 psu in Figure 1a, 0.1 psu in Figures 1b and 1c.

Note that S_e is associated with two vertical processes: entrainment across the base of the mixed layer and mixing between the surface mixed layer and subsurface layer. The function M(x) accounts for the fact that SSS is affected by vertical advection only when subsurface water is entrained into the mixed layer; but SSS can always be influenced by subsurface salinity variability through vertical mixing. This SSSA model is embedded into a dynamical IOM recently developed by *Keenlyside and Kleeman* [2002] for the tropical Pacific Ocean. In order to close the SSSA model, S_e needs to be determined from other dynamical ocean variables.

3. An Empirical S_e Parameterization Scheme

[6] Data analyses and modeling studies suggest that wind-driven pycnocline fluctuations are a primary source of interannual SSS variability throughout the upper equatorial Pacific Ocean [e.g., *Vialard and Delecluse*, 1998]. For example, ocean dynamical responses forced by wind stress anomalies can induce the vertical displacement of the pycnocline in the equatorial ocean, remotely generating a salinity perturbation at the base of the mixed layer. When subsurface waters entrain into the surface mixed layer, SSS anomalies can be generated. This scientific understanding provides a physical basis to improve SSSA simulations via a better S_e parameterization. Since S_e is not observed due to a lack of high resolution observations, we propose here an empirical scheme to parameterize S_e in terms of sea level (SL) anomalies.

3.1. An Inverse Modeling Approach to Estimating S_e

[7] The basic idea of inverse modeling is to use historical observational data, together with numerical models to estimate parameters that are difficult to determine directly. The entrained salinity beneath the mixed layer is such a field, since its geographic distribution and temporal evolution are not available from observations. In the SSSA equation (shown above), S_e is associated with two terms: entrainment by upwelling and the vertical mixing between the surface mixed layer and subsurface layer. Since the SSS tendency on the left side can be estimated from observational data, it is possible to determine S_e anomalies by inverting the SSSA equation using observations and model fields.

[8] Mean and anomalous currents are obtained from the dynamical ocean model run forced by the NCEP-NCAR reanalysis wind data for the periods 1962–1999 [*Kalnay et al.*, 1996]. Observed SSS data (Figure 1a) are from the in-situ sea surface salinity measurements in the tropical Pacific provided by the Institut de Recherche pour le Developpement IRD/ECOP, France [e.g., *Delcroix and Hénin*, 1991; *Maes*, 2000; *Ballabrera-Poy et al.*, 2002]. The fresh water flux (E-P) data are also from the same NCEP-NCAR reanalysis products. These data are used in the inverse modeling of the SSSA equation to estimate S_e for the period 1969–1995.

[9] An important point to note here is that the S_e anomalies calculated by this inverse method are, by definition, exactly those required by the SSSA model to perfectly simulate observed SSSAs. However, with this method, any systematic errors in various terms of the SSSA equation that describes processes controlling SSS changes (unresolved physics by the model, uncertainty in the model parameters and atmospheric forcing fields, and model errors in simulated ocean fields) are effectively lumped together in the derived S_e field, possibly resulting in a biased estimate. Since vertical processes at the base of the mixed layer (entrainment and mixing), represented by S_e, are the dominant process affecting SSS variability in the equatorial Pacific on interannual time scales, the aliasing problem may not be serious in the region. The feasibility of the approach can be ultimately justified by its success or not in improving SSSA simulations.

3.2. An EOF-Based Empirical Relationship Between S_e and SL Variations

[10] Sea level well represents tropical ocean dynamical responses which are a primary process producing subsurface salinity variability in the equatorial Pacific on interannual time scales [e.g., *Vialard and Delecluse*, 1998]. Since variations in sea level and SSS are correlated quite well particularly in the western and central equatorial Pacific [e.g., *Ballabrera-Poy et al.*, 2002], a statistical relationship between S_e and SL anomalies can be developed from historical data to parameterize S_e in terms of SL anomalies.

[11] To determine statistically significant modes of interannual variability between S_e and SL, an EOF technique is adopted [e.g., *Zhang et al.*, 2003, 2005]. Monthly S_e and SL anomaly data are normalized by their spatially averaged standard deviation to form the variance matrix from which an EOF decomposition is made into dominant spatial modes and the corresponding time coefficients. The latter are then used to obtain the matrix of regression coefficients relating the EOFs of these two fields. Thus, a given SL anomaly pattern can be converted into an S_e anomaly using the

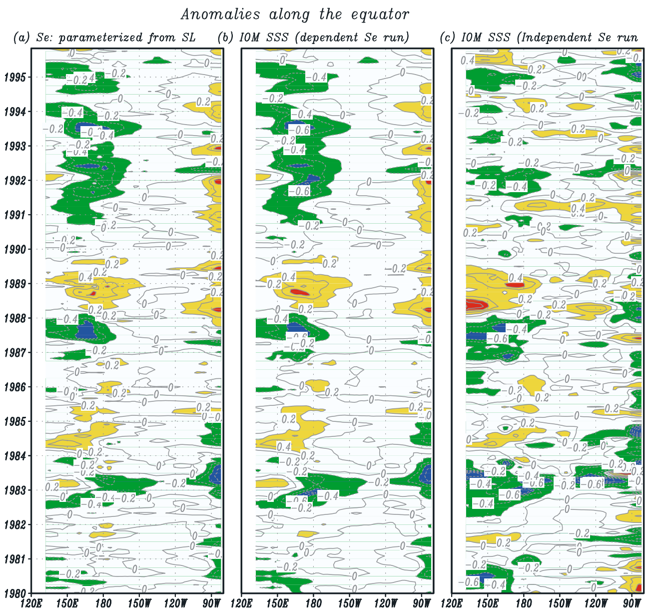

Figure 2. (a) Anomalies along the equator of S_e parameterized from SL anomalies and SSS simulated with (b) dependent and (c) independent empirical S_e parameterization schemes. The contour interval is 0.2.

derived spatial EOF modes and temporal regression coefficients. We use the seasonally varying version (monthly model). The EOF analysis was performed for the period 1969–1995 (a total of 27 years of SSS data) using SL anomalies simulated from the IOM and S_e anomalies estimated from the inverse modeling. As an example, S_e anomalies parameterized from SL anomalies are shown in Figure 2a. Large interannual variability can be seen to be associated with El Niño and La Niña events.

4. SSSA Simulations in the Tropical Pacific

[12] As a comparison, SSSA simulations from two OGCMs are examined: one is the GFDL MOM3 [e.g., *Zhang et al.*, 2001], another is the Gent-Cane ocean model [e.g., *Murtugudde and Busalacchi*, 1998]. The former is a z-coordinate level model with advanced KPP vertical mixing scheme, while the latter is a sigma-coordinate layer model with an explicit bulk mixed layer. Figures 1b–1c show the simulated SSS anomalies along the equator from the two OGCMs; Figures 3a–3b demonstrate the quantitative performance in terms of anomaly correlation. Clearly, the state-of-the-art OGCMs still have very large systematic errors in the SSS simulations in the tropical Pacific Ocean.

[13] Using the IOM with the empirical S_e parameterization scheme, SSSA simulations can be significantly improved (Figures 2b–2c and 3c–3d). Note that, in the case called dependent (Figure 2b), the training period and the simulation period overlap. As such, the skill for SSSA simulations (e.g., as measured by the anomaly correlation in Figure 3c) is known to be overly optimistic, because of observational information of S_e and SSS variability covering the simulation period being already included in the training period. Thus, a cross-validation experiment is performed by dividing the period (1969–1995) further into two sub-periods 1969–1979 and 1980–1995, from which two S_e^{69-79} and S_e^{80-95} models are separately constructed and are then cross-used to simulate SSSAs independently for the two periods (i.e., the S_e^{69-79} model is used for the period 1980–95 and the S_e^{80-95} model for 1969–1979, respectively). The simulated SSSA for the period 1980–95 using the S_e^{69-79} model (independent case) is shown in Figure 2c, and the anomaly correlation in Figure 3d.

[14] Note that the simulation skills presented in Figures 3d and 3c present the worst and best cases in our experiments because the S_e models constructed from independent (Figure 3d) and dependent (Figure 3c) periods are used for SSSA simulations. Yet, the simulated skill obtained even from the independent (worst) case (Figure 3d) is still not worse than that from the two OGCMs' simulations (Figures 3a–3b). Given the fact that there is a climate shift (that is, the real ocean states between these two periods experienced significant decadal changes in the tropical

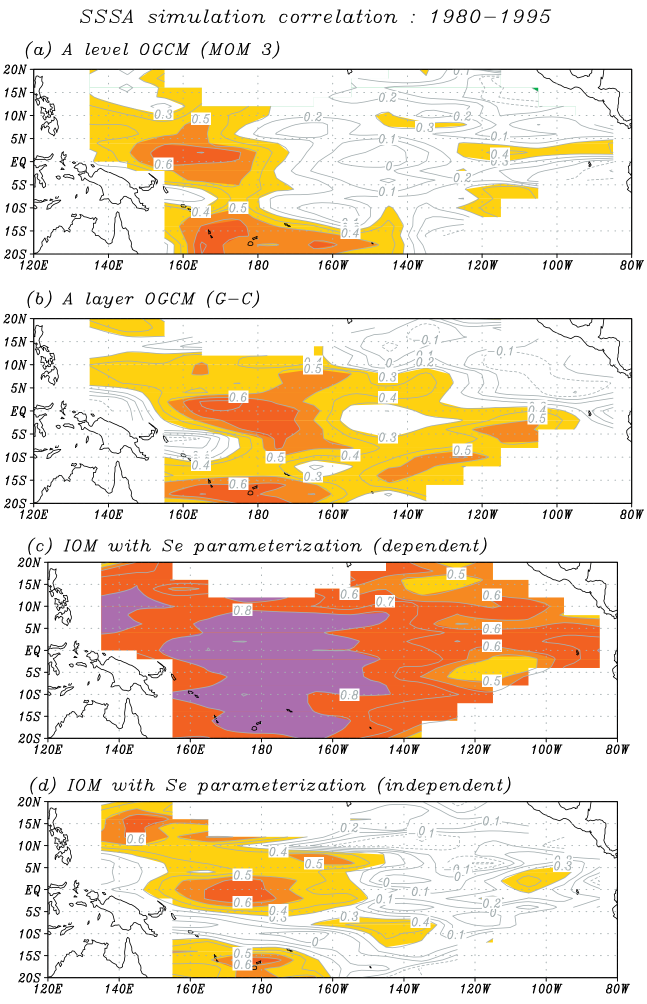

Figure 3. Anomaly correlations during the period 1980–1995 between SSS anomalies observed and simulated from (a) MOM 3, (b) the Gent-Cane model, and the IOM with an empirical S_e parameterization that is derived from a (c) dependent and (d) independent period, respectively. The time series at each point have been smoothed by a five-month running mean filter. The contour interval is 0.1.

Pacific), these results are encouraging to the extent that the S_e model constructed from the pre-climate shift period can be used to simulate SSS variability during the post-climate shift period with the skill that is comparable to the state-of-the-art OGCM simulations. Although the periods selected for the cross validation are too short to produce stable statistics for the EOF analysis, it clearly suggests that the performance of the empirical S_e scheme is not unduly sensitive to the training period selected nor to the application period. Other cross-validated skills (e.g., taking one year data out to construct S_e model and then simulating SSSAs for the year that has been taken out; figures not given) are between those in Figures 3c and 3d, which are better than those in OGCM simulations. These cross validation experiments indicate that the empirical approach is quite effective at improving SSSA simulations.

5. Discussion

[15] Salinity in the tropical Pacific has been shown to be important to the tropical dynamics and ENSO, and also has important implications for the use, interpretation of sea level, and for data assimilation in ocean models. In this study, we attempt to improve SSSA simulations in an IOM via an empirical parameterization of S_e.

[16] Here, an empirical S_e parameterization scheme is developed in two steps. First, an inverse modeling is used to estimate S_e from an SSSA equation, using observations (SSS fields and their tendency) and model fields (mean and anomaly currents). This inverse approach incorporates observations and models in a consistent way to allow the best possible estimate of S_e; best in the sense that it is exactly the S_e field required by the model to perfectly simulate the observed SSS. Second, using an EOF analysis, a relation can be constructed between SL anomalies simulated from the dynamical ocean model and S_e anomalies estimated from the inverse modeling, allowing the major features of interannual variability associated with ENSO to be captured. As a result, for a given SSSA equation, the inverted S_e anomalies, by balancing various terms in the salt budget of the mixed layer, yield an optimized estimate of S_e for use in simulating SSSAs. As tested in an IOM, the approach yields a good SSSA simulation in the tropical Pacific. The robustness and effectiveness are further demonstrated by validation experiments.

[17] While this is just a demonstration of the proof of concept, the potential applications for improving coupled climate prediction are self-evident. Further improvements and applications of the scheme are underway in several directions. Due to the limited number of observations the SSS field used for the inverse modeling is inherently undersampled. This raises concerns about the inverse approach in that errors in the SSS tendency and atmospheric forcing fields are transferred into the estimated S_e. The purpose here has been to demonstrate that once high space-time sampling of SSS is available from remote sensing by satellites (e.g., Aquarius [*Lagerloef*, 2002]) this methodology can be used on a routine base to better estimate S_e. A more accurate precipitation data set, available now from CMAP and GPCP [e.g., *Xie and Arkin*, 1997], is also being used for the inverse modeling to determine S_e. The SSSA simulations in the eastern equatorial Pacific are degraded considerably in the independent case (Figure 2c) and the reason is being investigated. The improved model of SSS variability will be embedded into an intermediate coupled model [*Zhang et al.*, 2003] to examine the role of ocean salinity and temperature in the upper ocean dynamics, air-sea interaction and climate.

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P. A. Arkin, J. Ballabrera-Poy, A. J. Busalacchi, R. G. Murtugudde, and R.-H. Zhang, Earth System Science Interdisciplinary Center (ESSIC), University of Maryland, College Park, MD 20742, USA. (rzhang@essic.umd.edu)