RESEARCH ARTICLE

10.1002/2013JC009697

Special Section:

Early scientific results from the salinity measuring satellites Aquarius/SAC-D and SMOS

Key Points:

- Assimilation of sea surface salinity (SSS) improves coupled forecasts
- Aquarius outperforms in situ SSS assimilation
- SSS assimilation imparts a relative improved upwelling signal

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Citation:

Hackert, E., A. J. Busalacchi, and J. Ballabrera-Poy (2014), Impact of Aquarius sea surface salinity observations on coupled forecasts for the tropical Indo-Pacific Ocean, *J. Geophys. Res. Oceans*, 119, 4045–4067, doi:10.1002/2013JC009697.

Received 3 DEC 2013

Accepted 3 JUN 2014

Accepted article online 9 JUN 2014

Published online 3 JULY 2014

Impact of Aquarius sea surface salinity observations on coupled forecasts for the tropical Indo-Pacific Ocean

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Abstract This study demonstrates the impact of gridded in situ and Aquarius sea surface salinity (SSS) on coupled forecasts for August 2011 until February 2014. Assimilation of all available subsurface temperature (ASSIM_ T_z) is chosen as the baseline and an optimal interpolation of all in situ salinity (ASSIM_ T_z -SSS_{IS}) and Aquarius SSS (ASSIM_ T_z -SSS_{AQ}) are added in separate assimilation experiments. These three are then used to initialize coupled experiments. Including SSS generally improves NINO3 sea surface temperature anomaly validation. For ASSIM_ T_z -SSS_{IS}, correlation is improved after 7 months, but the root mean square error is degraded with respect to ASSIM_ T_z after 5 months. On the other hand, assimilating Aquarius gives significant improvement versus ASSIM_ T_z for all forecast lead times after 5 months. Analysis of the initialization differences with the baseline indicates that SSS assimilation results in an upwelling Rossby wave near the dateline. In the coupled model, this upwelling signal reflects at the western boundary eventually cooling the NINO3 region. For this period, coupled models tend to erroneously predict NINO3 warming, so SSS assimilation corrects this defect. Aquarius is more efficient at cooling the NINO3 region since it is relatively more salty in the eastern Pacific than in situ SSS which leads to increased mixing and upwelling which in turn sets up enhanced west-to-east SST gradient and intensified Bjerknes coupling. A final experiment that uses subsampled Aquarius at in situ locations infers that high-density spatial sampling of Aquarius is the reason for the superior performance of Aquarius versus in situ SSS.

1. Introduction

An important focus of operational seasonal climate prediction centers is the full utilization of recently implemented Argo vertical profiles of subsurface salinity (S_z) via ocean data assimilation. In a survey paper, Oke *et al.* [2009] highlight the relative importance of various observing systems to ocean analyses using the Global Ocean Data Assimilation Experiment (GODAE) models and they find that Argo is the only observing system that constrains subsurface temperature (T_z) and salinity (S_z). Specifically, the ECMWF ocean reanalysis system (ORA-S3) coupled with atmospheric fluxes from the ERA-40 reanalysis (analyses after 2002) shows the impact of withholding different ocean observing systems at different locations [Balmaseda and Anderson, 2009]. Their results indicate that inclusion of Argo data significantly improves SST hindcasts for all regions (except in the Atlantic) and Argo outperforms both altimetry and mooring information for the western tropical Pacific (i.e., NINO4 region) and the entire tropical Indian Ocean between 10°N and 10°S. Unfortunately, their work did not differentiate between the relative contribution of temperature and salinity data, and it did not specifically analyze the contribution of sea surface salinity (SSS) likely because quality SSS data were at that time lacking.

For the Pacific, Yang *et al.* [2010] show that assimilating the subsurface structure of salinity accurately contributes to improved prediction of the 2006 El Niño. In particular, they show that the simultaneous assimilation of both T_z and S_z captures the correct warming for 2006. Assimilation of salinity data improves the amplitude of the downwelling Kelvin wave, successfully capturing the two-stage deepening of the thermocline and the east/west displacement of the warm/fresh pool in the western Pacific. By swapping out variables from different measurement techniques, these authors show that the salinity impact on stratification, especially near the thermocline in the western Pacific, is important for successful predictions.

For the Indian Ocean, Huang *et al.* [2008] explore what impact Argo salinity assimilation would have on the NCEP GODAS system for the tropical Indian Ocean by differencing two experiments that both assimilate T_z . In one, they include real Argo salinity profiles, and for the other they assimilate the GODAS standard synthetic salinity profiles for 2001–2006. Although temperature is relatively unaffected by Argo versus synthetic

S_z assimilation (due to the fact that both experiments assimilate the same T_z), salinity shows large differences between experiments. The resulting salinity fields are improved in the Bay of Bengal (0.8 psu), Arabian Sea (0.2 psu), and the eastern Indian Ocean (0.4 psu) due to Argo S_z assimilation. In each of these regions, assimilation of Argo S_z leads to a significant reduction of the systematic error in sea level (SL), and the overall -1 cm basin-wide improvement in SL as measured by satellite altimetry is attributed to increased salinity from Argo S_z assimilation.

Unfortunately, few studies have examined the impact that SSS has on ENSO predictions. An exception is the study of *Ballabrera-Poy et al.* [2002] who showed that SSS observations, independent of SST and SL, have a significant impact on the 6–12 month lead ENSO forecasts in the context of statistical prediction. They used the observed SSS product from *Delcroix* [1998] along with COAPS wind stress [*Stricherz et al.*, 1997], SST [*Reynolds and Smith*, 1994], sea surface height from ocean model hindcasts [*Behringer et al.*, 1998], and precipitation [*Xie and Arkin*, 1996] minus evaporation [*Kalnay et al.*, 1996] for multiple regression analysis of ENSO and found that SSS would have little impact on ENSO nowcasts. However, statistical ENSO forecasts are significantly improved with lead times of 6–12 months in advance. In particular, key regions of SSS variability contributing to improved forecasts included the central basin near 20°S at 6 month leads and the western equatorial Pacific including the South Pacific Convergence Zone (SPCZ) from 9 to 12 month lead times [see *Ballabrera-Poy et al.*, 2002 for details] (Figures 2–6).

Following upon this earlier work, *Hackert et al.* [2011] showed that the initialization of a coupled model by assimilating gridded in situ SSS improves the resulting coupled forecasts for the tropical Pacific. Coupled simulations were initiated from these assimilation results and ran for 12 months for each month, 1993–2007. The resulting hindcasts showed that adding SSS to T_z assimilation improves coupled forecasts for 6–12 month lead times. Assimilation of SSS data helped to ameliorate the Spring Predictability Barrier (SPB) problem. Indeed, by assimilating SSS observations the NINO3 correlation for 6–12 month forecasts increases by 0.2–0.5 and reduces the RMS error by 0.3 – 0.6°C for forecasts initiated between December and March, a period key to long-lead ENSO forecasts. The positive impact of SSS assimilation originates from warm pool and Southern Hemisphere salinity anomalies. Improvements are brought about by fresh anomalies advected to the equator via subduction processes. Negative SSS anomalies (i.e., freshening) serve to increase the barrier layer thickness (BLT) near the equator leading to a shallower mixed layer. Thus, the net effect of assimilating SSS is to increase stability, reduce mixing, and shoal the thermocline which concentrates the wind impact of ENSO coupling. Monthly analyses indicate that this effect is most pronounced in June to August helping to explain the improvement in the SPB. In addition, regional assimilation of SSS determined that the western Pacific and the Southern Hemisphere has relatively greater influence on improving coupled forecasts reaffirming the work of *Ballabrera-Poy et al.* [2002].

In June 2011, NASA launched Aquarius which is designed to monitor SSS on a global scale. Up until remote sensing of SSS, achieving a high-resolution, uniform global view of surface salinity had not been possible due to sparse in situ salinity measurements. The overlaying scientific goal of the Aquarius mission is to quantify and understand the linkages among ocean circulation, the global water cycle, and climate by accurately measuring SSS [*Lagerloef et al.*, 2008]. In the following work, a combination of ocean models, coupled ocean-atmosphere models, and data assimilation of satellite and in situ salinity are used to investigate if satellite SSS data help to improve short-term ENSO predictions.

The current study extends the previous works of *Hackert et al.* [2011] and *Ballabrera-Poy et al.* [2002] by expanding to the Indo-Pacific region and by incorporating assimilation of Aquarius and in situ SSS products. The impact of SSS is assessed by comparing data assimilation experiments that assimilate SSS data versus one that does not. The reference simulation assimilates subsurface temperature (ASSIM_ T_z) only. Previous authors have shown that assimilation of subsurface temperature tends to produce reasonable coupled ENSO forecasts [*Ruiz et al.*, 2005; *Drosowsky*, 2006; *Lima et al.*, 2009]. The reference simulation does not assimilate SST and SL data, as these variables overly constrain the initialization of the coupled ocean-atmosphere model, and given their covariance with SSS muddle the impact of SSS assimilation.

The purpose of this study is to show how assimilation of SSS data impacts the initialization of a coupled model in general and how in situ SSS initialization compares to Aquarius. Thus, the role of the SSS data will be investigated using two different SSS products. One is an optimal interpolation (OI) of all available in situ mixed layer salinity observations, and the other is the latest satellite SSS product provided by the Aquarius

project. The general philosophy of this paper is to difference coupled model experiments with SSS assimilation minus the baseline without SSS assimilation using the NINO3 (i.e., 5°S–5°N, 150°W–90°W) SST anomaly index as the validation target.

This paper is arranged in the following manner. Section 2 will discuss the background ENSO state and data processing for the subsurface temperature and salinity fields to be assimilated. Section 3 describes all the model/data assimilation techniques used in this study and puts our results in context to the broader coupled model community. Section 4 presents the results of initialization using in situ and satellite SSS versus the baseline and also presents the impact of in situ versus Aquarius SSS. Section 5 contains the discussion of various topics including the impact of data coverage and our study period, and the impact of SSS in the framework of assimilating other ancillary data. Section 6 summarizes this work.

2. Observations and Data Processing

The period under consideration in this study is from August 2011 until February 2014. During this period, the NINO3 index (e.g., <http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices>) indicates a minor La Niña from September 2011 to January 2012 (i.e., NINO3 region SST anomaly less than -0.5°C) with a minimum of -1°C in December 2012. During 2012, the NINO3 SST anomaly rose peaking in July 2012 at 0.92°C . While this warming was taking place, many coupled models predicted El Niño for late 2012 (see, e.g., the forecast discussion provided in http://iri.columbia.edu/climate/ENSO/currentinfo/archive/201207/SST_table.html). However, these El Niño forecasts proved inaccurate. Instead, cooling returned in the eastern Pacific for early 2013 with minimum negative anomalies in January 2013 of -0.57°C . After that, cooling subsided in Boreal spring but returned in May to August 2013 (as low as -0.69°C in June). The repeated cooling episodes correspond to an overall mean weak La Niña state (-0.25°C) for the tropical eastern Pacific from August 2011 until February 2014.

In situ temperature and salinity data used in this work come from the Global Temperature Salinity Profile Project (GTSP), and the World Ocean Atlas 2009 (WOA09) observation databases. For the GTSP “best copy” data set [Sun *et al.*, 2010], both real time from the Global Telecommunications System (GTS) and delayed mode data received by the NODC are included in a continually managed database which maintains all available subsurface information removing duplicate entries. This data set includes profiles from instruments such as CTD and XBT measurements from ships, TAO/RAMA buoys, and Argo profiling floats. Only data classified as “good,” “probably good,” or “modified” are included in our data set after location, date, gradient, density validation, climatological, and profile consistency tests are performed (http://www.nodc.noaa.gov/GTSP/access_data/gtspp-bc.html). The WOA09 [Locarnini *et al.*, 2010] includes research quality temperature profile data on standard levels (<http://www.nodc.noaa.gov/OC5/WOA09/pubwoa09.html>). Extensive quality controls are performed, and only data of the “highest quality” (i.e., depth and temperature with error flag set to zero) are retained in our database. In addition to the profile data, grids of the seasonal cycle for temperature provided by World Ocean Database 2009 (WOD09) [Boyer *et al.*, 2009] are used to calculate monthly anomalies.

In order to extend the influence of the limited number of temperature profiles, the optimal interpolation (OI) technique of Carton and Hackert [1989] is employed to convert point-wise profile data to gridded fields. The first step is to interpolate each temperature profile to the standard Levitus depths down to 1500 m. Next, the nearest grid point of the WOD09 seasonal cycle is used to calculate anomalies. All the resulting anomaly profiles are binned onto $1^{\circ} \times 1^{\circ}$ grids for each month from January 1993 until February 2014. The OI is then performed on this binned data using decorrelation scales of 15° longitude, 3° latitude, and 1 month matching the values for SST estimated by Meyers *et al.* [1991]. This process is repeated for each month and for each depth to obtain temperature anomaly grids with $1^{\circ} \times 1^{\circ} \times 1$ month resolution at standard Levitus depths. Since our OI technique and period differ from that used in WOD09 processing, the mean of the seasonal cycle of the resulting OI-gridded anomalies is nonzero. As is, assimilation of these data would cause spurious drifts of the data assimilation algorithm. Therefore, we remove the mean of the seasonal cycle of the monthly OI-gridded fields so that the final seasonal cycle calculated over 1993–2013 has zero mean. This period is used as a baseline to calculate these long-term biases between OI methodologies since it encompasses realistic ENSO variability and has reasonable data coverage. Henceforth, all assimilation observation anomalies will be treated in this same manner and will simply be referred to as anomalies.

In this work two different in situ SSS products will be assimilated. To create the first one, all in situ salinity observations shallower than 10 m depth are binned in a $1^\circ \times 1^\circ \times 1$ month grid, anomalies are calculated using WOD09, and then OI was performed in a similar manner as T_z to produce a monthly SSS anomaly field. This SSS product is abbreviated as SSS_{ISMON} (for SSS in situ monthly) and is comparable to satellite SSS since SSS errors estimated through cross-validation studies (e.g., performing several analyses by randomly withholding 10% data) provide an estimated salinity error of ~ 0.22 psu which is comparable to the expected accuracy of Aquarius retrievals [Le Vine et al., 2007; Yueh et al., 2001].

The second SSS product is created from in situ salinity in order to capture the sampling coverage of Argo profilers with the same temporal resolution as the Aquarius data. As before, profile anomalies are formulated with respect to the WOD09 climatology and the shallowest observations of the profile are binned for the tropical Indo-Pacific region on a weekly basis using a 10 day window. Now the OI is performed in the same manner as SSS_{ISMON} anomalies except that decorrelation scales are 9.5° for longitude and 4.5° for latitude, matching those estimated using Aquarius SSS. This weekly product is differenced from the monthly product by designating it as SSS_{IS} (for SSS in situ). Note that gridding salinity data shallower than 10 m and treating them as surface observations is a reasonable preliminary assumption based on studies that have shown that over 84% of the time salinity differences between 1 and 10 m are less than 0.05 psu for the TAO moorings [Henocq et al., 2010].

In addition to the two gridded in situ products described above, this study will also utilize the Aquarius satellite SSS product. At present, Aquarius Version 2.9.1 is the latest available product (ftp.podaac.jpl.nasa.gov, cd L3/mapped/V2.9.1/7day/). Both mapped (Level 3) and along-track (Level 2) data will be utilized depending on the application. The details of the Level 3 mapping are found in Lilly and Lagerloef [2008]. Since the data assimilation method used here requires unbiased anomalies, these are formulated using the same methodology employed for SSS_{ISMON} and SSS_{IS} anomalies.

The mean and standard deviation of our in situ SSS and Aquarius SSS anomalies over the Aquarius period (August 2011 to February 2014) are presented in Figure 1. Despite the many similarities between the two products there are important differences between the Aquarius satellite SSS and our in situ SSS product (Figure 1c). An example is the relatively saltier values for Aquarius east of 180° near the equator and east of 120°W in the Southern Hemisphere. In addition, Aquarius minus in situ SSS (Figure 1c) shows negative values in the ITCZ between 5°N and 20°N and in the SPCZ in the Pacific. In the Indian Ocean, Aquarius is generally fresher especially from the equator to 10°S and in the Arabian Sea with the exception of the Bay of Bengal.

Although there are significant differences between the mean SSS, most of the features of the variability are similar in both the Aquarius and in situ SSS plots (Figures 1d and 1e, respectively). High variability in the far western Pacific along the equator stretches east and south into the South Pacific Convergence Zone (SPCZ) at roughly 170°W , 15°S . Common regions of high variability can also be seen in the eastern/central Indian Ocean to the Bay of Bengal and in the far eastern Pacific under the ITCZ and especially at 5°N at the eastern boundary for both products. The other interesting feature is that the amplitude of the Aquarius variability is significantly larger than the in situ SSS product.

3. Models and Data Assimilation Description

3.1. Ocean Model

The primitive-equation, sigma-coordinate model with variable depth oceanic mixed layer is described in Gent and Cane [1989] and Murtugudde et al. [1996]. This ocean model is described and validated in a series of simulation studies of circulation in all three tropical ocean basins [Hackert et al., 2001; Murtugudde and Busalacchi, 1998; Murtugudde et al., 1996, 1998] and proves accurate in analyzing the thermohaline structure of subtropical cells and subduction pathways [Chen et al., 1994a; Luo et al., 2005; Rothstein et al., 1998]. Solar radiation (Earth Radiation Budget Experiment—ERBE) and precipitation from a combination of Global Precipitation Climate Project (GPCP) [Adler et al., 2003] before and Tropical Rainfall Measuring Mission (TRMM) [Kummerow et al., 2000] after December 2013 are specified externally. Monthly anomalies of the cloud data (NCEP Reanalysis) [Kalnay et al., 1996] are added to the Interannual Satellite Cloud Climatology Project—ISCCP seasonal cycle [Rossow and Schiffer, 1991] in order to provide a more realistic mean.

Figure 1. Mean of SSS anomaly for (a) OI of all near-surface in situ data (SSS_{IS}), (b) Aquarius L3-gridded product (SSS_{AQ}). (c) The mean difference between Aquarius minus in situ. (Note that the color bar is half that of the means.) Standard deviation is also presented for (d) in situ and (e) satellite SSS. Anomalies are all formulated with respect to Levitus SSS. All observations cover the period, August 2011 to February 2014, and all maps have been smoothed for plotting using a bilinear smoother.

Our OGCM uses the hybrid vertical mixing scheme of *Chen et al.* [1994b] which combines the advantages of the traditional bulk mixed layer of *Kraus and Turner* [1967] with the dynamic instability model of *Price et al.* [1986]. This allows simulation of all three major processes of oceanic vertical turbulent mixing—atmospheric forcing is related to mixed layer entrainment/detrainment, gradient Richardson number accounts for shear flow, and instantaneous adjustment simulates high-frequency convection in the thermocline. Implementation of this mixing scheme has led to accurate simulation of the mixed layer temperature and salinity and subduction pathways [*Luo et al.*, 2005]. Surface fluxes are calculated interactively by coupling the OGCM to a thermodynamic atmospheric mixed layer model [*Murtugudde et al.*, 1996], thus allowing

feedbacks between sea surface temperature (SST) and salinity (SSS) and surface fluxes. It is important to note that this model does not relax back to climatology for SST and SSS, but is allowed to vary freely as a natural boundary condition [Huang, 1993].

The model configuration used for the baseline simulation, all data assimilation scenarios, and coupled model experiments covers the tropical Indo-Pacific basin (34°E–76°W, 30°N–30°S) with a homogeneous longitudinal grid and a variable latitudinal grid (down to 1/3° within 10° of the equator). The spatial resolution permits the development of mesoscale eddies and the existence of a realistic Indonesian Through Flow (ITF) that averages 12 ± 4 Sv which closely matches observed values for 2004–2006 [e.g., Sprintall et al., 2009]. The open boundaries are treated as a sponge layer within 5° of the north and south borders smoothly relaxing to WOD09. The vertical structure consists of a variable depth mixed layer and 19 sigma layers with a deep motionless boundary being specified as $T_{bottom} = 6^\circ\text{C}$ and $S_{bottom} = 35$ psu.

The model is spun up from rest using climatological winds with the initial conditions derived from WOD09 fields and is allowed to come to equilibrium after 30 years of forcing by the ECMWF [1994] analysis climatology. Interannual runs are initialized from this climatological spin-up, and the wind speeds required for sensible and latent heat fluxes are computed from interannual ECMWF wind converted to stress using the bulk formula ($\rho = 1.2 \text{ kg/m}^3$, $C_D = 1.2 \times 10^{-3}$). This model is an improvement upon previous versions since riverine fresh water flux has been added using the river flow data of Dai and Trenberth [2002]. The river seasonal cycle has been estimated from the annual flow using the monthly ratio of the local precipitation.

3.2. Ensemble Reduced Order Kalman Filter Data Assimilation

In order to assimilate in situ and satellite observations into our ocean model, we utilize the Ensemble Reduced Order Kalman Filter. The equations of the reduced order Kalman filter are obtained by projecting the equations of the Kalman Filter upon a basis of Multivariate Empirical Orthogonal Functions (MEOFs) from a 20 year free-run of the model, 1985–2004. This basis, which describes the ocean model state, is comprised of sea level (SL), mixed layer depth (MLD), subsurface layer thickness, and all layers of temperature, salinity, and currents. Preliminary experiments have shown that 30 MEOFs provide a reasonable compromise between accuracy, overfitting, and computational cost to estimate the ocean variability. However, neglecting the higher MEOFs (i.e., 31–240) leads to an underestimation of the analysis error covariance [see, for example, Cane et al., 1996]. Therefore, we utilize an ensemble technique to account for the missing analysis error covariance each month. At each assimilation cycle, the observations are assimilated onto background states every 5 days. Averaging each month using six different ocean states and their associated high-frequency variability retains the amplitude of the analysis updates. In addition, the numerical stability of the scheme is guaranteed by adding the model forecast error (Q) to the reduced order background error covariance [see Verron et al., 1999, equation (10)]. Additional details of this technique and bibliographical references can be found in Ballabrera-Poy et al. [2001].

An additional quality control (QC) check to enforce the compatibility between observed and forecasted anomalies includes rejecting observed anomalies whose amplitude is larger than five standard deviations of the model anomalies at that point. This allows assimilating significant climate anomalies while filtering out data that are incompatible with the dynamics of the model. Our studies thus far have shown that typically less than 1% of the data are eliminated by this QC. Observations are projected onto the numerical grid. This approach strongly simplifies the forward observational operator, $\mathbf{H}$. Subsurface observations are averaged if they fall within the same model grid box. The error value for the subsurface temperature (T_z) was optimized by running a series of experiments assimilating T_z individually which led to the optimal error value of 0.75°C . For SSS, an observational error is chosen to be 0.2 psu to correspond to the estimated error of Aquarius [Lagerloef et al., 2008]. This value is also conservative relative to the Version 2.9.1 Aquarius error estimates of -0.14 and -0.17 psu for the tropical Pacific and Indian Oceans, respectively [e.g., Lagerloef et al., 2013]. In the reference experiment, all available subsurface temperature (T_z) profile observations are assimilated into the model using the Ensemble Reduced Order Kalman Filter (EROKF) for the period January 1993 to February 2014 (ASSIM_ T_z , see Table 1 for experiment summary).

In addition to the assimilation of subsurface temperature data, weekly gridded fields (i.e., Level 3 data) of SSS from both Aquarius V2.9.1 (ASSIM_ T_z _SSS_{AQ}) and our weekly in situ SSS product (ASSIM_ T_z _SSS_{IS}) are assimilated to assess the impact of SSS assimilation on initialization of coupled forecasts. Each SSS data

Table 1. Summary of the Coupled Model Experiments Used in This Paper^a

Experiment Name	Period	Assimilation Variables
ASSIM_T _z	Jan 1993 to Feb 2014	T _z
ASSIM_T _z -SSS _{ISMON} *	Jan 1993 to Feb 2014	SSS from OI of all available near-surface salinity with depth ≤10 m and T _z , monthly
ASSIM_T _z -SSS _{IS}	Aug 2011 to Feb 2014	SSS from OI of all available near-surface salinity with depth ≤10 m and T _z , weekly
ASSIM_T _z -SSS _{AQ}	Aug 2011 to Feb 2014	SSS from Aquarius Version 2.9.1 Level 3 data and T _z , weekly
ASSIM_T _z -SSS _{AQ@IS}	Aug 2011 to Feb 2014	SSS from OI of Aquarius along-track data subsampled at in situ locations and times and T _z , weekly

^aThe first column is the experiment designation, the second indicates the period, and the third describes the data used to initialize these coupled model experiments. T_z stands for subsurface temperature. The asterisk indicates that the ASSIM_T_z-SSS_{ISMON} experiment is used to initialize all other assimilation experiments that assimilate SSS starting in August 2011.

assimilation experiment is initialized using the ASSIM_T_z-SSS_{ISMON} results for July 2011, and then assimilation of additional various SSS data takes place starting from August 2011 to February 2014.

3.3. Hybrid Coupled Model

In order to investigate the coupled ocean-atmosphere response to the assimilation of the various data sets, a Hybrid Coupled Model (HCM) will be used. The HCM couples our OGCM (described in section 3.1) to a statistical atmospheric model (SAM). The SAM estimates wind stress (τ) anomalies based on a singular value decomposition (SVD) analysis of the SST- τ covariance of a long simulation of the observed SST-forced ECHAM4.5 model [Zhang *et al.*, 2006; Zhang and Busalacchi, 2008, 2009]. The SST anomalies are from the extended SST reconstruction of Smith *et al.* [2008], and wind stress anomalies are simulated from the Max Planck Institute for Meteorology (MPI) Atmospheric GCM (ECHAM4.5) [Roeckner, 1996]. Wind stress data used to construct the τ model are the ensemble mean of a 24 member ECHAM 4.5 simulation for the period 1950–1999 with roughly 2.8° resolution and 19 hybrid levels, forced by observed SST anomalies. As demonstrated by Barnett *et al.* [1993] and Syu *et al.* [1995], the seasonality of the atmosphere can have an important effect on the onset and evolution of El Niño. Thus, to construct seasonally dependent models for τ , the SVD analyses are performed separately for each calendar month and so consist of 12 different submodels, one for each calendar month. The first five SVD modes provide reasonable amplitudes of the wind stress from the model SST anomalies accounting for between 98.1% (June to July) and 99.5% (October to January) of the total explained variance.

The NINO3 prediction skill of our HCM is comparable with most coupled systems incorporating sophisticated ocean data assimilation [e.g., Ji *et al.*, 1995; Chen *et al.*, 2000]. Figure 2 validates the correlation and Root Mean Square (RMS) of the model results against the observed NINO3 SST anomaly [Reynolds *et al.*, 2002]. The experiments reported in Figure 2 are ASSIM_T_z (black solid line), ASSIM_T_z-SSS_{ISMON} (blue dashed line), and the NCEP Climate Forecast System Reanalysis Reforecast (CFSRR) results. The CFSRR coupled hindcasts (Figure 2, red dotted line) are comprised of the atmospheric assimilation/model with resolution ~38 km (detailed in Saha *et al.* [2010]) along with the MOM4 ocean model [Griffies *et al.*, 2004] with 0.5° resolution within 30°N–30°S and the GODAS ocean assimilation [Behringer, 2007] of all available oceanic in situ data. The CFSRR model was chosen to substantiate our HCM since it represents a diametric counterpoint to our HCM system. The ocean model (level versus sigma layer), data assimilation (OI versus EROKF), and atmospheric model (full dynamic atmosphere versus SAM) are all dissimilar for CFSRR with respect to our HCM, respectively. Figure 2 confirms that both the CFSRR and our HCM results validate well against observations with correlation exceeding the 99.5% confidence limits (i.e., the light black dashed line in Figure 2a) out to 9 month lead times. In addition, RMS difference validation of our HCMs using NINO3 SST anomaly observations is comparable to the CFSRR results after 1 month lead times. Note that early in the forecast period the high correlation and low RMS for CFSRR are attributed to the fact that CFSRR assimilates SST (i.e., including assimilation in the NINO3 region) whereas our coupled models were specifically formulated to allow independent SST evolution. Thus, both these models provide useful and independent tools to diagnose ENSO prediction improvements brought about by SSS assimilation. This validation shows that our model/data assimilation/coupled model system which are initialized using only T_z and additionally SSS_{ISMON} are comparable to other, widely used, operational systems that assimilate SST, T_z, and S_z.

The various experiments discussed in this paper are summarized in Table 1 and detailed in the following: the ocean model is run for 30 years using ECMWF climatological forcing. Then, starting in 1993, subsurface

Figure 2. Our Indo-Pacific HCM experiments and CFSRR coupled model results are validated with observed NINO3 SST anomaly for January 1993 to March 2011 using (a) correlation and (b) RMS. ASSIM_T_z assimilates all subsurface temperature information (black) and ASSIM_T_z-SSS_{IS} additionally assimilates the monthly SSS product (blue dashed line), whereas the NCEP CFSRR (red dotted line) coupled model assimilates SST and in situ salinity (S₂) in addition to T_z. The thin dotted line on Figure 2a corresponds to the 99.5% confidence limits (assuming seasonal independence). Note that our HCM validation statistics are comparable to the NCEP operational CFSRR results and all validate well against observations.

temperature is assimilated (abbreviated as ASSIM_T_z) until February 2014 using realistic interannual forcing (both ECMWF winds and GPCP/TRMM precipitation). A benefit of using 1993–2013 for our model baseline analysis is that other ancillary data, such as satellite altimetry are available to validate model/data assimilation results. Another experiment that assimilates the monthly SSS in situ product along with T_z is run from 1993 until February 2014 (abbreviated as ASSIM_T_z-SSS_{IS}MON). Monthly OI is required prior to the Aquarius period due to the scarcity of in situ SSS observations (e.g., Argo) early in the record. Two additional experiments that, in addition to T_z, also assimilate weekly gridded Aquarius SSS (ASSIM_T_z-SSS_{AQ}) and an OI of in situ SSS (ASSIM_T_z-SSS_{IS}) are initialized from July 2011 ASSIM_T_z-SSS_{IS}MON results and cover the period from August 2011 until February 2014 (30 months). Anomalies are formulated for each SSS experiment with respect to the 1993–2013 mean seasonal cycle of the ASSIM_T_z-SSS_{IS}MON experiment and then these anomalies are added to the climatological ECMWF results and used as initial conditions for coupled experiments. Then for each month from August 2011 until February 2014, free coupled model experiments are initiated from the three forced experiments and are run for 12 months each (for a total of 360 months). Note that adding anomalies to ECMWF climatology model results are required since the SAM needs a fixed seasonal cycle of model SST.

4. Results

4.1. Impact of SSS Assimilation on Coupled Forecast Results

In order to assess the quality of a particular forecast, the observed NINO3 region SST anomaly from Reynolds *et al.* [2002] is used as a target. For all experiments, we calculate mean statistics, correlation, and RMS differences, over the period August 2011 to February 2014. Figure 3 displays the correlation and RMS versus lead time for three simulations, ASSIM_T_z, ASSIM_T_z-SSS_{IS}, and ASSIM_T_z-SSS_{AQ}. For short-term forecasts, from month 1 to month 3, the experiment that includes assimilation of in situ SSS barely outperforms ASSIM_T_z. Forecast results are indistinguishable from one another from 3 to 5 month lead times. However, after 7 month forecast lead times, ASSIM_T_z-SSS_{IS} correlations outperform ASSIM_T_z. The Fisher-Z statistic [from Press *et al.*, 1986, equation (13.7.10)] indicates that such an increase of correlation is 85% significant for 9 month lead times (indicated by thin blue dashed line). Thus, assimilation of our in situ OI SSS product significantly improves coupled forecasts with respect to subsurface temperature assimilation alone for this period.

These results agree with previous work of Ballabrera-Poy *et al.* [2002] and Hackert *et al.* [2011] who found that SSS did not so much impact short-term coupled forecasts, but after 6–9 months SSS information did significantly improve ENSO forecasts. The existence of such a lag is explained by the fact that anomalies of

Figure 3. Validation of coupled model results for the Aquarius period, August 2011 to February 2014 using (a) correlation and (b) RMS versus observed NINO3 SST anomaly. The solid black curve is initialized using assimilation of subsurface temperature (ASSIM_T_z), the thick dotted red curve from T_z and Aquarius SSS (ASSIM_T_z_SSSAQ) and the dash blue curve from T_z and weekly OI of all available near-surface salinity (ASSIM_T_z_SSS_{IS}). The thin dotted lines show the significance of the differences assuming ASSIM_T_z_SSSAQ (red) and ASSIM_T_z_SSS_{IS} (blue) are greater than ASSIM_T_z and ASSIM_T_z_SSSAQ is greater than ASSIM_T_z_SSS_{IS} (black) using the Fisher Z test. Note that Fisher Z test is undefined (thus missing) when this condition fails.

the salt concentration in the subtropical Southern Hemisphere gyre regions may subduct along the pycnocline to the equator and later modulate ENSO Kelvin/Rossby waves especially in the western equatorial Pacific via density perturbations above the depth of the thermocline.

The RMS differences between the predicted and observed NINO3 SST anomalies are shown in Figure 3b. Although the differences between the curves associated with ASSIM_T_z (black line) and ASSIM_T_z_SSS_{IS} (blue dash) are small, assimilation of in situ SSS actually degrades the statistics after 5 month lead time forecasts. This result is inconsistent with Hackert *et al.* [2011] who found that RMS is reduced when coupled predictions are initialized with in situ gridded SSS starting with 3 month lead times. The degradation of ASSIM_T_z_SSS_{IS} RMS versus ASSIM_T_z is also inconsistent with the longer assimilation experiments shown in Figure 2b.

Figure 3 also highlights the impact of assimilating Aquarius data (ASSIM_T_z_SSSAQ, red dotted line). Like the weekly gridded in situ SSS results, assimilation of Aquarius SSS improves the correlation of the coupled forecasts. This is especially evident by month 6, when the correlation for ASSIM_T_z_SSSAQ versus observed NINO3 SST anomaly is 0.46 while the ASSIM_T_z experiment correlation is only 0.25. By month 9, the results have diverged further since ASSIM_T_z_SSSAQ remains at $r = 0.40$ while the ASSIM_T_z results falls to $r = 0.0$. In this case, the differences between ASSIM_T_z_SSSAQ and the baseline (i.e., ASSIM_T_z) are statistically significant. The Fisher Z statistic climbs from 76% significant at 5 months lead time to exceeding 92% at 6 month to peak in month 9 at 99% significance (thin red dashed line). The impact of the SSS assimilation is felt after 5 months and differences peak at 9 month lead times matching our previous work [e.g., Ballabrera-Poy *et al.*, 2002]. Therefore, assimilation of satellite SSS significantly improves the temporal evolution of coupled forecasts after 5 month lead times.

Unlike ASSIM_T_z_SSS_{IS}, now the RMS results for ASSIM_T_z_SSSAQ are consistently lower than ASSIM_T_z for all lead times (Figure 3b). Prior to month 5 these differences are small. However, after 5 month lead times the differences climb to an average of roughly 0.3°C with ASSIM_T_z_SSSAQ having a lower RMS than ASSIM_T_z by 0.45°C at 9 month lead times. For each lead time, the ASSIM_T_z_SSSAQ results (red dotted line) have lower RMS and thus outperform the ASSIM_T_z experiments.

A key result of this study to this point is that not only does assimilation of satellite SSS significantly improve coupled forecasts in general, but that Aquarius gives better results than assimilation of the in situ SSS product alone. Figure 3 shows the validation versus observed NINO3 SST anomalies of both ASSIM_T_z_SSS_{IS} (blue dashed line) and ASSIM_T_z_SSSAQ (red dotted line). The correlation plots show that Aquarius outperforms the in situ SSS assimilation for 5 month lead forecasts. Correlations of ASSIM_T_z_SSSAQ exceed

ASSIM_T_z-SSS_{IS} by an average of roughly $r = 0.15$ for months 5–10. During this period, the significance of the differences, as measured by the Fisher-Z test (thin black dotted line), generally exceeds the 85% significance level. Therefore, coupled experiments that assimilate satellite SSS (i.e., Aquarius) improve coupled forecasts for 5–10 month lead times with respect to assimilation of in situ SSS. The improved statistics for satellite versus in situ SSS assimilation is similar for validation using RMS differences with observed NINO3 SST anomalies. Even though the RMS is similar prior to 5 month lead time forecasts, Figure 3b shows that after 5 month lead times, the assimilation of satellite SSS outperforms the in situ SSS by an average of 0.4°C RMS (compare red dotted to blue dash lines).

To summarize, adding SSS to T_z assimilation generally improves the forecast skill of coupled forecasts versus observed NINO3 SST anomalies. Correlation is improved when our in situ SSS product is assimilated (i.e., ASSIM_T_z-SSS_{IS}). In addition, when Aquarius SSS is assimilated into the initial conditions (ASSIM_T_z-SSS_{AQ}), both the correlation and RMS are improved with respect to the ASSIM_T_z experiments. When testing the relative improvement of SSS assimilation, satellite SSS outperforms in situ SSS for correlation with the significance of the differences exceeding 85% for months 5–10 and RMS is lower for all lead times after 5 months. In the remaining part of this section, we will examine the reasons for these improvements by presenting the initialization differences from the data assimilation results. Then we will present the monthly lead time average forecast differences to show the temporal evolution (in a mean sense) of the impact of SSS assimilation.

4.2. Mean Differences of Coupled Initialization Due to SSS Assimilation

In order to diagnose why assimilation of SSS improves coupled forecasts, mean differences between the ASSIM_T_z-SSS_{IS} and ASSIM_T_z data assimilation results (i.e., the initialization of the coupled models over August 2011 until February 2014) are presented. It is important to note that these differences include not only the short-term impact of weekly SSS assimilation (i.e., August 2011 to February 2014), but also the long-term (January 1993 to July 2011) bias between assimilation scenarios built into the initial conditions. Remember that ASSIM_T_z was initialized from its continuing, identical long-term experiment whereas ASSIM_T_z-SSS_{IS} was initialized in August 2011 using the July 2011 ASSIM_T_z-SSS_{ISMON} experiment. In other words, these differences contain both the long-term bias between experiments, but also the differences due to assimilation of salinity for August 2011 to February 2014.

In Figure 4a, the model SSS for ASSIM_T_z-SSS_{IS} minus ASSIM_T_z is presented. The SSS assimilation experiment is fresher over most of the Indian Ocean with the exception of the Bay of Bengal. Over the Indonesian Seas, in a zonal band between roughly 100°E and 140°E, assimilation of in situ SSS produces anomalous salting with respect to the ASSIM_T_z experiment. In the Pacific, both in the ITCZ (east of 160°E, between the equator and 10°N) and in the South Pacific Convergence Zone (SPCZ) (5°S–15°S from the coast of New Guinea to 140°W) negative differences show that the ASSIM_T_z-SSS_{IS} is fresher than the ASSIM_T_z experiment.

For the sea level ASSIM_T_z-SSS_{IS} minus ASSIM_T_z difference plot (Figure 4b) the main feature here is suggestive of an upwelling Rossby wave with negative values at 5° straddling the equator near the dateline. South of the equator, the minor asymmetric values peak at −2 cm whereas the Northern Hemisphere values are −4 cm. The Indian Ocean shows positive SL differences (except in the Bay of Bengal), the Indonesian Seas are negative, and the far western equatorial Pacific is positive, as is east of 140°W. The values south of 10°S are generally positive east of 140°E for the SL plot.

Next we present the differences between ASSIM_T_z-SSS_{IS} minus ASSIM_T_z for SST in Figure 4c. Many features of the SST difference plot closely match those of SL. For example, note the pattern for the equatorial upwelling Rossby wave is evident by the negative region where ASSIM_T_z-SSS_{IS} has lower SST than ASSIM_T_z between 160°E and 140°W near the dateline with lowest values (lower than −0.5°C) located in a zonal band roughly 5° off the equator. In addition, the SST differences show a meridional banded structure across the Indo-Pacific with positive values over the western Indian Ocean, negative over the Indonesian Seas region (especially in the upwelling region off Sumatra), a small region of positive values in the far western Pacific warm pool, negative values between 160°E and 140°W and positive differences east of 140°W in the eastern Pacific with maximums found in the NINO3 area and at 12°S, 100°W.

The feature in the mean fields of SL and SST that looks similar to a Rossby wave is actually the result of two separate Rossby waves during our study period. The first is spawned in the far eastern Pacific in December 2011 to February 2012. This feature, evident in a longitude versus time analysis (not shown) as negative SSS

Figure 4. Results of the mean difference between ASSIM_Tz_SSSIS minus ASSIM_Tz initial conditions for (a) SSS, (b) SL, and (c) SST for August 2011 to February 2014. Units are psu, cm, and °C, respectively.

ASSIM_Tz_SSSIS minus ASSIM_Tz differences, travels west starting from 120°W to 100°W along 3°N and arrives at the dateline by June/July 2012. A weaker but symmetric fresh SSS feature can be found in the Southern Hemisphere. As the negative SSS Rossby wave traverses west, the surface layer density and model thickness is reduced with the biggest impact between 170°W and 130°W at 3°N for April to July 2012. Somewhat lagging the reduction in the model surface layer thickness, sea level shoals between 160°E and 150°W at 3°N for May to August 2012. The timing and location of the SST signal is well synchronized with SL and SSS diagnoses. During this period, SST is primarily negative with the biggest signal between 160°E and 170°W at 5°N coinciding with the upwelling SL signal. For all these variables, the timing of the symmetric feature in the Southern Hemisphere brought about by SSS assimilation is similar, but the amplitude is somewhat weaker. Later in our study period, a second Rossby wave is initiated due to SSS assimilation in February 2013. These features along with the relative positive SSS values in the NINO3 region are important components of the coupled forecast improvements brought about by SSS assimilation and so will be discussed in more detail later.

A similar set of plots as the previous figure are presented for the differences between the Aquarius assimilation (ASSIM_Tz_SSSAQ) minus ASSIM_Tz for August 2011 to February 2014 (Figure 5). Mostly all of the features are similar for salinity differences (Figures 4a and 5a). Namely, negative salinity differences are seen over most of the Indian Ocean except the Bay of Bengal, negative values can be seen in the ITCZ and SPCZ in the Pacific, and positive salting in the southeast Pacific. The main differences between Figures 4a and 5a are found in the off-equatorial western Pacific and in the Indonesian Seas region where assimilation of Aquarius gives fresher results than the in situ product. In addition, ASSIM_Tz_SSSIS is significantly fresher than ASSIM_Tz_SSSAQ in the NINO3 region of the eastern Pacific just north of the equator. A more

Figure 5. Results of the mean difference between ASSIM_Tz_SSSAQ minus ASSIM_Tz initial conditions for (a) SSS, (b) SL, and (c) SST for August 2011 to February 2014. Units are psu, cm, and °C, respectively.

convenient way to highlight the differences between SSS assimilation experiments is to difference these directly. Figure 6a shows the ASSIM_Tz_SSSAQ minus ASSIM_Tz_SSSIS differences. Here the differences in the Indonesian Seas and off-equatorial western Pacific are evident with ASSIM_Tz_SSSAQ having a fresher mean than ASSIM_Tz_SSSIS results. The other significant region is the eastern Pacific north of the equator (0°–5°N, 140°W–90°W) where ASSIM_Tz_SSSAQ is saltier than ASSIM_Tz_SSSIS assimilation results by as much as 0.15 psu. It is reassuring to note that in the Pacific our data assimilation differences (i.e., Figure 6a) are qualitatively consistent with observation differences of Aquarius minus in situ SSS found in Figure 1c.

Just like SSS, the SL results are mostly similar for ASSIM_Tz_SSSAQ minus ASSIM_Tz (Figure 5b) as compared to ASSIM_Tz_SSSIS minus ASSIM_Tz (Figure 4b). High SL is evident over most of the Indian Ocean and low in the Indonesian Seas region (between 100°E and 130°E). The low SL in the northwest Pacific connects to the low SL straddling 5° off the equator and 170°W. In addition, the high values in the SPCZ and positive values east of 180° between 5°N and 10°N are common to all SSS assimilation results. The differences between ASSIM_Tz_SSSAQ minus ASSIM_Tz_SSSIS are shown in Figure 6b. Aquarius assimilation has overall lower SL in the Indian Ocean with the minimum value at 10°S, 70°E. In the Pacific, the ASSIM_Tz_SSSAQ minus ASSIM_Tz_SSSIS has positive SL in the equatorial western Pacific stretching east all the way to the eastern boundary within 3° of the equator. In addition, negative values (i.e., lower SL for ASSIM_Tz_SSSAQ versus ASSIM_Tz_SSSIS) are present in the western half of the Pacific at 8°N, and this region of negative values is squeezed to the south to 5°N by positive values at 10°N, 130°W in the eastern half. In the Southern Hemisphere, the negative values stretch across most the basin, and the minimum is centered on 10°S. The overall pattern of Figure 6b can be envisioned as a downwelling Kelvin wave being followed by an upwelling Rossby wave whereas Figures 4b and 5b look more like an upwelling Rossby wave centered just east of the dateline.

Figure 6. Same as Figure 5 but for mean difference, ASSIM_Tz_SSSAQ minus ASSIM_Tz_SSSIS.

For SST results (Figure 5c), the main feature for the ASSIM_Tz_SSSAQ minus ASSIM_Tz is the meridional banding generally matching the pattern for SST differences in Figure 4c. Positive values are found over the western Indian Ocean, negative in the Indonesian Seas, positive in the far western equatorial warm pool in the Pacific, negative values between 160°E and 140°W, and positive values east of 140°W. By differencing the two SSS assimilation experiments, ASSIM_Tz_SSSAQ minus ASSIM_Tz_SSSIS, the discrepancy between these two can be shown more directly (Figure 6c). A negative Indian Ocean Dipole Zonal Mode pattern can be seen in the Indian Ocean, with negative values centered on 10°S, 60°E and positive along the coast of Sumatra. The ASSIM_Tz_SSSAQ experiment is warmer than ASSIM_Tz_SSSIS over most of the western/central Pacific between Indonesia and 130°W with maximum positive differences at 10°N and 5°S at 155°W and at the western boundary. An exception is the weak negative pattern (−0.05°C) at the eastern edge of the warm pool centered along the equator at 170°E. East of 130°W, the ASSIM_Tz_SSSIS experiment SST is warmer than the ASSIM_Tz_SSSAQ experiment (compare Figure 4c to Figure 5c) and these differences manifest as a cold La Niña pattern with negative values within 10° of the equator east of 140°W in the eastern Pacific (Figure 6c). Just considering the equator in the eastern Pacific, the strong east to west gradient of SST differences (ASSIM_Tz_SSSAQ minus ASSIM_Tz_SSSIS) should lead to relative enhanced easterlies, Bjerknes feedback, and cooling in the upwelling region of the eastern Pacific. We shall see that these SST differences and the resultant relative SST gradient across the equatorial Pacific are critical for improved Aquarius forecasts as opposed to assimilation of in situ SSS.

4.3. Forecast Lead Time Evolution of Impact of SSS Assimilation

In order to examine the impact on ENSO forecasts, the temporal evolution of the mean forecast difference ASSIM_Tz_SSSIS minus ASSIM_Tz is presented. For each month from August 2011 until February 2014 the

Figure 7. SST results for ASSIM_Tz_SSSIS minus ASSIM_Tz forecast means for (a) 1 month, (b) 2 month, (c) 3 month, (d) 4 month, (e) 5 month, and (f) 6 month forecast lead times averaged over all start months, August 2011 to February 2014. Units are in $^{\circ}\text{C}$.

average of all 1 month, 2 month, and so on to 6 month forecast differences are presented for SST (Figures 7a–7f). Recall that Figure 3a showed that ASSIM_Tz_SSSIS had improved forecast validation with respect to ASSIM_Tz only after 7 months. The evolution of the mean forecast differences provides a hint about the reason for this lead time in NINO3 forecast improvement. In month 1, SST in the NINO3 region for ASSIM_Tz_SSSIS is warmer than for ASSIM_Tz with SST differences as large as 0.3°C (Figure 7a). The negative differences over the central Pacific straddle the equator with values lower than -0.3°C , but dissipate with time. On the contrary, the once-positive values in the NINO3 region have cooled with values now near 0°C (Figure 7f).

Similar plots for ASSIM_Tz_SSSAQ minus ASSIM_Tz (Figure 8) show a more dramatic story. Propagation from the central to eastern Pacific and amplification in the eastern Pacific is readily apparent (resembling La Niña

Figure 8. SST results for ASSIM_Tz_SSSAQ minus ASSIM_Tz forecast means for (a) 1 month, (b) 2 month, (c) 3 month, (d) 4 month, (e) 5 month, and (f) 6 month forecast lead times averaged over all start months, August 2011 to February 2014. Units are in °C.

cooling). For SST (Figures 8a–8f) the time sequence looks very much like an upwelling Rossby wave reflecting at the western boundary into an upwelling Kelvin wave arriving at the eastern boundary in month 6 (Figure 8f). For Figure 8a the NINO3 SST starts out weak and near 0°C in month 1. As time progresses the negative differences drop to a minimum in month 6 (Figure 8f) with contours as low as -0.35°C . Also note that the coolest contours arrive in the eastern tropical Pacific at the very time when the coupled forecast begins to show significant improvement from Figures 3a and 3b in month 5. As we shall see, the impact of satellite SSS assimilation is to pull the forecast more toward the observed weakly negative conditions rather than toward an El Niño condition as is the tendency without SSS assimilation.

Another way to envision the relative impact of SSS assimilation is to examine the longitude versus time history of the equatorial mean of the differences averaged over all start months. Figure 9 shows the time evolution of the meridional averaged differences within 2° of the equator for SST and the resulting differences in zonal wind stress anomaly from the coupled model statistical atmospheric model (SAM). Figure 9a shows

Figure 9. Equatorial Indo-Pacific longitude versus time sections for forecast mean of ASSIM_Tz_SSSIS minus ASSIM_Tz for (a) SST and (b) zonal wind stress within 2° of the equator. The x axis is longitude and the y axis is forecast lead time (increasing length forecasts up). On the right is the same for ASSIM_Tz_SSSAQ minus ASSIM_Tz for (c) SST and (d) zonal wind stress. Contours are 0.1°C and range is -0.7 to 0.7°C for SST and 1×10^{-2} dynes/cm² and range is -0.07 to 0.07 dyn/cm² for zonal wind stress.

that early in the mean forecast, ASSIM_Tz_SSSIS minus ASSIM_Tz SST is positive east of 135°W peaking at 110°W prior to month 3. By month 5 the positive values have diminished and after month 7 the values in the NINO3 region begin to turn negative. In the central Pacific, the negative values of SST centered at the dateline dissipate from months 6 to 9. The corresponding plot of zonal wind stress (TAUX) is presented in Figure 9b. As expected, winds react to the SST differences by converging into warm water and diverging from cold SST differences. During the strongest west-to-east zonal gradient from month 0 to month 5, westerly winds, just to the west of the warmest water, converge into the NINO3 region and easterly winds just to the west of the coldest differences are seen west of the dateline. In this case, the downwelling signal associated with the east Pacific SST gradient should somewhat offset any western Pacific upwelling signal. However, this coupling in the east breaks down by month 6 and the winds die down leaving the NINO3 region slightly cooler for the ASSIM_Tz_SSSIS experiment versus ASSIM_Tz. After forecast lead time of 5 months the relatively cooler waters in the central and eastern Pacific are reinforced by weak easterlies east of the dateline.

The forecast trajectory is quite different for the longitude versus time plots of the ASSIM_Tz_SSSAQ minus ASSIM_Tz results in Figures 9c (SST) and 9d (TAUX). Here the small area of positive SST differences in the NINO3 region vanishes by month 3. In this case, the upwelling in the west/central Pacific grows unencumbered by any downwelling signal in the east (as is the case for the ASSIM_Tz_SSSIS minus ASSIM_Tz). As time progresses, negative values intensify so that by month 8 the negative values for ASSIM_Tz_SSSAQ minus ASSIM_Tz are less than -0.5°C . Note that the start of the coldest anomaly in the NINO3 region, i.e., month 9, is the same forecast lead time that corresponds to the most significant improvement brought about by satellite SSS assimilation as seen in Figure 3a. Not coincidentally month 9 also corresponds to the maximum relative upwelling signal below the mixed layer (not shown). The wind response shows weak

Figure 10. Mean forecast for NINO3 SST forecast anomaly ($^{\circ}\text{C}$) from August 2011 to February 2014 for ASSIM_ T_z (black solid line), ASSIM_ T_z -SSS_{IS} (blue dashed line), and ASSIM_ T_z -SSS_{AQ} (red dotted line). In addition, the IRI dynamical model mean for NINO3.4 region for the same period is provided (solid green line) along with one standard deviation of the temporal variability (green error bars). All these mean forecasts are normalized using the long-term mean, 1993–2013, for our HCM results and presumably 1970–2000 for IRI. The horizontal black dashed line corresponds to the mean observation anomaly over this period, -0.25°C .

forecasts, the mean forecast for all start months, August 2011 to February 2014, is presented. Figure 10 shows the NINO3 SST anomaly results for all coupled experiments discussed previously (ASSIM_ T_z —black solid line, ASSIM_ T_z -SSS_{IS}—blue dashed line, and ASSIM_ T_z -SSS_{AQ}—red dotted line). In addition, we present the dynamical model mean from the IRI web site (<http://iri.columbia.edu/climate/ENSO/currentinfo/archive/index.html>)—solid green line) for the NINO3.4 region (5°N – 5°S , 120°W – 170°W) for all forecasts initiated for the Aquarius period. Although referring to a slightly different region, these results are included to show general features of community forecasts for this period. All our HCM results along with the IRI mean tend toward warming over time in the eastern Pacific. The extreme example of this is the mean forecast for ASSIM_ T_z which rises past 0.4°C by 12 month forecasts. After 10 month lead forecasts, ASSIM_ T_z -SSS_{IS} is a slight improvement on ASSIM_ T_z tending more toward the real observation mean of -0.25°C over this period (thin horizontal black dashed line in Figure 10). Overall the most realistic forecast is the ASSIM_ T_z -SSS_{AQ} result that overlays ASSIM_ T_z until about 3 month forecast lead times. After that, ASSIM_ T_z -SSS_{AQ} clearly diverges from ASSIM_ T_z approaching the slightly negative mean conditions that prevailed over this period (i.e., -0.25°C). In addition, this representation shows the clear divergence of the forecasts trajectories for ASSIM_ T_z -SSS_{AQ} versus ASSIM_ T_z -SSS_{IS}. The Aquarius assimilation tends more toward the cooler/neutral conditions after about 5 months, while ASSIM_ T_z -SSS_{IS} starts tending away from -0.25°C and more toward warmer NINO3 reiterating the timing and sense of the results of Figure 3a.

In general, SSS assimilation gives cool, upwelling in the central Pacific which manifests as an upwelling Rossby wave. This feature is consistent for both experiments that assimilate SSS and is present in the initial conditions for ASSIM_ T_z -SSS_{IS} (Figures 4b and 4c) and for ASSIM_ T_z -SSS_{AQ} (Figures 5b and 5c). For example, the relative vertical velocity (i.e., ASSIM_ T_z -SSS_{AQ} – ASSIM_ T_z) is strong and positive early in the mean forecast whereas ASSIM_ T_z -SSS_{IS} – ASSIM_ T_z is near zero at the base of the mixed layer. After month 2 lead times, the vertical velocity is positive (i.e., upwelling) for both SSS assimilation scenarios relative to ASSIM_ T_z with Aquarius tending toward stronger upwelling than in situ SSS assimilation. As the forecast develops, this upwelling signal makes its way to the NINO3 region (Figures 7 and 8a–8f) where it reduces the tendency for the HCM to forecast too warm NINO3 SST anomalies. This tendency for warm NINO3 forecast is not only a problem for our ASSIM_ T_z forecasts, but is also habitual for coupled models in general as is evident by the warm forecasts for the IRI mean in Figure 10 (solid green line).

The two SSS assimilation experiments differ in that for ASSIM_ T_z -SSS_{IS} the eastern Pacific is relatively warmer than ASSIM_ T_z -SSS_{AQ} (compare Figure 9a to Figure 9c) at the forecast initialization. Thus the more intense SST gradient for ASSIM_ T_z -SSS_{IS} from the dateline to the eastern boundary leads to stronger westerlies and a relative downwelling signal (compare Figure 9b to Figure 9d). This downwelling signal offsets the

easterlies at the beginning of the mean forecast period strengthening and migrating slightly eastward (from 170°E to roughly 170°W). The coupled response of the ASSIM_ T_z -SSS_{AQ} minus ASSIM_ T_z is typical of a relative growing La Niña pattern.

In summary, the general impact of the assimilation of SSS during this period is to cool the NINO3 region. Figures 7f, 8f, 9a, and 9c all show that assimilation of SSS cools the eastern Pacific to some degree. In particular, the assimilation of satellite SSS from Aquarius (ASSIM_ T_z -SSS_{AQ}) is more effective at cooling the NINO3 region than the in situ product.

In order to highlight the impact of SSS assimilation on coupled

Figure 11. SSS (a) mean and (b) standard deviation of OI anomalies of Aquarius along-track data subsampled at nearest collocation with in situ observations.

upwelling in the central Pacific leading to a muted cooling for $ASSIM_T_z_SSS_{IS}$ with respect to $ASSIM_T_z_SSS_{AQ}$ for the NINO3 region (see Figures 9a and 9c). Another way to look at it is that $ASSIM_T_z_SSS_{AQ}$ has a larger east to west SST gradient (see especially Figure 6c) leading to enhanced easterlies, enhanced Bjerknes coupling, and more intense NINO3 upwelling. Therefore, the mean forecast for $ASSIM_T_z_SSS_{AQ}$ is closer to the observed conditions than $ASSIM_T_z_SSS_{IS}$ due to this enhanced cooling in the eastern Pacific (Figure 10) counteracting the $ASSIM_T_z$ tendency toward warm NINO3 for this period.

So why it is that $ASSIM_T_z_SSS_{AQ}$ has cooler SST in the NINO3 region and warmer SST in the far west than $ASSIM_T_z_SSS_{IS}$? As is shown in Figures 1c and 6a, Aquarius SSS is saltier in the eastern Pacific and fresher in the far western Pacific. In the NINO3 region this relatively high SSS leads to a density increase and enhanced buoyancy forcing. Vertical mixing is increased leading to increased entrainment of cold water from the bottom of the mixed layer resulting in decreased SST in the NINO3 region. In the west, the opposite is true. Relatively fresher SSS leads to increased stratification, decreased mixing, and warmer SST when Aquarius SSS is assimilated. The increased east to west SST gradient at the initialization of the forecasts leads to broadly enhanced easterlies for the forecast period and enhanced upwelling in the east.

5. Discussion

5.1. Role of Aquarius Data Sampling

The high correspondence between in situ and Aquarius observations [Lagerloef *et al.*, 2013] would lead one to assume that the gridded fields of in situ SSS should look similar to the satellite SSS. However, there are clear differences between the mean salinity patterns. To address the question of whether the sampling of the relatively sparse in situ observations impacts the mean fields, we subsampled the Aquarius Version 2.9.1 along-track (i.e., Level 2) data using the nearest collocation to available near-surface in situ observations. Data were rejected if any Aquarius radiometer flag failed at the moderate level (e.g., RFI, rain, land, ice, etc.) matching the validation data flagging of Lagerloef *et al.* [2013]. Only the closest Aquarius data point was included if it fell within 1° and within the same day of the in situ observation. After subsampling the Aquarius data at in situ observation times and locations, the data were gridded using the same technique as for the weekly in situ data. The results of this OI of Aquarius data at in situ collocations are presented for the mean and standard deviation in Figures 11a and 11b, respectively.

The gridded fields of Aquarius SSS subsampled at in situ locations/times (Figure 11a) reproduce much of the patterns found in the original Aquarius fields (Figure 1b). For example, the subsampled Aquarius product has positive SSS anomalies along the equator with the maximum just to the west of the dateline, negative values in the SPCZ (180° – 100° W, 10° S– 20° S), western Pacific (west of 160° E), in the IO, and at the eastern boundary of the Pacific at 5° N. However, the mean for the subsampled OI of Aquarius is quite different from the original Aquarius data product along the equator especially in the eastern Pacific. For the full

Figure 12. Validation of coupled model results for the Aquarius period, August 2011 to February 2014 using (a) correlation and (b) RMS versus observed NINO3 SST anomaly. Dashed blue curve is initialized from the experiment that assimilates weekly OI of all available near-surface salinity and subsurface temperature (ASSIM_Tz_SSS_{IS}), solid black curve is the experiment that assimilates the OI of Aquarius data at the closest collocation with in situ and subsurface temperature (ASSIM_Tz_SSS_{AQ@IS}), and the dotted red curve is initialized using weekly gridded Aquarius SSS and subsurface temperature (ASSIM_Tz_SSS_{AQ}). The thin dotted blue and red lines show the significance of the differences assuming ASSIM_Tz_SSS_{AQ@IS} is greater than ASSIM_Tz_SSS_{IS} and ASSIM_Tz_SSS_{AQ} is greater than ASSIM_Tz_SSS_{AQ@IS}, respectively, using the Fisher Z test. Note that Fisher Z test is undefined when this condition fails.

Aquarius L3 data, the maximum of the NINO3 region is greater than 0.2 psu (Figure 1b). In this same region, the subsampled product is more in line with the in situ product shown in Figure 1a with slightly negative values to the north and positive SSS anomaly to the south of the equator. In other words, subsampling Aquarius data at the in situ locations fails to reproduce the key salty anomaly in the eastern Pacific. Note that although visual inspection of the data coverage maps of the in situ locations reveals relatively consistent coverage from one week to the next, the overall number of observations is small relative to Aquarius satellite coverage. For example, only 5–8% of the bins have in situ data for the NINO3 region for any particular week. Therefore, the general similarity between the subsampled Aquarius data (Figure 11a) and gridded in situ data (Figure 1a) suggests that differences between the full Aquarius-gridded and in situ products are mostly due to the sparse distribution of in situ data.

To confirm this hypothesis, we completed an additional assimilation experiment using the optimal interpolation product that subsampled Aquarius SSS at the in situ locations and times. This experiment is abbreviated as ASSIM_Tz_SSS_{AQ@IS}. Just like the other experiments, the assimilation results were used as initial conditions and the coupled experiments were run for 12 months for each month from August 2011 until February 2014. The results indicate that ASSIM_Tz_SSS_{AQ@IS} is degraded with respect to the ASSIM_Tz_SSS_{AQ} experiment. For correlation, the ASSIM_Tz_SSS_{AQ@IS} and ASSIM_Tz_SSS_{AQ} are indistinguishable until about 5 months (Figure 12a). After that time the Aquarius subsampled SSS product (ASSIM_Tz_SSS_{AQ@IS}) is slightly degraded for all lead times. However, the Fisher Z test indicates that the significance of the difference never exceeds the 71% confidence limits (thin dashed red line in Figure 12a), indicating that these experiments are not significantly different. On the other hand, the subsampled Aquarius-gridded product (ASSIM_Tz_SSS_{AQ@IS}) has a higher correlation than the in situ product (ASSIM_Tz_SSS_{IS}) after 5 month forecast lead time. Now the Fisher Z test indicates that ASSIM_Tz_SSS_{AQ@IS} is higher than ASSIM_Tz_SSS_{IS} and the significance of the differences generally exceed 80% from 7 to 10 month lead times peaking at 82% at 9 month lead time (blue dashed line in Figure 12a). The RMS differences presented in Figure 12b reiterate the conclusion that the subsampled Aquarius product has forecast statistics that are slightly degraded with respect to ASSIM_Tz_SSS_{AQ}, but still outperform the ASSIM_Tz_SSS_{IS}. Therefore, we conclude that the spatial resolution afforded by satellite SSS is what makes initialization of Aquarius superior to the in situ product for coupled predictions.

5.2. Impact of the Aquarius Period

Unfortunately our study period, August 2011 through February 2014, encompasses only 30 months and so is a rather short time to perform rigorous statistical tests. To see if our period is representative of the longer period statistics, we utilized the full ASSIM_Tz experiment that spans January 1993 to February 2014 (or 254

months). First we calculated the mean 12 month lead time correlation statistics versus observed NINO3 SST anomalies using a specified number of months. For example, starting in January 1993 we performed NINO3 SST anomaly correlation versus observations for 10 months, then February 1993 for 10 months and so on. Next we recalculated the mean 12 month forecast lead time statistics using a varying number of months at 10 month increments from 10 to 140 months. In addition we calculated statistics using 30 months (to match our study length) and the full period, 1993 to February 2014, was included as the single realization (i.e., Figure 2, black line). As the number of consecutive months increases, the mean correlation increases. The mean correlation solutions appear to converge near 50 months (not shown). This length of time makes sense in light of the typical 3–7 year ENSO cycle. So to summarize, the limitation of having only 30 months of Aquarius data does not allow statistical convergence of the correlation. On the other hand, the Aquarius period is representative of a typical 30 month period since the correlation statistics for August 2011 to February 2014 generally overlays the mean calculated from all realizations of 30 consecutive months and all 12 months of lead times fall within one standard deviation of this mean.

5.3. Impact of Other Ancillary Data

The work that has been presented so far assimilates a limited number of data sources, namely, subsurface temperature and in situ and satellite SSS, in order to most easily isolate the impacts of assimilating SSS. However, standard forecasts from operational centers include assimilation of all available ocean data including T_z , S_z , and satellite SST and SL (in varying capacities and degrees). Therefore, we repeated our experiments except now the baseline experiment assimilates gridded SL [from AVISO (<http://www.aviso.oceanobs.com/en/data/products/sea-surface-height-products/global/msla/index.html>), AVISO], SST [Reynolds *et al.*, 2002], and S_z [Sun *et al.*, 2010] as well as T_z . As before, we added assimilation of SSS_{AQ} in separate experiments and assessed the impact using correlation and RMS versus observed NINO3 SST anomaly. These results (not shown) were qualitatively similar to the results in section 4, and so the conclusions drawn are the same. Namely, that the inclusion of Aquarius SSS improves the forecast (i.e., gave the highest correlation and lower RMS) after 5 month lead times. For RMS, the assimilation of satellite SSS slightly improved upon the baseline from 4 to 9 months, but after 9 months the RMS was slightly degraded. Although the differences never exceed 65% significance (using the Fisher Z test) due to SSS impact depreciation brought about by inclusion of other dependent data (such as SL) into our multivariate EOF assimilation scheme, assimilation of Aquarius SSS still improves the forecast statistics.

The purpose of this study is to highlight the impact of SSS assimilation in general and examine the impact of in situ versus satellite SSS. The studies of Yang *et al.* [2010] in the Pacific and Huang *et al.* [2008] in the Indian Ocean have shown the importance of S_z assimilation for ENSO prediction. However, the relative impact of subsurface salinity (S_z) versus SSS has not yet been demonstrated. Therefore, parallel experiments that assimilate subsurface temperature and salinity (ASSIM_ T_zS_z) have been completed, and these results have been validated using observed NINO3 SST anomalies (not shown). Comparison between ASSIM_ T_zSSS_{AQ} and ASSIM_ T_zS_z reveals that ASSIM_ T_zSSS_{AQ} significantly outperforms ASSIM_ T_zS_z for correlation after 4 month lead times (Fisher Z statistic rising as high as 97% at 9 months) and RMS is lower for all lead times and ASSIM_ T_zSSS_{AQ} is reduced by as much as 0.3°C for 9 month lead times. Therefore, these results indicate that assimilation of satellite SSS has higher relative impact than subsurface salinity even though both produce improved coupled forecasts relative to ASSIM_ T_z .

6. Summary and Conclusions

The control experiment for this study was one in which subsurface temperature (ASSIM_ T_z) was assimilated into our ocean model in order to initialize coupled hybrid forecasts for the Indo-Pacific system. In addition to subsurface temperature, SSS-gridded fields from in situ (ASSIM_ T_zSSS_{IS}) and Aquarius (ASSIM_ T_zSSS_{AQ}) were assimilated into our ocean model and then were used for subsequent initialization of coupled experiments. Every time that SSS is used during the initialization process, coupled forecast correlation statistics were improved after 5 month lead times with respect to ASSIM_ T_z . In all cases, a cold upwelling SST signal in the central Pacific migrates to the NINO3 region resulting in cooler SST anomalies. When SSS data are assimilated, the eastward propagation of the cold upwelling signal pulled the forecasts more toward the observed moderate La Niña conditions that were present during this period. Like most coupled models from the IRI composite forecast, our ASSIM_ T_z coupled model predicted a warming in the NINO3 region for

this period and assimilation of SSS mitigates this phenomenon. Assimilation of Aquarius SSS fields outperforms the assimilation of in situ SSS assimilation, for both correlation and RMS in the NINO3 region since cooling in the east is more pronounced for the former experiment. In the eastern Pacific, ASSIM_T_z-SSS_{AQ} starts out saltier and so has increased density, increased buoyancy forcing, and thus increased mixing. This leads to relative enhanced upwelling and colder SST in the NINO3 region for Aquarius assimilation. This feature, along with relatively fresher/warmer water for the ASSIM_T_z-SSS_{AQ} versus ASSIM_T_z-SSS_{IS} in the western Pacific, leads to an enhanced zonal temperature gradient across the entire tropical Pacific resulting in increased easterlies and enhanced Bjerknes feedback.

In order to test if it is the Aquarius SSS values or the data sampling afforded by satellite coverage that gives the ASSIM_T_z-SSS_{AQ} experiment the advantage over ASSIM_T_z-SSS_{IS}, we subsampled the Aquarius data at in situ locations/times. The mean of the OI-gridded fields of this subsampled product is more similar to in situ SSS near the equator rather than the Aquarius mean. Next we applied the subsampled fields to assimilation and then initialized coupled experiments from these data assimilation results. Again, the Aquarius-subsampled at in situ coupled results (i.e., ASSIM_T_z-SSS_{AQ@IS}) were an improvement upon the in situ results (ASSIM_T_z-SSS_{IS}). However, the full Aquarius-gridded product (ASSIM_T_z-SSS_{AQ}) still achieves superior coupled forecasts with correlation and RMS outperforming ASSIM_T_z-SSS_{AQ@IS} for the NINO3 region for August 2011 until February 2014. Therefore, we conclude that it is the spatial sampling afforded by the Aquarius satellite, especially in the equatorial band, that is responsible for the relative improvement of the Aquarius versus in situ coupled results.

Unfortunately, this paper is not able to address the issue of the vertical dependency of near-surface salinity. The problem arises since Aquarius observations use the forward radiative transform model of T_b measuring the salinity of the top 1 cm of the ocean surface, whereas in situ observations are typically calculated from conductivity/temperature sensors (CTD) on board Argo profiling floats that measure the salinity up to 5 m depth since CTD sensors shut off to prevent bio fouling [Riser *et al.*, 2008]. The salinity gradient from 8 to 0.05 m can be as high as 1.1 psu following a rain event in the tropical Pacific (e.g., W. E. Asher *et al.*, 2014, Observations of rain-induced near surface salinity anomalies, submitted to *Journal of Geophysical Research: Oceans*). In addition, Boutin *et al.* [2013] showed that SMOS minus in situ biases are as large as −0.1 psu for rain contaminated collocations. We have shown that the spatial sampling of in situ observations is currently suboptimal as compared to the sampling afforded by Aquarius in light of coupled forecasting results. However, until full utilization of the envisioned enhanced Argo floats with 5 cm maximum observing depth [e.g., Roemmich *et al.*, 2009] or other near-surface observations [e.g., Reverdin *et al.*, 2012], we are limited to use what data we have available. Therefore, given the focus of this study on SSS, it remains an open issue as to the ability of in situ platforms such as Argo to measure salinity close enough to the surface and with sufficient spatial sampling to give similar quality forecasts as Aquarius.

Acknowledgments

We would like to thank the many universities and Government agencies, without whose efforts the compilation and development of the Argo, CFSRR, ECMWF analysis, GPCP/TRMM, GTSP, NCEP reanalysis, and WOD09 data products would not have been possible. In addition, we would like to recognize all the hard work that went into developing hardware and algorithms, processing the data, and improving the various Aquarius products. We would also like to acknowledge the contribution of the reviewers whose suggestions improved this paper significantly. This research is supported by NASA Physical Oceanography grant NNX12AN08G and the Ocean Salinity Science Team (NNX09AU74G). Ballabrera-Poy was supported by the MIDAS-7 AYA2012-39356-C05-03 Spanish grant.

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