Impact of Salinity Constraints on the Simulated Mean State and Variability in a Coupled Seasonal Forecast Model

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ABSTRACT

The authors assess the sensitivity of the simulated mean state and coupled variability to systematic initial state salinity errors in seasonal forecasts using the Australian Bureau of Meteorology Predictive Ocean Atmosphere Model for Australia (POAMA) coupled model. This analysis is based on two sets of hindcasts that were initialized from old and new ocean initial conditions, respectively. The new ocean initial conditions are provided by an ensemble multivariate analysis system that assimilates subsurface temperatures and salinity and is a clear improvement over the previous system, which was based on univariate optimal interpolation, using static error covariances and assimilating only temperature without updating salinity.

Large systematic errors in the salinity field around the thermocline region of the tropical western and central Pacific produced by the old assimilation scheme are shown to have strong impacts on the predicted mean state and variability in the tropical Pacific for the entire 9 months of the forecast. Forecasts initialized from the old scheme undergo a rapid and systematic adjustment of density that causes large persistent changes in temperature both locally in the western and central Pacific thermocline, but also remotely in the eastern Pacific via excitation of equatorial waves. The initial subsurface salinity errors in the western and central Pacific ultimately result in an altered surface climate because of induced temperature changes in the thermocline that trigger a coupled feedback in the eastern Pacific. These results highlight the importance of accurately representing salinity in initial conditions for climate prediction on seasonal and potentially multyear time scales.

1. Introduction

The ability to make skillful seasonal climate forecasts using dynamical coupled atmosphere–ocean models derives mainly from the ability to predict El Niño–Southern Oscillation (ENSO). Prediction of ENSO depends largely on the ability to accurately depict the initial ocean state, especially the upper-ocean thermal structure in the tropical Pacific. Skillful forecasts of El Niño can be derived from initial ocean states that are estimated without explicit assimilation of in situ observations, for example, by forcing an ocean model with observed surface forcing (Cane et al. 1986) or by nudging model sea surface temperature (SST) to SST analyses derived from observations (Luo et al. 2008). However, the most realistic and hence potentially most useful ocean initial states are generated by assimilating available ocean observations into the forecast model (e.g., Alves et al. 2004; Balmaseda and Anderson 2009). Numerous studies have shown that improved prediction of El Niño follows from improvements in the ocean assimilation systems (e.g., Ji and Leetmaa 1997; Rosati et al. 1997; Wang et al. 2002; Balmaseda et al. 2008; Stockdale et al. 2011).

In addition, recent studies have shown that accurately representing the salinity stratification is also important, for instance at the onset of El Niño (Maes and Picaut 2002; Maes et al. 2005), and that surface salinity has the potential to impact ENSO prediction (Ballabrera-Poy et al. 2002; Hackert et al. 2011). The first generation of ocean assimilation systems for seasonal forecasting concentrated mainly on assimilating upper-ocean temperatures because of the key role that temperature variations play for the relatively fast
evolution of El Niño. Salinity was typically ignored or constrained by climatological relationships with temperature because prior to Argo (http://www.argo.net/) there was a paucity of salinity observations and there was an underlying belief that temperature variations were of primary importance for prediction of El Niño. First-generation systems include the univariate (temperature-only and no-salinity updating) optimal interpolation (OI) scheme that runs routinely at the Australian Bureau of Meteorology (Smith et al. 1991) and that provided initial conditions for the Predictive Ocean Atmosphere Model for Australia, version 1.5b (POAMA 1.5b; Alves et al. 2003; Hudson et al. 2011). We refer to this univariate OI analysis as POI.

The second-generation systems use more sophisticated error covariances (e.g., flow dependent and multivariate) and they include the assimilation of salinity (e.g., Balmaseda et al. 2008; Yin et al. 2011). These second-generation systems clearly provide a more faithful and consistent depiction of the upper-ocean state and produce improved seasonal forecasts of El Niño (e.g., Balmaseda et al. 2008; Balmaseda and Anderson 2009). Although salinity variation, especially in the mixed layer of the western Pacific warm pool, has been identified to play an active role in the evolution of El Niño (Cooper 1988; Troccoli et al. 2002; Maes and Picaut 2002; Maes et al. 2005; Yang et al. 2010) there is little evidence yet from seasonal hindcasts that improved skill of predicting El Niño relies on improvement of salinity stratification or better dynamical balanced between subsurface temperature and salinity. Rather, reported improvement in forecast skill derives from an improved analysis of the upper-ocean thermal structure. Nonetheless, because both salinity and temperature affect the density field, reduced errors in the analysis of salinity should lead to an improved depiction of the initial density field thereby leading to improved predictions.

This present study is motivated by the recent improvement in the ocean assimilation used in the POAMA seasonal prediction system. This new assimilation is ensemble based with flow-varying error covariances and includes the assimilation of both temperature and salinity (Yin et al. 2011). It is referred to as the POAMA Ensemble Ocean Data Assimilation System (PEODAS). Yin et al. (2011) showed that PEODAS provides a substantially improved ocean analysis especially in terms of dynamical balanced between subsurface temperature and salinity (i.e., a more realistic salinity stratification), as compared to the original univariate POI scheme.

A preliminary assessment of the impact of the improved ocean initial states for seasonal climate predictions shows a positive benefit for prediction of El Niño (Wang et al. 2011). However, in conducting that assessment of skill, the simulated level of variability of El Niño, as measured by the standard deviation of the Niño-3.4 SST index, was observed to be significantly different in the two systems, noting that the only change between the two systems was the initial conditions. This can be seen by examining the average standard deviation of the Niño-3.4 SST index for each ensemble member (Fig. 1, details of the forecast model and hindcasts are provided in section 2). El Niño behavior, as expressed by the variability of the Niño-3.4 SST index, is clearly weaker in the system using new ocean initial conditions and this difference develops as early as 2–3 months into the forecast and then persists to the end of the 9-month forecast. A similar reduction in simulated El Niño variability was shown in the European Centre for Medium-Range Weather Forecasts (ECMWF) System 3 when initialized with improved ocean initial states (Balmaseda and Anderson 2009); however, they did not mention this long-lived difference or explain it.

The purpose of the present study is to understand how these systematic differences in simulated variability seen in Fig. 1 [also see the black (equivalent to our solid line) and green (equivalent to our dash–dot line) lines in Fig. 1 in Wang et al. (2011)] can rapidly develop and then persist for at least 9 months, acknowledging that the primary difference between the old and new initial ocean analyses is in the depiction of subsurface salinity (Yin et al. 2011). The focus is on the impact of the systematic differences in salinity in the initial states on the long-term model variability, rather than on the details of
how those systematic differences arose during the assimilation cycle. As we will show below, these rapid changes in simulated variability derive from rapid and systematic changes in the model’s mean thermal stratification as a result of mean differences in subsurface salinity at the initial time. The mean subsurface salinity difference causes a density perturbation that causes temperature to rapidly adjust, but differences also persist to the end of the forecast because the adjustment time for salinity is much longer than for temperature due to weaker horizontal and vertical gradients.

A brief description of the old (POI) and new (PEODAS) POAMA ocean data assimilation systems, the key differences in the analysis of the mean state between these two systems, and the POAMA forecast system and seasonal hindcasts initialized from the two ocean analyses are presented in section 2. Systematic differences in the evolution of the ocean mean state (temperature and salinity) and simulated variability of El Niño in the initial state that cause systematic differences in the mean state at long lead times. Conclusions are given in section 5.

2. The POAMA forecast and ocean assimilation systems

a. POAMA forecast model and hindcast experiments

The POAMA seasonal forecast system is based on a coupled ocean–atmosphere general circulation model. The atmosphere model uses a spectral transform with resolution T47L17 (Alves et al. 2003). The ocean model is version 2 of the Australia Community Ocean Model (ACOM2; Schiller et al. 2002), which is based on version 2 of the Modular Ocean Model (MOM2; Pacanowski 1995). More detail about the model configurations can be found in Alves et al. (2003) and Zhao and Hendon (2009).

Atmospheric initial conditions are derived from an atmosphere–land initialization system (ALI; Hudson and Alves 2007; Hudson et al. 2011). Ocean initial conditions are derived from the POI or PEODAS systems. Details of the two assimilation systems are described in section 2b.

The analysis in this study is based on two sets of seasonal hindcasts out to nine months using POAMA version 1.5b. In both sets, atmospheric initial conditions are provided by ALI. However, one set is initialized using the old POI ocean initial conditions. Forecast from this system are referred to as V1_POI [named as POAMA 1.5b in Wang et al. (2011), the black line in their Fig. 1], where V1 indicates that the ocean–atmosphere models are based on the POAMA 1.5b version and POI refers to the ocean initial conditions from the old POI system. The other set of hindcasts is initialized using the new ocean initial conditions from PEODAS. These hindcasts use the same version of the coupled model (V1) and are referred to as V1_PEO. Note that these hindcasts are similar to those from POAMA 2.4c as reported in Wang et al. (2011, the green line in their Fig. 1).

Seasonal hindcasts are generated on the first day of each month for the period 1982–2006 at 0000 UTC. A 10-member ensemble was generated using perturbed initial conditions. Because POI produced only a single estimate of the initial ocean state, perturbed initial conditions for V1_POI were obtained by successively picking the atmospheric analysis from 6 h earlier (i.e., the tenth member was initialized with atmospheric conditions 2.5 days earlier than the first member). The PEODAS is an ensemble-based assimilation scheme, so it naturally provides an ensemble of ocean initial conditions. For V1_PEO, we used 10-member ocean initial conditions provided by PEODAS and a single atmospheric initial condition (at 0000 UTC) from ALI to generate the ensemble hindcasts. In Table 1 we list the details of each hindcast set. In this study, we adopt the terminology that a lead time of 1 month means a hindcast initialized on 1 January is valid for the month of January. Hindcast results are based on ensemble means or, as noted, using the individual ensemble members (e.g., the standard deviation shown in Fig. 1).

b. POI and PEODAS ocean assimilation systems

In both POI and PEODAS, ocean observations are assimilated into the ocean model component of the POAMA forecast system. More details about the ocean model configuration can be found in Yin et al. (2011). In both assimilations, available in situ observations are assimilated in a 3-day analysis cycle into the ocean model that is driven by observed surface fluxes derived from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalyses (Kalnay et al. 1996) for POI and from the 40-yr ECMWF Re-Analysis (ERA-40; Uppala et al. 2005) for PEODAS. We note the ERA-40 ends in 2002, so fluxes from NCEP2 (Kanamitsu et al. 2002) are used from 2002 onward for PEODAS.

The POI data assimilation system is based on a univariate, two-dimensional, optimal interpolation (Smith et al. 1991) and assimilates only temperature observations in the top 500 m of the ocean; velocity fields are updated using the geostrophic relation similar to Burgers
et al. (2002). Salinity is not updated, although surface salinity, while free to respond to imposed freshwater flux and advection, is relaxed (3-day relaxation) to the climatology from the World Ocean Atlas 2001 (WOA2001; Stephens et al. 2002; Boyer et al. 2002). Surface temperature is strongly relaxed (3-day relaxation) to an available SST analysis (for POI we use NCEP skin temperature reanalysis). In contrast to PEODAS, there is no relaxation of subsurface temperature and salinity to climatology in the POI system.

**PEODAS** is a computationally efficient ensemble-based data assimilation system and is easier to implement for operational seasonal forecasting than a four-dimensional variational method. It also yields an ensemble of initial conditions that are used for ensemble seasonal forecasting. The ensemble of initial ocean states potentially spans the actual uncertainty in the estimate of the initial condition (Yin et al. 2011). In contrast to POI, both temperature and salinity profiles are assimilated and also temperature, salinity, and velocity fields are all updated at all model levels using flow-dependent, three-dimensional error cross covariances. Together with the strong relaxation (1-day relaxation) of the surface temperature to an existing SST analysis (Reynolds et al. 2002), subsurface temperature and salinity are also weakly relaxed (2-yr time-scale relaxation) to the climatology from WOA2001. The surface salinity is also relaxed to WOA2001 (monthly climatology) at the 1-yr time scale because of large uncertainties in the freshwater fluxes from the atmospheric reanalyses. PEODAS provides a more comprehensive and more accurate analysis with less bias than POI. More details about the comparison between PEODAS and POI systems and which aspects of PEODAS outperform those of POI can be found in Yin et al. (2011).

c. **Differences between POI and PEODAS mean states**

Prior to assessing the impact on the forecasts of using different ocean initial conditions from POI and PEODAS, we first examine some of the mean differences in the two analyses that are used as initial conditions in the hindcasts. Figures 2a,b show the mean differences in the analysis of the top-300-m-averaged temperature (T300) and salinity (S300), respectively. For reference, the mean state from the PEODAS analysis is overlaid as contours. The differences in T300 between the analyses from PEODAS and POI in the tropical Pacific (Fig. 2a) are small, particularly in the tropical Pacific where the difference is generally less than 0.4°C. This difference is not only due to different data assimilation techniques, but also due to the different surface forcing used in the assimilation cycle (i.e., NCEP for POI and ERA-40 for PEODAS). One might think that the differences in the analysis of temperature should be small, withstanding the differences in assimilation technique and surface forcing, because both systems assimilate the same observed temperature data, but as we will later see this is overly simplistic.

In contrast to temperature, the differences in the analysis of salinity are large, with PEODAS depicting a much saltier western and central Pacific than POI, especially south of the equator where differences exceed 0.4 practical salinity unit (psu) (Fig. 2b). The magnitude of this salinity difference is placed into context by noting that in the west Pacific thermocline region a 0.4-psu salinity difference has the same impact on density as a 1.1°C temperature difference (Gill 1982). Interestingly, the largest differences in salinity (shaded) occur to the west of the maximum climatological salinity off the equator in the western Pacific (contours, Fig. 2b). This location of largest difference in analysis of salinity, however, does coincide with where the largest increment to temperature is made in both systems, which can be seen in Fig. 5a from Yin et al. (2011). Assimilating temperature drives the thermocline deeper in the western Pacific and if density is to stay largely unchanged then salinity should increase in response. Thus, temperature-only assimilation (POI) generates an unrealistic water mass consistent with the results showed in Troccoli et al. (2002). In PEODAS, the salinity adjustment in the assimilation cycle occurs not only from the direct assimilation of salinity, but also from the covariation of salinity and temperature that is explicitly accounted for in PEODAS. Neither process is present in POI, so salinity is not dynamically adjusted in POI when temperature is incremented. As this assimilation process in the POI system

<table>
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<th>Experiment name</th>
<th>Ocean initial condition</th>
<th>Assimilated obs</th>
<th>Updated variables in the assimilation</th>
<th>Perturbation of initial condition</th>
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<tbody>
<tr>
<td>V1_POI</td>
<td>POI</td>
<td>Subsurface temperature</td>
<td>Temperature with geostrophic adjustment to currents</td>
<td>No</td>
</tr>
<tr>
<td>V1_PEO</td>
<td>PEODAS</td>
<td>Subsurface temperature and salinity</td>
<td>Temperature, salinity, and currents using ensemble cross covariances</td>
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is continued through many cycles, a large systematic error in salinity gradually builds up in the analyses over the course of 3–4 years in those regions where large increments to temperature are made (see Fig. 10f in Yin et al. 2011).

In the Indian Ocean, the differences of T300 between the two analyses are mainly located in the northern and eastern regions of the basin, while only small areas of differences in S300 are seen within the tropics (Figs. 2a,b). The lack of difference in S300 between POI and PEODAS results because of a much weaker vertical gradient of salinity in the tropical Indian Ocean compared to the western Pacific so that incrementing temperature without adjusting salinity in POI has less impact on salinity there.

The vertical structure of the mean differences of the analyzed temperature and salinity along the equator are shown in Figs. 2c,d. Relative to POI, PEODAS has raised the equatorial thermocline (approximated by the location of the 20°C isotherm) in the eastern Pacific.

**Fig. 2.** Mean differences (shading) in the analysis of the upper-300-m-averaged (a) temperature (T300) and (b) salinity (S300) between the PEODAS and POI analyze for 1982–2006. Contours are the mean states of (a) T300 (contour interval 4°C) and (b) S300 (contour interval 0.4 psu) based on PEODAS. Mean differences of vertical section (c) temperature and (d) salinity (shading) along the equator between PEODAS and POI. Contours are the mean (c) temperature (contour interval 4°C) and (d) salinity (0.2 psu) from the PEODAS analysis. (e),(f) As in (c),(d), but for the mean differences between the PEODAS and control analyses.
and depressed the thermocline in the western Pacific. Comparison with Fig. 2a indicates that this depression of the thermocline in the west is concentrated off the equator, while the elevation in the east is concentrated on the equator. These differences in temperature have a magnitude about $\frac{1}{3}$ of the interannual variation of temperature as depicted in the PEODAS analysis (e.g., see Fig. 4a) and so are judged to be of a moderate amplitude. The big difference in salinity between PEODAS and POI occurs just above the western Pacific thermocline, where PEODAS is much saltier (Fig. 2d). In contrast to temperature, these differences in salinity are up to 5 times larger than the interannual standard deviation of salinity as depicted in PEODAS (not shown), and are thus judged to be extremely large.

In Figs. 2e,f, we also show the vertical structure of the mean differences of the temperature and salinity along the equator between PEODAS and a control analysis that used no in situ data in the assimilation. This control analysis is used as a reference for the magnitude of the differences between PEODAS and POI. The control analysis used the same surface forcing and relaxation to observed SST as PEODAS, but withheld assimilating all in situ subsurface data (Yin et al. 2011 provide more detail). The temperature differences between PEODAS and the control along the thermocline, especially in the eastern Pacific are relatively large, reaching over 1°C. However, the salinity differences are around 3 times less than the differences between PEODAS and POI. Hence, assimilating temperature only in POI without updating salinity, while significantly reducing the temperature error, leads to dynamical imbalance between temperature and salinity that generates mean salinity errors with impact on density comparable to or larger than the temperature errors when no in situ data are assimilated.

In the Indian Ocean, the thermocline is shallower in the eastern Indian Ocean (EIO) and slightly deeper in the western Indian Ocean (WIO) in POI compared to PEODAS (Fig. 2c). This may be because the temperatures at the western edge of the western Pacific are warmer in PEODAS and this difference eventually affects the temperature in the eastern Indian Ocean via the throughflow in Indonesia. In contrast, the large salinity differences below 100 m seen in the western Pacific are not apparent in the EIO.

In summary, there are moderate mean differences between the two analyses of the subsurface temperature field in the eastern Pacific and in the eastern Indian Ocean, but much larger mean differences in the analysis of subsurface salinity field especially above or along the thermocline in the western and central Pacific. We now assess the impact of these mean differences in initial conditions on the simulated mean state and variability of the forecast model.

3. Simulated differences in mean state and variability

a. Mean state differences at the 9-month lead time

We consider now how the mean differences in the initial conditions affect the simulated mean state and variability during the seasonal forecasts. We do not consider the impact of the different ocean initial conditions on forecast skill but note that a companion study does show an improvement in predicting El Niño based on the new initial conditions from PEODAS (Wang et al. 2011). Rather, here we concentrate on understanding the different dynamic adjustments to the systematic differences in the initial states that take place within the coupled model, influencing both the model mean state and its variability many months into the forecast.

In Figs. 3a,b we show horizontal maps of the mean differences between V1_PEO and V1_POI at a 9-month lead time for T300 and S300. In Figs. 3c,d we show vertical sections along the equator of the mean differences in temperature and salinity. The large salinity difference in the western and central Pacific thermocline region in the initial conditions provided by PEODAS and POI at the initial stage (Fig. 2b) is still evident in the mean difference between V1_PEO and V1_POI at a 9-month lead time. However, the maximum difference in salinity south of the equator in the western Pacific appears to have shifted slightly westward toward the western Pacific boundary (Fig. 3b). In contrast, the modest initial mean differences in temperature in the initial conditions (Figs. 2a,c) evolve to a strikingly large positive mean temperature difference at a 9-month lead time (Figs. 3a,c), with maximum difference coinciding with maximum salinity difference in the western and central Pacific (Figs. 3b,d). Positive temperature differences also appear to have spread eastward in a narrow tongue along the equator from the western Pacific into the eastern Pacific. The negative temperature differences along the equator in the eastern Pacific at the initial stage (Fig. 2c) seem to have propagated eastward to the South American coast possibly as a Kelvin wave and then spread poleward along the American coasts and also spread westward off of the equator from the coast. The poleward spread is consistent with a coastally trapped Kelvin wave and the off-equatorial westward expansion is consistent with Rossby waves that are fed by reflection of the equatorial Kelvin wave. In the Indian Ocean we do not see much change between the initial
stage and a 9-month lead time for the mean differences of T300 or S300.

b. Variability differences

We have already seen in Fig. 1 that the simulated ENSO variability, as depicted by the standard deviation of the Niño-3.4 SST anomaly index, is weaker at longer lead times for forecasts initialized with PEODAS (V1_PEO) as compared to those initialized with POI (V1_POI). One would expect the forecast for any given start time to be sensitive to the initial conditions and that different sequences of ENSO would then result. However, Fig. 1 is an average over many realizations (12 start times per year spanning 25 years for each different set of initial conditions) and so one might expect such random effects to average out. This is likely to be the case beyond some long forecast lead time when the simulated climate is determined solely by the model internal dynamics and physics, but Fig. 1 shows that this takes much longer than 9 months and that dependencies on the initial conditions are still evident. We now address the question of how the systematic difference in ocean initial conditions can affect the simulated variability as far as 9 months into the forecast. We will show below that this impact occurs through rapid and persistent changes in the means states that are kicked off by a coupled response to the mean difference in initial conditions and that this coupled response takes many months to equilibrate.

At the initial forecast time, PEODAS depicts more variability in subsurface temperature than POI, with the maximum difference in variability (shading in Fig. 4a) coinciding with the location of maximum interannual standard deviation in the thermocline (contours in Fig. 4a). The maximum difference in standard deviation has a magnitude of about 10% of the interannual standard deviation. This depiction of systematically increased variability in the PEODAS analyses reflects that the PEODAS analyses are a better fit to the observations than are the POI analyses (Yin et al. 2011). At a lead time of 9 months (Fig. 4b), the difference in the standard deviation of temperature between V1_PEO and V1_POI is now oppositely signed to that at the initial state (note that for the hindcast data the standard deviation was computed using each ensemble member and then averaged over all 10 members before differencing). Variability was depicted to be stronger at the initial time in PEODAS compared to POI, but is now simulated to be weaker in the forecasts at a 9-month lead time. The region of maximum reduced subsurface temperature variability coincides with the region of deeper mean thermocline in V1_PEO compared to V1_POI.
to V1_POI (Fig. 3c) and is consistent with the reduced Niño-3.4 variability in V1_PEO depicted in Fig. 1. Hence, changes in the subsurface temperature ultimately affect the surface climate as evident in Fig. 4b.

c. Evolution of mean state and variability differences

The development of the mean differences in the simulated mean states and variability during the forecasts is displayed in Fig. 5, which shows time–longitude plots along the equator for the mean differences of T300, S300, density, UA (zonal wind at 10 m), and SST as well as the difference of standard deviation of SST anomaly between V1_PEO and V1_POI. Density was simply calculated from the value of T300 and S300 using a linearized relationship (Gill 1982). The plots run from the analyzed initial condition to 9 months into the forecast and focus on the Pacific basin. The large initial systematic difference in S300, where PEODAS is more saline with maximum difference centered on about the date line, is seen to be maintained throughout the forecasts (Fig. 5b). In contrast to the S300 behavior, which only slowly evolves during the forecasts, T300 systematic differences are seen to initially grow and rapidly evolve, but large differences are then sustained to the end of the forecasts (Fig. 5a). Specifically, T300 is depicted to be initially warmer in the far western Pacific and colder in the east Pacific in PEODAS. Then, the positive difference in the west rapidly expands eastward into the east Pacific and grows in magnitude, while the initial negative difference in the eastern Pacific contracts toward the South American coast and also strengthens.

Interpreting these T300 differences as being indicative of changes in the thermocline suggests that the thermocline initially deepens in the west and central Pacific and elevates to the east in response to the more saline (denser) water depicted in PEODAS compared to POI. The positive density anomaly is initially transmitted eastward as an equatorial upwelling Kelvin wave (negative temperature anomaly). We examined the evolution of this temperature adjustment using daily data rather than monthly means (figure not shown). The eastward adjustment of temperature is consistent with the eastward propagation of an upwelling Kelvin wave that transmits the initial density perturbation in the central Pacific to the east Pacific. After 1–2 months, the positive density anomaly in the west has contracted eastward along the thermocline into the eastern Pacific (and reflects from the eastern boundary) and largely disappeared in the western and central Pacific. Locally the density disturbance in the central and western Pacific in the vicinity of the salinity anomaly is removed by a compensating change in temperature, whereby the column warms to counteract the increased density due to salinity. Because the salinity anomaly changes little through the course of the integration (Fig. 5b), the temperature differences shown in Fig. 5a are maintained in the western and central Pacific until the end of the forecast.

Ultimately, the initial salinity perturbation will cause a coupled (surface) response if the induced temperature change is communicated to the surface. Consistent with the evolution of T300, the SST difference evolves to a state of a colder eastern Pacific and warmer western Pacific (Fig. 5e). The coupled nature of this response is confirmed by the development of easterly wind differences across most of the Pacific during the forecasts (Fig. 5d). The easterly differences develop rapidly by a 1-month lead time in response to initially colder east Pacific and warmer west Pacific in PEODAS relative to POI and then are maintained throughout the forecasts.
FIG. 5. Differences for the mean states for (a) T300, (b) S300, (c) density (simply calculated from the value of T300 and S300 using a linearized relationship; Gill 1982), (d) zonal wind at 10 m (UA), (e) SST, and (f) for the standard deviation SST anomaly along the equator between V1_PEO and V1_POI from the initial condition (IC) through to a lead time of 9 months. Ensemble mean differences are shown in (a)–(e) where the average standard deviation over all 10 ensemble members is used in (f). Contour intervals are (a) 0.1°C, (b) 0.05 psu, (c) $0.05 \times 10^3$ kg m$^{-3}$, (d) 0.2 m s$^{-1}$ above 0.1 m s$^{-1}$, (e) 0.1°C, and (f) 0.05°C above 0.05°C.
The easterly anomalies act to increase equatorial upwelling of cold water to the surface, to elevate the thermocline in the east, and to suppress the thermocline in the west. Hence, the initial subsurface salinity difference in the central and western Pacific results in both a rapid and sustained change in the surface climate due to induced and sustained changes in temperature.

The impact of these differences in mean state on ENSO variability, as depicted by the standard deviation of SST anomaly along the equator, is shown in Fig. 5f. The initially greater SST variability in the central and eastern Pacific in PEODAS (discussed in Fig. 4) is replaced by decreased variability at longer lead times in V1_PEO. This decreased SST variability in the central and east Pacific coincides with the expansion of the deeper thermocline into the east Pacific, which acts to weaken the Bjerknes feedback.

A key feature of this evolution of the differences in mean states between the two sets of forecasts is that the mean temperature differences develop rapidly and sustainedly during the forecasts, whereas the salinity difference is large at the initial time and hardly changes during the forecasts. The saltier (denser) water in the central Pacific appears to rapidly cause a shallower thermocline to radiate into the eastern Pacific and the thermocline to deepen locally, but this deeper (and saltier) thermocline in the west then does not evolve much after ~2 months of lead time. Away from the equator the maximum salinity difference at 10°S at the initial time (Fig. 2b) does display some westward displacement toward to the western boundary (Fig. 3b), which is probably associated with westward advection by the South Equatorial Current and could contribute to the sustained temperature differences along the equator if these salinity differences, upon reaching the western boundary, are then fed into the thermocline by the equatorial undercurrent. A slow time scale for the evolution of the temperature fields on the equator could also come about because the off-equatorial salinity differences will cause a density perturbation that is carried westward by a temperature perturbation in the form of a downwelling Rossby wave, that upon encountering the western boundary reflects as a downwelling equatorial Kelvin wave. We investigate below the primary cause of the slow evolution of the differences in mean states between V1_PEO and V1_POI.

4. Sensitivity experiments

The analysis in section 3 suggests that the large mean systematic difference in subsurface salinity at the initial time in the central and western Pacific causes the thermocline to rapidly and sustainedly deepen in V1_PEO relative to V1_POI and that this deeper thermocline is maintained until the end of the forecast. The deeper thermocline encroaches eastward into the central Pacific, eventually acting to reduce the Bjerknes feedback there, thereby reducing the simulated coupled variability associated with ENSO. We now conduct some sensitivity experiments to confirm that most of the impact of the mean differences in the initial conditions on the difference in the simulated mean states is indeed coming from the mean differences in the initial subsurface salinity fields. The experiments are also used to illustrate the contrasting adjustment to an initial salinity perturbation in the thermocline region in comparison to a temperature perturbation.

We first performed a sensitivity experiment whereby the mean differences between PEODAS and POI in the initial states for temperature, salinity, and ocean currents, as depicted in Fig. 2, were subtracted from the initial states of PEODAS that are used as initial conditions in V1_PEO. Hindcasts were then remade just for the year 1990 (an ENSO neutral year) using initial conditions for 1 January and 1 July. The ensemble size is 10 for each of the two start dates and they use the same initial perturbations as the original hindcasts for these two dates. This experiment with the mean difference between PEODAS and POI subtracted is referred to as V1*_TSUV (Table 2 summarizes the sensitivity experiments). The subset of the original hindcasts using PEODAS initial conditions for these two start dates is referred to as V1*_PEO (asterisk indicates just the two start dates in 1990).

The idea behind these experiments is to see whether using V1*_PEO minus V1*_TSUV can recover the mean differences in simulated mean states between V1_PEO and V1_POI when all hindcasts are considered as revealed in section 3. If the differences in simulated mean states based can be reproduced from this simple protocol that uses just two start times from a single year, we will then be able to efficiently conduct sensitivity experiments to diagnose which aspect of the mean difference in the initial condition is most important.

To further explore which aspects of the mean differences in the initial conditions matter most, additional experiments were performed subtracting different components of the differences in the mean states from the initial conditions. For experiments V1-_T we subtracted the mean difference between the two analyses for temperature only and for V1-_S we subtracted the mean difference in salinity only. We also conducted experiments where we subtracted the mean differences due to ocean currents only, temperature and currents, and salinity and currents, but these experiments are not reported here as we found that the impact of subtracting
the mean difference in currents to be relatively small. The experiments are summarized in Table 2.

The evolution of mean T300, S300, density, and UA along the equator for V1*_PEO minus V1*_TSUV is shown in Figs. 6a–d. The comparison of Figs. 6a–d with their counterparts in Fig. 5 that use the entire hindcast set show that the experimental design was able to reproduce the general characteristics of the differences in simulated mean states based on the full set of hindcasts. In particular the long-lived impact was simulated. However, there are some differences. For example, in the perturbation experiments there is less evidence of initial eastward propagation. This is seen in both the heat content and surface wind fields. This difference in behavior based on the full hindcast and the subset used in the experiments can be mostly explained because the mean state of the atmosphere was the same in the V1*_TSUV and V1*_PEO experiments (i.e., it used the mean atmospheric state based in ERA-40 that was used in the assimilation for PEOAS). However, as can be seen in Fig. 5d, there is a systematic difference in the initial winds between the V1_PEO and V1_POI. V1_PEO has enhanced easterlies in the central/west Pacific compared to V1_POI. This difference in mean atmospheric states was not added to V1*_TSUV, hence different transient behavior in the first few months develops (i.e., a stronger initial atmospheric Kelvin wave is seen in V1_PEO minus V1_POI because of coupling with the atmosphere perturbation because of coupling with the atmosphere through the surface wind. It also has a temperature signal associated with it, but no salinity signal because the vertical movement of water associated with the Kelvin wave acts on the thermocline to produce temperature anomalies, but since vertical stratification of salinity is weak, it does not produce a noticeable salinity signal.

What is most interesting in Figs. 6i–l, however, is that there is a local sustained temperature response to the initial salinity difference in the western and central Pacific that persists throughout the forecast. The temperature difference in the western and central Pacific are sustained through the forecast as the salinity differences only decay very slowly. The initial adjustment to the salinity difference in the western Pacific results in positive temperature changes that compensate for the initial salinity differences in order to remove the density difference, and because the salinity differences are slow to be removed, the local positive temperature changes in the west and central Pacific are maintained.

<table>
<thead>
<tr>
<th>Expt name</th>
<th>Changed quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1*_TSUV</td>
<td>Temperature, salinity, and ocean currents</td>
</tr>
<tr>
<td>V1*_T</td>
<td>Temperature only</td>
</tr>
<tr>
<td>V1*_S</td>
<td>Salinity only</td>
</tr>
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FIG. 6. Differences for the mean states for T300, S300, density, and zonal wind (UA) along the equator between V1*_PEO and (a)–(d) V1*_TSUV, (e)–(h) V1*_T, and (i)–(l) V1*_S from the initial condition (IC) through to a lead time of 9 months for forecasts initialized on 1 Jan and 1 Jul 1990. Contour intervals are the same as in Fig. 5.
Changes in the thermocline can cause changes in the surface temperature (e.g., by changing the temperature of the water upwelled in the cold tongue) thereby leading to a long-lived impact on the atmosphere (i.e., a coupled response). For V1* T there is only weak indication of generation of a coupled response (i.e., Fig. 6h show only weak surface westerly anomalies). For V1* S there is a more pronounced coupled response because of the sustained deepening of the thermocline in the western and central Pacific and shoaling of the thermocline in the eastern Pacific, which act to cool the surface in the east and warm it in the west. This leads to enhanced easterlies in the west Pacific (Fig. 6l), although the UA field in the sensitivity studies is slightly different from the full set of hindcasts due to nonlinearities and noise from using only two start times. Importantly, the coupled response due to salinity differences alone (Fig. 6l) is very similar to that resulting from including the mean difference in T, S, U, and V differences (Fig. 6d). The mean differences of SST (figure not show) also match what is expected considering the Fig. 5 patterns. Only the salinity differences at the initial stage can cause the SST cooling in the eastern Pacific.

In summary, these sensitivity experiments explain well the different evolution of the mean states in our two hindcast experiments and confirm that the initial mean salinity difference is the major contributor to long-lived change in the coupled mean state.

5. Conclusions

We compared the simulated mean state and variability from two sets of hindcasts using the POAMA seasonal forecast coupled model that differed only in their initial conditions. In one set, the ocean initial conditions were generated by an assimilation of upper-ocean temperatures without any increments to salinity (POI old data assimilation system) and in the other they were generated by an assimilation of both temperature and salinity using the PEODAS system. The PEODAS analysis clearly provides an improved depiction of the upper-ocean state, especially the depiction of salinity (Yin et al. 2011), and ongoing work (e.g., Wang et al. 2011) indicates that it results in improved prediction of ENSO. However, the motivation for the present study was the observation that ENSO variability was simulated to be weaker in the hindcasts initialized from PEODAS compared to POI, even at lead times up to 9 months and even though the analyzed temperature fields from both assimilations are similar. Our analysis here indicates that mean differences in the initial conditions for subsurface salinity along the equatorial Pacific lead to long-lived differences in the simulated mean states, which then affect the simulated coupled variability associated with ENSO. The main contributor to the difference in the simulated mean states was the large difference between the PEODAS and POI depiction of salinity above the thermocline in the western and central Pacific. The lack of any increment on salinity in the POI assimilation cycle leads to a strong negative salinity bias along the thermocline in the POI analyses.

Sensitivity experiments were designed to explore which aspects of the mean difference in the initial conditions matter most. We subtracted the mean state difference to the initial conditions as a perturbation to forecasts from just two start times. These sensitivity experiments clearly showed that subtracting only the salinity differences at the initial time can recover the differences in simulated mean states as seen in Fig. 5 based on the full set of hindcasts. The results show that subsurface salinity differences lead to two responses: a local adjustment of the temperature field to compensate for the impact of salinity on density and a dynamical response to the initial density anomaly, which projects onto equatorial Kelvin and Rossby waves. Even though the initial perturbation is to the salinity field, the resulting Kelvin wave has a temperature, rather than salinity, signature because of the strong vertical temperature stratification and weak salinity stratification. Perhaps more interesting though is the local adjustment of the temperature to the salinity perturbation, which persists throughout the 9 months of the forecast. This is because local salinity perturbations can only be removed through relatively slow advective processes (weak currents acting on relatively weak salinity gradients). Importantly, the temperature changes due to subsurface salinity perturbations impact the coupling to the atmosphere and lead to a coupled response, which can be seen as early as 2 months into the forecast. These results demonstrate a mechanism by which subsurface salinity constraints in the initial state can have a significant impact on the coupled climate. Previous studies have shown a similar impact in data assimilation process or in forecast case studies, but none of them emphasize the short and long time scale of the impact.

Salinity has small interannual variability below the surface mixed layer and so assimilation of salinity from the perspective of seasonal climate forecasting is not as important as assimilating temperature. Furthermore, the mean differences in subsurface salinity between the PEODAS and POI analyses are more than 5 times larger than the interannual standard deviation of salinity, and largely reflect inadequacies of the old POI assimilation due to dynamical imbalance resulting from only assimilating temperature. The results thus
demonstrate the importance of balanced data assimilation, and that salinity errors can have a significant impact on coupled forecasts.

Nonetheless, our results point to salinity variations in the western Pacific thermocline as potentially important sources of long lead-time predictability. Ballabrera-Poy et al. (2002) pointed out the potential impact on ENSO predictions of surface salinity observations over regions that are consistent with our results and with an impact with a similar time scale. We show that subsurface salinity variations in the western Pacific can drive long-lived effects in the thermocline in the equatorial central and eastern Pacific where the ocean and atmosphere are dynamically coupled. Hence, they have the potential to contribute to multiyear and longer time-scale variability and predictability of ENSO. From this perspective, initialization of subsurface near- and off-equatorial salinity may be as important as the initialization of ocean temperatures, not only for seasonal, but also for potentially longer multiyear prediction of the coupled atmosphere–ocean system.

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REFERENCES


