Satellite Sea Surface Salinity Observations Impact on El Niño/Southern Oscillation Predictions: Case Studies From the NASA GEOS Seasonal Forecast System

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Abstract El Niño/Southern Oscillation (ENSO) has far reaching global climatic impacts and so extending useful ENSO forecasts would have great societal benefit. However, one key variable that has yet to be fully exploited within coupled forecast systems is accurate estimation of near-surface ocean salinity. Satellite sea surface salinity (SSS), combined with temperature, help to improve the estimates of ocean density changes and associated near-surface mixing. For the first time, we assess the impact of satellite SSS observations for improving near-surface dynamics within ocean reanalyses and how these initializations impact dynamical ENSO forecasts using NASA’s coupled forecast system (GEOS-S2S-2). For all initialization experiments, all available sea level and in situ temperature and salinity observations are assimilated. Separate observing system experiments additionally assimilate Aquarius, SMAP, SMOS, and these data sets combined. We highlight the impact of satellite SSS on ocean reanalyses by comparing experiments with and without the application of SSS assimilation. Next, we compare case studies of coupled forecasts for the big 2015 El Niño, the 2017 La Nina, and the weak El Niño in 2018 that are initialized from GEOS-S2S-2 spring reanalyses that assimilate and withhold along-track SSS. For each of these ENSO-event case studies, assimilation of satellite SSS improves the forecast validation with respect to observed NINO3.4 anomalies (or at least reduces the forecast uncertainty). Satellite SSS assimilation improved characterization of the mixed layer depth leading to more accurate coupled air/sea interaction and better forecasts. These results further underline the value of satellite SSS assimilation into operational forecast systems.

Plain Language Summary Improving the prediction of El Niño/Southern Oscillation (ENSO) is important because of the global impacts of ENSO and the associated socioeconomic implications. Only recently has satellite sea surface salinity (SSS) become available for improving our characterization of the global hydrological cycle. SSS, combined with temperature, helps to improve the estimates of near-surface density changes and associated ocean mixing. Here we show results of experiments designed to highlight the impact of SSS on ENSO forecasts. In the control experiment, we assimilate a comprehensive set of in situ oceanographic information and satellite altimetry, as typically done in operational ocean data assimilation, but exclude satellite SSS. In the second set of reanalyses, we add different satellite SSS products to our assimilation. Air/sea coupled model hindcasts are then initialized for various case studies including the big El Niño (2015), the moderate La Niña (2017), and a weak El Niño (2018). For each example, satellite SSS assimilation improves coupled forecasts by adjusting the large-scale equatorial waves that are integral to ENSO development. For 2015, SSS damp these waves resulting in a more realistic ENSO prediction. In 2017 and 2018, SSS assimilation acts to change the sign of ENSO forecasts, again leading to more realistic ENSO forecasts.

1. Introduction

The El Niño/Southern Oscillation (ENSO) phenomenon has a significant impact on climate variability throughout the world and so has been the key focus for improving coupled forecasts. Yet the state of the art for seasonal-to-interannual prediction still has much to improve upon (e.g., National Academies of Sciences, 2016; National Research Council, 2010). Assimilation of satellite sea level (SL) from altimetry (e.g., Ji et al., 2000) and subsurface temperature and salinity from (mostly) Argo (e.g., Yang et al., 2010)
help to improve the initialization of the thermocline, while satellite sea surface temperature (SST) also aids in specifying surface heat-flux forcing (e.g., Zhou et al., 2009), leading to improved short-term forecasts of the coupled system. However, much less emphasis has been given to examining the impact of the near-surface ocean density structure and mixed layer processes on air-sea coupled prediction. Thus, sea surface salinity (SSS) is the key measurement that has not yet become fully operational in ocean data assimilation and forecast systems as have other more mature satellite observations such as SL from altimeters or SST from AVHRR and infrared satellites.

Prior to 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. However, since 2010 the continuous stream of satellite SSS from European Space Agency (ESA) Soil Moisture/Ocean Salinity (SMOS), Aquarius, and now NASA’s Soil Moisture Active Passive (SMAP) for the first time allows us to rigorously evaluate the impact of satellite SSS on air-sea coupling and subsequent ENSO predictions.

Up until now, only a few studies have addressed the impact of satellite SSS on ocean reanalyses. For example, Tranchant et al. (2018) and Martin et al. (2019) showed that assimilation of SSS from the SMOS satellite (using similar L-band radiometer technology as Aquarius and SMAP) can add additional constraints to the coupled system to somewhat overcome deficiencies of atmospheric model evaporation and precipitation forcing from atmospheric analyses or reanalyses. In particular, ocean model SSS assimilation has reduced the observational bias of salinity over much of the tropical Pacific including the Intertropical Convergence Zone (ITCZ), South Pacific Convergence Zone (SPCZ), and the western equatorial Pacific (all regions of strong precipitation) with the improvement extending down 30–50 m into the water column. During a simulation of the 2015 El Niño, Tranchant et al. (2018) found that patterns associated with SMOS assimilation acted to enhance the propagation of tropical instability waves (TIW) in the eastern Pacific and increase the acceleration of the warm/fresh pool migration to the east for the 2015 El Niño. On the other hand, Martin et al. (2019) found that the meridional SSS gradient is reduced near 5°N by SMOS assimilation, leading to SL changes and a reduction in TIW activity and a more zonal North Equatorial Counter Current. Near the equator, SMOS assimilation was shown to lead to shallower MLD across the entire Pacific and eastward currents east of 150°E enhancing the anomalous eastward currents of the 2015 El Niño. Chakraborty et al. (2015) also found shallower values and an overall improvement in MLD for the tropical Pacific when assimilating Aquarius data. In addition to SMOS, Martin et al. (2019) performed experiments using multiple SSS satellites (i.e., SMOS and Aquarius and SMOS and SMAP) that further improved the ocean analyses. Thus, the results of Tranchant et al. (2018) and Martin et al. (2019) have clear implications for ENSO prediction and these improvements justify the implementation of SSS assimilation into operational forecast systems.

Although a limited number of studies have focused on the impact of SSS on ocean reanalyses, even fewer studies have been conducted examining the impact of assimilating SSS data to initialize coupled ocean models. In one example, Ballabrera-Poy et al. (2002) showed that gridded in situ SSS observations could add significant, independent information for statistical prediction of ENSO for 6 to 12 month lead times. Prior to the availability of satellite SSS, Hackert et al. (2011) also showed that assimilation of a surrogate for satellite SSS, an optimal interpolation (OI) of all available near-surface in situ salinity observations, improved ENSO coupled predictions and, in particular, alleviated the well-known Spring Prediction Barrier (SPB) problem. The added benefit of assimilating Aquarius gridded SSS was tested by comparing coupled experiments initiated from satellite versus in situ SSS assimilation (Hackert et al., 2014). They found that coupled experiments initialized from assimilation of any SSS extend the forecast skill with respect to the baseline (i.e., assimilation of subsurface temperature) from 5 to 11 months. Satellite SSS assimilation reduces the MLD with respect to both the in situ SSS assimilation and the baseline leading to more efficient ocean/atmosphere coupling near the equator. During the limited period of that study (September 2011 to February 2014) La Niña conditions prevailed. For this case, the buoyancy forcing of relatively less-fresh satellite SSS mixed throughout the model surface layer adds an off-equatorial upwelling signal (i.e., denser water sinks and mixes with colder water at depth generating an upwelling Rossby wave). This upwelling Rossby wave reflects at the western boundary and propagates to the NINO3 region along the equator as an upwelling Kelvin wave leading to reduction of positive SST anomaly-biased forecasts for this particular period.

In a recent study, Hackert et al. (2019) demonstrated a significant, positive impact of SSS assimilation on seasonal ENSO forecasts using the Intermediate Complexity Coupled Model (ICCM) of Hackert (2016)
that combines the Ensemble Reduced-Order Kalman Filter assimilation, the reduced-gravity, primitive-equation Indo-Pacific ocean model (Gent & Cane, 1989), and the global SPEEDY atmospheric model (Molteni, 2003). Observing system experiments (OSEs) were conducted to isolate the impact of satellite SSS on ENSO forecasts of the NINO3.4 region SST anomalies for the 6-year period from September 2011 to September 2017. For the baseline, a comprehensive set of in situ and satellite observations were assimilated but satellite SSS observations were excluded. These results were then compared against an experiment that added gridded fields of both Aquarius and SMAP SSS (i.e., following GODAE OSE protocols; Oke et al., 2009). Useful forecasts were extended from ~4 months without SSS assimilation to more than 7 months with satellite SSS assimilation (i.e., forecasts where correlations versus observed SST anomalies $r > 0.38$ at the 95% significance level). The positive impact of SSS assimilation on forecast accuracy originated from the improvement in representation of ocean mixed layer dynamics due to improved representation of salinity anomalies in the western Pacific warm/fresh pool and the southern tropical Pacific Ocean. Along the equator and in the southern tropics, freshening SSS increased the barrier layer thickness (BLT) which in turn led to shallower MLD. Thus, assimilating SSS as part of the forecast initialization generally increased the stability of the mixed layer, reduced mixing, and shoaled the thermocline which, in turn, enhanced the equatorial Kelvin waves and concentrated the wind impact of ENSO coupling. Again, the shallower MLD lead to enhanced Kelvin wave amplitude. Another way to say this is that the Kelvin wave amplitude is inversely proportional to MLD since MLD is in the denominator of the Kelvin wave SL amplitude equation (e.g., equation (2) of Cravatte et al., 2003 and also provided in Supplemental Material).

Although Hackert et al. (2019) demonstrated the improvement of ENSO prediction through satellite SSS using an ICCM, the impact of satellite SSS on ENSO prediction using fully coupled GCMs has not yet been explored. This study reports on the results of assimilating SSS data into a full complexity coupled data assimilation and forecast system. The paper is organized as follows: In section 2, a brief account of the coupled model is provided, with a listing of the observational data inventory, and a detailed description of the data assimilation methodology is also presented. In addition, a brief discussion of the production of the seasonal forecast system is included in section 2 to put these SSS OSEs into context. Section 3 describes the experiment design and section 4 explains the results. Finally, a summary and conclusions are provided in section 5.

2. Models and Data Assimilation Description

2.1. GEOS Subseasonal to Seasonal Coupled Forecast System

This current research builds on the initial studies describing SSS OSEs (e.g., Hackert et al., 2019; Martin et al., 2019 and Tranchant et al., 2018), but now uses the NASA Global Modelling and Assimilation Office (GMAO) Subseasonal-To-Seasonal (S2S) coupled ocean/atmosphere forecasting system, to assess the impact of SSS on specific ENSO case studies. This system, known as the NASA GEOS-S2S-2 coupled forecast system (or S2S-2 for short), consists of the Goddard Earth Observing System (GEOS) general circulation atmosphere model coupled to a GFDL MOM5-based general circulation ocean. Both atmosphere and ocean have comprehensive data assimilation systems and observational data sets as well as diagnostic codes. The NASA GEOS-S2S-2 is currently being used as a forecast testbed as part of the community North American Multi-Model Ensemble (NMME) effort (Kirtman et al., 2014) for ENSO prediction. The various components of the S2S-2 are summarized in Table 1 and for a more detailed description of the current GEOS-S2S-2 system see Molod et al. (2020).

The coupled model consists of the following components:

1. Ocean: Ocean physics and dynamics are provided by the GFDL Modular Ocean Model-5 (MOM5) with $0.5^\circ \times 0.5^\circ \times 40^\circ$ level resolution (Griffies, 2012; Griffies et al., 2005).
2. Atmosphere: The atmospheric model is the Goddard Earth Observing System (GEOS) atmospheric general circulation model with 72 layers and approximately $0.5^\circ$ resolution (Rienecker et al., 2008, and recent improvements documented by Molod et al., 2015). The atmospheric data assimilation is detailed in Gelaro et al. (2017).
3. Land surface model: The land surface model is the catchment model of Koster et al. (2000), with simple river routing.
4. Aerosols: Interactive aerosols are evolved using the Goddard Chemistry Aerosol Radiation and Transport (GOCART) aerosol model (Chin et al., 2002; Colarco et al., 2010).

5. Sea Ice: Sea ice is calculated by the Community Ice Code V4 (CICE4) sea ice model developed at Los Alamos National Lab (Hunke & Lipscomb, 2008).

6. Coupling: All components are coupled together using the Earth System Modeling Framework (ESMF, Hill et al., 2004) and the Modeling and Analysis Program Language (MAPL) package interface layer (Suarez et al., 2007).

The ocean component has nominal 10 m resolution in the upper 100 m and employs the nonlocal K-profile parameterization of Large et al. (1994) and a parameterization of tidal mixing. Horizontal mixing uses the isoneutral method of Gent and McWilliams (1990). The horizontal viscosity uses the anisotropic scheme of Large et al. (2001) for better representation of equatorial currents, upwelling, and mixing. The exchange with some marginal seas is parameterized as discussed in Griffies (2012). The ocean/atmosphere exchange of fluxes for momentum, heat, and fresh water are carried out through a "skin layer" interface which includes a parameterization of the diurnal cycle (Price et al., 1978). The model is mass-conserving, with an explicit free surface and real fresh water forcing.

2.2. Ocean Observing Systems for Seasonal Forecasting

The control S2S-2 system routinely assimilates a wide range of global ocean in situ and satellite observations. Here we briefly list all assimilated observational data sets. In situ temperature and salinity are provided by (1) tropical moorings from Research Moored Array for African-Asian-Australian Monsoon Analysis and Prediction (RAMA; McPhaden et al., 2009), Tropical Atmosphere Ocean/Triangle Trans Ocean Buoy Network (TAO/TRITRON; McPhaden et al., 2010), and the PiLot Research moored Array in the Tropical Atlantic (PIRATA; Servain et al., 1998) for the Indian, Pacific, and Atlantic Oceans, respectively. All moorings maintain an array of surface meteorological observations and subsurface thermistor chains, while many moorings include salinity measurements. (2) The Argo float array, which provides profiles of temperature and salinity to 2 km depth every few degrees on average, every 10 days (Roemmich et al., 2009). These in situ measurements are supplemented by a smaller amount of shipborne quality-controlled profile temperature and salinity observations from Conductivity/Temperature/Depth (CTD) profilers and temperature profiles from expendable bathythermographs (XBT) (Good et al., 2013). Along-track (Level 2) sea level (SL) data are obtained from the Archiving, Validation and Interpretation of Satellite Oceanographic Data (AVISO, https://www.aviso.altimetry.fr/data/products/sea-surface-height-products/global/along-track-sea-level-heights.html), combined with gravity data from the Gravity and Ocean Explorer (GOCE; Johannessen et al., 2003) and the Gravity Recovery and Climate Experiment (GRACE; Tapley et al., 2004), and assimilated as absolute dynamic topography (ADT) as described in section 2.3. Over the period of our forecast experiments, active altimeters include Jason-2 and 3, CryoSat2, Saral-Altika, HY-2A, and Sentinel 3A, but we include all available satellite sea level data that were available for assimilation into the retrospective reanalyses.

Although the production GEOS-S2S-2 system routinely assimilates all in situ profiles of temperature and salinity and altimetry data, an important component of the ocean state, namely, density, is still

<table>
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<tr>
<th>Component</th>
<th>Ocean</th>
<th>Atmosphere</th>
<th>Land</th>
<th>Sea ice</th>
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<tr>
<td>Dynamic core Physics</td>
<td>MOM5a</td>
<td>GEOS non-hydrostatic finite volume cubed sphereb</td>
<td>Catchment Land Surface Modelc</td>
<td>CICE4</td>
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<td>Aerosols Resolution</td>
<td>0.5° × 0.5° × 40°</td>
<td>Single moment interactive aerosold</td>
<td>Arakawa–Schubert convectione</td>
<td>0.5° × 0.5°</td>
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<tr>
<td>Assimilation</td>
<td>LETKFb</td>
<td>0.5° × 0.5° × 72°</td>
<td>Grid point Statistical Interpolation 3DVarh</td>
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Note: Many aspects of the atmospheric analysis system are described in Rienecker et al. (2011). Also see Molod et al. (2020) for more details.

underutilized from the satellite suite and is so far lacking from operational systems. Global SSS, which can be estimated by converting L-band radiometer brightness temperatures using the technique of, e.g., Piepmeier et al. (2015), can be utilized to give better estimates of near-surface density. In this paper, we test the impact of satellite SSS by adding assimilation of satellite SSS to the control experiment. In separate experiments, we assimilate all available along-track satellite SSS from Aquarius (NASA_Aquarius_Project, 2017) for 2011–2015 and SMAP (Fore et al., 2016) for 2015–present, and SMOS (Boutin et al., 2018) from 2010–present to demonstrate that improved estimates of near-surface density can improve ENSO predictions. (Note that in this paper we treat the combination of all Aquarius and SMAP data together as a single product and abbreviate this combination as AQ/SMAP.)

2.3. Initial Conditions and Ocean Data Assimilation

Initial conditions and verification for the land and atmosphere are provided by a data assimilation system similar to the NASA MERRA-2 reanalysis (Gelaro et al., 2017), which is being produced using a fixed GEOS atmosphere/land model, data assimilation system, and observations types (GMAOFPIT, 2016). Initial conditions and verification for the ocean, as well as for our OSEs, rely on the GMAO ocean reanalysis system which assimilates the ocean observation sets listed in section 2.2 using a technique similar to the Local Ensemble Transform Kalman Filter (LETKF) implementation of Penny et al. (2013). In addition to assimilation, the ocean SST is strongly relaxed (1-day relaxation time scale) to the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA; Donlon et al., 2012) so that the ocean is consistent with atmospheric (i.e., GMAOFPIT) forcing. The OSTIA product is made up of several satellite infrared (MODIS, VIIRS) and microwave satellite SST products and in situ data and are used for ocean relaxation but not assimilation. SSS is weakly relaxed to the World Ocean Atlas 2013 (Zweng et al., 2013) with time scale of 30-days in addition to satellite SSS assimilation.

Our implementation of the LETKF is applied on a 5 day assimilation cycle with 20 fixed ensemble members (Vernieres et al., 2012). The advantage of this ensemble Kalman Filter ocean data assimilation system (ODAS) over a less expensive deterministic filter such as the 3-dimensional variational (3DVar) data assimilation approach is that it allows the error covariances to more accurately evolve with the seasonal cycle and the phase of ENSO. We localize these error covariances to eliminate spurious correlations between distant grid points and inflate the error covariances to prevent the ensemble members from becoming too similar (Houtekamer & Zhang, 2016). For profile data, we only localize in the horizontal, with a decorrelation length-scale that is proportional to the Rossby deformation radius (Chelton et al., 1998). The quality of the initial conditions also depends on our specification of observation error (the sum of the intrinsic instrument error and the error due to physical processes such as internal waves that are unresolved in our system; Janjić et al., 2018). Within the data assimilation code, profile data are assigned observational error depending on the depth gradient of the observation. For the S2S-2 ODAS code, vertical temperature and salinity gradients are scaled by a factor of 10 to give the final profile observation error. In this way, the highest observation errors are assigned at depths where the thermocline and hence the greatest uncertainty resides. Vertical localization is turned off for profile data. This has the benefit of calculating the analysis only once (as opposed to 40 times for 40 levels) and unique vertical localization profiles for each observation type are no longer required (as was required, e.g., in Vernieres et al., 2012). This technique has the additional benefit of allowing assimilation of vertical profiles and satellite altimetry data within a single ODAS process.

While the assimilation of most profile observations is quite straightforward, assimilating sea level as ADT is a little more complicated. ADT’s main impact on the ocean state is through its covariance with temperature and salinity (and thus the depth of the pycnocline). Because of the sheer volume of the data, ADT observations are thinned prior to assimilation (see https://www.aviso.altimetry.fr/data/products/sea-surface-height-products/global/along-track-sea-level-heights.html for resolution details). A Gaussian weighted mean is calculated for the central point of ±10 along-track observations using a decorrelation scale of 1,000 km. This mean is then output for assimilation. The observation error we assign to ADT is estimated via the variability of the data within the Gaussian length scale and increases from <2 cm at the equator to a maximum of 10 cm at high latitudes to reflect the decreasing error covariance between ADT and density. Finally, the mean of all ADT observations for the assimilation period is removed prior to assimilation and then this mean is added back after assimilation to prevent the sea level observations from affecting the time-mean barotropic circulation.
For SSS assimilation, we follow a thinning procedure similar to the technique for assimilating ADT. Data are thinned along-track using the same Gaussian weighted filter. SMOS, Aquarius, and SMAP have effective resolution of 50, 100, and 40 km respectively. However, the observation error is treated differently than for ADT. For SSS assimilation, we simply use the error provided by the various product teams. For example, in the SMAP processing of Fore et al. (2016), it is difficult to separate wind speed and salinity effects on the brightness temperature. Therefore, these two variables are combined into a single maximum-likelihood processing equation (Yueh & Chauell, 2012). The uncertainty is then estimated as an exponential decomposition of this equation. Since this equation incorporates SSS effects such as cold water, radio frequency interference (RFI), and measurement and geophysical model errors, this technique accounts for the major components of the SSS error. By way of validation, these error estimates reproduce the meridional distribution and amplitude of the RMS differences between a Hybrid Coordinate Ocean Model (HYCOM; Chassignet et al., 2007) SSS and SMAP observations. For more details on the SSS methodology and the HYCOM/SMAP SSS estimated error see https://podaatools.jpl.nasa.gov/drive/files/SalinityDensity/smap/docs/JPL-CAP_V42/SMAP-SSS_JPL-V4.2_Documentation.pdf, section 3.4.1.

2.4. Production Aspects of the GEOS-S2S-2 System

This project builds on our ongoing participation in the NMME and the International Research Institute for Climate and Society (IRI) multimodel ENSO seasonal forecast (https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/). Each month, the GMAO produces an ensemble of 10 real-time coupled model forecasts. This ensemble is created by initializing the forecast system every 5 days over the last 20 days of the month (giving four forecasts), and then adding an additional six forecasts begun from perturbed states of the last date of the month to reduce errors due to random flow instabilities by ensemble averaging and thus the more predictable components of seasonal forecasts are emphasized. An example of a recent seasonal forecast comparison of SST in the eastern tropical Pacific NINO3.4 region can be found at https://www.cpc.ncep.noaa.gov/products/NMME/current/plume.html. Results from multiple such forecast comparisons show that GEOS-S2S-2 ENSO forecast error statistics are competitive with other operational forecast systems.

To accompany the forecasts produced in “near-real-time,” the GMAO has also produced a suite of hindcasts (1982–2016) using a hybrid of the S2S-2 system. This archive of S2S-2 system hindcasts is particularly useful for us because we can calibrate ENSO forecasts using statistics over many years of forecasts encompassing many ENSO cycles.

3. Experiment Design

As pointed out above in section 1, the several previous examinations of the relative contributions of SSS assimilation were carried out with an ocean-only testbed (e.g., Martin et al., 2019; Tranchant et al., 2018) or with an Intermediate Complexity Coupled Model (e.g., Hackert et al., 2019). In this study, our goal is to explore the impact of SSS assimilation in the context of a complete, quasi-operational, coupled forecast system using the fully coupled S2S-2 model testbed with full data assimilation systems. In this work, we focus on isolating the impact of satellite SSS observations for case studies of spring ENSO hindcasts for the big El Niño in 2015, the moderate La Niña of 2017, and the weak El Niño of 2018. Spring initialization is chosen for our case studies since this season spans the well-known ENSO spring prediction barrier (Jin et al., 2008) and so is the hardest case to test for impacts on ENSO prediction. We will compare/contrast experiments with SSS versus those withholding SSS and our design of these OSEs will follow, e.g., Oke et al. (2009), while the forecast diagnostics will be adopted based on NMME and Global Ocean Data Assimilation Experiment (GODAE) protocols (e.g., Hernandez et al., 2009).

The experiment design is summarized in Table 2 and described herein. For each experiment, the reanalysis starts in April 2012 and runs through to near real-time. There are four experiments, (1) No_SSS is the control that assimilates all available in situ temperature and salinity and along-track ADT data; (2) ASSIM_AQ/SMAP assimilates all data that No_SSS has plus all available, along-track Aquarius and SMAP SSS; (3) ASSIM_SMOS is No_SSS plus assimilates along-track SMOS data; and (4) ASSIM_ALL_SSS assimilates all that No_SSS does plus all satellite SSS (i.e., along-track Aquarius, SMAP, and SMOS data). Coupled forecast experiments are initialized every 5 days for each data assimilation scenario. For the El Niño case studies of 2015 and 2018, the dates of 11, 16, 21, and 26 April were chosen and for the 2017 La Niña, ENSO forecasts
were initialized on 16, 21, 26, and 31 May. Although we were limited to only four dates, these dates were chosen to span the month and avoid the large computational resources required to execute more 9 month ENSO forecasts. These initialization dates were also chosen to match the production timetable so that there are multiple years of hindcasts (i.e., 1981–2016) using the S2S-2 system available to detrend ENSO forecasts (as is common for, e.g., NMME comparisons). Note that each of the four coupled forecast experiments were detrended using the same 35-year mean forecast date mean from the S2S-2 system. For example, the 11 April 2015 No_SSS, ASSIM_AQ/SMAP, ASSIM_SMOS, and ASSIM_ALL_SSS forecasts all used the same No_SSS 11 April 1981–2016 forecast mean to detrend all of the forecasts. All four 16 April 2015 experiment forecasts used the 16 April mean to detrend, and so on (see https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/?enso-tab=enso-sst_table for details and the latest forecast plume).

4. Results

In previous results, Hackert et al. (2019) found that satellite SSS assimilation led to an overall freshening in the equatorial waveguide which led to decreased MLD. Decreased MLD then increased the Kelvin wave amplitude associated with ENSO acting to amplify ENSO. It was shown that improved specification of the MLD through SSS assimilation led to significantly improved ENSO forecasts. However, these results used a simpler model and data assimilation system and calculated general ENSO statistics over an extended period of September 2011 to September 2017. Now we shall show that the more realistic quasi-operational GEOS-S2S-2 seasonal prediction system also responds positively to assimilating satellite SSS for ENSO case studies.

As a particularly interesting example, May 2015 ASSIM_AQ/SMAP minus No_SSS OSE was chosen to highlight the initialization prior to the big El Niño in 2015 (Figure 1). (For the readers’ interest, analogous plots for ASSIM_SMOS and ASSIM_ALL_SSS scenarios are presented in the supporting information available in Figures S1 and S2, respectively). Figure 1 shows the differences between the experiment that assimilates both Aquarius and SMAP along-track SSS (ASSIM_AQ/SMAP) minus the one that withholds SSS (No_SSS). Figure 1a shows these differences for SSS. Assimilation of along-track Aquarius and SMAP SSS causes an overall salinification of the equatorial waveguide with particularly high positive differences in the western tropical Pacific near the dateline. Not surprisingly, SST differences are small (Figure 1b) since SST is strongly relaxed to OSTIA observations with a 1-day relaxation timescale for both No_SSS and ASSIM_AQ/SMAP experiments. With increased salinity, near-surface density also increases (not shown since this plot duplicates SSS differences closely). Density changes near the surface directly impact the MLD. MLD is defined by the density criteria (i.e., the depth that the vertical density gradient equals the surface density value plus the equivalent density change assuming the temperature gradient is 0.2 °C keeping salinity at depth equal to the SSS, Sprintall & Tomczak, 1992). Increasing the SSS leads to increased density and MLD in the equatorial waveguide as seen in Figure 1c. At the same time, BLT (defined as difference between a 0.2 °C isothermal mixed layer minus the density defined MLD, Figure 1d) is decreased between 170°E and 150°W near the equator. This shoaling barrier layer would correspond to a relative upwelling (or equivalently a weaker downwelling) signal due to SSS assimilation.

| Table 2 |
| List of Reanalysis Experiments From the GMAO GEOS-S2S-2 System Utilized in This Study |
| Experiment name | Assimilation Data |
| No_SSS | Along track SL; in situ T and S; NO SSS |
| ASSIM_AQ/SMAP | Along track SL; in situ T and S; Along-track SSS from Aquarius<sup>a</sup> and SMAP<sup>b</sup> |
| ASSIM_SMOS | Along track SL; in situ T and S; Along-track SSS from SMOS<sup>c</sup> |
| ASSIM_ALL_SSS | Along track SL; in situ T and S; Along-track SSS from Aquarius<sup>a</sup>, SMAP<sup>b</sup>, and SMOS<sup>c</sup> |

Note. No_SSS stands for no SSS assimilation, ASSIM_AQ/SMAP assimilates both Aquarius and SMAP data, ASSIM_SMOS assimilates SMOS data, and ASSIM_ALL_SSS assimilates Aquarius, SMAP, and SMOS data. As the reanalysis was running, the version of the SSS data was continuously updated to latest available product, hence the experiment encompassed Versions 4.0 to 4.2.<n/o/Aquarius Version 5 from September 2011 until May 2015 (NASA_Aquarius_Project, 2017). SMAP Version 4.0 to 4.2 from April 2015–present (Fore et al., 2016). SMOS Version 3.0 from January 2010–present (Boutin et al., 2018).
Since MLD is in the denominator of the first baroclinic mode Kelvin wave SL amplitude equation (e.g., equation (2) of Cravatte et al., 2003 and Supplemental Material), a deeper MLD would lead to a damping of the Kelvin wave amplitude. Hovmöller plots of the equatorial Kelvin wave amplitude are presented in Figure 2 to demonstrate this feature over the period of interest. To construct these plots, sea level from each reanalysis are first converted to geostrophic currents using the technique of Picaut and Tournier (1991), then these geostrophic currents are converted to Kelvin wave amplitude using the methodology of Delcroix et al. (1994). This Hovmöller diagram covers the period extending from January 2013 until December 2018. Each of the major ENSO features can be seen in Figure 2a. During early 2015 the four distinct downwelling Kelvin waves (shown in red in Figure 2a) originate near the dateline and propagate to the east arriving in the upwelling region of the eastern equatorial Pacific approximately 3 months later. The repeated arrival of the downwelling signal in the east suppresses the normal upwelling leading to the major El Niño which peaks in December 2015 (indicated by the red arrow on the right side of Figure 2a). Later, the strong upwelling (blue) Kelvin waves of the 2016 and 2017 La Niñas are evident arriving at the eastern boundary in April and October in 2016 and September and November 2017. These waves originate in the western Pacific and when they arrive, the normal upwelling in the eastern Pacific is enhanced. Finally, the weak El Niño downwelling signal can be seen arriving in November 2018.

The No_SSS (Figure 2a) shows all the general features of the Kelvin wave propagation. However, it is instructive to point out the differences, ASSIM_AQ/SMAP minus No_SSS, in Figure 2b to isolate the impact of SSS. A close examination of Figure 2b indicates that this plot is generally anticorrelated with the total signal from, e.g., Figure 2a. In fact, the equatorial time series of these Kelvin wave differences are significantly anticorrelated with the observed NINO3.4 SST (from Reynolds et al., 2002) anomaly index which is the common metric for ENSO activity and includes the average of the SST anomaly over 170°–120°W, 5°N–5°S. The NINO3.4 SST anomaly and the Kelvin wave differences are correlated at $r = -0.46$ which is significant at the
95% significance level (Quenouille, 1952) and SST anomaly lags Kelvin wave amplitude by 4 months accounting for the transit time of a first mode equatorial Kelvin wave across the Pacific (e.g., Kessler & McPhaden, 1995).

The damped Kelvin wave due to SSS assimilation for Spring 2015 can be seen clearly in the Kelvin wave difference plot, Figure 2b. The solid line marks the May 2015 initialization date, and it shows negative values corresponding to a damped Kelvin wave due to the SSS assimilation. Similar Kelvin wave Hovmöller plots for ASSIM_SMOS–No_SSS and ASSIM_ALL_SSS–No_SSS are provided in Figures 2c and 2d, respectively, and show similar relative upwelling signal at initialization of these experiments.

Figure 2. Plots showing the Kelvin wave decomposition of (a) No_SSS, (b) the difference ASSIM_AQ/SMAP–No_SSS, (c) ASSIM_SMOS–No_SSS, and (d) ASSIM_ALL_SSS–No_SSS. Note the strong negative correspondence between the differences and the totals in (a). Correlation between panel (b) versus NINO3.4 SST' = −0.46 (signif. at 95%, SST lag UKEL by 4 months). Red (blue) arrows on panel (a) mark the peak of El Niño (La Niña) discussed in this paper. Solid (dashed) lines mark the forecast initialization dates for 2015, 2018 El Niños (2017 La Niña).
To summarize the results of Figures 1 and 2, assimilating satellite SSS leads to increased SSS near the equator, which in turn leads to a higher density and increased MLD. The larger MLD acts to dampen downwelling Kelvin waves that are associated with ENSO. Now we show examples of the impact that satellite SSS assimilation has on actual ENSO predictions. Figure 3 shows the forecasts from four different initialization times in April 2015 for (a) NO_SSS and (b) ASSIM_AQ/SMAP. The NO_SSS experiment (Figure 3a) severely overestimates the amplitude of the 2015 El Niño by almost 1.5 °C for the 5-month lead forecast in September 2015. On the other hand, the damped Kelvin wave provided by the satellite SSS assimilation initialization in Figure 3b shows that forecasts generated from ASSIM_AQ/SMAP have significantly improved ENSO predictions for the big 2015 El Niño. In this case, the damping of the downwelling Kelvin wave brought about by the SSS assimilation leads to a significantly improved forecast for the 2015 El Niño.

For the ASSIM_SMOS and ASSIM_ALL_SSS experiments in Figures 3c and 3d, respectively, the story is similar. Satellite salinity acts to dampen the downwelling Kelvin wave leading to a more realistic ENSO prediction. However, the ASSIM_SMOS experiment appears to damp the Kelvin wave a little less than the ASSIM_AQ/SMAP results leading to a slightly warmer ensemble mean. For the ASSIM_ALL_SSS results in Figure 3d, the forecast ensemble mean would fall just above the observations (black line in Figure 3). The slightly weaker damping from the SMOS is offset by the AQ/SMAP assimilation but the ASSIM_ALL_SSS has a broader spread.

The 2017 La Niña is a more challenging forecast example. The IRI forecast plume for May 2017 actually forecasted an El Niño (Figure 4). In fact, the mean for all IRI dynamical forecasts models (heavy red line in Figure 4) called for an El Niño of ~0.75 °C at 6-month lead time for November 2017 and none predicted the observed La Niña. The GEOS-S2S-2 was as guilty of this error as the other forecast systems with a 6-month lead NINO3.4 SST anomaly forecast of 1.3 °C. In reality, the NINO3.4 SST anomaly of ~1.1 °C showed a La Niña for this period. Needless to say, this was a uniformly difficult forecast to get correct.

The impacts of satellite SSS will be demonstrated for this difficult forecast initialization case. Figure 5 shows the same differences as for Figure 1 but for June 2017. However, unlike Figure 1, where the MLD has a
Figure 4. NINO3.4 forecast plume plots initialized from May 2017. Graphic provided by the International Research Institute for Climate and Society, Columbia University (https://iri.columbia.edu/our-expertise/climate/forecasts/enso/2017-May-quick-look/?enso_tab=enso-sst_table).

Figure 5. Same as Figure 1 but for June 2017.
Figure 6. Same as Figure 3 but initialized from May 2017 forecasts for the 2017 La Niña.

Figure 7. Similar to Figure 5 but for ASSIM_SMOS results. Plots showing (a) SSS, (b) SST, (c) MLD, and (d) BLT for June 2017 for experiment ASSIM_SMOS minus the No_SSS experiment.
generally positive signal straddling the equator leading to damping of downwelling Kelvin waves in 2015, Figure 5c shows negative values right on the equator for most longitudes. Negative values of MLD would imply a relative change of sign (i.e., relative upwelling signal for any forecast downwelling Kelvin waves traversing the Pacific).

Figure 6 shows the coupled forecast results for the June 2017 initialization. Figure 6a shows that three of the four ensemble members without SSS assimilation tend toward erroneous El Niño conditions with only the May 31 ensemble getting the forecast reasonably correct (note that perturbed forecasts from May 31 are missing from this experiment ensemble as would normally be present for NASA’s NMME contribution forecast ensemble). As stated before, this was a typical poor forecast similar to other NMME operational systems. For the ASSIM_AQ/SMAP initialization with satellite SSS (in this case just SMAP data since Aquarius was no longer available at this time), each of the four ensembles tend toward neutral ENSO conditions. In other words, the negative MLD differences would counteract the erroneous downwelling signal with upwelling. Although this is not an ideal forecast, it is a substantial improvement upon the No_SSS that is calling for El Niño. At the very least, the ASSIM_AQ/SMAP forecasts in Figure 6b help to expand the uncertainty of the ensemble forecasts for ENSO predictions. Such a forecast would have added uncertainty to the NMME El Niño forecasts and perhaps tempered NOAA’s call for El Niño (http://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/enso_disc_may2017/ensodisc.shtml).

In the case for 2017, the model initialization without SSS assimilation wants to forecast El Niño. However, the negative MLD differences and the concomitant relative upwelling signal during June 2017 counteracts this downwelling (i.e., El Niño) tendency for the ASSIM_AQ/SMAP forecast and the resulting forecasts show improvement by predicting neutral ENSO conditions. Again, the SSS assimilation leads to more realistic mixed layer density and tends to damp the ENSO Kelvin wave, in this case imparting an upwelling signal to an erroneous downwelling Kelvin wave.

The ASSIM_SMOS initialized experiment (Figure 6c) forecasts a strong El Niño for 21 and 26 May initializations but neutral conditions (like SMAP) for the beginning and ending forecasts of the month. The upwelling
signal (i.e., change of sign for Kelvin wave) seen along the equator west of 105°W for Figure 7c is offset by the strong downwelling (red) in the far eastern Pacific at initialization for the Kelvin wave differences in Figure 2c (follow along the dashed line). In any case, this forecast group is an improvement upon the No_SSS results. Finally, Figure 6d shows the results of the ENSO forecasts initialized by the ASSIM_SSS_ALL experiment. As expected, this group of ensembles acts as a compromise between the ASSIM_AQ/SMAP and ASSIM_SMOS experiments. The forecasts average toward neutral ENSO but have a large spread. Again, having a neutral ENSO forecast rather than predicting a faulty El Niño is an improvement and, at the very least, the increased uncertainty in these forecasts help forecasters to correctly temper the ENSO forecast.

For the 2018 El Niño, the NINO3.4 SST anomaly peaked just over 1 °C in October 2018. However, the No_SSS experiment does a poor job of reproducing the observed NINO3.4 SST anomaly (Figure 10a). The ensemble mean of these four forecasts would indicate weak La Niña ENSO forecast. Like the case for 2015, the initial condition differences for 2018 would suggest that the SSS assimilation should act to dampen the Kelvin signal. Figures 8a and 8c show overall positive SSS and MLD differences in the equatorial wave-guide for the ASSIM_AQ/SMAP experiment with respect to the No_SSS. When assimilating SMAP SSS, Figure 10b shows a tighter grouping of the ensemble near neutral conditions indicating a damping due to the positive sign of the difference of ASSIM_AQ/SMAP MLD relative to the No_SSS. In this case, the damping due to assimilating SMAP SSS modulates the erroneous upwelling and gives weak neutral conditions (except for the 26 April ensemble that correctly forecast the amplitude and timing of the real observations). Thus, the ASSIM_AQ/SMAP results produce a slight improvement on the mistaken predictions of a weak La Niña for the No_SSS forecasts.

Unlike the ASSIM_AQ/SMAP experiment, the forecasts with SMOS assimilation do an exceptional job at reproducing the weak 2018 El Niño. All ensembles that include SMOS assimilation in Figures 10c and
10d match the amplitude and the timing of the observations. Unlike the ASSIM_AQ/SMAP experiment, the ASSIM_SMOS experiment has fresher SSS and large regions of negative MLD along the equator (e.g., compare Figures 9c versus 8c for MLD differences). The negative MLD difference for the ASSIM_SMOS relative to the No_SSS experiment acts to change the sign of the weak upwelling Kelvin wave to the correct observed downwelling signal. This feature is also well demonstrated for Figure 9a where the salinity difference is overall negative whereas the ASSIM_AQ/SMAP (Figure 8a) shows an overall salination relative to the No_SSS experiment near the equator. These results are manifest when comparing the Kelvin wave signal and a key to the success of the ASSIM_SMOS relative to the ASSIM_AQ/SMAP results can be seen by comparing Figure 2b to Figure 2c. Note the much stronger downwelling (red) signal for the SMOS results relative to SMAP especially in the eastern Pacific (east of 120°W). Negative MLD differences for SMOS assimilation effectively flips the sign of the Kelvin wave giving the proper weak El Niño signal resulting in improved ENSO forecasts for May 2018.

5. Summary and Conclusions

In this paper, a series of OSEs were conducted in order to assess the impact of satellite SSS assimilation on ENSO forecast case studies. A reanalysis that assimilates standard ocean observations including all available in situ mooring, profile temperature and salinity, and satellite sea level was used as the baseline (No_SSS). In addition to these standard data, we tested the impacts of assimilating along-track Aquarius/SMAP, SMOS, and a combination of all available satellite SSS (ASSIM_AQ/SMAP, ASSIM_SMOS, ASSIM_ALL_SSS, respectively). A series of ENSO forecasts were then initialized in spring of 2015, 2017, and 2018 for each of these reanalysis experiments and then these were compared to the observed NINO3.4 SST anomalies. Taken as a whole, coupled forecasts that are initialized with assimilation of satellite SSS do an overall better job of reproducing the observations as compared to the No_SSS forecasts.

A reason for the improved forecast for the big El Niño in 2015 is explained as follows: assimilation of Aquarius and SMAP SSS led to salination and increased density near the equator. This salination and increased density resulted in a relatively increased MLD which, in turn, led to damped ENSO downwelling Kelvin waves. Without assimilation of SSS, the No_SSS experiment overpredicted the amplitude of the

Figure 10. Same as Figure 3 but initialized from April 2018 forecasts for the weak 2018 El Niño.
2015 El Niño by ~1.5 °C at 5-month lead time. However, the damping effect of satellite SSS assimilation led to a much more realistic forecast for the April 2015 case and forecasts generated with SSS initialization reproduced well the observed signal. SMOS and the combination of Aquarius, SMAP, and SMOS also improved upon the No_SSS case.

For the June 2017 initialization, practically all the operational forecasts, including GEOS-S2S-2, mistakenly forecast El Niño for summer/winter of 2017. However, a La Niña was actually observed troughing in November 2017 to ~1.2 °C for the NINO3.4 SST anomaly. Although not a perfect forecast, we assert that assimilation of satellite SSS improved the forecast since the ASSIM_AQ/SMAP experiment generally predicted neutral ENSO forecasts and brought the forecasts more in line with observations. For the 2017 case, freshening SSS and negative MLD differences with respect to the No_SSS experiment changed the sign turning the erroneous downwelling (i.e., warming) Kelvin wave to a weak upwelling (cooling) signal. SMOS and the combination of SMAP and SMOS worked in a similar manner but generated a greater spread in the forecast ensembles.

For May 2018, the ENSO forecasts initialized without SSS (i.e., No_SSS) predicted a weak La Niña, whereas in reality, a weak El Niño scenario (peaking at 1.1 °C for the NINO3.4 SST anomaly in October 2018) was observed. For the experiment that assimilated SMAP SSS (ASSIM_AQ/SMAP), near-surface salification in the equatorial waveguide from SMAP SSS assimilation led to increased MLD and these features acted to damp the inappropriate La Niña forecasts. The ensemble mean corresponded to a near-neutral ENSO forecast for ASSIM_AQ/SMAP forecasts so assimilation of SMAP data somewhat mitigated a poor, wrong-sign ENSO forecast. On the other hand, SMOS assimilation did an excellent job of reproducing the observed NINO3.4 SST anomaly. In this case, relative freshening and a shoaling of the MLD lead to a change in sign for the forecasts. Upwelling-La Niña forecasts from No_SSS were switched to downwelling Kelvin waves due to the impact of SMOS satellite SSS. The ASSIM_SMOS results faithfully reproduced the observed NINO3.4 SST anomaly. Like the SMOS results, the experiment that assimilated SMAP and SMOS (i.e., ASSIM_SSS_ALL) also does a good job of reproducing observations.

In the previous sections we have shown that inclusion of satellite SSS into initialization reanalyses has the potential to improve coupled ENSO forecasts. Even with the assimilation of all available observations, including precipitation, into the atmospheric component of the GEOS-S2S-2 coupled system (see Gelaro et al., 2017, for details), unfortunately there are still significant errors in the fresh-water fluxes (FWF) into the ocean. These deficiencies impact the near surface of the ocean within the MLD and adversely affect the ability of coupled systems to properly forecast ENSO (as is evident by the relatively poor No_SSS forecasts presented herein). However, assimilation of a relatively new observation type, satellite SSS, provides a unique opportunity to potentially ameliorate these issues with FWF. Previous work by Tranchant et al. (2018), Martin et al. (2019), and others has shown the improvement in ocean reanalyses by assimilating satellite SSS. Now we demonstrate the potential benefits of assimilating satellite SSS into a quasi-operational coupled forecast system such as the GEOS-S2S-2. In each case presented here, satellite SSS improves the SSS, density, and MLD leading to more accurate Kelvin wave amplitude and sign and improved ENSO forecasts. Therefore, we strongly advocate for including satellite SSS assimilation into operational coupled forecast systems. In addition, the results presented herein, and many other societal benefits as described in Vinogradova et al. (2019), would strongly suggest that satellite SSS should be considered an essential observable and continuity of space-based SSS should be ensured.

In this paper, we suggest that the positive impacts of SSS assimilation somewhat offset the deficiencies of evaporation and precipitation (E-P) forcing from the MERRA2 reanalysis. In our example, the forecast for 2017 changed from El Niño to neutral conditions which better matched the observed weak La Niña state. However, the relatively poor forecast from other NMME forecasts might suggest that these coupled models also suffer from suboptimal E-P forcing (e.g., mostly all NMME models called for El Niño in 2017—see Figure 4). Although it is beyond the scope of this paper to test all the NMME E-P forcing, we hope this paper opens some discussion for the seasonal prediction community: Could common errors in E-P in NMME prediction models contribute to the erroneous predictions of the 2017 La Niña? If yes, this would provide important insight for improving ENSO prediction. If there are no common errors in atmospheric reanalyses E-P, then causes for the poor predictions of the El Niño in 2017 still need to be explored and satellite SSS assimilation would be a useful tool.
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