Constraining Wind Stress Products with Sea Surface Height Observations and Implications for Pacific Ocean Sea Level Trend Attribution*

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ABSTRACT

A number of global surface wind datasets are available that are commonly used to examine climate variability or trends and as boundary conditions for ocean circulation models. However, discrepancies exist among these products. This study uses observed Archiving, Validation, and Interpretation of Satellite Oceanographic (AVISO) sea surface height anomalies (SSHAs) as a means to help constrain the fidelity of these products in the tropical region. Each wind stress product is used to force a linear shallow water model (SWM) and the resulting hindcast thermocline depth anomalies are converted to SSHAs. The resulting SSHAs are then assessed to see how well they reproduce the dominant EOF modes of observed variability and the regional (global mean removed) sea level trend (1993–2007) in each of the three ocean basins. While the results suggest that all wind datasets reproduce the observed interannual variability with reasonable fidelity, the two SWM hindcasts that produce the observed linear trend with the highest fidelity are those incorporating interim ECMWF Re-Analysis (ERA-Interim) and Wave- and Anemometer-Based Sea Surface Wind (WASWind) forcing. The role of surface wind forcing (i.e., upper ocean heat content redistribution) versus global mean sea level change (i.e., including the additional contributions of glacier and ice sheet melt along with ocean thermal expansion) on the recent dramatic increase in western equatorial Pacific island sea level is then reassessed. The results suggest that the recent sea level increase cannot be explained solely by wind stress forcing, regardless of the dataset used; rather, the global mean sea level signal is required to fully explain this observed recent abrupt sea level rise and to better explain the sea level variability of the last 50–60 years.

1. Introduction

The tropical ocean can be effectively characterized as a two-layer system where the warm upper layer is separated from the underlying cold deep layer by a steep thermocline. In these regions fluctuations in sea surface height anomalies (SSHAs) tend to mirror those of thermocline depth (Rebert et al. 1985; Wyrski 1985). Furthermore, wind stress curl anomalies, which alter near-surface Ekman transport, Ekman pumping, and the resulting oceanic Rossby waves, are predominantly responsible for changes in the thermocline depth. This

relationship between thermocline depth anomalies and SSHAs has been used to examine the drivers of long-term historical trends and future projections of regional sea level change in models of phase 3 of the Coupled Model Intercomparison Project (CMIP3) (Timmermann et al. 2010; Suzuki and Ishii 2011). As such, high-quality surface wind stress data are critical for both the simulation of realistic oceanic variability and the realistic reproduction of SSHA and regional patterns of sea level rise in the tropical oceans (Tokinaga et al. 2012).

There are numerous surface wind products available that can be used to force global ocean models (see Fig. 1). However, although these products are validated against some form of observational data, there remain large differences among the different wind products (e.g., Wittenberg 2004). Ocean models forced with different wind stress products may therefore produce quite distinct solutions (Merrifield and Maltrud 2011). Despite this, there have been few studies that have compared how accurately simulations using different global wind products can reproduce the interannual variability and

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FIG. 1. Wind stress product temporal availability. The monthly mean wind products are from the ECMWF Tropical Ocean and Global Atmosphere (TOGA) global advanced operational surface analysis (in this figure labeled as ECMWF), 40-yr ECMWF Re-Analysis (ERA-40; Uppala et al. 2005), interim ECMWF Re-Analysis (ERA-Interim; Dee and Uppala 2009), Japanese 25-yr reanalysis (JRA; Onogi et al. 2007), NCEP–NCAR reanalysis (NCEP-I; Kistler et al. 2001), NCEP–DOE Atmospheric Model Intercomparison Project (AMIP-II) reanalysis (NCEP-II; Kanamitsu et al. 2002), ECMWF Ocean Reanalysis System (ORA-S3; Balmaseda et al. 2008), Simple Ocean Data Assimilation model, version 2.1.6 (SODA; Carton and Giese 2008; Czeschel et al. 2011), and Wave- and Anemometer-Based Sea Surface Wind (WasWinds; Tokinaga and Xie 2011a). The rectangular dashed box indicates the time period for which the AVISO data are compared with the SWM hindcasts. All but the ERA-40 wind product span this period. Note, however, that the ERA-40 wind forcing is incorporated in both the ORA-S3 and SODA-2.1.6 wind products.

the long-term trends in the tropical regions. This is the goal of the present paper.

In this study we specifically use observed SSHAs as an independent test of the fidelity of available wind stress products. To this end, all available global wind stress datasets spanning the period 1993–2007 are used to force a series of linear shallow water model (SWM) simulations. Simulated thermocline depth and inferred SSHAs are subsequently compared against observations to ascertain which wind products are associated with the most realistic oceanic response. The remainder of this paper is set out as follows. Section 2 provides details of the linear SWM and the hindcast simulations and discusses how anomalies of SWM thermocline depth are translated into SSHA. How well each of the SWM hindcasts can reproduce the observed interannual variability and long-term trend of each tropical ocean basin is evaluated in section 3, and section 4 details the implications for Pacific Ocean sea level trend attribution. The discussion and conclusions are presented in section 5.

2. Methods

a. Shallow water model

The linear shallow water model used here is a 1.5-layer reduced gravity model of the stratified ocean. The upper

and lower model layers are separated by an interface that approximates the sharp tropical thermocline. Applied anomalous wind stresses drive motion in the upper layer, while the lower layer is assumed to be motionless and infinitely deep. The associated response of the SWM is characterized by the vertical displacement of the thermocline and the horizontal components of upper-layer flow velocity. These upper-layer dynamics are described by the linear reduced gravity form of the shallow water equations (McGregor et al. 2007; Holbrook et al. 2011). Here we prescribe the reduced gravity parameter, $g' = 0.0265 \text{ m s}^{-2}$, and the mean depth of the upper layer is 300 m. This gives a first baroclinic mode gravity wave speed of 2.8 m s^{-1} . The model has a 1° resolution and is configured for the global ocean between 51°S and 51°N . It also includes realistic continental boundaries that were calculated as the locations where the bathymetric dataset of Smith and Sandwell (1997) has a depth less than the model mean thermocline of 300 m. We conducted eight hindcast experiments with the SWM where each experiment was forced by one of the eight different global wind products presented in Fig. 1. Surface wind stress data was only available for the European Centre for Medium-Range Weather Forecasts (ECMWF) Ocean Reanalysis System (ORA-S3) and Simple Ocean Data Assimilation model, version 2.1.6 (SODA-2.1.6), datasets. For all other

FIG. 2. Multihindcast average spatial map of (a) regression ($\bar{\beta}$) and (c) correlation coefficients between observed (detrended) sea level anomalies for the period 1993–2007 (AVISO) and the SWM results obtained when forced with historical wind stresses from the eight different wind stress products available for this period. The overlying dashed black line represents the statistically significant (above the 99% level) 0.35 correlation coefficient contour, while the solid black line represents the 0.7 correlation coefficient contour. (b), (d) The zonal means of the regression and correlation coefficient spatial maps, respectively.

datasets the surface winds were converted to wind stresses using the quadratic stress law: $(\tau_x, \tau_y) = C_d \rho_a (U, V)W$, where U and V are the zonal and meridional surface winds respectively, W is the surface wind speed, and drag coefficient C_d and reference atmospheric density ρ_a have values of 1.5×10^{-3} (dimensionless) and 1.2 kg m^{-3} , respectively. We note here that the ORA-S3 wind stresses incorporate 40-yr ECMWF Re-Analysis (ERA-40) winds prior to June 2002 and then NWP operational analyses thereafter (Balmaseda et al. 2008), while SODA-2.1.6 also uses ERA-40 wind stresses prior to January 2002 but then merges to interim ECMWF Re-Analysis (ERA-Interim) data thereafter (Czeschel et al. 2011).

b. Translating SWM thermocline depth into sea level

Thermocline anomalies (h) from the eight SWM hindcasts are translated to sea level using a linear relationship between the two parameters. Linear regression coefficients (β) are calculated at each spatial location between the observed monthly-mean sea surface height anomalies (linear trend removed) from the Archiving, Validation, and Interpretation of Satellite Oceanographic (AVISO) dataset and the results from the eight SWM hindcast simulations (Fig. 1). This results in eight separate maps of regression coefficients (β). The average of

these eight regression coefficient spatial maps ($\bar{\beta}$, Fig. 2a) is then used to convert thermocline depths (h) from the SWM hindcasts into SSHA ($\text{SSHA}_{\text{SWM}} = h\bar{\beta}$) at each grid point of each of the SWM hindcasts. The most prominent feature of this mean regression coefficient spatial map is the decrease in magnitude of the regression coefficient with increasing latitude. This is apparent in all eight of the regression maps that were averaged to make the mean map displayed in Fig. 2a. As discussed in Timmermann et al. (2010), this fall off in regression coefficient value with latitude is realistic and occurs because of the decreasing stratification with increasing distance from the equator. We note here that each of the eight individual SWM hindcast regression coefficient spatial maps has spatial correlations ≥ 0.87 (with a mean of 0.91) when compared with the hindcast average regression coefficient spatial map ($\bar{\beta}$).

Considering that the regression coefficient spatial map used to convert SWM thermocline depth to sea surface height (SSH) is meant to represent the physical processes linking changes of ocean thermocline depth on sea level, rather than tuning the individual SWM hindcasts to better reproduce the observed SSH, it would be ideal if the average regression coefficient spatial map used to convert SWM thermocline depth to SSHA was

independent of the given SWM hindcasts regression coefficients. However, in the absence of an independent means of conversion we note that the results presented in this manuscript are robust regardless of whether the individual regression map, average regression map, or the latitudinal mean of the average regression map is used in the conversion of thermocline depth to SSH.

One issue with the use of regression coefficients to convert anomalies of SWM thermocline depth to SSHA is that regions with relatively low correlation coefficients will produce a reduced total SSHA variance compared to the observations ($r = \sqrt{\sigma_{\text{SWM}}^2 / \sigma_{\text{Obs}}^2}$). The area-averaged correlation coefficients (r) for the Pacific, Indian, and Atlantic Ocean basins, calculated where the SWM approximations are deemed to be appropriate (see section 2c below), are 0.62, 0.52, and 0.41, respectively (Fig. 2c). Thus, Pacific basin hindcast SSHA standard deviations should be approximately 62% of the size of the observed and the Indian Ocean basin roughly 52% of the observed, while the Atlantic basin should display standard deviations that are approximately 41% of the observed.

c. Validation of the SWM

The simple linear SWM represents a relatively crude representation of the physics of the tropical ocean despite the tropical ocean effectively being characterized as a two-layer system. To identify regions where the reduced physics of the SWM realistically reproduces ocean variability, pointwise correlation coefficients are calculated between the SSHA from the eight SWM hindcasts and the observed AVISO SSHA. The average of these eight correlation coefficient spatial maps is then calculated (Fig. 2b). This average correlation coefficient spatial map demonstrates that the simple linear SWM does a respectable job in representing the observed SSHA across most of the tropical domain, with the majority of the region displaying strong positive correlation coefficients. Using the reduced effective degrees of freedom of Davis (1976), correlation coefficients that are ≥ 0.35 are considered statistically significant above the 99% level. It is only within these regions ($r \geq 0.35$) that we compare the SSHA from the eight wind stress forced SWM hindcasts with the observed AVISO SSHA (global mean removed).

It is interesting to note that only 30% of the tropical Atlantic Ocean basin area has statistically significant correlation coefficients when compared with the observed SSHA. This is significantly smaller than the 63% or 80% of the tropical Indian and Pacific Ocean basins, respectively, which display statistically significant correlation coefficients. This difference suggests that either the majority of the wind products in the Atlantic region are poorly representing the actual wind stresses of the

FIG. 3. SSHA standard deviation calculated from (a) observed AVISO and (b) SWM hindcast ensemble (cm).

basin, or that processes not represented in the linear SWM are responsible for observed SSH variability. For example, the SWM does not represent the effects of nonlinearities, temperature advection, freshwater inputs, and salinity-induced density changes, etc. Given that the variance of the wind stress forced response is much smaller over the Atlantic Ocean than the other basins (Fig. 3), we expect that processes not represented in the linear SWM are likely to be more prominent.

3. Results

a. Interannual variability

We first assess the SWM simulations forced by the different wind stress products in terms of their skill in reproducing the dominant modes of SSHA variability in each tropical ocean basin. To this end, we calculate the dominant EOF of observed tropical AVISO SSHA (between 20°S and 20°N) for each of the three basins (Fig. 4). Note that for the tropical Atlantic Ocean basin a 5° square around the mouth of the Amazon River was masked out in order to ensure that the first EOF mode represents basinwide variability. We then linearly regress the corresponding principal component time series onto the SSHA from each of the eight wind stress forced SWM hindcasts, giving eight spatial maps of regression coefficients for each of the three ocean basins leading EOFs (not shown). Each of these spatial patterns is then compared to the observed SSHA leading EOF mode for each basin, based on the spatial correlation, spatial standard deviation, and the centered root-mean-square difference (RMSD) in the regions where the SWM dynamics are deemed to represent the prominent SSHA dynamics (see section 2c). The standard deviations (and the related RMSD) are then scaled to account for the

FIG. 4. The first EOF of observed AVISO SSHA (cm) in the tropical (a) Indian, (b) Pacific, and (c) Atlantic Oceans. Comparisons of hindcast and observed SSHA are restricted to the nonmottled areas. (d)–(f) The corresponding Taylor plots displaying the SWM hindcast spatial pattern standard deviation (black), correlation coefficient (blue), and RMSD (magenta).

fact that we can only expect to reproduce 52%, 62%, and 41% of the tropical Indian, Pacific, and Atlantic SSHA standard deviations, respectively. These assessment measures are then displayed in a Taylor plot (Taylor 2001) in Fig. 4.

1) INDIAN OCEAN

The first tropical Indian Ocean basin EOF mode (20°S–20°N, 20°–120°E; Fig. 4a) accounts for 25% of the total SSHA variance. This mode is associated with Indian Ocean dipole (IOD)-type variability in combination with variability in the south equatorial Indian Ocean. As can be seen, the western pole of the IOD is not overly prominent in this pattern, and a much higher signal exists around 10°S, 50°–90°E. However, there is a correlation coefficient of 0.6 (statistically significant above the 99% level) between the corresponding principal component time series and the Indian Ocean dipole mode index of Saji et al. (1999).

Looking at the Taylor plot shown in Fig. 4d it is clear that all SWM hindcasts reproduce this dominant mode with a high degree of fidelity as each of the simulations have spatial correlations of ≥ 0.9 when compared with the observed spatial pattern (Table 1). Small differences among the hindcasts become apparent when considering the respective spatial pattern standard deviations (i.e., the magnitude of the associated wind stresses) as the majority of the hindcasts produce spatial variability with

too much variance. The two hindcasts with the highest spatial correlations and spatial pattern variances closest to observed are those incorporating Wave- and Anemometer-Based Sea Surface Wind (WASWind) and ORA-S3 wind stress forcing.

2) PACIFIC OCEAN

The first EOF mode of the tropical Pacific Ocean basin (20°S–20°N, 120°E–60°W) accounts for 39% of the total SSHA variance (Fig. 4b). The spatial structure of this dominant EOF displays an east–west tilting of SSHA that is consistent with the thermocline depth variability of the El Niño–Southern Oscillation (ENSO). This is supported by the correlation coefficient of 0.94 (statistically significant above the 99% level) between the

TABLE 1. Spatial pattern correlation coefficients calculated between the interannual variability patterns of each of the SWM hindcasts and the corresponding observed SSHA.

	Indian Ocean	Pacific Ocean	Atlantic Ocean
ECMWF	0.932	0.976	0.899
ERA-Interim	0.965	0.977	0.909
JRA	0.944	0.964	0.895
NCEP1	0.906	0.970	0.856
NCEP2	0.931	0.941	0.855
ORA-S3	0.970	0.972	0.900
SODA-2.1.6	0.972	0.973	0.918
WASWind	0.971	0.963	0.753

corresponding principal component time series and Niño-3.4 region SSTA.

Looking at the corresponding Taylor plot shown in Fig. 4e it is again clear that all of the eight SWM hindcasts do a good job reproducing the spatial SSHA structure of this dominant mode of variability, with all simulated regression patterns having spatial correlations ≥ 0.94 when compared with the observed pattern (Table 1). Again, however, small differences among the hindcasts become apparent when considering the spatial standard deviation (i.e., the magnitude of the associated wind stresses). It is clear that the majority of the hindcasts slightly overestimate the spatial pattern variability as five of the eight models have spatial pattern variances roughly 1.3 times that of the observations. The three hindcasts with spatial pattern standard deviations closest to the observed are the National Centers for Environmental Prediction (NCEP)–National Center for Atmospheric Research (NCAR) Global Reanalysis 1 (NCEP1), NCEP–Department of Energy (DOE) Global Reanalysis 2 (NCEP2), and WASWind, with the NCEP1 hindcast being the closest to observed values.

3) ATLANTIC OCEAN

The first EOF of the tropical Atlantic Ocean basin SSHA (20°S–20°N, 60°W–20°E) accounts for 12% of the basinwide variance and is displayed in Fig. 4c. This mode appears to be associated with the equatorial Atlantic Oscillation as the corresponding principal component time series has a correlation coefficient of 0.7 (statistically significant above the 99% level) with that SSTA of the equatorial Atlantic Oscillation index of Latif et al. (2000).

It is interesting to note that the regions of highest variance from the first EOF often do not coincide with those regions where the SWM SSHA hindcasts are significantly correlated with the observations (i.e., the area over which we are testing the wind products). In spite of this, seven of the eight SWM hindcasts produce correlation coefficients between 0.85 and 0.9, with the WASWind forced SWM hindcast producing a spatial correlation coefficient of 0.75 when compared to the observed. Thus, all hindcasts appear to reproduce the spatial structure of the Atlantic Ocean basin's dominant mode of SSHA variability with a fair degree of fidelity (Fig. 4f). In contrast to the other basins, each hindcast underestimates the spatial pattern variance of the Atlantic Ocean's dominant mode of SSHA variability. The hindcasts with the spatial pattern variance closest to the observed are the ECMWF and ERA-Interim wind stress forced simulations. However, we note that given the region in which we are comparing the SWM hindcasts with observations of SSHA does not include the regions of highest variance of this

first EOF, the results from the Atlantic Ocean basin region should be viewed with caution.

4) GLOBAL INTERANNUAL VARIABILITY SUMMARY

There is relatively little difference between hindcasts in the Indian and Pacific Ocean basins. As such, the choice of wind stress forcing should have little impact on the representation of each of these basins dominant mode of SSHA. For the Atlantic Ocean basin all hindcasts appear to systematically underestimate the spatial pattern variance to various degrees. While all the wind products are equally proficient in reproducing the spatial pattern of variability, the choice of wind product can have a large effect on the strength of this variability. However, we believe that the results from the Atlantic Ocean basin region should be viewed with caution. As such, we do not recommend a specific wind dataset that best reproduces the interannual variability of the tropical Atlantic SSHA.

b. Linear trends (1993–2007)

This methodology can also be applied to longer-term changes in sea level. The studies of Tokinaga et al. (2012) and Timmermann et al. (2010) respectively emphasized the importance of surface wind forcing with realistic long-term trends for simulating the oceanic variability and regional patterns of sea level rise. To assess which of the wind stress products can best reproduce the linear SSHA trend in each of the tropical ocean basins, we first calculate the global linear trend in AVISO SSHA (between 20°S and 20°N) for the period 1993–2007 (Fig. 5). We then calculate the linear SSHA trend from the eight SWM hindcast simulations (not shown). Each of these SWM SSHA linear trend spatial patterns is then compared with the observed SSHA trend in each of the three ocean basins by calculating the spatial correlation, the spatial standard deviation, and the centered RMSD in the regions where the SWM was found to be adequate in capturing the prominent SSHA dynamics (as detailed in section 2c). As above, these standard deviations (and the related RMSD) are then adjusted to account for the fact that we can only expect to reproduce 52%, 62% and 41% of the tropical Indian, Pacific, and Atlantic SSHA standard deviations, respectively. These assessment measures are then displayed in a Taylor plot (Taylor 2001) in Figs. 5d–f.

1) INDIAN OCEAN

In the Indian Ocean basin the agreement between the linear trends of the SWM hindcasts and observed SSHA over the period 1993–2007 is basically split into two main clusters, with the JRA hindcast falling between the two

FIG. 5. The linear trend (global mean removed) of observed AVISO SSHA (cm yr^{-1}) in the tropical (a) Indian, (b) Pacific, and (c) Atlantic Oceans calculated over the period 1993–2007. Comparison of hindcast and observed SSHA are restricted to the nonmottled areas. (d)–(f) The corresponding Taylor plots displaying the SWM hindcast linear trend spatial pattern standard deviation (black), correlation coefficient (blue), and RMSD (magenta).

clusters (Fig. 5d). The first cluster contains two of the SWM hindcasts, specifically the ERA-Interim and WASWind hindcast, and each of these hindcasts appear to reproduce the observed SSHA trend spatial pattern and standard deviation with reasonable fidelity. These hindcasts each display spatial correlations of >0.73 (Table 2), with spatial standard deviations consistent with expected and root-mean-square differences less than one standard deviation. The remaining cluster of models, which includes the ECMWF, NCEP1, NCEP2, ORA-S3, and SODA-2.1.6 hindcasts, display very weak correlations, indicating that they have little skill in reproducing the spatial pattern of the observed Indian Ocean trend.

Representative wind stress and wind stress curl trends from each of the two clusters of hindcasts, along with that of the JRA hindcast, reveal the product-to-product differences (Fig. 6). Looking at Fig. 6b, the linear stress trend example from the cluster of “good” hindcasts, the ERA-Interim forced hindcast, produces relatively smooth bands of curl that extend from the southwest to the northeast (highlighted by the overlying dashed magenta lines). This bandlike structure is reasonably well represented by the JRA hindcast; however, it is clear that the JRA wind stress trend (Fig. 6c) and its associated curl (Fig. 6d) are significantly stronger than that of the ERA-Interim product. Selecting a product that our results suggest has little skill in reproducing the spatial pattern of the observed Indian Ocean trend, it is clear

that the wind stress trend and its associated curl are much larger than that of the ERA-Interim product. Furthermore, the wind stress anomalies are generally noisier, producing sharper wind stress curl changes that dominate the curl pattern.

2) PACIFIC OCEAN

The SWM hindcasts generally exhibit greater skill in reproducing the spatial trend in the Pacific Ocean, with all except the NCEP2 hindcast (0.41) producing correlation coefficients exceeding 0.58 (Fig. 5e; Table 2). However, there is considerable spread in the standard deviation of the trend patterns from the different SWM hindcasts. For instance, the WASWind hindcast trend pattern, which has a spatial correlation of 0.65, has a standard

TABLE 2. Spatial pattern correlation coefficients calculated between the long-term trend patterns of each of the SWM hindcasts and the corresponding observed SSHA.

	Indian Ocean	Pacific Ocean	Atlantic Ocean
ECMWF	−0.163	0.737	0.332
ERA-Interim	0.778	0.838	0.434
JRA	0.571	0.726	0.383
NCEP1	0.171	0.585	0.1795
NCEP2	0.115	0.411	0.431
ORA-S3	0.219	0.866	0.003
SODA-2.1.6	0.248	0.840	−0.236
WASWind	0.733	0.652	0.238

FIG. 6. The Indian Ocean basin linear trend of surface wind stresses (vectors, N m^{-2}) and zonal wind stress (shaded) for the (a) ERA-Interim, (c) JRA, and (e) ECMWF wind products, and (b),(d),(f) each product's associated curl. To aid comparison, the black contours overlaying the shaded wind stress curl of JRA and ECMWF, in (d) and (f) respectively, represent the curl of the ERA-Interim wind stresses (from -0.75×10^{-9} to 0.75×10^{-9} by a 0.5×10^{-9} interval; dashed contours indicate negative values), while the overlying dashed magenta lines highlight the prominent bands of wind stress curl seen in (b).

deviation that is a little over half the size expected. On the other hand, the ECMWF hindcast trend pattern, which has a spatial correlation of 0.73, has a standard deviation more than 2 times larger than expected. Based on the RMSD, which can be described as a function of both correlation coefficient and spatial standard deviation, we find that the three best performing hindcasts are those using ERA-Interim, SODA-2.6.1, and WASWind forcing.

Plotting representative wind stress trends and their associated curl from one of the best performing products (SODA-2.1.6), along with one deemed to have too strong a trend (ECMWF) and a further with a relatively poor spatial correlation, reveals the product similarities and differences (Fig. 7). The main commonality is that all panels display an increase in the zonal equatorial trade winds (blowing from east to west) along with an increase in the off-equatorial trade winds (wind blowing from

northeast to southwest in the Northern Hemisphere, and southeast to northwest in the Southern Hemisphere) (Figs. 7a,c,e). These off-equatorial trade wind increases produce a wind stress curl pattern that is prominently asymmetric about a circle of latitude at 5°N of the equator. This curl pattern can be described as chevron-shaped bands of curl that start in the western-central equatorial Pacific and extend poleward to the east (highlighted by overlying dashed magenta lines) (Figs. 7b,d,f).

What varies among the products, however, is the strength of this off-equatorial trade wind increase and the path of the trade wind increase. An example of the differences in the strength of this trade wind increase can be seen in the ECMWF product, which produces this chevron-shaped band like structure well, consistent with expectations due to the good spatial correlation between the hindcast and observed SSH trend. However, consistent with high spatial standard deviation of this hindcast,

FIG. 7. The Pacific Ocean basin linear trend of surface wind stresses (vectors, N m^{-2}) and zonal wind stress (shaded) for the (a) SODA-2.1.6, (c) ECMWF, and (e) NCEP2 wind products, and (b), (d), (f) each product's associated curl. To aid comparison, the black contours overlaying the shaded wind stress curl of ECMWF and NCEP2, in (d) and (f) respectively, represent the curl of the SODA-2.1.6 wind stresses (from 1.5×10^{-9} to 1.5×10^{-9} by a 1×10^{-9} interval; dashed contours indicate negative values). Again, the overlying dashed magenta lines highlight the prominent bands of wind stress curl seen in (b).

it is clear that the ECMWF wind stress trend (Fig. 7c) and its associated curl (Fig. 7d) are significantly stronger than that of the SODA-2.1.6 product. An example of differences in the path of the trade wind increase can be seen looking at the NCEP2 product, which has a kink in the path of the Northern Hemisphere trade wind increase. This slight change in path produces large-magnitude, almost zonally oriented curl anomalies in the central North Pacific (5° – 20°N , 160° – 120°W). Off the equator, westward propagating Rossby waves ensure that the SSH response to curl changes at any longitude can be basically represented by the integral of the curl changes to the east of that location. At around 10°N , the large central Pacific curl changes in the NCEP2 trend ensure that they would dominate the SSH changes to the west (see SWM SSH trend spatial maps in the supplementary material available online at <http://dx.doi.org/10.1175/JCLI-D-12-00105.s1>,

especially Fig. S1f). This is in contrast to the curl of the two previously presented wind stress products in which the opposite sign curl west of this box would dominate those changes in the east (see SWM SSH trend spatial maps in the supplementary material, Figs. S1b and S1h).

3) ATLANTIC OCEAN

In the Atlantic Ocean basin the SWM hindcasts generally exhibit reasonably low skill in producing the spatial structure of the linear trend (Fig. 5f). For instance, the products with the best hindcasts, ERA-Interim, NCEP2, and JRA, only have spatial correlations of 0.4 with the observed SSHA (Table 2). We believe that because only subtle trend features are apparent in the relatively small region where we are carrying out this assessment, results from the Atlantic Ocean basin region should again be viewed with caution.

4) TREND SUMMARY

Because of the relatively weak trends apparent in the regions under consideration in the tropical Atlantic, we believe that the results from this basin region should again be viewed with caution. As such, we do not attempt to identify the products that reproduce the spatial structure of the Atlantic Ocean basin sea level trend with the highest degree of fidelity. However, we are more confident in our assessment of the wind products for the other basins, as the hindcasts do considerably better in reproducing the observed trends and the SWM works well over a much larger area. In the Indian Ocean basin the ERA-Interim and WASWind hindcasts are the best performing hindcasts (i.e., those with the highest spatial correlation and the smallest RMSD). In the Pacific Ocean, on the other hand, seven out of the eight hindcasts produce high spatial correlations when compared with observations, indicating that each of these wind products is able to produce linear trends with a realistic spatial structure. Because we are concerned with how well the SWM hindcasts produce the overall Indo-Pacific trend, we would have lower confidence in the ECMWF, NCEP1, NCEP2, ORA-S3, and SODA-2.1.6 hindcasts as each of these demonstrate little to no skill in reproducing the spatial structure of the Indian Ocean basin trends. Comparing the spatial standard deviation (i.e., the magnitude of the wind stress trend) of the remaining hindcasts (ERA-Interim, JRA, and WASWind), the WASWind and ERA-Interim hindcasts emerge as the best performing hindcasts in the Pacific Ocean basin. Thus, based on comparisons of simulated and observed SSHA trends it would appear that ERA-Interim or WASWind products have the highest fidelity.

4. Implications for western equatorial Pacific sea level trend attribution

In a recent study by Merrifield (2011), utilizing ORA-S3 wind stress forcing, it was speculated that the dramatic increase in observed western equatorial Pacific Island sea level (no global mean removed) seen since the early 1990s could be attributed to a strengthening of the Pacific Ocean trade winds. This is somewhat different from the results of earlier studies that suggest that the majority of the spatial pattern of sea level rise (global mean removed) can be attributed to wind stress forced upper ocean dynamics (Timmermann et al. 2010; Suzuki and Ishii 2011). The two facts that led Merrifield (2011) to this speculation were 1) the dramatic increase in equatorial Pacific trade wind strength seen since the early 1990s and 2) the fact that the ORA-S3 wind stresses did not display a trade wind weakening trend

during the period 1950–90, which would generate a regional sea level change opposing the global mean sea level signal. This implies that the western Pacific islands display a negligible global mean sea level increase. As suggested by the Merrifield (2011) study, it is important to investigate whether other wind stress products are consistent with the view that western Pacific sea level changes can be adequately described by wind stress forcing alone.

To this end, we compare the western tropical Pacific sea level (averaged in the North Pacific over 5°–15°N, 130°E–180° and the South Pacific over 5°–15°S, 150°E–180°) of each of the SWM hindcasts with the observed island station sea level data utilized in Merrifield (2011). The island station locations along with the SWM hindcast WTP regions for comparison are displayed in Fig. 8a.

We note that because a given wind stress product hindcast produces a linear SSH trend with too much variability (larger spatial standard deviation than the observations), this does not imply that SSHAs in the western Pacific will be larger than the observed as the spatial structure of these patterns are not perfectly correlated. Three prominent examples of this are the SSHAs of the JRA, NCEP1, and NCEP2 products, which spatially have negative SSH trends in the North Pacific box offsetting the positive sea level trends in the South Pacific box (see supplementary Figs. S1d–f). These three products have linear SSH trend spatial patterns that have too much variability; however, their associated time series of western equatorial Pacific sea levels clearly underestimates the recent increase in observed island station sea level data seen in the most recent 20-yr period (Fig. 8b). Also noteworthy are the eastern equatorial Pacific SSH trends, which are larger in the majority of the SWM hindcasts than those observed. These high eastern equatorial Pacific sea level trends act to increase the SSH trend spatial standard deviation while not directly affecting the western tropical Pacific sea level variability (Fig. S1).

We focus the results of this analysis on the SWM hindcasts incorporating WASWind and SODA-2.1.6 wind stress forcing because these two hindcasts are shown to produce the Pacific Ocean's linear trend with a high degree of fidelity. It is clear that both the WASWind and SODA-2.1.6 hindcasts have a good temporal correspondence with the observed sea levels. However, these two time series begin to diverge from the observed sea level around the year 1990 (Fig. 8b). In fact, all hindcasts of western tropical Pacific sea level begin to diverge from the observations of sea level between the mid-1980s and the mid-1990s (Fig. 8d). When the observed estimates of global mean sea level (Church and White 2011) are added to the SWM hindcast sea levels, the SWM hindcast sea levels appear to better reproduce the

FIG. 8. (a) Linear trend in AVISO SSH (1993–2007) with the 12 tide gauge locations of Merrifield (2011) overlaid (solid dots). The boxes indicate the regions where the SWM hindcast SSHA WTP were calculated for comparison with the tide gauge data. (b) The 5-yr running mean of observed station averaged SSH (black) and SWM hindcast SSH averaged over the boxed regions shown in (a) for WASWind (thick dashed red), SODA-2.1.6 (thick dashed blue line), and six other hindcasts (see legend). (c) As in (b), but with global mean SSH added to the hindcast time series. (d) Difference between hindcasts in (b) and observations. (e) Difference between adjusted hindcasts in (c) and observations. The data are presented relative to the mean of each record computed between 1970 and 1990.

observed sea level changes. Supporting this observation, the RMSE calculated between the observations and the SWM hindcasts improves on average by roughly 25% when the global mean sea level signal is added to the SWM hindcast western tropical Pacific sea levels. Specifically, the WASWind and SODA-2.1.6 hindcasts improve by 10% and 28%, respectively. This suggests that in addition to wind stress changes, which were suggested to be the primary driver of change in the western Pacific by Merrifield (2011), accounting for global eustatic changes can significantly improve the fit to observations. Thus, the results of our study suggest that the sea level increase observed in the western tropical Pacific Ocean likely includes a significant component due to mountain glacier and ice sheet melt along with ocean thermal expansion.

However, as the SODA-2.1.6 and WASWind hindcasts have no real trend prior to 1980, the addition of the global mean signal to these hindcasts introduces an error pre-1970. This additional error could have three

potential sources. First, these wind stress datasets do not realistically represent the wind of the region seen pre-1980. Second, the three western Pacific Island sea level stations that have data prior to the 1970s are not representative of the sea level changes for the wider region. Third, the sea levels of the western equatorial Pacific and the wind stress products are both correct and the global mean sea level signal was negligible in the region until the mid to late 1980s (i.e., global mean sea level changes are not spatially homogenous). However, with the current data available it is not possible to identify which of these sources of error are likely to dominate. Thus, we can only conclude that wind stress forcing alone is not sufficient to reproduce the full extent of the dramatic sea level rise of the western tropical Pacific Ocean region seen since the 1990s.

One piece of evidence suggesting that the wind stress datasets are not realistically representing the wind of the region prior to the 1980s is the fact that the NCEP1

hindcast displays a strong negative trend throughout this period that is large enough to easily cancel out the global mean sea level signal. This effectively allows the observed sea levels prior to 1980 to be contained within the broad envelope of SWM hindcast sea levels (with the global mean sea level signal added) produced by the different wind products (Fig. 8c).

5. Discussion and conclusions

Previous studies have used relatively sparse observations of thermocline depth and upper ocean heat content to constrain wind datasets (Wu and Xie 2003; Tokinaga et al. 2012; Tokinaga and Xie 2011b). Given the robust relationship between anomalous thermocline depth and SSHa in the tropical region (e.g., Rebert et al. 1985), these ideas have been extended in the current study by using observed anomalies of SSH to constrain the fidelity of the different global surface wind products in the tropical region (see Fig. 1). This leads to a more robust spatial constraint, as satellite observed SSHa have a much greater spatial and temporal coverage than in situ ocean observations over the last two decades. To this end, each available wind stress product was used to force a linear SWM and the resulting hindcast thermocline depth anomalies were converted to SSHa using a linear relationship between the two variables. The wind stress product hindcasts were then assessed to see how well they reproduced the dominant EOF modes of observed SSHa variability and the regional (global mean removed) sea level trend in each of the three ocean basins.

First, assessing the interannual variability of the SWM hindcasts we find that all hindcasts produce the spatial structure and magnitude (standard deviation) of each basin's leading mode of observed AVISO SSHa variability with a fair degree of fidelity. This indicates that the choice of wind stress product is relatively unimportant if the focus is only on high-frequency variability.

Assessing the longer-term linear trends (1993–2007) from each of the SWM hindcasts versus those of the observed AVISO SSHa, we find that the choice of wind product is extremely important as some wind products have little skill in producing the observed long-term SSHa trends. We note that because of an apparent lack of prominence of wind stress forcing on the sea level variability of the Atlantic Ocean basin, we have a lack of confidence in the results from the Atlantic Ocean basin. As such, we do not recommend a specific wind dataset that best produces the spatial structure of the Atlantic Ocean basin SSH trend. Our analysis does suggest, however, that the ERA-Interim or WASWind products produce the regional patterns of sea level rise in the Indo-Pacific basin with the highest fidelity.

While using a relatively simple ocean model, this study has investigated the use of observed SSHa to constrain global wind stress products in the tropical regions. As discussed above, thermocline depth from the linear SWM was translated to SSHa via a linear relationship between the two variables (see section 2b). The specifics of this transformation have minimal impact on the spatial correlations presented or on the spread between model spatial pattern variances as the results presented in this manuscript are robust regardless of the regression coefficient map used. Ideally this study should be followed up using a similar methodology, within an ocean general circulation model rather than the linear SWM. We note that, consistent with the results presented here, Merrifield and Maltrud (2011) found two rather different trend spatial patterns that qualitatively agree with the corresponding SWM hindcast spatial structures, when forcing an ocean general circulation model with the linear trends of two separate wind stress products.

Using the SWM hindcast SSHa of this study we reassessed the role of surface wind forcing (i.e., upper ocean heat content redistribution) versus global mean sea level change (i.e., including the additional contributions of glacier and ice sheet melt along with ocean thermal expansion) on the recent dramatic increase in western equatorial Pacific Island sea level. We find that when the observed estimates of global mean sea level (Church and White 2011) are added to the SWM hindcast sea levels, the SWM hindcast sea levels more closely match the observed island sea level changes of the western tropical Pacific Ocean. This result is robust regardless of the wind stress dataset used, and suggests that the global mean sea level signal is required in addition to the wind-driven response to fully explain the dramatic sea level rise seen in the western tropical Pacific region since the early 1990s.

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REFERENCES

- Balmaseda, M. A., A. Vidard, and D. L. T. Anderson, 2008: The ECMWF Ocean Analysis System: ORA-S3. *Mon. Wea. Rev.*, **136**, 3018–3034.
- Carton, J. A., and B. S. Giese, 2008: A reanalysis of ocean climate using Simple Ocean Data Assimilation (SODA). *Mon. Wea. Rev.*, **136**, 2999–3017.

- Church, J. A., and N. J. White, 2011: Sea-level rise from the late 19th to the early 21st century. *Surv. Geophys.*, **32**, 585–682, doi:10.1007/s10712-011-9119-1.
- Czeschel, R., L. Stramma, F. U. Schwarzkopf, B. S. Giese, A. Funk, and J. Karstensen, 2011: Middepth circulation of the eastern tropical South Pacific and its link to the oxygen minimum zone. *J. Geophys. Res.*, **116**, C01015, doi:10.1029/2010JC006565.
- Davis, R., 1976: Predictability of sea surface temperature and sea level pressure anomalies over the North Pacific Ocean. *J. Phys. Oceanogr.*, **6**, 249–266.
- Dee, D. P., and S. P. Uppala, 2009: Variational bias correction of satellite radiance data in the ERA-Interim reanalysis. *Quart. J. Roy. Meteor. Soc.*, **135**, 1830–1841.
- Holbrook, N. J., I. D. Goodwin, S. McGregor, E. Molina, and S. Power, 2011: ENSO to multi-decadal time scale changes in East Australian Current transports and Fort Denison sea level: Oceanic Rossby waves as the connecting mechanism. *Deep-Sea Res. II*, **58**, 547–558, doi:10.1016/j.dsr2.2010.06.007.
- Kanamitsu, M., W. Ebisuzaki, J. Woollen, S. Yang, J. J. Hnilo, M. Fiorino, and G. L. Potter, 2002: NCEP–DOE AMIP-II reanalysis (R-2). *Bull. Amer. Meteor. Soc.*, **83**, 1631–1643.
- Kistler, R., and Coauthors, 2001: The NCEP–NCAR 50-Year Reanalysis: Monthly means CD-ROM and documentation. *Bull. Amer. Meteor. Soc.*, **82**, 247–267.
- Latif, M., E. Roeckner, U. Mikolajewicz, and R. Voss, 2000: Tropical stabilization of the thermohaline circulation in a greenhouse warming simulation. *J. Climate*, **13**, 1809–1813.
- McGregor, S., N. J. Holbrook, and S. B. Power, 2007: Interdecadal sea surface temperature variability in the equatorial Pacific Ocean. Part I: The role of off-equatorial wind stresses and oceanic Rossby waves. *J. Climate*, **20**, 2643–2658.
- Merrifield, M., 2011: A shift in western tropical Pacific sea level trends during the 1990s. *J. Climate*, **24**, 4126–4138.
- , and M. E. Maltrud, 2011: Regional sea level trends due to a Pacific trade wind intensification. *Geophys. Res. Lett.*, **38**, L21605, doi:10.1029/2011GL049576.
- Onogi, K., and Coauthors, 2007: The JRA-25 Reanalysis. *J. Meteor. Soc. Japan*, **85**, 369–432.
- Rebert, J. P., J. R. Donguy, G. Eldin, and K. Wyrtki, 1985: Relations between sea level, thermocline depth, heat content, and dynamic height in the tropical Pacific Ocean. *J. Geophys. Res.*, **90**, 719–725.
- Saji, N. H., B. N. Goswami, P. N. Vinayachandran, and T. Yamagata, 1999: A dipole mode in the tropical Indian Ocean. *Nature*, **401**, 360–363.
- Smith, W., and D. Sandwell, 1997: Global seafloor topography from satellite altimetry and ship depth soundings. *Science*, **277**, 1956–1962.
- Suzuki, T., and M. Ishii, 2011: Regional distribution of sea level changes resulting from enhanced greenhouse warming in the Model for Interdisciplinary Research on Climate version 3.2. *Geophys. Res. Lett.*, **38**, L02601, doi:10.1029/2010GL045693.
- Taylor, K. E., 2001: Summarizing multiple aspects of model performance in a single diagram. *J. Geophys. Res.*, **106**, 7183–7192.
- Timmermann, A., S. McGregor, and F. Jin, 2010: Wind effects on past and future regional sea level trends in the southern Indo-Pacific. *J. Climate*, **23**, 4429–4437.
- Tokinaga, H., and S.-P. Xie, 2011a: Wave- and anemometer-based sea surface wind (WASWind) for climate change analysis. *J. Climate*, **24**, 267–285.
- , and —, 2011b: Weakening of the equatorial Atlantic cold tongue over the past six decades. *Nat. Geosci.*, **4**, 222–226, doi:10.1038/ngeo1078.
- , —, A. Timmermann, S. McGregor, T. Ogata, H. Kubota, and Y. M. Okumura, 2012: Regional patterns of tropical Indo-Pacific Climate Change: Evidence of the Walker circulation weakening. *J. Climate*, **25**, 1689–1710.
- Uppala, S. M., and Coauthors, 2005: The ERA-40 Re-Analysis. *Quart. J. Roy. Meteor. Soc.*, **131**, 2961–3012.
- Wittenberg, A. T., 2004: Extended wind stress analysis for ENSO. *J. Climate*, **17**, 2526–2540.
- Wu, R., and S. Xie, 2003: On equatorial Pacific surface wind changes around 1977: NCEP–NCAR reanalysis versus COADS observations. *J. Climate*, **16**, 167–173.
- Wyrtki, K., 1985: Water displacements in the Pacific and the genesis of El Niño cycles. *J. Geophys. Res.*, **90**, 7129–7132.