An Empirical Model for Surface Wind Stress Response to SST Forcing Induced by Tropical Instability Waves (TIWs) in the Eastern Equatorial Pacific

RONG-HUA ZHANG AND ANTONIO J. BUSALACCHI

Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland

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ABSTRACT

High-resolution space-based observations reveal significant two-way air–sea interactions associated with tropical instability waves (TIWs); their roles in budgets of heat, salt, momentum, and biogeochemical fields in the tropical oceans have been recently demonstrated. However, dynamical model-based simulations of the atmospheric response to TIW-induced sea surface temperature (SST\textsubscript{TIW}) perturbations remain a great challenge because of the limitation in spatial resolution and realistic representations of the related processes in the atmospheric planetary boundary layer (PBL) and their interactions with the overlying free troposphere. Using microwave remote sensing data, an empirical model is derived to depict wind stress perturbations induced by TIW-related SST forcing in the eastern tropical Pacific Ocean. Wind data are based on space–time blending of Quick Scatterometer (QuikSCAT) Direction Interval Retrieval with Thresholded Nudging (DIRTH) satellite observations and NCEP analysis fields; SST data are from the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI). These daily data are first subject to a spatial filter of $12^\circ$ moving average in the zonal direction to extract TIW-related wind stress ($\tau_{\text{TIW}}$) and SST\textsubscript{TIW} perturbations. A combined singular value decomposition (SVD) analysis is then applied to these zonal high-pass-filtered $\tau_{\text{TIW}}$ and SST\textsubscript{TIW} fields. It is demonstrated that the SVD-based analysis technique can effectively extract TIW-induced covariability patterns in the atmosphere and ocean, acting as a filter by passing wind signals that are directly related with the SST\textsubscript{TIW} forcing over the TIW active regions. As a result, the empirical model can well represent TIW-induced wind stress responses as revealed directly from satellite measurements (e.g., the structure and phase), but the amplitude can be underestimated significantly. Validation and sensitivity experiments are performed to illustrate the robustness of the empirical $\tau_{\text{TIW}}$ model. Further applications are discussed for taking into account the TIW-induced wind responses and feedback effects that are missing in large-scale climate models and atmospheric reanalysis data, as well as for uncoupled ocean and coupled mesoscale and large-scale air–sea modeling studies.

1. Introduction

Recently, there has been an increased interest in tropical instability waves (TIWs) in the tropical oceans, since they were first detected from satellite SST observations about three decades ago (Legeckis 1977). In the tropical Pacific Ocean, for example, TIWs arise in the far eastern basin and then propagate westward as prominent mesoscale signals. Associated with these, SST fields show cusplike waves in the eastern equatorial Pacific, propagating westward along both the northern and southern flanks of the eastern cold tongue, with periods of 20–40 days, wavelengths of 1000–2000 km, and a phase speed of $0.5 \text{ m s}^{-1}$.

Over the past decade, microwave remote sensing has allowed great progress in observing and describing these mesoscale signals over the tropical oceans. For example, SST\textsubscript{ts} can be now measured with unprecedented accuracy by the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI; e.g., Wentz et al. 2000; Chelton et al. 2000). More recently, the SeaWinds Scatterometer on the Quick Scatterometer (QuikSCAT) satellite can also provide accurate observations of sea surface vector winds (e.g., Liu et al. 1998, 2000; Chelton et al. 2004). These high-quality satellite data can now resolve TIW-related mesoscale signals both in the atmosphere and in the ocean. In particular, satellite-based high-resolution
measurements have shown observational evidence of mesoscale air–sea coupling related to TIWs in the eastern tropical oceans (e.g., Xie et al. 1998). More recently, a coherent covariability pattern between TIW-related surface winds and SSTs has been depicted over the eastern tropical Pacific (e.g., Chelton et al. 2001; Hashizume et al. 2001; Xie 2004).

These microwave measurements have led to significant advances in physical understanding, interpretation, and modeling efforts of TIW-related mesoscale air–sea interactions. On the oceanic side, TIWs are generated in the ocean in association with instabilities in the equatorial ocean current/countercurrent system (e.g., Hansen and Paul 1984; Qiao and Weisberg 1998; Masina and Philander 1999). Data analyses and modeling studies indicate that they have significant effects on ocean thermal and dynamical fields. For example, it has been demonstrated that TIWs are important to the meridional transport of heat near the equator (e.g., Bryden and Brady 1989; Kessler et al. 1998; Vialard et al. 2003; Jochum and Murtugudde 2006; Jochum et al. 2005, 2007; Menkes et al. 2006). In particular, Kessler et al. (1998) illustrate that equatorial heat flux due to TIW mixing across the sharp SST front near 2°N is a first-order term in the low-frequency heat balance in the eastern tropical Pacific, as large as that from upwelling or the surface heat flux contribution. Also, TIWs can make a great contribution to momentum transport in the upper-equatorial current system. For example, Kessler et al. (2003) demonstrate that the magnitude of mean zonal momentum transport due to the poleward flux caused by the TIW mixing can be comparable to the wind-driven Sverdrup transport. Therefore, TIWs need to be appropriately accounted for in diagnostic and modeling studies. Fortunately, ocean general circulation models (OGCMs) of diverse types with adequate horizontal resolution can easily depict TIW signals well, whether forced with realistic or highly simplified winds (e.g., Hansen and Paul 1984; Masina and Philander 1999; Allen et al. 1995; Benestad et al. 2001; Small et al. 2003).

On the atmospheric side, satellite data indicate that surface winds have a coherent covariability pattern with TIW-induced SST (SST_{TIW}) fields over the eastern tropical Pacific frontal region. As SST_{TIW} perturbations are generated in the eastern tropical Pacific Ocean, a response can be simultaneously seen in the atmospheric planetary boundary layer (PBL). Chelton et al. (2001) have demonstrated how quickly and strongly surface winds respond to changes in SST using data from two independent satellites: QuikSCAT and TRMM. As estimated from satellite data, the TIW-induced SST perturbations can be 2°–3°C in magnitude, which are accompanied by large atmospheric fluctuations. The TIW-induced surface wind perturbations amount to 20%–30% of its climatological mean; the corresponding wind stress divergence and curl perturbations can be as large as their mean values.

It has recently become clear that the characteristics of the atmospheric responses to TIW-related SST perturbations differ significantly from those associated with El Niño (e.g., Xie 2004). As the TIW-related waves meander over the frontal region, the accompanied SST perturbations induce surface wind changes. Over cool oceans like the TIW active regions of the eastern tropical Pacific, the atmospheric wind response is local and shallow, confined to the vicinity of large SST_{TIW}-forcing regions in the horizontal and to the atmospheric PBL in the vertical. Although the precise mechanisms by which the atmospheric response to SST_{TIW} perturbations are still not fully understood, recent analyses suggest that the response involves vertical mixing of momentum within the atmospheric PBL (e.g., Wallace et al. 1989; Hayes et al. 1991; de Szoeke and Bretherton 2004). Through the adjustment of the static stability within the shallow PBL, surface winds can vary very rapidly in response to SST_{TIW} perturbations. Another dynamical mechanism for the TIW-induced atmospheric wind response is the pressure gradient forcing proposed by Lindzen and Nigam (1987). For example, Small et al. (2003) and Cronin et al. (2003) show that barometric pressure perturbations are important for the acceleration of winds across the equatorial SST front. Clearly, these two mechanisms for TIW-related atmospheric responses are not mutually exclusive.

Modeling mesoscale atmospheric responses to SST_{TIW} perturbations requires not only high resolution, but also realistic parameterizations of the relevant physics. For example, simple dynamical atmospheric models, such as the first-baroclinic-mode models or the vertically integrated barotropic boundary layer models that have been successfully used in large-scale air–sea interaction studies, fail to realistically depict TIW-related responses in the atmospheric PBL. The highly baroclinic response of the inversion-topped PBL in the atmosphere to SST_{TIW} perturbations calls for the inclusion of higher baroclinic modes for surface wind variability simulations (e.g., Xie 2004). Comprehensive atmospheric general circulation models (AGCMs) are available that have the potential for better modeling of TIW-related atmospheric responses, but resolving these mesoscale signals explicitly needs high resolution both in the horizontal and vertical, which increases computational costs enormously (e.g., Small et al. 2003; Seo et al. 2006). So far, AGCM-based modeling efforts for mesoscale air–sea interactions are limited to regional studies; only a few regionally coupled ocean–atmosphere modeling efforts have attempted to investigate TIW-related mesoscale air–sea interactions in the tropics (e.g., Small et al. 2003; Seo et al. 2006; Xie et al. 2007).
Because of the substantial difficulty of realistically simulating the TIW-related atmospheric responses, mesoscale coupled air–sea modeling efforts are still in the early stage. Although observations show two-way interactions between the ocean and atmosphere in association with TIWs, the feedback from the atmosphere onto the ocean has not been taken into account adequately in operational numerical weather prediction models (e.g., Chelton 2005; Chelton and Freilich 2005). The effects of TIW-induced mesoscale air–sea coupling on basin-scale climate variability and predictability have not been examined. Clearly, a major challenge toward modeling mesoscale air–sea interactions and their feedback effects on large-scale coupled climate variability is how to realistically depict the atmospheric response to TIW-induced SST forcing.

In this work, we continue to exploit an alternative statistical approach to modeling the TIW-related mesoscale atmospheric variability in the eastern tropical Pacific; a similar approach has been previously taken by Pezzi et al. (2004) who already tested a simple empirical model for TIW–wind feedback that is based on a regression pattern relative to geographically fixed location at 2°N, 140°W (e.g., Hashizume et al. 2001). Here, we adopt a combined singular value decomposition (SVD) analysis technique to derive a nonlocal empirical feedback model for atmospheric surface wind stress responses to TIW-induced SST forcing, an approach that has been successfully used in large-scale air–sea modeling studies (e.g., Bretherton et al. 1992; Barnett et al. 1993; Syu et al. 1995; Chang et al. 2001; Zhang and Zebiak 2004; Zhang et al. 2003, 2006).

The paper is organized as follows. Section 2 briefly describes the satellite data and section 3 presents an analysis of the covariability patterns between SST_{TIW} and τ_{TTW} fields using a SVD analysis technique. Section 4 deals with the SVD-based empirical model. The evaluation of the empirical model is presented in section 5. Section 6 deals with some validation and sensitivity experiments. Conclusions and a discussion are given in section 7. Some details of the SVD-based empirical model are presented in the appendix.

2. Satellite-based observational data

Daily data from satellite measurements are used for our TIW-related analyses and statistical modeling studies. SST fields are from the TMI measurements (e.g., Wentz et al. 2000; Chelton et al. 2000). Wind fields are from a space and time blend of QuikSCAT Direction Interval Retrieval with Thresholded Nudging (DIRTH) scatterometer observations (e.g., Liu 1998) and the National Centers for Environmental Prediction (NCEP) analyses, which are the products of the NCEP Climate Data Assimilation System (CDAS; e.g., Milliff et al. 1999; Milliff and Morzel 2001). Satellite observations are mostly available on the ocean surface; land points are filled with the NCEP analyses, whose zonal and meridional wind components (U and V) at 10-m height above the sea level are available at a resolution of 0.5° × 0.5°. This blending method creates global fields by retaining QuikSCAT wind retrievals in swath regions, and in the unsampled regions between swaths and in data gaps augmenting the low-wavenumber NCEP fields with a high-wavenumber component that is derived from monthly regional QuikSCAT statistics (Milliff et al. 1999; Milliff and Morzel 2001). The QuikSCAT wind data are available from July 1999; the TMI SST data are available from December 1997. Any missing data gaps in space are filled by using an interpolation utility subroutine distributed by Pacanowski and Griffies (1998) for the NOAA/Geophysical Fluid Dynamics Laboratory Modular Ocean Model (MOM 3).

To extract the TIW-induced oceanic and atmospheric signals, a spatial filter of 12° moving average in the zonal direction is applied to the daily SST and wind stress data to remove the slow-varying basin-scale mean state, a procedure designed by Hashizume et al. (2001). In addition, the zonal high-pass-filtered fields are subject to a 5-day running mean in time. The resultant SST_{TIW} and τ_{TTW} fields are the base fields, which will be used for various analyses in this paper.

A snapshot of SST_{TIW} fields for 1 October 2000 is shown in Fig. 1a. Large signals are concentrated predominantly on the eastern equatorial Pacific, with a banded structure over the TIW active regions. From the total SST fields (not shown), a front is centered at 1°–2°N over the eastern basin, which separates the equatorial cold tongue from the warmer water to the north. TIWs cause large meanders in SST fields, leading to pronounced SST perturbations (Fig. 1a). A map of standard deviation of the zonal high-pass-filtered SST field is shown in Fig. 2a (also see Chelton et al. 2000). A large TIW-induced SST variability region is located in the eastern equatorial Pacific, with the northern band much stronger than the southern one. Figure 3a further illustrates the longitude–time sections of TIW-related SST perturbations along 3°N for the year 2000. This longitudinal section more clearly exhibits the presence of TIW-induced energetic mesoscale signals, characterized by a well-defined banded structure, which propagates westward coherently at a typical wavelength of 1000 km and periods of 30 days.

The zonal high-pass-filtered wind stress fields also exhibit large perturbations in the eastern tropical Pacific (Figs. 1b,c and 3b,c). In association with the SST_{TIW}
fields, a coherent covariability $\tau_{TW}$ pattern can be seen over the TIW active regions. The winds slow down over cooler water and speed up over warmer water. Chelton et al. (2001) have provided detailed analyses of how surface winds and other related atmospheric fields respond to the SST$_{TW}$ field in the region. For example, covarying with SST$_{TW}$ fields, surface wind perturbations also propagate westward along both the northern and southern flanks of the eastern cold tongue, with periods of 20–40 days and a phase speed of 0.5 m s$^{-1}$. Furthermore, the related wind speed and SST fields are positively correlated; the induced wind perturbations are in such a way that the prevailing southeasterly trade winds are accelerated over positive SST$_{TW}$ regions but decelerated over

Fig. 1. Horizontal distributions of the zonal high-pass-filtered fields of (a) SST, and of (b) zonal and (c) meridional wind stress components in the eastern tropical Pacific for 1 Oct 2000, analyzed from the TMI and QuikSCAT satellite data. The contour interval is 0.4°C in (a) and 0.02 dyn cm$^{-2}$ in (b) and (c).
negative SST\textsubscript{TW} regions. How TIWs affect the surface heat fluxes are detailed in Thum et al. (2002).

The relationships between SST\textsubscript{TW} and \(\tau\textsubscript{TW}\) fields are further quantified by a simple correlation analysis (Figs. 2b,c). Two bands of the high correlations between \(\tau\textsubscript{TW}\) and SST\textsubscript{TW} fields are restricted to the regions where large SST\textsubscript{TW} variability is present (Fig. 2a). Perturbed SST fields are correlated negatively with the zonal \(\tau\textsubscript{TW}\) component but positively with the meridional \(\tau\textsubscript{TW}\) component over the TIW active region.

While the SST\textsubscript{TW} fields indicate a clean TIW signature predominantly evident in the eastern equatorial
regions (e.g., Fig. 1a), the zonal high-pass-filtered wind stress fields not only show corresponding signals in the TIW region, but also contain large disturbances in other regions where there are no TIW activities in the ocean (e.g., Figs. 1b,c). For example, large surface wind perturbations are also seen over the intertropical convergence zone (ITCZ) along 10°N (Figs. 1b,c). Since these atmospheric wind perturbations have no corresponding signature in the SST\textsubscript{TW} fields (Fig. 1a), they are not related with TIWs. As further shown in Figs. 2b,c, those regions off the equator along 10°N indeed show no correlation with the SST\textsubscript{TW} fields (Figs. 1b,c).

Clearly, the zonal high-pass-filtered surface wind stress fields include signals and noises that are of different origins. In the TIW active regions, the wind perturbations correspond well with TIW-induced SST forcing. However, the large wind disturbances seen off the equator over the ITCZ are not TIW related. A method is needed to separate wind signals that are TIW induced from those that are not.

Fig. 3. Longitude–time sections of the zonal high-pass-filtered fields of (a) SST and of (b) zonal and (c) meridional wind stress components along 3°N for 2000, analyzed from the satellite data. The contour interval is 0.3°C in (a) and 0.03 dyn cm\textsuperscript{-2} in (b) and (c).
3. Covariability patterns of $\text{SST}_{\text{TIW}}$ and $\tau_{\text{TIW}}$ fields

To further characterize the covarying nature between TIW-induced surface wind and SST perturbations, a combined SVD analysis is applied to the three filtered fields ($\text{SST}_{\text{TIW}}$ and zonal and meridional $\tau_{\text{TIW}}$ components). This statistical approach has been widely and successfully used to extract coherent covariability patterns between coupled ocean–atmosphere fields in large-scale tropical climate studies (e.g., Syu et al. 1995; Chang et al. 2001; Zhang and Zebiak 2004; Zhang et al. 2005, 2006).

The SVD analysis technique adopted here is the same as that described in detail by Chang et al. (2001) and in the appendix. Because of computational limitations in performing SVD calculations, the SVD analysis domain is confined over the eastern equatorial Pacific from $9^\circ$S to $9^\circ$N and from $180^\circ$ to $76^\circ$W, which is an active region of TIWs. The horizontal grid has a resolution of $1^\circ$ in longitude and $0.5^\circ$ in latitude, respectively. Over time, the SVD analysis is performed on all daily $\text{SST}_{\text{TIW}}$ and $\tau_{\text{TIW}}$ data during an 8-yr period from January 2000 to December 2007. With this space–time resolution, the dimension of the matrix for SVD analyses is $105 \times 37 \times 32920$ (zonal and meridional grid points in the eastern tropical Pacific with daily sampling over the 8-yr period).

These daily $\text{SST}_{\text{TIW}}$ and $\tau_{\text{TIW}}$ fields are first normalized by their spatially averaged standard deviation to form the covariance matrix. The SVD analysis is then performed to get singular values and eigenvectors, and their corresponding time coefficients. The first 10 SVD modes calculated from the covariance matrix of $\text{SST}_{\text{TIW}}$ and $\tau_{\text{TIW}}$ fields have singular values of about 186, 179, 132, 87, 83, 68, 65, 49, and 48, with a squared covariance fraction of about 5.7%, 5.4%, 4.2%, 4.0%, 2.6%, 2.5%, 2.1%, 2.0%, 1.5%, and 1.5%. The correlation coefficients of the first 10 pairs of the SVD modes are 0.91, 0.91, 0.90, 0.90, 0.89, 0.88, 0.88, 0.87, 0.84, and 0.86, respectively. Figure 4a illustrates the singular values of modes 1–20 from the SVD analysis, which represent the squared covariance accounted for by each pair of eigenvectors. The covariance (the singular values) decreases with SVD modes, which is not uniform. The sharp dropoff points can be seen after modes 2, 4, 6, and 8. The subsequent higher-order modes (beyond 9) have much smaller singular values, thus making smaller contributions to the covariance. The accumulated covariance (Fig. 4b) increases sharply for the first leading 20 modes but slowly for higher modes. The explained covariance by the first 10, 20, 40, and 100 modes are about 31%, 43%, 54%, and 73%, respectively.

Figure 5 exhibits the derived spatial eigenvectors of the first leading pair mode for $\text{SST}_{\text{TIW}}$ and $\tau_{\text{TIW}}$ components and their associated time series. The SST forcing and wind stress response are well correlated in the TIW active region of the eastern equatorial Pacific. The temporal expansion coefficients (Fig. 5d) clearly indicate that variations in $\tau_{\text{TIW}}$ follow those in $\text{SST}_{\text{TIW}}$ very closely. This indicates that the wind response in the atmospheric PBL to changes in SST is very fast and almost simultaneous. Calculated from the 8-yr period, the correlation coefficient is as high as 0.91 in Fig. 5c. In addition, the amplitude is clearly large during the TIW active periods in autumn and winter, but small during summer when TIWs are absent, consistent with the seasonality of TIWs in the eastern tropical Pacific (e.g., Contreras 2002).

The spatial structure of the first eigenvector represents TIW-revealing wavy patterns in all three fields in the eastern equatorial Pacific. As evident in the original zonal high-pass-filtered fields (e.g., Fig. 1a), large $\text{SST}_{\text{TIW}}$ signals in the SVD eigenvector (Fig. 5a) are concentrated only in the TIW active regions. The spatial patterns for $\tau_{\text{TIW}}$ (Figs. 5b,c) indicate that large wind
perturbations are present predominantly in regions where large SST\textsubscript{TTW} signals are also present. In particular, no pronounced disturbances are seen in the wind eigenvectors off the equator.

Furthermore, detailed inspections of these spatial eigenvectors reveal a coherent covariability pattern between SST\textsubscript{TTW} and \tau\textsubscript{TTW} fields. The SST\textsubscript{TTW}-induced forcing is seen to have instant effects on the low-level atmosphere in such a way that surface winds accelerate or decelerate when blowing across positive or negative SST\textsubscript{TTW} perturbations, respectively. Thus, the perturbation surface winds converge north of the warm SST\textsubscript{TTW} center and diverge south of it. As clearly demonstrated in Chelton et al. (2001), this coherent covariability pattern

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**FIG. 5.** Spatial patterns of the first pair of eigenvectors for (a) SST\textsubscript{TTW} and for (b) zonal and (c) meridional \tau\textsubscript{TTW} components, and (d) the associated time series (only shown for a 4-yr time period from 2000 to 2003), respectively. The SVD analysis is performed on the satellite data during the period 2000–07. The contour interval is 0.3 in (a) and 0.1 in (b) and (c).
between the wind response and SST forcing can be best described by the derivative wind stress fields, divergence, and curl. Figure 6 illustrates the spatial eigenvectors for the divergence and curl as calculated from the corresponding wind stress eigenvectors (Figs. 5b,c). The TIW-induced divergence and curl signals are most pronounced over the TIW region. The geographical locations of divergence and curl maxima show clear differences in their spatial relationship with SSTTIW forcing. When the winds blow across positive/negative SSTTIW perturbation regions and get accelerated/decelerated, prolonged bands of strong wind stress divergence are induced to the northeast–southwest, with the most intensive centers being locally overlapped with the zonally banded SSTTIW forcing regions. Also, the horizontal variations in the wind response generate positive/negative wind stress curl bands, which are most intensive nonlocally to the west and to the east of the SSTTIW forcing centers, shifted zonally by a quarter of wavelength. It is also evident that these two derived fields have different perturbation amplitude as represented in their eigenvectors, with the divergence being more pronounced and coherent than the curl. This indicates that the TIW-induced SSTTIW forcing has stronger effects on the divergence field than on the curl field.

Higher-order SVD modes are typically smaller in amplitude, with less coherent structure in space and time. However, the subsequent SVD modes of the 2nd to at least the 15th also show TIW-revealing space–time patterns between SSTTIW forcing and $\tau_{TIW}$ response. Figure 7 presents one example for the spatial eigenvectors of the 10th SVD mode and its associated time series. Even though at this high order, the 10th SVD mode still indicates a coherent space–time relationship between TIW-related SST forcing and wind response. In time (Fig. 7d), variations in $\tau_{TIW}$ follow those in SSTTIW very closely; in space, the SSTTIW fields still have clear TIW signature predominantly in the eastern equatorial Pacific (Fig. 7a). While the original zonal high-pass-filtered wind fields contain large disturbances in the non-TIW regions (Figs. 1b,c), large response signals in the wind eigenvectors show up mostly in regions where large SSTTIW perturbations are correspondingly present (Figs. 7b,c). In particular, no pronounced perturbations are evident off the equator. Moreover, a covariability pattern between $\tau_{TIW}$ and SSTTIW fields is still clearly evident, characterized by the perturbation

![Figure 6](image_url)

**Fig. 6.** The eigenvectors for wind stress (a) divergence and (b) curl calculated from the first pair of zonal and meridional eigenvectors shown in Figs. 5b,c. The contour interval is $0.1 \times 10^{-3}$. 
surface winds converging north of the warm SST$_{\text{TIW}}$ center and diverging south of it. Further inspections of the higher-order modes indicate that the TIW-related covariability pattern can be still coherently seen at modes as high as the 20th or so. For the SVD modes beyond 21 and higher, their spatial patterns become noisy and less coherent and TIW signals are lost.

4. An SVD-based empirical $\tau_{\text{TIW}}$ model

As mentioned in the introduction, current dynamical atmospheric models still have considerable difficulty in realistically depicting the TIW-induced surface wind responses to SST$_{\text{TIW}}$ forcing, partly because of low resolutions in the horizontal and vertical, and/or because of unrealistic parameterizations of relevant processes in the atmospheric PBL [another limitations are in the accuracy and resolution of the SST boundary conditions specified for dynamical atmospheric models (Chelton 2005)]. In this work, we adopt a statistical approach to modeling TIW-induced surface wind variability, specifically relating $\tau_{\text{TIW}}$ response to SST$_{\text{TIW}}$ forcing over the TIW active region of the eastern tropical Pacific. This kind of statistical approach has been successfully used in many large-scale tropical ocean–atmosphere modeling studies associated with El Niño (e.g., Barnett et al. 1993; Syu et al. 1995; Chang et al. 2001; Zhang and Zebiak 2004; Zhang et al. 2006).

The physical basis for developing an empirical model for a $\tau_{\text{TIW}}$ response to SST$_{\text{TIW}}$ forcing can be argued as follows. As SST$_{\text{TIW}}$ perturbations are generated in the ocean over the eastern equatorial basin and propagate westward coherently, the atmospheric wind response in the PBL is fast and almost simultaneous (e.g., Fig. 3). Moreover, a positive correlation exists between perturbations of SST and wind speed fields, indicating the dominant SST$_{\text{TIW}}$ influence on $\tau_{\text{TIW}}$ (e.g., Xie et al. 1998). In addition, as shown in the last section, the first several leading SVD modes all show the existence of a coherent covariability pattern between SST$_{\text{TIW}}$ and $\tau_{\text{TIW}}$ fields. In particular, the spatial eigenvectors derived from the combined SVD analysis can be seen to serve as a filter in such a way that large wind signals are represented predominantly only in the TIW active regions where large SST$_{\text{TIW}}$ perturbations are correspondingly present, while non-TIW-related disturbances are selectively excluded off the equator over the ITCZ.

As detailed by Syu et al. (1995) and Chang et al. (2001), and in the appendix, the spatial eigenvectors and time series of the leading SVD modes derived can be used to construct a relationship between $\tau_{\text{TIW}}$ and SST$_{\text{TIW}}$ fields. Symbolically, the SVD-based empirical model for the $\tau_{\text{TIW}}$ response to SST$_{\text{TIW}}$ forcing can be written as

$$\tau_{\text{TIW}} = \alpha_{\text{TIW}} F(\text{SST}_{\text{TIW}}),$$

where $F$ represents an empirical relationship between $\tau_{\text{TIW}}$ response and SST$_{\text{TIW}}$ forcing, which is determined empirically by the spatial eigenvectors of the SVD modes; $\alpha_{\text{TIW}}$ is a scalar coefficient indicating the strength of the $\tau_{\text{TIW}}$ response to SST$_{\text{TIW}}$ forcing (i.e., the coupling coefficient). Accordingly, a given SST$_{\text{TIW}}$ forcing field can be converted to a $\tau_{\text{TIW}}$ response (see the appendix for more details).

As indicated, the structure and amplitude of the $\tau_{\text{TIW}}$ response calculated from the model are determined by the spatial eigenvectors of the SVD modes, which can be sensitive to several factors, including the SVD analysis resolution, the SVD modes retained, and the length of the data record. To resolve TIW signals adequately both in the atmosphere and ocean, SST and wind data used for their SVD analysis should have sufficiently high horizontal resolution. In this paper, a baseline empirical model is constructed from the SVD analysis that is performed on a $1^\circ \times 0.5^\circ$ resolution in space.

Sampling errors in data fields are known to cause uncertainties in the eigenvalues (or in our case, the singular values) of the cross-covariance matrix in empirical orthogonal functions (EOFs; North et al. 1982). Sampling errors come from a variety of sources, including short time sampling in which they are only a small number of independent realizations. Here we use a 8-yr data record in time. The longer record should lead to more accurate estimates of the SVD modes and also allow the retention of more higher-order SVD modes than those used by Zhang and Busalacchi (2008). In addition, since the SVD analysis is performed on all time series data irrespective of months (i.e., F is not seasonally varying), the seasonality of the wind response to SST$_{\text{TIW}}$ forcing has not been taken into account in the current version of the empirical model.

Also, a certain limited number of SVD modes need to be retained in the SVD-based statistical model. The subsequence of singular values and the spatial structure of eigenvectors can be guided to determine the number of SVD modes retained. As shown in Fig. 4, the decrease of the covariance (singular values) with the order of the SVD modes is not uniform; obvious drop off points are seen after modes of 4, 6, and 8, respectively. Thus, a cutoff can be chosen at these modes for the model to maximize the covariance to be represented. Examinations of the spatial eigenvectors indicate that
the leading 20 modes all represent prominent TIW signals both in SST and wind fields over the eastern equatorial Pacific, and at the same time they do not contain non-TIW-related disturbances off the equator. Thus, these high-order SVD modes need to be retained for the SVD-based model to adequately describe the TIW-induced wind response.

In addition, since only limited SVD modes are included in the statistical model-based simulation for $r_{\text{TIW}}$ response, part of the variance is inevitably lost (Fig. 4).
As a result, the amplitude of calculated $\tau_{\text{TIW}}$ response is expected to be smaller as compared with the original satellite observations. A rescaling factor $\alpha_{\text{TIW}}$ is introduced so that the response amplitude can be rescaled back to match up with what is observed in the satellite data (e.g., the value of $\alpha_{\text{TIW}}$ can be chosen larger than 1.0).

5. The evaluation of the empirical model

The performance of the empirical $\tau_{\text{TIW}}$ model can be sensitive to a variety of factors. For example, as is inherent to any statistical method, its performance can depend on the period taken to derive the $\tau_{\text{TIW}}$ model (the training period), and the period adopted for its application (the application period). We perform some cross-validation experiments, in which a $\tau_{\text{TIW}}$ model that is trained during one period is used to calculate $\tau_{\text{TIW}}$ fields for other independent periods. Good performance is obtained if the training and application periods are the same or overlapping somehow. In this section, the $\tau_{\text{TIW}}$ model derived during the period 2000–07 is used to calculate $\tau_{\text{TIW}}$ fields for the year 1999. In this way, information about the SST$_{\text{TIW}}$–$\tau_{\text{TIW}}$ relationship covering the application period (the year 1999) has not been included in the training period (the years 2000–07). This provides an independent validation of the empirical $\tau_{\text{TIW}}$ model and, thus, clearly demonstrates that the $\tau_{\text{TIW}}$ model is not sensitive to the data periods selected for the training and for application.

Based on the sequence of the covariance explained by the SVD modes (Fig. 4) and the testing for reconstructions of $\tau_{\text{TIW}}$ fields from a given SST$_{\text{TIW}}$ forcing, the first 20 leading SVD modes are retained in the model, which explain about 43% covariance of the original zonal high-pass-filtered satellite data. Since the reconstructed stress fields using the model with the first 20 SVD modes selectively extract a covariability pattern predominantly over the TIW active regions. Clearly, this empirical model, based on the combined SVD analysis, acts as an effective filter for $\tau_{\text{TIW}}$ fields by passing SST$_{\text{TIW}}$-induced response signals only in the eastern equatorial Pacific, while excluding non-TIW-related noises off the equator. For example, as with the SST$_{\text{TIW}}$ forcing (Fig. 8d), large $\tau_{\text{TIW}}$ signals simulated are predominantly located in regions where TIWs are active in the eastern equatorial Pacific.

Model performance is further evaluated in terms of perturbation correlation between simulated and observed $\tau_{\text{TIW}}$ fields calculated during the period 21 July 1999–31 December 1999 (Figs. 10a,b). The model has good simulation skill over the TIW active regions of the eastern tropical Pacific; the correlation values exceeding 0.60 cover a broad region in the eastern equatorial Pacific.

While the structure and phase of the surface wind stress response is well simulated, the amplitude is evidently weak, about half as compared with that of the original zonal high-pass-filtered satellite data. Since the reconstructed stress fields using the model with the first 20 SVD modes retained capture roughly 40%–50% of the original covariance (Fig. 4b), a significant fraction of covariance is lost in the process of the model reconstruction and calculation. The underestimation of the amplitude can be taken into account by increasing the coupling coefficient ($\alpha_{\text{TIW}}$), which will be examined below.
b. The TIW-induced ocean–atmosphere coupling

As demonstrated by Chelton et al. (2001), the TIW-induced ocean–atmosphere coupling is most clearly manifest in the divergence and curl fields of the surface wind stress, which are linearly related to the downwind and crosswind components of the SST gradient, respectively. Using the empirical $r_{TW}$ model, we can further evaluate these parameters that represent the TIW-induced coupling between SST and atmospheric wind fields. This can be a high-order test of consistency between the mesoscale air–sea coupling deduced from...
FIG. 9. Longitude–time sections of TIW-induced (a),(c) zonal and (b),(d) meridional $\tau_{\text{TW}}$ components along 3°N for (top) satellite observations and for (bottom) simulations using the SVD-based model with the first 20 SVD modes retained. The time shown is from 1 Aug 1999 to 31 Dec 1999. The contour interval is 0.03 dyn cm$^{-2}$.
FIG. 10. Correlation for (a),(c),(e) zonal and (b),(d),(f) meridional components between $\tau_{TW}$ fields analyzed from the QuikSCAT data and simulated using the SVD-based $\tau_{TW}$ model with the first (top) 20, (middle) 10, and (bottom) 4 modes retained. The calculation is made from 21 Jul to 31 Dec 1999. The time series at each point have been smoothed by a 5-day running mean filter before calculating the correlations. The contour interval is 0.1.
this empirical model and that deduced from more direct analyses (i.e., without the SVD filtering) in the previous satellite observations (Chelton et al. 2001; Chelton 2005).

Following Chelton et al. (2001), the zonal high-pass-filtered downwind component of the SST gradient can be written as

$$(\nabla S_{\text{ST}} \cdot \tau | \tau |)'$$,

where $S = S_{\text{ST,Clim}} + S_{\text{ST,TIW}}$ and $\tau = \tau_{\text{Clim}} + \tau_{\text{TIW}}$, in which $S_{\text{ST,Clim}}$ and $\tau_{\text{Clim}}$ are the daily climatological fields calculated from the TMI and QuikSCAT observations during 2000–07; $S_{\text{ST,TIW}}$ and $\tau_{\text{TIW}}$ are the TIW-induced fields. For the empirical model simulation, the SST$_{\text{TIW}}$ fields are used as an input to calculate the $\tau_{\text{TIW}}$ fields. Then, the coupling parameters can be estimated accordingly, including the divergence and curl fields, and the downwind and crosswind components of the SST gradient (e.g., Chelton et al. 2001). Figure 13 illustrates model results for the coupling derived from the model is about 50%–60% as strong as in nature. These underestimations of the amplitudes can be partly attributed to the low spatial resolution adopted in the SVD analysis ($1^\circ \times 0.5^\circ$) and the limited number of SVD modes retained in the model.

6. Sensitivity analyses

As mentioned above, the performance of the empirical $\tau_{\text{TIW}}$ model depends on a variety of factors. For example, since only limited SVD modes are included in the statistical model-based simulation, part of the covariance is lost. As a result, the amplitude of calculated $\tau_{\text{TIW}}$ responses is small as compared with the original satellite observations. To compensate for the covariance loss, the rescaling factor $\alpha_{\text{TIW}}$ can be taken into account to enhance model skill. In this section we will examine these issues to optimize the model performance in more detail.

a. Effect of the SVD modes retained

A major uncertainty in the $\tau_{\text{TIW}}$ simulation using the empirical model is how many SVD modes should be retained, which directly affects both the structure and amplitude of the wind stress response to a given SST$_{\text{TIW}}$
Forcing. As shown in Fig. 4, the covariance accounted for by each SVD mode is quite small, as compared with a similar SVD analysis for large-scale wind and SST covariability associated with ENSO in the tropical Pacific (e.g., Zhang and Zebiak 2004). This is due to the fact that TIW-related variations in SST and wind stress fields are too complicated in details (e.g., the multibanded structure), both temporally and spatially, to be accounted for by a small number of SVDs. To adequately describe the structure and amplitude of the \( \tau_{\text{TW}} \) response using the SVD-based empirical model, a large number of SVD modes need to be retained; including

**Fig. 11.** Time–longitude sections along 2\(^\circ\)N during August 1999–December 1999 for the zonal high-pass-filtered downwind component of the (a) SST gradient and (b) wind stress divergence analyzed from satellite observations, and (c) for the wind stress divergence calculated using the empirical \( \tau_{\text{TW}} \) model with the first 20 SVD modes retained. The contour is 0.3°C (100 km)\(^{-1}\) in (a) and 0.3 N m\(^{-2}\) (10\(^4\) km)\(^{-1}\) in (b) and (c).
too few SVD mode leaves important aspects of covariability unrepresented. However, retaining statistically insignificant SVD modes will contain non-TIW-related noise that contaminates the TIW-induced $\tau_{TIW}$ response signals. In this sense, less SVD modes retained are preferred in order to capture the TIW-related signals only while filtering out noise that has nothing to do with TIWs. Therefore, a trade-off is needed in determining how many SVD modes should be retained. A basic guidance in this practice is to see if, given a $\tau_{TIW}$ forcing, TIW-induced $\tau_{TIW}$ responses can be captured reasonably well in terms of the structure and amplitude as compared with the original satellite observations.

We have examined the sensitivity of the $\tau_{TIW}$ simulations to the number of SVD modes retained. As an example, Fig. 15 displays the horizontal distributions of

FIG. 12. Horizontal distributions in 1 Oct 1999 for the (a) zonal high-pass-filtered downwind component of the SST gradient and (b) wind stress divergence analyzed from satellite observations, and (c) for the wind stress divergence calculated using the empirical $\tau_{TIW}$ model with the first 20 modes retained. The contour is $0.3^\circ C (100 \text{ km})^{-1}$ in (a) and $0.3 \text{ N m}^{-2} (10^4 \text{ km})^{-1}$ in (b) and (c).
the simulated \( \tau_{\text{TIW}} \) fields for 1 October 1999, using the empirical model with the first 4, 10, and 15 leading SVD modes retained; the corresponding simulations with the first 20 modes retained have been presented in Figs. 8e,f. It can be seen that the simulated structure is quite similar, with the TIW-induced wind response signals being predominantly located in the TIW active regions of the eastern equatorial Pacific. As shown, including only the first 4 or 6 modes can already represent the structure well (but the amplitude is apparently weak, particularly west of 140°W); when the first 8 or 10 modes are included, the amplitude west of 140°W has increased noticeably. Further inclusion of higher modes, say the modes from 10 to 15 (Figs. 15e,f), has not led to a large change in the structure. This indicates that the structure of the simulated wind response is determined predominantly by the first 10–15 leading modes.

In terms of the amplitude, the contributions of different-order SVD modes to the variance are not equal, as seen in Fig. 4. The first few modes make largest contributions, with clear sharp increases in the simulated amplitude of the wind stress response occurring when the first four, six, or eight modes are retained. While the structure is not significantly affected by the inclusion of the 9th and higher modes, the amplitude is still increasing slightly when including more higher
modes for the model simulations. When more higher-order modes (beyond 20) are included, their contributions to the amplitude are not significant. For example, the simulated wind fields with the first 25 modes included show no obvious differences from those with the first 20 modes retained.

The effects of the retained number of SVD modes on \( \tau_{\text{TIW}} \) simulation are assessed further in Fig. 10, showing the correlations between the \( \tau_{\text{TIW}} \) fields analyzed from the satellite data and simulated from the empirical model with different modes included. As expected, the more SVD modes retained, the higher correlation with larger spatial extent (e.g., Fig. 10). The structure of the spatial correlation patterns with different modes retained are all quite similar, indicating high correlation over the TIW region while no correlation off the equator. However, large increases in the correlation take place when low-order modes are included, particularly with the first leading two, four, or six modes. For example, retaining the first four SVD modes can already have the correlation of more than 0.6 in a broad area, with the maximum being about 0.8 (Figs. 10e,f). The

![Fig. 15. Horizontal distributions of the (a),(c),(e) zonal and (b),(d),(f) meridional \( \tau_{\text{TIW}} \) components for 1 Oct 1999, simulated using the SVD-based empirical model with the first (top) 4, (middle) 10, and (bottom) 15 modes retained. The contour interval is 0.03 dyn cm\(^{-2}\).](image-url)
correlation shows no significant differences when including higher modes 21 and beyond, as compared to that with the 20 SVD modes retained (Figs. 10a,b). So, retaining the first 20 SVD modes may be sufficient for the model to have the realistic simulations for the structure and strength of the observed TIW-induced TIW response.

In addition, the dependence of the model skill on some selected SVD modes retained is quantified in Table 1, as represented by the slopes of simulated and observed fields, and of the coupling coefficients for observations and model simulations, respectively. As expected, the slopes increase as more modes are included. So, the more modes retained, the better model performance is, and the stronger is the coupling. Since low-order modes make a greater contribution to the covariance (Fig. 4), they play a more dominant role in improving the accuracy of the empirical model to represent observed TIW-induced wind stress responses and coupling. For example, when the first four modes are included, the slopes for wind stress responses are about 30% as strong as in the satellite-based estimates. When the first eight modes are retained, the slopes increase by more than 10%. The further inclusion of more higher modes has smaller impacts on the increase in the slopes.

### Table 1. The binned slopes of the empirically calculated zonal ($\tau_x$) and meridional ($\tau_y$) $\tau_{TIW}$ fields, derived divergence and curl perturbations as functions of corresponding observed fields, and the downwind coupling coefficient calculated as the binned slope between the zonal high-pass-filtered wind stress divergence and the downwind component of the SST gradient, and the cross-wind coupling coefficient between the zonal high-pass-filtered wind stress curl and the cross-wind component of the SST gradient, respectively.

<table>
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<tr>
<th>$a_{TIW}$</th>
<th>$m$</th>
<th>$\tau_x$ slope</th>
<th>$\tau_y$ slope</th>
<th>Divergence slope</th>
<th>Curl slope</th>
<th>Downwind coupling coef</th>
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The rescaling factor ($a_{TIW}$)

Note that the spatial patterns of the wind responses are determined predominantly by the first few leading...
modes (Fig. 15). The introduced rescaling coefficient \( \alpha_{\text{TIW}} \) can be used to adjust the response amplitude in order to compensate for the loss of the covariance in the SVD-based model calculation. For example, the value of \( \alpha_{\text{TIW}} \) can be chosen larger than 1.0 so that the response amplitude is increased (but the structure is not changed). This allows us to rescale the amplitude back to match up with what is observed. This approach has been often adopted in the statistical modeling studies for large-scale wind simulations associated with ENSO (Barnett et al. 1993; Syu et al. 1995; Zhang et al. 2006).

Table 1 illustrates some examples for the rescaling effects on the model performance, as represented in terms of the slopes between simulated and observed fields, and the coupling coefficients. As \( \alpha_{\text{TIW}} \) increases, the slopes increase. So, the agreements between simulations and observations are improved. Such improvements in the model skill with the increase in \( \alpha_{\text{TIW}} \) are linearly for wind stress fields. For example, when the first 20 modes are included, the amplitude is about half as strong as in the observations for \( \alpha_{\text{TIW}} = 1 \); the slopes are almost doubled for \( \alpha_{\text{TIW}} = 2 \), which brings the simulation very close to the observations.

Also significant improvement can be achieved for the divergence and curl fields and thus the coupling strength, although the extent to which it is achieved is different from the wind stress fields. For example, as \( \alpha_{\text{TIW}} \) increases, the increases in the slopes are not linearly in proportion to the value of \( \alpha_{\text{TIW}} \) for the wind stress divergence/curl fields and coupling coefficients. When the first 20 modes are included, the coupling strength in terms of the cross-wind coupling is only about 50% as strong as in the observations for \( \alpha_{\text{TIW}} = 1 \); the slopes increases to about 80% of the observations for \( \alpha_{\text{TIW}} = 2 \) (but are not doubled). Though still weaker, the response amplitude of the divergence and curl fields and coupling strength can be more than 80% as strong as in observations when the first 20 modes are retained and \( \alpha_{\text{TIW}} \) is taken to be 2.0. Thus, accounting for this rescaling factor presents an effective way to optimize model performance. Taking together the number of modes retained and the rescaling factor (\( \alpha_{\text{TIW}} \)), the model skill can be optimized. As such, good simulations of TIW-induced wind stress response to SST forcing can be achieved both in terms of the structure (determined by the first few leading modes) and amplitude (adjusted by the rescaling factor), respectively.

7. Discussion and conclusions

In this work, satellite observations are first used to quantify the relationship between surface wind stress responses and SST-TIW forcing that are induced by TIWs in the eastern tropical Pacific. A simple 12° zonal mean filter is applied to the satellite data to isolate the TIW signals (e.g., Hashizume et al. 2001). While the SST-TIW fields show clean and clear TIW signals in the ocean of the eastern equatorial Pacific, the resultant zonal high-pass-filtered surface wind stress data contain both signals and noises which are of different origins. In the TIW active regions, the wind perturbations are clearly associated with TIW-induced SST-TIW forcing; but the large wind disturbances seen off the equator over the ITCZ are not TIW-related since there is no corresponding signature in the SST-TIW fields.

To allow for the dominant patterns of the TIW-induced SST-TIW and \( \tau_{\text{TIW}} \) covariability to be captured, a combined SVD technique is adopted. As clearly demonstrated by previous observational analyses, a good correlation exists between \( \tau_{\text{TIW}} \) and SST-TIW perturbations over the TIW active region. In particular, the atmospheric surface wind response to SST-TIW forcing is such a way that wind speed perturbations are positively correlated with SST-TIW variability. This is a clear indication that the ocean executes an active influence on the atmosphere while the atmospheric surface winds represent a passive response to the SST-TIW perturbations. Surprisingly, the spatial eigenvectors of the first several leading SVD modes derived from satellite observations indicate that large wind signals show up predominantly only in regions where large SST-TIW perturbations are also present.

Then, the spatial eigenvectors are used to build an empirical model for \( \tau_{\text{TIW}} \) response to SST-TIW forcing. This SVD-based model is more effective to represent the TIW-induced covarying patterns of wind responses with SST forcing that a similar regression-based statistical model previously designed by Pezzi et al. (2004). It is demonstrated that the empirical \( \tau_{\text{TIW}} \) model can well reproduce TIW-induced wind stress perturbations that are directly observed from satellite measurements, including the well-defined spatial structure and time evolution. But the magnitudes can be underestimated significantly. Validation and sensitivity experiments are performed to demonstrate the robustness and usefulness of the empirical \( \tau_{\text{TIW}} \) model. In particular, the SVD-based analysis technique can effectively extract TIW-induced covariability patterns in the atmosphere and ocean, acting as a filter for TIW-induced wind stress response by passing only its signals that are related with SST-TIW forcing. This is consistent with the contention that the empirical model is capturing only the TIW-related portion of the wind stress perturbations, while other non-TIW-related wind signals are largely excluded, including those over the ITCZ.

The \( \tau_{\text{TIW}} \) empirical approach we propose here is simple and computationally economical. As an example,
we demonstrate how to estimate the TIW-induced surface wind perturbations from a given SST$_{TIW}$ field, the variable most relevant to mesoscale air–sea interactions. Other atmospheric fields can also be derived in a similar way, such as heat flux components, cloud, and precipitation fields. The approach can also be applicable to other tropical oceans where the TIWs are active and coherent relations exist between SST and atmospheric perturbation fields in association with TIWs.

The $\tau_{TIW}$ model can be very useful for a variety of applications. One is for large-scale ocean modeling studies. Ocean models with reasonably high resolution, when forced by prescribed atmospheric fields, can well depict TIW signals in SST fields. However, conventional climate datasets (e.g., traditional ship-based measurements) and model-based reanalyses products are commonly archived on monthly basis at low spatial resolution, which can severely underestimate the TIW-induced mesoscale signals in the atmosphere. For example, when using such atmospheric data to force ocean models, TIW-related mesoscale atmospheric variability and the feedback from the atmosphere to the ocean are missing over the TIW active regions. Since the empirical $\tau_{TIW}$ model we present here is able to simulate TIW-induced surface wind variability from a given SST$_{TIW}$ field, the TIW-induced wind feedback from the atmosphere to the ocean can be taken into account in the context of a forced ocean model simulation. An example has been given by Zhang and Busalacchi (2008) for an OGCM simulation of the tropical Pacific, forced by prescribed monthly wind data. It is demonstrated that TIWs cannot only have an effect on mesoscale variability, but also a rectified effect on large-scale ocean fields. Furthermore, the effects of TIW-related mesoscale variability on oceanic biogeochemical processes can be examined in a similar way.

The $\tau_{TIW}$ model can be used for mesoscale air–sea coupling studies in the TIW active regions of the tropical oceans. Recent satellite data indicate a two-way mesoscale interaction between the ocean and atmosphere, which has not been adequately taken into account in many mesoscale modeling studies because of the difficulty of realistically simulating atmospheric wind response associated with TIWs. Now, the empirical $\tau_{TIW}$ model we propose here can be used to form an atmospheric component for the mesoscale coupled air–sea system, in which mesoscale variability can develop internally and interactively on its own both in the ocean and in the atmosphere, allowing to examine two-way coupling over the eastern tropical oceans.

The empirical $\tau_{TIW}$ model can be used to examine the rectified effects of TIW-related mesoscale wind perturbations on large-scale coupled climate variability in the tropics. Recently, the roles of TIWs in budgets of heat, salt, momentum, and biogeochemical fields in the tropical oceans have been demonstrated (e.g., Vialard et al. 2003; Jochum and Murtugudde 2006; Jochum et al. 2005, 2007; Menkes et al. 2006). Because of large perturbations of SST and surface winds induced by TIWs, it is expected that TIWs can have effects on large-scale coupled climate variability. However, global climate models are not able to capture the consequent TIW-induced atmospheric signals and the feedback effect on the ocean and thus the associated coupling. Since the empirical $\tau_{TIW}$ model can estimate mesoscale wind stress response in the atmosphere, it provides a simple way to parameterize the TIW effects for global climate models. That is, as long as the ocean component model has high resolution that can resolve TIW-induced SST$_{TIW}$ signals, the empirical model can be used to depict the corresponding wind response. In this way, the TIW-induced wind feedback from the atmosphere to the ocean and further the interactions between mesoscale and large-scale coupled variability can be taken into account appropriately.

In particular, the TIW active region in the eastern tropical Pacific is also a region important to large-scale coupled climate variability associated with El Niño–Southern Oscillation (ENSO). Since TIWs can be an important factor in determining the heat balance in the region, accounting for TIW-related wind feedback and air–sea coupling adequately in basin-scale coupled ocean–atmosphere models is expected to have rectified effects on ENSO simulation and prediction. Moreover, ENSO has been observed to change significantly from one event to another; many factors have been identified that can modulate ENSO amplitude (e.g., Zhang et al. 2008). As an oceanic form of stochastic forcing, TIWs are expected to play a role in modulating ENSO, as recently demonstrated by Zhang and Busalacchi (2008). Further modeling studies are clearly needed to describe and understand the impacts of TIW-related feedback and air–sea coupling on large-scale coupled climate variability and predictability in the tropical Pacific climate system.

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APPENDIX

The Construction of the SVD-Based Model

The details of SVD analyses can be found in Bretherton et al. (1992). Let \( \text{SST}(t, x, y) \) be the TIW-related forcing field and \( \tau(t, x, y) \) be the corresponding wind stress response. They are written as column vectors whose spatial dimension (grid points) is \( N \) for SST and \( 2N \) for wind stress, respectively (the two zonal and meridional components), when performing a combined SVD analysis. The covariance matrix between these two fields is defined as

\[
C = \langle \text{SST}(t, x, y) \tau^T(t, x, y) \rangle,
\]
where the angle brackets denote the time average and the transpose operator is denoted as a superscript \( T \).

The SVD technique allows \( C \) to be decomposed into a form consisting of spatial patterns as follows:

\[
C = \sum_{k=1}^{N} \alpha_k \mathbf{f}_k(x,y) \mathbf{r}_k^T(x,y),
\]
where \( \mathbf{f}_k(x,y) \) and \( \mathbf{r}_k(x,y) \) are eigenvectors of \( (CC^T) \)

\[
\mathbf{f}_k(x,y) = \sigma^2_k \mathbf{f}_k(x,y) \text{ and } (C^T C) \mathbf{r}_k(x,y) = \sigma^2_k \mathbf{r}_k(x,y),
\]
respectively.

The eigenvalues \( \sigma^2_k \) are the total squared covariance explained by each eigenvector pair. The two time series of expansion coefficients associated with the \( k \)th mode are

\[
\alpha_k(t) = \mathbf{r}_k^T(x,y) \tau(t,x,y) \quad \text{and} \quad \beta_k(t) = \mathbf{f}_k^T(x,y) \text{SST}(t,x,y).
\]

Spatial patterns associated with the \( k \)th eigenvector are represented by \( \mathbf{f}_k(x,y) \) and \( \mathbf{r}_k(x,y) \), which can be calculated from historical data. The spatial patterns (eigenvectors) and time variations are illustrated in Fig. 5 for the first mode and in Fig. 7 for the 10th mode, respectively.

From these SVDs, the \( \tau_{TIW} \) response can be related to the \( \text{SST}_{TIW} \) forcing as follows:

\[
\tau(t,x,y) = \alpha_{TIW} \sum_{k=1}^{M} \beta_k(t) c_k \mathbf{r}_k(x,y),
\]
where

\[
p_k(t) = \frac{\sum_{x,y} \text{SST}(t,x,y) \mathbf{f}_k(x,y)}{\sum_{x,y} \mathbf{f}_k^2(x,y)}
\]
is the projection of the \( \text{SST}_{TIW} \) perturbations onto \( \mathbf{f}_k(x,y) \), \( M \) is the number of SVD modes retained, \( c_k \) is the coupling coefficient relating the \( \text{SST}_{TIW} \) patterns to the \( \tau_{TIW} \) pattern associated with the \( k \)th SVD mode, and the operator \( \Sigma_{x,y} ( \cdot ) \) denotes summation over the zonal \( (x) \) and meridional \( (y) \) grid points in physical space.

The time series of the expansion coefficients associated with the \( k \)th SVD mode are defined as

\[
c_k = \frac{\beta_k(t) \alpha_k(t)}{\langle \beta_k^2(t) \rangle}.
\]

The procedures to calculate \( \tau_{TIW} \) response by a given \( \text{SST}_{TIW} \) forcing with the leading \( M \) pairs of eigenvectors included are as follows:

1) Perform SVD analyses to obtain the eigenvectors (\( \mathbf{f}_k \) and \( \mathbf{r}_k \)), and time series (\( \alpha_k \) and \( \beta_k \)) from historical data (e.g., Figs. 5 and 7).
2) Compute \( c_k \) from \( \alpha_k(t) \) and \( \beta_k(t) \).
3) Calculate \( p_k(t) \) by projecting the \( \text{SST}_{TIW} \) forcing onto the leading \( M \) singular vectors, \( \mathbf{f}_k(x,y) \).
4) Obtain the \( \tau_{TIW} \) response by taking a sum of the \( \tau_{TIW} \) eigenvectors from mode 1 to \( M \), weighted by \( p_k(t) c_k \).

The model codes and data are available from the authors upon the request.

REFERENCES


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