Scale Dependence of Midlatitude Air–Sea Interaction

STUART P. BISHOP
North Carolina State University, Raleigh, North Carolina

R. JUSTIN SMALL, FRANK O. BRYAN, AND ROBERT A. TOMAS
National Center for Atmospheric Research, Boulder, Colorado

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ABSTRACT

It has traditionally been thought that midlatitude sea surface temperature (SST) variability is predominantly driven by variations in air–sea surface heat fluxes (SHFs) associated with synoptic weather variability. Here it is shown that in regions marked by the highest climatological SST gradients and SHF loss to the atmosphere, the variability in SST and SHF at monthly and longer time scales is driven by internal ocean processes, termed here “oceanic weather.” This is shown within the context of an energy balance model of coupled air–sea interaction that includes both stochastic forcing for the atmosphere and ocean. The functional form of the lagged correlation between SST and SHF allows us to discriminate between variability that is driven by atmospheric versus oceanic weather. Observations show that the lagged functional relationship of SST–SHF and SST tendency–SHF correlation is indicative of ocean-driven SST variability in the western boundary currents (WBCs) and the Antarctic Circumpolar Current (ACC). By applying spatial and temporal smoothing, thereby dampening the signature SST anomalies generated by eddy stirring, it is shown that the oceanic influence on SST variability increases with time scale but decreases with increasing spatial scale. The scale at which SST variability in the WBCs and the ACC transitions from ocean to atmosphere driven occurs at scales less than 500 km. This transition scale highlights the need to resolve mesoscale eddies in coupled climate models to adequately simulate the variability of air–sea interaction. Away from strong SST fronts the lagged functional relationships are indicative of the traditional paradigm of atmospherically driven SST variability.

1. Introduction

The exchange of energy between the atmosphere and ocean is a key process in regulating both the mean state and the variability of the climate system. It is driven by the thermal disequilibrium between the near-surface atmosphere and ocean boundary layer temperatures. Understanding the processes that drive the surface temperatures away from equilibrium, along with their space and time scales, is thus one of the fundamental problems in climate science. This study will address the following question: What are the relative contributions of intrinsic variability in the atmosphere (e.g., synoptic weather) and intrinsic variability in the ocean (e.g., mesoscale eddies) to variability in the exchange of energy across the air–sea interface as a function of time and space scales?

Corresponding author: Stuart P. Bishop, spbishop@ncsu.edu

The methodology to be applied in this investigation derives from the statistical relationships between variability in sea surface temperature (SST) and turbulent surface heat fluxes (SHFs) that are revealed by simple stochastic climate models (Hasselmann 1976; Frankignoul and Hasselmann 1977; Reynolds 1978; von Storch 2000). In particular, the functional form of the lead–lag correlation between SST or upper-ocean heat content and SHF allows us to discriminate between variability that is driven primarily by weather versus variability driven primarily by interior ocean processes. A large literature of observational and modeling studies (e.g., Frankignoul and Hasselmann 1977; Cayan 1992; Hall and Manabe 1997; Burszgli and Battisti 1998; von Storch 2000; Frankignoul and Kestenare 2002; Park et al. 2005; Wu et al. 2006) has examined ocean–atmosphere interaction using the Hasselmann (1976) paradigm, showing that the thermal inertia of the upper ocean serves to integrate high-frequency atmospheric weather forcing...
to produce a lower-frequency SST response; that is, the thermal inertia of the upper ocean serves to redden the white noise atmospheric forcing. These studies have been remarkably successful in explaining variability in SST and surface heat flux over much of the ocean. However, nearly all of the studies investigating climate variability under this conceptual framework have been conducted with rather coarse-resolution observational estimates of SST and SHFs that obscure the signature of ocean mesoscale eddies or with coarse-resolution coupled global climate models in which the ocean component is non-eddy-resolving. Many have noted the limitations of these resolution constraints and have qualified their results as being applicable outside of regions of strong oceanic currents, though with little guidance on what constitutes “strong.” To our knowledge, there has been little consideration of the spatial or temporal scales at which these limitations emerge.

In addition to indications of regions where the Hasselmann (1976) paradigm fails to explain surface variability, there are a number of studies that propose the alternative paradigm—intrinsic ocean variability acting as the driver of surface variations. There are two primary circumstances where this alternative perspective has been applied. The first is in energetic western boundary current regions and their recirculation gyres. In such regions it has been shown (e.g., by Kelly 2004) that on interannual to decadal time scales anomalous convergence of oceanic heat transport accounts for the storage of heat in these areas better than do SHF anomalies. The second example is related to low-frequency variations in basin-scale ocean heat transport through changes in the Atlantic meridional overturning circulation (AMOC). A recent example of such an analysis is the study of Gulev et al. (2013), who find evidence for an oceanic origin for variations in subpolar North Atlantic SHF on decadal time scales. While the starting point for their investigation was different from the examples described above using stochastic climate models, the analysis methods were quite similar—quantifying the lead–lag correlation between local surface temperature and SHFs.

We will build on the methodology inspired by these earlier investigations and exploit the available state-of-the-art SST and SHF observational products to characterize the mechanisms that lead to variability in air–sea heat fluxes globally, including those areas where “strong” ocean currents are an important component of the variability. In section 2 we describe the methodology for determining atmospheric- versus oceanic-driven variability in SST. Section 3 lists the observational datasets used in this study, and section 4 discusses the methodology. Sections 5 and 6 show and discuss the results in light of the stochastic climate model theory. Last, section 7 concludes the paper.

2. Theoretical background

The theoretical background is a simple local energy balance model of the coupled ocean–atmosphere system (Wu et al. 2006):

\[
\frac{dT_a}{dt} = \alpha(T_o - T_a) - \gamma_a T_a + N_a, \quad \text{and} \quad (1)
\]

\[
\frac{dT_o}{dt} = \beta(T_a - T_o) - \gamma_o T_o + N_o, \quad (2)
\]

where \(T_a\) is the near-surface atmospheric temperature, \(T_o\) is the SST, \((\alpha, \beta)\) are exchange coefficients normalized by the respective heat capacities of the atmosphere and ocean with \(\beta \ll \alpha\), \((\gamma_a, \gamma_o)\) are radiative damping coefficients, and \((N_a, N_o)\) represent stochastic forcing arising from weather or turbulent eddies in the atmosphere and ocean, respectively. The original (Hasselmann 1976) formulation of the problem considered all stochastic forcing to arise in the atmosphere [i.e., \(N_o = 0\) in Eq. (2)]. The lag correlation function between SST or upper-ocean heat content \(T_o\) and SHF \(\alpha(T_o - T_a)\) for this model is shown in Fig. 1a. We adopt a sign convention where positive SHF is out of the ocean into the atmosphere. See the appendix for specifics on the solutions to the local energy balance model [Eqs. (1) and (2)]. In this case we expect (e.g., von Storch 2000) an antisymmetric lag correlation function, with near-zero simultaneous correlation between SST and SHF. Additionally, the correlation between upper-ocean heat content tendency \(dT_o/dt\) and SHF is symmetric about zero lag, with strongly negative simultaneous correlation. In other words, when the atmosphere is driving SST variability, we expect the SST and SHF to be roughly in quadrature with each other and positive SHF (ocean cooling) to be associated with negative SST tendency. The alternative case of variability arising primarily for stochastic processes in the ocean is obtained by taking \(N_o = 0\) in Eq. (1). The expected lag correlation between SST or upper-ocean heat content and SHF for this case is shown in Fig. 1b. Now, the simultaneous correlation is strongly positive, while the lag correlation function between SST tendency and SHF is antisymmetric about zero lag. Here, the SHF is acting to damp the upper-ocean heat content anomalies generated by interior ocean processes, with the flux directly proportional to the SST itself.

An example of this conceptual framework applied to the analysis of variability in climate models is shown in Kirtman et al. (2012). Their study compares aspects of
climate variability in simulations with versions of a climate model in which the ocean component explicitly resolves mesoscale eddies (∼10-km grid spacing) versus a version in which mesoscale eddies are parameterized (∼100-km grid spacing). In the low-resolution model, the aggregate transport effect of the mesoscale eddies is represented, but any explicit variability arising from them is suppressed. The correlations between SST or SST tendency and surface turbulent (latent plus sensible) heat flux are shown in Fig. 19 of Kirtman et al. (2012). For the lower-resolution model the strongest simultaneous correlation through the midlatitudes is the negative correlation between SST tendency and SHF, with quite weak correlation between SST itself and SHF. This situation is consistent with the model represented in Fig. 1a, providing an indication that the variability is dominated by stochastic atmospheric forcing. On the other hand, for the high-resolution model, a strong positive correlation between SST and SHF emerges in the western boundary currents and their extensions, as well as along the Antarctic Circumpolar Current (ACC), particularly in the Agulhas Return Current (ARC) region. This is consistent with the scenario illustrated in Fig. 1b, which indicates the dominance of oceanic forcing of the variability in these regions. Away from these regions, areas where the ocean–atmosphere interaction is dominated by atmospheric forcing persist in the high-resolution model.

Solutions to the local energy balance model [Eqs. (1) and (2)] in Figs. 1c,d show that the magnitude and structure of the lagged correlation are dependent on the relative sizes of the stochastic atmosphere and ocean forcing frequencies. When the ocean stochastic forcing frequency $\omega_o$ is sufficiently high the lagged correlation resembles the ocean-forcing atmosphere scenario in Fig. 1b. As $\omega_o$ is reduced there is a transition to the atmosphere-forcing ocean scenario in Fig. 1a. In the climate model example above, Kirtman et al. (2012) compare non-eddy- and eddy-resolving simulations using monthly time series data at the spatial resolution of each model. However, there is no a priori understanding of the time-scale dependence and at what spatial scale the midlatitudes transition from ocean-driven to atmospherically driven SST variability. Guided by these
analytical and model results in this paper we use the most up-to-date global observational products of SST and SHF to estimate SST–SHF and SST tendency–SHF lead–lag covariance and examine the symmetry of the lead–lag relationship guided by Fig. 1 as a function of time and space scale. The observational datasets used in the study are described next in section 3.

3. Observational datasets

In this study we use version 2 of the National Oceanic and Atmospheric Administration Optimum Interpolation 1/4° daily SST (AVHRR-only product) (NOAA OISST; Reynolds et al. 2007) for years 1985–2013. Monthly time series were then calculated from the daily SST data. While higher-resolution products are available, the lack of correspondingly high-resolution heat flux products precludes analysis below this resolution.

For turbulent SHFs we use sensible and latent heat flux from the Woods Hole Oceanographic Institution objectively analyzed air–sea fluxes (OAFlux) for the global oceans product. The data are available daily from 1985 to present and at 1° spatial resolution (Yu et al. 2008). We calculated monthly averages to match the SST data from 1985 to 2013 and remapped the data to the 1/4° SST grid using linear interpolation. We are aware that higher spatial resolution (1/4°) SHF products exist, but OAFlux has a longer available time series than SeaFlux (http://seaflux.org/) or Japanese ocean flux data sets with use of remote sensing observations (J-OFURO) (http://dtsv.scc.u-tokai.ac.jp/j-ofuro/), which are rather short, spanning 1998–2007 and 2002–07, respectively. For statistical robustness we focus on results from OAFlux in this study, but we do show comparisons with the J-OFURO product (see Fig. 7 below) that are in good agreement with OAFlux. This analysis will also be focused on times scales from monthly (Nyquist frequency of 1/2 month⁻¹) to interannual and spatial scales from mesoscale to basin scale owing to using monthly averaged and 0.25° spatial data (Nyquist frequency of 1/0.5° ≈ 1/50 km⁻¹).

4. Methodology

To examine the time-scale dependence we start with monthly averaged time series of SST and SHF, remove the monthly climatology, and low-pass filter the data sets using a fourth-order Butterworth filter with cutoff frequencies \( f_c \) increasing in 1/3 month⁻¹ increments from 1/21–1/3 month⁻¹. To examine the space-scale dependence we start with the grid spacing of the observational datasets and use a boxcar filter to smooth at box sizes of side length \( \delta_c \), increasing incrementally by 0.5° from 0.5° to 10°. For regions where the boxcar approaches a coastline, only values within the box that are ocean values are used. SST tendency was calculated using a centered-difference approximation with monthly time steps.

The focus of the paper is on the midlatitudes, so we additionally remove potential teleconnections between the El Niño–Southern Oscillation (ENSO) in the tropics and midlatitudes, before low-pass or spatial filtering, by removing the simultaneous SST regression with the Niño-3.4 index from the SST time series. Niño-3.4 is defined as the averaged SST from 5°S to 5°N and 170° to 120°W. Frankignoul et al. (2011) removed teleconnections associated with ENSO by removing the first three EOFs of monthly SST between 12.5°S and 12.5°N in the tropical
Pacific. The first mode represented 61% of the variance and had a spatial structure consistent with Niño-3.4. The second and third EOFs represented 14% and 4% of the variance, respectively. A comparison of the SST variance with only Niño-3.4 removed and with the methods employed by Frankignoul et al. (2011) showed virtually no difference in the midlatitudes (not shown).

To get an idea of the variability of the two datasets, Fig. 2 shows the climatological mean and standard deviation of SST (Fig. 2a) and SHF (Fig. 2b). In both datasets the standard deviation is highest in the western boundary currents (WBCs) [e.g., Gulf Stream (GS) and Kuroshio Extension (KE)] and ARC in the Southern Ocean between South Africa and west Australia with peaks in excess of 1.5°C and 50 W m\(^{-2}\), respectively. One notable exception is high SST standard deviation in the eastern tropical Pacific along the equator but relatively low SHF standard deviation, which is likely related to the second and third EOFs of SST (Frankignoul et al. 2011). The WBCs and ARC are also regions marked with high climatological mean meridional SST gradients and are the regions of highest SHFs with values upward of 200 W m\(^{-2}\). Regions at high latitude are neglected owing to significant ice cover throughout most of the year.

To diagnose ocean- versus atmosphere-driven SST variability we calculate the lagged covariance of SST–SHF and SST tendency–SHF as follows:

\[
C_{TQ}(x, y, \tau) = \frac{T_o(x, y, t + \tau)}{Q_o(x, y, t)},
\]

(3)

\[
C_{T,\tau}(x, y, \tau) = \frac{\partial T_o}{\partial t}(x, y, t + \tau)Q_o(x, y, t),
\]

(4)

where \(\tau\) are lags, \(Q_o\) are turbulent SHFs (latent plus sensible), primes are deviations from the climatological annual cycle, and the overbar indicates a temporal mean, using the monthly average SST and SHF data at the base grid of 0.25°. Here we adopt a negative lag as SST leading SHF. We will be guided by the stochastic air–sea interaction model in Eqs. (1) and (2) and structure of the lead–lag correlation in Fig. 1 to determine globally where oceanic and atmospheric weather lead to ocean- versus atmosphere-driven variability.

As a metric to assess the scale dependence of the lagged correlation of SST–SHF and SST tendency–SHF we define a transition length scale \(L_c\) at a given low-pass
Filter cutoff $f_c$ as the value of $\delta_c$ where the correlations intersect at zero lag. This is written for all length scales ($L$) as

$$|r_{TQ}(x, y, 0)^L| \geq |r_{T_tQ}(x, y, 0)^L| \forall L < L_c,$$

(5)

where $r_{TQ}$ and $r_{T_tQ}$ are the lagged correlations between SST–SHF and SST tendency–SHF, respectively, and the overbar with superscript $L$ indicates spatial smoothing at that boxcar cutoff. Note the use of the absolute values because SST tendency–SHF correlation $r_{T_tQ}$ is predominantly negative or near zero. In practice $L_c$ is determined by fitting a fourth-order polynomial to $r_{TQ}$ and $|r_{T_tQ}|$ as a function of $\delta_c$ and using interpolation to determine $\delta_c$, where $r_{TQ} - |r_{T_tQ}| = 0$. (An example of this method is discussed later and shown in Fig. 11 below.)

5. Results

a. Lagged covariance

Figure 3 shows the global distribution of lagged covariance $C_{TQ}$ and $C_{T_tQ}$. First we examine the zero-lag ($\tau = 0$) covariance. The $C_{TQ}(x, y, 0)$ is generally positive over broad geographical regions and largest in the WBC regions and ARC (Fig. 3b). There are also notable regions in Eastern Boundary Current (EBC) systems that have positive covariance along the southwestern Australian coast, along the southwestern coast of Africa in the Benguela Current system, and along the Baja and central coast of Mexico within the California Current system (Fig. 3b). The eastern tropical Pacific also has positive covariance likely associated with the second and third EOFs associated with ENSO (Frankignoul et al. 2011). With the exception of the EBC systems and eastern tropical Pacific, $C_{TQ}(x, y, 0)$ is near zero outside of the WBCs and ARC. In contrast to $C_{TQ}(x, y, 0)$, $C_{T_tQ}(x, y, 0)$ is mostly negative and geographically the most negative in midlatitudes under the atmospheric storm tracks. The large negative values within the GS and KE (Fig. 3e) do not contradict the dominance of ocean-driven SST variability since the symmetry of the lagged structure of $C_{T_tQ}(x, y, \tau)$ crosses zero at less than \pm 1 month within the resolution of the monthly datasets. The symmetry of the lagged covariance is discussed next.

Guided by Fig. 1, atmosphere-driven SST variability has a near-zero SST–SHF simultaneous correlation with an asymmetrical lead-lag structure while the SST
tendency–SHF correlation is strongly negative at zero lag with a symmetric lead–lag structure (Fig. 1a). Ocean-driven SST variability has a positive and symmetric SST–SHF lead–lag covariance, and SST tendency–SHF has a zero simultaneous correlation with an asymmetrical lead–lag structure (Fig. 1b). Figure 3 shows that geographically there are both regions of the global ocean that have atmosphere- and ocean-driven variability. In the same regions listed above that have strong positive SST–SHF covariance at zero lag (i.e., WBCs) $C_{TQ}(x, y, \tau)$ has a symmetric lead–lag structure (Figs. 3a–c) and also an asymmetric $C_{TQ}(x, y, \tau)$ lead–lag covariance structure (Figs. 3d–f) with both having a diminishing covariance toward $\pm 3$-month lags (not shown), indicative of ocean-driven SST variability. Outside of the WBCs, ARC, and some portions of the EBC systems, in particular the subtropical gyres, the $C_{TQ}(x, y, \tau)$ is weak with asymmetric lead–lag structure while $C_{TQ}(x, y, \tau)$ is strongly negative with a symmetric lead–lag structure also with both having a diminishing covariance toward $\pm 3$-month lags (not shown), indicative of atmosphere-driven SST variability.

As an example, we can take a closer look at the geographical differences in atmosphere- versus ocean-driven variability by examining $C_{TQ}(x, y, \tau)$ and $C_{TQ}(x, y, \tau)$ in the regions centered on strong covariance in the North Atlantic (Fig. 4), North Pacific (Fig. 5), and ARC south of South Africa (Fig. 6). There is a clear difference between the lead–lag covariance structure in the Gulf Stream, marked by the strong climatological SST gradient, and the subtropical gyre. Within the Gulf Stream the $C_{TQ}(x, y, \tau)$ is positive and symmetric about zero lag, while within the subtropical gyre there is weaker covariance with an asymmetric structure about zero lag (Figs. 4a–c). Examining next $C_{TQ}(x, y, \tau)$, the Gulf Stream shows up again with a different lead–lag structure than the subtropical gyre (Figs. 4d–f). The $C_{TQ}(x, y, \tau)$ in the Gulf Stream has an asymmetric lead–lag structure, while the subtropical gyre has a symmetric structure about zero lag.

The North Pacific (Fig. 5) and Southern Ocean ARC region (Fig. 6) have similar characteristics to the North Atlantic (Fig. 4). Like the Gulf Stream, the Kuroshio Extension and ARC, which are marked by strong climatological SST gradients, have high $C_{TQ}(x, y, 0)$. The area with high $C_{TQ}(x, y, 0)$ surrounding the Kuroshio Extension has a larger meridional extent and the strongest covariance is in the first 1000 km east of Japan (Fig. 5b), while the Gulf Stream (Fig. 4b) and ARC...
have high covariance that extends farther downstream with a smaller meridional extent. However, the lead–lag $C_{TQ}(x, y, \tau)$ and $C_{TtQ}(x, y, \tau)$ structures of the Kuroshio Extension (Fig. 5) and ARC (Fig. 6) resemble those of the Gulf Stream (Fig. 4). Notably, the ARC region has covariance closer to zero at zero lag for $C_{TtQ}(x, y, 0)$ than the other WBC regions.

For comparison with Fig. 1, Fig. 7 shows the structure of the lagged correlations at locations within and equatorward of the WBC jets in each respective system (Figs. 4, 5, and 6). There is nothing special about these particular locations; they are typical of the respective regimes. Figures 7a,c,e show the lagged structure of $r_{TQ}(x, y, \tau)$ and $r_{TtQ}(x, y, \tau)$ in the regions outside of the WBC jets away from strong meridional SST gradients. The solutions in Fig. 1a are superimposed for comparison with the idealized case. Lagged correlations using the J-OFURO product are also superimposed, which show consistency with OAFlux but are a little noisier. Differences between OAFlux and J-OFURO for the same averaging period (2002–07) are smaller (not shown), which implies that the shortness of the J-OFURO record is the main source of difference between lag correlation functions rather than the native resolution of the products. The lead–lag structures of $r_{TQ}$ and $r_{TtQ}$ in the North Atlantic, North Pacific, and southern Indian Ocean subtropical gyre interiors all have a structure indicative of atmosphere-driven SST variability.

Figures 7b,d,f show the lagged structure of $r_{TQ}$ and $r_{TtQ}$ for locations within the WBC jets marked by strong climatological meridional SST gradients. Like in Figs. 7a,c,e, Figs. 7b,d,f have the solutions in Fig. 1b superimposed. Here the lead–lag structures of $r_{TQ}$ and $r_{TtQ}$ in the Gulf Stream, Kuroshio Extension, and ARC all correspond to the ocean-driven SST variability scenario.

For completeness the seasonal cycle of covariance was explored. Though not a focus of this paper, the covariance between SST and SHF does exhibit a seasonal cycle (Fig. 8), as expected from previous studies (Wu and Kirtman 2007; Wu and Kinter 2010). Positive covariance is found to be highest during winter months as seen for the Gulf Stream and Kuroshio Extension in boreal winter (Figs. 8a,d) and the ARC for austral winter (Figs. 8b,c). The Southern Ocean does not vary as much between seasons as the midlatitude Northern Hemisphere, which can be seen by comparing Figs. 8a and 8c, but is weakest during the transition from austral spring to summer (Fig. 8d). The reason covariance is highest during winter months stems from...
higher-amplitude SHF anomalies when SST meridional gradients are enhanced. The seasonal cycle in the tropics is less pronounced than in the midlatitudes, likely due to our efforts to remove SST variability associated with ENSO.

b. Spatiotemporal dependence of lagged covariance

1) TIME-SCALE DEPENDENCE

Figure 9 shows the lagged correlation within the Gulf Stream, Kuroshio Extension, and ARC as a function of time scale (low-pass filter cutoff). At zero lag \( r_{TQ} \) increases with time scale to greater than 0.5 for the Gulf Stream (Fig. 9a) and greater than 0.75 for the Kuroshio Extension and ARC at 21-month time scales (Figs. 9b,c). The lagged symmetric structure broadens as a result of filter cutoff with correlations of 0.25 occurring at ±6- to 8-month lags at 21-month time scales compared to near zero at 1-month time scales.

At zero lag \( r_{TQ} \) remains close to zero but has an asymmetric lagged structure that also broadens with increasing filter cutoff (Figs. 9d–f). The positive correlation with SST tendency leading increases with time scale with peak correlation being greater than 0.25 for the Gulf Stream (Fig. 9d) and 0.5 for the Kuroshio Extension and ARC (Figs. 9e,f) at −6- to −6-month lags. When SST tendency lags, correlation similarly decreases with minimum correlation being less than −0.25 for the Kuroshio Extension (Fig. 9e) and less than −0.5 for the Gulf Stream and ARC (Figs. 9d,f) occurring at 6–8-month lags for 21-month time scales compared to near-zero correlation at 1-month time scales.
2) SPACE-SCALE DEPENDENCE

Figure 10 shows the lagged correlation functions within the WBC jets as a function of space scale with no temporal filtering. The lagged structure of $r_{TQ}$ is symmetric and narrows at increasing spatial scale until a critical spatial scale (Figs. 10a–c) where it transitions to asymmetric. At zero lag $r_{TQ}$ is greater than 0.25 for the Gulf Stream (Fig. 10a) and greater than 0.5 for the Kuroshio Extension and ARC (Figs. 10b,c) at spatial scales less than $\frac{3}{8}$ and decreases to zero for longer space scales. The transition length scale $L_c$ [Eq. (5)] varies between systems and occurs at critical spatial scales of $1.37 \pm 0.53$ (113 ± 44 km) for the Gulf Stream (Fig. 10a), $2.47 \pm 0.9^\circ$ (218 ± 79 km) for the Kuroshio Extension (Fig. 10b), and $1.94 \pm 0.77$ (162 ± 64 km) for the ARC (Fig. 10c). The method for determining $L_c$ is shown in Fig. 11. In this example the fourth-order polynomial fits to the Gulf Stream, Kuroshio Extension, and ARC for $r_{TQ}$ versus $\delta_c$ have a norm of the residuals of 0.12 for each current system and those for $r_{TtQ}$ versus $\delta_c$ have a norm of the residuals of 0.05, 0.07, and 0.05, respectively.

Maps of the Northern and Southern Hemisphere geographical distribution of $L_c$ in degrees is shown in Fig. 12. The $L_c$ is near zero over most of the ocean except in the WBCs, ACC, and along the west coast of Australia. The Gulf Stream and Kuroshio Extension have $L_c$ upward of $1^\circ$–$2^\circ$, while the ACC has values in excess of $3^\circ$ along the ARC.

3) TIME- AND SPACE-SCALE DEPENDENCE

Correlation at zero lag as a function of $\delta_c$ up to $10^\circ$ and $t_c$ up to 12 months is shown for the Gulf Stream, Kuroshio Extension, and ARC in Fig. 13 at the same locations used in Figs. 9 and 10. The $r_{TQ}$ increases with increasing time scale but decreases with increasing spatial scale (Figs. 13a–c). At time scales up to annual (12 months) the correlation has values in excess of 0.5 for the Gulf Stream and 0.75 for the Kuroshio Extension and ARC for small spatial scales as in Fig. 9 but decreases to near zero with increasing spatial scale. The $r_{TtQ}$ is negative or close to zero and continues to approach zero with increasing time scale but becomes more negative with increasing spatial scale (Figs. 13d–f). The transition length scale $L_c$ is shown in Fig. 13 and increases with increasing time scale for the Gulf Stream, Kuroshio Extension, and ARC over $1.37^\circ$–$2.00^\circ$.
(113–166 km), 2.47°–4.40° (218–388 km), and 1.94°–2.48° (162–207 km), respectively.

6. Discussion

Outside of regions with high mean climatological SST gradients, the ocean is best represented by the atmosphere-driven model (Fig. 1a) at all time and spatial scales under consideration in this study. In the WBCs and Southern Ocean ACC, SST variability is best represented by ocean-driven processes. Notably these are regions with highest climatological mean SST gradients and turbulent heat fluxes from the ocean to atmosphere in the ocean (Fig. 2).

One way to think about the time- and space-scale dependence of air–sea interaction in these regions is to compare the simple energy balance equation for SST [Eq. (2)] with the mixed layer temperature equation:

\[ \frac{dT_v}{dt} = \frac{Q_o}{\rho_o c_p h} - \nabla \cdot (u_v T_v) + F, \tag{6} \]

where \( T_v \) is the vertically averaged temperature within the mixed layer and representative of SST, \( Q_o \) is the net turbulent heat flux, \( \rho_o \) is a constant reference density for a Boussinesq fluid, \( c_p \) is the specific heat of seawater at constant pressure, \( h \) is the mixed layer depth, \( u_v \) is the vertically averaged horizontal velocity within the mixed layer, and \( F \) represents all other terms in the mixed layer temperature equation, including, for example, mixing and vertical entrainment at the base of the mixed layer [see Cronin et al. (2013) and references therein for the full mixed layer temperature equation]. Comparing Eq. (2) with Eq. (6), the stochastic forcing term in Eq. (2) \( N_o \) represents the advection of SST [second term on RHS in Eq. (6)] and damping \( -\gamma_o T_o \) is included in \( F \).

For the moment let us ignore \( F \) and consider the three-way balance in the mixed layer temperature equation between SST tendency, turbulent heat fluxes, and the advection of SST. In regions of weak SST gradients it is clear that advection would be small and SST tendency would be driven by turbulent heat fluxes (atmosphere-driven model). Essentially, if the ocean loses heat from the mixed layer, SST cools. Another scenario would be where SST gradients are not weak, which will disrupt this relationship by contributions from advection. With increasing time scales SST tendency will diminish. If SST tendency is negligible in
the regions of strong SST gradients, SST anomalies will be correlated with turbulent heat flux anomalies. Recent work shows that the advection of SST in the mixed layer is an important contribution to the upper-ocean heat content in the WBCs, marked by strong meridional SST gradients (Roberts et al. 2017). The relationship between oceanic stochastic forcing and advection can be seen by comparing Figs. 10 and 1. The SST–SHF and SST tendency–SHF lagged correlation as a function of oceanic stochastic forcing and spatial-scale $\delta_c$ make similar transitions from ocean-driven to atmosphere-driven SST variability. A reduction in oceanic stochastic forcing can be thought of similarly as the spatial-scale smoother, which reduces SST gradients and removes contributions from advection. Since advection represents the nonlinear term in the mixed layer temperature equation, this is the term in which “oceanic weather” arises. This work aims to determine the time and space scales at which anomalous advection becomes negligible.

The spatial scale is associated with the area $A$ over which the upper-ocean temperature budget [Eq. (6)] is to be integrated. At the basin scale it is expected that advection will vanish. By definition from the divergence theorem, the divergence of temperature flux vanishes at the scale of an ocean basin with closed boundaries. However, the scale at which the divergence of the heat flux becomes negligible may be significantly smaller than the basin scale. The oceanic noise term represents a

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**Fig. 10.** Space-scale dependence of lagged correlation in the Western Boundary Current Extensions using monthly data with no low-pass filtering. SST–SHF lagged correlation for the (a) Gulf Stream, (b) Kuroshio Extension, and (c) Agulhas at the locations in Figs. 7b, 7d, and 7f, respectively. (d)–(f) As in (a)–(c), but for SST tendency–SHF lagged correlation. Black and gray contours are positive and negative correlations, respectively ($\rho = 0.25$), and the black dashed contour is the zero correlation contour. The green circle is the transition length scale.

**Fig. 11.** Method for determining the transition length scale $L_c$. Solid curves are best fit to $\tau_{Q0}$ and dashed curves are best fit to $|\tau_{Q0}|$ at monthly time scales as a function of space scale $\delta_c$ at the WBC locations in Fig. 10. Open circles are the raw data, and larger colored circles are the intersection locations [Eq. (5)].
redistribution of heat within the ocean, not a source or sink. At sufficiently large scale, the ocean transient eddy fluxes integrated through the boundary of the domain become small relative to the other terms in the balance.

In this work we have developed a metric for determining what scales are important to capture ocean-driven SST variability by calculating $L_c$ [Eq. (5)]. This metric shows that length scales smaller than 100–400 km (Fig. 12) are important for capturing ocean-driven SST variability but that $L_c$ also depends on time scale as well (Fig. 13). One of the intriguing results is that this transition length scale varies widely geographically (Fig. 12).

![Fig. 12. Transition length scale $L_c$ at monthly time scales (color contours). Black contours are the climatological mean SST.](image1)

![Fig. 13. Space vs time scale dependence of SST–SHF and SST tendency–SHF correlation at zero lag. SST–SHF correlation in the (a) Gulf Stream, (b) Kuroshio Extension, and (c) Agulhas at the locations in Figs. 7b, 7d, and 7f, respectively. (d)–(f) As in (a)–(c), but for SST tendency–SHF correlation. Black and gray contours are positive and negative correlations, respectively ($ci = 0.25$), the black dashed contour is the zero correlation contour, and the magenta contour is the transition length scale.](image2)
Notably, the Kuroshio Extension transitions from ocean- to atmosphere-driven SST variability at longer length scales and also increases more with time scale (Fig. 13) than the Gulf Stream. The Kuroshio Extension exhibits interannual to decadal variability in its meridional jet axis position and meander amplitude that lags the Pacific decadal oscillation by 3–4 years (Qiu and Chen 2005). It is possible that the meridional migration of the Kuroshio Extension axis is imprinted in the calculation of $L_c$, especially at longer time scales. The ACC has also been shown to have variability characterized by coherent shifts in frontal position and merging and splitting of the multiple jets within the broader ACC system (Thompson et al. 2010; Thompson and Richards 2011). The longer transition length scales in some parts of the ACC might be associated with this type of variability. Future work will explore how frontal versus eddy variability impacts $L_c$.

7. Conclusions

In this work we found that the simple energy balance model for the coupled ocean–atmosphere system [Eqs. (1) and (2)] model works well for describing the nature of air–sea interaction in the midlatitude ocean, based on results derived from state-of-the-art analyses of SST and SHF. The ocean exhibits ocean-driven SST variability in regions of high climatological mean SST gradients and SHFs. These regions specifically are the WBCs and Southern Ocean ACC. The lagged correlation between SST and SHF is positive and symmetric about zero lag for lags ±12 months, while the correlation between SST tendency and SHF has a near-zero simultaneous correlation with an asymmetric lagged structure about zero lag using monthly averaged NOAA OISST and OAFlux data products from 1985 to 2013 (Figs. 7b,d,f). This follows the solutions to Eqs. (1) and (2) in Fig. 1b for strong oceanic stochastic forcing. This result is in contrast to previous work arguing that the ocean is passive and that SST variability is driven by the atmosphere (e.g., von Storch 2000). Outside of the WBC regions and Southern Ocean ACC (e.g., subtropical gyres) where climatological mean SST gradients are weak, the ocean does indeed exhibit the atmosphere-driven SST variability described in von Storch (2000) (Figs. 7a,c,e).

After applying spatial filtering from 0.5° to 10° and temporal filtering up to annual time scales to the SST and SHF data products it was found that the WBC regions and Southern Ocean ACC transition from ocean-to atmosphere-driven SST variability at spatial scales ranging from 1° to 4° using Eq. (5) as a metric for this transition. The transition length scale increased with time scale, most notably for the Kuroshio Extension in the WBCs. By comparing Figs. 1 and 10 it is clear that stochastic ocean forcing and anomalous advection of SST correspond.

Capturing the influence of “oceanic weather” poses a significant challenge in coupled climate models. Current climate models typically have spatial resolution near 1°. While this might allow the representation of the larger spatial scale and lower-frequency end of oceanic weather (Fig. 13), the models in this resolution range lack the dynamics that gives rise to the anomalies of upper-ocean advection. These effects are instead parameterized in an ensemble sense as an aggregate effect on tracer transports without providing an explicit source of variability. Recent work has highlighted the importance of representing the variability in air–sea fluxes arising from mesoscale eddies (e.g., Ma et al. 2016; Bishop et al. 2015) on larger-scale dynamics. Future work needs to be focused on how to represent the variability in small-scale air–sea interaction effects of mesoscale eddies in coupled climate models.

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APPENDIX

Solution to Simple Local Energy Balance Model

The solutions to Eqs. (1) and (2) shown in Fig. 1 were found using a forward-difference approximation to the temperature tendency and using initial conditions of $T_a^0 = T_o^0 = 0$:

$$T_a^{n+1} = [1 - (\alpha + \gamma_o)\Delta t]T_a^n + \alpha \Delta t T_o^n + \Delta t N_o^n,$$

and

$$T_o^{n+1} = [1 - (\beta + \gamma_o)\Delta t]T_o^n + \beta \Delta t T_a^n + \Delta t N_a^n.$$  \hspace{1cm} (A1)

The stochastic ocean and atmospheric forcing are represented as a forcing frequency $\omega$ times a Gaussian
random number generator for temperature anomalies between \( \pm 1^\circ C \). The atmospheric forcing frequency \( \omega_a \) was set to 1 day\(^{-1} \) while the ocean forcing frequency \( \omega_o \) was set to 1/500 day\(^{-1} \) for atmosphere-driven (Fig. 1a) and 1/5 day\(^{-1} \) for ocean-driven (Fig. 1b). The \( \omega_o \) was varied from 10\(^{-5} \) to 10\(^{-1} \) day\(^{-1} \) to produce Figs. 1b,c. A time series 60,000 days long of \( T_a \) and \( T_o \) was generated using a time step \( \Delta t \) of 1 day. Temperatures \( T_a \) and \( T_o \) were then 30-day averaged to create a monthly time series, and \( dT_a /dt \) was estimated from the monthly data using a central-difference approximation. Correlations of \( T_o \) and \( dT_o /dt \) with turbulent heat fluxes \( \beta(T_a - T_o) \) were then calculated using parameters appropriate for the atmosphere-driven (Fig. 1a) and ocean-driven systems (Fig. 1b) based on values used in the literature (Wu et al. 2006; Barsugli and Battisti 1998) and are listed in Table 1.

REFERENCES


