Mechanisms Governing Interannual Variability of Upper-Ocean Temperature in a Global Ocean Hindcast Simulation

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ABSTRACT

The interannual variability in upper-ocean (0–400 m) temperature and governing mechanisms for the period 1968–97 are quantified from a global ocean hindcast simulation driven by atmospheric reanalysis and satellite data products. The unconstrained simulation exhibits considerable skill in replicating the observed interannual variability in vertically integrated heat content estimated from hydrographic data and monthly satellite sea surface temperature and sea surface height data. Globally, the most significant interannual variability modes arise from El Niño–Southern Oscillation and the Indian Ocean zonal mode, with substantial extension beyond the Tropics into the midlatitudes. In the well-stratified Tropics and subtropics, net annual heat storage variability is driven predominately by the convergence of the advective heat transport, mostly reflecting velocity anomalies times the mean temperature field. Vertical velocity variability is caused by remote wind forcing, and subsurface temperature anomalies are governed mostly by isopycnal displacements (heave). The dynamics at mid- to high latitudes are qualitatively different and vary regionally. Interannual temperature variability is more coherent with depth because of deep winter mixing and variations in western boundary currents and the Antarctic Circumpolar Current that span the upper thermocline.

Net annual heat storage variability is forced by a mixture of local air–sea heat fluxes and the convergence of the advective heat transport, the latter resulting from both velocity and temperature anomalies. Also, density-compensated temperature changes on isopycnal surfaces (spice) are quantitatively significant.

1. Introduction

The ocean exhibits significant low-frequency variability across a range of spatial scales from subgyre to global. Some of the most prominent nonseasonal signals are in upper-ocean temperature structure, often associated with large-scale climate modes such as El Niño–Southern Oscillation (ENSO), the North Atlantic Oscillation, and the Pacific decadal oscillation. Interannual to decadal variations in sea surface temperature (SST) and upper-ocean heat storage potentially have important climate implications, and substantial observational efforts are now underway to monitor the temporal evolution of upper-ocean thermal structure using XBTs, altimetry, and profiling floats (e.g., White 1995; White and Tai 1995; Willis et al. 2003). Reconstructions of past historical variations have been used extensively to characterize ocean thermal variability (e.g., Deser et al. 1996; Willis et al. 2004), but such efforts are often limited by the sparsity of in situ data. Numerical hindcast simulations (e.g., Maltrud et al. 1998) offer an alternative approach that also allows for direct examination of the underlying mechanisms.

A number of physical processes contribute to the generation of interannual upper-ocean temperature anomalies. Locally, changes in air–sea heat fluxes alter ocean heat storage, and year-to-year variations in
ocean boundary layer mixing affect the vertical distribution of heat and thus SST. Alterations in the magnitude and pattern of wind stress curl drive local vertical displacements of the thermocline through changes in Ekman pumping while, on gyre to basin scales, wind field variability leads to reorganizations in the wind-driven circulation (e.g., Sverdrup balance) and to changes in the lateral advection of heat. The temperature profile at a particular location can be strongly influenced by atmospheric forcing at a remote location either via wave dynamics (e.g., fast Kelvin waves along the coasts and equatorial waveguide and slower Rossby waves in the interior) or formation and advection of anomalous water mass properties. Many of these physical processes interact, and the relative contributions across regions and time are not well delineated.

Here we quantify the pattern, magnitude, and mechanisms governing interannual variability in upper-ocean temperature for the period 1968–97 from a global ocean hindcast simulation (Doney et al. 2003). One aspect that differentiates this study from earlier work is the combination of a global spatial domain, multidecadal duration, and consistent heat, freshwater, and momentum forcing, to the extent possible, based on atmospheric reanalysis and assorted satellite data products (section 2). We show that the simulations exhibit statistically significant skill in capturing the observed interannual variability in hydrographic data (Levitus et al. 1998), monthly satellite SST (Smith et al. 1996), and sea surface height (SSH) (Cheney et al. 2000), the satellite data spanning approximately the final one to two decades of the simulation (section 3). In section 4, we partition the vertically integrated, annual net heat storage anomalies into the contributions from air–sea heat flux and the convergence of the advective heat transport. We also decompose the model upper-ocean salinity and temperature anomalies into components due to density preserving variability in water properties on isopycnal surfaces (spice) and vertical and lateral displacements (heave). We conclude with a summary and discussion (section 5).

2. Ocean hindcast simulation

a. Ocean model and surface forcing

As detailed in Doney et al. (2003), a multidecadal ocean hindcast simulation is conducted for the period 1958–97 using the ocean component of the National Center for Atmospheric Research (NCAR) Climate System Model (CSM-1) (Large et al. 1997; Gent et al. 1998). The global ocean general circulation model is non-eddy-resolving with a zonal resolution of 2.4° and variable meridional resolution, ~0.6° at the equator increasing to ~1.2° poleward of 30°. The model has a z coordinate with 45 levels with grid spacing increasing from about 8 to 258 m at depth. The model incorporates Gent–McWilliams (GM) mesoscale eddy mixing (Gent and McWilliams 1990; Danabasoglu et al. 1994), K-profile parameterization (KPP) surface boundary layer dynamics (Large et al. 1994), air–sea bulk flux forcing (Large et al. 1997; Doney et al. 1998), and a spatially varying, anisotropic horizontal viscosity scheme (Large et al. 2001).

The model is driven by the net surface fluxes of momentum \(\tau\), heat \(q_{net}\), and freshwater following the general form of Large et al. (1997). The atmosphere–ocean fluxes dominate in regions of greatest interest (ice free and away from river mouths), so they have received the most attention. Historical atmospheric data for the 40-yr period 1958–97 are reconstructed based on the 6-hourly National Centers for Environmental Prediction (NCEP)–NCAR atmospheric reanalysis data (surface winds, air temperature, and humidity) (Kalnay et al. 1996) supplemented by monthly satellite estimates of cloud fraction (Rosso and Schiffer 1991), surface insolation (Bishop and Rosso 1991; Bishop et al. 1997), and precipitation (Xie and Arkin 1996; Spencer 1993). The satellite forcing datasets cover only a portion of the full 40-yr historical period: radiation and clouds (July 1983–June 1991) and precipitation (1979 and later). In the periods with no satellite coverage, we use the long-term monthly climatological values.

The air–sea fluxes are calculated from these data using traditional bulk formulas (NCAR Oceanography Section 1996) and the model SST. The monthly data are interpolated to the reanalysis times, and the coupling interval for model forcing is once a day. An important feature of this bulk forcing scheme is that open-ocean heat flux and evaporation represent best estimates of the true fluxes whenever and wherever the model SST is correct, but this state can be maintained only if the ocean heat transport is well represented. Small adjustments are made globally to solar insolation, surface humidity, and precipitation to balance the long-term heat and freshwater (salinity) budgets. The model forcing for river runoff, sea ice concentration, and ice–ocean fluxes are described in more detail in Large et al. (1997). They are relatively unsophisticated, so oceanic variability in regions significantly impacted by those processes is not expected to be well reproduced.

The physical model is integrated with historical forcing over four 40-yr forcing cycles (160 yr total). The spinup procedure reduces, but does not eliminate, model drift, especially in the lower thermocline and deep waters (Fig. 1). We focus our analysis on upper-ocean variability for the final 30 yr of the last forcing
Our emphasis is on the global scale. More regional analyses are presented in related works (e.g., Lysne and Deser 2002; Capotondi and Alexander 2001; McWilliams and Danabasoglu 2002; Yeager and Large 2004; see also Spall et al. 2000).

b. Satellite and in situ evaluation data

Observational data are crucial for evaluating the model-forced historical variability. The simulated temperature fields are compared with 1° × 1° gridded, annual mean estimates from the National Oceanographic Data Center (NODC) World Ocean Atlas 1998 (WOA98) (Levitus et al. 1998, 2000b), generated from vertical profiles from bottle data, CTDs, MBTs, and XBTs. Yearly mean fields of integrated heat content (0–400 m) are also derived from the NODC dataset. The subsurface data coverage, particularly prior to the late 1960s and in the Southern Hemisphere, has significant temporal and spatial gaps. Further, choices made in the treatment of data (e.g., quality control, inter-polation scales) can result in divergent interannual variability estimates (Chepurin and Carton 1999; Lysne and Deser 2002) between comparable historical reconstructions (White 1995; Levitus et al. 1998). The model–data temperature comparisons should be viewed as a joint evaluation of two imperfect records, with neither presumed a priori a better measure of reality.

Salinity data are not available with sufficient time/ space coverage to generate global maps of interannual variability. Model–data salinity comparisons are further complicated by uncertainties in the prescribed precipitation as illustrated by Béranger et al. (2006), who show that there is a large scatter among various historical climatologies. However, their choice for forcing ocean models is the composite Xie and Arkin (1996) product used here. In Doney et al. (2003) comparisons are made against regional estimates, in particular the Etudes Climatiques de l’Océan Pacifique (ECOP) monthly tropical Pacific surface salinity fields (Delcroix et al. 2000). A model–data comparison limited to late 1975–early 1992, a period of relatively complete sampling coverage, shows good general agreement in the spatial structure and magnitude and temporal variations of the monthly sea surface salinity (SSS) anomaly variability.

Monthly satellite time records are utilized to evaluate SST [blended Advanced Very High Resolution Radiometer (AVHRR) and in situ data product; Smith et al. 1996] and SSH [gridded monthly Ocean Topography Experiment (TOPEX)/Poseidon (T/P) altimeter anomaly data product; Cheney et al. 1997, 2000]. The Reynolds–Smith (R/S) SST product is on a 1° × 1° grid and is available from November 1981. The gridded T/P anomaly fields (4° longitude × 1° latitude boxes) are available from October 1992. We further smooth the T/P data to eliminate some grid-scale features in favor of large spatial scales, using three passes of a local, five-point Gaussian filter. Note that the satellite datasets provide relatively complete spatial coverage but are available only for the latter part of the simulation period.

3. Evaluation of model skill

Model–data evaluation in this section is based on direct comparisons of some property $X$ at identical loca-
tion and time in the observations and hindcast; that is, $X_{\text{model}}(x, y, t)$ versus $X_{\text{obs}}(x, y, t)$. When observational sampling is sufficiently dense and spatially extensive, empirical orthogonal functions (EOFs) and their principal component (PCs) time series are preferred to display concisely the most important spatial and temporal variability in the model and observations. The PC time series are normalized to have a variance of 1.0, and the projection of the original data onto an EOF at any particular point in time is recovered by $PC(t) \times EOF(x, y)$. When the observational coverage is not uniform, with large regions/times with poor sampling, we instead map the spatial patterns of rms variability and the local point cross correlation of the model and observations over time.

One measure of model skill is whether the correlation between the model and observed variability is statistically significant; that is, is the absolute value of the linear correlation coefficient $|r|$ greater than that expected statistically for two uncorrelated, random variables. We evaluate the statistical significance of $r$ for the PC time series, EOF spatial patterns, and local point temporal cross correlations using a two-tailed test at a significance level of 0.05 (95% confidence level) (Bevington and Robinson 2003). For example, the threshold value is $|r_{\text{crit}}| > 0.361$ for a comparison of 30 yr of model and data annual means (1968–97). We also assess the impact of the reduction in the effective degrees of freedom in the linear correlation analysis due to low-frequency variability (i.e., time/space autocorrelation) (Emery and Thomson 2004).

The analyses utilize monthly mean properties $X$, from which we compute annual means $\overline{X}$, long-term means $\langle X \rangle$, and mean annual cycles $X''$ (i.e., mean January, mean February, etc.). Various anomalies are then formed:

$$X' = \overline{X} - \langle X \rangle,$$

$$X'' = X - \langle X \rangle,$$

$$X* = X - X'',$$

where $X'$ are the annual mean anomalies, $X''$ are the monthly anomalies, and $X*$ are the monthly deseasonalized anomalies. To exclude some particularly data sparse years and transients resulting from cycling back from 1997 to 1958 forcing, we focus solely on the the 30-yr span 1968–97.

a. Sea surface height

With the availability of nearly global coverage from satellite altimeters, SSH variability provides a useful metric for evaluating the hindcast. On scales larger than the mesoscale (>500 km), the dominant factors contributing to intraseasonal and interannual SSH variations include barotropic and baroclinic adjustments to surface wind stress variations and steric anomalies due to heat and freshwater surface fluxes and lateral heat and freshwater convergence.

A main focus here is on the SSH signatures generated by interannual variability in upper-ocean temperature or equivalently heat content. Because seawater expands as it warms, a positive monthly deseasonalized temperature anomaly $T*$ results in a positive SSH anomaly $\eta*$:

$$\eta* = \int_{0}^{-z_{0}} \alpha T* dz,$$  \hspace{1cm} (2)

where $\alpha$ is the thermal expansion coefficient, and $z_{0}$ is an appropriate upper-ocean depth scale. For an $\alpha$ appropriate to the tropical and midlatitude upper thermocline ($T = 15^\circ C$), a uniform 0.1°C anomaly over the upper 400 m leads to an $\eta* \approx 1$ cm; as $\alpha$ drops sharply with temperature, the steric SSH anomaly for the same temperature anomaly at polar latitude would be 3–4 times smaller. A similar calculation could be done to estimate the generally smaller effect of freshwater (salinity) anomalies on $\eta*$ using $\beta S*$.

To reduce the data size for the EOF analysis, the model SSH is binned in boxes $7.2^\circ$ in longitude, varying between $1.2^\circ$ and $2.4^\circ$ in latitude. The monthly T/P SSH is binned in latitude using $2^\circ$ boxes. The first two EOFs, accounting for about one-half of the respective variances (47% for T/P and 55% for model), are presented in Fig. 2 together with the principal component time series. The majority of the monthly rms variability in the model deseasonalized SSH signal from the model arises because of dynamic adjustments to surface wind forcing and resulting advective redistribution of upper-ocean heat and salt content, consistent with previous findings (e.g., Stammer 1997; Fu 2003).

The hindcast simulation reproduces well the dominant space/time patterns of SSH variability seen in the T/P data, particularly in the Tropics. The agreement of principal component time series is quite encouraging, with temporal model–data correlations of 0.99 and 0.98 for EOF1 and EOF2, respectively. EOF1 is well separated from EOF2 and is associated with ENSO variability. The onset and evolution of the 1997 ENSO event is clearly depicted in the EOF1 principal component time series. The second EOF is weaker and concentrated in the Indian Ocean, with a stronger extension into tropical South Pacific in the observations than in the model; EOF2 is sometimes referred to as the Indian Ocean zonal mode (e.g., Saji et al. 1999; Yu and
EOF1 and EOF2 also contain smaller-amplitude, far-field signals in the midlatitudes with some commonalities between the model and data (e.g., positive band in midlatitude North Atlantic in EOF2).

The amplitude of the model EOF1 SSH variability is somewhat weaker (25%–30%) than observed in the T/P data, and some of the observed extratropical EOF patterns are not fully captured by the model. Similar results with weak model variability have been seen in comparison studies involving finer-resolution simulations (Stammer et al. 1996; Stammer 1997). The issue is most striking in western boundary currents and the Antarctic Circumpolar Current (ACC). Inadequacy of the surface wind-forcing fields may also play a role in both the Tropics and extratropics.

b. Sea surface temperature

Another key criterion for assessing hindcast simulations is the ability of the model to accurately reconstruct variability in sea surface temperature, as this is the principal route by which the ocean influences the atmosphere and a necessary condition for proper air–sea fluxes and water mass formation. There is excellent model–data agreement in the spatial EOF patterns and PC time series with the monthly R/S SST satellite data.
product (1982–97) (Fig. 3). The first SST EOF captures 20%–25% of the total variance and displays the classic ENSO pattern, with anomalies in the eastern tropical Pacific and along the North American west coast out of phase with those in the western tropical Pacific and subtropical gyres (Neelin et al. 1998). The second EOF (6%–8% of total variance) projects more into the temperate and subpolar North Pacific and North Atlantic. Quantitative measures of model skill are high with spatial and temporal correlations of 0.96 and 0.98 (EOF1) and 0.84 and 0.89 (EOF2). Similar spatial variability patterns and model–data agreement are found for annual mean SST anomalies from the model and the in situ WOA98 data for the full analysis time period (1968–97; Doney et al. 2003).

The model skill in replicating observed SST interannual variability could, in theory, represent compensating errors in model physics and surface heat fluxes. For ocean models forced by a prescribed atmospheric state, the atmosphere has a large effective heat capacity, and the ocean SST will, perhaps incorrectly, closely track the prescribed air temperature (e.g., Seager et al. 1995). To examine this issue, we include here a short diversion into the mechanisms underlying interannual SST variability. Figure 4 displays the correlation coefficient at each model grid point between the annual average heat

Fig. 3. Spatial maps of the (left) first and (right) second EOF mode for the (top) model and (middle) R/S monthly SST anomalies (1982–97) after removal of the average seasonal cycle. The spatial pattern correlation is 0.96. The contour interval is 0.2°C, and the variances associated with each EOF are given as percentages of the respective total variances. (bottom) The time series of the Reynolds–Smith (red) and model (black) first-mode principal components.

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flux anomaly and change in SST for the corresponding year. The “observational” fluxes are obtained by simply replacing the model SST with R/S SST in the bulk forcing procedure. The spatial patterns in the model and observation correlation maps are similar but with lower correlation values in the observations, perhaps due to measurement error and data sparseness in either the SSTs or atmospheric forcing and because in the model surface fluxes do not alter the air temperature and humidity as they do in nature.

High positive correlations, such as in the subtropics, indicate regions where interannual SST variability could result largely from the specified atmospheric forcing. At midlatitudes the correlation tends to be
lower, suggesting at least some role for ocean processes, for example, variability in the effective depth to which surface fluxes are mixed or lateral circulation. Negative correlations occur at high latitudes where sea ice processes appear to play a dominant role; colder SSTs are indicative of ice formation, which tends to reduce air–sea heat loss leading to negative correlation. There are also significant regions of high negative correlation along the equator of both the Atlantic and Pacific basins. The negative correlation arises when the ocean surface is cooling despite anomalous surface flux warming, or the reverse. This can only occur if internal ocean processes are generating the SST changes. The surface heat flux anomalies are then likely a response, in part, to the SST anomalies, and in terms of the upper-ocean heat budget are acting to damp the ocean-driven variability, cooling warm anomalies and heating cold ones.

To demonstrate, consider the thermal budget for the tropical Pacific, shown in more detail in Fig. 5 as a time series of the first EOF principal components for the model and diagnosed net surface heat fluxes (upper panel) and the model net surface heat flux and temporal derivative of model SST (lower panel). The similarity of the model and diagnosed net heat flux EOFs, indicative of ENSO variability, is marked by high spatial pattern (0.73; Doney et al. 2003) and temporal (0.79) correlations over the eastern tropical Pacific. The temporal heat flux correlation is somewhat lower than that for the first SST EOF (0.98; Fig. 3, left panels) because of nonlinearities in the heat flux calculation and the different spatial domains. The \( r_{\text{crit}} \) value would be 0.14 for the temporal correlation with \( N = 192 \) samples if the individual months were independent. In actuality, the effective degrees of freedom are closer to \( \sim 16 \) due to the temporal autocorrelation of about a year; this leads to a revised \( r_{\text{crit}} \approx 0.47 \), which is still greatly below the observed value of 0.79. A similar exercise for the spatial EOF patterns comes to the same basic conclusion, balancing the large number of grid points with the reduction in degrees of freedom due to the spatial correlation scales (500–5000 km depending on meridional or zonal direction).

If SST in the model was simply being driven by net surface heat fluxes, one would expect a positive correlation near 1 for \( \partial \text{SST}/\partial t \) and \( q_{\text{net}} \); in fact, the correlation for the tropical Pacific is essentially zero (0.004). The warming associated with the ENSO events of 1982–83, 1986–87, 1991–92, and 1997–98 is accompanied by negative (cooling) net heat flux, as indicated by the shading in Fig. 5. There are also significant regions of high nega-

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**Fig. 5.** Time series of the first EOF principal components (1982–97) for the thermal budget for the tropical Pacific (from 10°S to 10°N east of 150°E). (top) The model (solid) and diagnosed (dashed) net surface heat flux \( q_{\text{net}} \) EOFs, where the diagnosed fluxes are computed using the R/S SST and the same atmospheric forcing as the model simulations. (bottom) The first EOFs for model net surface heat flux (solid) and the temporal derivative of the model SST, \( \partial \text{SST}/\partial t \) (dashed). Shading denotes periods when the model temporal derivative is opposite in sign to the net heat flux.
tive correlation along the equator of both the Atlantic and Pacific basins. The out-of-phase SST–heat flux relationship shows that the model net heat flux anomalies are mostly a response to increasing SST (not the reverse) and that the model SST signal (and thus model–data skill) reflects success in replicating the oceanic physics.

c. Heat content and subsurface temperature

We utilize integrated annual-mean heat content anomalies from the surface to 400 m as a third evaluation metric for the hindcast. Heat content provides a single, compact method for displaying upper-ocean temperature variability, and variability in upper-ocean heat content can be estimated with some confidence from observations over many parts of the ocean. The annual mean heat content anomaly $H'$ is computed from

$$H' = \int_0^{400} \rho c_p T^* dz,$$

where $c_p$ and $\rho$ are the specific heat and density. The uniform temperature anomaly of 0.1°C discussed above for scaling $\eta^*$ anomalies with representative $c_p$ and $\rho$ values produces $H' \approx 0.16 \text{ GJ m}^{-2}$; an anomaly of this size would be generated by a net surface heat flux anomaly of about 5 W m$^{-2}$ applied over a full year.

The main spatial patterns of rms($H'$) (Fig. 6) are comparable across the hindcast and WOA98 data, with maxima in the tropical Indo–Pacific, western boundary currents, Southern Ocean, and subpolar North Atlantic. The spatial patterns of SST and heat content variability differ considerably. In the Tropics, temperature variability shifts progressively westward and off equator moving down the water column, decoupled from the surface due to stratification. In the extratropics, temperature anomalies are more coherent in the vertical because of deep winter mixing and because the variability in the location and strength of the western boundary currents and the ACC tend to span the upper thermocline.

Relative to WOA98, the model heat content variability in the tropical Pacific is more localized into discrete, zonal off-equatorial bands (Lysne and Deser 2002). The hindcast also contains considerably weaker variability in the Agulhas retroreflection and Brazil–Malvinas confluence, which almost certainly reflects the fact that the coarse-resolution model is still too viscous to capture fully the dynamics in these regions. The model variability is lower than that in WOA98 along the Antarctic Circumpolar Current in the Southern Ocean, but here the model–data differences likely are a combination of model and forcing errors together with inadequate in situ sampling.

The model–data cross correlations for the local annual heat storage anomalies (Fig. 6, bottom panel) are large and significant ($>0.6$) in the North Pacific, tropical Pacific, and northern North Atlantic. The comparison shows essentially no relationship in the Southern Ocean and the Brazil–Malvinas confluence, where the observed data coverage is more limited, and the field data provide poor estimates of heat content variability. Even specific features such as the sampling hole in the central and eastern tropical North Atlantic (Levitus et al. 1998; see also Fig. 2 in Doney et al. 2003) show up distinctly as minima in the cross-correlation field. An EOF analysis for 1968–97 of the annual heat content anomalies (not shown) highlights the same basic ENSO-driven tropical spatial patterns as found for the SSH analysis.
4. Dynamics of interannual variability

We then use the model solutions to explore the mechanisms generating the variability, focusing on interannual variability of the dominant upper-ocean heat budget terms. For many ocean regions, subsurface observations are too sparse to reconstruct historical variations in the storage, ocean transport, and, to some extent, even surface flux terms. The hindcast simulation, on the other hand, computes a dynamically consistent, closed heat budget for the global ocean from which we can develop hypotheses testable against past and/or future observations on more regional scale.

a. Net annual heat storage anomalies

Over the course of a year, upper-ocean (400 m) heat content \( H \) changes by an amount \( \Delta H \), the net annual heat storage, due to the combined effect of the net surface heat flux and the divergence of ocean heat transport. From the hindcast simulation, we compute \( \Delta H \) over the depth interval 0–400 m (GJ m\(^{-2}\)) (or effectively the annual heat budget imbalance integrated over that depth range; see below) for each year at each grid point using monthly mean model output. Because model temperature was stored as monthly means rather than as instantaneous values at the end of months, \( \Delta H \) is computed using \( H \) values averaged for December and the following January. To remove the effects of any long-term model drift, net annual heat storage anomalies \( \Delta H' \) are computed by subtracting \( \langle \Delta H \rangle \) [Eq. (1)]. With this normalization, we also remove any net long-term, secular warming (Levitus et al. 2000a; Willis et al. 2004). The annual heat content anomaly (section 3c) is approximately the net integral over time of the past net annual heat storage anomalies, \( H' = \int \Delta H' \, dt \), differences arising from the different temporal averaging/analysis periods (cf. top panel, Fig. 7 with Fig. 6).

b. Partitioning heat budget variability by mechanism

We partition the contributions to the net annual heat storage anomalies (GJ m\(^{-2}\)) into specific physical components:

\[
\Delta H' = Q' + A' + E' + V' + R,
\]

where each of the terms on the right-hand side (rhs) are integrated in time over the year and, if appropriate, over depth (0–400 m). The rhs terms are given as the surface heat flux \( Q' \):

\[
Q = \int_t^{t+\Delta t} q_{\text{net}} \, dt,
\]

the vertical integral of the convergence of the resolved horizontal advective heat transport \( A \):

\[
A = - \int_t^{t+\Delta t} \int_{-400}^{0} \rho c_p \nabla_h \cdot (UT) \, dz \, dt,
\]

the vertical integral of the convergence of the eddy-parameterized horizontal advective heat transport \( E \):

\[
E = - \int_t^{t+\Delta t} \int_{-400}^{0} \rho c_p \nabla_h \cdot (U_{\text{bolus}} T) \, dz \, dt,
\]

and the vertical integral of the convergence of the resolved vertical advective heat transport \( V \):

\[
V = \int_t^{t+\Delta t} \rho c_p (WT)_{400 \, m} \, dt,
\]

where \( \Delta t = 1 \) yr, \( U \) is horizontal vector velocity, \( W \) is vertical velocity (positive up), and the velocity and temperature terms in \( V \) are evaluated at 400 m (the vertical advective heat transport at the surface is zero). All terms are defined such that positive values result in net heating of the upper ocean.

The residual term \( R \) contains other terms such as vertical heat transport by parameterized eddies and diffusion; \( R \) is computed by difference [Eq. (4)]. Because the transport terms \( A, E, \) and \( V \) are calculated from monthly averages of \( U, W, \) and \( T \), submonthly correlated fluctuations in velocity and temperature are neglected and therefore will contribute to the residual \( R \). Figure 7 (bottom panel) shows the slope from linearly regressing the sum \( Q' + A' + E' + V' \) on \( \Delta H' \). Low values of this slope indicate that the resolved terms do not capture fully the variability in \( \Delta H' \) and that the residual \( R \) is nonnegligible. Therefore, the following analysis is incomplete in certain isolated regions of the Southern and Arctic Oceans, in the central Indian Ocean, and at various near-coastal sites, particularly in the western North Pacific.

A somewhat novel approach is required to display our analysis of the heat budget [Eq. (4)] to highlight the contributions of the heat flux and transport terms to the interannual variations in \( \Delta H \). Multivariate regressions and simple rms plots, by themselves, fall short because of nontrivial correlations between the different terms. Instead, we examine the slope from linearly regressing each rhs term individually onto \( \Delta H' \):

\[
X' = \beta_X \Delta H' \tag{9}
\]

(the intercept is approximately zero because the average of the anomalies is zero). A slope \( \beta_X \) near 1 indicates that a particular term produces in-phase heat budget anomalies of comparable magnitude to \( \Delta H' \). A slope greater than 1 indicates that the term is producing...
even bigger anomalies, but other terms are compensating. A negative slope indicates such a compensating term, and the more negative the slope the more effective the compensation. A slope near zero indicates that the term is not important in generating the heat storage anomalies.

Our treatment differs somewhat from traditional multiple linear regression where the focus is often on deconvolving the effect of cross-correlated forcing variables on the predicted variable. This is often done by estimating the unknown partial regression slopes and correlation coefficients for individual forcing variables on the predicted variable, holding all other forcing variables constant (e.g., Snedecor and Cochran 1980). For the hindcast model solutions, the partial regression slopes \( \partial X_j / \partial H'_T \) are known and equal to 1.0 by construction from the \( H'_T \) budget equation [Eq. (4)]. Our objective, in contrast, is to highlight the relative dominance of terms compared to overall variance in \( H'_T \) for which we need to include the interconnection or cross

Fig. 7. Spatial map of the rms variability of net annual heat storage anomaly (integrated 0–400 m) \( \Delta H' \) (GJ m\(^{-2}\)) for the period 1968–97 from the hindcast simulation: (bottom) spatial map of the linear slope of the sum of the heat budget terms \( (A' + \dot{Q} + E' + V) \) [Eq. (4)] regressed on \( \Delta H' \) [Eq. (9)]; a slope near 1 indicates that the resolved terms capture most of the variability in \( \Delta H' \). The station locations used in Fig. 8 are marked by + symbols on both panels.
correlation among the different budget terms. The regression slopes $\beta_X$ [Eq. (9)] reflect this and differ from 1.0 either because the variance of variable $X'_r$ is substantially smaller than other forcing terms or because $X'_r$ is out of phase or anticorrelated with more dominant terms. Further, the model regression slopes can be used with observed ocean heat content anomalies to give diagnoses typically unknown and difficult to measure processes.

Time series for $\Delta H'$ and corresponding local budget terms from Eq. (4) are shown in Fig. 8 for five locations where $\text{rms}(\Delta H')$ is relatively high (marked by plus signs in Figs. 7, 9, and 10). The primary driver for interannual variability is $A'$ (green), especially in the Tropics; $V'$ (magenta) is the next most significant term in the budget and tends to be anticorrelated to $\Delta H'$. These patterns are well defined in the scatterplots from the tropical Pacific (Fig. 8, top panel) and Indian (Fig. 8, second panel from top) Oceans (right column) where the slope of $A'$ on $\Delta H'$ is greater than 1, the slope of $V'$ on $\Delta H'$ is smaller and less than 0, and the small scatter about straight lines indicates that the forcing terms are highly correlated with the net heat storage response. The opposing signals in $A'$ and $V'$ reflect the fact that the horizontal and vertical components are partially coupled due to mass conservation; the regression slope of their sum (not shown) on $\Delta H'$ is positive and close to 1.0, indicating the dominance of advection.

At extratropical sites $A'$ remains positive, but $\Delta H'$ evolution is often governed by a mix of forcing terms. The net heat flux term $Q'$ (dark blue) contributes to interannual net heat storage anomalies while the eddy-parameterized transport term $E'$ (light blue) evolves on longer, multyear scales. The linear correlations for individual terms tend to be lower than in the Tropics (more scatter about the regression lines). At the Southern Ocean site (Fig. 8, second panel from bottom), $Q'$ is as significant as $A'$, although the variance in $\Delta H'$ at this location is much lower than in the Tropics. At a temperate North Atlantic site (bottom panel), the balance of terms is time dependent. Whereas $A'$ drives large $\Delta H'$ variations in the 1980s, significant $E'$ anomalies in the early 1970s and 1990s damp the effects of the resolved heat transport, resulting in lower $\Delta H'$ during these periods. The inclusion of only four rhs terms ($Q', A', E', \text{and } V'$) in the heat budget analysis is certainly justified at the tropical locations (top two panels), as the sum of the four (red line) is very nearly equal to the storage anomaly (black line). The exclusion of other budget terms introduces somewhat larger discrepancies in the extratropics (Fig. 8, bottom three panels).

Figure 9 displays global spatial maps of the regression slopes of the four rhs physical terms regressed on $\Delta H'$. The maps are masked (gray) in regions where $\text{rms}(\Delta H')$ is small and/or the regression slope is statistically insignificant. In those regions of the Tropics and Northern Hemisphere extratropics where $\text{rms}(\Delta H')$ (Fig. 7) is substantial, $A'$ dominates (slopes of 0.8–1.2), is often partially compensated by other terms (slope $>$1.2; mostly $V'$), and is strongly correlated with $\Delta H'$ (not shown). The $A'$ regression slope decreases ($0.3 < \beta_A < 0.8$) in the Southern Ocean, where other terms grow in importance. The slope of the resolved vertical advective heat convergence $V'$ regressed on $\Delta H'$ slope is negative for most of the global ocean, with large regions in the subpolar basins, Southern Ocean, subpolar North Atlantic, and Arctic. In summary, the partitioning of the heat budget shows that anomalies in the convergence of the advective heat transport ($A'$ and $V'$) dominate net annual heat storage variability in the well-stratified Tropics and subpolar basins, Southern Ocean, and Arctic. In summary, the partitioning of the heat budget shows that anomalies in the convergence of the advective heat transport ($A'$ and $V'$) dominate net annual heat storage variability in the well-stratified Tropics and subpolar basins, Southern Ocean, and Arctic. In summary, the partitioning of the heat budget shows that anomalies in the convergence of the advective heat transport ($A'$ and $V'$) dominate net annual heat storage variability in the well-stratified Tropics and subpolar basins, Southern Ocean, and Arctic. In summary, the partitioning of the heat budget shows that anomalies in the convergence of the advective heat transport ($A'$ and $V'$) dominate net annual heat storage variability in the well-stratified Tropics and subpolar basins, Southern Ocean, and Arctic.

c. Decomposing mean and time-varying velocity and temperature components

The $A'$ term [Eq. (6)] can be decomposed based on the mean and time-varying components of velocity and temperature:

$$A' = -\int_0^{t+\Delta t} \int_{-400}^{400} \rho c_p \nabla_h \cdot [(U)T'] + (U<T') \, d z \, d t.$$  

(10)

The three terms on the rhs represent, respectively, the annual net heat storage anomaly due to the convergence of the mean velocity acting on temperature anomalies, velocity anomalies acting on mean tempera-
Fig. 8. Time series of model upper-ocean heat budgets for five model locations with large rms variability in net annual heat storage anomaly, rms($\Delta H$) (see Fig. 7): (from top to bottom) eastern tropical Pacific; tropical Indian; northern central Pacific; Southern Ocean; and subpolar North Atlantic. (left) Time series of the annual change in net heat storage anomaly (integrated 0–400 m) $\Delta H$ (black with + symbols) together with the annual heat budget anomalies [Eq. (4)]: surface heat flux $Q$ (blue); convergence of resolved $A'$ (green) and eddy-parameterized $E'$ (cyan) horizontal advective heat transport; and convergence of the resolved vertical advective heat convergence $V'$ (magenta). The sum of the four rhs terms is shown in red. (right) Display of x–y scatterplots of the individual budget terms (y axis) vs $\Delta H$ (x axis); all variables: GJ m$^{-2}$. 
ture, and the correlation arising from monthly deseasonalized velocity and temperature anomalies, \( U^* \) and \( T^* \) [Eq. (1)]. The third term is generally small (Jayne and Marotzke 2001, 2002) and will be neglected. In a similar fashion as in Fig. 9, the remaining two terms are regressed on \( A'/H_{1,1032} \) (Fig. 10).

Over much of the model ocean, \( A' \) is dominated by \( \nabla_h \cdot U(T) \) (Fig. 10). The \( \nabla_h \cdot (U)T' \) term becomes important in the south equatorial Indian Ocean, western North Atlantic, and ACC where the mean advective currents are moderate to strong. Note the regions of strong negative \( \nabla_h \cdot (U)T' \) regression slope \((-0.8 < \beta < -0.3)\) in the ACC and Gulf Stream, indicating that velocity anomalies and temperature anomalies are working against each other. Correlated \( U' \) and \( T' \) anomalies arise due to changes in current strength and lateral shifts in current location.

The vertical term \( V' \) can be decomposed in a similar manner:

\[
V' = \int_{t}^{t+\Delta t} \rho c_p [\langle W \rangle T' + W' \langle T \rangle + (W^* T^*)'] \, dt. \tag{11}
\]

As with horizontal convergence, \( V' \) is dominated by \( W' \langle T \rangle \) (not shown). Indeed, the spatial patterns of \( \text{rms}(W') \) at the base of the analysis domain (396 m) (bottom left panel of Fig. 11) match well those of the off-equator tropical \( \text{rms}(\Delta H') \) variability (Fig. 7).

To examine the degree to which vertical velocity variability \( \text{rms}(W') \) is related to anomalies in local wind forcing, we compare \( W' \) with the anomalies in vertical

Fig. 9. Spatial maps displaying linear slope of heat budget anomaly terms regressed on hindcast net annual heat storage anomaly \( \Delta H' \) [Eq. (4)]: (top left) the convergence of resolved horizontal advective heat transport \( A' \); (top right) surface net heat flux \( Q' \); (bottom left) convergence of vertical advective heat transport \( V' \); and (bottom right) convergence of eddy-parameterized horizontal advective heat transport \( E' \). A slope near 1 indicates a dominant forcing term. A slope greater than 1 indicates that the term is producing even bigger anomalies, but other terms are compensating. A negative slope indicates such a compensating term, and the more negative the slope the more effective the compensation. A slope near zero indicates that the term is not important in generating the heat budget anomalies. The maps are grayed out in regions where the regression correlation is not significant at the 95% level and where \( \text{rms}(\Delta H') < 0.16 \, \text{GJ m}^{-2} \) (Fig. 7).
Ekman velocity $W_{Ek}$ computed from the curl of the wind stress (Fig. 11). We concentrate on two depths, the approximate base of the surface wind-driven layer (50 m) and the base of the analysis domain (396 m). The right column of Fig. 11 displays spatial maps of the regression slope of $W_{Ek}$ on $\nabla \cdot (U \times \nabla T)$. The maps are grayed out in regions where the regression correlation is not significant at the 95% level and where $\text{rms}(\Delta H') < 0.16 \text{ GJ m}^{-2}$ (Fig. 7).

### d. Heave and spice analysis of $T$ and $S$ anomalies

The vertically integrated heat budget analysis of $\Delta H'$ conceals the considerable vertical structure of the interannual tracer anomalies in the upper 400 m. Averaged over basin to global scales, the subsurface interannual $\text{rms}(T')$ in the hindcast and observations peaks at about 0.45°C between 50 and 150 m before declining with depth to about 0.15°C by 400 m (not shown; see Doney et al. 2003). The magnitude of model $\text{rms}(T')$ is about 25% lower than that in the WOA98 observational data. Globally, model $\text{rms}(S')$ peaks shallower in the water column (50–100 m) at about 0.06 psu. Salinity observations are limited, especially at depth, so the hindcast provides a view to interannual subsurface salinity variability.

The simulated subsurface temperature and salinity fields often vary in phase, indicating a common underlying mechanism. To explore this behavior, we partition the subsurface temperature and salinity variability at a given location and depth into two terms: changes in the water mass characteristics on surfaces of constant density (spice) and changes due to vertical displacement of isopycnal surfaces (heave). Both vertical and lateral processes could contribute to the heaving of isopycnals at a given location. Similarly, a spice anomaly could arise through either lateral advection along an isopycnal or through vertical diapycnal mixing across an isopycnal (Yeager and Large 2004). The derivation outlined below differs somewhat from other methods proposed in the literature (e.g., Bindoff and McDougall 1994), but the overall objective is similar.

The analysis starts with the annual mean tracer values $\overline{X}$, long-term means $\langle X \rangle$, and anomalies $X'$ computed for both $T$ and $S$ at each model grid cell for year $y$ on fixed depth surfaces $z$. The spice anomaly for a given year is defined then as the difference between the annual mean tracer value and the long-term mean of the tracer $\langle X \rangle_{\rho(y)}$ on the isopycnal $\rho(y)$ found at depth $z$ in year $y$:  

![Fig. 10. Spatial maps displaying the decomposition of the convergence of the resolved horizontal advective heat transport anomaly $A'$ [Eq. (10)] based on the mean and time-varying components of velocity and temperature. Each panel shows the linear slope of the individual terms regressed on $A'$: (left) heat convergence anomalies due to velocity anomalies $\overline{U} \overline{T}$ and (right) mean velocity time temperature anomalies $\langle U \rangle \langle T \rangle$. The maps are grayed out in regions where the regression correlation is not significant at the 95% level and where $\text{rms}(\Delta H') < 0.16 \text{ GJ m}^{-2}$ (Fig. 7).](image-url)
Because the density field evolves in time, \( \rho (y) \) and \( \langle X (\rho, y) \rangle \) also vary with time and are computed separately for each individual year. The heave component of the tracer anomaly is defined as the difference between the climatological mean of the tracer on the isopycnal surface and on the fixed depth surface:

\[
X_H' = \langle X (\rho, y) \rangle - \langle X \rangle_z.
\]

By construction, the annual mean tracer anomaly is the sum of the spice and heave anomalies:

\[
X' = X_S' + X_H'.
\]

In the special case where water mass characteristics on isopycnal surfaces remain constant in time and tracer anomalies are due solely to vertical isopycnal displacement, then \( T_S' = S_S' = 0 \), \( T' = T_H' \), and \( S' = S_H' \) (pure heave). In the opposite extreme of no vertical displacement of isopycnal surfaces, \( \bar{\rho} (y) = \langle \rho \rangle_z \), \( \langle X (\rho, y) \rangle = \langle X \rangle_z \), and \( T' = T_S', S' = S_S' \) (pure spice). In general, both \( X_S' \) and \( X_H' \) are nonzero, with the first term reflecting processes creating tracer anomalies on the \( \rho (y) \) isopycnal and the second term associated with isopycnal displacements.

In the tropical and subtropical thermocline, \( \text{rms}(T') \) is generally dominated by heave \( (T_H') \) at both 102 and 262 m (Fig. 12). By contrast tropical and subtropical \( \text{rms}(S') \) at 102 m is primarily spice driven \( (S_S') \) (Fig. 13). The heave component for salinity grows in importance deeper in the thermocline (262 m), particularly in the zonal high \( \text{rms}(S') \) bands in the western tropical Pacific. As noted by Yeager and Large (2004), significant spice variability is evident (in both \( T \) and \( S \)) in and downstream of formation zones in the western subtropical North and South Pacific. Thus the apparent continuous tracer variability maximum at 262 m in the

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**Fig. 11** Spatial maps of the vertical Ekman velocity anomaly contribution \( W_{E \kappa} \) to model variability of annual vertical velocity anomalies \( W \) from the hindcast simulation (1968–97). The figure displays the (left) \( \text{rms} W \) and the (right) linear slope of the regression of \( W_{E \kappa} \) on \( W \) for (top) 50 and (bottom) 396 m. The regression maps are grayed out in regions where the regression correlation is not significant at the 95% level and where \( \text{rms}(W) < 0.2 \times 10^{-4} \) cm s\(^{-1}\).
tropical South Pacific is actually driven by different mechanisms in the west and east.

Mid- and high-latitude rms($T'$) and rms($S'$) maxima reflect a mixture of spice and heave, with the relative contributions varying regionally. The band of high $T'$ and $S'$ variability in the western North Atlantic is a combination of a primarily heave-driven signal in the subtropics and a spice-driven signal in the subpolar gyre. A similar feature along the subtropical/subpolar gyre boundary in the western North Pacific is caused mostly by spice variability. Surface heat and freshwater flux variability introduces spice that is then mixed downward by winter convection. The strong rms($S'$) maxima in the North Pacific and Arctic are trapped near the surface because of the shallow halocline and limited convection and are due almost entirely to heave working on the strong salinity gradients across the base of the halocline.

A band in the Southern Ocean exhibits large, anticorrelated signals in heave and spice [note zones of significant negative regression slope, $\beta < -0.3$ in both $T$ (Fig. 12) and $S$ (Fig. 13)]. The two signals predominantly cancel, leaving relatively weak total variability signatures in rms($T'$) and rms($S'$). The zones are collocated with areas of high interannual variability of surface heat and freshwater flux in the seasonal ice zone. During winter, anomalously strong sea ice formation, for example, would contribute to $T' < 0$ and $S' > 0$ anomalies; given the mean $T/S$ and $\rho(T, S)$ relationships, this translates on isopycnals to $T_S' < 0$, $T_H' > 0$, and the observed regression relationships.

5. Summary and discussion

Historical oceanic data provide an intriguing, yet incomplete, picture of low-frequency (interannual) oceanic variability. It is of course now too late to acquire new observations of past events; thus the burden of describing such signals and understanding their dynam-

![Fig. 12](image-url)
ics falls jointly on data synthesis and modeling studies, with data assimilation playing an increasingly significant role. We demonstrate that a significant fraction of the observed low-frequency signal in upper-ocean temperature can be captured in an unconstrained simulation forced with atmospheric reanalysis and satellite data.

The model–data agreement is encouraging because neither the ocean model nor the atmospheric forcing were specifically tuned to improve the skill of the interannual simulations, though significant efforts have been invested to improve the underlying simulated mean ocean state (Large et al. 1997; Gent et al. 1998). This suggests that numerical simulation of many basic aspects of the observed large-scale ocean variability is robust to particular details of the formulation of the model and surface forcing.

Satellite data records (SST, SSH), apart from being confined to the surface and of limited duration, serve as excellent comparative datasets because of the relatively frequent global coverage. Model agreement with these data is generally very good in both magnitude and phase of interannual variability, with the exception of the weak midlatitude SSH variability. The model comparison with in situ (WOA98) SST variability is also favorable. Not surprisingly, large model–data differences emerge in regions of sparse sampling, and in many regions the model simulations may provide the only viable, historical estimate of oceanic variability.

Our hindcast simulation is conducted in fully prognostic mode, reserving the oceanic observational datasets as independent measures of model skill. Data assimilation and state estimation provide a complementary approach for describing and quantifying oceanic variability (e.g., Ji et al. 1995; Rosati et al. 1995; Carton et al. 2000a,b; Stammer et al. 2003). The experience from synoptic weather forecasting suggests that improved understanding of the system depends critically

![Spatial maps of variability of annual salinity anomalies](image-url)
on identifying and incorporating the correct physical dynamics into the underlying prognostic ocean models and on continuously evaluating those models in forward mode against observations.

The hindcast simulation provides a tool for quantifying the underlying mechanisms relating surface forcing to ocean response. Globally, the most significant interannual variability modes for SSH, heat content, and SST arise from ENSO and the Indian Ocean zonal mode, with substantial extension beyond the Tropics into the midlatitudes (e.g., Willis et al. 2004). In the well-stratified Tropics and subtropics, thermal variability is dominated by the convergence of the resolved heat transport, mostly due to velocity anomalies times the mean temperature field. The impact of local air–sea heat flux anomalies on heat content in the tropical Pacific are typically small and often oppose changes in SST and upper-ocean heat content; that is, ocean dynamics associated with ENSO changes in circulation generates SST changes, and the surface heat flux response is a negative feedback that cools (heats) warm (cold) anomalies. Tropical and subtropical subsurface temperature variations arise almost entirely due to the vertical and lateral displacements of isopycnal surfaces (heave) governed predominately by remote wind forcing rather than local Ekman pumping. Thus the high degree of skill of the hindcast in replicating tropical/subtropical thermal variability is tied, largely, to the ability of the model to properly move water in response to wind variations.

The dynamics at mid- to high latitudes are qualitatively different and vary regionally. Interannual temperature variability is more coherent with depth because of deep winter mixing and variations in strength and location of western boundary currents and the Antarctic Circumpolar Current that span the upper thermocline. Net annual heat storage variability is forced by local air–sea heat fluxes and convergence of advective heat transport, the latter reflecting both velocity and temperature anomalies. Density-compensated temperature changes on isopycnal surfaces (spice) is quantitatively significant.

Roemmich et al. (2005) present an observational analysis of heat budget for the “Tasman box” in western South Pacific, which is centered about 30°S and includes the East Australian western boundary current. Similar to our hindcast, they find that interannual variability in the convergence of horizontal advective heat transport is a significant factor in ocean heat content variability. Air–sea heat fluxes and the heat transport term tend to oppose each other; net heat storage occurs when variability in the two are offset in magnitude or phase.

In agreement with our analysis, related modeling studies also show a dominance of the advective heat transport terms to interannual heat budget variability in other western boundary current regions in the North Pacific (e.g., Kelly 2004) and North Atlantic (Dong and Kelly 2004). Dong and Kelly (2004) found that the advective term arises in the western Gulf Stream from advection of temperature anomalies; anomalous advection of the mean field comes into play in the eastern Gulf Stream and south of Gulf Stream. This differs somewhat from our findings, which suggest that \( \nabla_h \cdot \mathbf{U}'(T) \) dominates in the western Gulf Stream and is opposed by \( \nabla_h \cdot \mathbf{U}(T)' \).

We outline here an analysis method for partitioning the mechanisms driving historical regional patterns of interannual variability in the upper-ocean heat budget. Although we use a purely unconstrained, forward hindcast simulation, a similar approach could be applied to data assimilation solutions as long as care is taken to account for any subsurface diabatic heat terms introduced as part of the assimilation technique. Such artificial diabatic terms can arise, for example, in objective analysis and variational methods that directly adjust subsurface temperature and salinity over the evolution of the solution when model and data fields are merged during each analysis step; this is in contrast to assimilation approaches that indirectly affect subsurface fields by modifying surface forcing fields, though this may have the effect of transferring internal ocean dynamics errors to the poorly constrained surface fluxes (e.g., Stammer et al. 2002). The hindcast simulations illustrate the rich, regional-scale texture of local and remote dynamical processes driving ocean climate variability and highlight the difficulties and opportunities in interpreting the growing satellite and in situ ocean observing network.

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