On the Air-Sea Exchange of Mechanical Energy: A Meso to Large-Scale Assessment Using Concurrent Drifter and Satellite Observations

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ON THE AIR-SEA EXCHANGE OF MECHANICAL ENERGY:
A MESO TO LARGE-SCALE ASSESSMENT USING CONCURRENT DRIFTER
AND SATELLITE OBSERVATIONS

By

Lucas Cardoso Laurindo

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of the University of Miami
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On the Air-Sea Exchange of Mechanical Energy: A Meso to Large-Scale Assessment Using Concurrent Drifter and Satellite Observations  

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This dissertation uses near-surface current velocity observations from Global Drifter Program (GDP) drifters, combined with a suite of satellite products, to investigate the air-sea exchange of mechanical energy at global scales. In particular, this work tests the conclusions of recent numerical studies that air-sea coupling mechanisms operating at the ocean mesoscales, arising from the dependence of wind stress on surface currents and on mesoscale SST fluctuations, can create non-zero air-sea fluxes of mechanical energy associated with the quasi-geostrophic ocean variability.

First, the slip bias of undrogued drifters is corrected, thus recovering about half of the GDP dataset; and a new approach for decomposing Lagrangian data into mean, seasonal and eddy components is developed to reduce the smoothing of spatial gradients inherent in data binning methods. The sensitivity of the results to method parameters, the method performance relative to other techniques, and the associated estimation errors, are evaluated using statistics calculated for a test dataset consisting of altimeter-derived geostrophic velocities subsampled at the drifter locations, and for the full altimeter-derived geostrophic velocity fields. It is demonstrated that (1) the correction of drifter slip bias produces statistically similar mean velocities for both drogued and undrogued drifter datasets at most latitudes and reduces differences between their variance estimates, (2) the proposed decomposition method produces pseudo-Eulerian mean fields with magnitudes and horizontal scales closer to time-averaged Eulerian observations than other methods, and (3) standard errors
calculated for pseudo-Eulerian quantities underestimate the real errors by a factor of almost two.

Next, the influence of mesoscale SST anomalies on the near-surface winds is analyzed, aiming to determine the intrinsic spatial-temporal scales where the effect takes place and its association with the mesoscale eddy field. Specifically, cross-spectral methods are used to examine the linear spectral relationship between SST and equivalent-neutral 10-m wind speed ($w$) fields from satellite products at scales between $10^2$–$10^4$ km and $10^1$–$10^3$ days. The transition from negative SST/$w$ correlations at large-scales, to positive at oceanic mesoscales, is found to occur at wavelengths coinciding with the atmospheric first baroclinic Rossby radius of deformation; and that the dispersion of positively-correlated signals is compatible with tropical instability waves near the equator, and with Rossby waves and/or mesoscale eddies in the extratropics. Transfer functions for the spectral linear SST/$w$ relationship are used to estimate the SST-driven $w$ response in physical space, a signal that explains 5–40% of the mesoscale $w$ variance in the equatorial cold tongues, and 2–25% at extratropical SST fronts. The signature of coherent ocean eddies is clearly visible in the SST-driven $w$, accounting for 20–60% of its variability in eddy-rich regions. The cross-spectral analysis is repeated in two climate model (CCSM) simulations based on ocean grid resolutions of $1^\circ$ (eddy-parameterized, LR) and $0.1^\circ$ (eddy-resolving, HR). A realistic relationship between both quantities is only obtained in HR, highlighting the importance of ocean phenomena with wavelengths between 20–250 km, typical of mesoscale ocean eddies, for conditioning the SST-driven coupling characteristics revealed by satellite observations.

Finally, concurrent drifter and satellite observations are used to estimate the contribution of time-mean, seasonal, and eddy components of the wind stress and surface geostrophic velocity fields to the total power exchange. It is found that, of the $\sim 1.22$ terawatts ($1 \text{ TW} = 10^{12} \text{ W}$) supplied by the winds to the general ocean circulation via the time-mean and seasonal components, about 0.23 TW is lost back to the atmosphere via the covariances between the eddy fluctuations in the winds stress and
the quasi-geostrophic velocity fields. Estimates of the impact of the wind stress dependency on surface ocean currents to the mechanical energy fluxes, obtained (a) via theoretical expressions, and (b) by recomputing the energy fluxes using wind stress estimates with the current influence removed using drifter observations, indicate that the negative covariances can be largely explained by the current-driven air-sea coupling. The influence of SST-driven coupling mechanism is detectable and produces well-defined large-scale patterns, although its magnitudes are, on average, about 30 times smaller than those driven by the current effect. These results provide observational evidence that the current-driven coupling gives rise to a non-negligible sink of kinetic energy for the oceanic quasi-geostrophic variability, and may serve as a basis for evaluating the competing conclusions of recent numerical experiments on the impact of the SST-driven coupling to the ocean energetics.
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CHAPTER 1

Introduction

This dissertation uses near-surface velocity observations from Global Drifter Program (GDP) drifters, combined with a suite of satellite datasets, to examine the exchange of mechanical energy between the atmosphere and the quasi-geostrophic ocean circulation. The importance of evaluating this quantity lies in the fact that it corresponds to the main energetic pathway through which the winds force the general ocean circulation, and rather counter-intuitively, it also constitutes a major source of mechanical energy for deep ocean diapycnal mixing, which produces a general upwelling tendency that ultimately drives the oceanic meridional overturning circulation (Munk and Wunsch 1998; Wunsch and Ferrari 2004; Ferrari and Wunsch 2009).

Of particular interest, an increasing body of literature is demonstrating that air-sea coupling mechanisms operating at the ocean mesoscales can significantly influence the air-sea fluxes of mechanical energy, with impacts on the evolution and propagation of coherent ocean eddies. The coupling arises from the dependence of wind stress on surface currents and on sea surface temperature (SST), and while recent regional numerical studies are converging on the conclusion that the current-driven coupling both reduce the wind work rate on the general ocean circulation and exert a net damping effect on the mesoscale eddy field, they diverge on the role of SST on ocean energet-
ics. Furthermore, currently available observational assessments based on altimeter-derived geostrophic velocities suggest that only 5% of the globally-integrated air-sea flux of mechanical energy is associated with time-dependent fluctuations in the ocean and the atmosphere, a result apparently at odds with the strong feedbacks of air-sea interaction to the ocean dynamics implied by numerical experiments.

This study aims to provide a comprehensive assessment to these questions. Particularly, the considered observational datasets are used to infer the relative role of the current and SST-driven air-sea coupling via wind stress in mediating the air-sea flux of mechanical energy, results that can provide further insight on the ocean energetics and on the physical mechanisms affecting the evolution of mesoscale ocean eddies. This introduction place the air-sea fluxes of mechanical energy into a dynamical context and describe the current state of knowledge on the subject (Section 1.1), also discussing about recent numerical and observational results suggesting that non-zero energy fluxes associated with the quasi-geostrophic ocean variability can arise in response to mesoscale air-sea coupling processes (1.2). Section 1.3 states the main research hypothesis and objectives of this dissertation, and present an outline of the conducted work.

1.1 Wind work on the general ocean circulation

The rate of mechanical energy transfer between the winds and the quasi-geostrophic ocean circulation can be written as:

\[
\int \int_{ocean} (\mathbf{u}_g \cdot \mathbf{\tau}) \, dA = \int \int_{ocean} \frac{1}{\rho_0} \left( \mathbf{M}_e \cdot \nabla_H \mathbf{p}_s \right) \, dA, \tag{1.1}
\]
where the multiplication on the equation’s left-hand side, between the surface geostrophic velocity vector $\mathbf{u}_g$ and the wind stress vector $\boldsymbol{\tau}$, corresponds to the work of the wind per unit area on the geostrophic circulation (hereafter $P_g$). This term is equaled on the right-hand side by the work of the vertically-integrated Ekman transport $\mathbf{M}_e$ on the pressure forces at the surface $\nabla H p_s/\rho_0$, where $\nabla H p_s$ is the horizontal pressure gradient, and $\rho_0$ is a reference density of seawater. The overlines denote time averages, and both quantities are integrated over the surface area of the ocean, represented as $A$. This relation states that the wind work on the surface geostrophic ocean circulation can be interpreted either as a direct production of geostrophic kinetic energy, or as a generation of potential energy at the ocean’s interior via pressure work (Gill et al. 1974; Stern 1975; Fofonoff 1981; Oort et al. 1994; Munk and Wunsch 1998; Wunsch and Ferrari 2004; Ferrari and Wunsch 2009).

Significant progress on the understanding of how the winds exchange mechanical energy with the ocean was made during the past two decades. Wunsch (1998) used altimeter-derived geostrophic velocities and wind stress data from the National Centers for Environmental Prediction (NCEP) reanalysis model to estimate $P_g$ for the period between 1992 and 1996. Specifically, that study analyzed the contribution of the mean and time-dependent (eddy) components of $\mathbf{u}_g$ and $\boldsymbol{\tau}$ to $P_g$, in the form:

$$P_g = \overline{\mathbf{u}_g} \cdot \overline{\boldsymbol{\tau}} + \mathbf{u}_g' \cdot \mathbf{\tau}'$$  \hspace{1cm} (1.2)

where the primes are fluctuations relative to the long-term mean. Wunsch (1998) obtained a globally-integrated wind power input to the general ocean circulation of about 0.88 terawatt ($1 \text{ TW} = 10^{12} \text{ watts}$). Only about 5% of the total power came from the time-dependent term $\overline{\mathbf{u}_g'} \cdot \overline{\boldsymbol{\tau}}'$, characteristic attributed by that study to the differing spatial-temporal scales of oceanic and the atmospheric motions, which would
result in poor correlations between the variability intrinsic to each medium. It was also observed that the Southern Ocean dominates the global integral, with about 70% of the mechanical energy input taking place poleward of 40°S. The later work of Huang et al. (2006) used an extended temporal series of altimetric observations and the output of a numerical ocean model to evaluate the decadal variability of energy fluxes, obtaining similar time-mean spatial patterns and magnitudes for $P_g$, and further reporting an increase of about 12% of the wind power input along the period between 1981 and 2006 that was mainly concentrated in the Southern Ocean and within the tropics. Neither Wunsch (1998) nor Huang et al. (2006) attempted to diagnose the uncertainty of the $P_g$ estimates, particularly due to the presence of spatially correlated errors on the reference geoid model used to retrieve sea surface height (SSH) data from altimeter measurements.

It is important to remark that Equation (1.1) is only applicable in regions of the global ocean where the dynamics can be described in terms of a quasi-geostrophic interior plus a wind-driven (Ekman) layer. It also assumes that the wind power expended on the generation of ageostrophic motions is entirely dissipated within the Ekman layer (Stern 1975; Oort et al. 1994; Wunsch 1998; Wang and Huang 2004). This prompted the study of Von Storch et al. (2007), that estimated the wind power input to the full subinertial ocean surface velocity field, rather than just to its geostrophic component, in an ocean general circulation model (OGCM) with a 0.1° horizontal resolution, interpreting its results based on an expression for the kinetic energy budget of the ocean mixed layer derived from the model’s primitive equations. The authors estimated that the wind provided a total of 3.8 TW at the air-sea interface, 1.06 TW of which reached below the Ekman layer. Von Storch et al. (2007) was
able to associate this downward energy flux with the wind work on the surface geostrophic flow, where all the wind power expended on the generation of ageostrophic motions appeared to be dissipated within the Ekman layer, supporting the validity of the $P_g$ estimates based on Equation (1.1) obtained in Wunsch (1998) and Huang et al. (2006). It is noted that the OGCM used in Von Storch et al. (2007) had a daily temporal resolution that could not resolve near-inertial forms of variability, in particular wind-forced inertial oscillations in the ocean. This phenomenon excite internal waves that are capable of propagating energy vertically, thus constituting a potential pathway for transporting the wind energy from the surface to the subsurface ocean (Elipot and Gille 2009b).

The next significant step was taken by Duhaut and Straub (2006), who demonstrated that previous estimates of $P_g$ were biased high because a dependence of $\tau$ on the surface ocean velocities was not taken into account. Specifically, $\tau$ was parameterized using the bulk formulation $\tau = c_d \rho_a |w| w$, where $c_d$ is an empirical drag coefficient, $\rho_a$ is the air density, and $w$ is the 10-meter height wind velocity vector; while a more accurate formulation would be $\tau_1 = c_d \rho_a |w - u| (w - u)$, where $u$ is the surface ocean current velocity vector. As the winds tend to move much faster than the currents, $\tau_1$ usually represents only a small modification relative to $\tau$, however this has a surprisingly large effect on $P_g$. This is due to the fact that accounting for wind stress dependence on ocean currents systematically reduces the time-averaged wind power input because it causes $|\tau|$ to be larger (smaller) when $u$ and $w$ have opposing (same) directions, both cases resulting in a smaller power input to the ocean circulation. The current-induced reduction in the time-averaged energy fluxes ($P_{\text{curr}}$)
can be predicted as

\[ P_{\text{curr}} = \left( \mathbf{u} \cdot \tau_1 \right) - \left( \mathbf{u} \cdot \tau \right) \approx -\rho_a c_d |w| \left( |\mathbf{u}|^2 + u_0^2 \right) \]  

(1.3)

where \( u_0 \) is the along-wind component of the ocean surface velocities. Equation (1.3) shows that \( P_{\text{curr}} \) depends on \( |\mathbf{u}|^2 \), the double of the oceanic surface kinetic energy. As the majority of the oceanic kinetic energy is contained in the mesoscale eddy field, \( P_{\text{curr}} \) is then predominantly modulated by the underlying eddy variability.

Using scaling arguments supported by estimates of the air-sea mechanical energy transfer in eddy-resolving, quasi-geostrophic numerical simulations of a classic double-gyre setting, Duhaut and Straub (2006) predicted a current-induced reduction on \( P_g \) between 20 and 35%. Supporting the conclusions of that study, variations in the wind power input arising from the current influence on \( \tau \) by fractions similar to those inferred by Duhaut and Straub (2006) were reported by a number of posterior realistic numerical experiments (e.g. Dawe and Thompson 2006; Zhai and Greatbatch 2007; Seo et al. 2007; Seo et al. 2016; Renault et al. 2016; Seo 2017; Renault et al. 2017).

Hughes and Wilson (2008) investigated the current-driven impact to \( P_g \) proposed by Duhaut and Straub (2006) in observational data, specifically using geostrophic velocities estimated from a merged, 1/4° resolution altimetric product, and wind stress data from the scatterometer onboard the QuikSCAT satellite, which includes the effects of ocean currents. The study obtained a globally-integrated \( P_g \) of 0.76 TW, and inferred \( P_{\text{curr}} \) via a formulation similar to that in Equation (1.2), that integrated to -0.19 TW. To independently test whether the scatterometer \( \tau \) data truly included the dependency on ocean currents, the authors low-pass filtered time-dependent fluctuations with oceanic mesoscale dimensions on instantaneous geostrophic velocity and wind stress horizontal fields, observing that the energy fluxes recomputed using both
or either low-passed quantity increased relative to the original $P_g$ estimates by similar margins, that integrated to about 62–71% of the value predicted for $P^{\text{curr}}$ at the extratropics. Equatorward of 20° latitude, however, the suppression of mesoscale fluctuations lead to an increase in the energy fluxes equivalent to only 6% of the theoretical prediction, which the authors theorized that could reflect the action of other air-sea coupling mechanisms operating at the ocean mesoscales, such as the SST-driven modifications on wind speed via boundary layer dynamics (e.g. Xie 2004; Small et al. 2008; Chelton and Xie 2010). Further estimates of $P_g$ and $P^{\text{curr}}$ based on a suite of altimeter and scatterometer-based products were presented by Xu and Scott (2008) and Scott and Xu (2009), which placed the global integral of $P_g$ between 0.86 and 1.02 TW, and of $P^{\text{curr}}$ between -0.30 and -0.10 TW.

Hughes and Wilson (2008) argued that, if currents and winds are poorly correlated owning to their differing spatial-temporal scales, then covariances between the surface currents and wind stress $(\mathbf{u}_g \cdot \mathbf{\tau})$ should predominantly reflect the $\mathbf{\tau}$ dependence on surface currents. That study observed that this quantity, when resolved by altimeter and scatterometer datasets, show predominantly negative values in the extratropics. More recently, Xu et al. (2016) isolated the mechanical energy fluxes associated with mesoscale ocean eddies detected in the altimeter record, and confirmed that they primarily represent a negative contribution to $P_g$. Such results indicate that, rather then solely reducing the wind power provided at the ocean surface, the current-driven air-sea coupling via $\mathbf{\tau}$ can actually give rise to energy fluxes directed from the ocean to the atmosphere associated with the oceanic quasi-geostrophic variability.

Despite of the predominantly negative $(\mathbf{u}_g \cdot \mathbf{\tau})$ values revealed by previous altimeter and scatterometer-based results, they all suggest that this term reduces the globally-
integrated $P_g$ by less than 5%. However, it is noted that the currently available altimeter-derived geostrophic velocity products underestimate the ocean variability at mesoscale ranges and smaller (e.g. Ducet et al. 2000; Fu and Ubelmann 2014; Poje et al. 2014), suggesting that previous assessments may have also underestimated the magnitude of the air-sea fluxes arising from covariances between time-dependent fluctuations in the surface current and wind stress fields. The importance of assessing this quantity lies in the fact that, if nonzero, it may constitute a direct energetic pathway through which the atmosphere can inject or remove kinetic energy from the oceanic quasi-geostrophic variability. The next Section briefly describes how the oceanic eddy kinetic energy (EKE) balance is maintained, and summarizes the numerical and observational evidence suggesting that the $\tau$ dependence on both surface currents and on mesoscale SST fluctuations can exert a non-negligible influence over the EKE budget.

### 1.2 Impacts of wind forcing to the quasi-geostrophic ocean variability

The oceanic eddy kinetic energy is defined as half of the current velocity variance ($\text{EKE} = \frac{\overline{u'^2}}{2}$), and its variation as a function of time and space can be described in terms of the following energetic balance:

$$\rho_0 \frac{d}{dt} \text{EKE} = \text{BC} + \text{BT} + P' + D \quad (1.4)$$

where $\text{BC}$ denotes the conversion of available potential energy to kinetic energy via baroclinic instability processes; $\text{BT}$ is the barotropic conversion of kinetic energy between the mean and eddy components of the flow, associated with time-mean eddy
advection across mean flow gradients; and $P'$ is wind forcing over the eddy variability, equivalent to the covariance between the total surface current velocities and wind stress $(\overline{u'} \cdot \overline{\tau'})$. Here, the term D groups the contribution of internal pressure work over the velocity fluctuations, small-scale shear instabilities such as Kelvin-Helmholtz instability, horizontal energy advection by velocity fluctuations, and effects of irreversible dissipation by viscous forces (Marchesiello et al. 2003; Seo et al. 2016; Renault et al. 2016).

In a quasi-geostrophic framework, the mesoscale eddy field is thought to develop mainly from baroclinic instabilities [BC in Eq. (1.4)] (Killworth and Blundell 2007; Smith 2007), where the available potential energy expended in the process is predominantly restored by the wind power input to the ocean general circulation [Eq. (1.1)] (Wunsch and Ferrari 2004; Ferrari and Wunsch 2009). The eddies themselves predominantly give up their energy to motion at larger scales, in accordance with the inverse kinetic energy cascade predicted by geostrophic turbulence theories (e.g. Charney 1971; Salmon 1980; Smith and Vallis 2002; Scott and Arbic 2007). The accumulation of energy at large scales implies that sinks of geostrophic kinetic energy must exist to balance the mechanical power supplied by the winds. Potential dissipation mechanisms include interactions with the bottom topography (e.g. Gille et al. 2000; Arbic and Flierl 2004; Sen et al. 2008; Nikurashin et al. 2013), loss of geostrophic balance as a result of frontogenesis in the upper ocean (e.g. Molemaker et al. 2005, 2010; D’Asaro et al. 2011), energy transfer to internal waves (Nikurashin and Ferrari 2011, 2013; Nikurashin et al. 2013), and scattering of eddy energy to high-wavenumber vertical modes upon contact with the western boundaries (Zhai et al. 2010). Early theoretical studies concluded that the $\tau$ dependence on ocean
currents creates a surface drag force that can also constitute a sink of kinetic energy for the quasi-geostrophic ocean variability (Bye 1986; Dewar and Flierl 1987).

As forementioned, Duhaut and Straub (2006) predicted that the current-driven air-sea coupling could reduce the net wind power supplied to the general ocean circulation by 20–35%, however available altimeter and scatterometer-based estimates suggest that only a small fraction of the inferred power variation is due to negative mechanical energy fluxes associated with the quasi-geostrophic ocean variability (Hughes and Wilson 2008; Xu and Scott 2008; Scott and Xu 2009; Xu et al. 2016). Conversely, recent high-resolution, air-sea coupled regional numerical experiments for the California Current System (Seo et al. 2016; Renault et al. 2016), Gulf Stream (Renault et al. 2016), Agulhas Current Retroflection (Renault et al. 2017), and the Arabian Sea (Seo 2017) showed that the current influence in $\tau$ can exert strong feedbacks to the oceanic eddy variability, ultimately reducing the depth-averaged EKE resolved in the simulations by fractions between 10–50%. These studies evaluated the physical mechanisms responsible for the observed EKE reduction by computing the terms of Equation (1.4), reporting that the current-driven air-sea coupling resulted in significantly negative energy fluxes in $P'$ while BC and BT remained relatively unchanged, indicative that the loss of mechanical energy by the ocean to the atmosphere was the chief cause for the suppression of the mesoscale eddy variability. Renault et al. (2016) further decomposed $P'$ into an Ekman and geostrophic components ($P' = P'_e + P'_g$, where $P'_e = \mathbf{u}'_e \cdot \mathbf{\tau}'$ and $P'_g = \mathbf{u}'_g \cdot \mathbf{\tau}'$), confirming that the current-induced negative energy fluxes are predominantly associated with the quasi-geostrophic variability.

In opposition with the definite-negative $P'_g$ induced by the $\mathbf{\tau}$ dependence on ocean currents, Frankignoul and Müller (1979) and Müller and Frankignoul (1981) proposed
that positive $P'_g$ values can arise via the resonance of the oceanic barotropic and baroclinic modes with stochastic wind fluctuations, potentially allowing the direct generation and/or reinforcement of mesoscale eddies by the atmosphere. There is also evidence that non-zero $P'_g$ values can develop due to the existence of positive correlations between mesoscale SST fluctuations and the near-surface wind speed ($w$). The SST/$w$ relationship arise from air-sea turbulent heat fluxes forced by the anomalous SST, that affect the stability of the boundary layer and ultimately modifies $w$ (c.f. Xie 2004; Small et al. 2008; Chelton and Xie 2010). Numerous studies reported that the SST-driven air-sea coupling modifies the $\tau$ divergence and curl on large-scale SST fronts and on mesoscale eddies, affecting the associated Ekman transport/pumping and influencing eddy propagation (e.g. White and Annis 2003; Chelton et al. 2004; O’Neill et al. 2012; Frenger et al. 2013; Souza et al. 2014; Gaube et al. 2015; Seo et al. 2016), however the feedback of the SST-driven coupling to the ocean energetics has been less explored.

particularly, the numerical study of Jin et al. (2009) used an empirical SST/$\tau$ relationship to investigate the impacts of the coupling to an idealized eastern boundary upwelling system, whose aftermath was a $\sim$25% decrease in EKE. The study attributed the reduction in eddy energy to anomalies in wind stress curl and divergence along the eddy domain induced by the SST-driven coupling, that acted to disrupt the approximate axisymmetric eddy structure. More recently, Seo et al. (2016) and Renault et al. (2016) analyzed the feedbacks of SST and current-driven air-sea coupling via SST and to ocean eddies in the California Current System using a regional high-resolution, fully-coupled ocean-atmosphere model. While $P'$ and EKE were unaffected by the SST coupling, the influence of ocean current enhanced the surface
drag and reduced EKE by 27-42%. Seo (2017) obtained similar conclusions from numerical experiments conducted for the Arabian Sea. Last, high-resolution coupled simulations of the South Atlantic by Byrne et al. (2016) showed that the SST/w coupling, when associated with large-scale horizontal wind gradients, can enhance $P'$ in mesoscale eddies, increasing the EKE by 10% in their simulations. Conversely, the study reported no significant changes in EKE when the air-sea system was allowed to interact only via current effects in $\tau$.

The strong feedbacks of the current and SST-driven air-sea coupling to ocean variability implied by numerical results appear to conflict with the small contribution of time-dependent fluctuations in $\tau$ and $u_g$ to the total air-sea fluxes of mechanical energy revealed by altimeter and scatterometer observations, characteristic potentially associated with limitations of altimeter-derived $u_g$ data for resolving the mesoscale variability. In this context, *in situ* observations of near-surface currents from the GDP drifter array (Lumpkin and Pazos 2007) figure as a possible alternative to diagnose the air-sea exchange of mechanical energy at global scales, considering that these instruments can sample all scales of motion down to the size of the drifter itself. However, the drifter observations are scattered in space and time and often autocorrelated in both dimensions, meaning that their decomposition into time-mean and fluctuating components require choices for averaging that can significantly influence the obtained results (Lumpkin 2003; Mariano and Ryan 2007; LaCasce 2008). Furthermore, about half of the GDP dataset are measurements obtained by drifters that had lost their drogues, condition that significantly increases the wind and wave-induced motion relative to the original drogued GDP drifter design and thus biases the inferred current velocities (Pazan and Niiler 2001; Poulain et al. 2009; Grodsky
et al. 2011; Lumpkin et al. 2013). The biases arising from the adopted approach for the decomposition of Lagrangian observations, and from the enhanced slip motion of undrogued drifters, must be properly addressed before the GDP dataset can be considered a viable observational basis for estimating the air-sea fluxes of mechanical energy.

Moreover, the differing conclusions on the impacts of SST/\(w\) coupling to ocean energetics, drawn from recent regional modeling studies, stresses that an assessment of the effect based on observational data and at global scales is desirable. In that sense, it is noted that the coupling is usually analyzed via linear regressions between oceanic and atmospheric parameters preliminarily filtered in both space and time to isolate the scales where the coupling takes place (c.f. Small et al. 2008; Chelton and Xie 2010). However, the filtering operation is usually done empirically and varies significantly between studies, indicating that the spatial-temporal scales where the SST-driven coupling takes place are not well established. Furthermore, observational studies to date focused on the SST/\(w\) relationship associated with either quasi-stationary, large-scale SST fronts (e.g. Chelton et al. 2004; O’Neill et al. 2010; O’Neill et al. 2012); Rossby waves and tropical instability waves (e.g. Polito et al. 2001; Small et al. 2005; O’Brien et al. 2013); or mesoscale eddies (e.g. Park et al. 2006; Frenger et al. 2013; Souza et al. 2014; Gaube et al. 2015). Estimates of the net impact of the SST-induced wind anomalies to the total wind variability are currently not available in literature, nor of how much of the effect can be ascribed to the action of each type of oceanic phenomenon.

These considerations indicate that an observational-based quantification of the air-sea fluxes of mechanical energy at the ocean mesoscales, in particular of the rela-
tive contributions of the current and SST-driven coupling mechanisms to the power exchange, require advances on the methods for estimating and mapping the statistical properties of near-surface currents from GDP drifter measurements, and for isolating the SST-driven wind response resolved by satellite datasets. Based on the presented discussion, the following Section outlines the main hypothesis and the objectives of this dissertation, briefly describing the strategies adopted to overcome the mentioned observational difficulties and thus address this work’s scientific questions.

1.3 Hypothesis and objectives

The main hypothesis of this dissertation is that air-sea coupling mechanisms operating at oceanic mesoscale ranges, arising from the influence of surface ocean currents and of SST on wind stress, play key roles in regulating the air-sea exchange of mechanical power, in particular that associated with the quasi-geostrophic ocean variability. Such influence was potentially underestimated by previous observational assessments due to limitations of altimeter data in resolving the ocean mesoscales.

To overcome this issue, this work examines the air-sea fluxes of mechanical energy using near-surface velocity measurements by GDP drifters and a suite of satellite products. The main objectives are to provide estimates of (a) the time-averaged wind power input to the general ocean circulation, (b) the air-sea fluxes of mechanical energy fluxes associated with the quasi-geostrophic ocean variability, and (c) the relative contribution of the current and SST-driven air-sea coupling mechanisms to the mechanical power exchange between the ocean and the atmosphere. As forementioned, assessing these quantities using the considered observational datasets runs into significant methodological difficulties, particularly regarding how to account for
the enhanced wind and wave-induced slip bias of undrogued GDP drifters, how to minimize the uncertainties arising from the decomposition of the spatially and temporally inhomogeneous drifter measurements into mean and fluctuating components, and how to isolate the near-surface wind fluctuations forced by the mesoscale SST variability. The conducted analysis initially focused on the development of methodological solutions for these issues (Chapters 2 and 3), which were then used to address the main objectives of this work (Chapter 4).

Specifically, Chapter 2 updates the methods of Lumpkin and Johnson (2013) to obtain an improved near-surface velocity climatology for the global ocean using observations from undrogued and 15-m drogued GDP drifters. Here, the wind and wave-induced slip motion of undrogued drifters is accounted for by referencing their velocities by those obtained by drogued instruments via a formulation introduced by Pazan and Niiler (2001); and a new approach is proposed for decomposing Lagrangian data into mean, seasonal and eddy components, designed to reduce the smoothing of spatial gradients inherent in data binning methods. The sensitivity of the results to method parameters, the method performance relative to other techniques, and the associated estimation errors, are evaluated using statistics calculated for a test dataset consisting of altimeter-derived geostrophic velocities subsampled at the drifter locations, and for the full altimeter-derived geostrophic velocity fields.

In Chapter 3, the linear relationship existing between SST and near-surface wind speed ($w$) fluctuations resolved by satellite products is evaluated at scales between $10^2$–$10^4$ km and $10^1$–$10^3$ days via cross-spectral methods, with the objective of defining the intrinsic spatial-temporal scales where negative SST/$w$ correlations, typical of large spatial scales and thought to predominantly reflect a wind-induced modulation
of SST via surface turbulent heat fluxes, give way to positive correlations toward the ocean mesoscales, indicative of a SST-induced modulation of the near-surface winds via boundary layer dynamics. The chapter also investigates the importance of coherent ocean eddies for mediating the SST-driven air-sea coupling relative to that of ocean phenomena with larger horizontal scales, such as Rossby waves and extratropical SST fronts. In that sense, transfer functions for the spectral linear SST/$w$ relationship are employed to estimate the SST-driven $w$ response in physical space, which are then used in concert with coherent mesoscale eddies detected in altimeter observations to quantify how much of this variability can be ascribed to the collective action of the eddy field. To gain further insight on the role of ocean eddies for conditioning the observed SST/$w$ coupling characteristics, the spectral analysis is repeated using the outputs of two global, fully-coupled simulations of the Community Climate Simulation Model (CCSM), based on identical atmospheric components, but using ocean models configured to the contrasting horizontal grid resolutions of 1° (eddy-parameterized) and 0.1° (eddy-resolving).

Finally, Chapter 4 combines the methods and results obtained in the previous chapters to estimate the time-averaged air-sea fluxes of mechanical energy and thus fulfill the main scientific objectives of this work. Here, collocated drifter and satellite observations are used to estimate the contribution of time-mean, seasonal, and eddy fluctuations to the total power exchange, each further expanded into geostrophic and Ekman components via an empirical formulation for the Ekman velocities retrieved from observations. The impact of the current and SST influence on wind stress to each diagnosed component of the mechanical energy fluxes is estimated (a) using theoretical expressions derived to quantify each effect, and (b) by directly removing
the wind stress dependence on currents and SST using drifter velocity measurements and satellite-based estimates of the SST-coupled wind response. An analysis focused on the mechanical energy fluxes associated with ocean eddies is also performed, based on data from looping drifter trajectories detected in the GDP dataset, aiming to evaluate potential asymmetries between the energy fluxes associated with each eddy polarity.
CHAPTER 2

An improved near-surface velocity climatology for the global ocean from drifter observations

This chapter updates the methods of Lumpkin and Johnson (2013) to obtain an improved global climatology of near-surface currents from Global Drifter Program (GDP) drifter observations. Here, a new procedure for decomposing the spatially and temporally inhomogeneous drifter observations into mean, seasonal, and fluctuating (eddy) components is developed, designed to reduce the spatial smoothing and smearing effect inherent to data binning methods; and a empirical formulation proposed by Pazan and Niiler (2001) is applied to correct the slip bias of undrogued GDP drifters at global scales, operation that doubles the number of drifter data available for the analysis. These methods enable the calculation of air-sea fluxes of mechanical energy at global scales using GDP data, operation described in Chapter 4.

2.1 Background

A global climatology of surface ocean currents is desirable for a variety of applications. For example, the statistical moments of the ocean velocity (mean, variance, and covariances) are used in the study of linear geophysical instabilities, ocean ener-
getics, and the turbulent transport of tracers and heat. In a Lagrangian framework, the fluctuations around the mean are used to infer eddy diffusivities and decorrelation time scales. Besides the investigation of the underlying ocean dynamics, the statistical description of the surface circulation is also relevant for ship routing, search and rescue operations, and for predicting the dispersion and transport pathways of biogeochemical tracers and of pollutants such as oil, microplastic, and floating marine debris.

The drifters of the Global Drifter Program (GDP) currently provide the most accurate set of measurements of the near-surface ocean velocities at global scales (Lumpkin and Pazos 2007; Maximenko et al. 2013). However, observations are scattered in space and time and often autocorrelated in both dimensions, making their decomposition into mean and fluctuating components a non-trivial exercise. A common approach involves ensemble-averaging data selected within spatial bins (e.g. Niiler 2001; Fratantoni 2001; Jakobsen et al. 2003; Reverdin et al. 2003; Maximenko et al. 2009; Zhurbas et al. 2014), however, this method has a number of associated biases whose effects are difficult to diagnose (Mariano and Ryan 2007). A particularly important source of uncertainty lies in the choice of bin size, whose definition involves a trade-off between the statistical reliability of the results and the resolution of the horizontal scales of the mean flow. Specifically, larger bins select more data points, which leads to a higher statistical significance of the estimates, however they smooth horizontal variations of the mean at scales smaller than the bin. Conversely, smaller bins better resolve spatial gradients, however the use of less data points increase the estimation errors. The bin size choice, therefore, influences the estimation of the
mean, consequently also affecting the residuals and thus second moment statistical properties (Fratantoni 2001; LaCasce 2008; Koszalka and LaCasce 2010).

Furthermore, while most studies based on binning methods employed fixed-sized bins, a consequence of this practice is obtaining pseudo-Eulerian estimates whose statistical reliability vary in space. To avoid this issue, Koszalka and LaCasce (2010) proposed selecting data in clusters covering unequal areas but with a similar number of observations. Notably, the application of this technique to GDP data in the Nordic seas resolved features of the time-mean circulation with scales \( \leq 10 \) km in well-sampled regions (Koszalka et al. 2011). However, the number of observations per cluster prescribed in that work results in an average selection radius of 75 km (\( \sim 0.67^\circ \) latitude and \( \sim 1.3-1.8^\circ \) longitude, in their study area), meaning that horizontal velocity gradients at mesoscale ranges are smoothed out when considering typical ocean sampling densities.

Another source of uncertainty is due to the fact that drifters do not perfectly track the horizontal flow. Differences between the measured velocities and the actual current velocities, an effect known as slip, are caused by wind drag on the drifter’s surface float and wave-induced phenomena, such as Stokes drift and drifter self-propulsion by wave surfing. GDP drifters include a drogue centered at 15-meter depth that minimizes the wind and wave-induced bias, however that also introduces another component to the slip via the vertical velocity shear between the surface float and the subsurface drogue. Despite the complex nature of the processes driving the slip motion, the drogued design of GDP drifters is calibrated to yield a predominantly downwind slip of less than \( \sim 0.1\% \) of the 10-m wind speed, for winds up to 10 m/s (Niiler et al. 1995). An assessment of the GDP dataset by Lumpkin et al. (2013)
showed that more than 50% of the available data previously believed to be from drogued drifters are actually from instruments that had lost their drogues, a condition that changes the sampling level from 15-m to the surface, and renders their trajectories more sensitive to wind and wave effects, increasing the slip to about 0.7-1.6% of the 10-m wind speed (e.g. Pazan and Niiler 2001; Poulain et al. 2009; Peng et al. 2015).

Nearly-global maps of the mean surface ocean circulation calculated from drifter observations using bin-averaging were presented by Niiler (2001) and Maximenko et al. (2009). Considering that these fields were biased by undrogued drifter data, and seeking to reduce the smoothing effect of data binning, Lumpkin and Johnson (2013) produced a global climatology using drogued-only observations and a new binning method that simultaneously models spatial and temporal variations. However, since the exclusion of undrogued data significantly reduces the observational density in many oceanic areas, Lumpkin and Johnson (2013) selected data within relatively large bins (specifically within ellipses oriented by the variance of the binned observations, with areas equivalent to 2° radius circles) to obtain statistically significant estimates homogeneously distributed throughout the oceans. Although the use of large bins better resolves large-scale circulation patterns, it has the potential to significantly smooth coherent structures at mesoscale ranges, such as the large cross-stream velocity gradient associated with western boundary currents.

Based on these considerations, this study applies a first-order correction to the slip of undrogued drifters by referencing their velocity estimates to 15-m using a formulation proposed by Pazan and Niiler (2001), and describes a new estimation method designed to further reduce the smoothing effect of data binning, in order to generate a
new comprehensive velocity climatology at 15-m depth (hereafter referred to as “near-surface”) of the global ocean. The mean fields obtained using the proposed approach recover well-known large-scale circulation features, and resolve coherent structures at mesoscale ranges whose visualization was only possible by time-averaging surface velocities indirectly inferred from satellite observations (e.g. Lagerloef et al. 1999; Maximenko et al. 2009). A thorough description of the circulation in light of the new results, including its seasonal variations and kinetic energy distribution, will be the subject of an upcoming publication. Here, focus is given to describing the proposed method and to analyzing its associated uncertainties.

This chapter is organized as follows. Section 2.2 describes the datasets, the correction of drifter slip bias, and the method proposed for the decomposition of Lagrangian data into mean, seasonal and eddy components. Section 2.3 presents the results of sensitivity tests to method parameters and an error analysis, describes the improvements of the new climatological fields relative to the results of Lumpkin and Johnson (2013), and briefly describes prominent new features observed in the obtained global maps. Finally, Section 2.4 summarizes this study and its conclusions.

2.2 Methods

2.2.1 Data description

2.2.1.1 Position/velocity observations from surface ocean drifters

This analysis uses position and horizontal velocity data from both undrogued and 15-m drogued drifters of the Global Drifter Program (GDP). This dataset is archived and distributed by the Atlantic Oceanographic and Meteorological Laboratory of
the National Oceanic and Atmospheric Administration (AOML/NOAA, www.aoml.noaa.gov/phod/dac/index.php). Its generation involves the quality control of the raw drifter position fixes, and their subsequent interpolation via kriging along their trajectories to regular 6 hour intervals, at which the \( u \) and \( v \) velocity components are calculated by 12 hour centered differencing the kriged positions (Hansen and Poulain 1996). The GDP dataset obtained for this study comprises more than 29 million, six hour position/velocity estimates scattered throughout the world’s ocean, from February 1979 to June 2015. About 56\% of the available data points are from undrogued drifters.

Figure 2.1 shows global distribution maps of the data obtained by drogued, undrogued and both types of drifters (top, middle and bottom panels, respectively), in observation days per square degree. The density of data obtained by drogued drifters is usually higher close to continental contours and to traditional deployment sites, such as the western North Atlantic, the western and eastern North Pacific, the tropical Pacific, Sea of Japan, and near the Antarctic Peninsula, while the distribution of data from undrogued instruments marks time-averaged convergence zones in the interior of the subtropical gyres, notably highlighting garbage patches in the eastern South Pacific, and within the subtropical gyres of the Atlantic ocean. These characteristics arise because (a) the probability of drogue loss increases as a function of drifter age, with about 30\% (90\%) of these instruments losing their drogues within the first 3 months (1.5 years) of operation (Grodsky et al. 2011); (b) a time scale of months to years is required for drifters deployed near coastal areas to travel to the interior of the gyres, meaning that instruments sampling these regions tend to be older and thus more frequently undrogued; and (c) the drifters ultimately tend to
move away from time-averaged divergence areas, such as the equatorial region, and
to accumulate at convergence zones, such as the interior of subtropical gyres. While
Ekman convergence plays a role in this effect, Beron-Vera et al. (2016) demonstrated
that the main mechanism driving the accumulation of undrogued drifters at large-
scale convergence zones is the combined action of wind and currents on finite-sized
floating objects.

2.2.1.2 Altimeter-derived geostrophic velocity fields

Altimeter-derived surface geostrophic velocity (GV) fields are produced by the Seg-
ment Sol Multimissions d’Altimétrie, d’Orbitographie et de Localisation Précise of the
Data Unification and Altimeter Combination (SSALTO/DUACS), and were obtained
from the Archiving, Validation and Interpretation of Satellite Ocean Data (AVISO,
www..aviso.altimetry.fr/duacs/). For its generation, regularly-gridded sea-surface
height (SSH) fields are initially obtained by merging data from two altimetric satel-
lites with different sampling characteristics. One is from the TOPEX/Jason missions,
with a 315 km equatorial ground track separation and a 9.9156 days global sampling
cycle, and the other is from the ERS/Envisat missions, with an 85 km equatorial
ground track separation and a 35 days sampling cycle. The use of simultaneous ob-
servations from these two sampling strategies allows the generation of SSH fields with
higher spatial-temporal resolution (Chelton et al. 2007), while using data from only
two satellites at a time ensures a homogeneous spatial-temporal error distribution
(Polito and Sato 2015). Geostrophic velocities are then calculated at the extratropics
using the geostrophic relations, and within a 5° band around the equator using a
β-plane formulation of the geostrophic equations (Lagerloef et al. 1999). The time
Figure 2.1: Number of drifter observation days per square degree for the period between February 1979 and June 2015, considering data obtained from drogued, undrogued, and both sampling regimes (top, middle and bottom panel, respectively).
series of GV maps obtained for this study has a $0.25^\circ \times 0.25^\circ \times 1$ day resolution, covering the oceans between 67.5$^\circ$S and 67.5$^\circ$N from October 1992 until June 2015.

### 2.2.1.3 Reanalysis 10-m wind fields

10 meter height wind velocity fields are from the European Centre for Medium-Range Weather Forecasts (ECMWF, [www.ecmwf.int](http://www.ecmwf.int)) ERA-Interim reanalysis model (Dee et al. 2011). The obtained time-series of maps have a $1^\circ \times 1^\circ \times 6$ hour resolution and spans the entire temporal coverage of the GDP dataset. The use of reanalysis winds is based on the assumption that, as this class of numerical models continually assimilates real geophysical measurements to redefine their initial conditions, their results constitute the best available representation of the surface wind field in the absence of actual observations.

### 2.2.2 Correction of drifter slip bias

Due to the significant slip of undrogued drifters, previous studies recommended not using their data for calculating pseudo-Eulerian flow statistics without first correcting for slip (e.g. Grodsky et al. 2011; Lumpkin and Johnson 2013). As shown by Figure 2.1, this significantly reduces the observational density in extensive oceanic regions, particularly in the Southern Ocean, the South Pacific, and the subtropical gyres of all three major ocean basins. Methods for correcting the downwind slip of undrogued drifters are available in the literature (e.g. Pazan and Niiler 2001; Poulain et al. 2009), whose application in the equatorial Atlantic and in the Indian Ocean reduced differences between pseudo-Eulerian statistical properties calculated using observations from each sampling regime (Perez et al. 2014; Peng et al. 2015). Based
on these considerations, this Section extends the correction of the undrogued drifter slip velocities to the global ocean, and evaluates the advantages and biases of this practice for calculating the ocean velocities’ pseudo-Eulerian mean and variance.

First, the ECMWF 10-m wind fields are linearly interpolated to the drifter locations. To account for the slip motion, a downwind velocity modeled as $\alpha \times W$ is subtracted from the drifter velocities, where $W$ is the 10-m wind speed, and $\alpha$ is the fraction of $W$ converted to the slip. For drogued instruments, $\alpha_d = 7 \times 10^{-4}$ (Niiler et al. 1995). For undrogued drifters, $\alpha_u$ is calculated using a formulation proposed in Pazan and Niiler (2001), given by

$$\alpha_u = \frac{\langle U_u \rangle - \langle U_d \rangle}{\langle W \rangle} + \alpha_d,$$

(2.1)

where the subscripts $d$ and $u$ respectively denote drogued and undrogued drifters, $U$ is the downwind component of the drifter velocities, and the brackets represent ensemble averages. Specifically, $\alpha_u$ is calculated using 6-h drogued and undrogued drifter observations selected within $4^\circ \times 4^\circ$ spatial bins centered at the grid points of a $1^\circ \times 1^\circ$ global grid. Only bins with more than 300 data points were considered, and where $\langle U_u \rangle \neq \langle U_d \rangle$ and $\langle W \rangle \neq 0$ within 95% confidence margins, assuming for simplicity that the observations are independent. Results for $\alpha_u$ more than 3 standard deviations away from the mean of the results of all bins were taken as outliers, and also excluded. The latter operation was iterated 3 times to guarantee convergence of the $\alpha_u$ histogram distribution.

Figure 2.2 shows the spatial and histogram distributions of the obtained $\alpha_u$ values (left and right panel, respectively). The global set of $\alpha_u$ retrievals have mean $\mu = 1.48 \times 10^{-2}$ and standard deviation $\sigma = 0.49 \times 10^{-2}$, where a Gaussian function fitted to the histogram (red line) indicates that this quantity can be approximately
Figure 2.2: Downwind slip coefficient for undrogued GDP drifters $\alpha_u$ calculated via Equation (2.1), using velocity observations from drogued and undrogued GDP drifters and 10-m wind data from the ECMWF ERA-Interim reanalysis selected within $4^\circ \times 4^\circ$ bins, centered on the grid points of a $1^\circ \times 1^\circ$ global grid. Left: global map of the retrieved $\alpha_u$ values. Right: histogram of this parameter, where the red line is a Gaussian function fitted to the $\alpha_u$ distribution.

described as a normally-distributed random variable. The histogram encompasses $\alpha_u$ estimates of previous studies, including $0.97 \times 10^{-2}$ for the Pacific and North Atlantic oceans (Pazan and Niiler 2001), $0.66 \times 10^{-2}$ in the eastern Mediterranean Sea (Poulain et al. 2009), and $1.64 \times 10^{-2}$ in the equatorial Atlantic and in the Indian Ocean (Perez et al. 2014; Peng et al. 2015). Conversely, the spatial distribution of $\alpha_u$ shows continuous large-scale patterns that would not be observed in the case of a purely random quantity, and that are also qualitatively different from the GDP data spatial distribution (Fig. 2.1). One possible explanation for the observed patterns is that they reflect the geographical distribution of drifters equipped with surface floats of different aerodynamic characteristics, that would thus react differently to direct wind forcing. However, estimates of $\alpha_u$ as a function of the float surface area (not shown) revealed a weak dependency between these two parameters, suggesting that the distribution in Figure 2.2 reflects different geophysical conditions, and are not merely the result of random chance, heterogeneous data distribution, and/or instrument-specific properties.
It is possible that the geographical dependency of $\alpha_u$ seen in Figure 2.2 reflects the response of the drifter velocities to a spatially-varying surface gravity wave field. This is suggested considering the fact that the correction proposed by Equation (2.1) is based on how the wind affects the trajectories of drogued drifters, not accounting for the increased sensitivity of undrogued instruments to wave-induced slip motion, which preferentially aligns itself with the direction of the swell propagation rather than with the 10-m winds. Testing this hypothesis is beyond the objectives of this work, although a possible venue of investigation involves using directional wave spectra, retrieved from global ocean wave numerical models and/or from satellite-based synthetic aperture radar observations, to estimate the surface Stokes drift velocities.

The downwind slip correction applied here accounts for the spatial variations of $\alpha_u$ by linearly interpolating the values shown in Figure (2.2) to the drifter locations. To evaluate this approach, drifter data was selected within 1° radius bins centered around the grid points of a 0.25° × 0.25° global grid, at which the velocity’s mean and variance were separately calculated for drogued and undrogued data before and after the slip correction. Figure 2.3 shows the results obtained for the zonal velocity component, in terms of the longitudinal averages of the pseudo-Eulerian mean (panels a and b) and variance (c, d). Panel (e) highlights the undrogued/drogued variance ratio before and after the correction.

Figure 2.3a shows that the mean velocities estimated using uncorrected data can differ by $\mathcal{O}[0.1 \text{ m/s}]$ due to the increased slip of undrogued drifters. This bias is visible across all latitudes, predominantly reflecting the magnitude and direction of the mean 10-m zonal winds, and is particularly intense in the Southern Ocean, where the undrogued drifter mean velocities can be a factor of two bigger than those estimated
Figure 2.3: Longitudinal average of the pseudo-Eulerian mean (panels a and b) and variance (c and d) for the zonal ocean velocities, estimated from drifter observations. The blue, red and gray lines are calculated using data from drogued, undrogued and both drifter types, respectively; shading around each line denotes 95% confidence intervals. The left panels (a, c) are obtained without accounting for drifter slip bias, while the right (b, d) are based on drifter velocities corrected for downwind slip, following the methods described in the text. Panel (e) shows the zonally-averaged undrogued/drogued variance ratio before and after correction (orange and black line, respectively).
from drogued instruments. Accounting for the downwind slip virtually eliminates these differences, leading to time and zonally-averaged velocities for drogued and undrogued drifters that are statistically identical within 95% confidence margins across most latitudes (Fig. 2.3b).

For the variances, a visual comparison between Figures 2.3c and 2.3d, and between the orange and black lines in Figure 3e, shows that the values calculated using observations from undrogued drifters surpass those from drogued instruments at most latitudes both before and after the slip correction, although the operation does significantly reduce their differences. In terms of global averages, the correction reduces the undrogued/drogued variance ratio from 1.88 to 1.36. Section 2.3.2 demonstrates that the remaining discrepancies can be largely attributed to factors unrelated to slip motion, such as the reduced sampling density of drogued drifters, methodological errors, and possible sampling biases of drogued and undrogued instruments.

## 2.2.3 Decomposition of Lagrangian data

### 2.2.3.1 Proposed method

Following Lumpkin and Johnson (2013), the slip-corrected 6-h drifter velocities are preliminarily low-pass filtered along the trajectories using a 5th degree Butterworth filter with a cutoff period at 5 days, to remove tidal and near-inertial variability, and then linearly interpolated to daily values, considering the fact that 6-h measurements are not independent within the Lagrangian integral time scale, estimated to be between 2-3 days. Although a 1-day resolution is still within this range, it reduces the amount of correlated data used in subsequent operations without significantly impacting the data coverage in sparsely sampled areas of the ocean.
Data subsets of the zonal and meridional drifter velocities, \( u \) and \( v \), are then selected within circular spatial bins centered on the grid points of a \( 0.25^\circ \times 0.25^\circ \) global grid. The bins have a radius equivalent to \( 1^\circ \) longitude, meaning that they overlap each other by \( 0.75^\circ \) in the zonal direction and that their area decreases poleward. The use of overlapping bins on a fixed Eulerian grid and the latitudinal dependence of their area seeks to increase the spatial resolution of the pseudo-Eulerian maps, and to reflect the poleward reduction of the Rossby deformation radius (Lumpkin and Johnson 2013).

Within each bin, \( u \) and \( v \) observations are treated as data series dependent on horizontal and temporal coordinates, \( V(x, y, t) \), that can be expanded as

\[
V(x, y, t) = \langle V \rangle + \hat{V}(x, y) + V^s(x, y, t) + V^e(x, y, t),
\]

where \( \langle V \rangle \) is an ensemble average, \( \hat{V}(x, y) \) describes horizontal variations of the mean structure, \( V^s(x, y, t) \) models seasonal variations, and \( V^e(x, y, t) \) are residual (eddy) fluctuations.

To estimate \( \hat{V} \), previous studies fitted 2-D functions to the binned data (e.g. Bauer et al. 1998; Johnson 2001; Lumpkin and Johnson 2013; Peng et al. 2015). Although this improves the definition of horizontal velocity gradients relative to bin-averaging (e.g. Fratantoni 2001; Jakobsen et al. 2003; Reverdin et al. 2003; Zhurbas et al. 2014), the retrieved pseudo-Eulerian mean velocity fields are still visually smooth when compared against mean maps obtained from true Eulerian records, such as satellite products and numerical model outputs. To further reduce the smoothing, this work uses 1-D functions to model \( \hat{V} \).

The 1-D approach is based on the premise that horizontal variations of the time-mean ocean velocity field are highly anisotropic, with larger scales along the mean
velocity isolines than across them (Huang et al. 2007). Given that the sharpest horizontal gradients of the general ocean circulation, those associated with western boundary currents, occur along mesoscale ranges, then the mean velocity structure within mesoscale bins can be approximately described as a function of the distance across the time-mean velocity isolines. The advantage of 1-D over 2-D functions lies in the fact that their fitting requires the determination of a smaller number of coefficients, making it less prone to estimation errors due to numerical instability, and at the same time that allowing the use of more complex functions to model mean horizontal gradients.

This work uses 1-D polynomials to retrieve $\hat{V}$, and a linear combination of harmonics to model $V^*$. Substituting these in Equation (2.2) and assuming a data subset with $N$ observations, $V_p(\hat{x}, t)$, $p = 1, 2, 3, ..., N$, a system with $N$ linear equations can be defined as

$$V_p(\hat{x}, t) = \sum_{i=0}^{n} a_i(\hat{x})^i + \sum_{j=1}^{m} \left[ b_j \sin \left( \frac{\theta t}{j} \right) + c_j \cos \left( \frac{\theta t}{j} \right) \right] + V^e_p(\hat{x}, t). \quad (2.3)$$

The first term on the right-hand side is the $n^{th}$ degree polynomial function used to describe spatial gradients, with $a_i$, $i = 0, 1, 2, ..., n$, as coefficients, where $\hat{x}$ denotes the coordinate system for the 1-D fitting. The $\hat{x}$ axis is expressed as the distance in km to the data centroid (i.e. the average position of all data points) normalized by the standard deviation of all distances, and is found separately for $u$ and $v$ by rotating the binned observations’ coordinates in angle increments of $4^\circ$ about the data centroid. At each angle, the 1-D polynomial is least-squares fitted to the data sorted along the rotated x-axis and a fitting error is calculated, with the axis $\hat{x}$ being defined at the angle with the smallest error. This procedure is illustrated in Figure 2.4, using $v$ measurements selected within a $0.5^\circ$ radius bin in the Florida Current.
Figure 2.4: Schematic representation of the 1-D curve fitting to drifter velocity data organized along the rotated x-axis. The dots are meridional velocity measurements selected within 0.5° of the coordinates 28°N, 79.75°W, region dominated by the northward flow of the Florida Current. The arrows labeled $x, y$ show the orientation of the original Cartesian coordinate system, while $x', y'$ are the rotated axes. In both diagrams, data is projected to the plane ($x', v$), along which the 1-D function is fitted (red lines). The transition from panel (a) to (b) shows that the data variance relative to the fitted function is minimized when $x'$ is aligned with the current’s mean velocity structure.

The transition from panel (a) to (b) shows that the variance relative to the fitted function (red line) is minimized when the rotated x-axis aligns with the axis of the current. The second term in the right-hand side of Equation (2.3) is the harmonic expansion used to model seasonal fluctuations, where $m$ is the number of harmonics; $t$ is the temporal coordinate, in years; $\theta$ is the frequency of the annual cycle; and $b_j$ and $c_j$, $j = 1, 2, 3, ... , m$, are the coefficients of the sine and cosine components of each harmonic. For the generation of the global climatology presented in this work, the parameters $n$ and $m$ are set to 4 and 2, respectively, resulting in nine coefficients to be estimated in Equation (2.3).

The system defined by Equation (2.3) can be written in matrix form as $V = Az + V^e$, where $A$ is a $N \times 9$ matrix containing the polynomial and periodic functions; $z$ is a column vector holding their 9 unknown coefficients; and $V^e$ is a column
vector with \( N \) elements containing the fitting error, which is a sum of eddy velocities, observational errors, and model errors from assuming (2.3). Following Lumpkin (2003) and Lumpkin and Johnson (2013), a best-fit solution for \( z \) is obtained via Gauss-Markov estimation (GME) (Wunsch 1996), an inverse curve fitting method that accounts for the fact that Lagrangian observations are correlated within the Lagrangian integral time scale, and therefore do not correspond to independent realizations of the velocity field. The variance-covariance matrix of the eddy residuals is defined prior to the fitting operation (\textit{a priori}) by assuming an idealized autocovariance function, which corrects the number of degrees of freedom for the fitting and thus reduces biases caused by the use of non-independent data points (Lumpkin 2003). The GME solution for \( z \) is

\[
z = R_z A^T (AR_z A^T + R_n)^{-1} V, \quad (2.4)
\]

where \( R_z \) and \( R_n \) are respectively variance-covariance matrices for the system’s coefficients and eddy fluctuations, both defined \textit{a priori}; and the superscript “T” denotes transposed matrices. \( R_z \) is an \( 9 \times 9 \) matrix, whose diagonal terms are assumed to be equal to the squared difference between the maximum and minimum binned velocity values (i.e. the square of the data range), while off-diagonal terms are set to zero. \( R_n \) has \( N \times N \) dimensions, and is built using the following autocovariance function,

\[
R_n = \sigma_V^2 \cos \left( \frac{\pi t}{2T_d} \right) \exp \left[ - \left( \frac{\pi t}{2\sqrt{2}T_d} \right) \right], \quad (2.5)
\]

where \( \sigma_V^2 \) is the data variance, and \( T_d \) is a decorrelation time scale, set to 6.33 days, corresponding to a Lagrangian integral time scale of 3 days (Lumpkin 2003; Lumpkin and Johnson 2013). Furthermore, off-diagonal values of \( R_n \) are multiplied by 0.9, under the assumption that 10% of the eddy variance is due to white noise and thus
uncorrelated from one observation to the next. Finally, it is assumed that observations of different drifters are always independent, meaning that the autocorrelated structure is only calculated along individual trajectories. Once the mean structure and the seasonal fluctuations are estimated, they are subtracted from the binned velocity observations to obtain the eddy residuals $V^e$.

Spurious pseudo-Eulerian estimates can arise due to low observational densities. Assuming a 3-day Lagrangian integral time scale, a minimum of 60 drifter observation days (10 degrees of freedom) is required to estimate the 9 coefficients of Equation (2.3). To minimize sampling-related errors, the coefficients of the periodic functions $b_j$ and $c_j$ are not estimated in bins with 40-90 data points, and no calculations are made in bins with less than 40 data points. However, even if such requirements are met, the fitting can be numerically unstable and produce spurious results. Thus, solutions for $z$ are considered valid if their absolute values are smaller than the data’s velocity range, and if more than 70% of the eddy residuals lies within two standard deviations of the data’s ensemble mean. Failing these criteria, the fitting operation is tentatively redone using progressively smaller polynomial degrees, to a minimum of one (where only the ensemble mean $\langle V \rangle$ is calculated). If valid estimates are still not obtained, the grid point is assigned a no data flag.

For mapping purposes, the best-fit coefficients of the spatial and seasonal functions are evaluated at the center of each bin, i.e., at the grid points of the $0.25^\circ \times 0.25^\circ$ grid. However, due to heterogeneous data distribution and the use of overlapping bins, the bin center can lay outside of the region covered by the selected data. With that in mind, an elliptical area is defined for each bin, with major and minor axes respectively equal to twice the length of the first and second eigenvalues of the data.
(x, y) coordinates, and rotated by the declination angle of the first eigenvalue. If the bin center lies outside this ellipse, the grid point is also assigned a no data flag.

Finally, to assess the statistical reliability of the modeled velocities, an *a posteriori* error variance-covariance matrix $P_z$ is obtained by

$$P_z = R_z - R_z A^T (A R_z A^T + R_n)^{-1} A R_z,$$

(2.6)

where $P_z$ is a $9 \times 9$ matrix, and the square root of its diagonal terms are the standard errors of the best-fit coefficients $a_i, b_j$ and $c_j$. It is noted that off-diagonal (covariance) terms in $P_z$ are different from zero, meaning that the coefficients have correlated errors. $P_z$ can be used to obtain a variance-covariance error matrix $P_n$ for the modeled velocities via error propagation

$$P_n = A P_z A^T.$$

(2.7)

Here, $P_n$ is $N \times N$, and the square root of its diagonal terms correspond to standard errors ($\epsilon_{SE}$) for the velocity estimates. In this study, the $\epsilon_{SE}$ of the mean and seasonal velocity estimates are analyzed separately. Specifically, errors for the mean are evaluated at the bin center, coinciding with the mapped mean velocities, using only variance-covariance terms in $P_z$ associated with the polynomial coefficients in Equation (2.3), while errors for the seasonal fluctuations are evaluated at the spatial-temporal positions of the binned observations using the remaining variance-covariance terms in $P_z$, associated with the coefficients of the periodic functions in (2.3), and cross-terms between coefficients of polynomial and periodic functions.

### 2.2.3.2 Decomposition evaluation

To evaluate the performance of the decomposition method described in Section 2.2.3.1, altimeter-derived geostrophic velocities (GV) from AVISO are linearly in-
terpolated to the GDP drifter locations. The proposed approach assumes that the statistical properties of the AVISO GV fields are perfect Eulerian references for estimating the errors of pseudo-Eulerian quantities calculated from the Lagrangian GV dataset.

This analysis is motivated by the fact that the decomposition method requires choices for the bin size/mapping resolution, and for the curve fitting parameters $n$, $m$, and $T_d$, whose definition affects the results. Furthermore, previous studies employed different decomposition methods and a wide range of bin sizes and grid resolutions, also using different Lagrangian datasets and/or data processing steps, implying that an objective comparison between methods should use the same Lagrangian dataset and averaging resolution. Finally, standard errors ($\epsilon_{SE}$) obtained from Equation (2.7) are scaled as $(\sigma^2/N)^{1/2}$, where $\sigma^2$ is the data variance and $N$ is the number of independent samples. This means that $\epsilon_{SE}$ estimates ignore errors introduced by, for example, the spatial smoothing effect of data binning, and to possible inadequacies of physical model proposed by Equations (2.3) and (2.5), and therefore can differ from the actual estimation errors.

It is noted that the pseudo-Eulerian statistical properties of the Lagrangian GV data differ from those of actual drifter observations, due to the following: (1) the GV estimates are subject to uncertainties of the geoid and the global tidal models used to reference the altimetric SSH measurements, which respectively introduce errors in the velocities’ magnitude and direction, and reduce the accuracy of the estimates in regions shallower than 1000 m, due to regional tidal effects forced by the local bathymetry and continental contours; (2) ageostrophic flows are absent, and the geostrophic approximation may not properly describe the circulation within coherent
mesoscale eddies, which an increasing body of literature suggests to be predominantly in cyclogeostrophic balance (e.g. Castelão and Johns 2011; Maximenko et al. 2013); and (3) the relatively large correlation length scales ($\mathcal{O}[10^2 \text{ km}]$) assumed for the generation of regularly-gridded SSH fields implies that variability at smaller scales are underestimated (e.g. Ducet et al. 2000; Poje et al. 2014). Despite these limitations, the altimeter-derived geostrophic velocities have variance levels comparable to those estimated from in situ data (Ducet and Le Traon 2001), implying that statistical quantities calculated from the Lagrangian GV dataset and from actual drifter velocity measurements should have similar variability.

Specifically, the Eulerian time-series of the $u$ and $v$ components of the AVISO geostrophic velocities at each grid point, $V(t)$, are decomposed as

$$V(t) = \overline{V} + V^s(t) + V^e(t), \quad (2.8)$$

where $\overline{V}$ is the long-term mean; $V^s$ are seasonal fluctuations, estimated by least-squares fitting $m = 5$ harmonics to the residuals about the mean; and $V^e$ are eddy residuals. Variance estimates of $V^s$ and $V^e$, respectively $\sigma^2_s$ and $\sigma^2_e$, are computed conventionally.

Errors ($\epsilon$) of pseudo-Eulerian estimates of $\overline{V}$, $V^s$, $\sigma^2_s$, and $\sigma^2_e$, are obtained by subtracting the correspondent Eulerian values at each grid point. For simplicity, the $\epsilon$ of the $u$ and $v$ components are analyzed in terms of its magnitude, $\epsilon_A = \sqrt{\epsilon^2_u + \epsilon^2_v}$, hereafter referred to as absolute errors. Due to the time dependence of $V^s$, its $\epsilon_A$ at each grid point is defined as the root mean square (RMS) magnitude of the errors of the seasonal velocities estimated for the binned drifter observations. Standard errors are processed similarly, to allow the comparison between $\epsilon_A$ and $\epsilon_{SE}$.
To investigate the factors governing the horizontal distribution of $\epsilon_A$ and $\epsilon_{SE}$, the $u$ and $v$ components of the reference Eulerian parameters are first used to calculate the magnitude of the mean velocity ($S = \sqrt{u^2 + v^2}$, hereafter referred to as mean speed), and the kinetic energy of seasonal and eddy fluctuations (SKE and EKE, defined as the average of the respective zonal and meridional variance estimates). The retrieved $\epsilon_A$ and $\epsilon_{SE}$ are then subsampled within intervals (i.e. classes) of the correspondent Eulerian $S$, SKE, and EKE, and simultaneously subsampled within intervals of the square roots of EKE and $N$. The error estimates obtained within each class are used to calculate RMS values ($\epsilon_{A}^{\text{RMS}}$ and $\epsilon_{SE}^{\text{RMS}}$), allowing analyzing their variation as a function of the considered parameters.

The choices for the adjustable parameters of the proposed decomposition method were defined based on the results of this analysis, which are presented and discussed in Section 2.3.1. Section 2.3.1.1 evaluates the amount of detail recovered by pseudo-Eulerian mean velocity magnitude maps at different resolutions, while Section 2.3.1.2 analyze the sensitivity of the results to the fitting parameters. Section 2.3.1.3 shows the impact of the choice of bin size on pseudo-Eulerian estimates, and compares the performance of the proposed decomposition method with that of other techniques. Finally, Section 2.3.1.4 assess the spatial distribution of errors, and compares the retrieved $\epsilon_A$ with $\epsilon_{SE}$ estimates.
2.3 Results and discussion

2.3.1 Decomposition evaluation

2.3.1.1 Spatial resolution of pseudo-Eulerian fields

This work maps pseudo-Eulerian estimates to a $0.25^\circ \times 0.25^\circ$ global grid. This resolution is adopted because it (a) corresponds to a lower bound limit required to resolve mesoscale features, and (b) coincides with the AVISO GV’s native grid, allowing a comparison between pseudo-Eulerian and Eulerian statistics. However, an important question is whether the proposed decomposition method can recover horizontal velocity gradients at the scales implied by this grid. To evaluate the amount of detail recovered by pseudo-Eulerian estimates subsampled at different resolutions, Figure 2.5 shows the Eulerian time-mean geostrophic speed for the Gulf of Mexico and Florida Current, alongside pseudo-Eulerian estimates obtained using data selected within $1^\circ$ radius bins, and then mapped to $1^\circ \times 1^\circ$, $0.5^\circ \times 0.5^\circ$ and $0.25^\circ \times 0.25^\circ$ grids.

Prominent features shown by the Eulerian field in Figure 2.5 includes the Loop and Florida Currents, with mean speeds of $\mathcal{O}[0.1 \text{ to } 1 \text{ m/s}]$, and smaller-scale coherent flows with $\mathcal{O}[0.1 \text{ m/s}]$ speeds, such as the Antilles Current and recirculation cells on the eastern flanks of the Florida and Antilles Currents. The $1^\circ \times 1^\circ$ field only resolves large-scale features, such as the along-stream structure of Loop and Florida Currents. At $0.5^\circ \times 0.5^\circ$, the major currents are better defined and $\mathcal{O}[0.1 \text{ m/s}]$ features can be discerned, however the resolution is still insufficient to resolve their cross-stream velocity profiles. Further refining to $0.25^\circ \times 0.25^\circ$ results in circulation patterns with horizontal scales and speed magnitudes visually compatible with
Figure 2.5: Long-term average of the AVISO geostrophic speed for the Gulf of Mexico and Florida Current. The reference Eulerian field is illustrated alongside pseudo-Eulerian estimates, mapped to $1.00^\circ \times 1.00^\circ$, $0.50^\circ \times 0.50^\circ$, and $0.25^\circ \times 0.25^\circ$ grids via the 1-D GME method.

Independent of the resolution, notable discrepancies relative to the Eulerian field are observed in the western portion of the Gulf of Mexico. Such features are attributed to low data densities ($<100$ data points), resulting in sparse realizations of the energetic eddy field.
2.3.1.2 Sensitivity to fitting parameters

The proposed decomposition technique requires \textit{a priori} specifications for the parameters $n$ and $m$ in Equation (2.3), respectively the polynomial degree and number of seasonal harmonics, and of the decorrelation time scale $T_d$ in Equation (2.5). The choice for $n$ affects the overall adjustment of the fitted curve to the data. A low $n$ distorts spatial features and/or underestimate their magnitudes, also reducing the sensitivity of the procedure illustrated in Figure 2.4 to obtain an angle aligning with the large-scale structure of the data. Conversely, a high $n$ may result in overfitting (i.e. the interpretation of eddy fluctuations as spatial structure), and increases the chance of estimation errors due to numerical instability.

For a quantitative evaluation, the left panel of Figure 2.6 shows the $\epsilon_{\Delta}^{\text{RMS}}$ of the pseudo-Eulerian mean geostrophic speed calculated as a function of the reference Eulerian values, for $n = 2, 3, 4$ and $5$ (red, green, black and blue lines, respectively). The shading around each line are 95% confidence margins, and the thin dashed line marks the 1:1 signal-to-noise ratio limit. The $\epsilon_{\Delta}^{\text{RMS}}$ of all estimates are statistically similar for reference velocity magnitudes between 0 and 0.9 m/s, gradually rising from $\sim0.02$ to 0.09 m/s within this interval. Above 0.9 m/s, the errors for $n = 2$ ($n = 3$) increase faster than for higher $n$, reaching $\sim0.32$ (0.27) m/s at Eulerian speeds of 1.4 m/s. Using 4th and 5th degree polynomials, both show similar errors for speeds up to 1.2 m/s, where it reaches values of $\sim0.1$ m/s. Past this limit, the $\epsilon_{\Delta}^{\text{RMS}}$ for $n = 4$ ($n = 5$) further increases to 0.16 (0.13) m/s at reference speeds of 1.4 m/s. Despite the better performance of $n = 5$ at higher velocities, the larger number of coefficients make the estimates more prone to stability errors and requires more data. To balance
Figure 2.6: Absolute errors of the pseudo-Eulerian mean geostrophic speed (left), and of the pseudo-Eulerian kinetic energy of the seasonal fluctuations (SKE) (right), calculated as a function of the correspondent Eulerian values ($\epsilon_{RMS}^A$). $n$ and $m$ denotes the polynomial degree and the number of harmonics used in the model proposed in Equation (2.3), while the red, green, black and blue curves correspond to values of 2, 3, 4 and 5 of each parameter. The shading around each line are 95% confidence margins, and the thin dashed line marks the 1:1 signal-to-noise ratio limit.

the definition of velocity gradients with the stability of the fitting operation, the climatological fields presented in this work were obtained using $n = 4$.

Regarding the number of seasonal harmonics, many drifter-based studies used $m = 2$, therefore resolving only annual and semiannual periods (e.g. Richardson and Walsh 1986; Lumpkin 2003; Lumpkin and Johnson 2013; Peng et al. 2015). Including more harmonics can improve the definition of the seasonal cycle, but also increases the chance of errors due to overfitting or numerical instability. To verify the sensitivity of the seasonal estimates to the choice of $m$, the right panel in Figure 2.6 shows the $\epsilon_{A}^{RMS}$ of SKE calculated as a function of the correspondent Eulerian values, where the red, green, black and blue lines respectively refers to $m = 2, 3, 4$ and 5. The errors calculated using $m = 2$ increase from $< 1 \times 10^{-3}$ to $\sim 1.5 \times 10^{-2} \text{m}^2/\text{s}^2$ for reference variances between 0 and $3.5 \times 10^{-2} \text{m}^2/\text{s}^2$. Within this range, adding one harmonic progressively increases the errors by $\sim 1 \times 10^{-3} \text{m}^2/\text{s}^2$ due to overfitting. For Eulerian SKE values above $3.5 \times 10^{-2} \text{m}^2/\text{s}^2$, the $\epsilon_{A}^{RMS}$ estimates obtained for all tested $m$ lies
within each other’s error margins, varying between $1.5 - 2.5 \times 10^{-2} \text{m}^2/\text{s}^2$. Based on these results, $m = 2$ is considered the optimum choice for the decomposition.

Finally, $T_d$ is the time scale used to define independent data points in the GME method. Here, values from to 0 to 20.33 days were tested. Statistically significant changes on the pseudo-Eulerian results to different $T_d$ are not obvious in $\epsilon^\text{RMS}_A$ estimates as the presented in Figure 2.6. However, a visual inspection of the mean speed maps show that, for $T_d \geq 6.33$ days, the mean speed of features such as the Loop Current, recirculation cells, branches of the Antarctic Circumpolar Current, and the eastward extensions of the Kuroshio and Gulf Stream Currents, increase by $\mathcal{O}[0.1 \text{ m/s}]$ relative to results obtained for $T_d = 0$. The lower speeds in $T_d = 0$ are caused by a sampling bias towards smaller speeds intrinsic in data binning, arising from the fact that slower drifters tend to spend more time within a limited area than faster ones (Lumpkin 2003; Mariano and Ryan 2007). By defining observations as independent if they are more than 6 days apart, the relative weight of correlated low speed measurements is reduced in the curve fitting, giving higher mean speed estimates for the mentioned features (Lumpkin 2003).

However, using $T_d > 0$ also increases the chance of errors due to numerical instability. This is attributed to the fact that (a) larger $T_d$’s reduces the number of degrees of freedom; and (b) by assuming an autocorrelated structure in time, the relative weight of the observations also change in space, which can cause estimation errors if the distribution of independent data points is asymmetric along the spatial domain. Specifically assuming $T_d = 10.33$ days (as in Lumpkin and Johnson 2013) and using the Lagrangian GV dataset, these effects caused the exclusion of estimates in $\sim 1800$ grid points ($\sim 0.3\%$ of the total), increased tenfold when using actual drifter
observations due to their larger variances. To minimize such errors, a lower-bound value of $T_d = 6.33$ days is adopted.

2.3.1.3 Sensitivity to bin size and comparison with other techniques

This section analyzes the sensitivity of pseudo-Eulerian estimates to the choice of bin size. Furthermore, since the proposed decomposition method is designed to reduce the smoothing effect of binning, its performance is compared against that of other methods, including (a) bin-averaging (e.g. Fratantoni 2001; Jakobsen et al. 2003; Reverdin et al. 2003; Zhurbas et al. 2014); (b) 2-D polynomial fitting via GME (Lumpkin and Johnson 2013; Lumpkin and Flament 2013; Peng et al. 2015); (c) least-squares smoothing 2-D cubic splines (LSS) (Bauer et al. 1998; Falco and Zambianchi 2011); and (d) a 1-D version of the LSS spline fitting.

Following Lumpkin and Johnson (2013), a 2$^{nd}$ degree polynomial is used in the 2-D GME. In a brief description of the LSS method, this technique requires $a$ priori assumptions of the smoothness level of the fitted curve, which allows more stable estimates than the traditional least-squares fit (Inoue 1986). The LSS uses cubic splines, which are functions constituted by a set of piece-wise cubic polynomials with continuous first and second derivatives at their connection points, known as knots. The LSS fitting parameters include the number of equispaced spline knots $(k)$, and the spline roughness and tension $(\rho$ and $\tau$, respectively). These were defined via sensitivity tests, resulting in $\rho, \tau = 1$ for both 1-D and 2-D versions, and $k = 3$ ($k = 2$) for 1-D (2-D).

Figure 2.7 shows pseudo-Eulerian mean geostrophic speed maps for the Loop and Florida Currents. The left, middle and right panels are calculated using circular bins
with radius equivalent to 0.5°, 1° and 1.5° degrees longitude, respectively. From top to bottom, results are respectively obtained via bin-averaging, 1-D and 2-D GME polynomial fitting, and 1-D and 2-D LSS spline fitting. This region was chosen to illustrate characteristics observed in the global fields because it simultaneously includes an intense western boundary current, recirculation cells, and coherent circulation structures in the basin interior, features whose cross-stream velocity gradients are frequently smoothed in pseudo-Eulerian estimates.

The bin-averaged fields in Figure 2.7 demonstrate the smoothing of spatial gradients due to the use of progressively larger bin areas. Particularly for 0.5° radius bins, the Loop and Florida Currents have cross-stream scales visually compatible with the Eulerian mean field (Fig. 2.5), and maximum core speeds of \( \sim 1 \) m/s, about 0.4 m/s smaller than the Eulerian values. The Antilles Current and recirculation cells can also be observed, with mean speeds of \( \mathcal{O}[0.1 \text{ m/s}] \). Increasing the bin size to 1° broadens the cross-stream structure of all currents and attenuates their speeds by a factor of 2. Using 1.5° radius bins, only the largest scales of the circulation are resolved, where features such as the Antilles Current, recirculation cells, and the cross-stream structure of the Loop and Florida Currents, are either absent or significantly smoothed. Contrasting with the bin-averaged maps, the fields calculated using curve fitting methods all show circulation patterns with spatial scales and speed magnitudes visually closer to the Eulerian field.

Comparing maps in Figure 2.7 calculated using 1-D and 2-D curve fitting methods, both produces visually similar results for 0.5° radius bins. However, increasing the bin radius to 1° (1.5°), the Florida Current velocities are more strongly attenuated in the 2-D version, being specifically \( \sim 0.4 \) (0.5) m/s smaller in the LSS, and \( \sim 0.1 \)
Figure 2.7: Pseudo-Eulerian mean geostrophic speed estimates for the Loop and Florida Currents, obtained from data selected within circular bins with radii equivalent to 0.5° (left column), 1° (middle) and 1.5° (right) degrees longitude. From top to bottom, the mean fields were respectively calculated via bin-averaging (e.g. Fratantoni 2001), 1-D and 2-D polynomial fitting via Gauss-Markov estimation (GME) (e.g. Lumpkin and Johnson 2013), and 1-D and 2-D least-squares smooth spline fitting (LSS) (e.g. Bauer et al. 1998).
(0.2) m/s in the GME. Conversely, the fields calculated using 1-D functions have gaps (blank grid points) not observed in their 2-D correspondents, that are particularly evident in the maps obtained using 1.5° radius bins at the Florida Straits and between the Florida peninsula and the Bahamas. As described in Section 2.2.3.1, grid points in the proposed 1-D approach are left blank when the bin center is outside the data coverage, criteria that was not adopted when using 2-D functions.

As for differences between maps obtained via GME and LSS in Figure 2.7, the GME fields show mean Loop Current speeds closer to the Eulerian values for all tested bin radii. Specifically, the reference Eulerian map in Figure 2.5 show speeds between 0.4-0.6 m/s for the Loop Current, in contrast with the 0.2-0.4 m/s range obtained via LSS, which is similar to the observed in the bin-averaged maps. The GME method also produces larger speeds for the Antilles Current and recirculation cells, surpassing the correspondent LSS values by \( \sim 0.05 \) m/s. As described in Section 2.3.1.2, data binning preferentially samples slower drifters, introducing the observed low speed bias in the bin-averaged and LSS results (Lumpkin 2003). The GME method reduces this effect because it redistributes degrees of freedom based on a prescribed decorrelation time scale, which reduces the relative weight of autocorrelated low-speed measurements. However, improvement is not observed in the Florida Current, where the 1-D LSS actually produces higher speeds than 1-D GME (\( \sim 0.1 \) m/s difference, using 1.5° radius bins). This is attributed to the use of more complex functions in LSS (3-knot cubic splines), which allow a better description of the intense Florida current’s cross-stream gradients than the 4\(^{th}\) degree polynomials used in the 1-D GME.

For a quantitative analysis, Figure 2.8 shows the \( \xi_{\alpha}^{\text{RMS}} \) of the global pseudo-Eulerian estimates of the mean geostrophic speed (left panels, a, c and e), and EKE (right, b, d
Figure 2.8: Same as Figure 2.6 for the pseudo-Eulerian mean geostrophic speed (left panels, a, c and e) and the eddy kinetic energy (EKE) (right, b, d and f), considering bin radii equivalent to 0.5° (panels a and b), 1° (c and d) and 1.5° (e and f) degrees longitude. Here, the $\epsilon_{\text{RMS}}^A$ of both quantities is calculated as a function of the reference Eulerian mean speed. The red, black and blue lines respectively refer to results obtained via bin-averaging (e.g. Fratantoni 2001), polynomial fitting via Gauss-Markov estimation (GME) (e.g. Lumpkin and Johnson 2013), and least-squares smoothing splines (LSS) (e.g. Bauer et al. 1998). The solid and dashed lines denote 1-D and 2-D versions of each curve fitting method.

and f), calculated as a function of the Eulerian mean speed for both parameters. The dependency of their absolute errors to the mean Eulerian speed is assumed because, as data binning attenuates horizontal velocity gradients, undiagnosed spatial structure would be interpreted as eddy fluctuations, thus introducing errors in the pseudo-Eulerian variances.

Considering first the results of bin-averaging, panel (a) of Figure 2.8 shows that, using 0.5° radius bins, the $\epsilon_{\text{RMS}}^A$ of mean speed estimates of all tested decomposition methods increase from 0.02 to 0.07 m/s for Eulerian speeds between 0 and 0.7 m/s.
Past this limit, the errors of the bin-averaged estimates increase faster than that of other methods, reaching 0.36 m/s at Eulerian speeds of 1.4 m/s. The $\epsilon_{\text{RMS}}^A$ values of the correspondent EKE estimates (b) increase approximately linearly as a function of the Eulerian values, varying from 0.002 to 0.04 m$^2$/s$^2$, becoming notably larger than the errors of other methods past 1.2 m/s. Panels (c) to (f) show that the errors of bin-averaged estimates of both quantities increases significantly at larger bin sizes. Particularly for 1° (1.5°) radius bins, the $\epsilon_{\text{RMS}}^A$ of mean speed estimates (c, e) exceeds that of other methods at Eulerian speeds of >0.4 (0.2) m/s, reaching maximum values of 0.77 (1.00) m/s. The larger errors in the mean are reflected in the correspondent EKE estimates (d, f), reaching maximum values of 0.11 (0.13) m$^2$/s$^2$ at Eulerian speeds of 1.4 m/s.

Although less pronounced, an increase of $\epsilon_{\text{RMS}}^A$ for larger bin sizes is also observed in results of curve fitting methods, particularly for the 2-D approach. Analyzing results from the 1-D and 2-D LSS, panels (a), (c), and (e) of in Figure 2.8 shows that estimates obtained by the 2-D version have consistently larger errors than 1-D for Eulerian speeds >0.6 m/s, for all bin radii. Specifically, mean speed obtained by the 2-D LSS show $\epsilon_{\text{RMS}}^A$ values of 0.26, 0.47 and 0.52 m/s (respectively for 0.5°, 1° and 1.5° radius bins) at Eulerian speed of 1.4 m/s, against 0.07, 0.10 and 0.13 m/s for the 1-D LSS. Panel (b) shows that the EKE errors for 1-D and 2-D LSS are statistically similar to each other for 0.5° radius bins, increasing from 0.002 to 0.035 m$^2$/s$^2$ for up to 1.2 m/s reference speeds, and decreasing to 0.002 m$^2$/s$^2$ at 1.4 m/s. For 1° (1.5°) radius bins (d, f), the $\epsilon_{\text{RMS}}^A$ of EKE estimates of both 1-D and 2-D versions are similar along most of the Eulerian speed range, reaching maximum values of ~ 0.04 m$^2$/s$^2$ within the 0.8-1.2 m/s range. For reference speeds above 1.3 m/s, the 2-D LSS show
larger errors than its 1-D version, reaching maximum values of $\sim 0.03 \text{ m}^2/\text{s}^2$ at the 1.4 m/s limit for both 1° and 1.5° radius bins, versus $\sim 0.01 \text{ m}^2/\text{s}^2$ for the 1-D LSS.

Comparing 1-D and 2-D GME methods, Figure 2.8a shows that, using 0.5° radius bins, the $\epsilon_{\text{RMS}}^A$ of the mean speed estimates of both versions are similar within 0.02 m/s, with maximum errors of 0.08 and 0.10 m/s, respectively. However, for 1° (1.5°) radius bins (c, e), the errors of the 2-D estimates exceed that of 1-D for reference speeds $>1 (>0.8) \text{ m/s}$, with maximum values of 0.31 (0.49) m/s for 2-D, and of 0.16 (0.29) m/s for 1-D. As for the $\epsilon_{\text{RMS}}^A$ of EKE estimates (panels b, d and f), the behavior is similar to that described for the LSS, except for the fact that the GME’s errors are $\sim 0.01 \text{ m}^2/\text{s}^2$ smaller for reference velocities between 0.5-1.2 m/s, and that, for 1.5° bin radius, the GME estimates obtained by both 1-D and 2-D GME surpass their LSS correspondents, reaching maximum values of 0.03 and 0.08 m$^2$/s$^2$, respectively.

Although the smoothing of mean spatial gradients caused by data binning introduces errors in the residuals, estimates of the seasonal cycle were not impacted by the increasing bin sizes. This is because the functions describing spatial and temporal variations are fitted along different dimensions, implying that errors in retrieving the velocity spatial structure should not significantly affect estimates of the seasonal velocities. However, estimation errors can occur in bins where the sampling is unevenly distributed between the seasons, and/or where seasonal variations have spatial scales smaller than the bin size. Binning also smooths horizontal gradients of the seasonal and eddy variances, albeit less pronounced than for the mean component since both quantities vary over larger scales than the mean velocities. Nevertheless, while this work uses curve fitting methods to model only the spatial structure of the mean, a
similar approach could be adopted to describe horizontal gradients of the squared residuals.

In summary, the use of curve fitting methods significantly improves the definition of spatial gradients relative to bin-averaging, where the proposed 1-D approach is less sensitive to smoothing effects than 2-D methods used in previous studies. Regarding differences between 1-D GME and LSS, the LSS fields show smaller errors for larger bin areas. In contrast, the GME fitting reduces biases caused by autocorrelated Lagrangian observations, leading to a better representation of features of the time-mean ocean circulation with speeds of $\mathcal{O}[0.1 \, \text{m/s}]$, such as the Loop Current and recirculation cells, while presenting errors similar to LSS for bin radii equal or smaller than $1^\circ$. Based on these results and seeking to maximize the number of estimates in sparsely-sampled areas, such as the Southern Ocean and near-equatorial regions, the climatological fields presented here are generated using the 1-D GME method and $1^\circ$ radius bins.

2.3.1.4 Error analysis

This Section analyses the spatial distribution of the absolute errors of pseudo-Eulerian estimates ($\epsilon_\Lambda$), and investigates whether the standard errors ($\epsilon_{SE}$) calculated via Equation (2.7) can be used to estimate $\epsilon_\Lambda$.

The left panels of Figure 2.9 show global maps of $\epsilon_\Lambda$ for the pseudo-Eulerian mean (a) and seasonal geostrophic speed (c). Both maps exhibit noisy spatial distributions, suggesting random errors. Conversely, large-scale patterns approximately coincident with the global EKE distribution can be discerned, with larger values marking more energetic regions. Specifically, (a) show errors for the mean speed estimates of 0.02
Figure 2.9: Panels (a) and (c) respectively show global maps of the absolute errors ($\epsilon_A$) of pseudo-Eulerian mean and seasonal geostrophic speed. The diagrams in (b) and (d) depict the root mean square value of $\epsilon_A$ estimates ($\epsilon_A^{\text{RMS}}$), subsampled as a function of the square roots of the number of drifter observation days ($N$) and of the reference Eulerian EKE from the fields in (a) and (c), respectively. The black contours in (b) and (d) delineate the number of $\epsilon_A$ values used in the calculation of $\epsilon_A^{\text{RMS}}$; gray shading masks regions where the number is smaller than 30.

m/s or smaller for quiescent areas, such as the interior of the subtropical gyres, and of $\sim$0.04-0.09 m/s for energetic regions, as near the equator and in the vicinity of strong current systems, such as western boundary currents and their seaward extensions, the ACC, the Agulhas Retroflection, and the Brazil-Malvinas Confluence. Values above 0.1 m/s are observed in the Indonesian Sea, associated with the low sampling densities in the region, and coinciding with the position of intense time-mean currents. The errors of the seasonal fluctuations in (c) are visibly larger than the errors in the mean, increasing from a base value of $\sim$0.02 m/s at mid oceanic regions to $\sim$0.05-0.14 m/s or larger at energetic regions.
Panels (b) and (d) of Figure 2.9 show diagrams of $\epsilon_{\text{RMS}}^A$ calculated as a function of the square roots of the number of drifter observation days ($N$) and of the Eulerian EKE, for the mean and seasonal speed estimates, respectively. The diagrams are visually similar, and clearly reveal that the obtained $\epsilon_{\text{RMS}}^A$ values increase for smaller $N^{1/2}$ and for larger $\text{EKE}^{1/2}$, characteristic compatible with theoretical standard errors, which are scaled as function of the ratio $(\sigma^2/N)^{1/2}$.

Figure 2.10 compares absolute and standard errors, showing global maps of the ratio $\epsilon_A/\epsilon_{\text{SE}}$ (left panels), and diagrams of the ratio $\epsilon_{\text{RMS}}^A/\epsilon_{\text{RMS}}^\text{SE}$ (right), for the pseudo-Eulerian mean (top) and seasonal speed (bottom). Analyzing first the mean speed errors, the $\epsilon_A/\epsilon_{\text{SE}}$ values in panel (a) have mean 1.61 and standard deviation 0.98. Ratios systematically larger than 3 coincide with the position of intense midlatitude currents, such as the Kuroshio and Gulf Stream Currents in the northern hemisphere, and the Agulhas, Brazil and South Indian Ocean Currents in the southern, a possible consequence of the smoothing of horizontal gradients due to data binning. Conversely, values equal or smaller than one are more frequently observed at near-equatorial regions. The $\epsilon_{\text{RMS}}^A/\epsilon_{\text{RMS}}^\text{SE}$ values in (b) reveal a more robust relationship between both error metrics, with mean 1.83 and standard deviation 0.48. Near-one ratios are more frequently associated with $N^{1/2}$ between 9.5 and 15 (90-225 drifter days), explaining the prevalence of such values near the equator, a relatively poorly-sampled region (Fig. 2.1). The discontinuity at $N^{1/2} = 9.5$ is associated with the sampling requirement defined for estimating seasonal fluctuations, whose inclusion in the analysis increases $\epsilon_{\text{SE}}$, since more parameters are estimated during the fitting operation.

Considering the errors of the seasonal speed estimates in Figure 2.10, the $\epsilon_A/\epsilon_{\text{SE}}$ values in (c) have mean 1.72 and standard deviation 0.49. Coherent spatial features
Figure 2.10: Similar to Figure 2.9, but showing the ratio between absolute ($\epsilon_A$) and standard errors ($\epsilon_{SE}$).

with ratios larger than 2.5 are observed near southeast Asia, along the western coasts of North and South America, the southwestern coast of Africa, and at the center of the North Atlantic subtropical gyre. While the discrepancies near southeast Asia and in the southern hemisphere could hypothetically be attributed to seasonal sampling biases, in the northern hemisphere the observed patterns coincide with some of the most densely sampled regions of the world’s oceans. The large ratios in these areas are attributed to the high observational density itself, which acts to reduce the statistical errors due to the increase of the available number of degrees of freedom, combined with the locally low SKE values. The $\epsilon_A^{RMS}/\epsilon_{SE}^{RMS}$ diagram (d) shows surprisingly small variations as a function of $EKE^{1/2}$ and $N^{1/2}$, with mean 1.83 and standard deviation 0.27. The diagram also demonstrates a gradual increase of the ratios as a function of
Table 2.1: Summary of absolute and standard errors ($\epsilon_A$ and $\epsilon_{SE}$, respectively) for pseudo-Eulerian mean and seasonal geostrophic velocity estimates, and of the $\epsilon_A$ values of the seasonal and eddy variances. Here, $\sqrt{\langle \epsilon_A^2 \rangle}$ and $\sqrt{\langle \epsilon_{SE}^2 \rangle}$ denotes the global root mean square value of each error metric. The percentages are fractions of the global set of $\epsilon_A$ values that are smaller than $n_e = 1, 2$ and 3 times the corresponding $\epsilon_{SE}$ estimates, and twice as large $\epsilon_{SE}$ values.

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<th></th>
<th>$\sqrt{\langle \epsilon_A^2 \rangle}$</th>
<th>$\sqrt{\langle \epsilon_{SE}^2 \rangle}$</th>
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<th>$\epsilon_A &lt; [n_e \times (2 \times \epsilon_{SE})]$</th>
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<td></td>
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<td>$\bar{u}$</td>
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<td>4.30 cm/s</td>
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<td>71.3%</td>
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<tr>
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<td>2.45 cm/s</td>
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the sampling density for $N^{1/2} > 35$ and $\text{EKE}^{1/2} < 0.2$ m/s, reflecting the enhanced $\epsilon_A/\epsilon_{SE}$ values at the center of the subtropical gyres observed in (c).

If the $\epsilon_A$ values in Figure 2.9 were purely random and normally-distributed around the reference Eulerian estimates, then about 68.4, 95.6 and 99.8% of the obtained values would respectively lie within 1, 2 and 3 standard error margins. However, the ratios between $\epsilon_A$ and $\epsilon_{SE}$ calculated globally (Fig. 2.10) reveals significantly smaller percentage values (Table 2.1). Fractions similar to theoretical expectations are only obtained when twice as large standard errors are assumed, in agreement with the mean $\epsilon_A^{\text{RMS}}/\epsilon_{SE}^{\text{RMS}}$ ratio of 1.83 obtained for both the mean and seasonal speed estimates. This result suggests that the $\epsilon_{SE}$ values calculated via Equation 2.7 are underestimated by about a factor of 2. This conclusion is valid for the set of optimum parameters used for calculating pseudo-Eulerian quantities in this study, and can vary if different choices are adopted.
For completeness, Figure 2.11 shows the global maps of $\epsilon_A$ (left panels), and of EKE$^{1/2}$ vs. $N^{1/2}$ diagrams of $\epsilon^\text{RMS}_A$ (right) for pseudo-Eulerian estimates of SKE (top) and EKE (bottom). The spatial distribution of $\epsilon_A$ in both maps coincide with the spatial patterns of the corresponding parameters, with errors $< 2.5 \times 10^{-3}\text{m}^2/\text{s}^2$ dominating the interior of the basins, increasing to between $1.5 - 4.0 \times 10^{-2}\text{m}^2/\text{s}^2$ in energetic regions. The $\epsilon^\text{RMS}_A$ diagrams reveal that the errors of both SKE and EKE (b and d, respectively) vary as a function of EKE$^{1/2}$ and $N^{1/2}$, although the errors of EKE estimates display a smaller dependency on $N^{1/2}$ for reference EKE$^{1/2}$ values larger than $\sim 0.2$ m/s.
2.3.2 Analysis of the variance bias of undrogued drifter velocity data

As described in Section 2.2.2, the pseudo-Eulerian variances calculated using slip-corrected velocity data from undrogued drifters surpasses those estimated for drogued instruments by, on average, 36%. This positive bias can stem from factors such as (a) undiagnosed slip, since the simple downwind slip model $\alpha_u \times W$ does not account for wave-induced drifter motion; and (b) the fact that undrogued drifters sample at the surface, implying that their velocity data should include a stronger response to surface-intensified ocean processes, such as Langmuir cells and Ekman currents (Zhurbas et al. 2014). However, maps of the difference between the variances calculated from data of drogued-only and both drogued and undrogued drifters shows spatial patterns and magnitudes similar to the observed in Figure 2.11, suggesting that the observed discrepancies may be due to factors unrelated to the water-tracking characteristics of undrogued drifters.

To test this hypothesis, Figure 2.12 shows the horizontal and histogram distributions of differences between SKE and EKE estimates calculated using observations from drogued drifters, and using data from both drogued and undrogued drifters. Specifically, panels (a), (b), (e), and (f) are obtained using slip-corrected drifter velocities, while (c), (d), (g) and (h) are from geostrophic velocities interpolated to the drifter locations. Figure 2.12 reveals spatial patterns of the SKE and EKE differences visually similar for both Lagrangian datasets. Interestingly, the EKE difference maps (panels e, g) show negative (positive) values at the cyclonic (anticyclonic) regions of the seaward extensions of the Kuroshio, Agulhas and Gulf Stream Currents, which can reflect a preferential sampling of cyclonic (anticyclonic) eddies by drogued (un-
drogued) drifters (c.f. Lumpkin 2016. Histogram distributions of the global SKE (EKE) differences are non-Gaussian, being skewed to positive (negative) values and showing long tails. The SKE difference histograms obtained for both Lagrangian datasets are strikingly similar to each other (b, d). Regarding the EKE differences, the histogram for slip-corrected drifter data is flatter and more skewed than that of the AVISO velocities, although it is notably closer to it than the distribution obtained for uncorrected drifter observations (f, h).

The Lagrangian geostrophic velocity dataset is, obviously, not affected by slip biases and by the different sampling depths of drogued and undrogued drifters, meaning that the SKE and EKE differences in panels (c), (d), (g), and (h) of Figure 2.12 should reflect effects such as biased sampling, estimation errors conditioned by the smaller sampling density of drogued drifters, and errors of the decomposition method. An estimate of the fraction of the variance of the errors in the drifter-based KE estimates, introduced by factors unrelated to the sampling characteristics of undrogued drifters, can be attempted by taking the ratio between the sum of the squares of the SKE (EKE) differences calculated using the Lagrangian geostrophic velocities and the actual drifter measurements, which results in a value of 0.62 (0.57).

2.3.3 New climatological fields

Figure 2.13 shows mean speed maps for the Gulf of Mexico and the western North Atlantic (panels a and b) and for the Nordic Seas (c, d), calculated using drifter observations. Panels (a, c) are the climatology of Lumpkin and Johnson (2013) (version 2.08, generated using GDP drifter observations from February 1979 to March 2016), which fitted 2-D, 2nd degree polynomials via GME to drogued drifter observations
Figure 2.12: Difference between the kinetic energy of seasonal fluctuations (SKE) and eddy residuals (EKE) estimated using data from drogued-only and from both drogued and undrogued drifters. The left (right) panels show the spatial (histogram) distribution of the kinetic energy differences, where (a), (b), (c) and (d) are obtained using slip-corrected drifter velocity observations, and (e), (f), (g) and (h) are based on AVISO geostrophic velocities subsampled at the drifter locations. The blue lines overlaid on the histograms are best-fit non-parametric kernel functions, while the red lines correspond to results obtained for drifter velocities not corrected for downwind slip.
selected within elliptical bins, with constant areas of $\pi(2\circ)^2$, oriented by the declination of the variance ellipse of the eddy fluctuations, and centered at the grid points of a $0.5\circ \times 0.5\circ$ global grid. Panels (b, d) are obtained using the method described in Section 2.2.3.1.

Considering the western North Atlantic and Gulf of Mexico (Fig. 2.13a, b), the map obtained using the proposed method (b) resolves mean core speeds for the Florida Current and Gulf Stream above 1 m/s between 25–37$\circ$N, with a maximum speed of 1.57 m/s between the Florida peninsula and the Bahamas, values up to 50% larger than in (a). Furthermore, (b) shows $\sim$0.1 m/s faster Antilles Current and recirculation cells in the eastern flanks of the Antilles and Florida/Gulf Stream Currents, and horizontal scales for all major features closer to those observed in the time-mean Eulerian geostrophic speed map in Figure 2.5. The field in (b) also includes coherent circulation patterns not observed in (a), particularly around the Caribbean islands and in the northern flank of the Gulf Stream after the current separates from the coast, north of 36$\circ$N.

In the Nordic Seas (Fig. 2.13c, d), prominent features includes the Norwegian Current, flowing primarily north/northeast along the coast of the Scandinavian peninsula; the clockwise circulation around Greenland, composed of the East and West Greenland Currents; and the southward-flowing Labrador Current, observed at the left edge of the maps. The proposed method (d) produces speeds 0.1–0.2 m/s larger than the climatological field in (c) for all major circulation components, resulting in maximum values of 0.5–0.6 m/s for the East/West Greenland and Labrador Currents, and of 0.35–0.45 m/s for the Norwegian Current. Also, the cross-stream structure of the main features are better defined in (d) and mesoscale details are recovered,
such as the currents around Iceland, and an anticyclonic eddy with $\sim$200 km diameter centered at approximately $70^\circ$N, $4^\circ$W, also resolved in Koszalka et al. (2011) by ensemble-averaging GDP drifter observations grouped within clusters (Koszalka and LaCasce 2010).

The improvements relative to the results of Lumpkin and Johnson (2013) shown in Figure 2.13, are due to (1) the use of smaller bins, which reduces errors for mean velocity estimates caused by the smoothing of the mean horizontal gradients (panel (a) shows horizontal scales and speed magnitudes visually similar to the observed in the pseudo-Eulerian mean geostrophic speed map calculated using the 2-D GME method and $1.5^\circ$ radii circular bins, presented in Figure 2.7); (2) the use of the proposed
1-D curve fitting and of higher-degree polynomials, which reduces the sensitivity of the results to changes in bin size, leading to a better representation of cross-stream velocity gradients; and (3) the inclusion of slip-corrected velocity data from undrogued drifters, which significantly increases the number of observations available for the analysis, particularly in mid-oceanic regions. At basin scales, these factors combined allow resolving mesoscale features of the general circulation. This is illustrated by Figure 2.14, which has global pseudo-Eulerian maps obtained from drifter velocity observations and using the proposed decomposition method.

Figure 2.14 clearly resolves the major currents composing the gyre and tropical circulation systems. Well-known features, such as the strong equatorial divergence in the Pacific and Atlantic oceans and the convergence in the interior of the subtropical gyres, can be observed in both the meridional velocities (b) and the streamlines (c) (Maximenko et al. 2009; Maximenko et al. 2012; Lumpkin and Johnson 2013). Unlike in previous studies, the streamlines are calculated using unsmoothed pseudo-Eulerian mean velocities, indicating the spatial consistency of the results even in regions where the speeds are low (<0.05 m/s). Figure 2.14 provides a clearer picture of the Antarctic Circumpolar Current (ACC) than in Lumpkin and Johnson (2013), particularly in the Indian and Pacific sectors, due to the inclusion of undrogued drifter data in the analysis (Fig. 2.1). Prominent features of the ACC absent in the previous climatology includes the southern branch of the ACC in the Indian Ocean between 10-80°E, which leads to a narrow “S”-shaped jet crossing the Kerguelen Plateau (55°S, 80°E), downstream of which the ACC merges with the South Indian Ocean Current. In the Pacific sector, two parallel jets are observed between 160-120°W, delineating
Figure 2.14: Global maps of the pseudo-Eulerian mean zonal and meridional velocities (panels a and b, respectively), and of the mean speeds (c), calculated from GDP drifter observations using the decomposition method proposed in this work. The curly vectors in (c) are streamlines calculated using the data depicted in (a) and (b), to indicate the general direction of the large-scale circulation.
fracture zones of the Antarctic-Pacific ridge. These jets display mean core speeds of up to 0.8 m/s, the largest estimated in the Southern Ocean.

The zonal velocities in Figure 2.14a reveal zonally-elongated jet-like features embedded in the large-scale circulation, such as the striation pattern in the South Pacific between 20-50°S, which occupies most of the basin’s zonal domain. The existence of such features in the ocean was first inferred in the numerical investigation of Treguier et al. (2003). Galperin et al. (2004), based on the results of high-resolution ocean simulations and on similarities of the wavenumber power spectra of oceanic motions to those estimated for the atmospheres of giant planets, argued that banded features should be ubiquitous in the ocean, as a consequence of the tendency of two-dimensional geophysical turbulence to form zonal jets. Observational evidence of their existence in the ocean was first reported by Maximenko et al. (2005) in high-passed altimeter-derived geostrophic velocity fields. Later, Maximenko et al. (2009) used a high-resolution mean dynamic topography model to improve geostrophic velocity estimates from altimeters, obtaining a time-mean map that suggested the existence of quasi-stationary striations in many oceanic regions. Although previous studies also reported the existence of such features in drifter-based mean maps (e.g. Maximenko et al. 2008; Maximenko et al. 2009), the obtained climatological fields now allow their visualization with a level of detail comparable with that of satellite products.

In the North Atlantic, the eastward flow of the Azores Current can be observed centered at 34°N (Fig. 2.14a), showing a predominantly zonal flow from approximately 60–6°W. Narrow bands of negative zonal velocities are seen flanking the Azores Current, where the westward flow in its northern flank forms a continuous band of negative velocities with the Gulf Stream’s recirculation, seen in the southern
limb of the Gulf Stream between 80-40°W. West of 50°W, the striation is characterized as elongated bands of alternating positive/negative velocities between 70-50°W. This striation connects with the Azores current in the east, and to a narrow band of positive velocities in the northern flank of the Antilles current in the west, forming a continuous pattern of positive zonal velocities from ∼76-6°W, virtually crossing the North Atlantic basin. Similarly in the North Pacific, the eastward flow of the Hawaiian Lee Countercurrent (HLCC) is seen centered at ∼19°N, extending from 156°W until approximately the dateline (Lumpkin and Flament 2013). However, another well-resolved band of eastward velocities is observed further west at the same latitude between 130-160°E, which can correspond to a westward extension of the HLCC. A narrow band of negative zonal velocities is observed in the northern flank of the HLCC, which is alternated by another band with positive values. Although not well resolved, a visual inspection suggests that the striation pattern continues further north, potentially connecting with the recirculation of the Kuroshio Current’s seaward extension. Alternating zonal jets are also prominently observed off the west coast of North America between 22-45°N, extending up to 20° longitude towards the basin’s interior. These features were described by Centurioni et al. (2008), and are associated with permanent meanders of the California Current. A similar pattern is observed along the west coast of South America from 10-35°S. Maximenko et al. (2009) reported striations also off of the west coast of southern Africa, however the low observational density in the region results in a poor definition of the local circulation.

Other notable zonally-elongated features in Figure 2.14a, not well resolved in previous drifter-based estimates, includes the eastward velocities off the east coast of South America between 15-30°S, extending ∼20° longitude seaward within the
large-scale, westward flow of the southern branch of the South Equatorial Current (Stramma and Schott 1999), and possibly associated with recirculation cells of the Brazil Current. Further south, the Zapiola Anticyclone can be observed at 45°S, 42°W (de Miranda et al. 1999; Volkov and Fu 2008). In the southern Indian Ocean, the eastward flow of the South Indian Ocean Countercurrent (SICC) is seen centered between 24-28°S (Siedler et al. 2006; Schott et al. 2009), originating from a recirculation of the Southeast Madagascar Current at ~40°E and observed as a jet until 100°E. The vectors in panel (c) suggests that the SICC merges with the southward flow of the Leeuwin Current (LC) offshore of western Australia at 30°S, 115°E; however the local circulation is not well resolved and the observed branching reflects relatively low observational densities combined with realizations of the eddy field. Finally, Figure 2.14 clearly shows the counter-clockwise flow of the LC along the western and southern coasts of Australia (Feng et al. 2009). South of Australia, panel (a) also shows a narrow band of negative zonal velocities in the southern limb of the LC, associated with the Flinders Current (Middleton and Cirano 2002; Middleton and Bye 2007).

2.4 Summary and conclusions

To obtain an improved, global near-surface velocity climatology from GDP drifter observations, this work updates the methods described in Lumpkin and Johnson (2013) by (a) correcting the downwind slip bias of undrogued drifters using a formulation proposed by Pazan and Niiler (2001), an operation that recovers about half of the GDP dataset; and (b) introducing a new method for decomposing drifter data into mean, seasonal and eddy components, designed to minimize the spatial smoothing and smearing effects of other data binning methods. The proposed procedure
accounts for spatial variations of the mean within spatial bins by fitting a 1-D, 4th degree polynomial to the binned observations, sorted along a coordinate axis defined at the rotation angle that minimizes the fitting error (Fig. 2.4).

The correction of the drifter slip bias is done by subtracting a downwind motion from the drifter velocities equal to a fraction $\alpha$ of the ECMWF ERA-Interim 10-m winds. For 15-m drogued drifters, $\alpha_d = 7 \times 10^{-4}$ (Niiler et al. 1995). For undrogued drifters, $\alpha_u$ is calculated via Equation (2.1) using data selected within $4^\circ \times 4^\circ$ bins centered at the grid points of a $1^\circ \times 1^\circ$ global grid. Although the obtained $\alpha_u$ values are normally-distributed in probability space, suggesting random fluctuations around the mean, its spatial distribution shows large-scale patterns that are indicative of a geophysical forcing mechanism (Fig. 2.2). Since (2.1) does not take into account the fact that undrogued drifters are more sensitive to wave effects, one possibility is that the observed spatial patterns reflect the response of undrogued drifters to a spatially-varying surface gravity wave field.

The correction of the slip motion of undrogued drifters takes into account the spatial variations of $\alpha_u$ by linearly interpolating the obtained values to the drifter locations, producing zonally-averaged, pseudo-Eulerian mean estimates for both drogued and undrogued drifters that are statistically similar across most latitudes (Fig. 2.3). This also reduces the globally-averaged drogued/undrogued variance ratio from 1.81 to 1.36, where most of the remaining differences can be attributed to factors unrelated to the slip bias of undrogued drifters, such as method errors, the smaller sampling density of drogued drifters, and biased sampling (Fig. 2.12).

However, it is noted that the linear downwind slip correction for drogued instruments was not validated for wind speeds $>10$ m/s nor in high wave amplitudes (Niiler
et al. 1995), meaning that the slip for both drogued and undrogued drifters can be underestimated in regions with strong winds and/or high wave energy, such as the Southern Ocean. Furthermore, the correction of the slip of undrogued drifters proposed by Equation (2.1) operates by removing part of the difference between the along-wind current velocity at 0-m and at 15-m that is correlated with wind speed, which includes not only the wave and wind-induced slip, but also the signature of wind-driven currents such as Ekman flows. Due to the vertical shear of Ekman velocities between the surface and 15-m (c.f. Rio et al. 2014), an undiagnosed cross-wind velocity component associated with the Ekman dynamics can be present in the slip-corrected undrogued drifter velocities, and thus contribute to the differences between the pseudo-Eulerian variances calculated using drogued and undrogued drifter data. Lastly, the $\alpha_u$ estimates have uncertainties of their own, whose origins and magnitude were not accessed, implying that biases due to the use of observations from undrogued drifters can still be significant. Nevertheless, the improvements obtained by the simple correction used in this study are encouraging. If the spatial patterns of $\alpha_u$ truly reflect wave effects, then a more accurate correction can possibly be achieved by first removing the instantaneous Stokes drift from the drifter measurements, estimated from numerical models or satellite/mooring/drifter observations, before calculating the downwind slip coefficient via (2.1).

The method proposed for the decomposition of Lagrangian data requires definitions for parameters whose adjustment affects the results, including (a) the bin size and mapping resolution; (b) the model used to describe spatial and temporal variations, particularly the polynomial degree $n$ and number of seasonal harmonics $m$ (Eq. 2.3); and (c) the decorrelation time scale $T_d$ (Eq. 2.5). Those were defined via
sensitivity tests using altimeter-derived geostrophic velocity (GV) data from AVISO subsampled at the drifter locations. Specifically, pseudo-Eulerian quantities were calculated from the Lagrangian GV dataset for ranges of the adjustable parameters and compared against the corresponding Eulerian values. This operation resulted in optimum values of $n = 4$, $m = 2$ and $T_d = 6.33$ days, and showed that coherent mesoscale features can be resolved by mapping estimates onto a $0.25^\circ \times 0.25^\circ$ grid.

Regarding bin size, the proposed 1-D approach better resolves the cross-stream velocity structure of narrow currents than other methods, from the $\mathcal{O}[1 \text{ m/s}]$ flow of western boundary currents, to $\mathcal{O}[0.1 \text{ m/s}]$ features such as recirculation cells (Fig. 2.7), and is less sensitive to variations of this parameter (Fig. 2.8). The new global climatological fields are generated using $1^\circ$ radii circular bins, to balance the smoothing effect of binning with the statistical reliability of the estimates in poorly-sampled regions. Figure 2.8 shows that this procedure produces mean core speeds for western boundary currents up to 0.2 m/s faster than the decomposition method of Lumpkin and Johnson (2013), 0.4 m/s faster than using 2-D smooth splines (e.g. Bauer et al. 1998; Falco and Zambianchi 2011), and 0.75 m/s faster than bin-averaging (e.g. Fratantoni 2001; Jakobsen et al. 2003; Maximenko et al. 2009).

Standard errors, calculated for the modeled velocities via (2.7), were compared against the root mean square (RMS) differences between pseudo-Eulerian and Eulerian estimates (absolute errors). Using optimum method parameters, standard errors are found to underestimate absolute errors by about a factor of 2. Differences between both error metrics arise because standard errors do not account for Eulerian binning biases, such as the smoothing of time-mean spatial gradients, and due to possible inadequacies of the model proposed by (2.3) and (2.5). The relatively small standard
errors can also reflect an underestimation of the decorrelation time scale $T_d$, which was fixed at all bins assuming a Lagrangian integral time scale of 3 days, when this parameter can actually range from less than one day to $O[1 \text{ week}]$.

The pseudo-Eulerian mean fields obtained using the presented methods and real drifter observations (Fig. 2.13) resolves details of the general ocean circulation absent in the climatology described by Lumpkin and Johnson (2013). Core speeds for the Florida/Gulf Stream Currents are up to 50\% larger, and recirculation cells and other relatively narrow circulation features are stronger and better-defined. Notably, the global fields also show zonally-elongated striation features in all major oceanic basins (Fig. 2.14), which previously could only be resolved at such spatial resolution by time-averaging surface velocities inferred from satellite observations (e.g. Maximenko et al. 2009).

These results support the consistency of the obtained mean fields. Since the reliability of the results can be assessed using the standard errors calculated from Equation (2.7), this new climatology can be used to validate satellite-derived surface velocity products and the output of realistic numerical simulations. From a methodological standpoint, Peng et al. (2015) demonstrated that accounting for horizontal velocity gradients improves the convergence of eddy diffusivity estimates, implying that further improvements can possibly be achieved by using the updated decomposition method presented in this study. The better performance of the proposed decomposition method in resolving spatial gradients can also improve estimates of Reynolds stresses, and of the turbulent transport of heat, salt, and tracers across large-scale oceanic fronts. Furthermore, the presented method is general and can be applied to other Lagrangian datasets, such as velocity observations from subsurface floats.
(e.g. SOFAR and RAFOS), and temperature and salinity data from Argo profilers. Considering that their historical observational density is smaller than that of surface drifters, the better performance of the proposed 1-D approach at larger bin sizes (Fig. 2.8) can improve the definition of spatial structures for in situ-based climatologies of the subsurface ocean.

Finally, Lumpkin and Johnson (2013) observed that interannual variability correlated with the Southern Oscillation Index (SOI) explained a significant fraction of the near-surface velocity’s variance in the tropical Pacific and tropical Indian Oceans. Following that study, the methods described here can be extended to account for forms of interannual variability by including a long-term trend and/or climate indexes as extra functions in the matrix $A$ used in the GME estimation (Eq. 2.4). By itself, adding an extra function increases the sampling requirement by one degree of freedom (6 drifter days, assuming a 3-day Lagrangian integral time scale), also increasing the standard errors calculated via Equations (2.6) and (2.7) due to the larger number of estimated parameters. If the extra function is a climate index such as the SOI, then its successful regression would require the sampling of multiple positive/negative phases of the index, implying that the actual sampling requirements can be significantly larger. For example, Lumpkin and Johnson (2013) estimated the SOI’s amplitude in bins with more than 365 drifter days, and other constraints can possibly be further adopted to restrict the estimation to bins where the drifter data is more homogeneously distributed across the years. The expected increase in sampling density promoted by the continued maintenance of the GDP drifter array in the coming years, besides refining the obtained time-mean and seasonal climatological fields, can potentially lead to a better resolution of interannual current variability.
correlated not only with the SOI, but also with the indexes of other low-frequency climate phenomena, such as the Indian Ocean Dipole and the Atlantic Multidecadal Oscillation.

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CHAPTER 3

Cross-spectral analysis of the SST/10-m wind speed coupling resolved by satellite products and climate model simulations

As described in Chapter 1, the results of recent numerical studies disagree on the relative impact of the mesoscale SST-induced modifications in the 10-m wind speed \( w \) to the air-sea fluxes of mechanical energy and on its feedbacks to ocean variability, in particular whether it exerts a negligible contribution (Seo et al. 2016; Renault et al. 2016; Seo 2017); leads to a net damping of the quasi-geostrophic eddy variability (Jin et al. 2009); or enhances the uptake of mechanical energy by the mesoscale eddy field (Byrne et al. 2016). The divergent conclusions may be due to the different regions of the world ocean investigated by these studies, although it can also be related to differences on how the atmospheric response to mesoscale SST anomalies is represented by the employed models. The latter is suggested considering that accurately simulating the SST-driven air-sea coupling is far from trivial, with effect being sensitive to the spatial resolution of both oceanic and atmospheric grids and relying on parameterizations of the air-sea turbulent fluxes and boundary layer dynamics that may not capture all the physical complexity of the real processes (e.g. Song et al. 2009; Bryan et al. 2010; Byrne et al. 2015).
In this context, comparing the SST/w relationship resolved by numerical simulations with that revealed by observations is critical for assessing the reliability of potential feedbacks to the oceanic and the atmospheric variability arising as a consequence of the SST-driven air-sea coupling. However, it is noted that this relationship is frequently analyzed via linear regressions between oceanic and atmospheric parameters, which does not provide information on potential variations of the coupling as a function of the spatial and temporal scales. Furthermore, most studies to date interpreted the SST-driven wind response as predominantly reflecting the action of quasi-stationary SST fronts and oceanic Rossby waves, whereas the role of the smaller but near-ubiquitous mesoscale ocean eddies for conditioning the observed air-sea coupling characteristics is still unclear.

Aiming to advance the knowledge on these topics, this chapter uses cross-spectral statistics to characterize the SST/w relationship resolved by satellite products at scales between $10^2$–$10^4$ km and $10^1$–$10^3$ days. The SST-induced $w$ response in physical space is retrieved by evaluating empirical transfer functions using SST data, that are used in concert with coherent eddies detected in altimeter data to infer the role of the eddy field in conditioning the observed SST/w relationship. To gain further insight on the importance of eddies in mediating the SST-driven coupling, the proposed cross-spectral analysis is also repeated using the outputs of two CCSM simulations run with eddy-parameterized and eddy-resolving ocean models. The SST-driven $w$ response isolated using the methods presented in this chapter are subsequently used to estimate the impact of the mesoscale SST/w coupling to the air-sea fluxes of mechanical energy resolved by drifter and satellite observations, investigation described in Chapter 4.
3.1 Background

It is now well established that sea surface temperature (SST) and near-surface wind speed show predominantly negative correlations at large spatial scales ($O(10^3-10^4 \text{ km})$), that transition to positive over the ocean mesoscales ($O(10^1-10^2 \text{ km})$), reflecting the action of distinct air-sea coupling mechanisms. At large-scales, the prevailing winds modulate turbulent heat fluxes and vertical mixing in the upper ocean, that lead to SST anomalies whose sign oppose those of the wind speed fluctuations (negative correlation) (e.g. Okumura et al. 2001; Xie 2004; Clement et al. 2015). Conversely at the ocean mesoscales, the air-sea temperature and humidity differences arising when an air parcel moves over a sharp SST gradient induce anomalous turbulent heat fluxes that affect the vertical mixing of momentum in the atmospheric boundary layer, inducing near-surface wind speed perturbations (e.g. Wallace et al. 1989; Kilpatrick et al. 2014; Byrne et al. 2015). Horizontal pressure gradients can also arise after the atmosphere achieves thermodynamical equilibrium with the anomalous turbulent air-sea fluxes, which drives secondary circulations within the boundary layer (e.g. Minobe et al. 2008; O’Neill et al. 2010; Shimada and Minobe 2011). The perturbations in wind speed induced by both the momentum mixing and pressure gradient effects have the same sign as the underlying SST anomaly (positive correlation).

Previous studies reported positive correlations between SST and near-surface winds at large-scale extratropical SST fronts coinciding with the seaward extensions of the Kuroshio and Gulf Stream Currents, the Agulhas Return Current, Brazil-Malvinas Confluence, and the Antarctic Circumpolar Current (ACC) (e.g. White and Annis 2003; Chelton et al. 2004; O’Neill et al. 2005; O’Neill et al. 2010; O’Neill
et al. 2012); at the warm and cold phases of tropical instability waves (TIWs) in the Pacific and Atlantic Oceans (e.g. Hayes et al. 1989; Hashizume et al. 2001; Polito et al. 2001); and at major oceanic upwelling systems such as the California, Peru-Chile, and Somalia Current Systems (Vecchi et al. 2004; Putrasahan et al. 2013b; Seo et al. 2016; Seo 2017). Positive SST/wind speed correlations were also observed associated with westward-propagating mesoscale signals with phase speeds compatible with those of first mode baroclinic Rossby waves (Small et al. 2005), and over coherent ocean eddies (Park et al. 2006; Chow and Liu 2012; Frenger et al. 2013; Souza et al. 2014; Gaube et al. 2015).

Rather than merely constituting a second-order correction to the near-surface atmospheric variability, there is increasing evidence that the mesoscale SST/near-surface wind coupling feedbacks into both oceanic and atmospheric circulations. In the ocean, it modifies the wind stress divergence and curl across large-scale SST fronts and within coherent eddies, affecting the Ekman pumping associated with these features and influencing eddy propagation (Chelton et al. 2004; O’Neill et al. 2010; Frenger et al. 2013; Souza et al. 2014; Gaube et al. 2015; Seo et al. 2016; Seo 2017). It was also shown to affect eddy energetics (Jin et al. 2009; Byrne et al. 2016), and to influence ocean variability across multiple spatial scales via turbulent nonlinear interactions, that can ultimately affect the basin-scale ocean circulation (Hogg et al. 2009). In the atmosphere, the coupling can force convergence of the near-surface winds, producing vertical motions in the atmospheric boundary layer that influence the formation of low level clouds and convective precipitation (O’Neill et al. 2005; Bryan et al. 2010; Frenger et al. 2013; Putrasahan et al. 2013a). A number of studies are also converging on the conclusion that mesoscale air-sea
coupling can affect variability into the free troposphere, potentially playing an active role on the maintenance of large-scale weather patterns and of low-frequency climate modes (e.g. Minobe et al. 2008; Siqueira and Kirtman 2016; Ma et al. 2017; Kirtman et al. 2017).

The tight association between ocean and atmosphere variability mediated by mesoscale air-sea coupling presents a challenge for climate simulations because it implies that results can be sensitive to dynamical processes with scales down to $\mathcal{O}[10 \text{ km}]$ in both mediums. In particular, the atmospheric response to SST anomalies is sensitive to the spatial resolution of both oceanic and atmospheric grids, and rely on parameterizations of the air-sea turbulent fluxes and boundary layer dynamics that may not capture all the physical complexity of the real processes (Maloney and Chelton 2006; Song et al. 2009; Bryan et al. 2010; Kirtman et al. 2012). In this context, comparisons of numerical results with observations are critical for determining model reliability and for guiding their development. It is noted, however, that air-sea coupling processes in both model and observational datasets are frequently analyzed via linear regressions between oceanic and atmospheric parameters, high-pass filtered in space to isolate the ocean mesoscales, and either low-pass filtered in time or averaged over a few weeks to minimize variability associated with synoptic weather (c.f. Small et al. 2008; Chelton and Xie 2010). The adopted filter cutoff scales are often defined empirically and vary significantly between studies, indicating that the spatial-temporal scales where the mesoscale air-sea coupling regime takes place are not well established. Furthermore, geophysical phenomena occurs along a broadband continuum in both frequency and wavenumber domains, implying that the use of simple regression models can mask spectral characteristics of the coupling of interest
not only for model/observations comparisons, but also in boundary layer dynamics studies.

Analyzes of the air-sea coupling under a spectral perspective were previously presented by Small et al. (2005) and O’Neill et al. (2012). Their results indicate that the fraction of the variance of the near-surface winds explained by SST peaks at zonal wavelengths larger than 400 km, suggesting that the role of mesoscale ocean eddies (diameters between 10-300 km) in mediating the coupling is secondary to that of planetary waves and of near-stationary SST fronts. However, recent conclusions that a significant fraction of the mesoscale sea surface height/surface current/chlorophyll variability, previously attributed to the action of linear Rossby waves, is actually forced by nonlinear eddies, are likely also applicable to this case (Early et al. 2011; Chelton et al. 2011a, b). Furthermore, it is noted that (a) Small et al. (2005) described the meridional variation of the cross-spectral characteristics of oceanic and atmospheric signals that yielded maximum cross-spectral power density in zonal wavenumber-frequency space, not analyzing their variation along the spectral continuum, while O’Neill et al. (2012) analyzed the spectral dependence solely in zonal wavenumber space; (b) Small et al. (2005) used atmospheric and ocean parameters preliminarily filtered in space and time, while the analysis of O’Neill et al. (2012) was based on monthly-averaged fields, and thus could not define the spatial-temporal scales over which the oceanic control of near-surface winds prevails over the atmospheric SST forcing; and (c) neither was global in scope, with Small et al. (2005) focusing on latitudes equatorward of 40°, and O’Neill et al. (2012) on the seaward extensions of the Kuroshio and Gulf Stream Currents, the South Atlantic, and on the Agulhas Return Current.
Based on these considerations, this study uses cross-spectral statistics calculated between SST inferred from satellite radiometers and equivalent-neutral 10-m wind speed \((w)\) observations by orbital scatterometers to characterize the spectral linear relationship between both parameters at scales between \(10^2\)–\(10^4\) km and \(10^1\)–\(10^3\) days for the Indian, Pacific, and Atlantic basins within \(55^\circ\text{S}–60^\circ\text{N}\). Here, transfer functions for the mesoscale SST-driven \(w\) response as a function of frequency are evaluated in physical space using observations, and the resulting fields are used to estimate the fraction of the mesoscale \(w\) variance that can be attributed to SST-driven anomalies, and how much of this variability can be ascribed to coherent ocean eddies. To provide further insight on the role of eddies in conditioning the observed SST/\(w\) coupling characteristics, the proposed cross-spectral analysis is repeated in simulations of the Community Climate Simulation Model (CCSM) run using a horizontal ocean resolution of \(1^\circ\) (eddy-parameterized), typical of IPCC-class models, and of \(0.1^\circ\) (eddy-resolving), expanding on the results of previous studies (Maloney and Chelton 2006; Bryan et al. 2010; Kirtman et al. 2012).

This chapter is organized as follows. Section 3.2 describes the satellite datasets, the CCSM model configuration and experimental design, and the methods employed in the cross-spectral analysis. Section 3.3 describes the cross-spectral estimates obtained using satellite observations, evaluate the impact of the mesoscale SST variability to the total \(w\) variance and how much of it can be attributed to coherent ocean eddies, and analyzes the model-based estimates under the light of the observational results. Finally, Section 3.4 summarizes this study and its conclusions.
3.2 Methods

3.2.1 Satellite products

3.2.1.1 Equivalent-neutral 10-m wind speed

Equivalent-neutral 10-m wind speed \((w)\) estimates are from the scatterometers onboard the QuikSCAT and MetOp-A satellites, dataset produced and distributed by Remote Sensing Systems (www.remss.com). Orbital scatterometers are active sensors that emit radar pulses on wide surface swaths around the satellite’s ground track, measuring the radar power reflected (i.e. backscattered) by surface roughness. Over the oceans, the backscatter intensity is predominantly modulated by the amplitude and phase velocity of centimeter-scale gravity-capillary waves, properties in equilibrium with the magnitude and direction of the wind stress vector (Weissman et al. 1994; Weissman and Graber 1999; Liu 2002). Despite of the physical connection between wind stress and backscatter intensity, \textit{in situ} estimates of surface stress are sparse in space and time, reason for which the scatterometer backscatter data are calibrated for the equivalent-neutral 10-m winds – that is, the winds at 10-m height that would be obtained in a neutrally-stratified atmosphere – parameter related to wind stress via a neutral-stability drag coefficient (Liu and Tang 1996; Large and Yeager 2004). However, as the ocean surface is not stationary, scatterometer \(w\) retrievals are better described as the equivalent-neutral 10-m wind speed measured relative to the surface ocean currents (e.g. Cornillon and Park 2001; Chelton et al. 2004; Park et al. 2006; Hughes and Wilson 2008). Scatterometers operate in the microwave band of the electromagnetic spectrum and thus can obtain measurements through clouds, however signal backscatter produced by rainfall can bias their wind
estimates. In rain-free conditions, their precision is better than 2 m/s for winds up to 35 m/s (Freilich and Dunbar 1999; Chelton and Freilich 2005; Verspeek et al. 2010; Ricciardulli and Wentz 2015).

The scatterometer on the QuikSCAT (MetOp-A) satellite can sample about 93% (70%) of the global ocean in 24 hours, with an in-swath resolution of ∼25 km (∼12.5 km) (Figa-Saldaña et al. 2002; Hoffman and Leidner 2005). The $w$ data acquired for this study from both satellites are mapped separately for their ascending and descending orbital segments onto an $0.25^\circ \times 0.25^\circ \times 1$-day grid (Ricciardulli et al. 2011; Ricciardulli and Wentz 2016). Here, estimates for both orbital segments are averaged, and a continuous 16 year-long time-series of daily maps is formed using QuikSCAT data between August 1999 and November 2009, and MetOp-A data between December 2009 and December 2016. Grid points with seasonally-varying ice coverage are preliminarily masked. Estimates flagged as obtained in rainy conditions are also excluded, with remaining temporal gaps filled via linear interpolation. As a last step, the data is low-pass filtered in time using a 10th degree Butterworth filter with cutoff period at 7 days. The filtering is needed since a complete sampling of the ocean by the MetOp-A scatterometer is achieved every ∼3.5 days, meaning that forms of variability with periods shorter than about one week are potentially aliased.

3.2.1.2 Sea surface temperature

SST fields are from the National Oceanic and Atmospheric Administration (NOAA) Optimum Interpolation Sea Surface Temperature (OISST) product (Reynolds et al. 2007; Banzon et al. 2016). This dataset is distributed by NOAA’s National Centers for Environmental Information (NCEI, www.ncdc.noaa.gov/oisst), and is gener-
ated by merging observations from microwave and/or infrared satellite radiometers (Reynolds et al. 2007). While SST estimates from microwave radiometers have the advantage of being unaffected by clouds, the planet’s emissivity in the microwave band is significantly smaller than in the infrared band, characteristic that limits the spatial resolution of microwave sensors relative to that of infrared radiometers. The data blending used for the generation of OISST is primarily designed to reduce the cloud contamination in infrared-based SST estimates, characteristic further ameliorated by the incorporation of the lower resolution but cloud-free microwave data (Reynolds et al. 2007; Reynolds and Chelton 2010).

The OISST dataset is organized onto a global $0.25^\circ \times 0.25^\circ \times 1$-day grid, and was obtained for the period between August 1999 and December 2016. Two versions are used, one based solely on infrared measurements from the Advanced Very High Resolution Radiometer (AVHRR) sensors in polar-orbiting NOAA satellites (hereafter AVHRR-only), with spatial resolution of 9 km or finer, and whose observations are available from October 1981 until today. The other version also incorporates, alongside with AVHRR data, microwave observations from the Advanced Microwave Scanning Radiometer onboard the National Aeronautics and Space Administration (NASA) Earth Observing System *Aqua* satellite (AMSR-E) (hereafter AVHRR+AMSR), with a 56 km resolution, and available from June 2002 until October 2011. Reynolds and Chelton (2010) showed that the AVHRR+AMSR better represents the SST zonal wavenumber power spectrum at oceanic regions with frequent cloud cover, which coincide with areas of intense eddy variability, such as the seaward extensions of western boundary currents and the Southern Ocean. For this
reason, the AVHRR+AMSR record is preferred over the AVHRR-only for the period when it is available.

3.2.1.3 Mesoscale eddies detected in altimeter data

Parameters of mesoscale eddies are obtained from the Mesoscale Eddy Trajectory Atlas (META), dataset produced by SSALTO/DUACS following the methods of Chelton et al. (2011), and distributed by AVISO+ (www.aviso.altimetry.fr/). Briefly, eddies in META are defined as closed contours in spatially high-pass filtered sea surface height (SSH) fields obtained by merging observations from the TOPEX/Jason and ERS/Envisat satellite altimeters, and includes features with radii larger than $\sim 40$ km, corresponding to the feature resolution of the used SSH product (Chelton et al. 2011). Here, the considered eddy parameters are (a) trajectory of the eddy center, (b) radius $L_s$, defined as the mean distance of the eddy center to the closed SSH contour with maximum average geostrophic speed, and (c) flow orientation, i.e. cyclonic or anticyclonic.

3.2.2 Climate model simulations

This study uses the National Center for Atmospheric Research (NCAR) Community Climate System Model Version 4 (CCSM4), a global climate simulation model composed of the Community Land Model (CLM), the Community Atmospheric Model (CAM), the Los Alamos Parallel Ocean Program (POP) ocean general circulation model, and the Community Ice Code (CICE), that exchange state information and fluxes via a coupler (Gent et al. 2011).
Two CCSM4 experiments are performed using atmospheric models configured to the same $0.5^\circ \times 0.625^\circ$ latitude/longitude grid, but ocean models of contrasting horizontal resolutions. In the first, the ocean component is configured to an asymmetric dipolar grid with $1.125^\circ$ zonal resolution and meridional resolution increasing from $0.27^\circ$ near the equator until a maximum of $0.54^\circ$ at midlatitudes, unable to resolve baroclinic instability processes and mesoscale ocean eddies (LR), while the second uses a $\sim0.1^\circ$ resolution tripolar ocean grid with the Northern Hemisphere’s poles located in North America and Asia, that allow eddy formation and evolution (HR) (c.f. Murray 1996). The LR (HR) is initialized from a 255-year (155-year) control run with fixed 1990 CO$_2$ forcing, where fluxes at the air-sea interface are calculated at 3-hour (6-hour) intervals using state variables from the atmospheric model linearly interpolated onto the oceanic grid. The updated fluxes are then conservatively remapped to the native grid of each CCSM4 component model, and used in the integration of the subsequent time step. Here, wind stress is computed using the wind velocity relative to the surface ocean currents, correction that (a) reduces the wind power input to the ocean circulation, and (b) creates a surface drag force that acts as a sink of kinetic energy for the mesoscale ocean variability (e.g. Dawe and Thompson 2006; Zhai and Greatbatch 2007; Seo et al. 2016; Renault et al. 2016), whose feedbacks to the ocean circulation were observed to alleviate biases in coupled simulations (e.g. Luo et al. 2005; Renault et al. 2016). The LR and HR are both integrated for a period of 14 years, with daily-averaged outputs saved every 2 and 5 days, respectively.

The CCSM4 outputs used in this study are daily-averaged global fields of SST and wind stress, mapped onto the atmospheric grid. For a direct comparison with the parameters obtained from the satellite products, the modeled wind stress data
are preliminarily used to calculate the equivalent-neutral 10-m wind speed \( (w) \) as described in Appendix A.

### 3.2.3 Cross-spectral analysis

#### 3.2.3.1 Squared coherency and transfer functions

Following Bendat and Piersol (1986), the squared coherency function between two data series \( a(j) \) and \( b(j) \) can be expressed as,

\[
\gamma_{ab}^2(\nu) = \frac{|G_{ab}(\nu)|}{G_{aa}(\nu)G_{bb}(\nu)},
\]

where \( \nu \) denotes the spectral domain, \( G_{aa} \) (\( G_{bb} \)) is the one-sided autospectral densities of \( a \) (\( b \)), and \( |G_{ab}| \) is the magnitude of the cross-spectral density between \( a \) and \( b \). Here, \( G_{ab} = |G_{ab}|e^{-i\theta_{ab}} \), with \( \theta_{ab} \) describing the phase difference between sinusoidal components of the spectral-domain representations of \( a \) and \( b \). For all \( \nu \), \( \gamma_{ab}^2 \) varies between 0 and 1, corresponding to the fraction of the variance in \( b \) that can be explained by \( a \), assuming the existence of a spectral linear relationship between both series. Such relationship can be described via a transfer function, computed as,

\[
H_{ab}(\nu) = \frac{|G_{ab}(\nu)|}{G_{aa}(\nu)}e^{-i\theta_{ab}(\nu)}.
\]

While \( \gamma_{ab}^2 \) is the spectral representation of the coefficient of determination \( R^2 \), \( H_{ab} \) can be interpreted as the slope of a linear regression of \( b \) on \( a \). Specifically, \( |H_{ab}| \) (gain factor) describes the absolute variation of \( b \) per unit amount of \( a \), and \( \theta_{ab} \) (phase factor) its sign, with absolute angles larger (smaller) than \( 90^\circ \) indicating that fluctuations in \( a \) and \( b \) more frequently display opposite (the same) signs, thus reflecting negative (positive) regression slopes. Approximate standard errors for \( \gamma_{ab}^2 \),
$|H_{ab}|$, and $\theta_{ab}$ can be estimated using the following expressions,

$$\epsilon [\gamma_{ab}^2] \approx \frac{\sqrt{2} (1 - \gamma_{ab}^2)}{|\gamma_{ab}| \sqrt{n_d}},$$  

(3.3)

$$\epsilon [|H_{ab}|, \theta_{ab}] \approx \frac{\sqrt{(1 - \gamma_{ab}^2)}}{|\gamma_{ab}| \sqrt{2n_d}},$$  

(3.4)

where $n_d$ refers to the number of degrees of freedom available for the analysis, equivalent to the number of independent spectral domain representations of $a$ and $b$ used for calculating autospectral and cross-spectral densities.

This study examines the spectral linear relationship between SST and $w$ (signals $a$ and $b$, respectively) in terms of $\gamma_{ab}^2$, $|H_{ab}|$, and $\theta_{ab}$, calculated simultaneously as a function of the zonal wavenumber and frequency domains ($k$ and $\omega$, respectively), and separately for each spectral domain. Particularly, basin masks for Indian, Pacific, and Atlantic Oceans are defined to guide the selection of zonal-temporal ($x, t$) diagrams of SST and $w$ (Fig. 3.1a), that are used to estimate the considered cross-spectral parameters. Not included in the basin masks are (a) regions shallower than 1000 m around the continental contours, to avoid the influence of coastal and shelf processes, and (b) relatively narrow seas, such as the Arabian Sea and the Bay of Bengal in the Indian Ocean, since their limited zonal extents result in low spectral resolutions in $k$. Prior to the spectral calculations, the time-series of SST and $w$ at each grid point are demeaned, detrended using a linear trend, and deseasonalized using annual and semiannual harmonics. Specifically for the spectral calculations as a function of $k$, zonal averages are also subtracted, while for the analysis in $\omega$, the horizontal fields of SST and $w$ are preliminarily high-pass filtered to isolate the ocean mesoscales. The high-passed fields are obtained by subtracting SST and $w$ anomaly maps from correspondent fields low-pass filtered using a two-dimensional Gaussian filter with a $7^\circ \times 7^\circ$ half-power cutoff.
Figure 3.1: Panel (a) shows the ocean current speed variance at 15-m depth from NOAA’s drifter-derived climatology of near-surface currents. The overlaid black, purple, and red contours respectively delineate basin masks for the Indian, Pacific, and Atlantic Oceans, defined to guide the selection of zonal-temporal diagrams used in the spectral analysis. Panels (b) and (c) respectively show the variance of fluctuations with spatial scales smaller than \( \sim 700 \) km in SST, obtained from the OISST product, and in equivalent-neutral 10-m wind speed \( (w) \), estimated from the scatterometers onboard the QuikSCAT and MetOp-A satellites. The contours in (b) [(c)] are time-mean SST (10-m wind zonal velocity) isolines plotted at 2.5 \( ^\circ \)C (1.5 m/s) intervals.
For the spectral analysis as a function of both $k$ and $\omega$, the zonal-temporal diagrams of SST and $w$ at each latitude are subdivided into 3-year segments with 50% temporal overlap, which are Fourier transformed to calculate $G_{aa}$, $G_{bb}$, and $G_{ab}$. Centered at each latitude, raw autospectral and cross-spectral densities obtained within a 4° latitudinal band are averaged, and the resulting mean spectrum is used to calculate $\gamma_{ab}^2$, $|H_{ab}|$, and $\theta_{ab}$. Due to the prescribed temporal overlap, the $n_d$ used to estimate $\epsilon$ via Equations (3.3) and (3.4) is assumed to be 25% smaller than the number of averaged raw spectra (Harris 1978). For the one-dimensional spectral analysis, autospectral and cross-spectral densities are calculated (a) as a function of $k$, using zonal data series of SST and $w$ at each time step and latitude, and (b) as a function of $\omega$, using time-series of both parameters obtained at each horizontal grid point. Here, spectral domain representations of each data series are calculated using the multitaper method (Thomson 1982; Park et al. 1987; Percival and Walden 1993). Briefly, this technique multiplies the data series by several orthogonal window functions, known as tapers, operation analogous to subsampling the data for the generation of independent realizations of the signal. The obtained data tapers are then Fourier transformed, and the resulting spectra are ensemble-averaged to obtain the final spectrum. At each latitudinal band, estimates of $G_{aa}$, $G_{bb}$, and $G_{ab}$ as a function of $k$ ($\omega$) are further temporally (zonally) averaged, and the resulting mean spectra are used to calculate $\gamma_{ab}^2$, $|H_{ab}|$, and $\theta_{ab}$. In this case, the $n_d$ used for estimating $\epsilon$ is given by the number of tapers, set to seven, multiplied by the number of averaged spectral estimates.
3.2.3.2 Estimating the SST-driven $w$ anomalies in physical space

The transfer function $H_{ab}$ [Eq. (3.2)], calculated at each horizontal grid point as a function of $\omega$, is used to estimate the response of the near-surface winds to SST forcing in physical space. Specifically, it is assumed that the spatially high-passed $w$ data can be decomposed as

$$w = w_n + w_c,$$  \hspace{1cm} (3.5)

where $w_n$ ($w_c$) correspond to mesoscale wind speed anomalies perfectly uncorrelated (correlated) in time with the mesoscale SST fluctuations, that is, whose squared coherency relative to the SST signal is equal to zero (one) at all frequencies. The time-evolving $w_c$ signal [$c(t)$] can be obtained via the convolution of the SST signal [$a(t)$] by an impulse response function $h_{ac}$, as $c(t) = h_{ac}(t) \ast a(t)$. Taking the Fourier transform, this equation becomes

$$C(\omega) = H_{ac}(\omega)A(\omega),$$  \hspace{1cm} (3.6)

where $C$, $H_{ac}$, and $A$ are the frequency domain representations of $c$, $h_{ac}$, and $a$, respectively. Here, $H_{ac}$ is the transfer function of the linear system, which is identical to $H_{ab}$ when assuming the decomposition in Equation (3.5) (Bendat and Piersol 1986, page 201). With $H_{ab}$ and $A$ known, $c$ can then be retrieved by taking the inverse Fourier transform of (3.6). This procedure is applied at every grid point covered by the satellite and model datasets used in this study for the obtention of time-evolving spatial fields of $w_c$.

It is noted that the $H_{ab}$ estimates are subject to random errors that introduce uncertainties in $w_c$. To isolate bands of $H_{ab}$ with a physically meaningful spectral content, a value of zero is attributed to frequencies where (a) the zonally-averaged $\gamma_{ab}^2$
for the correspondent latitude is smaller than 0.18, limit chosen to slightly overshoot the minimum zonally-averaged value of \( \sim 0.15 \) obtained in latitudinal spectrograms (c.f. Section 3.3.1.4); (b) the local \( \theta_{ab} \) have absolute values larger than 90°; and (c) the local \( |H_{ab}| \) is statistically similar to zero at 95% confidence margins. Differently from Section 3.2.3.1, where zonal averaging significantly increases the number of degrees of freedom \( (n_d) \) for the analysis, the fact that \( H_{ab} \) is retrieved here at each grid point limits \( n_d \) to seven, for which the approximate expression for \( \epsilon [ |H_{ab}| ] \) [Eq. (3.4)] yields too conservative estimates. For this reason, \( \epsilon [ |H_{ab}| ] \) is inferred here using a Monte Carlo approach. Specifically, \( n = 500 \) transfer function estimates, \( \tilde{H}_i, i = 1, 2, ..., n \), are calculated at each grid point using first-order autoregressive red noise models with coefficients estimated from the real SST and \( w \) time series. Autoregressive models are preferred over the more traditional bootstrap samples, built by randomly sampling with replacement the original time-series (e.g. Efron and Gong 1983; Elipot and Gille 2009a), because they can emulate the power spectral density of the real data (e.g. Allen and Robertson 1996; Siqueira and Kirtman 2016). From the obtained \( \tilde{H}_i \) samples, the gain factor’s standard error is estimated as

\[
\epsilon [ |H_{ab}| ] = \left[ \frac{1}{n (n - 1)} \sum_{i=1}^{n} (\tilde{H}_i - \langle \tilde{H} \rangle) (\tilde{H}_i - \langle \tilde{H} \rangle)^* \right]^{1/2},
\]

where the brackets denote an ensemble average, and the asterisk a complex conjugate.
3.3 Results and discussion

3.3.1 SST/\(w\) coupling resolved by satellite products

3.3.1.1 Variance of oceanic and atmospheric quantities at the ocean mesoscales

To provide context to the characteristics observed in the obtained \(\gamma_{ab}^2, |H_{ab}|,\) and \(\theta_{ab}\) spectra, this Section preliminarily describes the horizontal variance distribution of oceanic near-surface currents, and of high-passed SST and \(w\). A similar discussion is provided by Small et al. (2005) (their Section 3), here extended to include latitudes poleward of 40°, and updated in light of newer observations and analyzes.

Figure 3.1a shows the global map of the subinertial 15-m ocean currents’ speed variance \((\sigma_u^2)\), equal to twice the eddy kinetic energy, obtained from NOAA’s drifter-derived climatology of near-surface currents version 3.0 (Laurindo et al. 2017, available at www.aoml.noaa.gov/phod/dac/dac_meanvel.php). The largest values \((O[0.1–1 \text{ m}^2/\text{s}^2])\) occur in the vicinity of intense current systems, such as the equatorial currents, western boundary currents and their seaward extensions, the ACC, the Agulhas Retroflection, and the Brazil-Malvinas Confluence, indicative that the variability arises primarily from instabilities of the mean currents (e.g. Smith 2007; Ferrari and Wunsch 2009; Tulloch et al. 2011). Towards the ocean’s interior, broadly zonally-elongated bands with variances of \(O[0.1 \text{ m}^2/\text{s}^2]\) can be observed within the subtropical gyres of all major basins, referred to in Small et al. (2005) as waveguides. Several comparatively quiescent regions with variances of \(O[0.01 \text{ m}^2/\text{s}^2]\) can also be identified, previously reported in Lumpkin and Johnson (2013) and dubbed “eddy deserts” by that study. The most prominent eddy deserts are located in the South
Atlantic and eastern South Pacific between approximately 5–20°S. Other low variance regions can be observed between the South Pacific’s waveguide and the ACC; in the subpolar and eastern North Pacific; in the North Atlantic between 10–30°N; and in the Indian Ocean between Australia and the ACC, around New Zealand, and in the vicinity of the Kerguelen Islands.

Regarding the phenomena conditioning the $\sigma_u^2$ distribution (Fig. 3.1a), near the equator it predominantly reflects zonally-propagating intraseasonal Rossby waves and mixed Rossby-gravity (Yanai) waves, generically designated as tropical instability waves (TIWs), with intraseasonal periodicity and wavelengths of $\mathcal{O}[10^3 \text{ km}]$ (e.g. Polito and Sato 2003; Tulloch et al. 2009; Farrar 2011; Perez et al. 2012; Watanabe et al. 2016). Outside the tropical belt, the variability is dominated by westward-propagating signals whose power spectra span spatial scales of $\mathcal{O}[10^1-10^3 \text{ km}]$ and temporal scales from one month to years. There is an ongoing debate on whether this variability predominantly reflect linear Rossby waves, nonlinear mesoscale eddies, or their combined action. Variability forced by both phenomena should exist along the same wavenumber/frequency continuum, meaning that it is not trivial to isolate their individual effects.

Particularly, mesoscale eddies detected in altimeter-derived SSH products are found to explain up to 70% of $\sigma_u^2$, where approximately 90% of the detected eddies show ratios between their average rotational and translational speeds larger than one, indicating that they can trap fluid in their interiors and hence that they are nonlinear in nature (Chelton et al. 2011). Additionally, the power spectral density of altimetric SSH data suggests that the observed westward-propagating signals remain predominantly nondispersive at wavenumbers where the standard Rossby wave
theory predicts the existence of dispersive waves. This nondispersive behavior can be replicated in idealized nonlinear quasigeostrophic simulations, and in synthetic SSH fields built assuming that all variability consists of isolated Gaussian eddies, supporting the conclusion that the variability is primarily composed by nonlinear eddies not bound to Rossby wave dynamics (Early et al. 2011; Chelton et al. 2011). Conversely, an extension of the linear wave theory that takes into account the effects of background baroclinic flow and bottom topography significantly minimize discrepancies between the predicted dispersion characteristics of Rossby waves and those of the observed westward-propagating signals (Killworth and Blundell 2004; Killworth and Blundell 2005; O’Brien et al. 2013). Furthermore, Berloff and Kamenkovich (2013a, b) concluded, through idealized numerical experiments, that the dispersion of nonlinear eddies is strongly controlled by the underlying linear dynamics. Such results are consistent with recent observations by Polito and Sato (2015) that eddies detected in the SSH data often coincide with meridionally-elongated crests and troughs of westward-propagating signals with periods between 3 and 24 months, interpreted in that study as Rossby waves.

The net impact of mesoscale current variability to SST can be inferred via the global distribution of high-passed SST variance (\(\sigma^2\), Fig. 3.1b). The observed spatial patterns are generally similar to those of current speed variance (3.1a), with maximum values of \(O[1^\circ C^2]\) at the seaward extensions of western boundary currents, \(O[0.1^\circ C^2]\) at the subtropical waveguides, and of \(O[0.01^\circ C^2]\) or smaller within the eddy deserts. However, notable discrepancies can be perceived within the tropics, which appear as a quiescent region except in the eastern equatorial Pacific and Atlantic Oceans; and at the Northern Hemisphere’s waveguides, that are shifted northward and tilted in
the northeast direction. Such differences coincide with the local absence of significant mean SST gradients (highlighted by the time-mean SST isolines overlaid in 3.1b), suggesting that the mesoscale SST variability predominantly arise from the horizontal temperature advection by mesoscale ocean currents, in accordance with the conclusions of previous studies (e.g. Small et al. 2005; O’Brien et al. 2013; Gaube et al. 2015). Major oceanic upwelling zones are also visible, such as the Guinea and Angola Domes in the Atlantic, the California and Peru-Chile Current Systems in the Pacific, and the Somalia Current System in the Indian Ocean. Furthermore, the enhanced $\sigma^2$ values in the eastern equatorial Pacific and Atlantic Oceans highlight the equatorial cold tongues at these basins.

Finally, the global distribution of high-passed $w$ variance ($\sigma^2_w$, Fig. 3.1c) also resemble that described for near-surface ocean currents (3.1a) and high-passed SST (3.1b), with enhanced values ($O[0.1–1 \text{ m}^2/\text{s}^2]$) observed at the seaward extensions of western boundary currents, the ACC, and the subtropical waveguides; and of $O[0.1 \text{ m}^2/\text{s}^2]$ or smaller within the tropics, coinciding with regions with low current and high-passed SST variability. Such similarity suggests a strong oceanic influence on $w$, a conclusion supported by the fact that the outline of oceanic features, such as the Agulhas Return Current, branches of the ACC, the Brazil-Malvinas Confluence, and the equatorial Pacific’s cold tongue, can be clearly discerned. However, it is noted that the observed patterns also resemble that of long-term mean precipitation (e.g. Adler et al. 2003), and thus can reflect the action of relatively small scale convective systems, as evidenced by the imprint of the Intertropical Convergence Zone (ITCZ) at about 10°S in the Indian Ocean, and at 5°N in the Pacific and Atlantic basins (Small et al. 2005). The results of the cross-spectral analysis between the satellite-based
SST and $w$ signals, described next, shed light on the spatial-temporal scales where SST variability can affect the near-surface winds, and on its actual contribution to the mesoscale $w$ variance.

### 3.3.1.2 Zonal wavenumber-frequency spectra

Figure 3.2 shows estimates of $\gamma_{ab}^2$, $|H_{ab}|$, and $|\theta_{ab}|$, calculated simultaneously as a function of $k$ and $\omega$, for the Pacific Ocean at 50.125°S, 25.125°S, and 0.125°S, latitudes chosen to be emblematic of characteristics observed in spectral estimates from both hemispheres for all three ocean basins. It is noted that only absolute wavenumbers are considered, meaning that no distinction is made between eastward and westward-propagating signals, and that the noisy spectral distributions reflect random errors conditioned by the relatively small number of degrees of freedom available for the analysis ($n_d = 19$).

All $\gamma_{ab}^2$ spectra in Figure 3.2 (top row) show enhanced values at wavelengths larger than $\sim 2500$ km coinciding with $|\theta_{ab}|$ (bottom row) larger than 90°, indicating negative SST/$w$ correlations. This is consistent with the interpretation that, at large scales, SST fluctuations are controlled by the atmosphere (c.f. Xie 2004; Chelton and Xie 2010). Towards smaller wavelengths, $\gamma_{ab}^2$ becomes statistically similar to zero at 95% confidence level, before increasing to up to 0.6 between 250-1000 km at 50.125°S and 25.125°S, and between 500-2500 km at 0.125°S, coinciding with $|\theta_{ab}|$ values typically smaller than 30°. This reflects positive correlations between both signals, suggesting SST-driven anomalies in $w$. At these spatial scales, panels (a) to (c) also evidence a latitudinal variation of the periodicity of statistically significant $\gamma_{ab}^2$ values, from 100 to 1000 days at 50.125°S, 50 to 250 days at 25.125°S, and 10
Figure 3.2: Zonal wavenumber-frequency spectra of the squared coherency ($\gamma^2_{ab}$, top row), gain factor ($|H_{ab}|$, middle), and absolute phase factor ($|\theta_{ab}|$, bottom) of satellite-based SST and w for the Pacific Ocean at 50.125°S, 25.125°S, and 0.125°S (left, middle, and right column, respectively). $\gamma^2_{ab}$ estimates statistically similar to zero at 95% confidence level are shown in a grey scale, while $|H_{ab}|$ and $|\theta_{ab}|$ estimates where $|H_{ab}|$ is similar to zero are shaded in grey. The solid black lines in the left and middle columns are the dispersion relation for first baroclinic mode Rossby waves (curved line) and its non-dispersive limit (straight), and the dashed black line the eastward-propagating wavenumbers of the dispersion relation modified by a 0.1 m/s barotropic zonal flow. In the right column, the black lines are the dispersion relations for first baroclinic mode equatorial waves, specifically denoting, in order of increasing periods in the left-hand side of the panels, mixed Rossby–gravity waves and Rossby waves of the first and second equatorial modes.
to 250 days at 0.125°S. Correspondent scale-dependent regimes are observed in $|H_{ab}|$ (Fig. 3.2, bottom row), where values generally larger than 2 m/s per °C are observed at $O[10^2-10^4 \text{km}]$ wavelengths, that shift to values between 0.2-0.8 m/s per °C within the $O[10^3-10^4 \text{km}]$ range at 50.125°S and 25.125°S, and to between 0.8-1.8 m/s per °C at 0.125°S. At wavelengths smaller than $\sim 100 \text{ km}$, spectra for all latitudes display $\gamma_{ab}^2$ statistically similar to zero, a general increase of $|H_{ab}|$ as a function of frequency, and sharp $\theta_{ab}$ variations. Considering the $\sim 50 \text{ km}$ spatial resolution of the microwave-based SST data used in the generation of the AVHRR+AMSR OISST product, this is likely the result of aliased SST variability at spatial scales smaller than $\sim 100 \text{ km}$ (Reynolds and Chelton 2010).

The dispersion relation for first mode baroclinic oceanic waves are overlaid to the the zonal wavenumber-frequency spectra in Figure 3.2. At 50.125°S (left column), the solid black lines highlight the dispersion relation from the standard linear Rossby wave theory, given by $\omega = k\beta/(k^2 + R_1^{-2})$, where $\beta$ is the meridional variation of the Coriolis parameter $f$, and $R_1$ is the first internal Rossby radius of deformation, defined as the ratio $c_1/f$, where $c_1$ is the internal gravity wave phase speed for the first baroclinic mode considering a non-rotating fluid; and the dispersion relation’s non-dispersive limit. Here, $c_1$ are zonally-averaged values from the global atlas of Chelton et al. (1998) (available at www-po.coas.oregonstate.edu/research/po/research/rossby_radius/). Additionally, considering that the ocean circulation at this latitude is dominated by the ACC, the dashed black line shows the eastward-propagating portion of the Rossby wave dispersion relation modified for a background barotropic zonal flow, given by $\omega = Uk - k(\beta + UR_1^2)/(k^2 + R_1^{-2})$, using a mean zonal flow $U = 0.1 \text{ m/s}$. Figure 3.2a evidences that, while the broad frequency
range where enhanced $\gamma_{ab}^2$ values occur at the ocean mesoscales does not match the standard Rossby wave dispersion relation, it is qualitatively compatible with the wave dispersion under an eastward background flow. Such spectral distribution is similar to those observed at the latitudes of the western boundary currents’ seaward extensions, of the Agulhas Retroflection, and of the Brazil-Malvinas Confluence, all regions of energetic mesoscale variability and intense mean eastward currents.

Considering the significantly smaller current velocities within the South Pacific’s subtropical gyre, the spectra for 25.125°S in Figure 3.2 (middle column) show only the standard Rossby dispersion relation and its non-dispersive limit. At mesoscale ranges, $\gamma_{ab}^2 \sim 0.35$ is predominantly observed in frequencies higher than those of theoretical Rossby waves and distributed on the vicinity of the non-dispersive slope, characteristic frequently observed in spectral estimates of latitudes crossing the subtropical waveguides of all three ocean basins. The nondispersive character of the coherent SST/$w$ mesoscale signals is compatible with the signature of westward-propagating nonlinear eddies (Early et al. 2011; Chelton et al. 2011), however the discrepancy relative to the theoretical Rossby wave dispersion relation can be potentially minimized if the effects of background flow and of bottom topography are accounted for (Killworth and Blundell 2004, 2005), meaning that the action of long, approximately nondispersive Rossby waves cannot be ruled out.

Finally, the black lines overlaid to the spectra for the equatorial Pacific at 0.125°S (Fig. 3.2, right column) are solutions for the dispersion relation of free equatorial waves, given by $\omega^2/c_1^2 - k^2 - \beta k/\omega = (2j+1)\beta/c_1$, where $j$ denotes different meridional oscillation modes. In order of increasing periods in the left-hand side of the panels, the lines are solutions for mixed Rossby–gravity waves ($j = 0$), and for Rossby waves
of the first and second equatorial modes \((j = 1\) and \(2\), respectively\) (e.g. Matsuno 1966; Cane and Sarachik 1976; Gill 1982). Specifically, Figure 3.2c show statistically significant \(\gamma_{ab}^2\) on the vicinity of the dispersion solutions of all three wave regimes, being larger than 0.4 within the 750-2000 km and 15-50 day range, characteristics similar to those observed in spectrograms for the equatorial Atlantic, and compatible with the dispersion properties of TIWs in both basins (e.g. Qiao and Weisberg 1995; Polito and Sato 2003; Farrar 2011). The observed SST/\(w\) coupling is thought to arise from SST perturbations caused by horizontal advection of the meridional temperature gradient associated with the cold tongues by TIW currents (Chelton et al. 2000; Polito et al. 2001; Seo et al. 2007), and the consequent response of the overlying winds via boundary layer dynamics (e.g. Hayes et al. 1989; Wallace et al. 1989; Xie et al. 1998).

To summarize, the zonal wavenumber-frequency spectra of \(\gamma_{ab}^2\), \(|H_{ab}|\), and \(|\theta_{ab}|\) shown in Figure 3.2 suggest a shift from a predominantly atmosphere-forced to an ocean-forced regime at spatial scales of \(\sim 1000\) km at mid and high latitudes, and of \(\sim 2500\) km near the equator. Outside the tropical belt, the dispersion characteristics of the coherent SST/\(w\) signal that characterize the ocean forcing of the atmosphere is compatible with those expected for either nonlinear eddies or linear Rossby waves, while near the equator they reflect TIWs. The latitudinal variation of the considered cross-spectral parameters is analyzed in further detail next, using estimates calculated separately as function of \(k\) and \(\omega\).
3.3.1.3 Zonal wavenumber spectra

Figure 3.3 shows latitudinal spectrograms of $\gamma_{ab}^2$, $|H_{ab}|$, and $|\theta_{ab}|$, calculated as a function of $k$, for the Indian, Atlantic, and Pacific Oceans. In contrast with the noisy spectra in Figure 3.2, the smooth estimates here arise from the use of the multitaper method to calculate the raw $k$-spectra at each time step and their subsequent averaging, which significantly increase the number of degrees of freedom available for the analysis ($n_d = 42070$).

At wavelengths larger than $\sim 2000$ km in all three basins, the spectrograms in Figure 3.3 show $\gamma_{ab}^2$ and $|H_{ab}|$ values of up to 0.45 and 1.2 m/s per $°C$, respectively, associated with $|\theta_{ab}|$ of $\sim 140$-180$°$, indicating negative correlations between SST and $w$. Between $\sim 750$-2000 km, $\gamma_{ab}^2$ sharply decrease to $\sim 0.17$, and both $|H_{ab}|$ and $|\theta_{ab}|$ to near-zero values. However, at most latitudes between $\sim 100$-1500 km, $\gamma_{ab}^2$ and $|H_{ab}|$ re-enhance while associated with $|\theta_{ab}|$ between 0-60$°$, indicating that SST and $w$ are positively correlated. Particularly, the largest $\gamma_{ab}^2$ values within this range (up to 0.35) coincide with the latitudes of oceanic systems with high current and mesoscale SST variances (c.f. Figs. 3.1a and 3.1b). As for $|H_{ab}|$, the largest values within the $\sim 100$-1500 km range are observed in the equatorial Pacific and Atlantic Oceans (1.2 and 0.6 m/s per $°C$, respectively). Outside the equatorial belt, $|H_{ab}|$ varies between $\sim 0.2$-0.5 m/s per $°C$, being largest at the latitudes of the Agulhas Return Current in the Indian Ocean, and of the ACC in the Pacific. Interestingly, $|H_{ab}|$ is generally larger in the Southern Hemisphere than in the Northern. Furthermore, while near-zero $|\theta_{ab}|$ values are typical between 300-1000 km, at wavelengths smaller than 300 km they tend to increase towards smaller scales until maximum values of $\sim 60°$ at 100 km, suggesting the existence of a zonal offset between SST and $w$ within the 100-300
Figure 3.3: Latitudinal spectrograms of the squared coherency ($\gamma_{ab}^2$, top row), gain factor ($|H_{ab}|$, middle), and absolute phase factor ($|\theta_{ab}|$, bottom), calculated using satellite-based SST and $w$ as a function of zonal wavenumber, for the Indian (left column), Pacific (middle), and Atlantic (right) basins. The black dashed lines are, in order of increasing wavenumber, the zonally-averaged first baroclinic Rossby radius of deformation for the atmosphere (calculated using NCEP reanalysis data) and for the ocean. The dashed red line is equal to four times the zonally-averaged radius $L_s$ of eddies detected in altimeter-derived SSH data.
km range. At wavelengths smaller than 100 km, the low $\gamma_{ab}^2$ values and the sharp variations of $|H_{ab}|$ and $|\theta_{ab}|$ probably reflect aliased SST realizations, as discussed in Section 3.3.1.2.

Figure 3.3 evidences that the shift from positive to negative correlations between SST and $w$ at about 750-2000 km, also observed in the zonal wavenumber-frequency spectra (Fig. 3.2), occurs at most latitudes of all three basins. The spectrograms in Figure 3.3 are overlaid with the meridional profile of the zonally-averaged first baroclinic Rossby radius of deformation ($R_1$) for the atmosphere and the ocean (dashed black lines). Here, the atmospheric $R_1$ are calculated using long-term mean vertical potential temperature profiles for the troposphere obtained from the National Centers for Environmental Prediction (NCEP) reanalysis model (Kalnay et al. 1996, available at www.esrl.noaa.gov/psd/), assuming an unsaturated atmosphere and a transition from extratropical to tropical dynamics at 30° latitude (c.f. Durran and Klemp 1982; Gill 1982; Holton 2004), while the oceanic $R_1$ are from Chelton et al. (1998). Notably, the meridional profile of the atmospheric $R_1$ closely delineates the transition scale between negative and positive correlations in the spectrograms for the Pacific Ocean (Fig. 3.3, middle column). The relationship is less clear in the Indian and Atlantic basins (left and right columns, respectively), although the meridional tilt of the $\gamma_{ab}^2$ and $|H_{ab}|$ patterns poleward of 30° in both basins resemble that of $R_1$. Considering that the horizontal dimensions of quasi-geostrophic variability scale as a function of $R_1$, its correspondence with the spatial scale of the transition suggests that the influence of SST on the near-surface winds via boundary layer dynamics can prevail over the atmospheric control of SST via turbulent heat fluxes at scales where the geostrophic adjustment of atmospheric motions is no longer possible.
Finally, the zonal wavelengths where the mesoscale $\gamma_{ab}^2$ maxima occur tend to increase equatorward, varying from about 200 km at 60° latitude to 1500 km near the equator (Fig. 3.3, top row), scales significantly larger than the $\sim$40-200 km radii of eddies detected in SSH data (Chelton et al. 2011). However, considering that (a) the SSH variability appears largely dominated by nonlinear eddies and yet display a continuous, broadband power spectral distribution (Early et al. 2011; Chelton et al. 2011), and (b) recent studies indicate that eddies tend to propagate along well-defined paths, with cyclonic and anticyclonic eddies frequently alternating each other along the zonal direction (Polito and Sato 2015; Chen et al. 2016), one possibility is that the mesoscale coupled SST/$w$ signal reflect the collective action of the eddy field onto the atmosphere. To examine this hypothesis, the spectrograms in Figure 3.3 are overlaid with the zonally-averaged eddy radius $L_s$ multiplied by four (dashed red line), thus representing a full wavelength. Outside the equatorial belt, this scale closely trails the mesoscale $\gamma_{ab}^2$ maxima across the latitudes of all three ocean basins.

3.3.1.4 Frequency spectra

To determine the characteristic time-scales of the coupled SST/$w$ signal at the ocean mesoscales, Figures 3.4 and 3.5 show latitudinal spectrograms of $\gamma_{ab}^2$, $|H_{ab}|$, and $|\theta_{ab}|$ for the western and eastern portions of the three major ocean basins, respectively, calculated as function of $\omega$ and using spatially high-passed SST and $w$ satellite data. The west/east division is made referent to the midpoint of each basin’s zonal extent to accounts for the zonal asymmetry on the SST and $w$ variance distributions (Fig. 3.1). Virtually all estimates have signal-to-noise ratios larger than one, owning to the large number of degrees of freedom available for the analysis ($n_d \geq 476$).
Figure 3.4: Latitudinal spectrograms of the squared coherency ($\gamma_{ab}^2$, top row), gain factor ($|H_{ab}|$, middle), and absolute phase factor ($|\theta_{ab}|$, bottom), calculated as a function of frequency using spatially high-passed satellite estimates of SST and $w$ for the western Indian (left column), Pacific (middle), and Atlantic (right) basins. The dashed lines denote the biannual, annual, and semiannual periods.
Figure 3.5: Similar to Figure 3.4, but for the eastern Indian, Pacific, and Atlantic basins.
Figures 3.4 and 3.5 show $\gamma_{ab}^2 > \sim 0.18$ often coinciding with $|H_{ab}| > \sim 0.2 \text{ m/s per } ^\circ\text{C}$ and with near-zero $|\theta_{ab}|$, thus reflecting positive SST/$w$ correlations. This regime occur along a broadband frequency range, extending from the truncation limit of the analysis at 1000 days until 10-50 days near the equator, and until 25-300 days at mid to high latitudes. As discussed in Section 3.3.1.2, the dispersion characteristics of the coupled SST/$w$ signals are compatible with TIWs near the equator, and with Rossby waves and/or eddies at higher latitudes. Figures 3.4 and 3.5 supports these conclusions, as (a) the eastern Pacific and Atlantic Oceans show significant SST/$w$ coupling near the equator that is absent in the western basins, compatible with the action of TIW currents over the equatorial cold tongues; and (b) away from strong currents (e.g. in the extratropical eastern Pacific, Fig. 3.5b), the shortest periods where the coupling takes place decreases equatorward, from $\sim 150$-300 days at 60° to about 50 days at 20°, compatible with a reduction in the Rossby wave periodicity in response to the equatorward increase of $R_1$. Such latitudinal dependence does not hold in regions with strong eastward currents, such as at $\sim 45^\circ\text{S}$ in the western Indian Ocean, coinciding with the Agulhas Return Current (Fig. 3.4a), where the periodicity of the coupled SST/$w$ can be as short as 25 days, suggesting an influence of the background flow on the dispersion characteristics of mesoscale ocean phenomena (c.f. Fig. 3.2, left column).

Large coherence values ($\gamma_{ab}^2 > 0.4$) coincide with large scale SST fronts and subtropical waveguides in all three basins in Figures 3.4 and 3.5, with the largest values ($\gamma_{ab}^2 \geq 0.5$) prominently occurring in the Southern Hemisphere. Regarding $|H_{ab}|$, the largest values are observed near the equator ($\sim 1.2 \text{ m/s per } ^\circ\text{C}$), associated with TIWs. In the extratropics, $|H_{ab}|$ varies between 0.2-0.6 m/s per °C, being generally
larger in the Southern Hemisphere than in the Northern, as also observed in Figure 3.3. Interestingly, while the SST and current variances associated with the seaward extensions of the Kuroshio and Gulf Stream Currents are significantly larger in the western basins than in the eastern (Fig. 3.1), their associated $|H_{ab}|$ are about a factor of two smaller. Furthermore, the $|H_{ab}|$ associated with the Kuroshio and Gulf Stream Currents are 1.5–3 times smaller than at the latitudes of large-scale SST fronts in the Southern Hemisphere. Such geographic variability can be associated with differences in the background wind speed and boundary layer height, which were observed to influence the relative contribution of the two main physical mechanisms through which the boundary layer adjusts to mesoscale SST anomalies, namely the pressure adjustment and the vertical mixing of momentum (e.g. Spall 2007; O’Neill et al. 2010; Byrne et al. 2015).

### 3.3.1.5 Impact of mesoscale SST variability onto the near-surface winds

This Section uses the SST-driven wind speed signal $w_c$, calculated as described in Section 3.2.3.2, and mesoscale eddy parameters from META, to examine (a) to what extent mesoscale SST variability affect the near-surface winds, and (b) how much of this influence can be ascribed to coherent ocean eddies.

Figure 3.6a shows the horizontal distribution of the variance of $w_c$ ($\sigma^2_c$). The spatial patterns of $\sigma^2_c$ closely resemble those of high-passed SST variance ($\sigma^2_a$, Fig. 3.1b), a characteristic already expected due to the fact that SST and $w$ are positively correlated at the ocean mesoscales. However, differences exist on the relative magnitude of the $\sigma^2_a$ and $\sigma^2_c$ values observed at large-scale SST fronts, that arise from the spatial variability of $|H_{ab}|$ evidenced by Figures 3.2 to 3.5. Particularly, while the
seaward extensions of Kuroshio and Gulf Stream Currents show $\sigma^2_a$ values similar to those of the Agulhas Current System and Brazil-Malvinas Confluence, their $\sigma^2_c$ can be one order of magnitude smaller (\mathcal{O}[0.01 \, m^2/s^2] vs. \mathcal{O}[0.1 \, m^2/s^2]). Significant $\sigma^2_c$ also coincide with the equatorial cold tongues in the Pacific and Atlantic Oceans (\mathcal{O}[0.1 \, m^2/s^2]), regions whose $\sigma^2_a$ values are one order of magnitude smaller than that of extratropical SST fronts, but that in compensation show the largest $|H_{ab}|$ estimated at each basin.

Figure 3.6b shows the ratio between $\sigma^2_c$ and the high-passed $w$ variance ($\sigma^2_b$) multiplied by 100, thus indicating the percentage of $\sigma^2_b$ explained by $c$. The largest values (up to 40\%) coincide with the equatorial cold tongues in the Pacific and Atlantic Oceans, the Somalia Current System in the Indian Ocean, and the Peru-Chile Current System in the South Pacific. Other upwelling systems, namely the Guinea and Angola Domes in the Atlantic, and the California Current System in the North Pacific, display percentages between 5–15\%. Subtropical waveguides in all basins show values usually smaller than 5\%, and extratropical large-scale SST fronts between 5–15\% (2–10\%) in the Southern (Northern) Hemisphere. Maximum values in the Southern Hemisphere reach up to 25\% over the Agulhas Return Current, against up to 15\% in the Northern Hemisphere, observed at the Gulf Stream’s seaward extension.

The variance of $c$ attributed to coherent mesoscale eddies ($\sigma^2_{ce}$) can be estimated as

$$\sigma^2_{ce}(x, y) = \frac{1}{M} \sum_{t=1}^{M} \delta(x, y, t) \left[ w_c(x, y, t) - w_{cb}(x, y, t) \right]^2,$$

where $\delta(x, y, t)$, $t = 1, 2, 3, ..., M$, is a global eddy mask composed by $M = 6010$ daily fields, equal to 1 at grid points within one radii $L_s$ from the detected eddy centers, and to 0 otherwise. Here, $w_{cb}$ describes the SST-driven wind response associated with
Figure 3.6: Panel (a) shows the variance distribution of the SST-driven 10-m wind speed anomalies $w_c (\sigma^2_w)$, while panels (b) and (c) respectively show the percentage of the high-passed $w$ variance ($\sigma^2_w$) explained by $c$, and the percentage of $\sigma^2_w$ accounted for by mesoscale ocean eddies.
forms of ocean variability with spatial scales larger than that of the eddies, obtained by masking grid points less than one $L_s$ away from the detected eddy centers, and linearly interpolating the resulting gaps (c.f. Chelton et al. 2011, their Section 3.5). Figure 3.6c shows the ratio $\sigma_{ce}^2/\sigma_c^2$ multiplied by 100, corresponding to the percentage of $\sigma_c^2$ accounted for by coherent eddies. Eddy deserts identified in the near-surface current variance distribution (Fig. 3.1a) coincide with percentages typically smaller than 20%, subtropical waveguides with percentages between 20–40%, and extratropical SST fronts in both hemispheres with values between 20–60%.

To demonstrate that $\sigma_{ce}^2$ reflects the influence of coherent ocean eddies onto the near-surface winds, not arising simply from chance collocations of $c$ fluctuations with the numerous underlying eddies, Figure 3.7a shows the zonal-temporal diagram of $c$ for 40.125$^\circ$S in the Pacific Ocean overlaid with the rotational centers of eddies passing within 2$^\circ$ of the diagram’s latitude. Westward-propagating crests and troughs alternate each other in the zonal direction, pattern clearly delineated by the detected eddy centers, with anticyclonic (cyclonic) polarities frequently coinciding with positive (negative) fluctuations in $w_c$. Figures 3.7b–c show horizontal eddy-centric composites of $w_c$ for the anticyclonic and cyclonic eddies in 3.7a, normalized by their radii $L_s$. Both composites show an asymmetric dipolar structure extending until about two $L_s$ from the eddy centers, with predominantly positive (negative) values occurring within one $L_s$ of anticyclonic (cyclonic) eddies. This structure can be explained by the combination of a monopolar SST field centered within the eddy domain, created by an eddy-induced Ekman pumping, with a dipolar SST field associated with the horizontal temperature advection by the eddy while propagating along a background SST gradient (Gaube et al. 2015; Souza et al. 2014). Finally, Figures 3.7d and
3.7e show global maps of the time-averaged $w_c$ found within one $L_s$ of anticyclonic and cyclonic eddies, respectively. Both maps reveal spatial features visually similar to those observed in the global $\sigma_c^2$ distribution (Fig. 3.6a), however showing mostly positive (negative) time-mean values for anticyclonic (cyclonic) eddies, in agreement with the predominant sign of $w_c$ within the eddy core observed in the respective eddy-centric composites.

The eddy-centric composites in Figures 3.7b–c evidence that the circular area defined by the radius $L_s$ may not enclose all of the eddy-induced $w_c$ variability. It is
also noted that (a) if a Gaussian approximation of the eddy SSH profile is assumed, $L_s$ then underestimates the actual eddy radius by 30% (Chelton et al. 2011), and (b) eddy stirring give rise to SST variability outside the eddy domain, that can also have an associated $w_c$ response. These considerations suggest that $\sigma_{cc}^2$ [Eq. (3.8)] correspond to a conservative, lower bound estimate of the influence of mesoscale eddies to the observed $w_c$ variability, which nevertheless indicates that these features have a sizable contribution at the subtropical waveguides, and play a dominant role at extratropical SST fronts (Fig. 3.6c). The next Section contrasts the spectral linear SST/$w$ relationship in the LR and HR simulations, providing further insight on the importance of resolved mesoscale ocean phenomena for conditioning the air-sea coupling characteristics revealed by satellite observations, and identifying potential limitations of the CCSM4 model in resolving the physical mechanisms relevant for the coupling.

### 3.3.2 SST/$w$ coupling in climate model simulations

Figure 3.8 shows latitudinal spectrograms of $\gamma_{ab}^2$, $|H_{ab}|$, and $|\theta_{ab}|$ calculated using outputs from the HR and LR models, exemplifying results for the Pacific Ocean. Cross-spectral estimates obtained as function of $k$ from both experiments show negative SST/$w$ correlations at zonal wavelengths larger than the atmospheric $R_1$ (Figs. 3.8a-c, g-i), in agreement with satellite estimates (Fig. 3.3). However, the mesoscale air-sea coupling characteristics differ significantly between the simulations.

Starting with the HR, a transition to positive correlations is clearly observed toward mesoscale ranges (Fig. 3.8a-c). The dispersion of the coherent SST/$w$ mesoscale signals revealed by the zonal wavenumber-frequency cross-spectra (not shown)
Figure 3.8: Latitudinal spectrograms of the squared coherency ($\gamma_{ab}^2$, top row), gain factor ($|H_{ab}|$, middle), and absolute phase factor ($|\theta_{ab}|$, bottom) between SST and $w$ from the HR and LR experiments. Spectral estimates calculated as a function of zonal wavenumber refer to the Pacific Ocean (HR: panels a to c; LR: g to i), where the black dashed lines are, in order of increasing wavenumber, the zonally-averaged atmospheric and oceanic first baroclinic Rossby radius of deformation. Here, the thin dashed lines overlaid to the LR spectrograms delineate the Nyquist frequency for the oceanic zonal resolution of 1.125$^\circ$. Estimates obtained as a function of frequency are calculated using SST and $w$ data preliminarily high-pass filtered in horizontal space to isolate the ocean mesoscales, and refer to the eastern Pacific basin (HR: f to g; LR: i to l). The dashed lines highlight the biannual, annual, and semiannual periods.
are compatible with TIWs near the equator, and with first mode baroclinic Rossby waves and/or mesoscale eddies in the extratropics. These characteristics are manifested in the $\omega$ cross-spectra (Figs. 3.8d–f) as a general equatorward decrease on the periodicity of the coherent SST/$w$ signals, a trend that does not hold at latitudes dominated by strong eastward currents. Such characteristics broadly agree with those resolved by satellite data (Figs. 3.2-3.5), however quantitative differences exist in $|H_{ab}|$ and $\gamma_{ab}^2$.

Particularly, mesoscale $|H_{ab}|$ estimates calculated as a function of $k$ ($\omega$) from the HR are, on average, 45% (88%) smaller than the satellite results. This agrees with the findings of Bryan et al. (2010), which linearly regressed time-series of spatially high-passed SST and wind stress from CCSM simulations based on eddy-resolving ocean resolutions, obtaining regression slopes that underestimated satellite estimates by 20-72%. That study also found a weak sensitivity of the regression slopes to increasing horizontal atmospheric resolution, thus hypothesizing that the air–sea coupling strength in their simulations was limited by an insufficient vertical resolution and/or an inadequate parameterization scheme for subgrid-scale vertical mixing. Despite of the underestimated atmospheric response to SST forcing in HR, its mesoscale $\gamma_{ab}^2$ signal in the extratropics exceed the satellite estimates by a factor of up to three, thus indicating that the simulated SST variability explains a fraction of the mesoscale $w$ variance significantly larger than that inferred from satellite data. As further discussed later in this Section, this characteristic is associated with a larger (smaller) SST ($w$) variance in HR than shown by observations.

In the LR, the SST/$w$ relationship at zonal wavelengths between the atmospheric $R_1$ and $\sim$500 km show some characteristics compatible with the HR and satellite re-
sults. Specifically, $|\theta_{ab}|$ within this range is predominantly smaller than 90°, although an accompanying increase of $\gamma_{ab}^2$ and $|H_{ab}|$, indicative of positive SST/$w$ correlations, is only observed in the equatorial Pacific reflecting the action of TIWs, which are resolved due to their large zonal wavelengths and the refined meridional ocean resolution near the equator (Bryan et al. 2010; Kirtman et al. 2012). Towards smaller scales, however, a prominent regime change can be observed at all latitudes centered at zonal wavelengths varying from 140 km at 55° latitude to 250 km at the equator. At this band, $\gamma_{ab}^2$ of up to 0.6 coincide with $|\theta_{ab}| > 90^\circ$ for the most part, thus indicating negative SST/$w$ correlations. Estimates obtained as a function of $\omega$ (Fig. 3.8j-l) further show that the enhanced $\gamma_{ab}^2$ values occur at all frequencies, while $|\theta_{ab}|$ shifts to values smaller than 90° at periods smaller than $\sim 25$ days, and $|H_{ab}|$ increases approximately as a linear function of $\omega$.

The unrealistic mesoscale SST/$w$ relationship in LR is caused by the presence of striations in high-passed fields of both SST and $w$, that probably correspond to interpolation artifacts introduced when SST and wind stress data are mapped from the oceanic to the atmospheric grid at the CCSM4’s coupler. This is suggested considering that (a) the striations closely delineate the geometry of the ocean grid; (b) the zonal wavelengths of the coherent SST/$w$ signal coincides with the Nyquist frequency for the ocean grid’s zonal resolution of 1.125° (thin dashed line in Figs. 3.8g-i); and (c) the striations can be replicated in a simple interpolation exercise (not shown). It is noted that the calculation of air-sea fluxes at the ocean grid, as well as the mapping strategies adopted in the exchange of flux and state variables between the model components, were developed assuming that the ocean has higher horizontal resolution than the atmosphere (c.f. Craig 2010), suggesting that the
creation of interpolation artifacts when the ocean has lower horizontal resolution than the atmosphere is a chronic CCSM4 issue. For this study, this effect unfortunately precludes a proper evaluation of the linear spectral SST/$w$ relationship arising from the absence of resolved mesoscale SST anomalies at scales smaller than $\sim$500 km.

Under a different perspective, the net effect of ocean phenomena onto the near-surface wind variability in the CCSM4 model can also be examined via the $w$ power spectral density as a function of $k$ retrieved from the LR and HR simulations, using correspondent satellite results to assess their realism. This analysis is motivated by the fact that, in a turbulent fluid such as the atmosphere, different spatial scales of motion exchange energy continuously via nonlinear interactions, meaning that the injection of kinetic energy by mesoscale ocean phenomena can potentially affect the whole atmospheric spectrum. In this context, not only the spectral power ascribed to SST-driven $w$ anomalies can be relevant for climate simulations, but also the shape of the spectrum, considering that current turbulence theories demonstrate the existence of a physical link between the spectral slope and the direction that energy flows in wavenumber space.

Figure 3.9a exemplifies the $w$ power spectra as a function of $k$ for 40.125$^\circ$S in the Atlantic Ocean, obtained from the satellite and model datasets. Considering first the satellite results, its spectrum exhibits a shallow plateau at zonal wavelengths larger than about 2000 km, a $-3$ spectral slope between 1000-2000 km, and a $-5/3$ slope at scales smaller than 1000 km, that persists until the spatial Nyquist frequency of the satellite observations at about 50 km. The correspondent latitudinal spectrogram (Fig. 3.9b) evidences a meridional variation of the spectrum that resemble that of the atmospheric $R_1$, suggesting a physical connection between this quantity and the
Figure 3.9: Panel (a) shows the power spectral density as a function of zonal wavenumber of the equivalent-neutral 10-m wind speed \( w \) and its SST-uncorrelated component for 40.125°S in the Atlantic Ocean, inferred from satellite observations, and the HR and LR simulations. The -3 and -5/3 slopes are overlaid for reference. Panel (b) shows the latitudinal spectrogram of the \( w \) power density inferred from satellite data, (c) and (d) respectively show the ratio of HR and LR results LR relative to the observational estimates in (b), and (e) the ratio between the LR and HR results. The dashed lines in (b)-(e) delineate the zonally-averaged atmospheric and oceanic first baroclinic Rossby radius of deformation, and the horizontal black line highlight the 40.125°S latitude, for which the spectra shown in panel (a) refer to.

dransition between different spectral slopes. This spectral structure was previously reported for winds near the tropopause measured by aircraft (e.g. Nastrom and Gage 1985; Cho et al. 1999) and near-surface winds observed by satellite scatterometers (e.g. Patoux and Brown 2001; Patoux et al. 2010). Spectral estimates for mid-tropospheric winds are sparse, but existing results indicate an approximate -2 slope at wavelengths between 2-100 km (Gao and Meriwether 1998).
While the spectrum at wavelengths larger than 1000 km is compatible with predictions from the geostrophic turbulence theory of Charney (1971), reflecting synoptic-scale baroclinic systems whose kinetic energy is transferred toward smaller scales as function of $k^{-3}$, no consensus exist on the physical mechanisms driving the $k^{-5/3}$ relation at smaller wavenumbers. Recent theories propose that the $-5/3$ slope near the tropopause arise at scales where geostrophic adjustment is no longer possible, reflecting a forward energy cascade in response to either a highly nonlinear, three-dimensional stratified turbulence (Lindborg 2006), or the action of linear inertia-gravity waves (e.g. Callies et al. 2014; Žagar et al. 2017). Conversely, idealized quasi-geostrophic simulations by Tulloch and Smith (2009) taking into account the presence of sharp vertical buoyancy gradients near the lower and upper vertical boundaries, respectively representing the Earth’s surface and the tropopause, resulted in a spectral distribution at the boundaries compatible with that of observations while the interior flow maintained a $-3$ spectral slope characteristic of geostrophic turbulence.

The spectra from both HR and LR lack the $-5/3$ slope present in observations, maintaining instead an approximate $-3$ slope at wavelengths smaller than 1000 km (Fig. 3.9a). Figures 3.9c-d show the ratio of the latitudinal spectrograms from the HR and LR relative to observations, evidencing that the $-3$ slope in the model spectra leads to a significantly underestimated $w$ variance at scales smaller than $\sim 1000$ km. While the physical mechanisms driving the observed $-5/3$ slope remain subject to investigation, previous studies showed that this spectral feature is reproduced in atmospheric simulations run at higher horizontal/vertical resolutions than that used here (e.g. Koshyk and Hamilton 2001; Waite and Snyder 2009; Skamarock et al.
suggesting that it can be potentially resolved in CCSM simulations by refining the resolution of the atmospheric grid.

Regarding the impacts of the resolved mesoscale SST variability to the $w$ spectrum, a visual comparison between the HR and LR estimates for 40.125°S in the Atlantic shows that the HR is more energetic throughout the entire zonal wavenumber domain (Fig. 3.9a). Quantitatively, the ratio between the LR and HR latitudinal spectrograms (Fig. 3.9e) shows that the variance in HR at wavelengths larger than 1000 km is about 25% larger than in LR. At mesoscale ranges, the HR can be up to one order of magnitude larger than LR at the latitudes of energetic ocean systems. Here, the significantly enhanced spectral power at the smallest resolvable wavelengths in LR is a symptom of the mapping errors in CCSM4, described previously. The spectra for the component of $w$ uncorrelated with SST ($n$) shown in Figure 3.9a, calculated simply as $G_{nn} = G_{bb}(1 - \gamma_{ab}^2)$, indicate that about half of the increase in spectral power in HR relative to LR at the ocean mesoscales can be directly attributed to SST-driven near-surface wind anomalies. It is not trivial to establish a causal relationship between the resolved mesoscale ocean variability and the remaining excess variance in HR, particularly at large scales. However, it can correspond to the adjustment of the turbulent energy cascade to the mesoscale ocean forcing. It is also noted that the increase in ocean resolution for the HR experiment was performed without any changes to the parameterizations, meaning that the excess large-scale variance may also reflect unrealistic representations of subgrid-scale physical processes (Patoux and Brown 2001; Kirtman et al. 2012).

Finally, Figure 3.10a shows the global distribution of the SST-driven $w$ anomaly variance ($\sigma^2_c$) from HR. While the obtained spatial patterns resemble those of satellite
Figure 3.10: Panel (a) shows the variance distribution of the SST-driven 10-m wind speed anomalies ($\sigma_c^2$) inferred from HR data, and (b) the meridional profile of its zonally-averaged values (red line) compared with that from satellite observations (black).

estimates (Fig. 3.6a), the $\sigma_c^2$ magnitudes differ significantly between both datasets. For comparison, Figure 3.10b shows the meridional profile of the zonally-averaged $\sigma_c^2$ retrieved from HR and satellite data. Relative to observations, the HR overestimates this parameter in the extratropics, with values up to three times larger in the Southern Ocean, up to four at the latitudes of the seaward extensions of the Gulf Stream and Kuroshio Currents, and up to six at at the latitudes of the subpolar gyres of the Northern Hemisphere. Conversely, satellite estimates of $\sigma_c^2$ near the equator exceed the HR results by a factor of up to seven. The underestimated mesoscale SST/$w$ coupling strength $|H_{ab}|$ in HR (Figs. 3.8b, e) accounts for the small equatorial $\sigma_c^2$, however this characteristic is apparently at odds with the strong SST-induced $w$ variability in the extratropics. This is instead explained by the fact that, outside the equatorial belt, the mesoscale SST variance resolved by the HR model is significantly larger than implied by satellite observations.

The overestimated SST variability in HR warrants further investigation, in particular because the consequent excess $\sigma_c^2$ can lead to enhanced feedbacks of the mesoscale SST/$w$ coupling to both the oceanic and atmospheric circulations. Recall that the
SST balance is maintained by short and long wave radiation fluxes, turbulent heat fluxes, upper-ocean mixing, and advection by ocean currents. Although the presence of resolved mesoscale ocean phenomena can feedback into the radiative fluxes (Bryan et al. 2010; Frenger et al. 2013) and turbulent heat fluxes (Villas Bôas et al. 2015; Bishop et al. 2017), direct impacts would be observed into the mixing and advection properties of the flow, suggesting that the excess SST variance in HR can be associated with (a) an improper parameterization of subgrid-scale lateral eddy diffusivity in the ocean model, which was developed to represent the net effect of ocean variability at mesoscale ranges and smaller, and therefore may be inadequate to account for the influence of submesoscale phenomena (e.g. Haza et al. 2012); and/or (b) a more energetic mesoscale variability than in the real ocean, which can be associated with a smaller damping effect via mesoscale wind-current interactions (e.g. Hughes and Wilson 2008; Gaube et al. 2015; Seo et al. 2016; Renault et al. 2016; Seo 2017), caused by the underestimated $w$ variance at the ocean mesoscales (Fig. 3.9). Finally, the atmospheric control of SST via wind-forced turbulent heat fluxes and upper ocean mixing likely act to attenuate the SST modulation by mesoscale ocean phenomena, an effect that would be underestimated in the HR simulation due to the reduced mesoscale $w$ variance, and thus may contribute to the large SST variability resolved by the model.

### 3.4 Summary and conclusions

Although the occurrence of positive correlations between SST and near-surface wind speed over oceanic mesoscale ranges is well-known, the intrinsic spatial and temporal scales over which this air-sea coupling regime takes place are not well estab-
lished, nor is the contribution of the relatively small but near-ubiquitous mesoscale ocean eddies relative to that of larger-scale ocean phenomena, such as extratropical SST fronts and Rossby waves, in driving the observed coupling characteristics. This work addresses these questions using cross-spectral statistics calculated between SST and equivalent-neutral 10-m wind speed ($w$) from satellite products, and from two CCSM4 simulations based on identical atmospheric components but with contrasting horizontal ocean resolutions of 0.1°, capable of resolving mesoscale eddies (HR), and of 1°, whose eddy effects are parameterized (LR).

The spectral linear relationship between SST and $w$ is analyzed separately for the Indian, Pacific, and Atlantic basins at zonal wavelengths between $10^2$-$10^4$ km and periods between $10^1$-$10^3$ days, as a function of their meridional variation between 55°S and 60°N. Satellite-based results show that the large-scales are characterized by negative correlations between SST and $w$, indicating that SST variations are predominantly driven wind-induced turbulent heat fluxes and upper-ocean vertical mixing, that transitions to positive over ocean mesoscale ranges at zonal wavelengths compatible with the atmospheric first baroclinic Rossby radius of deformation $R_1$ (Fig. 3.3). This characteristic is potentially attributed to the fact that the most energetic near-surface wind variability occurs at scales near $R_1$ or larger, reflecting the action of baroclinic weather systems, whose kinetic energy decays toward smaller scales in a forward energy cascade (e.g. Charney 1971; Tulloch and Smith 2009; Callies et al. 2014). The reduced wind variability over oceanic mesoscale ranges may render the atmospheric SST modulation secondary to that driven by intrinsic ocean variability (Small et al. 2005; O’Brien et al. 2013; Oliveira and Polito 2013; Bishop et al. 2017;
Putrasahan et al. 2017), leading to a prevalence of the SST-induced modulation of the near-surface winds via boundary layer dynamics.

In agreement with the results of Small et al. (2005), the largest fractions of the mesoscale $w$ variance explained by SST occurs in the vicinity of the theoretical dispersion relations for TIWs near the equator, and for first mode baroclinic Rossby waves in the extratropics, although statistically significant values are also seen extending toward lower frequencies (Figs. 3.2–3.5). It is noted that the dispersion characteristics of coupled SST/$w$ mesoscale signals at the latitudes of strong extratropical current systems, such as the ACC, the Agulhas Return Current, and the seaward extensions of the Kuroshio and Gulf Stream Currents, deviate from those predicted by the standard Rossby wave theory, but are qualitatively compatible with that of Rossby waves under an eastward barotropic zonal flow (Fig. 3.2, left column). Significant spatial variations are also observed on the strength of the $w$ response to SST, described by $|H_{ab}|$ [Eq. (3.2)], being largest near the equator (up to 1.2 m/s per °C), and varying between 0.2-0.6 m/s per °C in the extratropics, however showing values generally larger in the Southern Hemisphere than in the Northern, asymmetry also reported by O’Neill et al. (2012). This geographical variability is potentially linked to differences in the background wind speed, which can influence the relative contribution of the pressure adjustment the vertical mixing mechanisms (Spall 2007; O’Neill et al. 2012; Byrne et al. 2015). The results obtained here further reveal that the SST/$w$ coupling characteristics can vary as a function of spectral space, with $|H_{ab}|$ peaking at zonal wavelengths compatible with those predicted from the Rossby wave dispersion relations, and generally increasing as a function of the signal periodicity. Furthermore, while mesoscale SST and $w$ signals are virtually in-phase at zonal wavelengths be-
tween about 300-1000 km, most latitudes of all three basins indicate phase shift of 20-60° between 100-300 km. This zonal offset can be indicative of an increase on the relative importance of the pressure adjustment mechanism relative to vertical mixing driving the near-surface wind response to SST forcing at these scales (c.f. Small et al. 2005).

To infer the contribution of the mesoscale SST/w coupling to the near-surface wind variability, and how much of it can be ascribed solely to the action of ocean eddies, time-series of the SST-driven w anomalies are estimated at every spatial grid point covered by the used satellite products using transfer functions describing the spectral linear SST/w relationship in frequency space (Sec. 3.2.3.2). This signal explains up to 40% of the mesoscale w variance at regions with enhanced SST variability near the equator, namely the equatorial cold tongues in the Pacific and Atlantic Oceans and the upwelling zones associated with the Somalia and Peru-Chile Current Systems; 2-25% at extratropical SST fronts, such as the ACC, Brazil-Malvinas Confluence, Agulhas Return Current, and the seaward extensions of the Kuroshio and Gulf Stream Currents; 5-15% at other upwelling zones, such as the Angola and Guinea Domes and the California Current System; and less than 5% within the subtropical waveguides (Figs. 3.6a–b). It is noted that the scatterometer w measurements include the signature of surface ocean currents (e.g. Park et al. 2006; Hughes and Wilson 2008) that should also contribute to the w variance, meaning that such fractions may correspond to lower-bound estimates of the impact of the SST/w coupling to the actual near-surface wind variability. The signature of mesoscale eddies detected in altimetric SSH measurements (Chelton et al. 2011) is clearly visible in the SST-driven w signal (Fig. 3.7), and lower-bound estimates of their contribution to the total variability reveal
typical values between 20-40% in eddy-rich regions (Fig. 3.6c). Notably, fractions of up to 60% are observed over extratropical SST fronts, suggesting that the SST-induced atmospheric feedbacks observed at these regions, previously attributed to the presence of the intense climatological near-meridional SST gradients (e.g. O’Neill et al. 2005; Minobe et al. 2008; Siqueira and Kirtman 2016), can be predominantly associated with the local eddy activity.

The sizable contribution of ocean eddies to the mesoscale SST/w coupling agrees with conclusions from previous studies that the mesoscale variability observed in satellite-based estimates of sea surface height, surface currents, and chlorophyll, previously attributed to the action of linear Rossby waves, is in fact largely driven by nonlinear coherent eddies (Early et al. 2011; Chelton et al. 2011a,b), although the similarity between their dispersion characteristics and those predicted for linear Rossby waves does not rule out an interconnection between both phenomena (Berloff and Kamenkovich 2013a; Berloff and Kamenkovich 2013b; Polito and Sato 2015; Chen et al. 2016). To provide further insight on the role of eddies on conditioning the observed coupling characteristics, the cross-spectral analysis is repeated using outputs of the HR and LR experiments.

The HR and LR models both reproduce the negative SST/w correlations at large-scales seen in satellite-based results, including the regime transition toward the ocean mesoscales at zonal wavelenghts compatible with the atmospheric $R_1$. However, the positively-correlated SST/w mesoscale signals in the extratropics are only realistically resolved in the HR (Fig. 3.9). In LR, the presence of mapping artifacts in both the SST and $w$ data (likely a chronic issue of the current CCSM4 release, arising when the ocean grid is configured to a lower resolution than the atmosphere) produces a
spurious covariance signal that obscures any physically meaningful SST/$w$ covariability at zonal wavelengths smaller than about 500 km. However, it is noted that the ocean resolution in LR can resolve spatial scales smaller than those where the fraction of the $w$ variance explained by SST is maximum in both the satellite and HR results, indicating that resolved ocean phenomena with spatial scales between 20-250 km are critical for driving the SST/$w$ coupling characteristics revealed by observations.

Despite the improvements achieved by the HR experiment in resolving the SST-mediated mesoscale air-sea coupling, its results revealed the following shortcomings: (a) an overall smaller $|H_{ab}|$ than inferred from satellite data, indicating a weaker $w$ response to SST fluctuations. This characteristic was also observed in eddy-resolving CCSM simulations by Bryan et al. (2010), and is potentially associated with an inadequate parameterization of vertical mixing processes within the atmospheric boundary layer; (b) a larger mesoscale SST variance in the extratropics than estimated from observations, resulting in a SST-driven $w$ variability up to a factor of seven larger than satellite-based estimates, despite of the smaller $|H_{ab}|$ (Fig. 3.10); and (c) differences between the power law followed by the $w$ power spectral density as a function of zonal wavenumber over mesoscale ranges inferred from satellite observations ($k^{-5/3}$) and both CCSM4 simulations ($k^{-3}$), potentially linked to an insufficient vertical/horizontal resolution in the atmospheric model component, which leads to a significantly smaller mesoscale $w$ variance in the model experiments relative to observations. This characteristic may be partly responsible for the enhanced mesoscale SST variability in HR, since it would implicate in a smaller mechanical damping of geostrophic ocean currents via current-driven mesoscale air-sea coupling mechanisms (e.g. Hughes and Wilson 2008; Seo et al. 2016; Renault et al. 2016), and a
smaller thermodynamic damping of ocean-forced SST variability via a wind-induced modulation of turbulent heat fluxes.

This study provides further evidence on the importance of resolved mesoscale ocean phenomena, in particular of coherent eddies, for conditioning the air-sea coupling characteristics revealed by satellite observations, and identifies potential limitations of the CCSM4 in resolving this interaction that should be addressed in future implementations of the model. It also argues in favor of the use of cross-spectral methods over simple linear regressions for objectively defining the characteristic spatial-temporal scales of different air-sea coupling regimes, and the variation of the coupling properties over different spatial and temporal scales, providing that enough data is available. It is noted that the method employed for estimating the SST-driven $w$ response in physical space, based on the use of transfer functions for the spectral linear SST/$w$ relationship as a function of frequency (Sec. 3.2.3.2), can be applied to other pairs of correlated oceanic and atmospheric parameters, such as SST and wind stress, SST/SST tendency and turbulent heat fluxes, downwind (crosswind) SST gradients and wind stress divergence (curl), etc. It can also be potentially extended to operate in zonal wavenumber-frequency space, which would allow examining the air-sea coupled response in physical space without a preliminary spatial-temporal filtering of the input datasets.
CHAPTER 4

Estimates of the subinertial air-sea flux of mechanical energy from concurrent drifter and satellite observations

This chapter employs the methods presented in Chapter 2 for the correction of slip bias of undrogued GDP drifters and for the decomposition of drifter observations into mean and time-dependent components, and the SST-driven wind anomalies isolated from satellite observations in Chapter 3, to address the main scientific questions of this dissertation. Specifically, collocated drifter and satellite observations are used to estimate the time-mean, seasonal, and eddy components of the air-sea exchange of mechanical power associated with the total, Ekman, and geostrophic surface ocean velocity fields. The impact of the wind stress dependence on surface ocean currents and SST on the energy fluxes is investigated via theoretical expressions derived to quantify each effect, and by recomputing the energy fluxes using satellite-based wind stress estimates whose influence on currents and SST was removed using observational data. Finally, data from looping drifter trajectories detected in the GDP dataset are used to assess potential asymmetries between the energy fluxes associated with cyclonic and anticyclonic ocean eddies.
4.1 Background

The air-sea flux of mechanical energy can be estimated via the dot product between the wind stress and surface ocean velocity vectors, \( P = u \cdot \tau \). As the surface velocity field can be decomposed into geostrophic and Ekman components (\( u = u_g + u_e \)), \( P \) can also be expanded as \( P = P_g + P_e \). Here, \( P_g \) is the rate of wind work on the geostrophic ocean velocities, which is the main energetic pathway driving the large-scale ocean circulation and a major source of mechanical energy for the deep ocean (e.g. Stern 1975; Oort et al. 1994; Munk and Wunsch 1998; Ferrari and Wunsch 2009). \( P_e \) is the mechanical energy input to the Ekman circulation, which powers turbulent mixing within the Ekman layer, that in turn helps maintain the upper ocean’s velocity and stratification fields (Wang and Huang 2004; Huang et al. 2006; Elipot and Gille 2009b).

Available estimates of the wind power input to the subinertial ocean circulation yield a time-averaged, globally-integrated value of 3.8 terawatts \((1 \text{ TW} = 10^{12} \text{ W})\), partitioned as 0.76-1.1 TW in \( P_g \) and 2.3-2.7 TW in \( P_e \). Observational estimates are only available for \( P_g \), based on altimeter-derived \( u_g \) combined with scatterometer and/or reanalysis \( \tau \) fields (Wunsch 1998; Huang et al. 2006; Hughes and Wilson 2008; Xu and Scott 2008; Scott and Xu 2009). \( P_e \) and \( P \) were calculated using \( \tau \) fields from reanalysis models (Wang and Huang 2004) and/or OGCM ocean velocities (Von Storch et al. 2007). All these values are likely to possess large error margins, however they have not been assessed due to the presence of spatially correlated errors in altimetry data, and of undiagnosed uncertainties in numerical outputs.

There is increasing evidence in support of the key role of air-sea coupling at the ocean mesoscales in regulating the air-sea exchange of mechanical power, as well
as affecting the life-cycle and propagation of ocean eddies. The coupling takes place through the influence of surface ocean currents and SST on $\tau$, that can be represented via the bulk parameterization $\tau = c_d \rho_a |w - u|(w - u)$, where $c_d$ is an equivalent-neutral drag coefficient, $\rho_a$ is the air density, and $w$ is the equivalent-neutral 10-m wind velocity vector. While the dependence of $\tau$ on $u$ is evident, the dependence on SST is due to positive correlations between this quantity and the wind velocity magnitude ($|w|$, hereafter denoted as $w$) at mesoscale ranges. The correlation arises from air-sea turbulent heat fluxes forced by the mesoscale SST fluctuations, which affects the stability of the atmospheric boundary layer that induces vertical momentum mixing and horizontal pressure gradient anomalies, effects that ultimately drive perturbations in $w$ of the same sign as the underlying SST anomalies (c.f. Small et al. 2008; Chelton and Xie 2010).

Accounting for the dependence of $\tau$ on $u$ systematically reduces $P$ because it causes $\tau$ to be larger (smaller) when $u$ and $w$ have opposing (same) directions, both cases resulting in a smaller power input to the ocean. Duhaut and Straub (2006) predicted that the wind-current coupling reduces the global integral of $P$ by $\sim$20-35%, acting primarily on the mesoscale eddy field since it holds the majority of the oceanic surface kinetic energy, a conclusion supported by subsequent observational (Hughes and Wilson 2008) and numerical results (Dawe and Thompson 2006; Zhai and Greatbatch 2007). Theoretical studies further show that the dependence of $\tau$ on $u$ creates a surface drag force that acts as a sink of kinetic energy for ocean currents (Bye 1986; Dewar and Flierl 1987). Results from recent numerical experiments focusing on the North Atlantic (Zhai and Greatbatch 2007; Eden and Dietze 2009; Renault et al. 2016), the California Current System (Seo et al. 2016; Renault et al. 2016),
the Somalia Current System (Seo 2017), and the Agulhas Return Current (Renault et al. 2017), indicate that the enhanced surface drag induced by the current influence in $\tau$ reduce the depth-integrated eddy kinetic energy (EKE) in the simulations by 10-50%.

In contrast, SST-induced changes to $P$ can be of either sign. While numerous studies showed that the SST/$w$ coupling modifies the $\tau$ divergence and curl on large-scale SST fronts and on mesoscale eddies, affecting the associated Ekman transport/pumping and influencing eddy propagation (e.g., Dewar and Flierl 1987; Seo et al. 2016; White and Annis 2003; Chelton et al. 2004; Frenger et al. 2013; Souza et al. 2014; Gaube et al. 2015; Villas Bôas et al. 2015), potential feedbacks of the coupling to the ocean energetics below the Ekman layer has received less attention. In particular, Jin et al. (2009) investigated the impacts of the SST-driven coupling in an idealized simulation of an eastern boundary upwelling system, parameterizing the boundary layer response to mesoscale SST forcing using an empirical SST/$\tau$ relationship, and found that the coupling disrupted the evolution of mesoscale eddies that led to a $\sim$25% decrease in EKE. Conversely, high-resolution, fully coupled experiments for the California Current System by Seo et al. (2016) and Renault et al. (2016) showed no impact of the SST-driven coupling to the eddy energetics, in contrast with a significant EKE reduction induced by the current-driven coupling (up to 42%). Similar conclusions were drawn by Seo (2017) for the Somali Current System, also based on high-resolution coupled experiments. Finally, Byrne et al. (2016) evaluated the current and SST-driven coupling in high-resolution coupled simulations of the South Atlantic, and observed that the SST/$w$ coupling in the region could not only fully counteract the dissipative effect of the current-driven coupling, but also led to a
net wind power input to coherent ocean eddies, ultimately leading to a 10% increase on the depth-averaged EKE resolved by the model.

Despite the strong air-sea coupling feedbacks to ocean variability implied by these results, observational estimates based on altimeter-derived geostrophic velocities suggest that the covariance between $\tau$ and $u$ fluctuations impacts the globally-integrated power input to the general ocean circulation by only $\sim 5\%$ (Wunsch 1998; Huang et al. 2006; Hughes and Wilson 2008; Xu and Scott 2008; Scott and Xu 2009; Xu et al. 2016). This can be due to a net cancellation of positive/negative power fluxes associated with cyclonic and anticyclonic eddies (c.f. Jin et al. 2009; Byrne et al. 2016; Xu et al. 2016), although it can also reflect limitations of altimetric data in resolving the mesoscale variability (e.g. Ducet et al. 2000; Fu and Ubelmann 2014; Poje et al. 2014). Furthermore, the lack of consensus on the impacts of SST/w coupling to the ocean energetics inferred from modeling studies underscores the need for an observational-based assessment of the effect.

This work uses near-surface velocity observations from Global Drifter Program (GDP) drifters to circumvent the limitations of the altimeter data for resolving the air-sea fluxes of mechanical energy at the ocean mesoscales. Here, concurrent drifter and satellite observations are processed and decomposed into time-mean, seasonal and eddy components following the methods described in Chapter 2 of this dissertation, and combined to estimate the contribution of the mean and time-dependent components of the total air-sea fluxes of mechanical energy, each further decomposed into the energy fluxes to the Ekman and geostrophic ocean circulation using an empirical model for the Ekman velocities. The drifter velocity measurements and SST-driven wind anomalies, the latter calculated using satellite observations as described in Chap-
ter 3, are used to estimate the impact of the $\tau$ dependence on surface currents and on SST. This is done in two ways, (a) via theoretical expressions derived to quantify each effect, obtained following the procedure proposed by Hughes and Wilson (2008), and (b) by recomputing the energy fluxes using $\tau$ estimates with both dependencies removed using drifter velocities and the satellite-based estimates of the SST-driven wind anomalies. Finally, observations from looping drifter trajectories identified by Lumpkin (2016) are used to evaluate potential asymmetries between the air-sea fluxes of mechanical energy associated with cyclonic and anticyclonic ocean eddies arising in response to air-sea coupling mechanisms, suggested by previous studies (Jin et al. 2009; Byrne et al. 2016; Xu et al. 2016).

The remainder of this chapter is organized as follows. Section 4.2 describes the used datasets and their preliminary processing; the methods employed to decompose the drifter velocities into geostrophic and Ekman components; the decomposition of the energy fluxes into time-mean, seasonal, and eddy components; and the theoretical equations used to quantify the impacts of the current and SST-driven air-sea coupling mechanisms to the energy fluxes. Section 4.3 presents the obtained drifter-derived air-sea fluxes of mechanical energy and compares them against correspondent estimates computed using altimeter data, evaluates the influence of the air-sea coupling mechanisms to the energy fluxes, and analyses the fluxes inferred from the looping drifter trajectories. Finally, Section 4.4 presents a summary of the conducted research and its conclusions.
4.2 Methods

4.2.1 Data description

4.2.1.1 Observations from ocean drifters

This study uses position and near-surface current velocity vector \( (\mathbf{u}) \) observations from NOAA’s Global Drifter Program (GDP) 15-m drogued and undrogued drifters, dataset thoroughly described in Section 2.2.1.1. The obtained data refer to the period between February 1979 and December 2016, and includes more than 33 million six-hour position/velocity estimates inhomogeneously distributed across the global ocean, about 56% of which from undrogued drifters (c.f. Fig. 2.1). Parameters from looping drifter trajectories identified in the GDP dataset, specifically their sense of rotation (cyclonic or anticyclonic) and orbital radius, are also used in this study (Lumpkin 2016, available at http://www.aoml.noaa.gov/phod/loopers/). The looping drifter trajectories are about 8% of the GDP data and likely reflect instances when the instruments were trapped within coherent ocean eddies, being therefore useful to investigate the air-sea exchange of mechanical power associated with these dynamical features.

4.2.1.2 Satellite products

The obtained satellite products include (a) altimeter-derived surface geostrophic velocities \( (\mathbf{u}_g, \text{ with magnitude } u_t) \) from AVISO (Sec. 2.2.1.2), (b) equivalent-neutral 10-m wind velocities \( (\mathbf{w}, \text{ magnitude } w) \) from satellite scatterometers (Sec. 3.2.1.1), and (c) SST-driven wind speed anomalies \( (u'_c) \), calculated using transfer functions for the spectral linear relationship between SST and \( w \) evaluated in physical space.
using satellite SST observations (Sec. 3.2.3.2). These datasets are mapped to a coincident 0.25° × 0.25° × 1 day global grid, and their time-series span from July 1999 to December 2016.

For the proposed analysis, the SST-driven wind velocity anomaly vector (\( \mathbf{w}_c \)) is further computed assuming that the \( w'_c \) fluctuations occur along the same direction of the scatterometer \( \mathbf{w} \) measurements, although it is noted that \( \mathbf{w}_c \) in reality veer anticyclonically (cyclonically) from \( \mathbf{w} \) by, on average, two angular degrees per positive (negative) degree Celsius of SST anomaly (O’Neill et al. 2010). The wind stress vector (\( \mathbf{\tau} \), with magnitude \( \tau \)) is also estimated using the scatterometer \( \mathbf{w} \) record via a conventional bulk formulation, given by

\[
\mathbf{\tau} = \rho_a c_d \mathbf{w},
\]

where \( \rho_a \) is the surface air density; and \( c_d \) is the equivalent-neutral drag coefficient at 10-m, parameterized as

\[
c_d = a w + b + \frac{c}{w},
\]

where \( a = 7.64 \times 10^{-5} \text{ m}^{-1}, b = 1.42 \times 10^{-4}, \) and \( c = 2.7 \times 10^{-3} \text{ m} \cdot \text{s}^{-1} \) are empirical coefficients (Large and Yeager 2004).

### 4.2.1.3 Reanalysis 10-m wind and wind stress fields

The scatterometer \( \mathbf{w} \) and \( \mathbf{\tau} \) estimates are supplemented with correspondent fields from the ECMWF ERA-Interim reanalysis model (Sec. 2.2.1.3), obtained at a 1° × 1° × 6 hour resolution and from February 1979 to December 2016. The reanalysis data is preferred over the scatterometer observations for estimating the spatially-varying downwind slip coefficients of undrogued drifters (Sec. 2.2.2) and the spatially and seasonally-varying coefficients of an empirical Ekman velocity model (Sec. 4.2.2.2).
due to its longer time series, which maximizes the number of concurrent wind, wind
stress, and near-surface current estimates available for these operations.

4.2.2 Preliminary processing

4.2.2.1 Data collocation and processing of Lagrangian datasets

Time-evolving fields of all the satellite and reanalysis datasets are first linearly in-
terpolated to the drifter locations. To account for wind and wave-induced drifter slip
bias, a downwind motion modeled simply as a fraction $\alpha$ of the scatterometer wind
speed ($w$) measurements is subtracted from the drifter velocities, using $\alpha = 7 \times 10^{-4}$
for drogued drifters (Niiler et al. 1995), and a spatially-varying $\alpha$ for undrogued
 drifters with global mean $1.48 \times 10^{-2}$ and standard deviation $0.49 \times 10^{-2}$ (Fig. 2.2),
calculated using velocity observations from both drogued and undrogued drifters and
reanalysis winds (c.f. Sec. 2.2.2). Here, the undrogued drifter slip coefficient $\alpha$
effectively corresponds to a first-order referencing factor of the surface velocity measured
by undrogued instruments to the 15-m depth level sampled by drogued drifters (Pazan
and Niiler 2001). The slip-corrected drifter velocities, and the altimeter-derived $u_g$
and scatterometer and reanalysis $\tau$ estimates collocated with the drifter data, are then
low-pass filtered at five days along the drifter trajectories to suppress tidal flows, iner-
tial oscillations, synoptic weather, and other forms of high-frequency variability. The
processed Lagrangian datasets are then finally decimated to daily values.

4.2.2.2 Calculation of drifter-based geostrophic and Ekman velocities

The processed drifter velocities are decomposed as $u = u_g + u_e + \epsilon$, where $u_g$
is the geostrophic component, $u_e$ is the ageostrophic velocity forced by wind stress
(Ekman component), and $\epsilon$ is a residual. In this study, $u_e$ is modeled using an empirical formulation that scales as the theoretical Ekman solutions, which is subtracted from the drifter velocity observations to isolate the geostrophic component. This Section describes the theoretical background and the methods involved in the calculation of $u_e$; evaluates potential biases arising from merging slip-corrected velocity observations from both drogued and undrogued drifters to estimate the Ekman model coefficients; and finally presents pseudo-Eulerian mean speed maps calculated using the drifter-based $u_g$ and $u_e$ retrievals to qualitatively assess the realism of the estimated velocities.

First, it is reminded that the classical Ekman solution for $u_e$ can be written as

$$u_e = \frac{e^{\frac{\tau}{\rho_0 \sqrt{|f|} A_z}}}{\tau e^{i\left(\frac{\pi}{4} - \frac{\pi}{4}\right)}}$$

where $z$ is depth, $\rho_0$ is a reference density of sea water, $f$ is the Coriolis parameter, $A_z$ is the vertical eddy viscosity, and $h_e = \sqrt{2A_z/|f|}$ is the solution’s $e$-folding scale, corresponding to the characteristic thickness of the layer where turbulent mixing induced by wind stress occur (Ekman layer). This expression predicts that the surface $u_e$ veers by $45^\circ$ to the left (right) of $\tau$ in the Southern (Northern) hemisphere, with magnitude proportional to that of $\tau$ and inversely proportional to the square roots of $f$ and $A_z$. For increasing depth, $u_e$ rotates anticyclonically at a $2\pi h_e$ periodicity, while its magnitude decays as a function of $e^{\frac{\tau}{\rho_0 \sqrt{|f|} A_z}}$, producing a spiral vertical structure of horizontal current vectors.

However, Equation (4.3) fails in the vicinity of the equator because $f$ tends to zero in the region. To circumvent this caveat, Lagerloef et al. (1999) proposed an equatorially-modified Ekman relation that takes into account the contribution of
viscous dissipation in balancing the wind stress forcing, that can be expressed as

\[ u_e = \frac{1}{(r^2 + f^2 h^2)^{1/2}} \tau e^{i \tan^{-1}(\frac{f}{r})}, \]  

(4.4)

where \( r \) is a linear drag coefficient that parameterizes the effects of the vertical eddy viscosity, and \( h \) is the thickness scale of the surface layer. As \( f \) approaches zero, the velocity component normal to \( \tau \) vanishes, resulting in \( u_e \) flowing along the same direction as \( \tau \), and with relative magnitude inversely proportional to \( r \).

Equations (4.3) and (4.4) indicate that both the extra-equatorial and equatorial \( u_e \) can be modeled using the following empirical formulation:

\[ u_e = \beta \tau e^{i \theta}, \]  

(4.5)

where \( \beta \) is an amplitude, and \( e^{i \theta} \) represents the rotation of \( u_e \) relative to \( \tau \) by the angle \( \theta \). Existing estimates of \( \beta \) and \( \theta \) at basin to global scales are based on near-surface velocity observations from either drogued or undrogued GDP drifters, or Argo floats (e.g. Ralph and Niiler 1999; Lagerloef et al. 1999; Niiler 2001; Rio and Hernandez 2003; Poulin et al. 2009; Rio 2012; Rio et al. 2014). Here, the coefficients are calculated using slip-corrected data from both drogued and undrogued drifters, with the objective of increasing the observational density available for the analysis in oceanic regions sparsely sampled by drogued instruments, such as the Southern Ocean, the South Pacific, and the subtropical gyres of the three major ocean basins (Fig. 2.1).

To estimate \( \beta \) and \( \theta \), ageostrophic velocities are first isolated by subtracting the altimeter-derived \( u_g \) from the drifter \( u \) measurements. Aiming to capture spatial and seasonal variations of both coefficients, the obtained ageostrophic velocities and the collocated reanalysis \( \tau \) data are then selected within \( 4^\circ \times 4^\circ \times 3 \)-month bins centered on the grid points of \( 1^\circ \times 1^\circ \times \sim 15 \)-day global grid. At each bin, \( \beta \) and \( \theta \) are estimated
by fitting Equation (4.5) to the selected data via a nonlinear least-squares scheme. Although these operations already produce seasonally-evolving maps of $\beta$ and $\theta$, the reliability of the estimates vary in both space and time due to the inhomogeneous drifter coverage. Thus, to minimize sampling-related errors, the annual mean and seasonal fluctuations of both coefficients are retrieved in a second step, consisting of fitting a model composed of a unit vector and of annual and semiannual harmonics to the time-series of $\beta$ and $\theta$ at each horizontal grid point via weighted least-squares, with weights set by the standard error of the individual $\beta$ and $\theta$ retrievals.

Figure 4.1 shows annual mean maps of $\beta$ and $\theta$ (panels a and c, respectively) and zonally and monthly-averaged estimates of both coefficients (b, d) obtained using the proposed procedure. The results are broadly consistent with drogued drifter-based estimates from previous studies. Particularly outside the equatorial belt, $\beta$ increases equatorward predominantly reflecting its inverse dependency on $\sqrt{f}$, while associated with $\theta$ values between 40-90° oriented to the left (right) of the wind stress vector in the Southern (Northern) hemisphere, in agreement with the classical Ekman theory (Van Meurs and Niiler 1997; Ralph and Niiler 1999; Niiler 2001; Rio and Hernandez 2003; Poulain et al. 2009; Rio 2012; Rio et al. 2014). An equatorward increase tendency also occurs in $\theta$, and can still be perceived in the $\beta$ estimates multiplied by $\sqrt{f}$, characteristics thought to reflect the increase on the upper ocean stratification towards lower latitudes (Rio and Hernandez 2003). In latitudes smaller than 5°, $\theta$ sharply decreases equatorward while $\beta$ maintains its growing tendency, with the former becoming zero and the latter peaking at the equator, as predicted by the equatorially-modified Ekman relation (Lagerloef et al. 1999; Perez and Kessler 2009; Perez et al. 2012; Perez et al. 2014). Finally, both coefficients show signifi-
Figure 4.1: Panels (a) and (c) are annual mean maps of the Ekman model coefficients $\beta$ and $\theta$, respectively, while (b) and (d) shows zonally and monthly-averaged estimates of the same parameters. The illustrated results are calculated using slip-corrected data from both 15-m drogued and undrogued GDP drifters.

cant seasonal variability, with larger (smaller) values occurring in summer (winter), potentially in response to the stronger (weaker) upper ocean stratification observed during these seasons (Rio and Hernandez 2003; Rio 2012; Rio et al. 2014).

However, considering that the correction of the wind and wave-induced slip motion of undrogued drifters is performed by referencing the along-wind component of their surface velocity measurements to those estimated by drogued drifters at 15-m depth, the rotation of Ekman velocities as a function of depth suggests that the slip-corrected undrogued drifter velocities can include a cross-wind component associated with Ekman dynamics and thus introduce systematic biases to the $\beta$ and $\theta$ estimates (Rio 2012; Rio et al. 2014). To test this hypothesis, Figure 4.2 shows zonally-averaged annual mean estimates of $\beta$ and $\theta$ obtained using data from drogued, undrogued, and from all drifters (panels a and c), and histogram distributions of the difference be-
tween spatially and seasonally-varying estimates calculated using observations from
drogued instruments and from both drifter types (b, d).

Figure 4.2a shows that, while the zonally-averaged $\beta$ from drogued and undrogued
 drifters are statistically similar within 95% confidence margins at latitudes smaller
than 15°, at higher latitudes the values for undrogued drifters surpass those for
drogued instruments and clearly introduce a positive bias on estimates obtained
using data from all drifters. Quantitatively, the globally-averaged ratio of the $\beta$
estimates from drogued drifters relative to those inferred from all drifters
(only undrogued instruments) is of approximately 0.96 (0.94), or 0.94 (0.91) if lati-
tudes smaller than 15° are excluded. Figure 4.2b shows the histogram distribution of
the difference between $\beta$ estimates inferred using data from drogued-only drifters and
from both drifter types ($\beta_{\text{diff}}$). The $\beta_{\text{diff}}$ set have mean $\mu = -0.02 \text{ m}^3/(\text{N.s})$, reflecting
the bias caused by the use of undrogued drifter data, and standard deviation $\sigma = 0.08$
$\text{m}^3/(\text{N.s})$. A Gaussian function fitted to the histogram (orange line) indicate that the
distribution is approximately normal, suggesting that the observed variability reflect
random errors associated with the different sampling density in each dataset.

Regarding the $\theta$ estimates, Figure 4.2c shows that the zonally-averaged values
calculated using drogued and undrogued drifter data are statistically different at
most latitudes. However, estimates from both datasets show the same latitudinal
dependence and cross each other along the meridional axis, suggesting that variations
in $\theta$ caused by the incorporation of undrogued drifter measurements to the analysis are
random rather than systematic. Figure 4.2d shows the histogram distribution of the
difference between the $\theta$ values calculated using data from drogued-only drifters and
from both drifter types ($\theta_{\text{diff}}$). Here, it is noted that the $\theta$ values used to obtain $\theta_{\text{diff}}$
Figure 4.2: Panels (a) and (c) show zonally-averaged annual mean estimates of the Ekman model coefficients $\beta$ and $\theta$ obtained using slip-corrected drifter velocity observations. The blue, red, and black lines are calculated using data from drogued, undrogued, and from all drifters, and the shading around each line denote 95% confidence intervals. Panels (b) and (d) are histogram distributions of the difference between spatially and seasonally-varying estimates of both coefficients calculated using observations from drogued instruments and from both drifter types ($\beta_{\text{diff}}$ and $\theta_{\text{diff}}$, respectively). The orange line is a Gaussian function fitted to the $\beta_{\text{diff}}$ and $\theta_{\text{diff}}$ distributions.
were preliminarily multiplied by the sign of the local Coriolis parameter, thus denoting a cyclonic or anticyclonic rotation relative to \( \tau \). The \( \theta_{\text{diff}} \) set have mean \( \mu = 0.51^\circ \), suggesting that the use of undrogued drifters does not introduce a systematic bias in \( \theta \), and standard deviation \( \sigma = 7.72^\circ \). Similarly to \( \beta_{\text{diff}} \), \( \theta_{\text{diff}} \) also shows an approximately normal distribution, indicative of random fluctuations about the mean.

Considering the small systematic bias in \( \beta \) (\( \sim4\text{-}6\% \) increase in magnitude) and \( \theta \) (\( 0.51^\circ \) anticyclonic rotation), it is thus considered advantageous to incorporate slip-corrected data from undrogued drifters in the analysis, since it increases the observational density and thus reduces random errors. Here, \( \beta \) and \( \theta \) estimates calculated using slip-corrected data from both drogued and undrogued instruments at a \( 1^\circ \times 1^\circ \times \sim15\text{-}day \) resolution are linearly interpolated to the drifter locations, and applied to Equation (4.5) alongside scatterometer \( \tau \) estimates to calculate \( u_e \). As previously mentioned, \( u_e \) is subtracted from the drifter \( u \) measurements to obtain point geostrophic velocity estimates, meaning that the drifter-based \( u_g \) in reality correspond to a sum of the actual geostrophic velocities and the residuals \( \epsilon \), which include (a) forms of subinertial variability that cannot be described in terms of quasi-geostrophic and Ekman dynamics, (b) observational errors, and (c) errors of the empirical models used to correct the drifter slip and to estimate the Ekman velocities.

To verify the consistency of the obtained drifter-based \( u_e \) and \( u_g \) estimates, Figure 4.3 shows pseudo-Eulerian annual mean speed fields calculated using each dataset following the methods described in Chapter 2, overlaid with streamlines to highlight the general direction of the large-scale flow. The Ekman circulation (Fig. 4.3a) clearly reveal the strong velocity divergence in the equatorial Pacific and Atlantic Oceans induced by the easterly winds acting in both sides of the equator. Convergence zones
Figure 4.3: Drifter-derived annual mean speed of Ekman and geostrophic currents (panels a and b, respectively) at 15-m depth. The curly vectors overlaid to both maps are streamlines calculated using the correspondent mean zonal and meridional velocity fields (not shown), and indicate the general direction of the large-scale circulation.

are also observed at about 30° latitude in all three major ocean basins, arising in the Southern hemisphere from the encounter of the southwestward Ekman flow forced by southeast trade winds with the northeastward flow driven by the westerlies, and in the Northern from the convergence of the northwestward Ekman flow forced by the northeast trades with the southeastward flow driven by the westerlies. These subtropical convergence zones highlight regions where the time-averaged anticyclonic wind stress curl peaks across the basin domain.

According to the Sverdrup relation, the water subsidence forced by the convergence of Ekman flows (on their turn forced by the wind stress curl) produce anticyclonic vorticity, that is balanced by the equatorward advection of planetary vorticity
by the geostrophic circulation. In agreement with these characteristics, the drifter-derived mean geostrophic circulation (Fig. 4.3b) show a predominantly equatorward transport within the subtropical gyres and is approximately non-divergent. Such results indicate that the drifter-based \( u_e \) and \( u_g \) estimates predominantly reflect the action of Ekman and geostrophic flows, as required for the proposed analysis.

### 4.2.3 Calculation of the time-averaged mechanical energy fluxes

#### 4.2.3.1 Drifter-based estimates

Drifter-based estimates of the time-averaged air-sea exchange of mechanical power are calculated using the original drifter near-surface velocity observations (hereafter referred to as “total” velocity, \( u_t \)) and its Ekman and geostrophic components (\( u_e \) and \( u_g \), respectively, obtained as described in Section 4.2.2.2), combined with scatterometer \( \tau \) data subsampled at the drifter locations. This study also examines the relative contribution of the mean, seasonal and fluctuating components of \( \tau \) and \( u \) to the energy flux.

Specifically, Lagrangian estimates of wind stress and near-surface velocity are first selected within circular bins centered on the grid points of an 0.25° × 0.25° global grid, and with radius equivalent to 1° longitude. For each bin, a pseudo-Eulerian estimate of the mean air-sea mechanical power exchange per unit area is computed as

\[
P_c = \langle u_e \cdot \tau \rangle,
\]

where the brackets denote an ensemble average, and the subscript \( c \) refers to each of the considered drifter velocity datasets. To estimate the contribution of the mean and
time-dependent components of $u_c$ and $\tau$ to the energy fluxes, the binned observations of each parameter are treated as data series that vary as a function of the horizontal space and time, and expanded as

$$u_c(x,y,t) = \langle u_c \rangle + u_c^{xy}(x,y) + u_c^s(x,y,t) + u_c^e(x,y,t), \text{ and}$$

$$\tau(x,y,t) = \langle \tau \rangle + \tau^{xy}(x,y) + \tau^s(x,y,t) + \tau^e(x,y,t),$$

where the superscript $xy$ refer to components describing horizontal variations of the mean structure, $s$ to seasonal variations, and $e$ to residual (eddy) fluctuations. This decomposition is performed using the 1-D GME method described in Section 2.2.3.1, where the spatial structures of the zonal and meridional components of $u_c$ and $\tau$ are modeled using 1-D 4th degree polynomials, and their seasonal variations using a sum of annual and semiannual harmonics, whose empirical coefficients are calculated via Gauss-Markov estimation under the assumption that the observations are correlated within a Lagrangian integral time scale of 3 days (Lumpkin 2003; Lumpkin and Johnson 2013; Laurindo et al. 2017).

Applying (4.7) in (4.6), $P_c$ can be rewritten in terms of the sum $P^m_c + P^s_c + P^e_c + P^{ct}_c$. Here, $P^m_c$ holds the sum of the product between the ensemble-averaged $u_c$ and $\tau$ to the covariance between their spatial structures of both parameters, $P^s_c$ ($P^e_c$) is the covariance between their seasonal (eddy) fluctuations, and $P^{ct}_c$ is the sum of the
resulting cross-covariance terms. More specifically,

\[ P_{m}^{c} = \langle u_{c} \rangle \cdot \langle \tau \rangle + \langle u_{c}^{xy} \cdot \tau^{xy} \rangle, \]  

(4.8a)

\[ P_{s}^{c} = \langle u_{c}^{s} \cdot \tau^{s} \rangle, \]  

(4.8b)

\[ P_{e}^{c} = \langle u_{c}^{e} \cdot \tau^{e} \rangle, \]  

(4.8c)

\[ P_{ct}^{c} = \langle u_{c}^{xy} \cdot \tau^{s} \rangle + \langle u_{c}^{xy} \cdot \tau^{e} \rangle + \langle u_{c}^{s} \cdot \tau^{xy} \rangle + \langle u_{c}^{s} \cdot \tau^{e} \rangle + \langle u_{c}^{e} \cdot \tau^{xy} \rangle + \langle u_{c}^{e} \cdot \tau^{s} \rangle. \]  

(4.8d)

Finally, it is noted that pseudo-Eulerian estimates of \( P_{c} \) and of its time-mean component \( P_{m}^{c} \) are biased low by the smoothing effect of data binning. This was minimized by computing the annual mean \( P_{c} \) using the 1-D GME method over binned estimates of the product \( u_{c} \cdot \tau \), and by calculating \( P_{m}^{c} \) via the product between annual mean fields of \( u_{c} \) and \( \tau \) retrieved via the same approach. However, the presence of both methodological and statistical errors in the retrieved climatological fields imply that the resulting \( P_{c} \) can differ from the sum \( P_{m}^{c} + P_{s}^{c} + P_{e}^{c} + P_{ct}^{c} \), issue that does not occur in estimates obtained via simple bin averaging. For this reason, estimates of \( P_{c} \) and \( P_{m}^{c} \) calculated using both the bin-averaging and 1-D GME methods are presented and discussed in this study.

### 4.2.3.2 Altimeter-based estimates

The air-sea flux of mechanical energy is also estimated using altimeter-derived geostrophic velocities (\( u_{sg} \)) from AVISO, including both the original Eulerian dataset and the velocities linearly interpolated to the drifter locations. These calculations are performed to (a) qualitatively assess how the pseudo-Eulerian estimates reproduce the reference Eulerian results, and (b) to evaluate differences between altimeter and drifter-based estimates.
Estimates based on the Lagrangian \( u_{sg} \) dataset are obtained as described in Section 4.2.3.1. Using Eulerian fields of \( u_{sg} \) and \( \tau \), the mean power exchange per unit area is calculated at each grid point as

\[
P_{sg} = \overline{u_{sg}} \cdot \overline{\tau},
\]

(4.9)

where the overline denotes a long-term average. To estimate the contribution of the mean and time-dependent components of \( u_{sg} \) and \( \tau \) to \( P_{sg} \), the time-series of each parameter are preliminarily decomposed as

\[
\begin{align*}
  u_{sg}(t) &= \overline{u_{sg}} + u_{sg}^s(t) + u_{sg}^e(t), \quad \text{and} \\
  \tau(t) &= \overline{\tau} + \tau^s(t) + \tau^e(t).
\end{align*}
\]

(4.10a, 4.10b)

Applying (4.10) in (4.9), \( P_{sg} \) can be written as the sum \( P_{sg}^m + P_{sg}^s + P_{sg}^e + P_{sg}^{ct} \), where each term can be expressed as

\[
\begin{align*}
  P_{sg}^m &= \overline{u_{sg}} \cdot \overline{\tau}, \\
  P_{sg}^s &= \overline{u_{sg}^s} \cdot \overline{\tau^s}, \\
  P_{sg}^e &= \overline{u_{sg}^e} \cdot \overline{\tau^e}, \\
  P_{sg}^{ct} &= \overline{u_{sg}^e} \cdot \overline{\tau^e} + \overline{u_{sg}^e} \cdot \overline{\tau^s}.
\end{align*}
\]

(4.11a, 4.11b, 4.11c, 4.11d)

### 4.2.3.3 Influence of surface currents and SST-driven wind anomalies

Previous studies showed that the scatterometer \( w \) measurements include the signature of surface ocean currents, being better described as the actual equivalent-neutral 10-m wind speed \( w_r \) subtracted by the surface ocean current speed, or \( w = w_r - u_t \) (e.g. Cornillon and Park 2001; Chelton et al. 2004; Park et al. 2006; Hughes and Wilson 2008; Gaube et al. 2015; Renault et al. 2017). Furthermore, Section 3.2.3.2 of
this thesis proposes that \( w \) can be decomposed as \( w = w_n + w'_c \), where \( w_n \) is the wind speed driven by internal atmospheric variability. This implies that scatterometer-based estimates of the wind stress vector without the dependence on ocean currents \( (\tau_{nc}) \) and without the dependence on the SST-driven wind anomalies \( (\tau_{nt}) \) can be obtained simply as

\[
\tau_{nc} = \rho_a c_d |\mathbf{w} + \mathbf{u}_t| (\mathbf{w} + \mathbf{u}_t), \quad \text{and} \\
\tau_{nt} = \rho_a c_d |\mathbf{w} - \mathbf{w}_c| (\mathbf{w} - \mathbf{w}_c),
\]  

(4.12)

(4.13)

Based on theoretical formulations presented by Duhaut and Straub (2006) and Hughes and Wilson (2008), Equations (4.12) and (4.13) are used to derive approximate expressions for the relative contribution of current and SST-driven air-sea coupling to the air-sea flux of mechanical energy, as detailed in Appendix B. Particularly, the effect of ocean currents in \( P_t \) can be computed as

\[
P_{0}^{\text{curr}} = \langle \mathbf{u}_t \cdot \tau \rangle - \langle \mathbf{u}_t \cdot \tau_{nc} \rangle \approx -\left( u_0^2 w \frac{\partial F}{\partial w} \right) - \langle u_t^2 F \rangle,
\]  

(4.14)

where \( u_0 \) is the along-wind component of \( \mathbf{u}_t \), and \( F \) is a scalar function obtained through the division of the scatterometer wind stress vector \( \tau \) by the vector winds \( \mathbf{w} \), thus equal to \( \rho_a c_d w \). Both terms in the rightmost-side of Equation (4.14) are negative definite, meaning that the dependence of \( \tau \) on ocean currents always reduces the wind power input to the ocean circulation relative to estimates that neglect the current effects.

Following Hughes and Wilson (2008), further approximations can be applied to (4.14). First, assuming that \( u_0 \) and \( w \) are uncorrelated, the equation reduces to

\[
P_{1}^{\text{curr}} = -\left( u_0^2 \right) \left( w \frac{\partial F}{\partial w} \right) - \langle u_t^2 \rangle \langle F \rangle.
\]  

(4.15)
If the direction of the current and wind vectors are also uncorrelated, then the cross and along-wind current velocity components should contribute about equally to the total current kinetic energy, which allows substituting $\langle u_0^2 \rangle$ by $\langle u_t^2 \rangle / 2$:

$$P_{2,\text{curr}} = -\langle u_t^2 \rangle \left( \frac{1}{2} \left( \langle w \frac{\partial F}{\partial w} \rangle + \langle F \rangle \right) \right). \quad (4.16)$$

One last approximation is obtained by assuming that the oceanic kinetic energy is dominated by eddy fluctuations, where $\langle u_t^2 \rangle$ is substituted by $\langle u_t^2 \rangle$:

$$P_{3,\text{curr}} = -\langle u_t^2 \rangle \left( \frac{1}{2} \left( \langle w \frac{\partial F}{\partial w} \rangle + \langle F \rangle \right) \right). \quad (4.17)$$

Similarly, the impact of the SST-driven air-sea coupling to the mechanical energy fluxes can be estimated as

$$P_{0,\text{sst}} = \langle \mathbf{u}_t \cdot \tau \rangle - \langle \mathbf{u}_t \cdot \tau_{nt} \rangle \approx \left( \langle u_t w w_c' \cos \theta \frac{\partial F}{\partial w} \rangle + \langle u_t w_c \cos \theta F \rangle \right). \quad (4.18)$$

where $\theta$ is the angle between the vectors $\mathbf{u}_t$ and $\mathbf{w}$. Considering that $u$ and $|w_c'| \ll w$, this relation can be simplified to

$$P_{1,\text{sst}} = \langle u_t w w_c' \cos \theta \rangle \left( \langle w \frac{\partial F}{\partial w} \rangle + \langle F \rangle \right). \quad (4.19)$$

Further assuming that the cross-wind component of $\mathbf{u}_t$ is unimportant, (4.19) then reduces to

$$P_{2,\text{sst}} = \langle u_0 w_c' \rangle \left( \langle w \frac{\partial F}{\partial w} \rangle + \langle F \rangle \right). \quad (4.20)$$

In contrast with the systematic reduction on the wind power input to the ocean circulation caused by the current-driven coupling, Equations (4.18) to (4.20) indicate that changes to $P_t$ induced by the SST effect can be of either sign, defined by the covariance between surface currents and the SST-driven wind anomalies.

In this work, the processed Lagrangian estimates of $\mathbf{u}_t$, $w_c$, $\mathbf{w}$, and $\tau$ are selected within circular bins with radius equivalent to 1° longitude and centered on the grid.
points of a $0.25^\circ \times 0.25^\circ$ global grid, and applied to Equations (4.14) to (4.19) to calculate pseudo-Eulerian estimates of $P^{\text{curr}}$ and $P^{\text{sst}}$. The use of the theoretical expressions aims to provide a physical interpretation of the mechanisms through which the current and SST-driven air-sea coupling can affect $P_t$, and to assess their relative magnitude.

A different approach is used to infer the influence of the current and SST effects coupling over the mean and time-dependent components of the power fluxes associated with the Ekman, geostrophic, and the total ocean circulation. In this case, slip-corrected 6-hour $u_t$ observations from GDP drifters collocated with satellite-based $w$ and $w_c$ data are preliminarily used to calculate Lagrangian estimates of $\tau_{nc}$ and $\tau_{nt}$ via Equations (4.12) and (4.13), which are low-pass filtered along the drifter trajectories and subsequently decimated to daily values as described in Section 4.2.2.1. The processed $\tau_{nc}$ and $\tau_{nt}$ data are combined with drifter-based $u_e$, $u_g$, and $u_t$ estimates to calculate the power fluxes following the methods described in Section 4.2.3.1, which are then compared with equivalent results obtained using the original scatterometer $\tau$ estimates.

4.3 Results and discussion

4.3.1 Time-averaged mechanical energy fluxes

4.3.1.1 Altimeter-based estimates

Figure 4.4 illustrates the time-averaged air-sea fluxes of mechanical energy calculated using altimeter-derived geostrophic velocities from AVISO. The left panels are global maps of the total energy flux ($P_{sg}$) and of its mean, seasonal, and eddy
components \( (P^m_{sg}, P^e_{sg}, \text{and } P^e_{sg}) \) calculated in an Eulerian framework, while the right panels show zonal and cumulative global integrals computed using both Eulerian and pseudo-Eulerian estimates. The contribution of cross-terms between seasonal and eddy fluctuations \( (P^{ct}) \) is small, and therefore omitted from the analysis. Here, positive values denote fluxes directed from the atmosphere to the ocean, and negative from the ocean to the atmosphere.

First considering the Eulerian estimates, the horizontal distribution and magnitude of the energy fluxes broadly agree with previous altimeter-based estimates (Wunsch 1998; Huang et al. 2006; Hughes and Wilson 2008; Xu and Scott 2008; Scott and Xu 2009). Particularly, the results show a globally-integrated wind power input of about one terawatt \( (1 \text{ TW} = 10^{12} \text{ watts}) \), more than 96% of which via the \( P^m_{sg} \) component (Table 4.1). The global integral is dominated by the Southern Ocean, with about 55% of the wind power input occurring south of \( 40^\circ S \), followed by the tropical band equatorward of \( 23^\circ \) latitude, where another 40% of the input takes place. Positive energy fluxes are prominently associated with the Antarctic Circumpolar Current (ACC), the western boundary current seaward extensions, and the westward-flowing currents of the equatorial circulation systems of all three major oceanic basins. Despite the net positive energy flux from the atmosphere into the ocean, significant negative values are seen associated with the North Equatorial Counter Currents (NACC) in the Pacific and Atlantic basins, and extensive regions of negative energy flux also occur in the interior of Indian and South Pacific subtropical gyres, and associated with the southern branch of the South Equatorial Current in the tropical Atlantic Ocean.
Figure 4.4: Time-averaged air-sea fluxes of mechanical energy calculated using altimeter-derived geostrophic velocities from AVISO and wind stress estimates from orbital scatterometers. From top to bottom row, the illustrated results refer to the total air-sea flux \( P_{sg} \) and its mean, seasonal, and eddy components \( P_{mg}, P_{sg}, \) and \( P_{eg}, \) respectively. Left: mean Eulerian global maps, in \( 10^{-3} \text{ m}^2/\text{s} \). Right: zonal integrals of the power exchange (blue lines), in \( 10^5 \text{ W/m} \), and their cumulative integrals starting at \( 63^\circ \text{S} \) (red), in terawatts. The thick lines refer to results obtained using the original Eulerian datasets (EUL), while the thin lines are pseudo-Eulerian estimates calculated using measurements subsampled at the GDP drifter locations via bin averaging (solid, PE1) and the 1-D GME method (dashed, PE2).
Table 4.1: Global integrals of the time-averaged air-sea flux of mechanical energy ($P$) and of its mean, seasonal, eddy, and cross-term components ($P^m$, $P^s$, $P^e$, and $P^{ct}$, respectively), associated with the Ekman, geostrophic, and the total oceanic velocity fields. Estimates are calculated using scatterometer wind stress data combined with near-surface velocities from GDP drifters, and with altimeter-derived geostrophic velocities from AVISO. PE1 and PE2 denote pseudo-Eulerian estimates obtained via bin-averaging and the 1-D GME methods, respectively, while EUL refer to Eulerian estimates. Estimates are in gigawatts.

<table>
<thead>
<tr>
<th></th>
<th>Total $P$</th>
<th>Total $P^m$</th>
<th>Total $P^s$</th>
<th>Total $P^e$</th>
<th>Total $P^{ct}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>1696.9</td>
<td>1267.9</td>
<td>173.6</td>
<td>302.7</td>
<td>-47.1</td>
</tr>
<tr>
<td>Pe1</td>
<td>1671.6</td>
<td>460.9</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pe2</td>
<td>1201.6</td>
<td>495.7</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pe1</td>
<td>578.9</td>
<td>807.1</td>
<td>52.5</td>
<td>-227.0</td>
<td>-227.0</td>
</tr>
<tr>
<td>Pe2</td>
<td>1249.5</td>
<td>1218.0</td>
<td>-</td>
<td>-2.8</td>
<td>-2.8</td>
</tr>
<tr>
<td>Pe1</td>
<td>810.6</td>
<td>781.6</td>
<td>-</td>
<td>-53.4</td>
<td>-53.4</td>
</tr>
<tr>
<td>Pe2</td>
<td>1169.9</td>
<td>1010.4</td>
<td>-</td>
<td>-24.3</td>
<td>-24.3</td>
</tr>
<tr>
<td>EUL</td>
<td>1027.1</td>
<td>995.3</td>
<td>-</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
</tbody>
</table>

The small contribution of time-dependent fluctuations to $P_{sg}$ is frequently attributed to the differing spatial-temporal scales of oceanic and atmospheric phenomena, which results in poor correlations between the internal variability of both mediums (e.g. Wunsch 1998; Ferrari and Wunsch 2009; Scott and Xu 2009). However, considering that (a) the results of recent studies indicate that air-sea coupling at the ocean mesoscales, arising from the dependence of wind stress on ocean currents and SST-driven wind speed anomalies, can have strong feedbacks to both the oceanic and atmospheric circulations (c.f. Section 4.1 and references herein); and (b) the relatively large decorrelation length scales ($O[10^2 \text{ km}]$) used for interpolating along-track SSH measurements from orbital altimeters to regular grids can underestimate the mesoscale ocean variability at smaller spatial scales (Ducet et al. 2000; Fu and Ubelmann 2014; Poje et al. 2014); it is then possible that the contribution of the time-dependent components to the mechanical energy fluxes has been underestimated.

Despite the small relative importance of time-dependent fluctuations to $P_{sg}$, its seasonal and eddy components ($P^s_{sg}$ and $P^e_{sg}$, respectively) both show well-defined spa-
tial distributions, suggestive that they reflect actual geophysical characteristics rather than being merely the product of random errors, and represent opposite contributions to the total power exchange. Particularly, the energy fluxes in $P_{sg}^s$ are predominantly positive and clearly delineates seasonally-evolving currents in all three major ocean basins, such as the complex equatorial current system in the Indian Ocean and the NECC in both Atlantic and Pacific basins (Fig. 4.4e), showing a globally-integrated value of about 49 gigawatts ($1 \text{ GW} = 10^9 \text{ watts}$) (Fig. 4.4f and Table 4.1).

In contrast, the eddy component $P_{sg}^e$ (Fig. 4.4g) is predominantly negative everywhere but in the eastern equatorial Indian and the western equatorial Pacific Oceans, showing larger magnitudes coinciding with energetic extratropical current systems, such as the ACC, the Brazil-Malvinas Confluence, the Agulhas Retroflection, and the seaward extensions of western boundary currents (c.f. Fig. 3.1a). $P_{sg}^e$ integrates to about -17 GW globally (Table 4.1), and to -40 GW if latitudes equatorward of $20^\circ$ are excluded. The observational study of Hughes and Wilson (2008), based on altimeter-derived geostrophic velocity fields and scatterometer wind stress data, also obtained predominantly negative covariances between both quantities outside the tropical band. The authors argued that, if the quasi-geostrophic currents and near-surface winds are poorly correlated owing to their differing intrinsic scales, then the negative fluxes in $P_{sg}^e$ should predominantly arise from the dependence of wind stress on ocean currents.

Regarding the positive $P_{sg}^e$ values in the equatorial Indian and Pacific Oceans (Fig. 4.4g), their origins are unclear, although it is noted that they coincide with the Indo-Pacific Warm Pool (IPWP), region characterized by year-long SSTs above $28^\circ$C (e.g. Fasullo and Webster 1999; de Deckker 2016; Weller et al. 2016). Despite the elevated
climatological temperatures, the IPWP shows a relatively small SST variability at scales smaller than 1000 km (Fig. 3.1a) and consequently a small associated $w'_c$ variability (Fig. 3.6a), suggesting that the SST-driven air-sea coupling via boundary layer dynamics is not the physical mechanism responsible for the observed positive $P^e_{sg}$ fluxes. Alternatively, considering (a) the short adjustment time scale of the quasi-geostrophic ocean circulation to atmospheric forcing near the equator, and (b) the fact that the tropical deep convection triggered by the high SSTs in the IPWP and its associated near-surface wind field display well-defined variability at intraseasonal, seasonal, and interannual time-scales (e.g. Madden and Julian 1994; Fasullo and Webster 1999; Weller et al. 2016), one possibility is that the positive energy fluxes in the region reflect the oceanic response to atmospheric forcing at non-zero frequencies different than seasonal (which is captured by the $P^s_{sg}$ component), locally overcoming the dissipative effect arising from the wind stress dependence on ocean currents.

As previously mentioned, the time-averaged air-sea fluxes of mechanical energy $P_{sg}$ and its components are also calculated using altimeter-derived geostrophic velocities subsampled at the drifter locations, in order to determine to which extent the pseudo-Eulerian estimates can reproduce the Eulerian results. Its respective global integrals are listed in Table 4.1. The spatial distributions of the pseudo-Eulerian energy fluxes (not shown) resolve the same main features identified in the correspondent Eulerian estimates. Regarding the time-dependent components $P^s_{sg}$ and $P^e_{sg}$, the zonally-integrated values inferred from both the Eulerian and Lagrangian datasets show visually similar meridional profiles, and their respective global integrals agree within 15 GW of each other (Figs. 4.4f and h). An increase on the magnitude of the cross-term $P^{ct}_{sg}$ is also observed, however this contribution mainly arises from co-
variances between the spatial components of wind stress and current signals with their seasonal and eddy fluctuations, that may be associated with the inhomogeneous drifter sampling and an imperfect decomposition of the observations into time-mean and fluctuating components, rather then reflect actual geophysical characteristics. Finally, the globally-integrated pseudo-Eulerian estimates of $P_{sg}$ and $P_{sg}^m$ mapped using a simple bin-averaging approach are found to underestimate the Eulerian values by about 200 GW (Figs. 4.4b and d).

As discussed in Chapter 2, simple bin-averaging methods tend to smooth horizontal gradients at scales smaller than the prescribed bin size, which leads to an underestimation of the magnitude of the energy fluxes associated with relatively narrow ocean currents. This effect is more prominently observed in the ACC, arising from the fact that the current is composed by a number of narrow branches with large associated energy fluxes. Mapping the power fluxes using the 1-D GME method reduces the smoothing effect of data binning in $P_{sg}^m$, leading to a globally-integrated power flux within 15 GW of the Eulerian value (Figs. 4.4b and d). It also reduces discrepancies between Eulerian and pseudo-Eulerian estimates of the total fluxes $P_{sg}$, although the global integral of the pseudo-Eulerian results now overestimates the reference Eulerian results by about 140 GW, most of this excess power originating from positively-biased estimates of the near-zero or negative energy fluxes observed at interior of the Southern Hemisphere’s subtropical gyres (Fig. 4.4a), that are absent in the $P_{sg}^m$ retrievals.

These results indicate that the globally-integrated pseudo-Eulerian estimates of $P_{sg}$ calculated using the 1-D GME approach can be taken as an upper bound limit for the total energy fluxes, although estimates closer to the actual Eulerian values can be
obtained by adding the the time-mean $P_{sg}^m$ component obtained via 1-D GME method to $P_{sg}^s$, $P_{sg}^e$, and $P_{sg}^{ct}$. These characteristics are used to support the interpretation of the drifter-based estimates of the air-sea fluxes of mechanical energy, presented next.

4.3.1.2 Drifter-based estimates

This section analyses drifter-based estimates of the air-sea mechanical energy fluxes associated with the total surface ocean currents ($P_t$) and its Ekman and geostrophic components ($P_e$ and $P_g$, respectively), each further decomposed into time-mean, seasonal, eddy, and cross-term components ($P_s^t$, $P_e^t$, and $P^{ct}_t$, respectively). As previously mentioned, the fluxes are computed using Lagrangian estimates preliminarily low-pass filtered to remove variability at periods shorter than five days. Global integrals of the considered components are listed in Table 4.1.

Figure 4.5 summarizes the results for $P_t$ and its components. Estimates obtained via simple bin-averaging and the 1-D GME method places the globally-integrated $P_t$ within the 1.70–2.45 TW range, with a more likely value, inferred from the sum of the global integral of $P_{m}^t$ retrieved via the 1-D GME approach to those of the time-dependent and cross-term components, of 2.14 TW. The spatial distribution of the energy fluxes in $P_t$ (Fig. 4.5a) is visually similar to those calculated using altimeter data (Fig. 4.4a), also highlighting the dominant contributions of the Southern Ocean and of the tropics to the total wind power input (about 47% and 38%, respectively). Differently from the altimeter-based estimates, here the time-dependent components $P_{t}^s$ and $P_{t}^e$ respectively contribute with about 7% and 15% of the best estimate of the wind power input (Figs. 4.4e–h). The predominantly positive values now observed in the eddy component $P_{t}^e$ (Figs. 4.4g) largely reflect the wind power input to the
Ekman circulation, known to take place for its most part via non-zero frequencies rather than via the mean (Wang and Huang 2004; Elipot and Gille 2009b), although negative fluxes can be seen associated with energetic current systems, prominently with the Agulhas Return Current and the seaward extensions of the Kuroshio and Gulf Stream Currents, which can reflect current-driven effects in the power exchange.

Figure 4.6 shows the air-sea fluxes of mechanical energy associated with the Ekman currents ($P_e$). The global integral of $P_e$ is between 1.12–1.20 TW, with a more likely value of 1.15 TW. This relatively narrow range indicates that the smoothing effect of data binning is not a significant source of bias to the pseudo-Eulerian $P_e$ fields. Considering that the Ekman velocities are computed as a function of the scatterometer $\tau$ measurements and of the empirical coefficients $\beta$ and $\theta$ [Eq. (4.5)], the small sensitivity to the smoothing effect is explained by the facts that (a) $\beta$ and $\theta$ are calculated using Lagrangian observations selected within spatial bins with a larger area than those used to retrieve the pseudo-Eulerian energy fluxes, meaning that variability of the resulting Ekman velocities at scales smaller than the prescribed bin size should originate entirely from $\tau$; and (b) horizontal variations of $\tau$ should scale predominantly as a function of the atmospheric first baroclinic Rossby radius of deformation ($O[10^3 \text{ km}]$), much larger than the cross-stream scale of quasi-geostrophic ocean currents ($O[10^1–10^2 \text{ km}]$).

The globally-integrated value of 1.15 TW inferred for $P_e$ is about a factor of two smaller than the 2.10–2.50 TW range estimated by Wang and Huang (2004) using wind stress data from the NCEP reanalysis model for the period between 1948 and 2002. The fact that Wang and Huang (2004) estimated the surface Ekman currents using the classical Ekman formulation [Eq. (4.3)], which assumes a 45° anticyclonic
Figure 4.5: Similar to Figure 4.4, but for pseudo-Eulerian estimates of the air-sea flux of mechanical energy associated with the total ocean circulation ($P_t$), calculated using near-surface velocity data from GDP drifters collocated with scatterometer wind stress measurements. Here, the global maps of $P_t$ and $P_m$ (panels a and c, respectively) are obtained using the 1-D GME method.
Figure 4.6: Similar to Figure 4.5, for the air-sea mechanical energy fluxes associated with the Ekman velocity field ($P_e$).
rotation of the surface velocities relative to the wind stress vector, is likely a major contributor to the larger wind power input reported by that study, considering that drifter-based $\theta$ estimates obtained here show predominantly larger veering angles (c.f. Figs. 4.1 and 4.2). Part of the discrepancy can also be attributed to the cutoff frequency employed in Wang and Huang (2004), equivalent to period of two days, in contrast with the five days used here. Drifter-based estimates of the cumulative wind power input to the Ekman layer as a function of frequency for the Southern Ocean, presented by Elipot and Gille (2009b) (their Figure 5), suggest that about 20% of the total power input calculated for periods between 0.5 and 40 days occur in the 2-5-day period range, fraction that would imply in an increase of about 0.1 TW to this study’s $P_e$ estimates.

Despite the smaller globally-integrated $P_e$, the spatial distribution of the energy fluxes (Fig. 4.6a) is visually similar to that retrieved by Wang and Huang (2004). It shows significant values in the Southern Ocean (about 34% to the total power input takes place south of 40°S), within the tropics (38% equatorward of $\sim$23° latitude), and the northern portions of the North Atlantic and North Pacific basins ($\sim$9% north of 40°N). The time-dependent fluctuations integrate to about 0.65 TW (56% of the total power input), with 0.12 TW in $P_e^s$ (11%) and 0.53 TW in $P_e^s$ (45%). Particularly regarding the seasonal component $P_e^s$ (Fig. 4.6e), enhanced energy fluxes coincide with the positions of the NACC in the tropical Pacific and tropical Atlantic Oceans, and with the seasonally-varying currents in the Indian Ocean, with the largest values notably delineating the Somali Current off of the western coast of Africa. On its turn, the spatial distribution of the energy fluxes in the eddy component $P_e^e$ (Fig. 4.6g) closely resemble that described for the total fluxes $P_e$. Notably, the magnitude
of the fluxes in $P_e$ generally exceed those inferred using the original drifter velocity estimates (Fig. 4.5e), leading to a globally-integrated wind power input 0.23 TW larger. As discussed later in this Section, this excess wind power input is balanced by the predominantly negative air-sea mechanical energy fluxes associated with the quasi-geostrophic ocean variability.

However, it is noted that the slip-corrected GDP drifter velocity observations have a nominal depth of 15 meters, implying that the empirical Ekman coefficients $\beta$ and $\theta$ inferred from the GDP dataset are smaller than at the surface due to the vertical shear of Ekman currents at subinertial frequencies (Weller and Plueddemann 1996, Elipot and Gille 2009a, 2009b, Rio et al. 2014), and hence that the estimates of wind power input to the Ekman layer obtained in this study are probably biased low. Furthermore, extensions of the Ekman theory observed that the current response to wind stress also vary as a function of the forcing frequency and display an asymmetric response to cyclonic and anticyclonic frequencies (Gonella 1972; Elipot and Gille 2009a).

Elipot and Gille (2009b) addressed these issues by deriving a spectral formulation for the wind power input to the Ekman layer in frequency space, demonstrating that it is equivalent to the integral of the cross-spectrum between wind stress and the Ekman velocities. To account for the vertical shear of Ekman currents, a theoretical Ekman model derived in spectral space in a previous study by the authors (Elipot and Gille 2009a) was used to obtain a shear correction factor that relates the cospectrum between wind stress and the Ekman currents at 15-m depth with that at the surface. Equipped with these expressions, Elipot and Gille (2009b) estimated the wind power input to the Ekman layer in the Southern Ocean using near-zonal trajectories of 15-m
drogued GDP drifters selected within 2° latitudinal bands, as means of increasing the number of individual spectral estimates available for their calculations. Specifically, that study used wind stress data from the ECMWF reanalysis model, and isolated the ageostrophic component of the drifter current measurements by subtracting altimeter-derived geostrophic velocities, applying these datasets to their theoretical relations to compute zonally-averaged energy fluxes.

In a comparison, zonal averages of the $P_e$ estimates obtained here (not shown) reveal a latitudinal dependency similar to that observed by Elipot and Gille (2009b) (their Figure 6), but is smaller than their energy fluxes by factors of up to five. The larger fluxes in Elipot and Gille (2009b) can be partly attributed to the broader frequency range analyzed (periods as short as 12 hours are considered) and to the shear correction applied in that study, however it can also reflect a positive bias introduced by the undetected presence of undrogued drifters observations. Specifically, a reassessment of the GDP dataset by Lumpkin et al. (2013) showed that a significant fraction of the drifters previously thought to have their drogues still attached were actually undrogued, an issue particularly acute in the Southern Ocean considering that the sampling of the region by undrogued drifters is significantly larger than by drogued instruments (c.f. Fig. 2.1). The presence of undiagnosed drifter slip biases would introduce spurious covariances between the drifter slip velocities and wind stress, which would lead to an overestimation of the energy fluxes obtained in Elipot and Gille (2009b).

These considerations suggest that the results for $P_e$ obtained in this work can be interpreted as lower-bound estimates of the actual wind power input to the Ekman layer. They expand on the results of previous studies for being based on scatterom-
etermining \( P_e \) at global scales remain a significant observational challenge. Conversely, considering the smaller vertical shear expected for quasi-geostrophic currents, and the low frequencies where the associated air-sea fluxes of mechanical energy takes place, greater confidence exist on the obtained pseudo-Eulerian estimates of \( P_g \), summarized by Figure 4.7.

Pseudo-Eulerian estimates of \( P_g \) yield a globally-integrated value between 0.58–1.17 TW, with a more likely value of 0.99 TW. This best estimate agree with the global integral of the altimeter-based Eulerian estimates within a 0.03 TW margin. The spatial distribution of the time-mean component obtained via the 1-D GME method (\( P_g^m \), shown in Fig. 4.7c) and of the seasonally-varying component (\( P_g^s \), Fig. 4.7e) reveal the same general features observed in the correspondent altimeter-based Eulerian estimates (Figs. 4.4c and 4.4e), although the global integral of \( P_g^m \) is found to exceed that inferred from altimeter data by about 0.2 TW. Notably, this excess power in \( P_g^m \) is fully compensated by the eddy component \( P_g^e \), which shows predominantly negative energy fluxes everywhere except in the western equatorial Pacific and the eastern equatorial Indian Ocean (Fig. 4.4g), thus integrating to -0.23 TW. This value is one order of magnitude larger than that retrieved from altimeter observations (Figs. 4.4e–f and Table 4.1), and implies that the quasi-geostrophic ocean variability loses mechanical energy to the atmosphere at a rate equivalent to about 19% of the wind power input to the general ocean circulation.

The negative values in \( P_g^e \) are compatible with a dependence of wind stress on surface ocean currents (Duhaut and Straub 2006; Hughes and Wilson 2008; Seo et al.)
Figure 4.7: Similar to Figure 4.5, for the air-sea mechanical energy fluxes calculated using the drifter-derived geostrophic velocities \( P_g \).
2016; Seo 2017; Renault et al. 2016; Renault et al. 2017), although covariances between surface currents and wind stress of either sign can also arise from SST-driven air-sea coupling mechanisms and thus potentially exert non-negligible contributions to the air-sea flux of mechanical energy (Jin et al. 2009; Byrne et al. 2016). It is also noted that the subtraction of drifter slip and of the empirical Ekman currents from the drifter measurements, both modeled as a function of wind speed, can produce spurious covariances that would bias the obtained results (Elipot and Gille 2009a, 2009b). The next Section estimates the relative contribution of the current and SST-driven air-sea coupling to the mechanical energy fluxes, and evaluates the potential impact of spurious covariances to the results.

4.3.2 Influence of current and SST-driven air-sea coupling

4.3.2.1 Impact of the \( \tau \) dependence on surface ocean currents

Figure 4.8 illustrates the inferred impacts of the dependence of wind stress on ocean currents to \( P_t \). Specifically, panel (a) shows the global distribution of the differences between bin-averaged \( P_t \) estimates obtained using the original scatterometer wind stress \( (\tau) \) data, and using wind stress estimates whose dependence on the surface ocean currents has been removed using drifter velocity observations \( (\tau_{nc}) \), quantity hereafter referred to as \( P_{\text{curr}}^{\text{obs}} \). Panel (b) shows the zonal integrals of \( P_{\text{curr}}^{\text{obs}} \) and of the theoretical estimates \( P_0^{\text{curr}} \) to \( P_3^{\text{curr}} \) [Eqs. (4.14) to (4.17)]; and (c) their correspondent cumulative global integrals, whose total values are listed in Table 4.2. It is reminded that \( P_0^{\text{curr}} \) corresponds to an estimate of the full current-induced reduction in the energy fluxes, while \( P_1^{\text{curr}} \) and \( P_2^{\text{curr}} \) are approximations that neglect the contribution
Figure 4.8: Impact of the wind stress dependence on ocean currents to $P_t$, computed using drifter and scatterometer observations. $P_{\text{obs}}$ is the difference between energy fluxes calculated using the original scatterometer wind stress estimates ($\tau$) and the fluxes calculated using stress data whose dependence on ocean currents was removed using drifter velocity observations ($\tau_{\text{nc}}$); while $P_0$ to $P_3$ refer to estimates obtained via Equations (4.14) to (4.17). Panel (a) illustrates the global distribution of $P_{\text{obs}}$, in $10^{-3}/m^2$; (b) shows the zonal integrals of $P_{\text{obs}}$, and of $P_0$ to $P_3$, in $10^5 W/m$; and (c) holds their respective cumulative global integrals starting at at $63^\circ S$, in terawatts.

of covariances between winds and currents to the effect, and $P_{\text{curr}}^3$ further isolates the fraction of the effect induced by oceanic eddy fluctuations.

The all-negative values in $P_{\text{curr}}^\text{obs}$ (Fig. 4.8a) agree with the conclusion that accounting for the dependence of $\tau$ on surface currents constitutes a definite-negative correction to $P_t$ (Duhaut and Straub 2006; Hughes and Wilson 2008; Xu and Scott 2008). Particularly, the resolved spatial patterns delineate time-mean ocean currents and areas of enhanced eddy kinetic energy, prominently highlighting the ACC, the
Table 4.2: Global integrals of $P_{\text{curr}}$ and $P_{\text{sst}}$, in gigawatts. $P_{\text{obs}}$ refer to estimates obtained by subtracting the mechanical power calculated using the original scatterometer wind stress ($\tau$) measurements by the power obtained using wind stress estimates without the dependence on currents ($\tau_{\text{nc}}$), and without the dependence on SST-driven wind anomalies ($\tau_{\text{nt}}$), while $P_0$ to $P_3$ denote results obtained via the theoretical expressions defined by Equations (4.14) to (4.20).

<table>
<thead>
<tr>
<th></th>
<th>$P_{\text{obs}}$</th>
<th>$P_0$</th>
<th>$P_1$</th>
<th>$P_2$</th>
<th>$P_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{\text{curr}}$</td>
<td>-399.8</td>
<td>-425.3</td>
<td>-411.1</td>
<td>-400.4</td>
<td>-250.4</td>
</tr>
<tr>
<td>$P_{\text{sst}}$</td>
<td>-0.6</td>
<td>1.6</td>
<td>0.7</td>
<td>0.6</td>
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seaward extensions of western boundary currents, the Agulhas Retroflection, Brazil-Malvinas Confluence, and the equatorial current systems in all three major ocean basins. Enhanced negative fluxes are also observed associated with the subtropical waveguides identified in drifter data, while regions with near-zero values coincide with quiescent regions known as eddy deserts (c.f. discussion in Section 3.3.1.1). $P_{\text{curr}}$ integrates to about $-400$ GW ($-0.40$ TW), most of it originating in the tropics (51% equatorward of 23° latitude); followed by the Southern Ocean, the Agulhas Current System, and the Brazil-Malvinas Confluence in the Southern Hemisphere (25% south of 35°S); and the seaward extensions of the Kuroshio and Gulf Stream Currents in the Northern (10% between 30°N and 50°N).

The estimates obtained for $P_{\text{curr}}^0$, $P_{\text{curr}}^1$, and $P_{\text{curr}}^2$ show spatial patterns and magnitudes visually similar with those resolved by $P_{\text{obs}}$, that lead to global integrals varying between $-0.43$ and $-0.40$ TW (Figs. 4.8b–c and Table 4.2), thus within 30 GW of the correspondent $P_{\text{obs}}$ value. This close agreement indicate that the current-driven reduction in $P_1$ scales predominantly as a function of the surface current kinetic energy and of the wind speed, with covariances between wind and currents not significantly contributing to the effect. Finally, $P_{\text{curr}}^3$ integrates to $-0.25$ TW, indicating that eddy fluctuations respond to about 59% of the total current-induced variation in the wind power input predicted by $P_{\text{obs}}$. 
Predictions of the impact of currents to the wind energy input to the geostrophic ocean circulation were previously obtained by Xu and Scott (2008) and Hughes and Wilson (2008), based on altimeter-derived geostrophic velocities and scatterometer winds. Particularly, Xu and Scott (2008) used an expression equivalent to assuming that $\partial F/\partial w = \rho_a c_d$ in Equation (4.17), obtaining a globally-integrated value of $-0.29$ TW. On its turn, Hughes and Wilson (2008) used the same set of expressions applied here, and also observed that covariances between surface geostrophic currents and 10-m winds were unimportant for the power reduction induced by current effects, although their estimates revealed generally smaller magnitudes, that lead to a variation in the wind power input a factor of two smaller than those obtained in this work ($-0.19$ TW). Their results also indicates a larger contribution of the eddy variance to the current-driven reduction in the wind power input ($\sim75\%$). However, these studies did not resolved whether the inferred changes correspond solely to a reduction of the total wind power provided at the ocean surface, or actually reflected a net loss of mechanical energy by the oceanic quasi-geostrophic variability to the atmosphere, as suggested by the predominantly negative fluxes observed in the drifter-based $P_g^e$ estimate (Figs. 4.5g–h and Table 4.1).

To investigate this question, the air-sea fluxes of mechanical energy associated with the Ekman, geostrophic, and the full surface oceanic velocity fields (each further decomposed into mean, seasonal, and eddy components) are recalculated using $\tau_{nc}$. Zonal and cumulative global integrals of the resulting energy fluxes are shown in Figures 4.9 and 4.10, respectively, alongside with estimates calculated using the original scatterometer $\tau$ measurements. Table 4.3 lists the total integrated power for
Figure 4.9: Zonal integrals of the time-averaged air-sea fluxes of mechanical energy, in $10^5$ W/m, associated with the total surface ocean circulation and its Ekman and geostrophic components ($P_t$, $P_e$, and $P_g$, respectively), each further decomposed into mean, seasonal, and eddy components ($P_{m}^{t}$, $P_{s}^{t}$, and $P_{e}^{t}$, respectively), calculated using drifter and scatterometers observations. Pseudo-Eulerian estimates computed with and without the wind stress dependence on the surface ocean currents are presented (black and orange lines, respectively), mapped via bin averaging (PE1, solid lines) and the 1-D GME method (PE2, dashed).

Each component when the current effects are removed, and the percentage variation relative to original estimates shown in Table 4.1.

Here, the global integral of the best estimate of total air-sea fluxes of mechanical energy $P_t$ (obtained by summing the $P_{m}^{t}$ component mapped via the 1-D GME method to $P_{s}^{t}$, $P_{e}^{t}$, and $P_{e}^{t}$) increases by 0.44 TW when the current effects are removed, equivalent to a variation of 21%. Only about 0.05 TW of this total takes place via the fluxes associated with the Ekman circulation, while 0.39 TW occurs via the geostrophic component, values that correspond to variations on the global
integrals of $P_e$ and $P_g$ of about 5% and 39%, respectively. The larger impact to $P_g$ is attributed to the fact that quasi-geostrophic motions largely dominates the kinetic energy of surface ocean currents (Duhaut and Straub 2006; Ferrari and Wunsch 2009), quantity that modulates the current-driven variation of the mechanical energy fluxes according to the theoretical predictions obtained via Equations (4.14) to (4.17). Of the 0.39 TW excess power in $P_g$, about 0.13 TW is contained in $P_g^{m}$, 0.04 TW in $P_g^{s}$, and the remaining 0.22 TW in $P_g^{e}$ (the variation in $P_g^{ct}$ is negative and has magnitude smaller than 1% of estimated power change). Notably, the inferred power variation in $P_g^{e}$ is equivalent to about 98% of its original globally-integrated value (Table 4.3),
Table 4.3: Globally-integrated power estimates when the current dependence is removed from the wind stress formulation, in gigawatts. The values between parentheses are the percentage variation relative to the global integrals in Table 4.1.

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
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<tr>
<td></td>
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<td>PE1</td>
<td>PE2</td>
<td>PE1</td>
<td>PE2</td>
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<td>2964.0</td>
<td>1166.4</td>
<td>1260.8</td>
<td>929.6</td>
<td>1701.9</td>
</tr>
<tr>
<td></td>
<td>(23.6%)</td>
<td>(20.9%)</td>
<td>(4.4%)</td>
<td>(4.9%)</td>
<td>(60.5%)</td>
<td>(36.2%)</td>
</tr>
<tr>
<td>$P_{m}$</td>
<td>1382.1</td>
<td>1870.6</td>
<td>483.3</td>
<td>522.6</td>
<td>899.0</td>
<td>1348.9</td>
</tr>
<tr>
<td></td>
<td>(9.6%)</td>
<td>(9.0%)</td>
<td>(4.8%)</td>
<td>(5.4%)</td>
<td>(11.4%)</td>
<td>(10.7%)</td>
</tr>
<tr>
<td>$P_{s}$</td>
<td>218.1</td>
<td>–</td>
<td>129.77</td>
<td>–</td>
<td>88.8</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(25.7%)</td>
<td>–</td>
<td>(6.8%)</td>
<td>–</td>
<td>(69.3%)</td>
<td>–</td>
</tr>
<tr>
<td>$P_{e}$</td>
<td>545.9</td>
<td>–</td>
<td>551.6</td>
<td>–</td>
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<td>–</td>
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<tr>
<td></td>
<td>(80.4%)</td>
<td>–</td>
<td>(3.6%)</td>
<td>–</td>
<td>(-98.4%)</td>
<td>–</td>
</tr>
<tr>
<td>$P_{ct}$</td>
<td>-49.4</td>
<td>–</td>
<td>1.74</td>
<td>–</td>
<td>-54.7</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(5.0%)</td>
<td>–</td>
<td>(-39.1%)</td>
<td>–</td>
<td>(2.5%)</td>
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suggesting that the negative mechanical energy fluxes associated with the component predominantly arise from the wind stress dependence on surface ocean currents.

However, the meridional profiles of the zonal and global integrals of the $P_{g}$ component estimated using $\tau_{nc}$ (Figs. 4.9f and 4.10f, respectively) indicate that the energy fluxes remain predominantly negative in the extratropics, being compensated by the significantly larger positive wind power input now observed equatorward of 10° latitude. The covariances between surface quasi-geostrophic currents and wind stress observed in this analysis can arise not only from the action of air-sea coupling mechanisms, but also from spurious correlations between both quantities introduced when wind-dependent empirical models for the drifter slip motion and Ekman currents are subtracted from the drifter velocity measurements.

Thus, to independently verify to what extent the negative energy fluxes in $P_{g}$ can be attributed to the $\tau$ dependence on ocean currents, Figure 4.11a compares the meridional profile of this component’s zonally-integrated fluxes against that of $P_{3}^{curr}$,
which holds the theoretical estimates of the current-driven reduction in the wind power input attributed to the variance of oceanic eddy fluctuations, and Figure 4.11b shows their difference \( P_g^e - P_3^{curr} \). North of 10°N, both quantities show a similar meridional variation and differ by values smaller than \( 0.08 \times 10^{-5} \) W/m, showing a mean difference of \( 0.003 \times 10^{-5} \) W/m and standard deviation of \( 0.036 \times 10^{-5} \) W/m, thus supporting the interpretation that the fluxes in \( P_g^e \) at this latitudinal range predominantly arise from the current-driven coupling. At the Southern Hemisphere, the zonal integrals of \( P_g^e \) and \( P_3^{curr} \) show a good visual agreement between 10-25°S, however the magnitudes of \( P_g^e \) south of 25°S become consistently larger than those of \( P_3^{curr} \), reaching values of up to \( 0.6 \times 10^{-5} \) W/m, with a mean difference of \( 0.027 \times 10^{-5} \) W/m and standard deviation of \( 0.192 \times 10^{-5} \) W/m, suggesting that other factors are contributing to the observed negative energy fluxes. Finally at latitudes smaller than 10°, the negative values in \( P_3^{curr} \) show a sharp increase in magnitude in response to the enhanced eddy variance associated with the action of equatorial waves, which is opposed almost symmetrically by the observed increase in \( P_g^e \) to positive values. The positive \( P_g^e \) values near the equator were also observed in the correspondent altimeter-derived estimates (Fig. 4.4g–h), and are theorized to reflect the oceanic response to atmospheric forcing at frequencies other than seasonal, whose resulting positive wind power input would exceed the negative energy fluxes induced by the current-driven air-sea coupling.

Considering that the empirical expressions used to model the drifter slip motion and Ekman currents should scale predominantly as a function of the prevailing winds, and that the positive values in \( P_g^e \) near the equator are theorized to reflect the oceanic adjustment to intrinsic atmospheric variability, then the covariances arising from these
Figure 4.11: Panel (a) shows the zonal integral of the predicted variation in the total wind power input at the ocean surface induced by oceanic eddy fluctuations ($P_{curr}^3$, green line), computed via Equation (4.17), and zonal integrals of drifter-based estimates of eddy component of the air-sea mechanical energy fluxes associated with the geostrophic ocean circulation, computed using the original scatterometer wind stress measurements ($P_{eg}^e$, blue) and wind stress fields preliminarily high-pass filtered to isolate the ocean mesoscales ($\hat{P}_{eg}^e$, red). Panel (b) shows the zonally-integrated difference of $P_{eg}^e$ and $\hat{P}_{eg}^e$ relative to $P_{curr}^3$.

effects can be suppressed by high-pass filtering the wind stress and/or current velocity fields in order to isolate the ocean mesoscales. Thus, the scatterometer wind stress fields are high-passed obtained by subtracting the $\tau$ maps from correspondent fields low-pass filtered using a two-dimensional Gaussian filter with a $7^\circ \times 7^\circ$ half-power cutoff, which are used to recompute the air-sea fluxes of mechanical energy.

Alongside the meridional profiles of the zonally-integrated $P_{eg}^e$ and $P_{curr}^3$, Figure 4.11 also shows correspondent estimates for $\hat{P}_{eg}^e$ calculated using high-passed $\tau$ data (hereafter $\hat{P}_{eg}^e$). $\hat{P}_{eg}^e$ shows a better visual agreement with $P_{curr}^3$ south of $30^\circ$S than the original $P_{eg}^e$ estimates, suggesting that the observed discrepancies between $P_{eg}^e$ and $P_{curr}^3$ were associated with the methodological biases mentioned previously. The sharp variation of the estimated fluxes to positive values equatorward of $10^\circ$ also disappears, supporting the interpretation that this feature predominantly reflected
the oceanic adjustment to non-seasonal atmospheric forcing. Equatorward of 30° in both hemispheres, however, the zonally-integrated fluxes in \( \hat{P}_g \) now systematically underestimates the magnitude of those predicted by \( P^{curr}_3 \), characteristic potentially associated with the adopted filter half-power cutoff scale, equivalent to zonal wavelengths varying meridionally from about 333 km at 60° latitude to 777 km at the equator. Considering that the horizontal scale of oceanic phenomena increases equatorward as a function of the Rossby radius of deformation, and hence as an inverse function of the Coriolis parameter, it is possible that a significant fraction of the influence of ocean currents on the mechanical energy fluxes at latitudes smaller than 30° is being filtered out. The sensitivity of the obtained results to the filtering cutoff scales will be further investigated in the continued development of this study.

4.3.2.2 Influence of SST-driven \( w \) anomalies

The agreement between the predominantly negative air-sea fluxes of mechanical energy inferred for \( P_g^e \), with estimates of the energy flux variations induced by eddy fluctuations in the surface currents (Figs. 4.9h, 4.10h, and 4.11), suggests that a potential influence of SST-driven air-sea coupling mechanisms is secondary to that of current-driven coupling. However, the differing conclusions on the role of the SST-induced coupling drawn from the results of recent numerical studies based on fully coupled, high-resolution regional models (e.g. Jin et al. 2009; Byrne et al. 2016; Seo et al. 2016; Renault et al. 2016; Seo 2017) calls for a quantitative assessment of the effect based on observational data.

Figure 4.12 summarizes the estimates of the variation in \( P_t \) induced by the dependence of wind stress on SST-induced wind speed anomalies \( (w'_e) \). Panel (a) illustrates
the global map of the differences between bin-averaged \( P_t \) estimates calculated using the scatterometer \( \tau \) data, and equivalent results obtained using \( \tau \) estimates whose dependence on \( w'_c \) has been removed using the satellite-based \( w'_c \) data (\( \tau_{nt} \)), hereafter referred to as \( P_{sst}^{nt} \). Panel (b) shows zonal integrals for \( P_{sst}^{nt} \), and for the theoretical estimates \( P_{sst}^0 \) to \( P_{sst}^2 \) obtained via Equations (4.18) to (4.20), while (c) shows their correspondent cumulative global integrals, whose total values are listed in Table 4.2. As forementioned, \( P_{sst}^0 \) estimates the full SST-induced impact to the energy fluxes; \( P_{sst}^1 \) is an approximation that assumes that the effect predominantly scales as a function of the covariance between the surface ocean currents and \( w'_c \) and as a function of wind speed \( w \); and \( P_{sst}^2 \) further assumes that only the along-wind component of the ocean currents is relevant for the SST-induced power change.

The globally-averaged magnitude of \( P_{sst}^{nt} \) is about 31 times smaller than that of \( P_{curr}^{nt} \). Despite the small values, the \( P_{sst}^{nt} \) spatial distribution reveals well-defined spatial features (Fig. 4.12a), with positive variations of the mechanical energy flux prominently observed south of about 35°S coinciding with the ACC, the Agulhas Return Current, and the Brazil-Malvinas Confluence. Positive values also prevail in the southeastern South Pacific, at the Pacific’s equatorial cold tongue, at the Somali Current, and at the seaward extensions of the Kuroshio and Gulf Stream Currents. Conversely, extensive regions with negative SST-induced variations in \( P_t \) are observed within the 15-35° latitudinal band in both hemispheres, particularly occurring at the interior of the South Indian and North Atlantic subtropical gyres, the western portion of South Pacific subtropical gyre, and over much of the tropical Atlantic Ocean. The meridional profile of the zonal and cumulative global integrals of \( P_{sst}^{nt} \) (Figs. 4.12b–c) show that the positive wind power input in the Southern Ocean
Figure 4.12: Similar to Figure 4.8, for the influence of SST-driven wind speed anomalies to $P_t$. Here, $P_{sst}^{obs}$ is the difference between the original $P_t$ estimates and those obtained wind stress data whose dependence on SST was removed using satellite-based $w'_c$ estimates ($\tau_{nt}$); while $P_{sst}^0$ to $P_{sst}^2$ are computed via Equations (4.18) to (4.20). The contours overlaid to the $P_{sst}^{obs}$ global map in panel (a) are time-mean 10-m meridional wind velocity isolines plotted at 1.5 m/s intervals, where the thick solid line marks the zero and the solid (dashed) lines denotes positive (negative) values. The zonal and cumulative integrals in (b) and (c) are given in kilowatts/m and in gigawatts, respectively.

is fully compensated by the negative fluxes observed within the 15-35° latitudinal band in both hemispheres, leading to a small global integral of about -0.6 GW.

The global distributions of $P_{sst}^0$, $P_{sst}^1$, and $P_{sst}^2$ (not shown) reveal the same large-scale features observed in $P_{sst}^{obs}$, also leading to positive zonally-integrated values south of 35°S, and negative integrals at the 15-35° latitudinal band. The magnitude of the negative energy flux variations are, however, smaller than implied by $P_{sst}^{obs}$, leading to positive (albeit still small) global integrals between 0.6–1.6 GW (Table 4.2). The
similarity between the spatial distributions shown by the theoretical estimates and \( P_{sst}^{obs} \) indicate that the SST-driven modifications in \( P_t \) predominantly vary as a function of the wind speed, a definite-positive term, and as a function of the covariance between the along-wind velocity component of the surface ocean currents and \( w'_c \), which can be either positive or negative (Eq. 4.20).

To understand how covariances between the along-wind currents and \( w'_c \) of either sign arise, it is first noted that a sizable fraction of the \( w'_c \) variability is associated with mesoscale SST anomalies driven by coherent ocean eddies (c.f. discussion in Section 3.3.1.5). As illustrated by Figure 3.7, the horizontal advection of the background SST gradients by the eddy currents creates a dipolar SST anomaly structure, implying that, for a northward (southward) background SST gradient, the meridional current velocity component will be negatively (positively) correlated with the SST anomalies induced by both cyclonic and anticyclonic eddies. Since the mesoscale SST anomalies are mirrored in the atmosphere by \( w'_c \), and considering that \( w'_c \) occurs along the same direction as the prevailing winds, then northward (southward) winds blowing across northward (southward) background SST gradients will generate negative (positive) covariances between the meridional components of the \( u_g \) and \( w_c \) vectors associated with eddies of both polarities. In other words, winds blowing along the same (opposite) direction of the background SST gradient will result in a negative (positive) air-sea flux of mechanical energy to the underlying eddies.

This effect is schematically illustrated in Figure 4.13, and is supported by the fact that negative (positive) time-mean 10-m wind velocities highlighted by the contours in Figure 4.12a predominantly coincide with positive (negative) \( P_{sst}^{obs} \) values in the Southern Hemisphere, and vice versa in the Northern. This theoretical model further
suggests that winds blowing in a direction normal to that of SST gradients can also affect the mechanical energy fluxes associated with ocean eddies, however with opposite contributions for each eddy polarity. While this implies that the SST-driven air-sea coupling can potentially induce asymmetries in the mechanical energy fluxes associated with cyclonic and anticyclonic eddies, this effect likely integrates to near-zero values and thus should not play a significant role in conditioning the observed $P_{sst}^{obs}$ spatial patterns (Fig. 4.12a).

The relatively small impact of SST-driven air-sea coupling to the eddy energetics is compatible with the results of the satellite-based investigation of Gaube et al. (2015), and of recent regional numerical studies (Seo et al. 2016; Seo 2017; Renault et al. 2016). Particularly, Gaube et al. (2015) observed that the dipolar SST anomaly structure associated with the eddies resulted in a dipolar wind stress curl anomaly field whose poles were offset from the eddy rotational center, and as such should primarily affect eddy propagation rather than play a significant role in reinforcing or attenuating the interior eddy circulation. These conclusions were supported by the results of a suite of numerical experiments performed with coupled high-resolution atmosphere–ocean models for the California Current System (Seo et al. 2016; Renault et al. 2016) and the Somali Current System (Seo 2017), which shown that the SST-driven air-sea coupling does not significantly affect the time-dependent component of the air-sea mechanical energy fluxes.

Conversely, high-resolution coupled simulations of the South Atlantic by Byrne et al. (2016) indicated that the mesoscale SST-driven coupling not only fully compensated the negative fluxes induced by the $\tau$ dependency on surface currents, but also lead to a net wind power input to the ocean circulation. The study attributed this
Figure 4.13: Schematic representation of the impacts of the SST-driven air-sea coupling to the air-sea fluxes of mechanical energy at coherent ocean eddies, considering cyclonic and anticyclonic eddies in the Northern and Southern Hemispheres, and assuming an equatorward SST gradient. The black arrows denote the direction of the zonal and meridional winds. Here, the eddy rotational velocities \( (u) \) distorts the background SST field, inducing a dipolar structure of positive and negative SST anomalies (red and blue regions, respectively) that is mirrored as anomalies in wind speed, and hence in wind stress \( (\tau) \). \( P \) denotes the air-sea flux of mechanical energy at the top and bottom eddy hemispheres (subscripts \( T \) and \( B \), respectively) calculated via the product between the zonal eddy currents and wind stress \( (u_x \cdot \tau_x) \), and at the left and right eddy hemispheres (\( L \) and \( R \)), calculated from the product between the meridional eddy velocities and wind stress \( (u_y \cdot \tau_y) \). In the absence of SST-driven wind anomalies, \( P \) estimates of opposing eddy hemispheres would cancel each other, however the coupling induces anomalies in wind stress \( (\tau') \) that leads to a non-zero air-sea mechanical power exchange.
effect to coherent eddies propagating within a large-scale wind gradient, combined
with wind speed anomalies driven by eddy-induced SST perturbations. Specifically,
the horizontal shear of the background winds create an imbalance between the posi-
tive and negative mechanical energy fluxes at eddy hemispheres opposing each other
in the cross-wind direction, leading to a net mechanical energy input (loss) by ed-
dies with the same (opposite) sense of rotation of the horizontal wind shear. Byrne
et al. (2016) argued that, under anticyclonic winds, the predominantly negative
(positive) SST-driven wind anomalies associated with cold-core cyclonic (warm-core
anticyclonic) eddies would further enhance the energy uptake by anticyclonic eddies
while reducing the energy loss by cyclonic eddies, leading to a net increase on the
wind power input to the ocean circulation. For eddies under cyclonic winds, such
interaction would result in a net loss of mechanical energy by the ocean. The effect
would be most intense in the Southern Ocean, with conditions for the SST-driven
net wind power input to the ocean circulation prevailing at latitudes equatorward of
50°S.

Similar to the results of Byrne et al. (2016), estimates of $P_{sst}^{obs}$ indicate that
the SST-driven air-sea coupling also enhances the wind power input in the Southern
Ocean (Fig. 4.12), however the inferred magnitude of the effect is significantly smaller.
Particularly, the zonal integrals of $P_{sst}^{obs}$ south of 35°S show magnitudes between 28
and 200 times smaller than those of $P_{curr}^{obs}$, although it is noted that the physical
interpretation of the SST influence on $P_t$ put forward by Byrne et al. (2016) is
fundamentally different from that proposed by Figure 4.13, requiring a non-zero air-
sea flux of mechanical energy at coherent ocean eddies induced by horizontal wind
gradients. To further examine the hypothesis of Byrne et al. (2016), the next Section
separately estimates the air-sea fluxes of mechanical energy associated with cyclonic and anticyclonic eddies, isolating the contributions of the current and SST-driven air-sea coupling, and that arising from the horizontal wind shear.

4.3.3 Air-sea flux of mechanical energy at coherent ocean eddies

In this Section, observations from looping drifter trajectories identified in the GDP dataset by Lumpkin (2016), referred to by that study as “loopers” and that likely reflect instances when the instruments were trapped within coherent ocean eddies, are used to investigate potential differences between the air-sea fluxes of mechanical energy associated with cyclonic and anticyclonic eddies.

Only trajectories with an inferred looping radius larger than 50 km are considered, a scale equivalent to the spatial Nyquist frequency of the scatterometer measurements. Here, drifter-based geostrophic velocity estimates are first isolated by subtracting empirical Ekman velocities from daily, slip-corrected drifter velocity measurements, which are subsequently combined with scatterometer $\tau$ data for the obtention of point estimates of the mechanical energy flux associated with the geostrophic ocean circulation ($P_g$). The resulting Lagrangian energy fluxes are then averaged within $4^\circ$ latitudinal bands separately for cyclonic and anticyclonic loopers, with the obtained estimates saved at a $0.25^\circ$ resolution along the meridional axis.

The zonally-averaged $P_g$ estimates obtained for each looper rotation sense are shown in Figure 4.14a. The retrieved mechanical energy fluxes are predominantly negative, in agreement with estimates of the eddy component $P_{ge}^e$ computed using all available drifter observations (Figs. 4.7g–h). However, the values obtained for
cyclonic and anticyclonic loopers are statistically different at a 95% confidence interval at most latitudes, with larger magnitudes more frequently associated with cyclonic polarities, and anticyclonic loopers showing positive fluxes across extensive latitudinal bands in both hemispheres.

To verify whether the observed discrepancies between the energy fluxes retrieved from cyclonic and anticyclonic loopers can be attributed to the wind stress dependency on surface ocean currents and/or on SST-driven wind speed anomalies, the fluxes were recalculated using $\tau$ estimates with the current and SST dependencies removed using observational data. In agreement with the results of Section 4.3.2, removing the current-driven effect leads to a definite-positive variation on the mechanical energy flux estimates for both looper polarities (Fig. 4.14b), resulting in predominantly positive energy fluxes for anticyclonic loopers that are mirrored by negative values of similar magnitude associated with their cyclonic counterparts in most latitudes within the 10-55° band, in both hemispheres. An opposite tendency is observed poleward of 55° latitude, with positive (negative) energy fluxes associated with cyclonic (anticyclonic) loopers. The influence of the SST-driven coupling is secondary, leading to variations of the $P_g$ estimates statistically indistinguishable from zero for both rotation senses, meaning that this mechanism cannot account for the apparent anticorrelation between the energy fluxes retrieved for cyclonic and anticyclonic loopers.

The numerical study of Byrne et al. (2016) proposed that horizontal gradients of the large scale winds could inject (remove) mechanical energy from eddies rotating along the same (opposite) direction than the background winds. Perturbations on wind speed induced by SST anomalies via boundary layer dynamics, on their turn
Figure 4.14: Panels (a) and (b) show zonally-averaged air-sea fluxes of mechanical energy associated with the geostrophic ocean circulation ($P_g$) calculated using velocity observations from cyclonically and anticyclonically-rotating looping drifter trajectories (blue and red lines, respectively), combined with the original scatterometer wind stress retrievals (panel a), and using wind stress estimates whose dependency on surface ocean currents removed using drifter data (b). The shading around each line denote 95% confidence intervals, and the gray line refers to the average between both lines. Panel (c) shows the difference between the gray and red lines in (b) ($P_g'$), and zonally-averaged estimates of the wind stress curl multiplied by the signal of the latitude ($\langle \nabla \times \tau \rangle \cdot \text{sng}(\text{lat})$). Last, panel (d) shows a scatterplot between the quantities plotted in (c), overlaid by the best-fit regression line. Here, $\alpha$ is the estimated regression slope in m$^2$/s, accompanied by its 95% confidence margin.
associated with long-lived cyclonic and anticyclonic eddies, would create an asymmetry between the mechanical energy provided to and removed from each eddy polarity via the lateral wind gradient mechanism, resulting in a net wind power input to the eddy variability in the case of anticyclonic winds, and a net loss of mechanical energy in the case of cyclonic winds. In opposition to the conclusions of Byrne et al. (2016), the observational estimates obtained here indicate that the SST-driven air-sea coupling does not significantly affect the air-sea fluxes of mechanical energy, however the lateral wind shear mechanism proposed by that work can potentially account for the differences on the energy fluxes associated with cyclonic and anticyclonic loopers observed in Figures 4.14a–b. Moreover, the contemporaneous study of Xu et al. (2016) used altimeter-derived geostrophic velocities and scatterometer wind stress data to estimate the air-sea fluxes of mechanical energy associated with cyclonic and anticyclonic eddies detected in altimeter data, which revealed a robust relationship between wind stress curl and the mechanical energy fluxes associated with each eddy polarity attributed to the same lateral wind shear mechanism described by Byrne et al. (2016).

To analyze whether horizontal wind gradients can account for the differences between the energy fluxes inferred for cyclonic and anticyclonic loopers observed in Figure 4.14b, variations relative to the average of the energy fluxes inferred for both rotation senses are first isolated \( P'_g \). This operation is performed to remove the contribution of the time-mean and seasonally-varying components to the energy fluxes, which should affect estimates of rotation senses approximately equally, and assumes that variations induced by the lateral wind shear possess the same magnitude but are of opposite signs for cyclonic and anticyclonic loopers. Figure 4.14c shows the merid-
ional profile of $P_g'$ for cyclonic loopers alongside with that of the zonally-averaged wind stress curl, the latter computed using scatterometer data, and multiplied by the sign of the latitude in order to express cyclonic and anticyclonic wind rotation tendencies (positive and negative values, respectively). The plotted curves show a good visual agreement in the Southern Hemisphere south of about $10^\circ$S, and in the Northern Hemisphere between $10^\circ$–$45^\circ$N. Quantitatively, Figure 4.14d shows a scatterplot of both quantities overlaid with a best-fit regression line, calculated via a weighted least-squares scheme with weights set by the standard error of the individual $P_g'$ retrievals. The obtained regression slope $\alpha$ is statistically different from zero within a 95% confidence margin, being positive for cyclonic loopers (as illustrated in Fig. 4.14d) and negative for anticyclonic, implying that the background winds tend to inject (remove) mechanical energy from quasi-geostrophic oceanic motions rotating along the same (opposite) direction than the overlying winds, in agreement with the results of Byrne et al. (2016) and Xu et al. (2016). It is noted, however, that the $\alpha$ inferred from drifter observations is a factor of two larger than that retrieved from altimeter data by Xu et al. (2016).

Figure 4.15 compares the mechanical energy fluxes induced by lateral wind shear ($P_{wsc}$) acting on cyclonic and anticyclonic eddies, inferred simply by evaluating $\alpha$ using the zonally-averaged wind stress curl data, with the energy fluxes induced by the current and SST-driven coupling ($P_{curr}$ and $P_{sst}$, respectively) calculated via the difference between estimates computed using the original scatterometer $\tau$ measurements, and those obtained using $\tau$ estimates whose dependency on surface currents and SST-driven wind speed anomalies was removed using observational data. While near-zero $P_{sst}$ values are obtained throughout the meridional axis, $P_{curr}$ and
$P_{wsc}$ are significant and display comparable magnitudes. Particularly, the anticyclonic wind stress curl associated with the subtropical gyres lead to negative air-sea fluxes of mechanical energy at cyclonic ocean eddies, that reinforce the dissipative effect arising from the current-driven air-sea coupling, while the cyclonic wind stress curl at the subpolar gyres induces a positive wind power input that act against the current-driven effect; and vice versa for anticyclonic eddies. The sum of $P_{sst}$, $P_{curr}$, and $P_{wsc}$ display a meridional variation and magnitudes visually similar to original estimates obtained for cyclonic and anticyclonic loopers (Fig. 4.15a), except near the equator at latitudes smaller than 10°, and in the Northern Hemisphere poleward of about 40°N, discrepancies that can be associated with the relatively small sampling densities in these latitudinal bands. Finally, while the combination of the estimated effects indicate that the globally-averaged energy fluxes for both eddy polarities remain negative, the lateral wind shear mechanism can potentially lead to positive mechanical energy fluxes for anticyclonic eddies within the subtropical gyres, and for cyclonic eddies in the Arctic Ocean and in the Southern Ocean poleward of about 50° latitude.

4.4 Summary and conclusions

This chapter uses near-surface current velocity observations from GDP drifters, combined with a number of satellite products, to provide observational-based estimates of (a) the air-sea fluxes of mechanical energy associated with the total, Ekman, and geostrophic surface ocean circulation ($P_t$, $P_e$, and $P_g$, respectively), (b) the energy fluxes associated with the quasi-geostrophic ocean variability, and (c) the fraction of the energy fluxes that can be ascribed to the influence of the current and SST-driven air-sea coupling.
Isolating variability with periods longer than five days, the resulting drifter and scatterometer-based estimates of $P_t$ yield a time-averaged, globally-integrated value of 2.14 TW, partitioned as 1.15 TW in $P_e$, and 0.99 TW in $P_g$. Considering first the obtained $P_e$ estimates, their spatial distribution is visually similar to that retrieved by Wang and Huang (2004) using reanalysis $\tau$ fields and surface Ekman velocities inferred from the classical Ekman solution, also indicating that the majority of the wind power input takes place via non-zero frequencies (about 0.65 TW, or 57% of the total). However, the globally-integrated wind power input to the Ekman circulation calculated here is a factor of two smaller than that of Wang and Huang (2004), characteristic attributed to the facts that (a) the empirical rotation angles relative to the wind stress vector estimated from the GDP drifter velocities are generally smaller than the 45° anticyclonic rotation assumed by that study, and (b) Wang and Huang (2004) used a higher cutoff frequency, equivalent to a period of two days, thus capturing a
larger fraction of the wind power input to the Ekman layer. Previous studies further demonstrated that the both Ekman coefficients varies as a function of the wind stress forcing frequency (Rio and Hernandez 2003; Elipot and Gille 2009a), dependency that can also influence the retrieved energy fluxes (Elipot and Gille 2009b).

The undiagnosed vertical shear of ageostrophic currents also constitutes a major source of uncertainty for the $P_e$ estimates obtained in this work. Such uncertainty is associated the fact that the slip-corrected drifter velocities have a nominal depth of 15-m, meaning that the empirical Ekman model coefficients inferred from drifter observations would differ from those obtained at the surface, specifically showing smaller amplitudes and wider veering angles relative to the overlying wind stress vector that would result in a systematic underestimation of the mechanical energy fluxes. Elipot and Gille (2009a, 2009b) addressed this issue by evaluating the 15-m drifter velocities against a suite of theoretical Ekman models, and using the inferred vertical structures to infer the Ekman velocities at the surface, and hence correct the vertical shear bias associated with drifter-based estimates of the mechanical energy fluxes. However, considering that Lumpkin et al. (2013) found that a significant number of observations previously thought to be from drogued drifters were actually obtained by undrogued instruments, the results of Elipot and Gille (2009a, 2009b) were likely biased by the undiagnosed presence of undrogued drifter measurements.

In this context, it is reminded that the method employed for the correction of the undrogued drifter slip motion (Sec. 2.2.2) operates by removing the part of the difference between the along-wind velocity component measured at the upper 30 cm and at 15-m that is correlated with wind speed, which includes not only the wind and wave-induced drifter slip motion, but also the along-wind component of Ekman
currents. Although this implies that the slip-corrected undrogued drifter velocities potentially include an undiagnosed cross-wind component associated with Ekman dynamics, the good agreement between the empirical Ekman coefficients calculated using the processed drogued and undrogued drifter data (Fig. 4.2) is suggestive of either (a) a small vertical shear of Ekman currents in the upper 15-m of the water column, or (b) that the vertical shear occurs predominantly downwind. Both cases are supported by the results of previous observational studies (e.g. Price et al. 1987; Chereskin 1995; Schudlich and Price 1998; Price and Sundermeyer 1999). Here, the estimated undrogued drifter downwind slip coefficients $\alpha_u$ (Fig. 2.2) appear to support the first hypothesis, considering that its spatial distribution does not show well-defined latitudinal dependency nor a symmetry between the Northern and Southern hemispheres, characteristics that would be expected if $\alpha_u$ predominantly reflected differences between the downwind Ekman velocities at the levels sampled by the GDP drifters, hence suggesting a small influence of the vertical shear bias on the obtained $P_e$ estimates.

Conversely, the recent study of Laxague et al. (2017) measured the current velocities on the first centimeters of the water column via a spectral analysis of ship-based polarized optical imagery of the ocean surface, and observed a intense vertical shear relative to the currents measured at $O[1 \text{ m}]$ depths or larger. The significant disconnection between the very near-surface flow and the underlying Ekman and geostrophic velocity fields shown by their results raises questions on how the momentum imprinted by wind stress at the ocean surface is transferred down the water column, in particular because it suggests a surface-intensified mixing arising from the enhanced vertical shear that contrasts with the assumptions typically used to model the Ekman circu-
lation of a surface boundary condition matching the wind stress to turbulent stress combined with a constant vertical viscosity coefficient within the Ekman layer (c.f. Elipot and Gille 2009a). It is noted that the investigation of Laxague et al. (2017) is based on quasi-synoptic estimates taken near the coast, and thus it still remains to be verified whether such disconnection holds in more general oceanic regions away from the continental shelf break, and at subinertial frequencies.

These considerations suggest that the obtained $P_e$ results can be interpreted as conservative, lower-bound estimates of the actual wind power input to the Ekman layer. In contrast, due to the smaller vertical shear expected for quasi-geostrophic ocean currents, greater confidence exist on the obtained drifter-based $P_g$ estimates. Particularly, the 0.99 TW global integral of $P_g$ inferred from drifter and scatterometer observations is notably close to the 1.03 TW calculated using altimeter-derived geostrophic velocity data, and lies within the 0.76–1.10 TW margin retrieved from previous assessments based on altimeter data (Wunsch 1998; Huang et al. 2006; Hughes and Wilson 2008; Xu and Scott 2008; Scott and Xu 2009). However, while the currently available altimeter and scatterometer-based estimates reveal a minor contribution of the covariance between $u_g$ and $\tau$ (referred to as $P_{eg}^e$) to the globally-integrated energy fluxes, equivalent to $-0.02$ TW obtained in this study, and varying between the positive values of 0.01–0.09 TW in literature (Hughes and Wilson 2008; Scott and Xu 2009) with $-0.02$ TW attributed solely to the action of coherent ocean eddies (Xu et al. 2016); the drifter-based estimates obtained here integrate to $-0.23$ TW. This result suggests that about 19% of the mechanical power supplied by the winds to the general ocean circulation is lost back to the atmosphere via $P_{eg}^e$. 

If internal variability in the ocean and in the atmosphere are uncorrelated with each other, owning to the difference between their intrinsic spatial-temporal scales, then non-zero $P_g^e$ values should predominantly reflect the $\tau$ dependence on surface ocean currents and/or on mesoscale SST-driven wind speed anomalies (Hughes and Wilson 2008; Ferrari and Wunsch 2009). The impact of the current and SST-driven air-sea coupling to the energy fluxes is evaluated in this study (a) via theoretical formulations derived to quantify the variation in the mechanical energy fluxes induced by each effect [Eqs. (4.13)–(4.20)], and (b) by recomputing the air-sea fluxes of mechanical energy using $\tau$ estimates with the dependency on both effects removed using observational data.

First regarding the current-driven air-sea coupling, this mechanism was found to reduce the global integral of $P_t$ by approximately 0.44 TW. Only about 0.05 TW of this variation takes place via the Ekman component $P_e$, characteristic attributed to the fact that the impact of ocean currents on the time-averaged energy fluxes varies as a function of the oceanic kinetic energy, which is largely dominated by the quasi-geostrophic ocean circulation. Of the remaining 0.39 TW reduction expected for $P_g$, 0.22 TW takes place via its eddy covariance term $P_g^e$, value that agree with the actual drifter and scatterometer-based estimates for this component within a 0.01 TW margin, thus suggesting that the negative mechanical energy fluxes associated with the quasi-geostrophic variability can be largely explained by the dependency of scatterometer-based $\tau$ measurements on surface ocean currents.

For an independent verification, a comparison between the meridional profile of the zonally-integrated $P_g^e$ against that for the current-driven reduction in the energy fluxes associated with time-dependent current fluctuations (Fig. 4.13) showed a good
agreement in most latitudes except (a) at latitudes smaller than $\sim 10^\circ$, where the $P_g^e$ magnitudes are significantly smaller than the predicted values, characteristic that was traced back to positive $P_g^e$ values associated with the Indo-Pacific Warm Pool (also observed in estimates obtained using altimeter data), thought to reflect the oceanic adjustment to atmospheric forcing at frequencies from semiannual to interannual; and (b) south of about $35^\circ$S, where the $P_g^e$ magnitude generally exceed that of the predicted values, potentially reflecting wind/current covariances introduced artificially by the subtraction of empirical models for the drifter slip and for the Ekman velocities from the drifter velocity measurements, both calculated as a function of the wind speed, to isolate drifter-based estimates of $u_g$. Considering that the both mechanisms theorized for conditioning the observed discrepancies should scale as a function of the large-scale winds, $P_g^e$ was recalculated using scatterometer $\tau$ measurements preliminarily high-pass filtered in space using a $7^\circ \times 7^\circ$ half-power cutoff scale to isolate the mesoscale variability, operation that lead to a better visual agreement between $P_g^e$ and the predicted energy fluxes in the Southern Ocean, and reduced their discrepancies within the equatorial belt. These results support the conclusion that the negative mechanical energy fluxes in $P_g^e$ predominantly arise from the current-driven influence on $\tau$, rather than merely reflecting biases introduced by adopted methods.

Regarding the impacts of the SST-driven air-sea coupling, the obtained estimates revealed well-defined spatial patterns (Fig. 4.12), with positive air-sea fluxes of mechanical energy observed in the Southern Ocean, at the equatorial cold tongue in the Pacific Ocean, and at the seaward extensions of the Kuroshio and Gulf Stream Currents; while negative energy fluxes predominantly occur at the interior of the subtropical gyres. The observed spatial features appear to be related to the dipolar SST
anomaly associated with coherent ocean eddies, induced via horizontal advection of the large-scale, background SST gradients by the eddy circulation (Figs. 3.7b–c). Here, while the along-frontal wind velocity component would induce air-sea fluxes of mechanical energy of opposite signs between cyclonic and anticyclonic eddies, that would thus largely cancel each other when integrated across oceanic basins, the cross-frontal winds would induce energy fluxes of the same sign for both eddy polarity, and thus result in a non-zero integrated air-sea exchange of mechanical power (c.f. Figs. 4.12a and 4.13). Nevertheless, the magnitude of the effect was found to be, on average, about 31 times smaller than that of the current-driven variation in the energy fluxes.

The small impact of SST-driven coupling in the ocean energetics implied by these results agree with the conclusions of the regional numerical studies of Seo et al. (2016), Renault et al. (2016), and Seo (2017). In contrast, simulations performed by Jin et al. (2009) for an idealized eastern boundary upwelling system analogous to the California Current System (CCS) indicated that the coupling would exert a net damping effect on the mesoscale eddy field, while experiments by Byrne et al. (2016) for the South Atlantic’s sector of the Antarctic Circumpolar Current (ACC) showed that the mechanism not only fully compensated the negative energy fluxes induced by the current-driven coupling, but resulted in positive energy fluxes that enhanced the oceanic eddy variability. Interestingly, the SST-induced changes on the mechanical energy fluxes estimated in this chapter show predominantly negative (positive) SST-induced energy fluxes coinciding with the CCS (ACC) (Fig. 4.12a), in agreement with the results of Jin et al. (2009) and Byrne et al. (2016), although it remains to be verified why the SST-driven coupling in these numerical experiments lead to such
strong feedbacks to the eddy field. One possibility is that their models significantly overestimated the mesoscale SST variance relative to observations and thus forced a more intense SST-driven wind speed variability, condition analogous to that observed for the CCSM4 HR experiment described in Chapter 3 (c.f. Fig. 3.10). As shown by the theoretical predictions obtained via Equations (4.18) to (4.20), the effect varies as a function of the covariance between the SST-driven wind speed anomalies and the surface ocean currents, implying that an excess SST-induced wind variability resolved by the model could potentially enhance the covariances between both quantities and hence the relative importance of the SST-driven effect to ocean energetics.

This work also evaluated potential asymmetries between the air-sea fluxes of mechanical energy associated with cyclonic and anticyclonic ocean eddies, suggested by previous studies (Jin et al. 2009; Byrne et al. 2016; Xu et al. 2016), using observations from looping drifter trajectories detected in the GDP dataset (Lumpkin 2016). Although estimates of the zonally-averaged energy fluxes reveal predominantly negative values for both looping senses, characteristic arising from the \( \tau \) dependency on surface ocean currents, the values obtained for cyclonic and anticyclonic loopers are found to be statistically different at a 95% confidence level across most latitudes. The difference relative to the average energy flux between both polarities is found to be positively (negatively) correlated with the overlying wind stress curl multiplied by the signal of the latitude, relationship first reported in the numerical study of Byrne et al. (2016), and confirmed to hold for coherent eddies detected in altimeter data by Xu et al. (2016). It was interpreted by these studies as arising from the horizontal shear of large-scale winds, that on average tends to provide (remove) mechanical energy to (from) eddies with the same (opposite) rotation sense of the overlying winds. Here,
the energy flux response to the wind stress curl inferred from drifter observations is found to be twice as large as inferred from altimeter data (Xu et al. 2016), displaying the same order of magnitude of the current-driven effect. Again, the contribution of the SST-driven coupling is found to be significant smaller than that associated with the lateral wind shear and the current-driven effects. The combination of the diagnosed mechanisms suggest that the atmosphere can actually energize anticyclonic eddies within the subtropical gyres, and energize cyclonic eddies in the Arctic and Southern Oceans.

To summarize, the results of this study indicate that the quasi-geostrophic eddy variability loses mechanical energy to the atmosphere at a rate equivalent to 19% of the rate at which the winds supply mechanical power to the general ocean circulation, an effect that predominantly arises as a consequence of the influence of surface ocean currents on $\tau$. They provide further evidence that current-driven air-sea coupling is a non-negligible sink of geostrophic kinetic energy, effect predicted by previous theoretical and numerical studies (e.g. Bye 1986; Dewar and Flierl 1987; Eden and Dietze 2009; Seo et al. 2016; Renault et al. 2016; Seo 2017), although whose observational confirmation remained elusive until now, potentially due to limitations of altimeter-derived geostrophic velocity products for resolving the mesoscale ocean variability. This study also provides observational-based estimates of the SST-driven wind anomalies to the energy fluxes at global scales, which can potentially help reconcile the differing conclusions drawn from recent regional modeling experiments on the relative contribution of the effect to the ocean energetics below the Ekman layer (Jin et al. 2009; Byrne et al. 2016; Seo et al. 2016; Renault et al. 2016; Seo 2017), and support its analysis in future studies. Finally, the observed relationship between
the mechanical energy fluxes associated with cyclonic and anticyclonic ocean eddies
and the overlying wind stress curl supports the conclusions of previous studies that
horizontal gradients of the background winds can induce non-zero air-sea fluxes of
mechanical energy at coherent eddies (Byrne et al. 2016; Xu et al. 2016), and ex-

pands on their results by revealing a empirical relationship a factor of two larger than
implied by altimeter-derived estimates.

Finally, it is noted that this work is part of an ongoing research. Further de-
velopments will involve (a) the investigation of the cross-spectral statistics between
scatterometer \( \tau \) measurements, and altimeter-derived \( u_g \) estimates obtained from the
AVISO two-sat merged product and from along-track SSH measurements, analysis
aimed to determine to what extent the merged product underestimates the negative
energy fluxes at ocean mesoscales, and the intrinsic spatial-temporal scales of the
effect; (b) a detailed error analysis of the drifter-derived energy flux estimates, whose
preliminary estimates based on error propagation and a bootstrap approach confirm
the conclusions that the zonal and global integrals of the estimated fluxes, in partic-
ular those associated with the eddy component, are statistically meaningful within
95% confidence margins; and (c) using the inferred energy fluxes associated with the
oceanic eddy variability to calculate the eddy spin-down scales, comparing them with
the eddy lifetimes inferred from altimeter observations (Chelton et al. 2011).
CHAPTER 5

Conclusions

This dissertation uses near-surface current velocity observations from GDP drifters and a suite of satellite products to examine the time-averaged air-sea exchange of mechanical energy, with the main objectives of quantifying the energy fluxes associated with the quasi-geostrophic variability, and how much of it can be ascribed to the air-sea coupling mechanisms arising from the influence of surface ocean currents, and of mesoscale SST anomalies, on wind stress. The main hypothesis tested in this work is that non-zero covariances between wind stress and the surface geostrophic velocities can arise in response to the current and SST-driven air-sea coupling mechanisms operating at the ocean mesoscales, and exert a non-negligible contribution to the total air-sea exchange of mechanical power. Previous observational assessments potentially underestimated the magnitude of such covariances due to limitations of altimeter-derived geostrophic velocity products for resolving the mesoscale ocean variability. This chapter briefly summarizes the research conducted in pursuit of these objectives, and highlights its main conclusions.

The use of drifter data is intended to overcome the limitations of altimeter products for resolving the ocean mesoscales, considering that these instruments have the potential of sampling all scales of motion down to their own size. However, the fact
that drifter observations are scattered in both space and time imposes difficulties for estimating the statistical properties of the near-surface flow. A common procedure involves ensemble-averaging data selected within finite spatial-temporal volumes (referred to as bins), although this approach has a number of associated biases that are not easily diagnosed, chief among them the choice of bin size. Specifically, the bin size is often chosen subjectively, based on a trade-off between the spatial resolution of the mean and the number of observations used for its calculation, with larger bins allowing the selection of more data points and thus increasing the statistical reliability of the obtained estimates, however at the cost of losing information on their spatial variability at scales smaller than the prescribed bin size, and vice versa for smaller bins (Fratantoni 2001; Mariano and Ryan 2007; LaCasce 2008; Koszalka and LaCasce 2010). Furthermore, it was recently found that about half of the GDP dataset was obtained by undrogued drifters, whose velocity measurements are significantly affected by the relative motion induced by wind drag on the drifter’s surface buoy and by surface gravity waves (slip bias) (Grodsky et al. 2011; Lumpkin et al. 2013).

Chapter 2 of this dissertation is devoted to the development of solutions for these observational issues. The methods described in Lumpkin and Johnson (2013) for estimating a near-surface velocity climatology from GDP drifters are used as starting point, which are updated by (a) applying a formulation proposed Pazan and Niiler (2001) to correct the slip bias of undrogued drifters at global scales, and (b) introducing a new procedure for decomposing drifter observations into mean, seasonal, and eddy components, designed to reduce the smoothing and smearing effects of other data binning methods. The proposed procedure accounts for horizontal variations of the mean at scales smaller than the prescribed bin size by fitting an one-dimensional,
4th degree polynomial to the binned drifter observations sorted along a coordinate axis defined at the rotation angle that maximizes the variance explained by the empirical model (Fig. 2.4). Here, a test dataset composed by altimeter-derived geostrophic velocity fields linearly interpolated to the drifter locations, and by the full altimeter-derived geostrophic velocity fields, is used to evaluate the sensitivity of the results to method parameters, the method performance relative to that of other techniques described in literature, and the associated estimation errors.

Chapter 2 first demonstrated that the correction of the slip bias of undrogued drifters leads to statistically similar mean velocities for both drogued and undrogued drifter datasets at most latitudes, and reduces differences between their variance estimates. Notably, the undrogued drifter downwind slip coefficient $\alpha_u$ retrieved over an $1^\circ \times 1^\circ$ global grid showed well-defined large-scale patterns (Fig. 2.2a). Considering that the correction operates by subtracting the fraction of the difference between the along-wind velocities measured at the surface by undrogued drifters and those at 15-m by drogued instruments that is correlated with wind speed [Eq. (2.1)], the spatial patterns then potentially reflect (a) the spatial distribution of drifters equipped with floats with distinct surface areas, that would hence respond differently to direct wind drag; (b) the vertical shear of Ekman currents between the surface and 15-m depth; and (c) the response of undrogued drifters to a spatially-varying surface gravity field.

In particular, estimates of $\alpha_u$ as a function of the float surface area revealed a weak dependency between both parameters, which appears to rule out the differential wind drag acting on the drifters as the main cause for the observed spatial patterns. It is also considered unlikely that they predominantly reflect differences between the Ekman velocities at the surface and at 15-m depth. If that was the
case, then a latitudinal dependency and some symmetry between the Northern and Southern Hemispheres should be observed, characteristics absent in the obtained map. Thus, it is theorized that the observed patterns mainly reflect the action of surface gravity waves, hypothesis supported by the results of Curcic et al. (2016), based on the outputs from high-resolution, atmosphere-wave-ocean coupled simulations of the Gulf of Mexico, that the wave-induced Stokes drift plays a significant role on the transport of floating material in the upper ocean. Testing this hypothesis is beyond the scope of this dissertation, although a possible venue of investigation for future studies involves using directional wave spectra retrieved from global wave models and/or observational platforms (satellites/moorings/drifters) to calculate the Stokes drift, and subsequently infer its statistical relationship with the overlying wind speed and with the retrieved $\alpha_u$ estimates.

Next, sensitivity tests using the “toy” geostrophic velocity dataset were performed to define optimal choices for the adjustable parameters involved in the proposed decomposition method, including the bin size and mapping resolution, and the model used to describe spatial and seasonal variations of the binned drifter observations [Eqs. (2.3) and (2.5)]. Using optimal parameters for the decomposition, the resulting statistical properties of the circulation are compared against those obtained by other decomposition methods available in literature, confirming that it produces mean fields with magnitudes and horizontal scales closer to time-averaged Eulerian observations than other techniques. It was also examined how the formal standard errors inferred from the analysis compare with the actual errors calculated relative to reference Eulerian estimates, which showed that the standard errors underestimated the real errors by a factor of almost two. Finally, the application of the improved
decomposition method developed in this study to slip-corrected velocity observations from both drogued and undrogued GDP drifters allowed resolving details of the time-mean circulation not well defined in previous drifter-based assessments, such as the cross-stream structure of western boundary currents, recirculation cells, and zonally-elongated mid-ocean striations. The consistency of the obtained statistical properties of the near-surface flow support the viability of using the proposed methods to calculates the air-sea fluxes of mechanical energy using the GDP dataset.

Another significant observational challenge for the analysis proposed in this dissertation regards how to isolate mesoscale SST-driven anomalies in the near-surface winds. In literature, the effect is usually analyzed via linear regressions between SST and 10-m wind speed estimates, preliminarily filtered in both space and time to isolate the scales of interest. However, the adopted filter cutoff scales vary significantly between studies and are often defined empirically, implying that the intrinsic spatial-temporal scales of the coupling are still not well established. Furthermore, considering that oceanic and atmospheric phenomena occur along a broadband continuum in both wavenumber and frequency spaces, then variability in both systems arising in response to air-sea coupling mechanisms should also display a spectral structure, characteristic that have not been explored by previous studies. Last, the role of the mesoscale eddy field in conditioning the observed SST/$w$ coupling characteristics relative to that of larger scale ocean phenomena, such as Rossby waves and near-stationary extratropical SST fronts, is still unclear.

These questions are addressed in Chapter 3, where cross-spectral methods are first used to characterize the linear spectral relationship between SST and equivalent-neutral 10-meter wind speed ($w$) fields obtained from satellite products at scales
between $10^2$–$10^4$ km and $10^3$–$10^3$ days. The results of the spectral analysis indicated that negative SST/$w$ correlations at large spatial scales transition to positive at the ocean mesoscales at wavelengths coinciding with the atmospheric first baroclinic Rossby radius of deformation ($R_1$). The negative correlations are thought to reflect an atmospheric control of SST via the dependence of turbulent heat fluxes on the strength of the prevailing winds, where the shift to positive over oceanic mesoscale ranges is indicative that this mechanism becomes secondary to the SST-driven modulation of the wind speed via boundary layer dynamics. The dispersion characteristics of positively-correlated SST/$w$ signals at the ocean mesoscales is compatible with that predicted for tropical instability waves near the equator, and for Rossby waves in the extratropics. However, recent studies observed that a significant fraction of the variability in SSH, surface currents, and chlorophyll previously ascribed to the action of Rossby waves was actually attributable to coherent ocean eddies, conclusion likely also applicable to the copropagating SST/$w$ signals revealed by the cross-spectral analysis.

Thus, to investigate the role of coherent ocean eddies in mediating the SST-driven coupling relative to that of Rossby waves, both the SST and $w$ fields are preliminarily high-pass filtered in order to isolate signals with mesoscale dimensions, which are used to derive transfer functions describing the spectral linear SST/$w$ relationship in frequency space. The transfer functions are then evaluated in physical space using SST observations to estimate the SST-driven wind speed anomaly ($w_c$), a signal found to explain between 5-40% of the mesoscale $w$ variance in the equatorial cold tongues, and 2-25% at extratropical SST fronts. Using parameters of coherent ocean eddies detected in the altimeter record (Chelton et al. 2011), it is found that the signature
of this phenomena is clearly visible in $w_c$, accounting for 20-60% of its variability in eddy-rich regions.

The cross-spectral analysis is repeated using the outputs of two simulations from the Community Climate System Model Version 4.0 (CCSM4) configured to the contrasting ocean grid resolutions of 1° (eddy-parameterized, LR) and 0.1° (eddy-resolving, HR), with the objective of gaining further insight on the importance of the mesoscale eddy field for conditioning the spectral linear SST/$w$ relationship revealed by satellite observations. It is found that both the LR and HR simulations are able to reproduce the negative SST/$w$ correlations at scales larger than the atmospheric $R_1$, however the transition to positive correlations over the oceanic mesoscale ranges is only realistically observed in HR, despite of the fact that the ocean resolution in LR is able to resolve the wavelengths both the satellite observations and the HR outputs show that SST is able to explain the largest fraction of the $w$ variance. This result indicates that ocean variability with wavelengths between about 20–250 km, unresolved by the LR simulation and typical of coherent ocean eddies, are critical for conditioning the spectral linear SST/$w$ relationship observed at the ocean mesoscales.

Although the improvements promoted by the use of an eddy-resolving ocean resolution for simulating the SST-driven air-sea coupling are encouraging, the HR simulation was found to underestimate the boundary layer response to mesoscale SST forcing, while significantly overestimating the $w_c$ variability, the latter associated with a larger SST variance in the model output than implied by observations. It is theorized that the large mesoscale SST variability resolved by the HR is associated with a $-3$ power law followed by its $w$ power spectral density computed as a function of zonal wavenumber at the ocean mesoscales, in contrast with the $-5/3$ shown by satellite
observations, which leads to a significantly smaller $w$ variance over mesoscale ranges. This can potentially induce (a) a smaller current-driven damping of the oceanic eddy field (effect further discussed in Chapter 4), and/or (b) a reduction on the wind-driven modulation of the turbulent heat fluxes at the ocean mesoscales; both effects resulting in an enhanced mesoscale SST variability driven by ocean phenomena. It is noted that recent numerical experiments using the CCSM4 configured to an eddy-resolving ocean resolution by Kirtman et al. (2017), performed by coupling the ocean to the averaged output of multiple atmospheric components in order to reduce the effects of random atmospheric noise (technique known as interactive ensemble, IE), also enhanced the obtained SST variability relative to their control run. Considering that the IE reduces the fraction of the mesoscale $w$ variance that is uncorrelated with the eddy variability, the results of Kirtman et al. (2017) are thought to support the second hypothesis, although further investigation is necessary to draw firm conclusions. These considerations suggest that research is necessary to better understand how the SST balance is maintained throughout its spatial-temporal continuum of variability, whose results would help guiding future climate model developments aimed to improve how the SST-driven air-sea coupling is resolved.

In Chapter 4, the methods employed for the correction of undrogued drifter slip bias and the decomposition of drifter observations into mean and time-dependent components described in Chapter 2, and the satellite-based estimates of the mesoscale SST-driven wind speed anomalies ($w_c$) obtained using the procedure developed in Chapter 3, are used to achieve the main objectives of this work. Here, concurrent drifter, altimeter, and scatterometer observations are used to analyze the air-sea flux of mechanical energy associated with the full subinertial surface ocean velocity field
(referred to as total energy flux, $P_t$), and its Ekman and geostrophic components ($P_e$ and $P_g$, respectively), each further expanded into mean, seasonal, and fluctuating components.

The obtained $P_t$ values yield a time-averaged, globally-integrated value of 2.14 terawatts ($1 \text{ TW} = 10^{12} \text{ W}$), partitioned as 1.15 TW in $P_e$, and 0.99 TW in $P_g$. In particular, the obtained $P_e$ results expand on those of previous studies based on numerical and reanalysis model data (Wang and Huang 2004; Von Storch et al. 2007) by providing fully observational-based estimates of this quantity. However, considering the vertical shear of Ekman currents predicted by theoretical solutions, the nominal sampling depth of the slip-corrected GDP drifter data at 15-m depth imply that the empirical Ekman velocity vectors, inferred from drifter and scatterometer observations, likely underestimate the magnitude and display a wider veering angle relative to the actual velocity vector at the surface. Thus, the drifter-based $P_e$ estimates obtained in this study likely underestimate the actual energy fluxes taking place at the surface.

Accounting for this shear bias requires an understanding of the upper ocean stratification in order to extrapolate the Ekman velocities inferred at 15-m to the surface. Elipot and Gille (2009a, 2009b) approached this problem by comparing the GDP drifter motion against theoretical Ekman models formulated in frequency space, although their estimates were likely biased by measurements from undrogued instruments thought to have their drogues still attached (Grodsky et al. 2011; Lumpkin et al. 2013). Nevertheless, recent results by Laxague et al. (2017) suggest an intense vertical shear between the flow on the first centimeters of the water column and that observed at $O[1 \text{ m}]$ or larger, which appear to be at odds with the typical assumptions
adopted by theoretical Ekman models of matching the turbulent stress at the surface with the wind stress, and of using a constant vertical viscosity within the Ekman layer, thus raising questions on how the momentum imprinted at the ocean surface by the wind stress actually drives the Ekman circulation. These considerations suggest that the $P_e$ results obtained in this study correspond to lower-bound estimates of the actual wind power input to the Ekman circulation, and that accurately assessing this quantity at global scales remains a significant observational challenge.

Due to the smaller vertical shear expected for geostrophic currents, greater confidence exists in the $P_g$ results. The spatial distribution, magnitudes, and global integral of the obtained values agree well with previous altimeter-based estimates (Wunsch 1998; Huang et al. 2006; Hughes and Wilson 2008; Xu and Scott 2008; Scott and Xu 2009). However, while the assessments using altimeter observations indicate that almost all of the $\sim 1$ TW mechanical power provided by the winds comes from the product between the time-mean geostrophic current and wind stress fields, with the covariances between both quantities impacting $P_g$ by less than 5%, the drifter-based estimates obtained in this study reveal that the time-mean component of $P_g$ integrates to 1.22 TW, the covariance between seasonal fluctuations in wind stress and the geostrophic currents to 0.05 TW, and the covariance between the eddy residuals of both quantities to $-0.23$ TW. Cross-terms integrate to $-0.05$ TW, mainly arising from cross-covariances between the spatial component of wind stress and currents artificially introduced by the inhomogeneous drifter sampling. These results indicate that, of the total mechanical power supplied by the winds to the general ocean circulation via the time-mean and seasonal components of $P_g$, about
19% of it is lost back to the atmosphere via the air-sea fluxes of mechanical energy associated with the quasi-geostrophic ocean variability.

To test whether the observed negative covariances can arise from the wind stress dependency on surface currents and/or on SST-driven wind anomalies, the impact of each effect to the air-sea fluxes of mechanical energy is estimated (a) using theoretical expressions derived to predict their magnitude, and (b) by using drifter velocity measurements and satellite-based $w_c$ estimates to directly remove such dependencies from the scatterometer wind stress estimates, which are then used to recompute the air-sea fluxes of mechanical energy. The results of both approaches are consistent, and indicate that virtually all the negative energy flux associated with the quasi-geostrophic variability can be ascribed to the influence of ocean currents on wind stress. This result supports the conclusions of recent regional, high-resolution coupled numerical experiments (Eden and Dietze 2009; Seo et al. 2016; Renault et al. 2016; Seo 2017; Renault et al. 2017), which further demonstrate that the mechanical energy fluxes out of the ocean induced by the current-driven air-sea coupling exert a net damping effect on the mesoscale eddy field, ultimately reducing the EKE by fractions between 10–50%.

Regarding the influence of the SST-driven coupling, this analysis revealed that the effect exerts a detectable influence on the energy fluxes and produces well-defined large-scale patterns, with positive energy fluxes coinciding with the ACC, Agulhas Return Current, the cold tongue in the Equatorial Pacific, and the seaward extensions of the Kuroshio and Gulf Stream Currents, and negative fluxes more prominently observed associated with the subtropical gyres. These spatial features are interpreted as arising from the interaction of the wind velocity component normal to the direction
of the large-scale background SST gradients, with the $w_c$ signal forced by the dipolar SST anomaly structure created via horizontal advection by coherent ocean eddies. However, the magnitude of the SST-driven effect was found to be, on average, about 30 times smaller than that induced by ocean currents. This secondary role of SST in mediating the mechanical energy fluxes was observed in recent high-resolution, fully-coupled numerical experiments (Seo et al. 2016; Renault et al. 2016; Seo 2017), however they contrast with the conclusions drawn from simulations performed by Jin et al. (2009) that it could disrupt the evolution of the eddy field in a idealized representation of the California Current System (CCS), reducing the EKE by about 25%, and by Byrne et al. (2016) for the South Atlantic sector of the ACC, which concluded that the SST-driven coupling would not only fully counteract dissipative effect of current-driven effect, but also enhance the energy uptake by geostrophic eddies, increasing EKE by 10%. It is noted that the sign of the energy flux variation induced by $w_c$ inferred in this study for the CCS and the ACC agree with that obtained by Jin et al. (2009) and Byrne et al. (2016). One possibility for the strong feedbacks to the eddy variability observed by these studies would be an enhanced SST variance resolved in their simulations, that would lead also to a larger $w_c$ variability, similar to what was observed for the HR CCSM4 simulation described in Chapter 3.

Finally in Chapter 4, looping drifter trajectories detected in the GDP dataset are used to analyze potential asymmetries between the air-sea fluxes of mechanical energy associated with cyclonic and anticyclonic ocean eddies suggested by previous studies (Jin et al. 2009; Byrne et al. 2016; Xu et al. 2016). Results indicate that horizontal gradients of large-scale winds can generate an asymmetry on the mechanical power exchange between the hemispheres of near-circular eddies, meaning that
cyclonic winds tend to inject mechanical power to cyclonic eddies while damping anticyclonic eddies, and vice versa. This agrees with conclusions drawn from altimeter observations (Xu et al. 2016), however the results obtained using drifter data show a factor of two larger response to this mechanism. It has the same order of magnitude as the current-driven effect, and their combination suggest that the atmosphere can actually energize anticyclonic eddies within the subtropical gyres, and energize cyclonic eddies in the Arctic and Southern Oceans poleward of about 50° latitude.

To summarize, this dissertation initially focused in advancing the methods for estimating statistical properties from the spatially and temporally inhomogeneous drifter measurements, and for analyzing the linear relationship between oceanic and atmospheric variability arising in response to the interaction between both mediums. The techniques that emerged from these studies enabled the use of drifter and satellite observations for estimating the air-sea exchange of mechanical power at global scales, in particular that associated with the quasi-geostrophic ocean variability. The obtained results further support the conclusion of recent numerical experiments that the current-driven air-sea coupling constitutes a non-negligible sink of kinetic energy for the oceanic quasi-geostrophic variability, and indicate that, albeit detectable, the SST-driven air-sea coupling exerts a secondary role in the ocean energetics. Further developments of this research will involve the calculation of cross-spectral statistics between scatterometer and along-track altimeter data, with the objective of determining the intrinsic spatial-temporal scales where the current-driven negative energy fluxes take place and the spatial variability of this relationship; and the evaluation of a potential link between the air-sea fluxes of mechanical energy inferred for the
quasi-geostrophic ocean variability with the time-scales of coherent eddies detected in altimeter data.
APPENDICES

A Calculating \( w \) from CCSM4 wind stress data

As the CCSM4 model currently cannot save the equivalent-neutral 10-m wind speed \( (w) \) in its output files, this parameter is estimated from the model’s wind stress data by solving a cubic equation defined from the CCSM4 air-sea flux parameterization expressions. Specifically, the model calculates wind stress using a traditional bulk formulation, where an expression for the wind stress magnitude \( (\tau) \) can be written as:

\[
\tau = \rho_a c_d w^2, \quad (A.1)
\]

where \( \rho_a \) is the surface atmospheric density, and \( c_d \) is the equivalent-neutral drag coefficient at 10-m. The latter is parameterized as:

\[
c_d = a w + b + \frac{c}{w}, \quad (A.2)
\]

where \( a = 7.64 \times 10^{-5} \) m\(^{-1}\), \( b = 1.42 \times 10^{-4} \), and \( c = 2.7 \times 10^{-3} \) m.s\(^{-1}\) are empirical coefficients (Large and Yeager 2004). Considering that \( \tau \) is known, and assuming a constant \( \rho_a = 1.225 \) kg/m\(^3\), a cubic equation for \( w \) can be obtained by substituting \( (A.2) \) in \( (A.1) \):

\[
aw^3 + bw^2 + cw - \frac{\tau}{\rho_a} = 0. \quad (A.3)
\]
For any ratio $\tau/\rho_a$, Eq. (A.3) have two complex conjugate roots (without physical meaning), and one real root. By preliminarily defining the parameters $\Delta_0$, $\Delta_1$, and $C$ as:

\[
\Delta_0 = b^2 - 3ac, \quad (A.4a)
\]
\[
\Delta_1 = 2b^3 - 9abc - 27a^2 \frac{\tau}{\rho_a}, \quad (A.4b)
\]
\[
C = \sqrt[3]{\frac{1}{2} \left( \Delta_1 + \sqrt[3]{\Delta_1^2 - 4\Delta_0^3} \right)}, \quad (A.4c)
\]

the general solution for the real root can then be expressed as:

\[
w = -\frac{1}{3a} \left( b + C + \frac{\Delta_0}{C} \right). \quad (A.5)
\]

B Theoretical expressions for the impact of current and SST-driven air-sea coupling to $P_t$

Duhaut and Straub (2006) derived an expression to predict the change in the time-averaged air-sea mechanical energy flux $P_t$ induced by the dependence of wind stress on ocean currents, that was extended in Hughes and Wilson (2008) to account for the fact that the equivalent-neutral drag coefficient $c_d$ used to calculate wind stress is not constant, but varies as a function of the magnitude of the equivalent-neutral 10-m wind velocity vector [Eq. (4.2)]. This study uses the formulation of Hughes and Wilson (2008) to predict the impact of the current effects in $P_t$ estimates obtained using concurrent drifter and satellite measurements, and further proposes a theoretical relation to estimate the change in $P_t$ induced by the SST-driven air-sea coupling in the same datasets. The derivation of both expressions is detailed in the following.
As discussed in Section 4.2.3.3, the scatterometer measurements of equivalent-neutral 10-m wind velocities (\(w\), with magnitude \(w\)) include the signatures of both the ocean current velocities (\(u_t\), magnitude \(u_t\)) and of the SST-driven wind velocity anomalies (\(w_c\), denoted as \(w'_c\) in along-wind coordinates). Thus, scatterometer-based estimates of the wind stress vector (\(\tau\), magnitude \(\tau\)) including the dependence on both currents and SST can be obtained as

\[
\tau = w F(w),
\]

where \(F(w) = \rho_a c_d w\). Using \(u_t\) and \(w_c\) measurements, \(\tau\) estimates without the dependence on ocean currents (\(\tau_{nc}\)) and without the dependence on the SST-driven wind anomalies (\(\tau_{nt}\)) can be computed as

\[
\tau_{nc} = (w + u_t) F(w + u_t), \quad \text{and}
\]

\[
\tau_{nt} = (w - w_c) F(w - w'_c).
\]

To obtain an expression for the impact of ocean currents on \(P_t\), instantaneous energy flux estimates calculated using \(\tau\) are first subtracted from results obtained using \(\tau_{nc}\), as

\[
P^i_t - P^i_{nc} = u_t (\tau - \tau_{nc}),
\]

Substituting (B.1) and (B.2) in (B.4) leads to

\[
P^i_t - P^i_{nc} = -(u_t \cdot w) [F(w + u_t) - F(w)] - u_t^2 F(w + u_t).
\]

Assuming that \(u_t \ll w\), then \(w\) should be predominantly affected by the along-wind component of the near-surface current velocity vector (\(u_0\)), implying that \(w + u_t \approx w + u_0\) and \(u_t \cdot w \approx u_0 w\). It also indicates that \(F(w + u_0)\) can be approximated
as $F(w) + u_0(∂F(w)/∂w)$. Applying these to (B.5) gives:

$$P_i^i - P_{nc}^i \approx -u_0^2 w \frac{∂F(w)}{∂w} - u_t^2 F(w) - u_t^2 u_0 \frac{∂F(w)}{∂w} . \quad (B.6)$$

A scaling analysis indicates that the last term in the right-hand side of (B.6) is between two and three orders of magnitude smaller than the leading term, and it is thus neglected. The resulting formulation is then ensemble-averaged for the obtention of the time-averaged fluxes, compatibilizing it with the pseudo-Eulerian estimates obtained in this study, leading to

$$P_{curr} = \langle \mathbf{u}_t \cdot \tau \rangle - \langle \mathbf{u}_t \cdot \tau_{nc} \rangle \approx -\left\langle u_0^2 w \frac{∂F(w)}{∂w} \right\rangle - \langle u_t^2 F(w) \rangle . \quad (B.7)$$

Similarly, an expression for the impact of the SST-driven air-sea coupling to $P_t$ is obtained by subtracting instantaneous power flux estimates calculated using $\tau$ and $\tau_{nt}$ from each other, as

$$P_i^i - P_{nt}^i = \mathbf{u}_t (\tau - \tau_{nt}) . \quad (B.8)$$

Using (B.1) and (B.3) in (B.8) gives

$$P_i^i - P_{nt}^i = (\mathbf{u}_t \cdot \mathbf{w}) [F(w) - F(w - w'_c)] + (\mathbf{u}_t \cdot \mathbf{w}_c) F(w - w'_c) . \quad (B.9)$$

where $\mathbf{u}_t \cdot \mathbf{w} = u_t w \cos \theta$, and $\mathbf{u}_t \cdot \mathbf{w}_c = u_t w_c \cos \theta$, with $\theta$ corresponding to the angle between the vectors $\mathbf{u}_t$ and $\mathbf{w}$. Approximation $F(w - w'_c)$ by $F(w) - w'_c(∂F(w)/∂w)$ gives

$$P_i^i - P_{nt}^i \approx u_t w'_c \cos(\theta - w'_c) \frac{∂F(w)}{∂w} + u_t w'_c \cos \theta F(w) . \quad (B.10)$$

Finally, considering that $|w'_c| \ll w$ and taking an ensemble average, Equation (B.10) becomes

$$P_{sst} = \langle \mathbf{u}_t \cdot \tau \rangle - \langle \mathbf{u}_t \cdot \tau_{nc} \rangle \approx \left\langle u_t w w'_c \cos \theta \frac{∂F(w)}{∂w} \right\rangle + \langle u_t w'_c \cos \theta F(w) \rangle . \quad (B.11)$$
References


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