

The Temporal Autocorrelation Structure of Sea Surface Winds

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Abstract

The temporal autocorrelation structures of sea surface vector winds and wind speeds are considered. Analyses of scatterometer and reanalysis wind data demonstrate that the autocorrelation functions (acf) of surface zonal wind, meridional wind, and wind speed generally drop off more rapidly in the middle latitudes than in the low latitudes. Furthermore, the meridional wind component and wind speed generally decorrelate more rapidly than the zonal wind component. The anisotropy in vector wind decorrelation scales is demonstrated to be most pronounced in the storm tracks and near the equator, and to be a feature of winds throughout depth of the troposphere. The extratropical anisotropy is interpreted in terms of an idealised kinematic eddy model as resulting from differences in the structure of wind anomalies in the directions along and across eddy paths. The equatorial anisotropy is interpreted in terms of the kinematics of large-scale equatorial waves and small-scale convection. Modelling the vector wind fluctuations as Gaussian, an explicit expression for the wind speed acf is obtained. This model predicts that the wind speed acf should decay more rapidly than that of at least one component of the vector winds. Furthermore, the model predicts a strong dependence of the wind speed acf on the ratios of the means of vector wind components to their standard deviations. These model results are shown to be broadly consistent with the relationship between the acfs of vector wind components and wind speed, despite the presence of non-Gaussian structure in the observed surface vector winds.

1 Introduction

Ocean winds are an important component of the global climate system, influencing (and being influenced by) surface fluxes of momentum, energy, and mass (e.g. Taylor, 2000; Jones and Toba, 2001; Donelan et al., 2002). As well, sea surface winds represent a potentially significant energy resource (e.g. Liu et al., 2008; Capps and Zender, 2009). Until recently, statistical characterisations of surface winds across the global ocean were not possible on fine space and time scales. Buoy-mounted anemometers measure wind at fine temporal resolution (e.g. 10-minute or hourly), but are virtually absent throughout most of the open ocean. In contrast, ship-based observations provide larger-scale coverage, but the transience of the observation platform and the concentration of ship tracks along major shipping routes result in only a small number of observations in a typical fine-scale domain (e.g. a $1^\circ \times 1^\circ$ box) within any typical month (e.g. Monahan, 2006a; Risien and Chelton, 2008). Furthermore, these ship-based estimates are heterogeneously distributed in space and time even within any such domain, complicating estimates of the temporal structure of surface wind variability on sub-monthly timescales.

With the advent of remotely sensed observations of vector winds, it has become possible to characterise global surface wind statistics on fine scales in space ($1^\circ \times 1^\circ$ or finer) and time (daily or finer). For example, global-scale 25-km resolution climatologies of surface wind stresses, along with their divergence and curl, were presented in Chelton et al. (2004) and Risien and Chelton (2008). These analyses produced a spatially high-resolution characterisation of large-scale wind forcing and revealed fine details in the surface flow resulting from local scale air-sea interactions. Sampe and Xie (2007) produced a global climatology of the frequency of high wind speeds (exceeding 20 ms^{-1}), relating maxima in occurrence frequency to the influence of large-scale dynamics and local surface stability and orographic effects. Chavas and Emanuel (2010) used scatterometer winds to develop a climatology of

tropical cyclone size. The first global-scale characterisation of the probability distribution function of day-to-day fluctuations in sea surface winds (both vector and wind speed) was presented in Monahan (2006a). This analysis revealed the existence of large-scale structure in the shapes of the probability distributions of the vector winds and wind speed, which could be understood mechanistically using an idealised model of the boundary layer momentum budget (Monahan, 2004, 2006a, 2007).

These earlier studies focused on the spatial fields of instantaneous, one-point temporal statistics of the surface winds and their spatial derivatives: means, standard deviations, and higher-order moments. Relatively little attention has been paid to the temporal autocorrelation structure of surface winds, although the rate at which fluctuations decorrelate is a basic feature of wind variability. For example, the memory of surface wind fluctuations plays an important role in determining their statistical predictability and in characterising the averaged features of air-sea exchanges (e.g. Monahan and Culina, 2011). The autocorrelation function (acf) of the time-evolving quantity z_t is defined as the correlation of the process with itself at different times:

$$c(t, s) = \text{corr}(z_t, z_{t+s}). \quad (1)$$

The acf is independent of the base time point t if the statistics are stationary. In this case, the acf depends only on the lag s . The rate at which $c(t, s)$ decreases with increasing $|s|$ is a measure of the memory of fluctuations in z_t .

In an analysis of sampling errors associated with scatterometer surface wind observations, Schlax et al. (2001) computed the acf of the zonal and meridional wind components at a number of locations in the western North Pacific Ocean. It was shown that the vector wind components in this region decorrelate with a timescale on the order of a few days, such that the acf of the meridional wind component decays much more quickly than that of the zonal wind component. Gille (2005), computing frequency spectra of remotely sensed and

reanalysis vector wind stresses averaged zonally over 5° latitude bands, found that spectral slopes are relatively shallow in the subtropics and high latitudes and relatively steep in the middle latitudes. Furthermore, Gille (2005) found that the meridional wind stresses tend to have shallower slopes than the zonal wind stresses, particularly in the extratropics. Shallower spectra imply proportionally larger contributions from high-frequency variability and therefore are associated with shorter autocorrelation times. We are not aware of any global-scale characterisations of the temporal autocorrelation structure of surface winds, considering both meridional and zonal variations, or of systematic comparisons between the autocorrelation structure of the vector wind components and wind speed.

The relatively limited number of studies of the temporal autocorrelation structure of winds contrasts strongly with the considerable amount of effort that has been directed towards characterising and understanding the spatial autocorrelation structure of winds, in terms of the spatial power spectrum. Particularly since the work of Nastrom and Gage (1985), a number of theoretical and observational studies have considered the spatial power spectrum of free-tropospheric winds; this analysis has recently been extended to surface winds by Xu et al. (2011). Although wavenumber and frequency spectra are simply related for flow that is statistically stationary in time and spatially homogeneous, no such simple connection exists for large-scale surface winds because the vector wind statistics are spatially inhomogeneous.

The goals of the present study are to characterise the lag acfs of sea surface vector wind components and wind speed on global scales, to investigate the relationships between these, and to develop idealised models of these relationships. This analysis makes use of wind data from both the SeaWinds scatterometer and from reanalysis products. Scatterometer winds are obtained from remotely sensed observations of surface wind stress, translated to 10-m winds assuming neutral stratification; the reanalysis winds are obtained by assimilating observations into a numerical forecast model. While the scatterometer data have the benefit of

being closer to direct observations of surface winds than wind data from reanalysis products, reanalyses allow consideration of winds over longer time periods and at levels above 10 m. In fact, we will demonstrate that for the statistical quantities being considered in this study, the scatterometer and reanalysis datasets are similar in their essential features (as has been found to be the case for the wind moments; e.g. Monahan, 2006b).

Autocorrelation maps at lags of 1, 2, and 3 days for zonal wind, meridional wind, and wind speed computed from the SeaWinds data (and assuming temporally stationary statistics) are displayed in Figure 1. These maps are not substantially different if the acf is computed separately in different seasons. Inspection of these maps reveals three particularly noteworthy features. First, there is considerable spatial variability in how rapidly the acfs decay: in general, autocorrelation values decrease faster in the middle latitudes than in the tropics and subtropics. Second, values of the wind speed autocorrelations are generally smaller than the larger of the zonal wind or meridional wind autocorrelation values. Third, the lag autocorrelation function is strongly anisotropic in the extratropics: in general, fluctuations in the meridional wind component generally have shorter memory than those in the zonal wind component. This last fact demonstrates that the vector wind acf anisotropy noted in the North Pacific by Schlax et al. (2001) is present across much of the ocean. As well, this result is consistent relatively shallow midlatitude meridional wind stress spectral slopes found by Gille (2005).

The data used in this study are discussed in detail in Section 2. Section 3 presents a detailed discussion of the vector wind acf anisotropy and its physical origin. The relationship between the autocorrelation structure of wind speed and those of the vector wind components are discussed in the context of an idealized Gaussian model of vector wind fluctuations in Section 4. A discussion and conclusions follow in Section 5.

2 Data and Notation

The primary surface wind dataset considered in this study consists of level 3.0 gridded SeaWinds scatterometer equivalent neutral 10-m zonal and meridional winds between 60°S and 60°N from the NASA QuikSCAT satellite (Jet Propulsion Laboratory, 2001), available twice daily at a resolution of $0.25^\circ \times 0.25^\circ$ from 19 July 1999 to November 23 2009. These data are available for download from the NASA Jet Propulsion Laboratory (JPL) Distributed Active Archive Center <http://podaac-www.jpl.nasa.gov/dataset/QSCAT-LEVEL-3>. Those data points flagged as having been possibly corrupted by rain were excluded from the analysis. No further processing (e.g. seasonal stratification or time averaging) of the dataset was carried out.

We also consider winds at 10 m and on a number of pressure levels from the European Centre for Medium-Range Weather Forecasting (ECMWF) ERA-40 Reanalysis, available from http://data-portal.ecmwf.int/data/d/era40_daily/. Relative to the SeaWinds data, the reanalysis winds are of long duration and high temporal resolution (45 years at 6-hourly resolution from 1957 to 2002). The spatial resolution of the ERA-40 winds is relatively coarse ($2.5^\circ \times 2.5^\circ$). As with the SeaWinds data, no further processing of these data was carried out.

Throughout this study, u and v will denote generic orthogonal horizontal vector wind components. The precise alignment of these components will be arbitrary, unless specifically noted. Zonal and meridional wind components will be denoted by U and V respectively. The wind speed will be denoted by $w = \sqrt{u^2 + v^2} = \sqrt{U^2 + V^2}$.

3 Anisotropy in Vector Wind Autocorrelation Structure

While the anisotropy in the vector wind acf is evident in the zonal and meridional wind autocorrelation structures (Figure 1), the maximum and minimum vector wind lag correlations at any particular point are not generally aligned along these latitude-longitude axes. A more complete characterisation of the magnitude and distribution of this anisotropy follows from considering vector wind components in all compass directions:

$$u(\theta) = U \cos \theta + V \sin \theta, \quad (2)$$

for values of θ ranging between 0° and 180° . From these vector wind components the one-day lag autocorrelation values were determined:

$$c_1(\theta) = \text{corr}(u_t(\theta), u_{t+1}(\theta)), \quad (3)$$

and from these the angles θ_{max} and θ_{min} of the largest and smallest one-day lag correlations were found. The difference between these correlations is measured by the ratio

$$R_1 = \frac{c_1(\theta_{min})}{c_1(\theta_{max})}. \quad (4)$$

A map of R_1 over the global ocean for the SeaWinds data is presented in Figure 2. The vector wind acf anisotropy is weakest in the subtropics and the high latitudes, where the value of R_1 is generally close to one. Elsewhere, R_1 is considerably less than one, particularly in the Atlantic-Indian Ocean sectors of the Southern Ocean; across the equatorial Pacific and Atlantic Oceans; and over the subpolar North Atlantic and Pacific oceans. The lowest values of R_1 , found in the Southern ocean, are below 0.2. The orientation of the maximum

one-day vector wind lag autocorrelation, θ_{max} , is primarily zonal in the midlatitude open ocean (Figure 3). Throughout the tropics and high latitudes, and near coastlines, θ_{max} takes a strong meridional orientation at many locations.

This acf anisotropy is characteristic not just of surface winds, but extends for winds throughout the troposphere. Maps of R_1 from 1000 hPa to 200 hPa computed from the ERA-40 reanalysis winds (Figure 4) demonstrate that in general throughout the midlatitudes, the acf anisotropy is strongest near the surface and decreases gradually with increasing altitude. In contrast, the acf anisotropy in the tropics is strongest between 850 and 700 hPa and is negligible above the mid-troposphere. The R_1 field computed from the ERA-40 1000 hPa winds compares favourably with that computed from the SeaWinds observations, in terms of both spatial distribution and magnitude, as does the R_1 field computed from the ERA-40 10-m winds (not shown). This lag autocorrelation anisotropy is not an artifact of either dataset.

The extratropical vector wind lag acf anisotropy is strongest in the storm tracks, in which variability is strongly influenced by the propagation of coherent synoptic-scale eddies (e.g. Jones and Simmonds, 1993; Hoskins and Hodges, 2002, 2005; Lim and Simmonds, 2007; Dos Santos Mesquita et al., 2008). As a storm passes a particular location, the character of wind anomalies is different in the along- and across-track directions. For a cyclonic eddy in the Northern Hemisphere, assuming circular symmetry for simplicity, the temporal profile of anomalous along-track winds will be monopolar: always westerly if the storm passes to the north of the given point and always easterly otherwise. In contrast, the anomalous across-track winds will be a dipole in time: first southerly, then switching to northerly as the centre of the storm passes. It follows that the winds in the across-track direction display more rapid changes than do those in the along-track direction. In the presence of a population of such storms with a preferred direction of motion, such as is characteristic of eddies in the storm track, this asymmetry will imprint itself on a corresponding anisotropy in the vector wind

lag acf structure.

The lag autocorrelation anisotropy associated with propagating synoptic scale systems can be quantified using an idealised kinematic model in which it is assumed that the vector wind variability is dominated by the passage of circularly-symmetric Gaussian eddies with specified strength, width, and propagation speed and direction, embedded in a uniform large-scale flow (Appendix A). With the further simplifying approximation that all eddies are of the same size and propagate at the same speed, the lag acfs of the along- and across-track winds (respectively u and v) can be shown to be

$$\text{corr}(u_t, u_{t+s}) \simeq \exp \left\{ -\frac{s^2}{\tau^2} \right\} \quad (5)$$

$$\text{corr}(v_t, v_{t+s}) \simeq \exp \left\{ -\frac{s^2}{\tau^2} \right\} \left(1 - 2\frac{s^2}{\tau^2} \right), \quad (6)$$

where the eddy passage timescale τ is given by the eddy width divided by its propagation speed. Plots of these functions are presented in Figure 5; clearly, the vector wind acf falls off more rapidly in the across-track direction than in the along-track direction. The model predicts that the lag acf in the across-track direction should be negative over a range of lags; the extent of this range and minimum value taken by $\text{corr}(v_t, v_{t+s})$ will decrease as the contribution to the wind variance from other “residual” variability becomes larger (Appendix A).

The idealised kinematic eddy model predicts that the vector wind lag acf anisotropy should be concentrated where the wind variance is dominated by propagating storms, that it should be oriented along the preferred direction of storm propagation, and that its magnitude should depend on the propagation speeds of storms relative to their sizes. In broad terms, these predictions are consistent with the observed midlatitude lag acf anisotropy. In the Northern Hemisphere extratropics, the surface anisotropy is strongest in the Pacific and Atlantic storm tracks where storm track density and intensity are the greatest (e.g. Hoskins

and Hodges, 2002; Dos Santos Mesquita et al., 2008); the orientation, ranging from westward to northwestward, is consistent with the typical lower-tropospheric trajectories of synoptic scale eddies (e.g. Hoskins and Hodges, 2002). The anisotropy in the Southern Hemisphere extratropics is similarly concentrated in the storm track, and is most pronounced over the Atlantic and Indian Ocean sector of the Southern Ocean where eddy speeds are largest (e.g. Jones and Simmonds, 1993; Hoskins and Hodges, 2005; Lim and Simmonds, 2007). The orientation of the maximum lag autocorrelation varies from westward to southwestward, again consistent with the preferred tracks of storms (e.g. Jones and Simmonds, 1993). The decrease in the magnitude of the anisotropy with altitude (Figure 4) over the Southern Ocean is consistent with the observation that lower-tropospheric eddies are smaller and faster than those in the mid-troposphere (Lim and Simmonds, 2007).

While it is natural to model variability in the midlatitude winds in terms of propagating synoptic eddies, in the low latitudes it is more natural to model the winds in terms of equatorial wave propagation (e.g. Gill, 1982; Kiladis et al., 2009). We will assume that to a first approximation variability in the vector winds can be decomposed into contributions from two processes: large-scale, coherent variability associated with equatorial waves and small-scale, disorganized convective variability. This decomposition is synthetic, but useful. In particular, we assume that at any location we may write:

$$U(t) = \beta_U f_w(t) + \beta_c f_c(t) \quad (7)$$

$$V(t) = \beta_V f_w(t) + \beta_c f_c(t), \quad (8)$$

where β_U^2 and β_V^2 are the equatorial wave variances in the zonal and meridional directions, and β_c^2 is the convective variance (assumed to be isotropic). The quantities $f_w(t)$ and $f_c(t)$ are respectively the standard deviation-normalized time series of wave and convective variability such that by assumption $f_c(t)$ is uncorrelated with $f_w(t)$, $f_w(t)$ has a nonzero lag

autocorrelation

$$\mathbb{E} \{f_w(t), f_w(t+s)\} = g(s), \quad (9)$$

and $f_c(t)$ is temporally uncorrelated for lags on the order of a day or greater:

$$\mathbb{E} \{f_c(t), f_c(t+s)\} \simeq 0. \quad (10)$$

It follows that

$$\text{corr}(U_t, U_{t+1}) = \frac{\beta_U^2 g(1)}{\beta_U^2 + \beta_c^2} \quad (11)$$

$$\text{corr}(V_t, V_{t+1}) = \frac{\beta_V^2 g(1)}{\beta_V^2 + \beta_c^2}, \quad (12)$$

and

$$R_1 = \frac{\text{corr}(V_t, V_{t+s})}{\text{corr}(U_t, U_{t+s})} = \frac{\beta_V^2 (\beta_U^2 + \beta_c^2)}{\beta_U^2 (\beta_V^2 + \beta_c^2)}. \quad (13)$$

Throughout the tropics, equatorial wave variance is observed to be dominated by equatorial Kelvin waves and first mode equatorial Rossby waves (e.g. Figure 5 of Kiladis et al., 2009). For equatorial Kelvin wave disturbances, the meridional component of the perturbation wind is much smaller than the zonal component; for the equatorial Rossby waves, the two are of roughly the same size (e.g. Figs. 7, 17, 18 of Kiladis et al., 2009). It follows that we can reasonably assume that $\beta_V < \beta_U$, from which we obtain the result that $R_1 < 1$. Note that for fixed β_U , β_V , R_1 decreases for increasing β_c : the stronger the contribution from small-scale convection to the variance, the more any asymmetry in wave variability is manifest in R_1 . This result is consistent with the maps of R_1 illustrated in Figure 4: in the lower troposphere, R_1 is smallest in regions of active shallow convection while in the mid- to upper-troposphere it is smallest in regions of deep convection.

4 Wind Speed Autocorrelation Function

As noted in Section 1, a feature evident from inspection of the maps in Figure 1 is that that the wind speed acf $\text{corr}(w_t, w_{t+s})$ drops off faster than the acf of at least one of the vector wind components. In fact, $\text{corr}(w_t, w_{t+1})$ is found to be bounded above everywhere by $c_1(\theta_{max})$ in SeaWinds data (Figure 6): across the entire ocean, the wind speed acf decreases faster than the acf of the vector wind component with the longest memory. We will investigate the relationship between the acf structures of the vector wind components and the wind speed by considering an idealised model in which the vector winds are assumed to be bivariate Gaussian. While the vector winds are in fact known to display markedly non-Gaussian structure (particularly in the tropics and the Southern Ocean, Monahan, 2004, 2006a, 2007), approximating the vector wind fluctuations as Gaussian greatly simplifies the following calculations. Monahan (2011) demonstrates that such a model can provide useful insight into the correlation structure of wind speeds in spite of the neglect of vector wind non-Gaussianity.

Specifically, we suppose that the wind field temporal statistics are stationary and Gaussian, such that at time t_1 the vector components are (u_1, v_1) and at t_2 they are (u_2, v_2) . By the assumption of stationarity:

$$\text{mean}(u_1) = \text{mean}(u_2) = \bar{u} \quad (14)$$

$$\text{mean}(v_1) = \text{mean}(v_2) = \bar{v} \quad (15)$$

$$\text{std}(u_1) = \text{std}(u_2) = \sigma_u \quad (16)$$

$$\text{std}(v_1) = \text{std}(v_2) = \sigma_v \quad (17)$$

$$\text{corr}(u_1, v_1) = \text{corr}(u_2, v_2) = r. \quad (18)$$

Furthermore, we define the vector wind lag correlations

$$\text{corr}(u_1, u_2) = \rho_{uu} \quad (19)$$

$$\text{corr}(u_1, v_2) = \rho_{uv} \quad (20)$$

$$\text{corr}(v_1, u_2) = \rho_{vu} \quad (21)$$

$$\text{corr}(v_1, v_2) = \rho_{vv}. \quad (22)$$

By assumption, the joint distribution of u_1, v_1, u_2, v_2 is a four-dimensional Gaussian; the requirement that the correlation matrix be non-negative definite (i.e. that its determinant is not negative) imposes the following constraint on the correlation parameters:

$$\begin{aligned} (\rho_{uu}\rho_{vv} - \rho_{uv}\rho_{vu})^2 + (1 - r^2)^2 \geq & (\rho_{uu} - r\rho_{uv})(\rho_{uu} - r\rho_{vu}) + (\rho_{uv} - r\rho_{uu})(\rho_{uv} - r\rho_{vv}) \\ & + (\rho_{vu} - r\rho_{uu})(\rho_{uv} - r\rho_{vv}) + (\rho_{vv} - r\rho_{uv})(\rho_{vv} - r\rho_{vu}). \end{aligned} \quad (23)$$

Explicit calculation of the correlation between the speeds w_1 and w_2 from this model is difficult: the speed statistics do not simply partition into separate contributions from the statistics of u and v . This difficulty can be circumvented by making use of the fact that the lag correlation of the squared speed, $\text{corr}(w_1^2, w_2^2)$, takes a value very similar to that of the speed itself, $\text{corr}(w_1, w_2)$, and is considerably simpler to calculate. That the correlation structure of the squared wind speed should closely approximate that of the wind speed itself is demonstrated in Figure 7, using data from the SeaWinds observations. The value of the squared wind speed autocorrelation slightly underestimates that of the wind speed autocorrelation, but in general the differences between the two quantities are small. As a heuristic justification of the similarity between the values of $\text{corr}(w_1, w_2)$ and $\text{corr}(w_1^2, w_2^2)$,

note that

$$w^2 = (\text{mean}(w) + \text{std}(w)w')^2 = \text{mean}(w)^2 \left[1 + 2\frac{\text{std}(w)}{\text{mean}(w)}w' + \frac{\text{std}^2(w)}{\text{mean}^2(w)}w'^2 \right], \quad (24)$$

where

$$w' = \frac{w - \text{mean}(w)}{\text{std}(w)} \quad (25)$$

is a standardized variable with mean zero and unit variance. The size of the term proportional to w' in Eqn. (24) relative to that proportional to w'^2 scales as $\text{std}(w)/\text{mean}(w)$. For observed sea surface winds, this ratio is always less than one and is generally less than one half (Monahan, 2006a, 2011). It follows that the term linear in w' in Eqn. (24) will generally dominate the quadratic term and that to a first approximation fluctuations in w^2 should be proportional to fluctuations in w . A more detailed discussion of the relationship between $\text{corr}(w_1, w_2)$ and $\text{corr}(w_1^2, w_2^2)$ is presented in Monahan (2011).

As is shown in Appendix B, the squared wind speed correlation expressed in terms of the vector wind statistics is:

$$\text{corr}(w_1^2, w_2^2) = \frac{\frac{\sigma_u^2}{\sigma_v^2} \left[\rho_{uu}^2 + 2 \left(\frac{\bar{u}}{\sigma_u} \right)^2 \rho_{uu} \right] + \rho_{uv}^2 + \rho_{vu}^2 + 2 \left(\frac{\bar{u}}{\sigma_u} \right) \left(\frac{\bar{v}}{\sigma_v} \right) [\rho_{uv} + \rho_{vu}] + \frac{\sigma_v^2}{\sigma_u^2} \left[\rho_{vv}^2 + 2 \left(\frac{\bar{v}}{\sigma_v} \right)^2 \rho_{vv} \right]}{\frac{\sigma_u^2}{\sigma_v^2} \left[1 + 2 \left(\frac{\bar{u}}{\sigma_u} \right)^2 \right] + 2r^2 + 4 \left(\frac{\bar{u}}{\sigma_u} \right) \left(\frac{\bar{v}}{\sigma_v} \right) r + \frac{\sigma_v^2}{\sigma_u^2} \left[1 + 2 \left(\frac{\bar{v}}{\sigma_v} \right)^2 \right]}. \quad (26)$$

As discussed above, we make the approximation that

$$\text{corr}(w_1, w_2) \simeq \text{corr}(w_1^2, w_2^2). \quad (27)$$

Fields of the statistical quantities $\bar{u}, \bar{v}, \sigma_u, \sigma_v, \rho_{uu}, \rho_{uv}, \rho_{vu}, \rho_{vv}$, and r were determined for lags of one through three days from the SeaWinds data. From these, modelled fields of

$\text{corr}(w_1, w_2)$ were obtained from Eqns. (26) and (27); kernel density estimates of the spatial scatter between modelled and observed wind speed lag correlations are presented in Figure 8. The agreement between the modelled and observed values of $\text{corr}(w_1, w_2)$ is generally good. The modelled correlations are on average slightly smaller than those observed, but overall the relationship between modelled and observed correlations closely follows the 1:1 line.

It is evident from Eqn. (26) for the squared wind speed autocorrelation structure that the sizes of the terms involving the vector wind lag autocorrelations ρ_{uu}, ρ_{vv} relative to those involving the lag cross-correlations ρ_{uv}, ρ_{vu} depend on the asymmetry of the vector wind fluctuations through the factor σ_u/σ_v . As this factor becomes much greater than one, the lag autocorrelations ρ_{uu} become increasingly important. Similarly, as this factor becomes much less than one, the influence of ρ_{vv} on $\text{corr}(w_1, w_2)$ increases. When the fluctuations are approximately isotropic (as is observed over most of the world ocean; Monahan, 2007), all of the vector wind lag auto- and cross-correlations contribute to the wind speed autocorrelations on equal footings.

Furthermore, we see that the contributions of the vector wind lag auto- and cross-correlations relative to their squares depends on the relative magnitudes of the mean vector winds to the vector wind fluctuations, $\bar{u}/\sigma_u$ and $\bar{v}/\sigma_v$. When the mean vector winds are large relative to the associated standard deviations, the terms linear in the vector wind correlations are dominant in the expression for $\text{corr}(w_1, w_2)$ so the wind speed correlations are on the same order as those of the vector winds. Conversely, when the mean vector winds are small compared to the vector wind standard deviations, $\text{corr}(w_1, w_2)$ will scale with the square of the vector wind correlations and will therefore be smaller (in general substantially so).

To a good approximation, the surface vector wind fluctuations are isotropic ($\sigma_u \simeq \sigma_v \simeq \sigma$) and without cross-correlations ($\rho_{uv} \simeq \rho_{vu} \simeq r \simeq 0$) (e.g. Monahan, 2007). In this

approximation, Eqns. (26)-(27) reduce to

$$\text{corr}(w_1, w_2) \simeq \text{corr}(w_1^2, w_2^2) = \frac{\frac{1}{2}\sigma^2(\rho_{uu}^2 + \rho_{vv}^2) + \bar{u}^2\rho_{uu} + \bar{v}^2\rho_{vv}}{\sigma^2 + \bar{u}^2 + \bar{v}^2}. \quad (28)$$

Predictions of $\text{corr}(w_1, w_2)$ made with this approximation are shown in Figure 8 over top of those of the full Eqn. (26). Differences between the full model and the approximation Eqn. (28) are clearly small; the assumption of isotropic, uncorrelated fluctuations still yields a reasonable description of the relation between the wind speed lag correlation field and those of the vector wind components. In this approximation, we have:

$$\begin{aligned} |\text{corr}(w_1^2, w_2^2)| &= \left| \left(\frac{\sigma^2\rho_{uu} + 2\bar{u}^2}{(\sigma^2 + 2\bar{u}^2) + (\sigma^2 + 2\bar{v}^2)} \right) \rho_{uu} + \left(\frac{\sigma^2\rho_{vv} + 2\bar{v}^2}{(\sigma^2 + 2\bar{u}^2) + (\sigma^2 + 2\bar{v}^2)} \right) \rho_{vv} \right| \\ &\leq \left(\frac{\sigma^2 + 2\bar{u}^2}{(\sigma^2 + 2\bar{u}^2) + (\sigma^2 + 2\bar{v}^2)} \right) |\rho_{uu}| + \left(\frac{\sigma^2 + 2\bar{v}^2}{(\sigma^2 + 2\bar{u}^2) + (\sigma^2 + 2\bar{v}^2)} \right) |\rho_{vv}| \\ &\leq \max(|\rho_{uu}|, |\rho_{vv}|). \end{aligned} \quad (29)$$

That is, the value of the wind speed lag autocorrelation is predicted to be bounded above by the larger of the vector wind lag autocorrelation values, consistent with the observed correlation structures presented in Figures 1 and 6.

It is instructive to consider the limits of extremely large or small vector wind fluctuations (relative to the mean vector wind amplitude), first writing Eqn. (28) as

$$\text{corr}(w_1, w_2) \simeq \frac{\frac{1}{2}(\rho_{uu}^2 + \rho_{vv}^2)}{1 + \left(\frac{\bar{u}}{\sigma}\right)^2 + \left(\frac{\bar{v}}{\sigma}\right)^2} + \frac{\left(\frac{\bar{u}}{\sigma}\right)^2 \rho_{uu} + \left(\frac{\bar{v}}{\sigma}\right)^2 \rho_{vv}}{1 + \left(\frac{\bar{u}}{\sigma}\right)^2 + \left(\frac{\bar{v}}{\sigma}\right)^2}. \quad (30)$$

As the mean vector wind becomes very large compared to σ ,

$$\text{corr}(w_1, w_2) \simeq \frac{\bar{u}^2}{\bar{u}^2 + \bar{v}^2} \rho_{uu} + \frac{\bar{v}^2}{\bar{u}^2 + \bar{v}^2} \rho_{vv}, \quad (31)$$

so in this limit

$$\min(\rho_{uu}, \rho_{vv}) \leq \text{corr}(w_1, w_2) \leq \max(\rho_{uu}, \rho_{vv}). \quad (32)$$

For regions of strong and sustained vector winds, the wind speed lag autocorrelation value is bounded above by the maximum and below by the minimum lag autocorrelation value and the wind speed lag autocorrelation value will be of the same size as that of the vector wind correlations. In contrast, as $\sqrt{u^2 + v^2}$ becomes very small compared to σ ,

$$\text{corr}(w_1, w_2) \simeq \frac{1}{2}(\rho_{uu}^2 + \rho_{vv}^2), \quad (33)$$

and the wind speed lag autocorrelation is the mean of the square of the vector wind component autocorrelations. This value will generally be much smaller than the larger of ρ_{uu} or ρ_{vv} .

These different wind speed autocorrelation regimes are illustrated by the lag acfs of vector wind components and wind speed displayed in Figure 9, computed from 10-m ERA-40 reanalysis winds rather than SeaWinds observations because of the relatively high temporal resolution and duration of the reanalysis product. At all three locations, the observed wind speed autocorrelation function is predicted well by Eqn. (28). The left panel of Figure 9 corresponds to a high- σ location, for which $\text{corr}(w_1, w_2)$ is well-approximated by Eqn. (33). In this case, the wind speed correlation decays faster than either of the vector wind components for the first two days, and is always much smaller than the larger of the vector wind autocorrelations. In contrast, the middle panel of Figure 9 corresponds to a low- σ regime for which $\text{corr}(w_1, w_2)$ is given by Eqn. (31). Over the first four days of lag, the wind speed lag autocorrelation function is bracketed above and below by the larger and smaller vector wind autocorrelation functions, respectively. The same is true of the rightmost panel of Figure 9, which also corresponds to a low- σ regime. The middle and right panels of this Figure differ in the degree of anisotropy in the vector wind one-day lag, which is greater at

the location corresponding to the right panel. Note that this third location is located in the Southern Hemisphere storm track, and the zonal and meridional lag acfs resemble the along- and across-track vector wind acfs predicted by the idealised kinematic eddy model (Figure 5).

5 Discussion and Conclusions

This study has reached the following conclusions:

- The lag autocorrelation functions of the surface vector wind components and wind speeds decrease at substantially different rates at different locations over the ocean. In particular, the autocorrelation functions tend to drop off more slowly in the tropics than in the extratropics.
- Over much of the ocean, and particularly in the extratropics, the autocorrelation function of the meridional wind decreases much more rapidly than that of the zonal wind. The wind speed autocorrelation also tends to decrease faster than that of the zonal wind. No general relationship is apparent between the decay rates of the meridional wind and the wind speed.
- The vector wind acf anisotropy is not aligned precisely along zonal and meridional coordinate axes. While in the middle latitudes, the alignment of the axis of longest memory is approximately zonal, in many locations throughout the tropics and extratropics the alignment has a strong meridional component. Furthermore, the anisotropy in vector wind decorrelation timescales is a feature not only of the surface winds, but extends into the free troposphere. In the extratropical storm tracks in particular, this anisotropy is evident throughout the troposphere.
- The vector wind lag acf anisotropy in the midlatitude storm tracks can be understood in

terms of the differences in the character of the along- and across-track wind anomalies in a moving synoptic-scale eddy. For the along-track component, the temporal structure of the vector wind anomaly is monopolar; in the cross-track direction, it is dipolar. An idealised kinematic model of propagating eddies predicts that the orientation of the lag acf anisotropy will be determined by the direction of eddy propagation, while its magnitude will be determined by the time it takes a single eddy to pass any particular location. The predictions of this model are broadly consistent with observed features of eddy activity in the storm tracks.

- In the tropics, the vector wind lag acf anisotropy can be understood in terms of the superposition of variability from equatorial waves and convection. The former is large-scale and anisotropic, while the latter is small-scale and isotropic. Because the meridional winds in equatorial Kelvin waves are much smaller than the zonal winds (exactly zero for linear waves around a state of rest), the small-scale convection contributes relatively more variance to the meridional wind fluctuations than to the zonal wind fluctuations. It follows that fluctuations of the meridional wind should decorrelate faster than those of the zonal wind.
- With the assumption that the vector surface winds are bivariate Gaussian with specified autocorrelation structure, an explicit expression for the autocorrelation structure of wind speed is obtained. This result is an approximation making use of the fact that the lag autocorrelation structures of the wind speed and the wind speed squared are quantitatively very similar, and the latter is easier to work with mathematically. We find that the wind speed lag autocorrelation is bounded above by the larger of the two vector wind component autocorrelations. Furthermore, the model predicts that when the vector wind fluctuations are relatively large compared to the mean vector wind, the wind speed autocorrelation should scale as the square of the vector wind

autocorrelation. In contrast, when the vector wind fluctuations are relatively weak, the autocorrelation should simply scale with the vector component fluctuations (bounded above by the larger, and below by the smaller). These results are consistent with the observed autocorrelation structure of wind speeds.

We have shown that the temporal autocorrelation structure of observed sea surface winds contains rich structure which to a first approximation can be understood in terms of idealised kinematic and probabilistic models. These models are highly simplified, and will be quantitatively incorrect in many particulars. Baroclinic eddies in the storm tracks are not circularly symmetric; if they were, there would be no eddy momentum transport. Neither are these eddies rectilinearly propagating at constant speed, with constant depth and extent. Furthermore, observed equatorial waves are not independent of convective activity: rather, these waves are convectively coupled (e.g. Kiladis et al., 2009). Finally, surface vector winds are both non-Gaussian (e.g. Monahan, 2004, 2006a) and non-stationary, with statistics that display both diurnal and annual modulations (e.g. Dai and Deser, 1999; Monahan, 2006b). Nevertheless, the approximate models considered in this study provide a useful - if idealised - framework for understanding the temporal structure of fluctuations in the vector winds and wind speed.

Appendix A: Idealised Kinematic Eddy Model

Consider a field of zonally-propagating eddies on a uniform background wind field with velocity $(\mathcal{U}, \mathcal{V})$, where the coordinate axes are aligned so that the eddies are propagating in the x -direction. For the sake of simplicity, the eddies will be assumed to be circularly symmetric with Gaussian cross-section. Suppose that N eddies pass through the domain

under consideration in a time period of duration $2T$. The associated streamfunction field is

$$\psi(x, y, t) = \mathcal{U}y - \mathcal{V}x + \sum_{k=1}^N a_k \sigma_k^2 \exp \left\{ -\frac{(x - U_k[t - t_k])^2}{2\sigma_k^2} - \frac{(y - y_k)^2}{2\sigma_k^2} \right\} + \psi_R(x, y, t), \quad (34)$$

where a_k , U_k , y_k and σ_k are respectively the strength, zonal propagation speed, central latitude, and width of the k th eddy; t_k is the time that the centre of this eddy is at $x = 0$. The field $\psi_R(x, y, t)$ denotes a residual component of the streamfunction field, associated with other variable contributions to the wind variability that will be modelled as uncorrelated with the propagating eddies. The along- and across-track velocity fields are then

$$\begin{aligned} u(x, y, t) &= \partial_y \psi \\ &= \mathcal{U} - \sum_{k=1}^N a_k (y - y_k) \exp \left\{ -\frac{(x - U_k[t - t_k])^2}{2\sigma_k^2} - \frac{(y - y_k)^2}{2\sigma_k^2} \right\} + u_R(x, y, t) \end{aligned} \quad (35)$$

$$\begin{aligned} v(x, y, t) &= -\partial_x \psi \\ &= \mathcal{V} + \sum_{k=1}^N a_k (x - U_k[t - t_k]) \exp \left\{ -\frac{(x - U_k[t - t_k])^2}{2\sigma_k^2} - \frac{(y - y_k)^2}{2\sigma_k^2} \right\} + v_R(x, y, t). \end{aligned} \quad (36)$$

For T sufficiently large, the time-mean along-track velocity is:

$$\begin{aligned} \bar{u}(x, y) &= \frac{1}{2T} \int_{-T}^T u(x, y, t) dt \\ &\simeq \mathcal{U} + \bar{u}_R(x, y) - \frac{1}{T} \sqrt{\frac{\pi}{2}} \sum_{k=1}^N \frac{a_k \sigma_k (y - y_k)}{U_k} \exp \left\{ -\frac{(y - y_k)^2}{2\sigma_k^2} \right\}. \end{aligned} \quad (37)$$

In the time mean, the eddy across-track velocity field vanishes, so

$$\bar{v}(x, y) = \mathcal{V} + \bar{v}_R(x, y). \quad (38)$$

The ratio

$$\tau_k = \frac{2\sigma_k}{U_k} \quad (39)$$

scales the time over which the k th eddy will influence any particular location, and τ_k/T scales the fraction of total averaging time influenced by this eddy. Assuming that the waiting time between eddies is not much shorter than the individual eddy influence time, so that

$$\frac{\sum \tau_k}{T} \lesssim 1, \quad (40)$$

the final term in Eqn. (37) will be small compared to the instantaneous along-track velocity anomalies in the presence of an eddy. Furthermore, assuming that eddy centres track to both sides of the location under consideration implies that $(y - y_k)$ will take both positive and negative signs, so there will be some cancellation between the terms of the sum over eddies in Eqn. (37). It is therefore reasonable to make the convenient approximation,

$$\bar{u}(x, y) \simeq \mathcal{U} + \bar{u}_R(x, y). \quad (41)$$

Computing the along-track wind autocovariance, we then have

$$\begin{aligned} \text{cov}(u_t, u_{t+s}) &\simeq \frac{1}{2T} \int_{-T}^T [u(x, y, t) - \bar{u}(x, y)][u(x, y, t+s) - \bar{u}(x, y)] dt \\ &\simeq \sum_{j=1}^N \sum_{k=1}^N a_j a_k (y - y_j)(y - y_k) \exp \left\{ -\frac{(y - y_j)^2}{2\sigma_j^2} - \frac{(y - y_k)^2}{2\sigma_k^2} \right\} \times \\ &\quad \frac{1}{2T} \int_{-T}^T \exp \left\{ -\frac{(x - U_j[t - t_j])^2}{2\sigma_j^2} - \frac{(x - U_k[t + s - t_k])^2}{2\sigma_k^2} \right\} dt + \mathcal{R}_u(x, y, s) \end{aligned} \quad (42)$$

where $R(x, y, s)$ is the autocovariance function of u_R . The approximation that the eddies tend to be separated by a typical eddy size scale allows us to neglect contributions to the

covariance from interactions between eddies to a first approximation, and so

$$\begin{aligned}
\text{cov}(u_t, u_{t+s}) &\simeq \sum_{k=1}^N a_k^2 (y - y_k)^2 \exp \left\{ -\frac{(y - y_k)^2}{\sigma_k^2} \right\} \times \\
&\quad \frac{1}{2T} \int_{-T}^T \exp \left\{ -\frac{(x - U_k[t - t_k])^2}{2\sigma_k^2} - \frac{(x - U_k[t + s - t_k])^2}{2\sigma_k^2} \right\} dt + \mathcal{R}_u(x, y, s) \\
&\simeq \sum_{k=1}^N \frac{\sqrt{\pi}}{2T} a_k^2 \frac{\sigma_k}{U_k} (y - y_k)^2 \exp \left\{ -\frac{(y - y_k)^2}{\sigma_k^2} \right\} \exp \left\{ -\frac{U_k^2 s^2}{4\sigma_k^2} \right\} + \mathcal{R}_u(x, y, s), \quad (43)
\end{aligned}$$

for T sufficiently large. Making the approximation that the eddies are of uniform size and speed,

$$\text{cov}(u_t, u_{t+s}) \simeq C_u(y) \exp \left\{ -\frac{U^2 s^2}{4\sigma^2} \right\} + \mathcal{R}_u(x, y, s), \quad (44)$$

where

$$C_u(y) = \frac{\sqrt{\pi}}{2T} \frac{\sigma}{U} \sum_{k=1}^N a_k^2 (y - y_k)^2 \exp \left\{ -\frac{(y - y_k)^2}{\sigma_k^2} \right\}. \quad (45)$$

The lag autocorrelation function for the vector wind component in the along-track direction is then

$$\text{corr}(u_t, u_{t+s}) \simeq \frac{C_u(y) \exp \left\{ -\frac{U^2 s^2}{4\sigma^2} \right\} + \mathcal{R}_u(x, y, s)}{C_u(y) + \mathcal{R}_u(x, y, 0)}. \quad (46)$$

In the across-track direction (again assuming eddies that are separated on average), we have:

$$\begin{aligned}
\text{cov}(v_t, v_{t+s}) &\simeq \sum_{k=1}^N a_k^2 \exp \left\{ -\frac{(y - y_k)^2}{\sigma_k^2} \right\} \frac{1}{2T} \int_{-T}^T (x - U_k[t - t_k])(x - U_k[t + s - t_k]) \times \\
&\quad \exp \left\{ -\frac{(x - U_k[t - t_k])^2}{2\sigma_k^2} - \frac{(x - U_k[t + s - t_k])^2}{2\sigma_k^2} \right\} dt + \mathcal{R}_v(x, y, s) \\
&\simeq \sum_{k=1}^N \frac{\sqrt{\pi}}{4T} \frac{\sigma_k^3}{U_k} a_k^2 \exp \left\{ -\frac{U_k^2 s^2}{4\sigma_k^2} \right\} \left(1 - \frac{U_k^2 s^2}{2\sigma_k^2} \right) + \mathcal{R}_v(x, y, s). \quad (47)
\end{aligned}$$

For eddies of uniform size and speed,

$$\text{corr}(v_t, v_{t+s}) \simeq \frac{C_v \exp \left\{ -\frac{U^2 s^2}{4\sigma^2} \right\} \left(1 - \frac{U^2 s^2}{2\sigma^2} \right) + \mathcal{R}_v(x, y, s)}{C_v + \mathcal{R}_v(x, y, 0)} \quad (48)$$

with

$$C_v = \frac{\sqrt{\pi}\sigma^3}{4TU} \sum_{k=1}^N a_k^2. \quad (49)$$

Assuming that in the storm tracks the residual variability $u_R(x, y, t)$ and $v_R(x, y, t)$ carry less variance than the eddies, we can make the further approximation:

$$\text{corr}(u_t, u_{t+s}) \simeq \exp\left\{-\frac{U^2 s^2}{4\sigma^2}\right\} + O\left(\frac{\mathcal{R}_u(x, y, 0)}{C_u(y)}\right) \quad (50)$$

$$\text{corr}(v_t, v_{t+s}) \simeq \exp\left\{-\frac{U^2 s^2}{4\sigma^2}\right\} \left(1 - \frac{U^2 s^2}{2\sigma^2}\right) + O\left(\frac{\mathcal{R}_v(x, y, 0)}{C_v}\right). \quad (51)$$

In both the along-track and across-track directions, the vector wind autocorrelation decreases on a timescale set by the eddy passage time $\tau = 2\sigma/U$. The across-track autocorrelation decreases more rapidly than the along-track autocorrelation, and the degree of this asymmetry is scaled by τ . For eddies of the same size, the asymmetry becomes more pronounced as the eddy speed increases.

Appendix B: Squared Wind Speed Autocorrelation Function

As a first step in calculating the correlation $\text{corr}(w_1^2, w_2^2)$, we compute the covariance

$$\begin{aligned} \text{cov}(w_1^2, w_2^2) &= \mathbb{E}\{w_1^2 w_2^2\} - \mathbb{E}\{w_1^2\} \mathbb{E}\{w_2^2\} \\ &= (\mathbb{E}\{u_1^2 u_2^2\} - \mathbb{E}\{u_1^2\} \mathbb{E}\{u_2^2\}) + (\mathbb{E}\{u_1^2 v_2^2\} - \mathbb{E}\{u_1^2\} \mathbb{E}\{v_2^2\}) \\ &\quad + (\mathbb{E}\{v_1^2 u_2^2\} - \mathbb{E}\{v_1^2\} \mathbb{E}\{u_2^2\}) + (\mathbb{E}\{v_1^2 v_2^2\} - \mathbb{E}\{v_1^2\} \mathbb{E}\{v_2^2\}) \\ &= \text{cov}(u_1^2, u_2^2) + \text{cov}(u_1^2, v_2^2) + \text{cov}(v_1^2, u_2^2) + \text{cov}(v_1^2, v_2^2). \end{aligned} \quad (52)$$

Defining the standardized variables x, y such that

$$u_1 = \sigma_u x + \bar{u} \quad (53)$$

$$v_2 = \sigma_v y + \bar{v}, \quad (54)$$

it follows that

$$\begin{aligned} \mathbb{E}\{u_1^2 v_2^2\} &= \mathbb{E}\{(\sigma_u x + \bar{u})^2 (\sigma_v y + \bar{v})^2\} \\ &= \sigma_u^2 \sigma_v^2 \mathbb{E}\{x^2 y^2\} + 2\sigma_u \sigma_v (\sigma_u \bar{v} \mathbb{E}\{x^2 y\} + \sigma_v \bar{u} \mathbb{E}\{xy^2\}) \\ &\quad + \sigma_u^2 \bar{v}^2 \mathbb{E}\{x^2\} + 4\sigma_u \sigma_v \bar{u} \bar{v} \mathbb{E}\{xy\} + \sigma_v^2 \bar{u}^2 \mathbb{E}\{y^2\} \\ &\quad + 2\bar{u} \bar{v} (\sigma_u \bar{v} \mathbb{E}\{x\} + \sigma_v \bar{u} \mathbb{E}\{y\}) + \bar{u}^2 \bar{v}^2 \\ &= \sigma_u^2 \sigma_v^2 (2\rho_{uv}^2 + 1) + \sigma_u^2 \bar{v}^2 + 4\sigma_u \sigma_v \bar{u} \bar{v} \rho_{uv} + \sigma_v^2 \bar{u}^2 + \bar{u}^2 \bar{v}^2. \end{aligned} \quad (55)$$

In this computation, we have made use of the fact that for standardized Gaussian variables α and β with correlation γ ,

$$\mathbb{E}\{\alpha^2 \beta^2\} = 2\gamma^2 + 1. \quad (56)$$

Had we not made the assumption of Gaussian vector wind fluctuations, we could not in general simply relate $\mathbb{E}\{x^2 y^2\}$ to $\mathbb{E}\{xy\}$. Finally, as

$$\mathbb{E}\{u_1^2\} = \bar{u}^2 + \sigma_u^2 \quad (57)$$

$$\mathbb{E}\{v_2^2\} = \bar{v}^2 + \sigma_v^2, \quad (58)$$

we have

$$\text{cov}(u_1^2, v_2^2) = \mathbb{E}\{u_1^2 v_2^2\} - \mathbb{E}\{u_1^2\} \mathbb{E}\{v_2^2\} = 2\sigma_u \sigma_v (\sigma_u \sigma_v \rho_{uv}^2 + 2\bar{u} \bar{v} \rho_{uv}). \quad (59)$$

Similar calculations yield expressions for $\text{cov}(u_1^2, u_2^2)$, $\text{cov}(v_1^2, u_2^2)$, and $\text{cov}(v_1^2, v_2^2)$, so:

$$\text{cov}(w_1^2, w_2^2) = 2\sigma_u^2(\sigma_u^2\rho_{uu}^2 + 2\bar{u}^2\rho_{uu}) + 2\sigma_u\sigma_v(\sigma_u\sigma_v[\rho_{uv}^2 + \rho_{vu}^2] + 2\bar{u}\bar{v}[\rho_{uv} + \rho_{vu}]) + 2\sigma_v^2(\sigma_v^2\rho_{vv}^2 + 2\bar{v}^2\rho_{vv}). \quad (60)$$

To compute $\text{corr}(w_1^2, w_2^2)$ from $\text{cov}(w_1^2, w_2^2)$ we need the squared wind speed variances:

$$\begin{aligned} \text{var}(w_1^2) &= \text{E}\{w_1^4\} - (\text{E}\{w_1^2\})^2 \\ &= \text{E}\{u_1^4\} + 2\text{E}\{u_1^2v_1^2\} + \text{E}\{v_1^4\} - (\text{E}\{u_1^2\})^2 - 2\text{E}\{u_1^2\}\text{E}\{v_1^2\} - (\text{E}\{v_1^2\})^2 \\ &= 3\sigma_u^4 + 6\bar{u}^2\sigma_u^2 + \bar{u}^4 + 2\sigma_u^2\sigma_v^2(2r^2 + 1) + 2\sigma_u^2\bar{v}^2 + 8\sigma_u\sigma_v\bar{u}\bar{v}r + 2\sigma_v^2\bar{u}^2 + 2\bar{u}^2\bar{v}^2 \\ &\quad + 3\sigma_v^4 + 6\bar{v}^2\sigma_v^2 + \bar{v}^4 - \bar{u}^4 - 2\bar{u}^2\sigma_u^2 - \sigma_u^4 - 2\sigma_u^2\sigma_v^2 - 2\bar{u}^2\sigma_v^2 - 2\bar{v}^2\sigma_u^2 - 2\bar{u}^2\bar{v}^2 \\ &\quad - \bar{v}^4 - 2\bar{v}^2\sigma_v^2 - \sigma_v^4 \\ &= 2\sigma_u^4 + 4\bar{u}^2\sigma_u^2 + 4\sigma_u^2\sigma_v^2r^2 + 8\sigma_u\sigma_v\bar{u}\bar{v}r + 2\sigma_v^4 + 4\bar{v}^2\sigma_v^2 \end{aligned} \quad (61)$$

$$= \text{var}(w_2^2), \quad (62)$$

where the last equality follows by the assumption of stationarity. It follows that

$$\text{corr}(w_1^2, w_2^2) = \frac{\sigma_u^2(\sigma_u^2\rho_{uu}^2 + 2\bar{u}^2\rho_{uu}) + \sigma_u\sigma_v(\sigma_u\sigma_v[\rho_{uv}^2 + \rho_{vu}^2] + 2\bar{u}\bar{v}[\rho_{uv} + \rho_{vu}]) + \sigma_v^2(\sigma_v^2\rho_{vv}^2 + 2\bar{v}^2\rho_{vv})}{\sigma_u^4 + 2\bar{u}^2\sigma_u^2 + 2\sigma_u^2\sigma_v^2r^2 + 4\sigma_u\sigma_v\bar{u}\bar{v}r + \sigma_v^4 + 2\bar{v}^2\sigma_v^2}. \quad (63)$$

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Figure Captions

Figure 1: Lag autocorrelation fields of surface zonal wind (left column), meridional wind (centre column), and wind speed (right column) for lags of one, two, and three days. These fields were computed from SeaWinds data.

Figure 2: Global distribution of the one-day vector wind lag autocorrelation anisotropy from SeaWinds data, as measured by the ratio R_1 of the smallest to the largest correlation value (Eqn. 4). The white circles indicate the positions of the three sets of acfs illustrated in Figure 9.

Figure 3: Orientation of the direction of maximum one-day vector wind lag autocorrelation, computed from SeaWinds data. The vectors show the unit vectors $\mathbf{e}_{max} = (\cos \theta_{max}, \sin \theta_{max})$, with magnitudes scaled by the degree of the autocorrelation anisotropy $(1 - R_1^2)$.

Figure 4: One-day lag vector wind anisotropy factor R_1 (Eqn. 4) at different pressure levels, as estimated from the ERA-40 reanalysis winds.

Figure 5: Lag autocorrelation functions of the along- and across-track vector wind components from the idealized model of propagating eddies in a storm track, neglecting other contributions to wind variability (i.e. $\mathcal{R}_u = \mathcal{R}_v = 0$ in Eqns. 44 and 47). The lag timescale is normalized by the eddy passage time, $\tau = 2\sigma/U$.

Figure 6: Kernel density estimate of the spatial scatter of the wind speed one day lag autocorrelation $\text{corr}(w_t, w_{t+1})$ and the maximum one-day lag vector wind autocorrelation, $c_1(\theta_{max}) = \text{corr}(u_t(\theta_{max}), u_{t+1}(\theta_{max}))$, estimated from the SeaWinds data.

Figure 7: Kernel density estimate of the joint distribution (in space) of the 1-day lag autocorrelation of wind speed, $\text{corr}(w_t, w_{t+1})$, and squared wind speed, $\text{corr}(w_t^2, w_{t+1}^2)$, from the SeaWinds observations.

Figure 8: Kernel density estimates of spatial scatter of observed and modelled wind speed lag correlations (left panel: one-day; right panel: two-day; right panel: three-day). Black contours correspond to predictions using the full model Eqn. (26), while red contours correspond to predictions made using the simplified model Eqn. (28). The observed and predicted values were determined using the SeaWinds data.

Figure 9: Observed lag autocorrelation functions of 10-m zonal wind (dashed line), meridional wind (dot-dashed line), and wind speed (solid black line) at three different locations over the ocean (Figure 2), as calculated from ERA-40 data. The grey solid line is the lag autocorrelation function predicted by Eqn. (28). The first location (197.5°E,32.5°S) is characterised by relatively strong vector wind fluctuations ($\bar{u}/\sigma_u = -0.02$, $\bar{v}/\sigma_v = 0.08$). The second location (185°E,17.5°N) is characterised by relatively weak vector wind fluctuations ($\bar{u}/\sigma_u = -2.30$, $\bar{v}/\sigma_v = -0.65$) and a weak one-day lag anisotropy ($R_1 = 0.80$). The third location (47.5°E,50°S) is characterised by relatively weak vector wind fluctuations ($\bar{u}/\sigma_u = 1.61$, $\bar{v}/\sigma_v = -0.23$) and a strong one-day lag asymmetry ($R_1 = 0.08$).

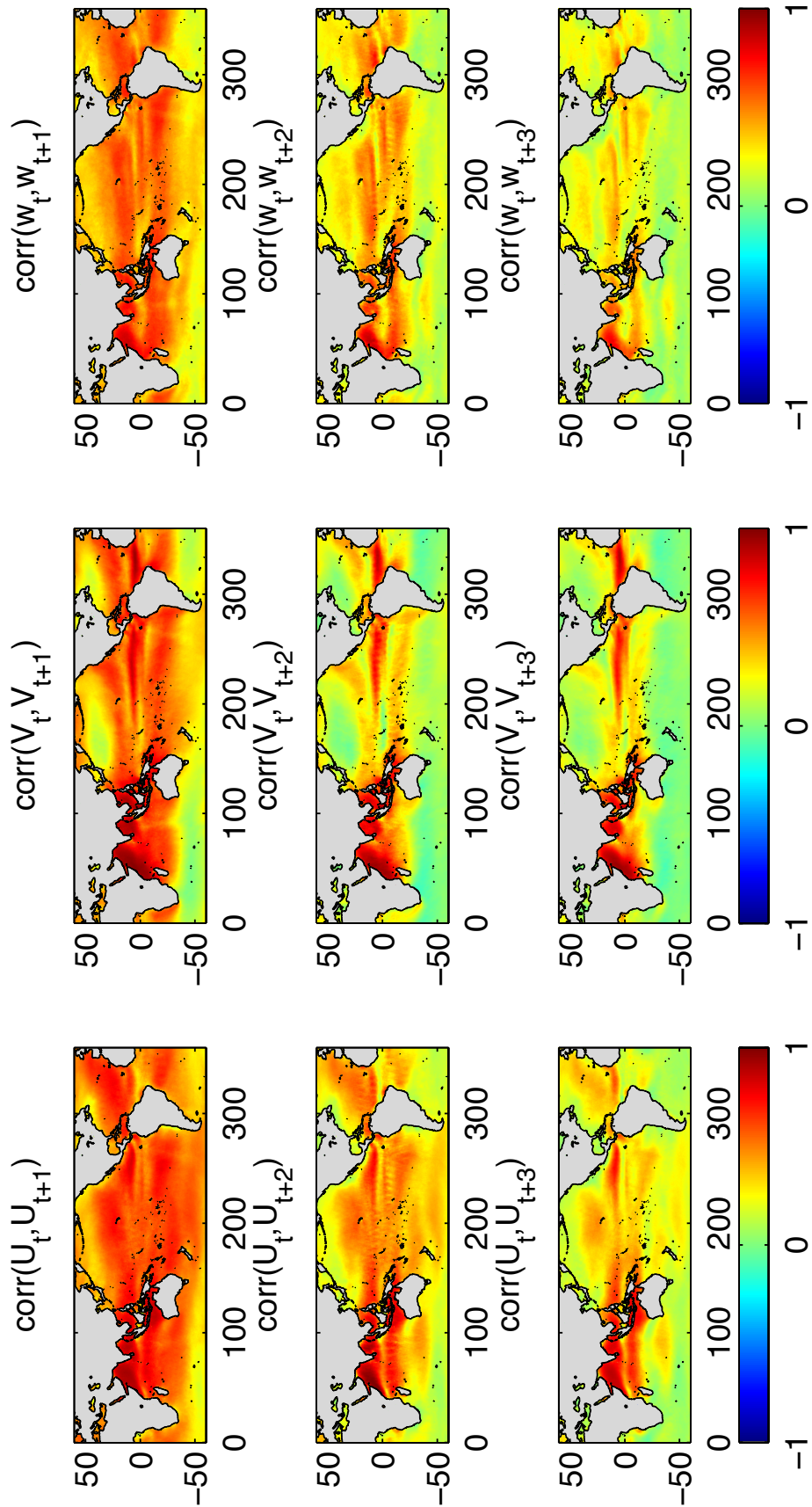


Figure 1: Lag autocorrelation fields of surface zonal wind (left column), meridional wind (centre column), and wind speed (right column) for lags of one, two, and three days. These fields were computed from SeaWinds data.

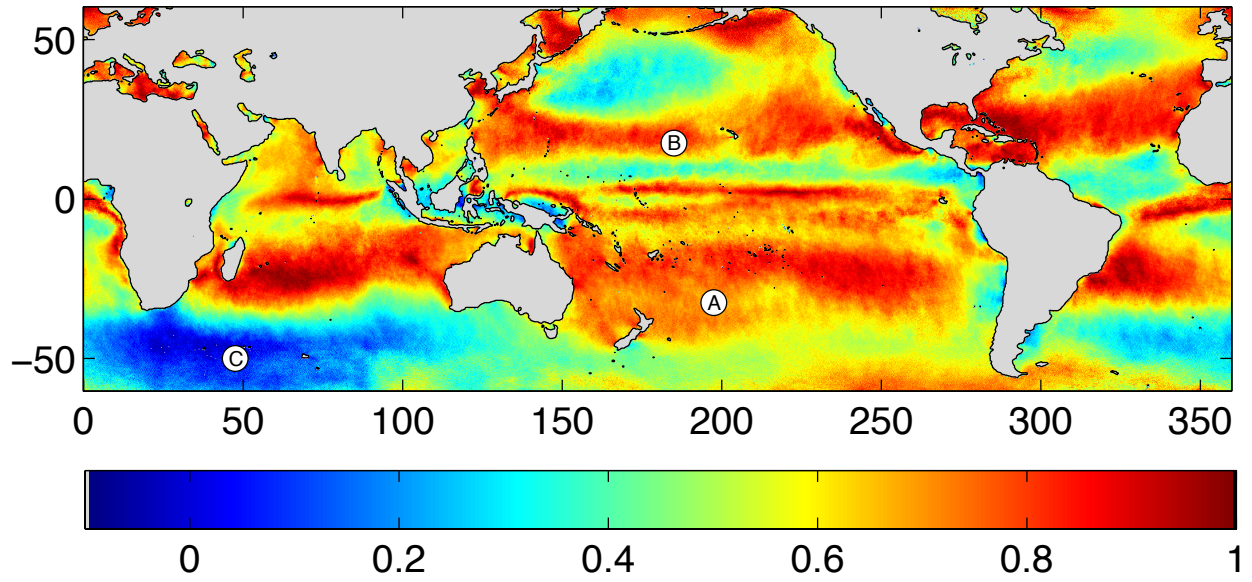


Figure 2: Global distribution of the one-day vector wind lag autocorrelation anisotropy from SeaWinds data, as measured by the ratio R_1 of the smallest to the largest correlation value (Eqn. 4). The white circles indicate the positions of the three sets of acfs illustrated in Figure 9.

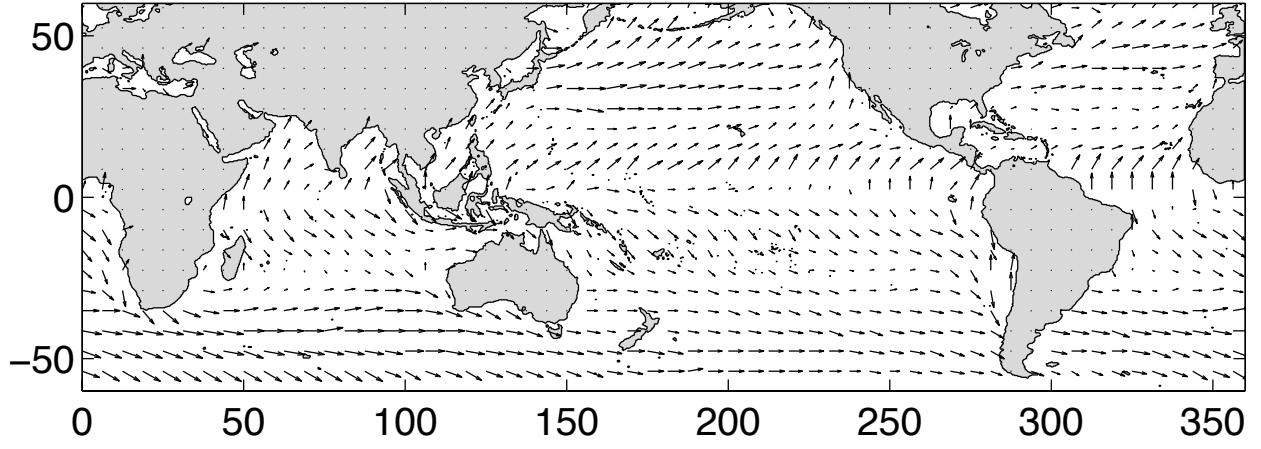


Figure 3: Orientation of the direction of maximum one-day vector wind lag autocorrelation, computed from SeaWinds data. The vectors show the unit vectors $\mathbf{e}_{max} = (\cos \theta_{max}, \sin \theta_{max})$, with magnitudes scaled by the degree of the autocorrelation anisotropy $(1 - R_1^2)$.

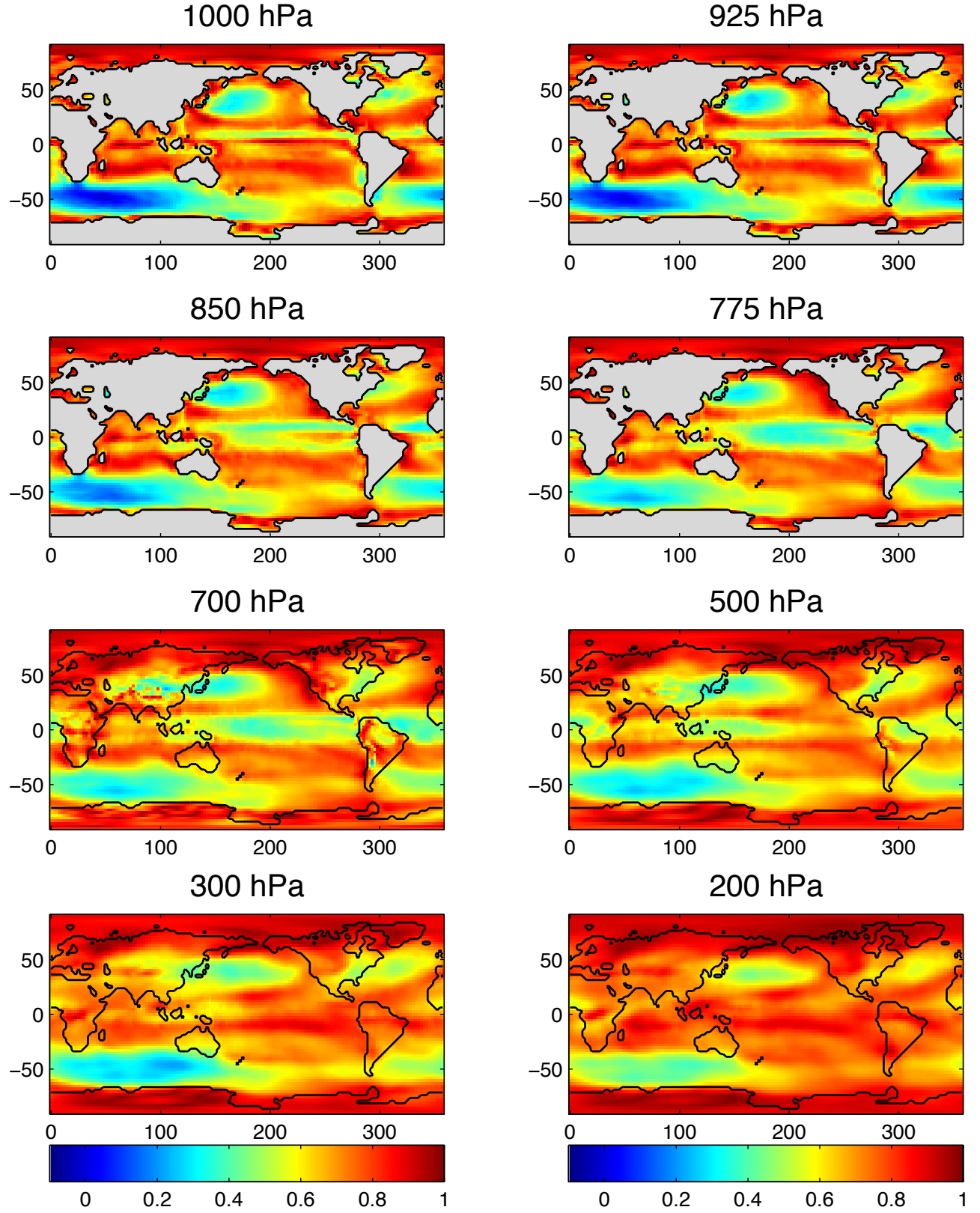


Figure 4: One-day lag vector wind anisotropy factor R_1 (Eqn. 4) at different pressure levels, as estimated from the ERA-40 reanalysis winds.

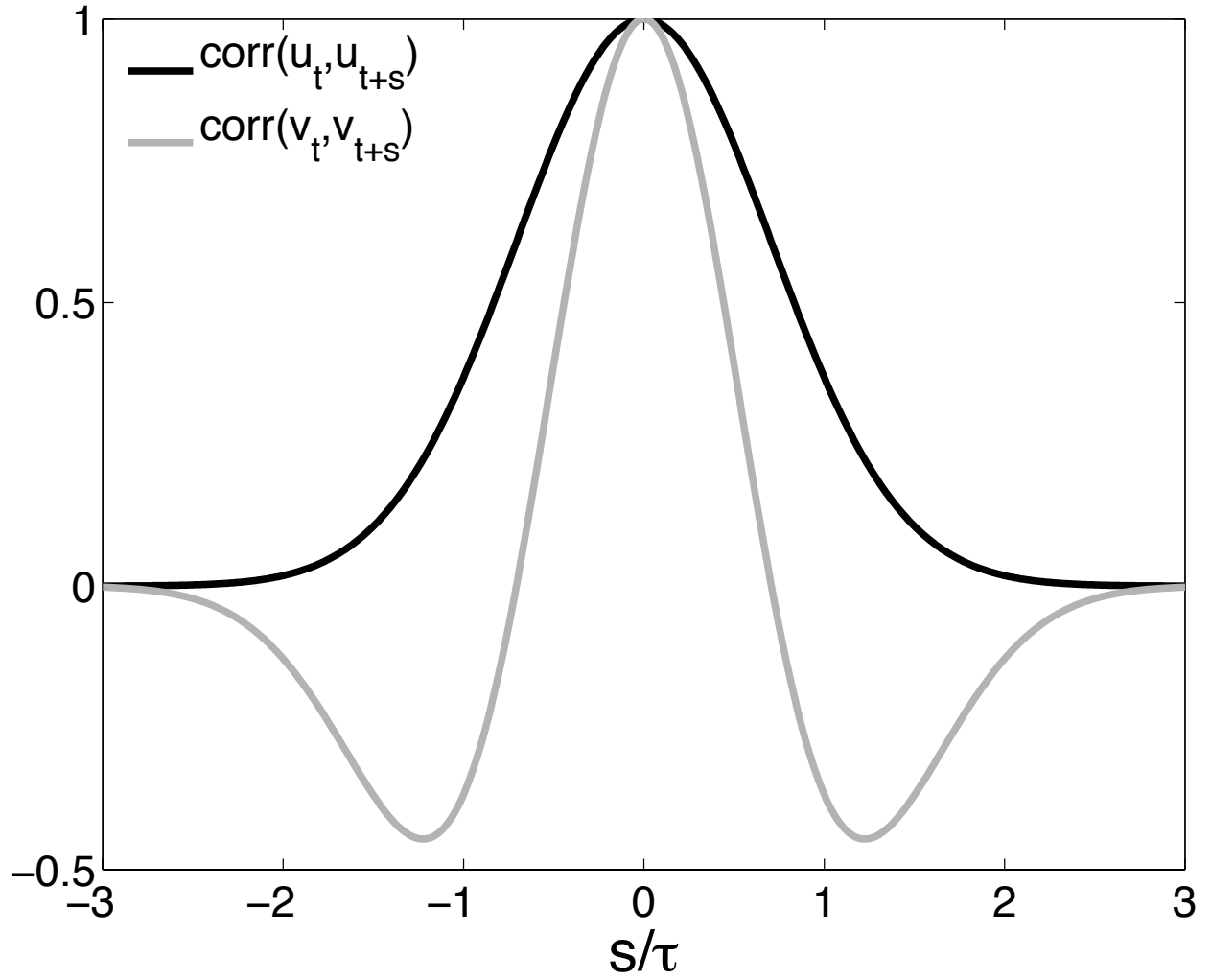


Figure 5: Lag autocorrelation functions of the along- and across-track vector wind components from the idealized model of propagating eddies in a storm track, neglecting other contributions to wind variability (i.e. $\mathcal{R}_u = \mathcal{R}_v = 0$ in Eqns. 44 and 47). The lag timescale is normalized by the eddy passage time, $\tau = 2\sigma/U$.

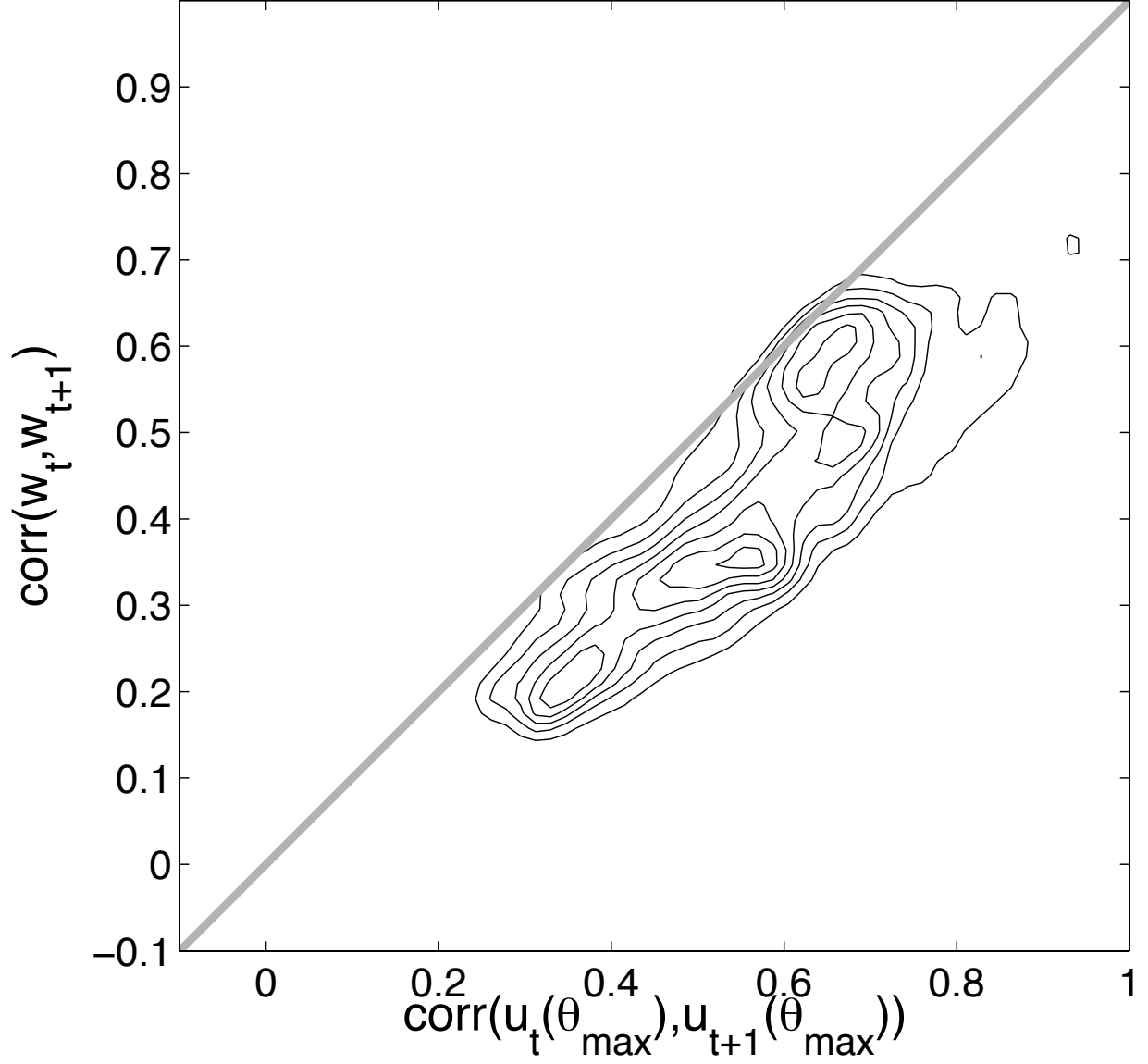


Figure 6: Kernel density estimate of the spatial scatter of the wind speed one day lag autocorrelation $\text{corr}(w_t, w_{t+1})$ and the maximum one-day lag vector wind autocorrelation, $c_1(\theta_{\max}) = \text{corr}(u_t(\theta_{\max}), u_{t+1}(\theta_{\max}))$, estimated from the SeaWinds data.

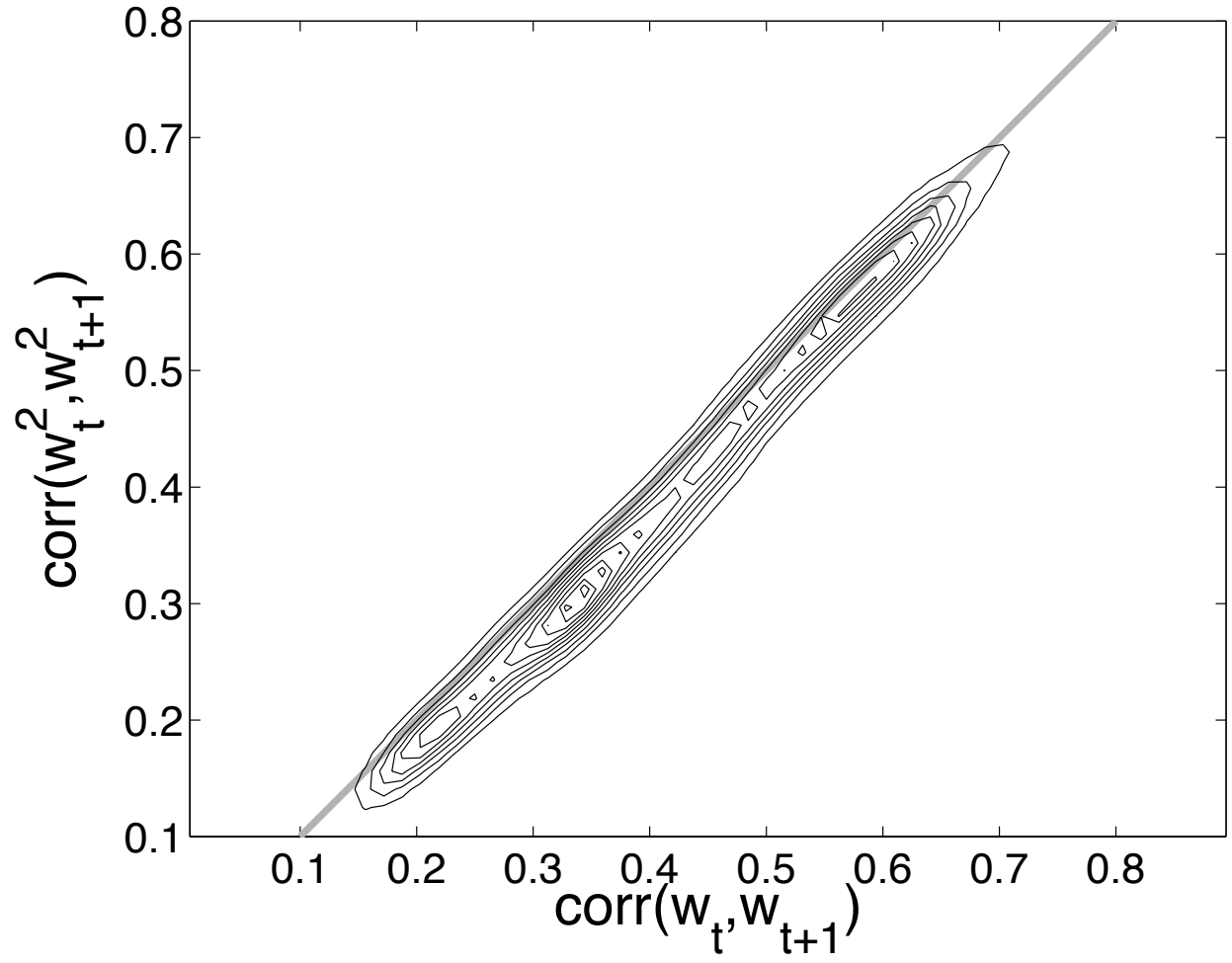


Figure 7: Kernel density estimate of the joint distribution (in space) of the 1-day lag auto-correlation of wind speed, $\text{corr}(w_t, w_{t+1})$, and squared wind speed, $\text{corr}(w_t^2, w_{t+1}^2)$, from the SeaWinds observations.

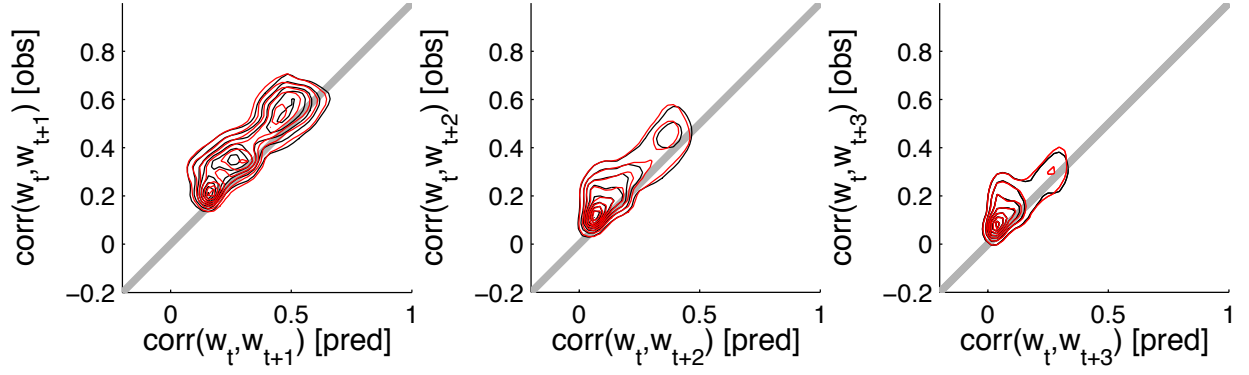


Figure 8: Kernel density estimates of spatial scatter of observed and modelled wind speed lag correlations (left panel: one-day; middle panel: two-day; right panel: three-day). Black contours correspond to predictions using the full model Eqn. (26), while red contours correspond to predictions made using the simplified model Eqn. (28). The observed and predicted values were determined using the SeaWinds data.

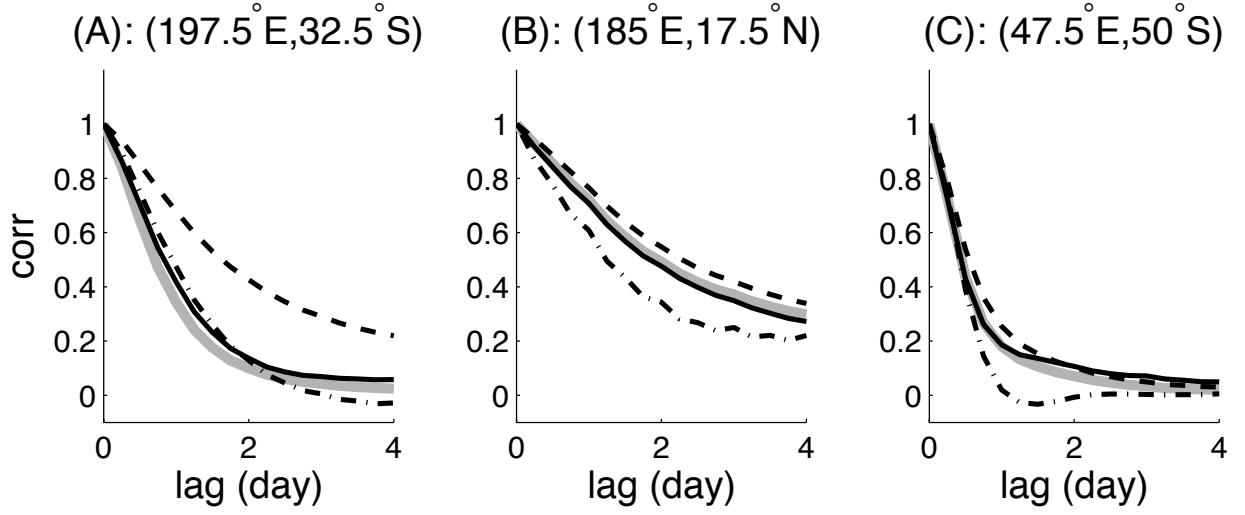


Figure 9: Observed lag autocorrelation functions of 10-m zonal wind (dashed line), meridional wind (dot-dashed line), and wind speed (solid black line) at three different locations over the ocean (Figure 2), as calculated from ERA-40 data. The grey solid line is the lag autocorrelation function predicted by Eqn. (28). The first location (197.5°E, 32.5°S) is characterised by relatively strong vector wind fluctuations ($\bar{u}/\sigma_u = -0.02$, $\bar{v}/\sigma_v = 0.08$). The second location (185°E, 17.5°N) is characterised by relatively weak vector wind fluctuations ($\bar{u}/\sigma_u = -2.30$, $\bar{v}/\sigma_v = -0.65$) and a weak one-day lag anisotropy ($R_1 = 0.80$). The third location (47.5°E, 50°S) is characterised by relatively weak vector wind fluctuations ($\bar{u}/\sigma_u = 1.61$, $\bar{v}/\sigma_v = -0.23$) and a strong one-day lag asymmetry ($R_1 = 0.08$).