Comparison of wind-stress algorithms and their influence on wind-stress curl using buoy measurements over the shelf off Bodega Bay, California

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Abstract

The main objectives of this study were to compare three wind-stress algorithms of varying intricacy and estimate the extent to which each method altered computed wind-stress curl. The algorithms included (1) a simple bulk formula for neutral conditions that is dependent only on wind velocity components; (2) a formula that in addition to dependence on wind components includes a simplified effect of thermal stability through differences in air and sea temperatures; and (3) an algorithm that includes full treatment of dynamics and atmospheric stability. Data for the analysis were from a field program that used a special buoy network off Bodega Bay during 28 June–4 August 2001.

A diamond-shaped setup of five closely separated buoys in Bodega Bay allowed for one of the first attempts to compute wind-stress curl over the ocean using buoy measurements. Based on an analysis of the available dataset, the marine layer over Bodega Bay is characterized by positive wind-stress curl with a median value around 0.2 Pa (100 km)\textsuperscript{-1} and maximum values reaching 2.5 Pa (100 km)\textsuperscript{-1}. Positive wind-stress curl was observed for all wind speed conditions, whereas negative wind-stress curl episodes were associated mostly with low-wind conditions.

Comparison of wind-stress curl computed using the three algorithms showed that differences among them can be significant. The first and third algorithms indicated similar stress curl (difference around 10%), but the differences between these two and the second algorithm were much higher (approximately 40%). The reason for the difference is the stability correction, which in the third algorithm strongly decreases with an increase in wind speeds, but stays at a similar level for all wind speeds in the second algorithm. Consequently, for higher wind speeds the variability of wind stress calculated using the second algorithm is greater than for the other two algorithms, causing significant differences in computed wind-stress curl (root mean-square error equal to 0.19 Pa (100 km)\textsuperscript{-1}).

Despite the apparent biases in computed wind stress and wind-stress curl among the algorithms, all of them show a significant trend of decreasing sea-surface temperature (SST) with increasing wind-stress curl. The bootstrapping analysis has revealed that both the along-shore wind stress and wind-stress curl have noticeable correlation with the changes in the sea-surface temperature as an indirect indication of the upwelling. An additional analysis, based on the low-pass filtered…

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data, showed also significant agreement between the measured divergence in the cross-shore surface transport and the wind-stress curl computed for all three algorithms.

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1. Introduction

Wind stress and wind-stress curl are crucial to ocean dynamics in coastal areas and over the open ocean (Jones and Toba, 2001). Routine measurements of wind and wind stress were sparse until recent years when satellite data became available. Satellite detection of surface winds and stress, however, is limited in coastal regions where the strongest gradients of wind and wind stress exist. Consequently, estimation of wind stress and wind-stress curl in these areas still relies on occasional aircraft measurements (Beardsley et al., 1997; Enriquez and Friehe, 1995; Rogers et al., 1998), sparse buoy measurements (Winant and Dorman, 1997), and numerical modeling (Beg-Paklar et al., 2001; Samelson et al., 2002; Koračin et al., 2004; Dorman et al., 2006).

Many algorithms for calculating wind stress using available buoy-measured winds have been developed, as reviewed by Jones and Toba (2001). It appears that the drag coefficient that relates wind velocity to wind stress is a complicated variable that depends on many factors, including wind velocity components, atmospheric stability, surface fluxes, sea-surface temperature (SST), and sea state. Since the relationship between wind and wind stress is not linear, differences in the calculated stress using various algorithms can induce significant differences in computed wind-stress curl.

Wind-stress algorithms are of varying degrees of intricacy. Drag-coefficient algorithms that use only wind velocity components, for instance, can induce similar computed stress and wind-stress curl (Samelson et al., 2002; Koračin et al., 2004). Algorithms for drag coefficient that also include simplified treatment of atmospheric stability through air–sea temperature differences (Hellerman and Rosenstein, 1983) and algorithms that include atmospheric stability (Fairall et al., 1996a, b) can produce significantly different results compared to algorithms including only wind velocity components. As shown by Beardsley et al. (1997) for the West Coast wind regime, however, even simple methods such as Large and Pond (1981) produce wind-stress values that in some cases differ by less than the measurement errors from more advanced algorithms, such as Fairall et al. (1996a).

In order to assess the differences in estimating wind stress by various algorithms and the related impact on wind-stress curl estimation, we examined three commonly used algorithms: (1) the Large and Pond (1981) algorithm based on wind velocity components; (2) the Hellerman and Rosenstein (1983) algorithm based on both wind velocity components and the correction due to the air–sea temperature difference; and (3) the Fairall et al. (1996a, b) algorithm based on wind velocity components, atmospheric stability, and skin SST. Since wind-stress curl is one of the forcing mechanisms of coastal ocean upwelling, it is important to understand the extent to which various wind-stress algorithms alter computed stress curl.

2. Description of wind-stress algorithms

2.1. Large and Pond (1981) scheme

Large and Pond (1981) developed a simple formula consisting of a bulk algorithm for calculating the drag coefficient using only wind velocity

\[ C_{D,LP} = 1.2 \times 10^{-3}, \text{ for } 4 \leq |V| \leq 11 \text{ m s}^{-1}, \]

\[ C_{D,LP} = (0.49 + 0.065|V|) \times 10^{-3}, \text{ for } 11 \leq |V| \leq 25 \text{ m s}^{-1}, \]

\[ \tau_{X,LP} = \rho C_{D,LP} u|V|, \]

\[ \tau_{Y,LP} = \rho C_{D,LP} v|V|, \]  

(1)

where \(|V|\) is the absolute value of the wind velocity (m s\(^{-1}\)), \(\tau_{X,LP}\) and \(\tau_{Y,LP}\) are the east–west and north–south wind-stress components (Pa), \(u\) and \(v\) are the east–west and north–south wind-speed components (m s\(^{-1}\)), and \(\rho\) is the air density (kg m\(^{-3}\)). This algorithm has been used in many studies such as Dorman et al. (2000), Samelson et al. (2002), and Koračin et al. (2004).

2.2. Hellerman and Rosenstein (1983) scheme

The next level of sophistication in calculating the drag coefficient and subsequently wind stress is to include air–sea temperature differences in addition to the wind velocity. This approach gives a relatively
simple formula for drag coefficient calculation but takes into account a simplified treatment of stability conditions. As a consequence, the Hellerman and Rosenstein (HR) formula has been used in many oceanographic models including the Geophysical Fluid Dynamics Laboratory-Modular Ocean Model “GDFL-MOM” (Roussenov et al., 1995); the Oceanic Component Model of Flexible Global Climate “FGCMO” (Jin et al., 1999); and the Naval Research Laboratory’s Layered Ocean Model “NLOM” (Metzger, 2003). According to the HR formula the drag coefficient is calculated as

\[ C_{D,HR} = x_1 + x_2|V| + x_3(T_a - T_s) + x_4|V|^2 + x_5(T_a - T_s)^2 + x_6|V|^2(T_a - T_s), \]

\[ \tau_{X,HR} = \rho C_{D,HR} u|V|, \]

\[ \tau_{Y,HR} = \rho C_{D,HR} v|V|, \]

(2)

where \(|V|\) is the absolute value of the wind velocity (m s\(^{-1}\)), \(T_a\) and \(T_s\) are the temperatures of the air and sea (K or °C), and \([x_1, \ldots, x_6]\) are the constants [0.934 \times 10^{-3}, 0.788 \times 10^{-4}, 0.868 \times 10^{-4}, -0.616 \times 10^{-6}, -0.120 \times 10^{-5}, -0.214 \times 10^{-5}], \(\tau_{X,HR}\) and \(\tau_{Y,HR}\) are the east–west and north–south wind-stress components (Pa), \(u\) and \(v\) are the east–west and north–south wind-speed components (m s\(^{-1}\)), and \(\rho\) is the air density (kg m\(^{-3}\)).

For calculation of the neutral drag coefficient, the temperature difference was assumed to be zero and the above formula was reduced to the following form:

\[ C_{D,N,HR} = x_1 + x_2V + x_4V^2. \]

(3)

The base formula (Eq. (2)) accounts for atmospheric stability in a limited way by inclusion of the polynomial of the first- and second-order air–sea temperature differences. One of the problems in using this expression is that the six constants were calibrated using global ocean data (Hellerman and Rosenstein, 1983). For the best results in coastal applications, the constants probably need to be recalibrated using measurements in each region of interest. A remaining question is how widely applicable these constants are to other areas and a full range of stability conditions.

2.3. Tropical ocean global atmosphere coupled ocean–atmosphere response experiment (TOGA COARE) scheme. Fairall et al. (1996a, b)

The TOGA COARE conducted between November 1992 and February 1993 led to the development of a comprehensive algorithm for the drag coefficient that takes into account both dynamical and thermodynamical processes presented by Fairall et al. (1996a, b). In the TOGA COARE algorithm (TC) the drag coefficient appears as a function of wind velocity, air temperature, SST, humidity, atmospheric pressure, shortwave and longwave radiation fluxes, and height of the atmospheric boundary layer. The algorithm requires several computational steps involving iterative estimation of scaling parameters and stability functions using the similarity theory as well as wind gustiness based on heat and moisture fluxes, temperature, and atmospheric boundary layer height. Final outputs of this algorithm include separate drag coefficients for wind, temperature and humidity. Details of the algorithm are described in Fairall et al. (1996a) and the computer code can be downloaded from the Web site: http://www.coaps.fsu.edu/COARE/flux_algor/. A flow diagram of the TC algorithm is shown in Fig. 1.

Input data to the TC algorithm are basic meteorological measurements—wind speed, air and sea temperature (including measurement height, sensor depth, as well as latitude and longitude), time of measurement, as well as shortwave and net longwave radiation fluxes at the sea-surface (step 1 in Fig. 1). When in situ measurements are used for evaluating SST (temperature sensor is located at a given depth), warm-layer depth is calculated in step 2; if the distance from the ocean surface to the sensor is less than the warm-layer depth, SST is corrected by the warm correction \(dT_{\text{warm}}\) (step 3). If SST is measured by infrared radiometer, no correction to SST is made and input data are directly used in all further computations.

Two SST corrections are present in the TC algorithm, the warm-layer and the cool-skin corrections. The former is calculated at the beginning of the algorithm, takes into account radiative heating of the sea-surface, and increases measured temperature if the sensor is located below the warm layer. The second represents evaporative cooling of the very top sea layer and is iteratively computed in the main loop. Because the cool-skin correction computation uses longwave and shortwave radiation as well as sensible and latent heat fluxes, it can be calculated when the first approximations of the fluxes are known. The cool-skin correction is used in step 15 for calculation of temperature and humidity scale parameters. The last step (19) in the main loop provides a new velocity corrected by gustiness.
Input data: U, Ta, Ts, Q, lat, lon, time, Lw, Sw, z, zt, zq

Initializing start values:
- Gustiness velocity Wg = 0.5
- Roughness length Z0 = 0.0005
- Velocity difference dU = U (assuming water current equal to zero)
- Corrected velocity dUwg = (U^2 + Wg^2)^0.5
- Scaling parameters U* = 0.04 * dUwg, T* = 0.04 * dT, Q* = 0.04 * dQ

Calculating:
- dT = Ta - Ts
- dU = U - Us, (Us = 0)
- dQ = Q – Qsat(Ts)

Calculating virtual temperature Tv, gravitational acceleration g

Calculating Monin Obukhov Length L = T* U*/(g * κ * T* V*) and ξ = z/L.

Calculating stability function for temperature and humidity ψt(ξ), ψq(ξ)

Calculating new scale parameters for temperature and humidity
T* = (dT + dTcor) / [(log(zt / zot) - ψt(ξ))],
Q* = (dQ + dQcor) / [(log(zq / zoq) - ψq(ξ))],
where Wc = 0.622 * Lw * 0.98 * Qsat(Ts).

Calculating cool skin correction dTcor as a function of shortwave radiation, latent and sensible heat flux, salinity expansion, water expansion coefficient, U*, T, ρa, ρw, νw.


Calculating gustiness velocity: if Bf = (g / Ta) U* TV* > 0
wg = β * (Bf * zi)^1/3,
for Bf ≤ 0 wg = 0

Calculating new corrected velocity dUwg = (dU^2 + Wg^2)^0.5

Calculating transfer coefficients using final values of scaling parameters and gustiness velocity:
C0 = U* / dUwg^2,
C1 = U.T. / (dUwg^2 (T* - Ta + 0.0098 * zt + dTcor)),
C2 = U.Q. / (dUwg^2 (Q - Qsat(T* - dQcor)) + dQcor).

Preparing output results, CD, CE, CH, U*, zo, τ, HL, HS.

Fig. 1. Flow chart of the TOGA COARE (TC) algorithm (Fairall et al., 1996a).
velocity $w_g$ (computed in step 18 using boundary layer height $z_i$). After that step, the calculation starts again from the Obukhov length ($L$) computation in step 6. The calculations in the main loop are repeated 20 times; and on the basis of the final scaling parameters, the cool-skin correction, corrected velocity, transfer coefficients for stress, and sensible heat are calculated. For the neutral drag coefficient calculations in the main loop, roughness length $z_{on}$ is calculated on the basis of neutral friction velocity, which is obtained in a manner similar to step 9 but with the stability function $\psi_u$ assumed to be zero.

3. Field program

As a part of the Coastal Ocean Processes (CoOP) program sponsored by the US National Science Foundation (NSF), a Wind Events and Shelf Transport (WEST) study was conducted over the northern California coastal waters (http://www.ccs.ucsd.edu/coop/west/). This comprehensive field program including meteorological, oceanic, and marine biology measurements was carried out over the shelf off Bodega Bay during 2001 and 2002. The main objective of the project was to investigate the effects of wind forcing on ocean dynamics and biology. A special set of five buoys and three coastal stations provided detailed wind measurements over the shelf. The buoys were arranged in the diamond formation shown in Fig. 2. To our knowledge, this setup allowed the first attempt to directly compute wind-stress curl using wind-stress spatial variation computed from the buoy winds. For the wind-stress curl calculations, a triangular set of buoys (D090, E090 and National Data Buoy Center (NDBC) buoy 46013) was used. Buoy measurements included wind speed components, air and sea-surface temperatures, radiation fluxes, and humidity.

For a comparison of the Large and Pond (LP), HR, and TC algorithms for other locations and wind regimes, the drag coefficient and wind stress also were calculated using additional data from NDBC buoys 46023, 46054, and 46062. The locations and specifics of these buoys are shown on the Web site: http://www.ndbc.noaa.gov. The NDBC buoy measurements included wind speed, wind direction, air and sea temperatures, and dew-point temperature. For the longwave flux calculation, the Bignami et al. (1995) formula was used. Shortwave flux was calculated from the Rosati and Miyakoda (1988) formula.

4. Differences in computed drag coefficient and wind stress using various algorithms

Based on the availability of complete data, the period from 28 June to 4 August 2001 was selected for
the analysis. As can be noticed in Fig. 3, which shows a time series of the non-neutral drag coefficient, the LP algorithm (due to its high-wind speed threshold and stability independence) shows low variability while the HR and TC algorithms exhibit significant variations. For reference, the wind speed is also plotted in the same figure. Differences in the computed stress are significantly greater for higher winds since wind stress is proportional to the second power of the wind speed. The root mean square (RMS) difference between LP and HR was over two times higher than the RMS difference between the LP and TC wind stress (0.04 and 0.02 Pa, respectively). The relative differences in wind stress exhibit important characteristics, however, which will be discussed in Section 5.2.

As can be seen in Fig. 4A, for neutral computations, the HR-computed drag coefficient exhibits the largest range ($0.9 	imes 10^{-3} - 2 \times 10^{-3}$), whereas the range of the TC-computed drag coefficient is much smaller ($0.9 \times 10^{-3} - 1.6 \times 10^{-3}$). For computations with stability corrections, the HR algorithm exhibits

![Fig. 3](image_url)

Fig. 3. (A) Wind speed at 10m height; and wind stress calculated from (B) Large and Pond, (C) Hellerman and Rosenstein and (D) TOGA COARE algorithms. The input data are from buoy D090; series correspond to the period 28 June–4 August 2001.
smaller amplitude variations and lower overall range of the drag coefficient than the TC algorithm. The differences among these algorithms are apparent in Fig. 4A and B (see further discussion in Section 5.2).

5. Sensitivity of computed stress to input parameters

We conducted a series of sensitivity tests to investigate the roles of the input parameters on the computed drag coefficient and, consequently, on wind stress. The inputs to the analyses and sensitivity tests were as follows:

- Buoy D090 (Fig. 2) data for the period from 28 June to 4 August 2001.
- NDBC buoys 46023 (34.71°N/120.97°W), 46054 (34.27°N/120.45°W), and 46062 (35.10°N/121.01°W) data from 28 June to 4 August 2001.
- One set of average data for buoy D090 from the period 28 June to 4 August 2001 (used as a baseline for the sensitivity tests).

The location, sensor heights and depths, and data used for the sensitivity tests are:

- 38.28°N; 123.16°W
- Wind speed \( U = 0–15 \text{ m s}^{-1} \)
- Sea-surface temperature \( T_{\text{sea}} = 12.2 ^\circ \text{C} \)
- Air temperature \( T_{\text{air}} = 11.7 ^\circ \text{C} \)
- Shortwave radiation flux \( \text{SWF} = 250 \text{ W m}^{-2} \)
- Longwave radiation flux \( \text{LWF} = 150 \text{ W m}^{-2} \)
- Relative humidity \( \text{RH} = 92\% \)
- Depth of atmospheric boundary layer \( z_i = 600 \text{ m} \)
- Height of wind sensor \( z = 3.2 \text{ m} \)
- Height of air temperature sensor \( z_t = 3.17 \text{ m} \)
- Depth of sea-surface temperature sensor \( z_{st} = 1 \text{ m} \)
Sensitivity tests were performed in such a way that one or two input parameters were varied within a specified range, while all other parameters were kept constant. For the humidity sensitivity test, the baseline data were used except for humidity that varied from 0% to 100%. During the stability tests, air temperature varied from 7 to 15°C and wind speed from 0 to 15 m s\(^{-1}\) (SST and all other parameters were kept constant in that case). In a similar way, the sensitivity tests focused on radiation fluxes were performed varying longwave flux from 0 to 350 W m\(^{-2}\) and shortwave flux from 0 to 1000 W m\(^{-2}\) while the wind speed ranged from 0 to 15 m s\(^{-1}\). This method of sensitivity testing ensures that for each value of the governing parameter (e.g., humidity, temperature, longwave and shortwave radiation flux), calculations performed for different wind speeds give information about the influence of the governing parameter on the drag coefficient and also help to evaluate wind conditions at which this influence is the most significant.

5.1. Air–sea interaction and characterization of surface layer parameters

To characterize atmospheric conditions during the analyzed period, it is valuable to examine the behavior of the surface sensible and latent heat fluxes as well as the main surface layer parameters (i.e. the roughness length, friction velocity, and the Obukhov length). Sensible heat flux was low during the analyzed period (26 June–4 August 2001), ranging from −40 to 20 W m\(^{-2}\). Latent heat flux also was relatively low—up to only 60 W m\(^{-2}\). The computed heat flux was mostly positive, which corresponds to the prevailing unstable conditions during the analyzed period. The effect of stability on the drag coefficient will be discussed in Section 5.3.

The roughness length calculated as a function of wind speed shows that there is a minimum roughness length of about 2 × 10\(^{-5}\) m for wind speeds between 2 and 3 m s\(^{-1}\) (see Fig. 5). This value also will determine the end of the wind speed range where the roughness length is affected by atmospheric stability. The friction velocity curve shows parabolic behavior for wind speeds less than about 5 m s\(^{-1}\) and becomes more linear for greater wind speeds. A more detailed discussion of the relationship between the roughness length and the friction velocity is presented in the next section.

5.2. Effect of wind speed on the drag coefficient and wind stress

Wind speed is the parameter with the greatest influence on the drag coefficient for all algorithms. The response of each analyzed algorithm to various wind conditions differs significantly, however. A comparison of LP and TC results reveals two different regimes. For wind speeds from 4 to 7 m s\(^{-1}\), the LP algorithm provides higher values of the drag coefficient, whereas in the range from 7 to 10 m s\(^{-1}\), the values of the drag coefficient from the TC algorithm are greater (see Fig. 4). Because

![Fig. 5. Roughness length as a function of the friction velocity for various wind speeds.](image-url)
the common point of lines representing these two parameterizations is situated exactly in the middle of the analyzed wind range (7 m s\(^{-1}\)), both methods give similar results for the average wind speed around this value.

According to Eq. (2) the HR drag coefficient may seem to be a strongly nonlinear function of the wind speed due to the presence of the fourth term in which \( z_0 \) is associated with the square of wind speed. However, since \( z_2 \) is two orders of magnitude greater than \( z_4 \), for the wind speed observed during the analyzed period (0–16 m s\(^{-1}\)) the second term is dominant (for the maximum observed wind speed it is 6 times greater than the fourth term). Consequently Eq. (2) generates practically linear dependence of the HR-computed drag coefficient on wind speed for the analyzed wind conditions. For higher wind speeds the line of the HR drag coefficient becomes almost parallel to the TC drag coefficient, with the mean bias between them around 3.4 \(\times\) 10\(^{-4}\) (see Fig. 4B). It is a consequence of the relationship between the roughness length and friction velocity used in the TC algorithm, which exhibits close to linear dependence in this range.

In order to investigate the effect of a broader range of wind speed on the mean drag coefficient, we also performed calculations for NDBC buoys 46023, 46054, and 46062, which were characterized during the same period by different wind conditions (average wind speeds of 6.3, 8.6, and 5.7 m s\(^{-1}\), respectively). Results show that for buoy 46054 with the greatest wind speed (average wind speed of 8.6 m s\(^{-1}\)), the difference between the LP and TC algorithms does not exceed 5%, whereas for the relatively low-wind conditions observed at buoy 46062 (average wind speed 5.7 m s\(^{-1}\)), the differences reached as high as 19%. This suggests that windier and consequently more neutral conditions reduce differences among the computed results. For higher wind speeds (above 11 m s\(^{-1}\)), all algorithms show similar linear drag coefficient dependence on wind speed, with the lowest drag coefficient obtained from the LP and the highest one from the HR.

In the computations of the wind stress for neutral conditions and the weak-wind regime (below 4 m s\(^{-1}\)), where only the HR and the TC algorithms are defined, two characteristic points are apparent. The first point, situated close to the wind speed of 1 m s\(^{-1}\) (where the HR and TC lines cross each other), defines the end of the range of higher TC results and the beginning of conditions for which the drag coefficient from the HR algorithm gives higher values than the TC algorithm. The second characteristic point is located around 3 m s\(^{-1}\), where the TC algorithm gives the minimum drag coefficient (see Fig. 4A). The reason for this behavior is the roughness length equation used in the TC algorithm (step 8 in Fig. 1):

\[
z_0 = z_C \frac{U_*^2}{g} + 0.11 \frac{v}{U_*},
\]

where \( z_0 \) is the roughness length, \( U_* \) is the friction velocity, \( g \) is the gravitational acceleration, \( v \) is the kinematic viscosity, and \( z_C \) is the Charnock constant (0.011). The formula used for the roughness length calculation takes into account two different processes, smooth flow for low wind speeds and rough flow for higher wind speeds. These processes are represented by the 0.11(v/\(U_*\)) and \( z_C U_*^2/g \) terms, respectively. The relationship between the roughness length and the friction velocity is shown in Fig. 5. A derivative of the roughness length \( z_0 \) computed with respect to \( U_* \), when set to zero, gives the friction velocity at which \( z_0 \) (and as a consequence the drag coefficient) has its minimum:

\[
U_* = \sqrt{\frac{0.11v}{2z_Cg}}.
\]

On the basis of the friction velocity calculated from Eq. (5), \( U_* = 0.0889 \) m s\(^{-1}\), the roughness length \( z_0 \) can be calculated to be 2.66 \(\times\) 10\(^{-5}\) m, and the wind speed corresponding to the minimum drag coefficient can be calculated from the logarithmic profile:

\[
U = \frac{U_*}{\kappa} \ln \left( \frac{z}{z_0} \right),
\]

where \( U \) is the wind speed at height \( z \) and \( \kappa \) is the von Kármán constant (0.4). The calculation performed for the baseline point (described in the previous section) shows that a wind speed of 2.85 m s\(^{-1}\) gives the minimum drag coefficient (9.7 \(\times\) 10\(^{-4}\)).

Calculations performed using stability corrections show significantly different results compared to neutral conditions. For the interval of low winds (less than 4 m s\(^{-1}\)), the TC algorithm shows great variability–greatest for wind speed less than 2 m s\(^{-1}\). The reason is the inclusion of stability, moisture, radiation, planetary boundary layer height, and skin-temperature correction in the TC algorithm. All these parameters are dominant for the low-wind
regime, which is explained by the relationship between the friction velocity and the temperature scale parameter that are both present in the equation for the stability parameter $\zeta = z/L$ (step 6 in Fig. 1).

For high winds, the roughness length increases with the friction velocity; and, consequently, the temperature scale parameter increases as well. In this case, both parameters tend to compensate for each other, since they are present in the numerator and denominator, respectively. For the low-wind-speed regime, however, the increase in the friction velocity reduces the temperature scale parameters, which amplifies the increase in the Obukhov length. Consequently, the stability correction function and final wind stress are altered. Introducing stability corrections into the HR and TC algorithms reduces the differences between the HR- and TC-computed drag coefficients for high wind speeds and amplifies them for low-wind-speed conditions (Fig. 4B). This is due mainly to the negative influence on the HR-computed drag coefficient and the positive influence of the stability correction in the TC algorithm (see discussion in the next section). It is important to keep in mind that because the wind stress is proportional to the wind velocity squared, the effect of the drag coefficient on wind stress for low winds will be relatively small compared to the effect on wind stress for high winds.

Fig. 6 shows the relative difference in wind stress between LP and TC results as a function of wind speed. The differences are generally less than 50%; for low wind speeds, however, due to small values in the denominator the differences can be more than 100%, while the differences are significantly less for higher winds. For wind speeds above 10 m s$^{-1}$, the differences are reduced and oscillate around 15%.

5.3. Effect of atmospheric stability on wind stress

Implementation of stability corrections reduces the difference between the HR- and TC-computed drag coefficients. Measurements from buoy D090 show mainly unstable conditions (average values of the air and sea temperatures were 11.74 and 12.14°C, respectively). Unstable conditions correspond to negative values of the stability parameter $\zeta = z/L$. In this case ($\zeta < 0$), the stability function $\Psi$ is positive; and, consequently, the drag coefficient (calculated in step 20, Fig. 1) increases with the friction velocity (calculated in step 7, Fig. 1). For the HR formula, the situation is different. At low wind speeds (where stability correction has the biggest influence) and unstable conditions, the HR-computed drag coefficient is reduced. This response to unstable stratification is the result of the third and the fifth terms in Eq. (2). Because $\alpha_3$ is an order of magnitude larger than $\alpha_5$ and $\alpha_6$ (0.868 × 10$^{-4}$, 0.12 × 10$^{-5}$, and 0.214 × 10$^{-5}$, respectively), the third term (which is negative for unstable conditions) is dominant and cannot be adequately compensated for by the last term at wind speeds lower than 40 m s$^{-1}$. As a result, the drag coefficient obtained from the HR algorithm is reduced for unstable conditions, and the bias between the HR and TC results becomes less (see Fig. 4A and B).
HR-computed stress shows much less scatter due to the relatively limited variation in the sea and air temperature difference in our dataset. Also, the selection of constants in the HR algorithm precludes the significant variation in the drag coefficient that can be observed in the TC results for wind speeds below 2 m s\(^{-1}\). The fifth term in Eq. (2) is always negative regardless of the stability conditions. On the other hand, terms 3 and 6, which are stability sensitive, always have opposite sign and tend to compensate for each other. As a consequence, stability change cannot cause the drag coefficient variation in the range observed in the TC results. For both the HR and TC algorithms, the scatter of the drag coefficient due to atmospheric stability decreases with increased wind speed. These high-wind conditions and associated mixing cause neutral and near-neutral stability conditions.

In order to clarify the roles of atmospheric stability and wind, we used input test conditions (average values calculated for buoy D090 data) to perform sensitivity tests of the impact of these parameters on the computation of the drag coefficient. The effect of atmospheric stability on the computation of the drag coefficient is shown in Fig. 4B. The greatest range of the computed drag coefficient is for wind speeds less than 4 m s\(^{-1}\). This is especially evident for the TC algorithm. For very low wind speeds, atmospheric stability can alter the drag coefficient from negligible values to more than 2 \(10^{-3}\). This variability is caused by the stability function, which changes very rapidly with temperature (especially for close to neutral conditions) and has a strong influence on the friction velocity (step 7 in Fig. 1). For slight sea–air temperature difference (from +1 to −1), the stability function can change the value from positive (around 2) to negative (around −7). Consequently, for the same low wind speed but different stability conditions, the TC algorithm can provide a wide range of drag coefficient values, which can be observed in Fig. 4B. The greatest stability variation occurs at low wind speeds and induces the smallest drag coefficient (less than 10\(^{-4}\)) for the most stable conditions, while the drag coefficient reaches 1.8 \(10^{-3}\) for the most unstable conditions.

To understand better the TC results, we examined the computed drag coefficient as a function of the sea and air temperature difference (Fig. 7). The greatest variation in the drag coefficient is at low wind speeds. This is true even for small sea and air temperature differences. For wind speeds greater than 3 m s\(^{-1}\), the change in the drag coefficient is small given a large range in sea and air temperature differences (from −3 to 5 K). This is explained by the effect of the friction velocity influence \((U^*)\) on the roughness length \((z_0)\)—see the discussion in the previous section. For stronger winds, \(z_0\) is proportional to \(U^2\) according to the first term in Eq. (4). For weaker winds, however, the second term is more significant and \(z_0\) becomes inversely proportional to \(U^*\). Because of this, \(U^*\) changes in the

\[
\text{CD} = f(T_{\text{sea}} - T_{\text{air}}) \quad (U = 1 \text{ m/s}, \quad \text{CD} = 1.8 \times 10^{-3})
\]

Fig. 7. Drag coefficient computed from the TOGA COARE algorithm as a function of the difference between sea and air temperatures for various wind speeds. Calculation performed for average values of air temperature \((T_a)\), humidity \((\text{RH})\), and shortwave (SWF) and longwave (LWF) radiation fluxes for buoy D090 data (period from 28 June to 4 August 2001) using \(T_a = 12^\circ\text{C}, \ \text{RH} = 92\%, \ \text{SWF} = 250 \text{ W m}^{-2}\), and \(\text{LWF} = 150 \text{ W m}^{-2}\), air temperatures from 7 to 15 \(^\circ\text{C}\), and wind speeds from 1 to 10 m s\(^{-1}\).
opposite direction to $T_v$. As a consequence, the Obukhov length, stability correction, and drag coefficient become strongly dependent on the heat flux represented by $T_v$.

5.4. Effect of temperature corrections on wind stress

Since the buoy sensors for measuring sea temperature are at 60 cm depth and the TC algorithm for wind stress uses surface-skin sea temperature, a correction factor needs to be applied to buoy data prior to input. To obtain the real interfacial temperature for flux calculations, two issues need to be taken into account—cool-skin and warm-layer corrections. The cool-skin correction corresponds to the cooling effect of outgoing longwave radiation, sensible heat flux, and latent heat flux. The warm-layer correction is applied because of solar warming of the upper few meters of the ocean. This warming cause the temperature measured by a sensor at some depth to be inaccurate for evaluation of the top layer temperature, especially in conditions of strong insolation and weak mixing. Because warm-layer correction takes into account the difference between the temperature at the sensor depth and the temperature of the layer close to the surface, the shallower the sensor, the smaller the warm-layer correction (Fairall et al., 1996b).

For the analyzed data from buoy D090, the average warm-layer correction was an order of magnitude lower than the cool-skin correction (+0.034 and −0.37 °C, respectively); hence, we only analyzed the influence of the cool-skin effect. Although this correction is generally less than a degree K, it can significantly influence estimation of the wind stress. Fig. 6 shows the effect of the skin-temperature correction on differences between LP- and TC-computed wind stress as a function of wind speed. For low wind speeds, the cool-skin temperature correction can induce large differences between the LP and TC algorithms. For the low-wind-speed regime, the drag coefficient is very sensitive to stability (Fig. 7) because of the strong influence of the sea–air temperature difference on the stability function. Even a relatively small cool-skin correction at near-neutral conditions can have significant influence on the drag coefficient because of switching the stability regime. For slightly unstable conditions when the sea and air temperature difference has a small positive value (stability parameter $z/L$ is negative), reduction in the sea-surface temperature by less than one degree can reverse the sign of temperature difference and stability function, causing a change of regime from slightly unstable into slightly stable. As a consequence, reducing SST by the cool-skin correction also reduces the drag coefficient (see Fig. 6).

5.5. Effect of air humidity on wind stress

In the process of wind-stress computation, based on the TC algorithm, fluxes of momentum as well as sensible and latent heat are taken into account. Therefore, in addition to wind speed, air temperature and humidity are also used in the computations. Air humidity has a strong influence on TC results since it affects both the latent heat and sensible heat fluxes. The virtual temperature used for stability computation takes into account the presence of water vapor. Also, the density of the air used for the final TC wind-stress computation is calculated on the basis of this temperature, so the influence of humidity on wind stress is evident even without consideration of latent heat flux. The TC algorithm provides as a final result the sensible and latent heat fluxes. However, they also are used in each iteration step for the calculation of the temperature correction. As a result, temperature is corrected by the humidity twice—first, by using the virtual temperature, and second, by computing the cool-skin and warm-layer corrections on the basis of heat balance. In order to evaluate the total effect of humidity on wind stress, we performed sensitivity tests based on the start point (representing average conditions for buoy D090) and changing the humidity from 0% to 100%, while the wind speed ranged from 0 to 15 m s$^{-1}$. The drag coefficient change due to humidity as a function of wind speed is presented in Fig. 8.

As can be seen in Fig. 8, the highest variability in the drag coefficient due to humidity corresponds to wind speeds below 4 m s$^{-1}$. In this range, a relatively small change in humidity causes a significant change in the drag coefficient. For RH below 80%, the drag coefficient increases with wind speed; however, humidity above 84% completely changes this behavior and causes a dramatic decrease in the drag coefficient for weak winds. The same type of drag coefficient variability also can be observed in Fig. 4B, which shows the TC drag coefficient calculated on the basis of buoy D090 data. In this case, for wind speeds below 2 m s$^{-1}$, values of the drag coefficient can vary in a wide range from near zero to around $2.3 \times 10^{-3}$. The main reason for this
pattern is the humidity correction in the virtual temperature. For the baseline conditions that were analyzed ($T_{\text{sea}} = 12.2^\circ \text{C}$, $T_{\text{air}} = 11.7^\circ \text{C}$), stratification is unstable. However, if the virtual temperature is calculated for a RH of 84%, the situation changes. The new corrected air temperature will be higher than SST and, as a consequence, the stability regime will change from unstable to stable, causing a dramatic decrease in the drag coefficient as presented in Fig. 7.

In addition to the virtual temperature effect, latent heat flux also affects the TC-computed drag coefficient. The way the drag coefficient is influenced by latent heat flux is a consequence of the relationship between the cool-skin temperature correction and humidity. Latent heat flux is one of the parameters used for the cool-skin correction calculation. The lower the latent heat flux, the less the evaporative cooling of the top sea layer and, consequently, the smaller the cool-skin correction. This means that the sea temperature after the correction is higher and conditions are more unstable. So, these two corrections act in opposite directions. Moisture in the air increases the virtual temperature and invokes stable conditions. Alternatively, the cool-skin temperature correction decreases with increasing humidity and restores unstable conditions. The change in the cool-skin correction caused by humidity (from 0.1 to 0.2°C) is less significant than the change due to virtual temperature. Therefore, the net effect is that an increase in humidity causes a decrease in wind stress due to reduction of the drag coefficient and air density.

6. Impact of computed wind stress differences on computation of wind-stress curl

The presence of closely separated buoys in Bodega Bay (Fig. 2) during the field program provided an excellent opportunity to compute the wind-stress curl from the buoy network. The diamond-shaped setup allowed for various computational procedures, as shown by Dorman et al. (2006). We chose one of the algorithms for wind-stress curl as a baseline for examining the effect of various wind-stress algorithms on computed wind-stress curl. Wind-stress curl was calculated using data from buoys D090, E090, and 46013 (see Fig. 2) in the coordinate system rotated clockwise by 320°. In this coordinate system, the first term in Eq. (7) corresponds to cross-shore variation of the along-shore wind stress and the second one corresponds to the along-shore variation of the cross-shore wind stress.

Wind-stress curl = $\frac{\Delta \tau_y}{\Delta x} - \frac{\Delta \tau_x}{\Delta y}$, (7)

where $\Delta \tau_y$ the $\tau_{\text{along-shore}, \text{D090}} - \tau_{\text{along-shore}, \text{46013}}$; $\Delta \tau_x$ the $\tau_{\text{cross-shore}, \text{E090}} - \tau_{\text{cross-shore}, \text{D090}}$; $\Delta x$ the cross-shore distance between buoys D090 and 46013; $\Delta y$ the...
the along-shore distance between buoys E090 and D090.

We applied the three wind-stress algorithms (LP, HR, and TC) to Eq. (7) and examined the extent to which selection of the wind-stress algorithm altered the wind-stress curl computation. Time series of average wind speed, wind stress, and wind-stress curl computed using the TC algorithm are presented in Fig. 9. Computed wind-stress curl is mostly positive for all wind-stress parameterizations; however, differences among average wind-stress curl for the different algorithms reaches up to 40%, as shown next.

Time series of the wind-stress curl calculated using the LP, HR, and TC algorithms are shown in Fig. 10. The lowest median wind-stress curl, obtained using the LP formula, was equal to 0.15 Pa (100 km); computations performed using the HR scheme provided the highest mean wind-stress curl equal to 0.24 Pa (100 km)\(^{-1}\), whereas the median curl, calculated using the TC algorithm, was equal to 0.17 Pa (100 km)\(^{-1}\). Differences between wind-stress curl obtained from these parameterizations correspond to the wind-stress variability. The standard deviation of the LP-computed wind stress calculated for buoy D090 for the analyzed period (28 June–4 August 2001) is the lowest (0.086 Pa), whereas the variability of the HR wind stress is the highest, with a standard deviation equal to 0.124 Pa. The TC variability is slightly greater than for the LP formula, which was equal to 0.10 Pa. These results can be explained by the stability correction, which is not included in the LP formula, stays on a similar high level for all wind speeds in the HR algorithm, and rapidly decreases with increasing wind speed in the TC algorithm. Consequently, the LP formula provided the most uniform wind stress corresponding to the lowest wind-stress curl, the HR-computed wind stress with the greatest variability provided the highest curl, whereas the TC algorithm with the lower wind-stress variability provided also lower wind-stress curl than the HR formula. Comparison of the range and variability in the wind-stress curl, however, does not correspond directly to variability of the drag coefficient shown in Fig. 4B. The strong influence of wind speed on wind stress (second power) reduces differences in low-wind-stress regimes and enhances differences in high-wind-stress regimes, which means that the algorithm providing the highest drag coefficient variability for relatively strong winds also provides the highest wind-stress curl (compare Figs. 3 and 10).

Generally, the central buoy D090 and buoy E090 experience similar but significantly lower wind speeds than buoy 46013 which is located farther offshore (averages of 5.29, 5.21, and 6.36 m s\(^{-1}\), with standard deviations 3.63, 3.72 and 4.59 m s\(^{-1}\), respectively). Since for the analyzed area prevailing winds blew from the northwest (a negative along-shore velocity component) the first, positive term in Eq. (7) dominates. As a consequence, the small negative along-shore gradient of the cross-shore stress (term 2 in Eq. (7)) is mostly offset by the larger, positive cross-shore gradient of the along shore wind stress, resulting in a mostly positive calculated curl (see Fig. 9C). However, in some cases, the computed curl has negative values. The negative curl is associated with a rapid change in wind direction, when the wind becomes more southward. This causes a smaller along-shore component of the wind speed, a reduction in the difference between along-shore wind stress calculated for buoys 46013 and D090, and, as a consequence, a lower value of the first term in Eq. (7), which cannot compensate for the second (negative) term calculated on the basis of the along-shore gradient in the cross-shore wind stress.

Positive curl is associated generally with conditions in which the wind speed at buoy 46013 is substantially greater than at buoy D090. To examine what wind conditions induce negative and positive curls, we computed the frequency of positive and negative wind-stress curl occurrence for wind speeds ranging from 0 to 16 m s\(^{-1}\). The results of these frequency computations show that negative wind-stress curl is associated mostly with low wind speed, whereas the positive curl is spread relatively uniformly along a wide range of wind speeds. This characteristic is valid for all algorithms; however, each differs slightly. The HR algorithm is associated with the strongest negative curl occurrence for the lowest wind speeds (below 6 m s\(^{-1}\)); however, for wind speeds above 8 m s\(^{-1}\) the highest occurrence of negative curl is associated with the TC algorithm. The opposite effect can be observed in the wind speed distribution associated with positive wind-stress curl. In this case, the highest frequency of positive curl is evident for the HR formula for wind speeds in the range from 8 to 14 m s\(^{-1}\). This situation changes for wind speeds below 8 m s\(^{-1}\) where the highest occurrence of positive curl is associated with the TC algorithm. For winds above 14 m s\(^{-1}\) (where all algorithms show similar dependence on wind speed), all methods give similar
frequencies of positive curl. Negative wind-stress curl is the result of the along-shore gradient in the cross-shore wind stress between buoys D090 and E090. Because the cross-shore gradient of the along-shore wind stress is dominant (wind speed at buoy 46013 is much higher than at buoy D090), the second term in Eq. (7) always gives a positive contribution to the wind-stress curl. This means that an algorithm able to provide high wind-stress variance for lower wind speeds will promote negative curl. On the other hand, an algorithm that provides higher variability for stronger winds causes

Fig. 9. Comparison of (A) average wind speed for buoys D090, E090, and 46103; (B) average TOGA COARE-computed wind stress for buoys D090, E090, and 46013; (C) wind-stress curl calculated using TOGA COARE-computed wind stress for buoys D090, E090, and 46013; (D) sea-surface temperature. Presented data correspond to the period from 28 June to 4 August 2001.
higher positive contribution of term 2 and promotes positive curl. For this reason, the HR algorithm promotes positive curl, whereas the TC algorithm tends toward negative curl.

In summary, the discussed frequency distributions of wind-stress curl seem to be the result of wind-stress variation, which is smallest for the LP algorithm, greatest (and similar for all wind speeds) for the HR algorithm, and slightly less (and decreasing with wind speed) for the TC algorithm. The LP and TC algorithms give very similar wind-stress curl results (average difference around 10%), whereas the wind-stress curl obtained from the HR algorithm is greater by 40%. This difference between HR and the two other algorithms is possibly due to calibration of the polynomial HR

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Fig. 10. Comparison of (A) average wind speed for buoys D090, E090, and 46103 and wind-stress curl calculated by (B) TOGA COARE, (C) Large and Pond, and (D) Hellerman and Rosenstein algorithms. Computations for the period from 28 June to 4 August 2001.
formulation, based on global data, which may not be fully appropriate for the considered coastal area. The most uniform wind-stress curl (from $-0.46$ to $1.54 \text{ Pa} (100 \text{ km})^{-1}$) is provided by the LP algorithm, whereas the HR algorithm exhibits the largest range $-0.63$ to $2.23 \text{ Pa} (100 \text{ km})^{-1}$ (see Fig. 10). The TC algorithm provides a slightly broader range of results than the LP formula (from $-0.5$ to $1.70 \text{ Pa} (100 \text{ km})^{-1}$), and much narrower than the HR polynomial. These observed results are a consequence of wind-stress variability due to the stability correction, which is on the same, relatively high level for the HR algorithm but decreases with the increase of the wind speed for the TC algorithm.

All three algorithms exhibit similar, asymmetric, unimodal distribution with dominant positive wind-stress curl in the range $-0.5$ to $0.2 \text{ Pa} (100 \text{ km})^{-1}$; however, the observed ranges of computed wind-stress curl as well as curl frequency in particular bins are different. Generally, the distribution of LP wind-stress curl is narrower than for the other algorithms due to the constant drag coefficient in the range from 4 to $11 \text{ m s}^{-1}$. Distribution of the HR wind-stress curl is biased strongly toward positive values and has a wider distribution compared to the LP algorithm. This result is the effect of the stability influence, which is more significant for higher winds. The TC wind-stress curl distribution has a slightly narrower spectrum than the HR curl, and is shifted toward the negative values. This may be the effect of the strong influence of the TC stability correction in the low-wind-speed regime.

7. Ocean response for the wind stress and wind-stress curl

The upward motion of the cold water induced by upwelling may lead to a decrease in the SST. Alternatively, downwelling or lack of circulation gives the sea-surface an opportunity to warm. SST changes, however, can result from other factors as well (e.g., ocean currents, cloudiness). Furthermore, the ocean’s response to change in a factor that induces mixing is generally not immediate. Therefore, we do not expect an ideal correlation between the factors inducing vertical mixing and SST. Nevertheless, some trends should be apparent. Since upwelling can be induced by the along-shore component of wind stress as well as wind-stress curl, both parameters should be examined with respect to variations in SST (Koračin et al., 2005).

In order to obtain the wind stress components parallel and perpendicular to the coast of Bodega Bay, we rotated the coordinate system clockwise by $320^\circ$. The relationship between the along-shore component of the TC wind stress ($\tau_x$) and SST is presented in Fig. 11A. Since the prevailing wind was from the northwest to southeast during the analyzed period, the along-shore wind-stress component is mostly negative. As can be seen in Fig. 11A, no obvious relationship exists between the along-shore wind-stress component and the SST due to the complexity of the ocean circulation and time scale of the ocean response to the atmospheric forcing.

In order to examine the influence of wind-stress curl on ocean dynamics, we compared the wind-stress curl calculated from the various algorithms to SST variation. The relationship between SST and wind-stress curl computed by the TC algorithm is presented in Fig. 11B. Despite the apparent scatter, a significant trend of decreasing SST with increasing wind-stress curl for the full range of measured temperatures can be noticed. A similar trend was observed also for the two other algorithms. The scatter apparent in Fig. 11B may be caused by the influence of oceanic processes, shelf structure, and meteorological conditions (cloudiness, radiation, etc.) on SST, as well as a possible lag between wind-stress curl forcing and the ocean response.

According to Fig. 11B, SST appears to be inversely proportional to the wind-stress curl. The wind-stress curl maximum (present at the beginning of the analyzed period) corresponds to the SST minimum (compare Figs. 9C and D). The following relaxation period with very low wind-stress curl (vertical dashed line in Fig. 9) and the change in sign of the wind-stress curl from positive to negative (indicating the change in wind-stress rotation from counterclockwise to clockwise) correlates with an increase in SST from 10 to 13.5 $^\circ\text{C}$. Further wind-stress curl fluctuations also correlate with SST, with evident cooling of the sea-surface corresponding to positive wind-stress curl and warming corresponding to negative curl in the relaxation periods. Wind-stress curl and SST are significantly correlated to upwelling in this area as described by Enriquez and Friehe (1995). The relationship between wind-stress curl and SST is apparent even for lower temperatures, where the trend in SST variation cannot be related to upwelling induced by the along-shore wind-stress component. This suggests that for cases of low SST, upwelling induced by wind-stress curl could be a significant factor.
To test correlation between the SST and the along-shore wind stress as well as between the SST and the wind-stress curl, we have performed a bootstrapping analysis (Cox and Tikvart, 1990; Efron and Tibshirani, 1993). Since this method uses multiple resampling, it is able to reveal the strength of a correlation by considering possible temporal lags between analyzed series. Therefore we deployed it to analyze the possibly time shifted ocean response, indicated by the SST, to the along-shore stress and the wind-stress curl. The results show that both the along-shore wind stress and wind-stress curl exhibit notable correlation with the SST for all analyzed wind-stress algorithms. As can be seen in Fig. 12, the mean correlation coefficients between the along-shore wind stress and SST (after bootstrapping) were equal to 0.35, 0.36 and 0.34 for the LP, HR and TC algorithms. The distributions of the correlation coefficients as well as medians indicate that wind-stress curl correlates slightly better with the SST, compared to the along-shore wind stress. The mean correlation coefficients

![Fig. 11](image-url)
between the wind-stress curl and SST were equal to 0.42, 0.43 and 0.40 for the LP, HR and TC algorithms, respectively. Consequently, both of these processes should be considered in the investigation of the coastal upwelling.

In order to examine whether the effect of the wind-stress curl can be verified using ocean measurements, we compared the time series of the wind-stress curl (LP and TC) with the observed divergence of the cross-shelf transport in the oceanic boundary layer between buoys D090 and D130—dUHPRT (Dever et al., 2006). Before the analysis data were 38 h low-pass filtered in order to remove tidal, inertial and diurnal oscillations from hourly data. As can be noticed in Fig. 13, in spite of some differences between the wind-stress curl and divergence in boundary layer transport, the wind-stress curl is closely associated with all major periods of upwelling and relaxation. The bootstrapping analysis revealed that the correlation between the low-pass filtered wind-stress curl and the measured surface divergence is even stronger than the correlation between the SST and the wind-stress curl. The median correlation coefficients for the LP and HR formulae were very similar (0.68) while the one for the TC algorithm was slightly lower (0.62). This suggests that, despite the evident differences between the wind-stress curl computed from the various schemes, they present similar agreement with the ocean response measured by the current meter.

It should be mentioned that the wind-stress curl can be generated or enhanced by the stratification of the near-surface atmospheric boundary layer over cooler sea-surface water upwelled by the along-shore wind stress alone. However, due to the inherent structure of the wind field near the coast, caused by the coastal topography and the coastline geometry (Koracin and Dorman, 2001; Samelson et al., 2002; Koracin et al., 2004), the wind-stress curl appears to be a persistent feature associated with the inhomogeneity of the wind field near the coast. Some of the preliminary atmospheric and oceanic simulations (Beg-Paklar et al., 2005) focused on the US West Coast indicate, on the other hand, that both the wind stress and wind-stress curl have to be considered in generating coastal upwelling. More future atmospheric and oceanic measurements as well as numerical experiments are needed to resolve the particular roles of the wind stress and the wind-stress curl in generating coastal upwelling.

8. Concluding remarks

Three wind-stress algorithms of varying sophistication were compared and their impact on wind-stress curl examined using buoy data from a field program conducted in Bodega Bay from the end of June until the beginning of August 2001. Inclusion of atmospheric stability significantly alters the wind-stress computation, and the greatest

![distribution of correlation coefficient between along-shore wind stress and SST](A)

![distribution of correlation coefficient between wind-stress curl and SST](B)

Fig. 12. Distribution of the correlation coefficient after bootstrapping for 10000 permutations between (A) along-shore wind stress and SST, (B) between the wind-stress curl and SST.
differences in estimated drag coefficients among the algorithms were for low wind speeds and non-neutral conditions. The high variability of TC results for the low-wind-speed regime corresponds to the physical processes taking place at the sea–air interface. For low wind-speed conditions, the transfer of momentum is influenced by heat and humidity fluxes. Humidity and temperature fluctuations in unstable conditions can intensify momentum transfer, which increases the drag coefficient. Stable stratification acts in the opposite way, inhibiting momentum transfer and consequently causing a decrease in the drag coefficient.

The TC algorithm estimates both cool-skin and warm-layer temperature corrections. The cool-skin temperature correction (up to a degree or less) due to evaporative heat loss appears to be an order of magnitude greater than the warm-layer temperature correction. For low wind speeds and small sea and air temperature differences, the former correction can produce a significant impact and even change stability conditions from unstable to stable. Stability change can significantly decrease the magnitude of the drag coefficient, which can be observed in Fig. 7.

Atmospheric humidity is treated only in the TC algorithm. It alters air density through the virtual temperature computation and also alters the cool-skin temperature through computation of latent heat flux. Sensitivity tests show that the former effect is dominant. For baseline conditions, there is a critical humidity threshold beyond which stratification will change from unstable to stable and vice versa. This implies that the drag coefficient will increase significantly during low wind speeds at less than the critical relative humidity, but decrease if the relative humidity is less than the critical value (Fig. 8). The magnitude of the critical relative humidity will be different for different baseline conditions.

Generally, even though the LP algorithm does not include stability corrections, it provides only slightly smaller (10%) average wind-stress values than the most advanced TC algorithm. Results obtained from the HR formula, however, exceed those obtained from the other analyzed algorithms by around 25%.

Different characteristics of the stability correction, which is similar for the entire speed range in the HR algorithm and strongly decreases with wind speed in the TC algorithm, determine the range and variability of computed wind stress and wind-stress curl. As a consequence, the highest wind-stress curl range is associated with the HR algorithm. The curl range computed from the HR algorithm is similar to that obtained from the TC algorithm in the case of negative curl, but is slightly broader for positive curl.

Regarding the roles of the along-shore wind stress and wind-stress curl in generating upwelling, both of them noticeably correlate with SST. The bootstrapping analysis that considers temporal lags in
the time series has shown that the medians of the correlation coefficients are in the range 0.34–0.36 for the along-shore wind stress and 0.4–0.43 for the wind-stress curl. The analysis further shows that the temporal evaluation of the stress curl closely corresponds to the variations in the divergence of the surface boundary layer transport indicating upwelling and relaxation periods. The median correlation coefficients between the 38-h low-pass-filtered wind-stress curl and the measured surface divergence were similar for the LP and HR formulae (0.68), and slightly lower for the TC algorithm (0.62). This suggests that all three analyzed algorithms provide wind-stress curl similarly correlated with the measured surface divergence.

Further studies and field programs including direct measurement of ocean dynamics as well as winds, wind stress, and wind-stress curl are needed to shed more light on the significance of atmospheric forcing on upwelling processes in coastal regions.

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