

Intercomparison of Bulk Aerodynamic Algorithms for the Computation of Sea Surface Fluxes Using TOGA COARE and TAO Data

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(Manuscript received 8 August 1997, in final form 9 December 1997)

ABSTRACT

A bulk aerodynamic algorithm is developed for all stability conditions for the computation of ocean surface fluxes. It provides roughness lengths of wind, humidity, and temperature for a wind speed range from 0 to 18 m s⁻¹: $z_o = 0.013u_*^2/g + 0.11\nu/u_*$ and $\ln(z_o/z_{oi}) = \ln(z_o/z_{oi}) = 2.67Re_*^{1/4} - 2.57$ as derived using the Tropical Oceans Global Atmosphere (TOGA) Coupled Ocean–Atmosphere Response Experiment (COARE) data constrained by other observations under high wind conditions.

Using the TOGA COARE ship data and the multiyear hourly TOGA Tropical Atmosphere–Ocean moored buoy data, intercomparison of six different algorithms, which are widely used in research, operational forecasting, and data reanalysis, shows that algorithms differ significantly in heat and momentum fluxes under both very weak and very strong wind conditions, but agree with each other under moderate wind conditions. Algorithms agree better for wind stress than for heat fluxes.

Based on past observations, probable deficiencies in roughness lengths (or neutral exchange coefficients) of some of the algorithms are identified along with possible solutions, and significant issues (particularly the trend of the neutral exchange coefficient for heat with wind speed under strong wind conditions) are raised for future experiments.

The vapor pressure reduction of 2% over saline seawater has a significant impact on the computation of surface latent heat flux under strong wind conditions and should be considered in any bulk aerodynamic algorithm.

1. Introduction

The atmosphere and ocean interact through the exchange of surface fluxes of heat, freshwater, and momentum. These fluxes provide upper boundary conditions for oceanic GCMs. Momentum flux drives ocean currents and surface mixing, which, with surface energy and freshwater fluxes, control SST. SST, in turn, provides the lower boundary conditions for atmospheric GCMs (AGCMs). Systematic biases in ocean surface fluxes have been found in AGCMs [e.g., by the Atmospheric Model Intercomparison Project; Gleckler and Randall (1996)], and become even more severe in ocean–atmosphere coupled climate models (e.g., Gates et al. 1996), so that flux adjustments (e.g., Roberts et al. 1997) have been applied in some of the coupled models.

Surface fluxes are computed using bulk aerodynamic

methods in numerical models and for data analyses. The sensitivity of surface fluxes to the choice of algorithms (particularly under low wind conditions) has been widely recognized (e.g., Webster and Lukas 1992). Miller et al. (1992) demonstrated that a revision of their bulk algorithm significantly improved almost all aspects of the simulation of the Tropics by the European Centre for Medium-Range Weather Forecasts (ECMWF). The sensitivity of cloud-resolving models to surface flux algorithms has also been reported (Wang et al. 1996). Various bulk algorithms have been developed in the past several decades [as reviewed in Liu et al. (1979), Smith (1988), and Garratt (1992)]. Fairall et al. (1996a) developed a comprehensive bulk algorithm using the data from the Tropical Oceans Global Atmosphere (TOGA) Coupled Ocean–Atmosphere Response Experiment (COARE) under weak to moderate wind conditions (e.g., less than 12 m s⁻¹). Using data from several ships and under weak to moderate wind conditions, Clayson et al. (1996) evaluated this algorithm, the Liu et al. (1979) algorithm, and their own algorithm based on surface renewal theory. Despite these efforts, no single algorithm is in use by the various research groups and forecast centers, and no systematic comparison of various algorithms being used has been performed. For this reason, the recent World Climate Research Program workshop on air–sea fluxes (White 1996) recommended an intercomparison of bulk algorithms.

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Such an intercomparison is now possible because of the availability of several observational datasets taken under various wind conditions. In particular, TOGA COARE provides simultaneous hourly data of fluxes and bulk environmental variables over the open ocean under weak to moderate wind conditions (i.e., less than 12 m s^{-1}), while the Humidity Exchange Over the Sea program (Katsaros et al. 1987; Smith et al. 1990; DeCosmo et al. 1996) provides data for near-coast areas under moderate to high wind conditions (wind speeds up to 18 m s^{-1}). Observations under various wind conditions are also reported elsewhere (e.g., Large and Pond 1982; Bradley et al. 1991). In addition to these short time series flux data, the use of the multiyear hourly data of air temperature, wind speed, and humidity from the TOGA Tropical Atmosphere–Ocean (TAO) moored buoys over the tropical Pacific Ocean and the derived hourly surface skin temperature data in Zeng et al. (1998, submitted to *J. Geophys. Res. Oceans*, hereafter ZE98) ensures the climatic relevance and significance of the algorithm intercomparisons.

The purpose of this study is to intercompare the COARE algorithm (version 2.5, Fairall et al. 1996a; hereafter referred to as COARE 2.5), algorithms used in the National Center for Atmospheric Research (NCAR) Community Climate Model version 3 (CCM3), the ECMWF forecast model, the National Centers for Environmental Prediction (NCEP) medium-range forecast model, and the Goddard Earth Observing System (GEOS) Data Assimilation System (DAS), and a new algorithm developed here. The derivation of the new algorithm is discussed in section 2, and all other algorithms are briefly summarized in the appendix. Intercomparison using the TOGA COARE data is given in section 3, and intercomparison using the TOGA TAO data is discussed in section 4. The intercomparisons are interpreted in section 5, and conclusions are given in section 6.

2. Bulk aerodynamic algorithm

Bulk aerodynamic algorithms for the computation of surface fluxes have two components: turbulent stability functions and the representation of roughness lengths for wind, temperature, and humidity (denoted as z_o, z_{ot} , and z_{oq} , respectively). While oceanic roughness lengths differ from those over land (Brutsaert 1982; Garratt 1992; Zeng and Dickinson 1998), atmospheric stability functions should be universal over any surface (ocean, land, or ice). Although surface fluxes and bulk environmental variables can be measured directly, roughness lengths require parameterization. Because the functional form (or constant value) of roughness lengths depends upon the turbulent stability functions, very different equations for roughness lengths have been suggested by different groups (see the appendix). The basis for the new bulk algorithm (denoted as UA) is presented here; all other algorithms are summarized in the appendix.

Dimensionless vertical wind and scalar (temperature and humidity) gradients in the atmospheric surface layer (typically a few tens of meters above surface) can be defined as

$$\phi_m = \frac{kz}{u_*} \frac{du}{dz}, \quad \text{and} \quad \phi_h = \frac{kz}{\theta_{v*}} \frac{d\theta_v}{dz}, \quad (1)$$

where k is the von Kármán constant (0.4), u is wind speed, θ_v is virtual potential temperature, u_* is friction velocity, and θ_{v*} is the temperature scaling parameter. Using the Monin–Obukhov similarity theory, the flux-gradient relations are (e.g., Dyer 1974)

$$\phi_m = \phi_h = 1 + 5\zeta \quad (2)$$

under stable conditions (i.e., $\zeta > 0$), and

$$\phi_m = (1 - 16\zeta)^{-1/4}, \quad \text{and} \quad \phi_h = (1 - 16\zeta)^{-1/2} \quad (3)$$

under unstable conditions (i.e., $\zeta < 0$). The dimensionless height ζ used in (2)–(3) is defined as

$$\zeta = \frac{z}{L}, \quad \text{and} \quad L = \frac{\theta_v u_*^2}{kg\theta_{v*}} \quad (4)$$

is the Monin–Obukhov length. Under very unstable conditions, the flux-gradient relations from Kader and Yaglom (1990) are used:

$$\phi_m = 0.7k^{2/3}(-\zeta)^{1/3}, \quad \text{and} \quad \phi_h = 0.9k^{4/3}(-\zeta)^{-1/3}. \quad (5)$$

To ensure continuous functions of $\phi_m(\zeta)$ and $\phi_h(\zeta)$, the simplest approach (i.e., without considering any transition regimes) is to match (5) with (3) at $\zeta_m = -1.574$ for $\phi_m(\zeta)$ and $\zeta_h = -0.465$ for $\phi_h(\zeta)$. Under very stable conditions, relations from Holtslag et al. (1990) can be used:

$$\phi_m = \phi_h = 5 + \zeta, \quad (6)$$

which matches (2) at $\zeta = 1$.

Integration of (1)–(6) gives wind profiles as

$$u(z) = \frac{u_*}{k} \left\{ \left[\ln \frac{\zeta_m L}{z_o} - \psi_m(\zeta_m) \right] + 1.14 \left[(-\zeta)^{1/3} - (-\zeta_m)^{1/3} \right] \right\} \quad (7)$$

(with ψ_m given later) for $\zeta < \zeta_m = -1.574$;

$$u(z) = \frac{u_*}{k} \left[\ln \frac{z}{z_o} - \psi_m(\zeta) \right] \quad (8)$$

for $\zeta_m < \zeta < 0$;

$$u(z) = \frac{u_*}{k} \left[\ln \frac{z}{z_o} + 5\zeta \right] \quad (9)$$

for $0 < \zeta < 1$; and

$$u(z) = \frac{u_*}{k} \left\{ \left(\ln \frac{L}{z_o} + 5 \right) + \left[5 \ln(\zeta) + \zeta - 1 \right] \right\} \quad (10)$$

for $\zeta > 1$. The potential temperature profiles are

$$\theta(z) - \theta_s = \frac{\theta_*}{k} \left\{ \left[\ln \frac{\zeta_h L}{z_{ot}} - \psi_h(\zeta_h) \right] + 0.8 \left[(-\zeta_h)^{-1/3} - (-\zeta)^{-1/3} \right] \right\} \quad (11)$$

(with ψ_h given later) for $\zeta < \zeta_h = -0.465$;

$$\theta(z) - \theta_s = \frac{\theta_*}{k} \left[\ln \frac{z}{z_{ot}} - \psi_h(\zeta) \right] \quad (12)$$

for $\zeta_h < \zeta < 0$;

$$\theta(z) - \theta_s = \frac{\theta_*}{k} \left(\ln \frac{z}{z_{ot}} + 5\zeta \right) \quad (13)$$

for $0 < \zeta < 1$; and

$$\theta(z) - \theta_s = \frac{\theta_*}{k} \left\{ \left(\ln \frac{L}{z_{ot}} + 5 \right) + \left[5 \ln(\zeta) + \zeta - 1 \right] \right\} \quad (14)$$

for $\zeta > 1$. Specific humidity profiles are the same as those for θ [(11)–(14)] except that $[\theta(z) - \theta_s]$ and z_{ot} should be replaced by $[q(z) - q_s]$ and z_{oq} , respectively. The stability functions in (7)–(8) and (11)–(12) (under unstable conditions) are

$$\psi_m = 2 \ln \left(\frac{1 + \chi}{2} \right) + \ln \left(\frac{1 + \chi^2}{2} \right) - 2 \tan^{-1} \chi + \frac{\pi}{2},$$

and

$$\psi_h = 2 \ln \left(\frac{1 + \chi^2}{2} \right), \quad (15)$$

where

$$\chi = (1 - 16\zeta)^{1/4}. \quad (16)$$

In (7)–(14), θ_s is surface potential temperature, and q_s is saturated specific humidity over saline seawater (Sverdrup et al. 1942):

$$q_s = 0.98 q_{sat}(T_s), \quad (17)$$

where T_s is the sea surface skin temperature (ZE98), and q_{sat} is the saturation specific humidity for pure water at T_s . The factor of 0.98 is an approximation to (1–0.527s) for the average oceanic salinity s of 34 parts per thousand (Kraus and Businger 1994). Under stable conditions, the wind speed u is defined as

$$u = \max[(u_x^2 + u_y^2)^{1/2}, 0.1] \quad (18)$$

to avoid a singularity at $u = 0$, whereas for unstable conditions, it is given as

$$u = [u_x^2 + u_y^2 + (\beta w_*)^2]^{1/2} \quad (19)$$

to account for the contribution of large eddies in the convective boundary layer to surface fluxes. In (18)–(19), u_x and u_y are mean wind components, and w_* is the convective velocity scale:

$$w_* = \left(-\frac{g}{\theta_v} \theta_* u_* z_i \right)^{1/3}, \quad (20)$$

where g is acceleration due to gravity and z_i is the convective boundary layer height. The value of z_i is taken as 1000 m in (20), whereas β in (19) is taken as unity.

Using the above equations, surface fluxes of momentum, sensible heat (SH), and latent heat (LH) can be obtained as

$$\tau = \rho_a u_*^2 (u_x^2 + u_y^2)^{1/2} / u, \quad (21)$$

$$\text{SH} = -\rho_a C_{pa} u_* \theta_*, \quad \text{and} \quad (22)$$

$$\text{LH} = -\rho_a L_e u_* q_*, \quad (23)$$

where ρ_a is air density, C_{pa} is specific heat of air, and L_e is latent heat of vaporization. The ratio of $(u_x^2 + u_y^2)^{1/2} / u$ in (21) ensures that zero mean wind would result in zero wind stress.

The functional form of Smith (1988) is used for roughness length of momentum (z_o):

$$z_o = a_1 \frac{u_*^2}{g} + a_2 \frac{\nu}{u_*}, \quad (24)$$

the functional form of Brutsaert (1982) is used for roughness length of humidity:

$$\ln \frac{z_o}{z_{oq}} = b_1 \text{Re}_*^{1/4} + b_2, \quad (25)$$

and the roughness length of temperature is assumed to be the same; that is,

$$z_{ot} = z_{oq}, \quad (26)$$

where a_1 , a_2 , b_1 , and b_2 are constant coefficients, $\text{Re}_* = u_* z_o / \nu$ is the roughness Reynolds number, and ν the kinematic viscosity of air. Using the simultaneous data of surface fluxes and bulk variables from TOGA COARE, we obtain $a_1 = 0.013$, $a_2 = 0.11$, $b_1 = 2.67$, and $b_2 = -2.57$ for the observed wind speed over a range from 0.5 to 10 m s⁻¹ (see Fig. 1 and discussions in section 3).

Other values than those above were obtained for b_1 and b_2 in (25) [and, to a lesser degree, a_1 and a_2 in (24)] that fit the TOGA COARE data equally well based on various statistical quantities (e.g., see Tables 1 and 2 and discussions in section 3) but were not appropriate for wind speeds beyond 10 m s⁻¹. The selected coefficients of b_1 and b_2 in (25) were chosen, in addition, to provide agreement of the neutral exchange coefficient for moisture (C_{qn}) with that observed under high wind conditions (e.g., DeCosmo et al. 1996). Hence, the above coefficient values ensure that (24)–(26) are ap-

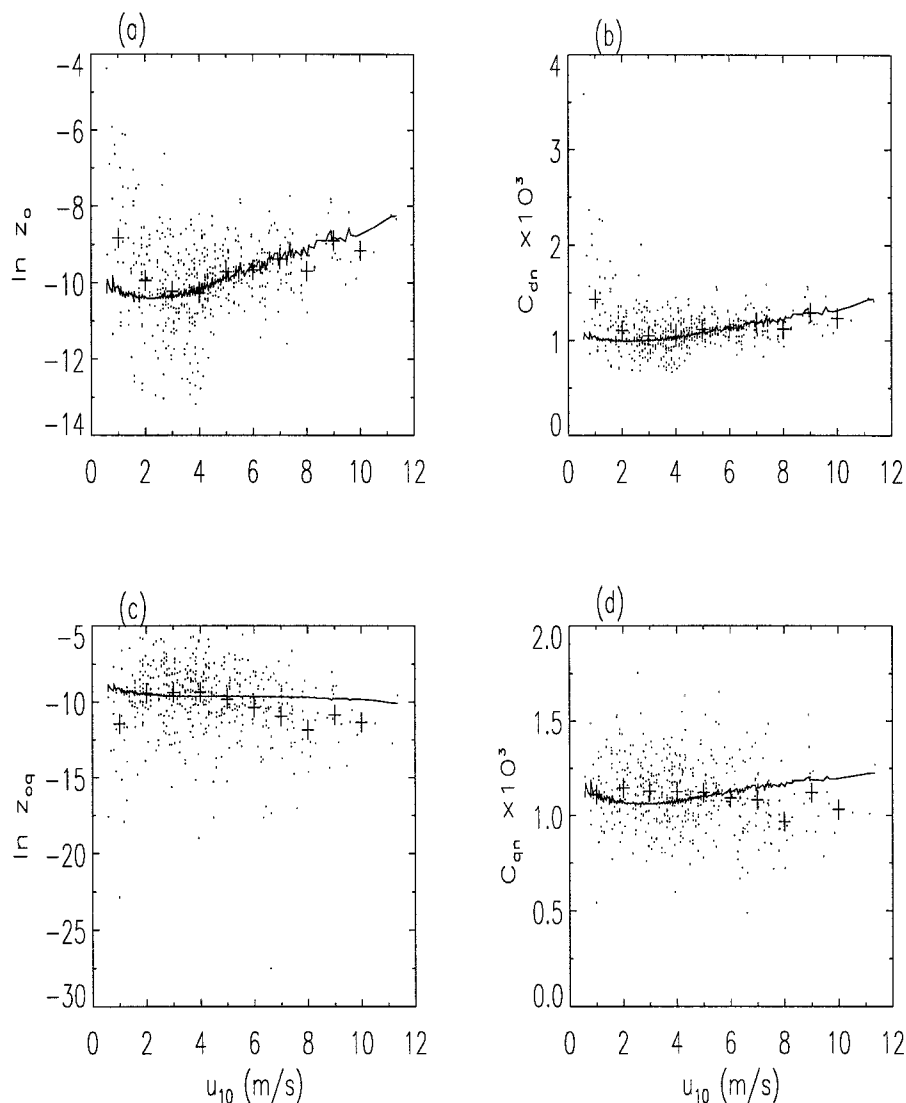


FIG. 1. Logarithms of roughness lengths for momentum in (a) and moisture in (c), and neutral exchange coefficients for momentum in (b) and moisture in (d) as a function of 10-m wind speed. Observed values as inferred from Eqs. (7)–(14) are denoted by dots. Their averaged values for wind speed bins with 1 m s^{-1} bin width are denoted by plus signs. The best fits [i.e., (24)–(25)] are given by the solid lines.

appropriate for mean wind from 0 up to 18 m s^{-1} (see Fig. 8 and discussions in section 5).

Equation (24) could attempt to partially account for the impact of wave ages on wind stress by replacing a_1 by $(a_0 + a_1 u_*)$ (Weber 1994); however, within the TOGA COARE wind speed range, both formulations give indistinguishable results. Lacking data under high wind speed (e.g., greater than $10\text{--}15 \text{ m s}^{-1}$) conditions, the COARE data are not sufficient to address this issue. However, even for wind speeds up to 18 m s^{-1} , (24) still agrees well with observations (see Fig. 8 and discussions in section 5).

The exponent in (25) fixed at 0.25 could be optimized by use of the COARE data. However, we found that

doing this changed insignificantly the results with respect to roughness lengths and surface fluxes. Therefore, the functional form of Brutsaert (1982), derived based on his theoretical model of heat transfer across the surface molecular sublayer, is retained but with his original coefficients replaced by those determined using the COARE data as given above.

Using z_0 and z_{0q} , neutral exchange coefficients for momentum and moisture at 10 m are computed from

$$C_{dn} = \left(k / \ln \frac{10}{z_0} \right)^2, \quad \text{and} \quad C_{qn} = k^2 / \left(\ln \frac{10}{z_0} \ln \frac{10}{z_{0q}} \right), \quad (27)$$

TABLE 1. Intercomparison of equations [i.e. (24)–(26) and (A1)–(A13)] for roughness lengths of momentum, sensible, and latent heat (denoted by z_o , z_{ot} , z_{oq} , respectively) using the 486 samples from the R/V *Moana Wave* during the TOGA COARE. The mean absolute differences (denoted as *mad*) between computed and observed logarithms of roughness lengths, and the ratio (denoted as *Rat*) of computed versus observed logarithmic average of roughness lengths are calculated. Bold numbers denote worst results in each row.

	COARE					
	UA	2.5	CCM3	ECMWF	NCEP	GEOS
Mad(ln z_o)	0.80	0.82	1.09	0.82	1.05	0.81
Mad(ln z_{ot})	4.70	5.13	5.04	5.18	4.44	5.22
Mad(ln z_{oq})	1.62	1.83	1.73	1.68	1.82	1.78
Rat(ln z_o)	1.01	1.03	0.94	0.99	1.07	1.01
Rat(ln z_{ot})	1.14	1.14	1.16	1.17	1.07	1.22
Rat(ln z_{oq})	0.98	0.94	0.93	0.96	0.92	1.05

respectively, which are used in algorithm evaluation with observations and algorithm intercomparison in sections 3–5. Previous theoretical studies (e.g., Brutsaert 1982) have usually assumed the neutral exchange coefficients for temperature (C_{tn}) to be smaller than C_{qn} since the Prandtl number is larger than the Schmidt number. However, the opposite was observed by Bradley et al. (1991). As summarized by Garratt (1992), the predicted larger value of C_{qn} (than C_{tn}) “is not apparent in any of the observations to date.” The COARE covariance data of sensible heat flux are not as reliable as, and are an order of magnitude smaller than, those of latent heat flux (Fairall et al. 1996a). Hence, uncertainty in sensible heat flux measurements does not significantly affect the measurements of surface energy balance, although it does significantly affect the determination of z_{ot} or C_{tn} . Furthermore, the determination of roughness lengths depends upon the turbulent stability functions used, and all algorithms assume the same turbulent transfer of [i.e., use the same equations (11)–(14) for] potential temperature, virtual potential temperature, and humidity. Therefore, here z_{ot} is assumed to be the same as z_{oq} in (26). Even though evaporation of ocean

spray may affect surface latent and sensible heat fluxes individually (by changing air temperature and humidity), it should not directly affect the total energy transfer from the ocean, as implied by (26) along with the same profile equations (11)–(14) for temperature and humidity, making treatment of ocean spray much easier for the computation of net surface fluxes and for some theoretical studies (e.g., Emanuel 1995).

3. Intercomparison using the COARE data

The R/V *Moana Wave* flux data are used to determine the coefficients in (24)–(25), and to compare the above algorithm with those summarized in the appendix with respect to roughness lengths and fluxes. Flux data over 1622 h were taken near 1.7°S and 156°E during three legs: 11 November to 3 December 1992, 17 December 1992 to 11 January 1993, and 28 January to 16 February 1993 during the TOGA COARE period. Wind speed, air temperature, and specific humidity were measured at 15-m height above ocean surface. The surface skin temperature was derived from bulk temperature at a 0.05-m depth by correcting for the cool skin effect (following Fairall et al. 1996b). Fluxes were measured using the covariance method and the inertial-dissipation method whose uncertainties were discussed in Fairall et al. (1996a and references therein). The latent and sensible heat fluxes determined as covariances are in general more reliable than the inertial-dissipation fluxes (Fairall et al. 1996a) and hence are used here. In contrast, the covariance wind stress data are less reliable mainly because of the difficulty in removing ship motion from the horizontal wind components, so the inertial-dissipation wind stress data are used instead. About 530 sets of hourly data (or about one-third of the original 1622 samples) remain to be used after application of vigorous rejection criteria (to avoid flow distortion and contamination of turbulence data): 1) relative wind direction within 30° of the bow; 2) no ship maneuvers and ship

TABLE 2. Intercomparison of algorithms for the computation of surface fluxes of momentum, sensible heat, and latent heat (denoted as τ , SH, and LH, respectively) using 486 samples from the R/V *Moana Wave*. Four statistical quantities are computed: 1) correlation coefficients and 2) mean absolute differences between computed and observed hourly fluxes, denoted as *r* and *Mad*, respectively; 3) bias (i.e., the difference between computed and observed mean fluxes); and 4) the mean of ratios of computed vs observed hourly fluxes. Observed mean values of τ , LH, and SH are 0.032 N m⁻², 100.1 W m⁻², and 7.9 W m⁻², respectively. They are close to 0.036 N m⁻², 102.4 W m⁻², and 7.4 W m⁻² using all 530 samples. Bold numbers denote worst results in each row.

		UA	COARE 2.5	CCM3	ECMWF	NCEP	GEOS
τ	<i>r</i>	0.99	0.96	0.99	0.99	0.99	0.99
	Mad (N m ⁻²)	3.3e ⁻³	4.9e⁻³	4.0e ⁻³	3.7e ⁻³	4.4e ⁻³	3.2e ⁻³
	Bias (N m ⁻²)	-2.7e ⁻⁴	-6.1e ⁻⁴	-1.0e ⁻³	7.8e ⁻⁴	-2.8e ⁻³	-8.5e ⁻⁴
	ratio	0.97	1.03	1.12	0.98	0.82	0.99
LH	<i>r</i>	0.87	0.83	0.87	0.86	0.86	0.87
	Mad (W m ⁻²)	15.9	18.2	15.9	17.3	21.2	16.0
	Bias (W m ⁻²)	-2.0	-2.3	2.8	6.3	4.9	-3.2
	ratio	1.00	1.00	1.08	1.10	1.03	0.99
SH	<i>r</i>	0.85	0.77	0.84	0.85	0.85	0.85
	Mad (W m ⁻²)	3.0	3.4	3.1	3.2	2.7	3.3
	Bias (W m ⁻²)	-2.3	-2.6	-2.4	-2.7	-1.6	-2.8
	ratio	0.87	0.87	0.88	0.81	0.95	0.78

not under way at full speed; 3) no sea salt, rain, or sun contamination; and 4) flow tilt within 10° . Furthermore, based on the usual definition of heat fluxes into the atmosphere as positive, sensible (or latent) heat flux and surface–air temperature (or humidity) difference should be of the same sign, assuming that countergradient heat fluxes are due to measurement errors of bulk variables or fluxes. This criterion further reduces the sample number to 486. Instantaneous countergradient heat transfer may occur over the ocean from mesoscale or synoptic perturbations, but this is not included in any bulk algorithms yet. For a specific flux (e.g., LH), some of the above restrictions are unnecessary, hence Fairall et al. (1996a) were able to use more than 530 samples. However, only these 486 samples were judged usable to determine coefficients in (24)–(25) and for the algorithm intercomparison.

From observed fluxes and bulk variables, u_* and q_* can be obtained using (21) and (23). Then roughness lengths for momentum and moisture (z_o and z_{oq}) can be computed from (7)–(10) and (11)–(14) (by replacing temperature by humidity), respectively. The logarithms of z_o and z_{oq} and their best fits [i.e., (24)–(25)] are shown in Fig. 1 as a function of 10-m wind speed (u_{10}) as computed from the observed 15-m wind using (7)–(10). As typical for flux observations over ocean, there is a large scatter in Fig. 1, which increases with the decrease of wind speed, since relative measurement uncertainties increase with the decrease of flux values. For this reason, averaged values for wind speed binned at intervals of 1 m s^{-1} are also given in Fig. 1. Both Fig. 1a and Table 1 show that (24) fits well the $\ln(z_o)$ values inferred from observations, leading to a good agreement in Fig. 1b between computed [using (27)] neutral exchange coefficients for momentum C_{dn} and those inferred from observations. While Table 1 shows that (25) agrees well statistically with observed values of $\ln(z_{oq})$, it appears from Fig. 1c that it is an overestimation under very weak wind conditions. This overestimation probably results from the relatively large measurement uncertainties under weak wind conditions; the abrupt decrease of the mean $\ln(z_{oq})$ inferred from observations with wind speed from 2 to 1 m s^{-1} is contrary to expectation from any theoretical work (e.g., Brutsaert 1982). The $\ln(z_{oq})$ inferred from observations in Fig. 1c also appears to decrease faster with wind speed than given by (25) for wind speed between 5 and 10 m s^{-1} ; hence, the observations suggest a slight decrease of the neutral exchange coefficient for heat C_{qn} with wind speed in Fig. 1d. In contrast, the fit (25) [along with (24)] results in a slight increase of C_{qn} with wind speed. These differences do not have much effect on fluxes within the TOGA COARE wind speed range of 0.5 – 10 m s^{-1} , as demonstrated by the overall excellent agreement between our algorithm and observations in Figs. 1–2 and Tables 1–2. However, an extension of the differences between values obtained from the fits and from observations in Fig. 1 beyond 10 m s^{-1} leads to significantly different

results, with the fit in better agreement with observed values of C_{qn} (see Fig. 8 and discussion in section 5).

Figure 1b also shows that C_{dn} as obtained from fits or observations reaches the minimum value of about 1.0×10^{-3} at $u_{10} = 3$ – 4 m s^{-1} , as consistent with previous studies (e.g., Garratt 1992). The mean value of both exchange coefficients over the wind speed range from 2 to 10 m s^{-1} is 1.1×10^{-3} , which is the same as that suggested by Garratt (1992), but slightly smaller than the then “consensus” value of 1.2×10^{-3} of Smith (1989), and larger than the 0.89×10^{-3} suggested by Bradley et al. (1991).

Figure 2 compares surface fluxes computed using our algorithm with the TOGA COARE data. Computed momentum (τ) and latent heat (LH) fluxes agree very well with observations, but the computed sensible heat fluxes (SH) are smaller than those observed. However, this underestimation of SH is characteristic of all six algorithms including the COARE 2.5 (see Table 2), and is interpreted to be largely due to measurement uncertainties of SH (Fairall et al. 1996a).

Tables 1–2 compare roughness lengths and fluxes from the six different algorithms (i.e., the UA, COARE 2.5, CCM3, ECMWF, NCEP, and GEOS) using the 486 samples from the R/V *Moana Wave* during the TOGA COARE. In addition, all 530 samples are used to evaluate the sensitivity of results in Tables 1–2 to random sampling errors in flux measurements. From observed fluxes and bulk variables, u_* , θ_* , and q_* can be obtained using (21)–(23). Then roughness lengths can be computed from (24)–(26) and (A1)–(A13). These values are then compared with those inferred from observations as derived from (7)–(14) and shown in Figs. 1a,c to isolate differences in roughness length equations. Table 1 shows that the mean absolute difference between computed and observed values for $\ln(z_o)$ [or $\ln(z_{oq})$] is largest for the CCM3 algorithm (or the COARE 2.5 and NCEP algorithms), while the ratio of computed versus observed average $\ln(z_o)$ [or $\ln(z_{oq})$] deviates most from unity using the NCEP and CCM3 algorithms (or the NCEP algorithm). The large errors shown in Table 1 with respect to $\ln(z_{oq})$ are interpreted as resulting from the unreliability of the measured SH values. Overall, the UA and ECMWF algorithms match the data somewhat better than the other four.

Table 2 shows that the correlation coefficients are larger for wind stress than for heat fluxes for all algorithms. The mean absolute difference between computed and observed LH is largest using the NCEP algorithm, whereas the bias (i.e., the difference between computed and observed mean fluxes) of wind stress (or LH) is largest using the NCEP (or ECMWF) algorithm. The average of ratios of computed versus observed hourly fluxes of wind stress (or LH) is farthest from unity using the NCEP and CCM3 (or ECMWF and CCM3) algorithms. The COARE 2.5 algorithm has the lowest correlation coefficients and the largest mean absolute difference in wind stress using 486 samples in Table 2.

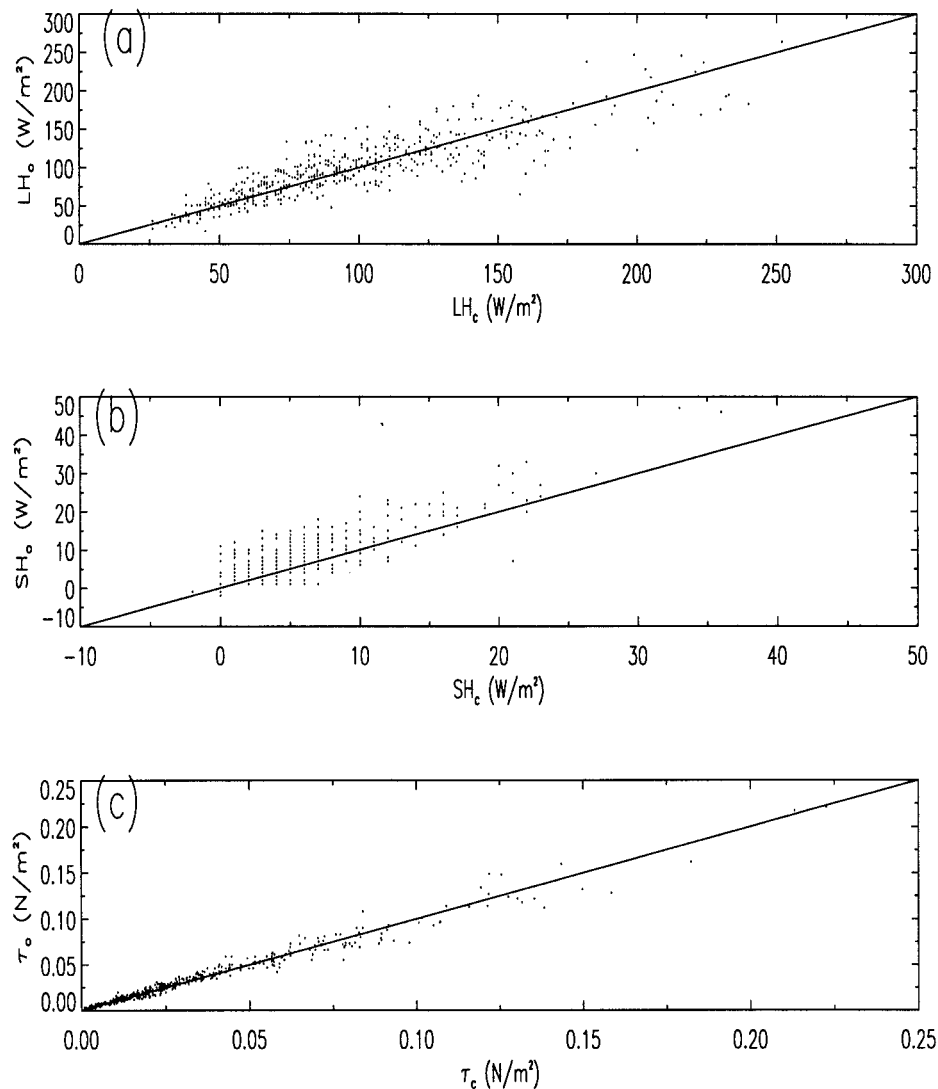


FIG. 2. (a) The covariance latent heat flux, (b) covariance sensible heat flux, and (c) inertial-dissipation wind stress from the R/V *Moana Wave* (the vertical axis) vs those computed using the UA algorithm.

When all 530 samples are used, however, the COARE 2.5 algorithm has the same correlation coefficients as other algorithms, and, along with the UA algorithm, has the smallest mean absolute difference in wind stress, as expected from the use of 530 samples in the COARE 2.5 algorithm development (Fairall et al. 1996a). In contrast, relative performances of other algorithms are not changed using 486 or 530 samples. Overall, the UA and GEOS algorithms perform slightly better than others for either set of samples. Tables 1 and 2 demonstrate that the UA algorithm consistently yields a slightly better fit than others using 486 or 530 samples, as should be expected (at least for the 486 samples) since the COARE data of 486 samples were used to obtain the coefficients in (24)–(25).

Because 68.5% of the TOGA COARE data fall within the 0.5–5 m s^{-1} range of wind speeds, the results in

Tables 1–2 are biased toward low wind regimes. To avoid such a bias, Fig. 3 compares the six algorithms with observed fluxes binned at wind speed intervals of 1 m s^{-1} . The LH results from four of the algorithms (i.e., the UA, COARE 2.5, GEOS, and CCM3) are in close agreement with each other and with the observations as seen in Fig. 3a except for an overestimate of LH under very weak wind conditions by the CCM3 algorithm. The NCEP algorithm overestimates LH for wind speeds greater than 6 m s^{-1} but underestimates it under very weak wind conditions. The ECMWF algorithm yields LH results between those from the NCEP and the remaining four algorithms. Figure 3b shows that the NCEP algorithm obtains SH results close to observations, whereas the remaining five algorithms yield lower results close to each other. Their being smaller than observations is probably a result of measurement

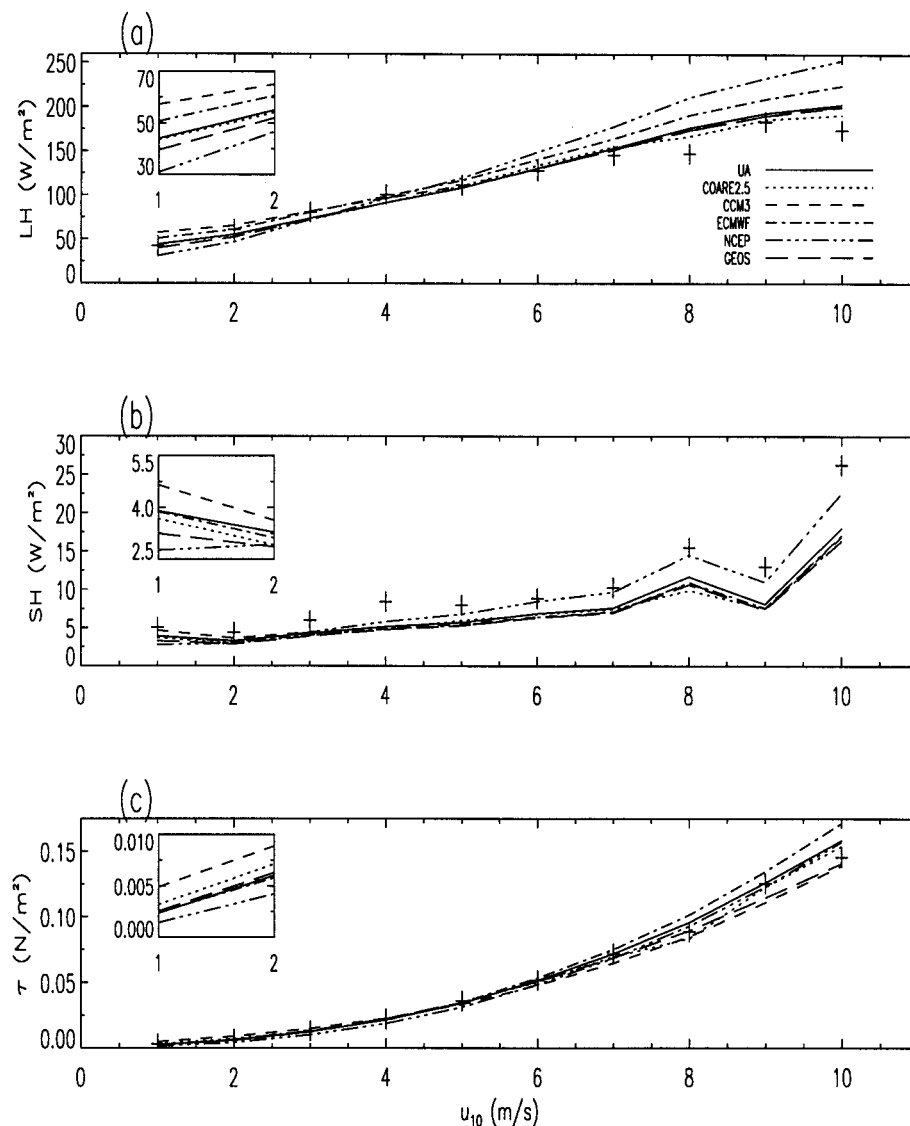


FIG. 3. (a) Latent heat, (b) sensible heat, and (c) momentum fluxes, averaged in wind speed bins with 1 m s^{-1} bin width, as a function of 10-m wind speed. Results under weak wind conditions are also shown in the inserts. Results using the algorithms of UA (solid lines), COARE 2.5 (dotted lines), CCM3 (short-dashed lines), ECMWF (dot-dashed lines), NCEP (triple-dot-dashed lines), and GEOS (long-dashed lines) are shown along with the R/V *Moana Wave* observed values (plus signs).

uncertainties, as mentioned before. The relative largeness of SH given by the NCEP algorithm is consistent with its apparent overestimate of LH in Fig. 3a.

Figure 3c shows that all of the six algorithms give wind stress in close agreement with observed values. At wind speeds of 10 m s^{-1} , the modeled wind stress from the CCM3 and GEOS algorithms is 0.14 N m^{-2} , that from the ECMWF algorithm is 0.171 N m^{-2} , and that from the other three algorithms is in between (at about 0.157 N m^{-2}). Under weak wind conditions, the CCM3 algorithm yields a wind stress that is significantly larger than that from the others. Because the absolute value of wind stress is small, this overestimate itself

may not be important for air–sea momentum exchange, but it is the primary reason for the apparent overestimate of LH by the CCM3 algorithm at weak wind conditions (Fig. 3a).

4. Intercomparison using the TAO data

The different slopes of the six algorithms in Fig. 3 imply that flux differences will be greater under stronger than 10 m s^{-1} or weaker than 1 m s^{-1} wind conditions. What might be the climatological implications of such differences for fluxes is explored here using the multiyear hourly data of wind speed at 4 m above the ocean

surface, and relative humidity and air temperature at 3 m above the surface from the TOGA TAO array of moored buoys (Hayes et al. 1991; McPhaden 1993; Kessler et al. 1996) along with the derived skin temperatures of ZE98. The nearly 70 moorings in the TAO array span the equatorial Pacific Ocean from 95°W in the eastern to 137°E in the western Pacific and are between 9°N and 8°S. The relative humidity, air, and ocean temperatures were all sampled every 10 min and averaged hourly, and winds were sampled at a rate of 2 Hz for 6 min centered at the top of each hour, then vector averaged. Esbensen and McPhaden (1996) showed that this sampling strategy, as driven by mean wind and temperature requirements as well as engineering considerations (e.g., power consumption), would introduce very small errors in estimating daily averaged fluxes from 24 hourly sampled values, although the errors could be larger for hourly fluxes. Thus, for the evaluation here of averaged flux differences among different algorithms, the details of the TAO buoy sampling strategy should be irrelevant.

We use only standard quality data (i.e., predeployment calibration applied) that are available for no less than 10 days in a month. The location, duration, and number of months when data are available for each of the 63 buoys used in this study are given in ZE98. The number of months varies from 2 at 2°N, 137°E to 55 at 5°S, 140°W. The earliest starting date is 1 May 1990 at 0°N, 140°W and the latest ending date (for data available at the beginning of 1997) is 11 November 1996 at 8°N, 180°W. Together, there are about 1.2×10^6 hourly samples.

Figure 4 compares fluxes computed using different algorithms as a function of wind speed in 0.5 m s⁻¹ bins. As expected from Fig. 3a, Fig. 4a shows a significant divergence of LH from different algorithms under high wind conditions. For instance, for wind speed around 15 m s⁻¹, the maximum LH difference between algorithms (i.e., between the COARE 2.5 and NCEP algorithms) is as large as 180 W m⁻², compared to the mean value of 360 W m⁻² as averaged over all algorithms. For wind speed between 0 and 0.5 m s⁻¹, the LH value from the CCM3 algorithm is 52 W m⁻², which is significantly larger than those (from 21° to 34°W m⁻²) obtained using the other five algorithms. The SH fluxes under strong wind conditions from the UA, CCM3, ECMWF, and GEOS are quite close (Fig. 4b), and significantly higher (or lower) than that from the COARE 2.5 (or NCEP) algorithm. The abrupt decrease of SH for wind speed between 14 and 15 m s⁻¹ is probably an artifact of insufficient data. The algorithms are in better agreement with respect to wind stress (Fig. 4c). However, at wind speeds around 15 m s⁻¹, the maximum wind stress difference between algorithms [i.e., between the GEOS (or CCM3) and ECMWF algorithms] is still as large as 0.13 N m⁻², compared with a mean value of 0.56 N m⁻² from all algorithms. For wind speed between 0 and 0.5 m s⁻¹, the wind stress from the CCM3

algorithm is 0.0015 N m⁻², while the average value from the other five algorithms is just 0.00042 N m⁻². Just as in Fig. 3c, the large difference in wind drag coefficient is primarily responsible for the overestimate of LH by the CCM3 algorithm under weak wind conditions in Fig. 4a.

Figure 5 compares flux results as a function of surface skin temperature (SST) in 0.5°C bins. High SSTs are characteristic of the western Pacific warm pool region under weak wind conditions, whereas low SSTs represent the eastern tropical Pacific Ocean usually under stable atmospheric stratification conditions. The significant scatter of results at high SSTs in Fig. 5 is consistent with those in Figs. 3–4 under weak wind conditions. At low SSTs, the UA, COARE 2.5, and CCM3 obtain similar LH results of about 3.5 W m⁻² (for SST = 18 to 18.5°C), whereas the other three give LH of about 8.2 W m⁻² (Fig. 5a). Furthermore, at low SSTs, the CCM3 algorithm significantly overestimates SH compared with the remaining algorithms (Fig. 5b), while all algorithms agree with each other regarding wind stress (Fig. 5c). At intermediate SSTs, all algorithms lead to similar SH results (Fig. 5b) but show significant differences in LH and wind stress (Figs. 5a,c). For instance, the maximum LH (or wind stress) difference between algorithms is 28 W m⁻² (or 0.015 N m⁻²) at SST = 27°C, which is 25% (or 20%) of the algorithm-averaged LH (or wind stress).

Figure 6 compares the averaged diurnal cycle of fluxes using buoy data located at 0° and 155°W. The diurnal variation is basically the same from different algorithms; however, systematic differences exist in LH and wind stress between algorithms. The daily mean LH is about 92 W m⁻² from the UA, COARE 2.5, CCM3, and GEOS algorithms, and it is 107 and 113 W m⁻² from the ECMWF and NCEP algorithms, respectively (Fig. 6a). The maximum difference in daily wind stress (between the CCM3 and ECMWF algorithms) is 0.011 N m⁻² compared to the algorithm-averaged mean of 0.060 N m⁻² (Fig. 6c). Most of the time, the NCEP algorithm overestimates SH relative to the others, whereas the CCM3 algorithm overestimates SH in the morning when SH is negative (Fig. 6b).

Next, monthly averaged fluxes are compared. Figure 7 shows that the maximum monthly LH, SH, and τ differences between algorithms can be as large as 59 W m⁻², 5.9 W m⁻², and 0.043 N m⁻² (or 34%, 22%, and 26% relative to the algorithm-averaged fluxes), respectively, whereas the maximum values of the mean absolute deviations of LH, SH, and τ using the six algorithms from the algorithm-averaged fluxes in each month can be as large as 18 W m⁻², 1.5 W m⁻², and 0.013 N m⁻² (or 10.6%, 5.5%, and 7.5% relatively), respectively. The monthly mean LH from all 1694 months is about 101 W m⁻² from the UA, COARE 2.5, CCM3, and GEOS, and it is 117 and 123 W m⁻² from the ECMWF and NCEP algorithms, respectively. The mean SH varies from 4.2 W m⁻² (from the GEOS algorithm) to 5.3 W m⁻² (from the NCEP algorithm), and

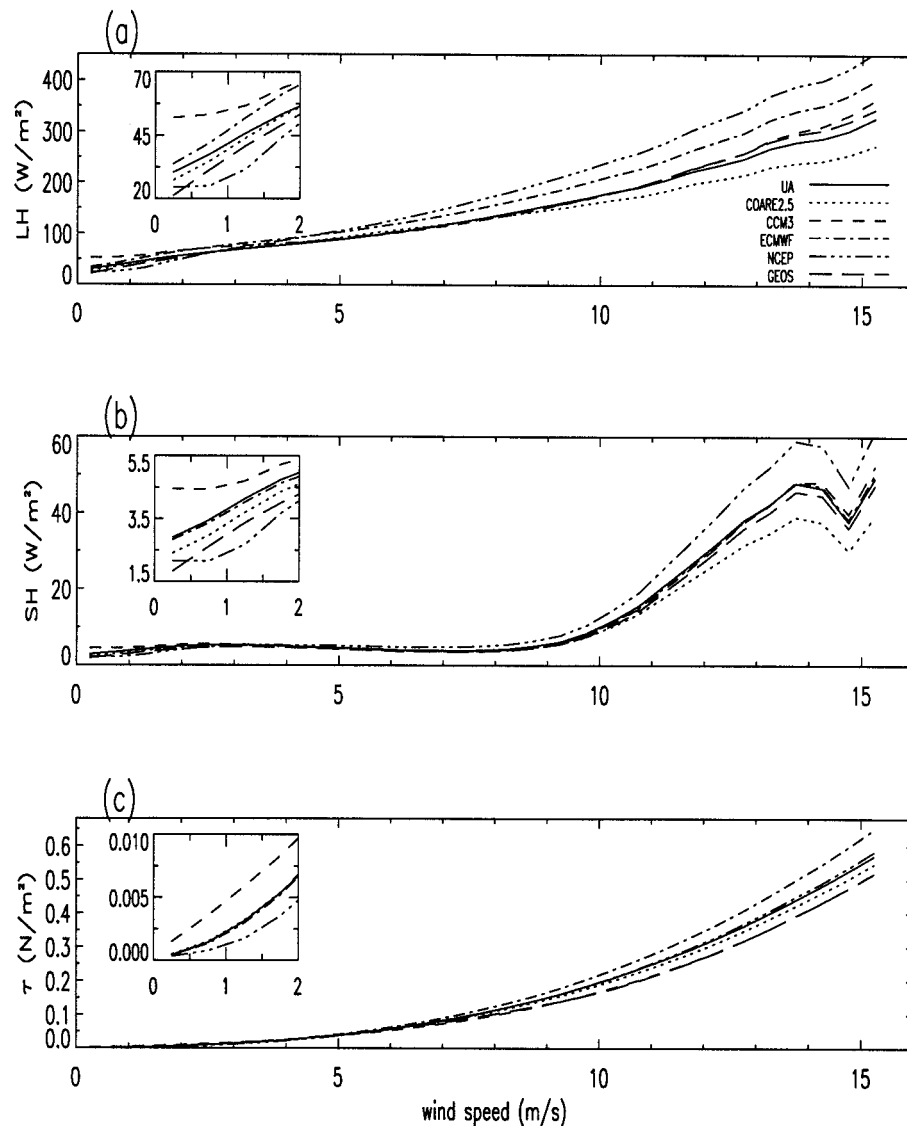


FIG. 4. Averaged hourly fluxes of latent heat in (a), sensible heat in (b), and momentum in (c) using data from all TAO buoys as a function of wind speed in 0.5 m s^{-1} bin width. Results under weak wind conditions are also shown in the inserts. Results using the algorithms of the UA (solid lines), COARE 2.5 (dotted lines), CCM3 (short-dashed lines), ECMWF (dot-dashed lines), NCEP (triple-dot-dashed lines), and GEOS (long-dashed lines) are shown.

the mean τ varies from 0.056 N m^{-2} (from the CCM3 algorithm) to 0.066 N m^{-2} (from the ECMWF algorithm).

5. Interpretation of results

The six algorithms discussed in the previous two sections were developed by different groups using different data within different parameter (e.g., wind speed) regimes so that some variations in results are expected. Furthermore, these algorithms are intended for global modeling studies with a typical grid spacing of 1° to 3° , although similar algorithms are also used in mesoscale,

cloud-resolving, and large-eddy simulations with much higher resolutions. This implies that the precise comparison of algorithm results with instantaneous point values (e.g., from buoys) may be questionable, and that small differences in fluxes averaged in time, space, or in parameter bins, as done in this paper, may not be significant. However, the differences between algorithms, as shown in sections 3–4 under very weak or strong wind conditions, are remarkable, and some explanation is required.

Under moderate wind conditions (e.g., between 3 and 6 m s^{-1}) results from different algorithms are very similar, because most of the previous observational data,

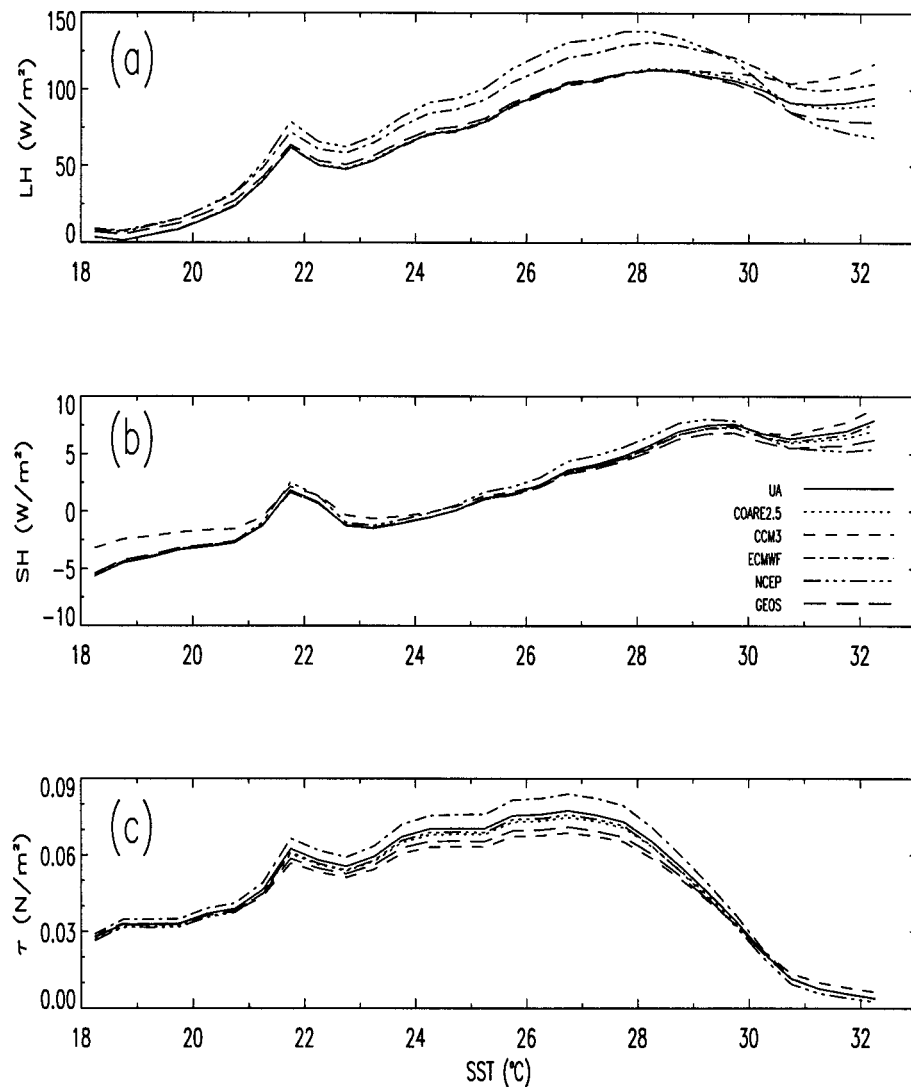


FIG. 5. Same as Fig. 4 except as a function of surface skin temperature in 0.5°C bin widths.

from which various algorithms were developed, fell within this range. Under weak wind conditions (e.g., between 0 and 2 m s^{-1}), the computation of surface fluxes is strongly dependent upon both the treatment of free convection in the turbulence scheme and on the equations chosen for roughness lengths. While the UA, COARE 2.5, and ECMWF algorithms consider the convective velocity scale w_* in (20), the other three algorithms use a different approach by limiting the mean wind to values no less than about 1 m s^{-1} . Observations from Bradley et al. (1991) show that LH is about 25 W m^{-2} when the mean wind approaches zero, which is also consistent with the extrapolated value from the TOGA COARE data in Fig. 2a. Therefore, the LH value of about 52 W m^{-2} from the CCM3 algorithm for wind speed between 0 and 0.5 m s^{-1} in Fig. 4a is likely an overestimate, and primarily caused by the direct extrapolation of (A4) [and to a lesser degree (A6)] to

convective conditions. Equations (A4) and (A6) were derived by Large and Pond (1982) using data with wind speeds between 3 and 25 m s^{-1} . This ensures the excellent performance of the CCM3 algorithm within this range, as demonstrated in Figs. 3–4, but does not warrant the applicability of (A4) and (A6) to convective conditions.

Under strong wind conditions, atmospheric stratification is always close to neutral so that the computation of surface fluxes is primarily affected by the equations for roughness length (or neutral exchange coefficients) and by the use of 0.98 or unity in (17). To evaluate the differences in roughness length equations, Fig. 8 shows the neutral exchange coefficients at 10-m height from (24)–(26) and (A1)–(A13) as a function of the equivalent neutral wind speed at 10-m height with $u_{10n} = u_*/k \ln(10/z_0)$ under moderate to strong wind conditions. Large and Pond (1982) observed a mean C_{qn} of $1.15 \times$

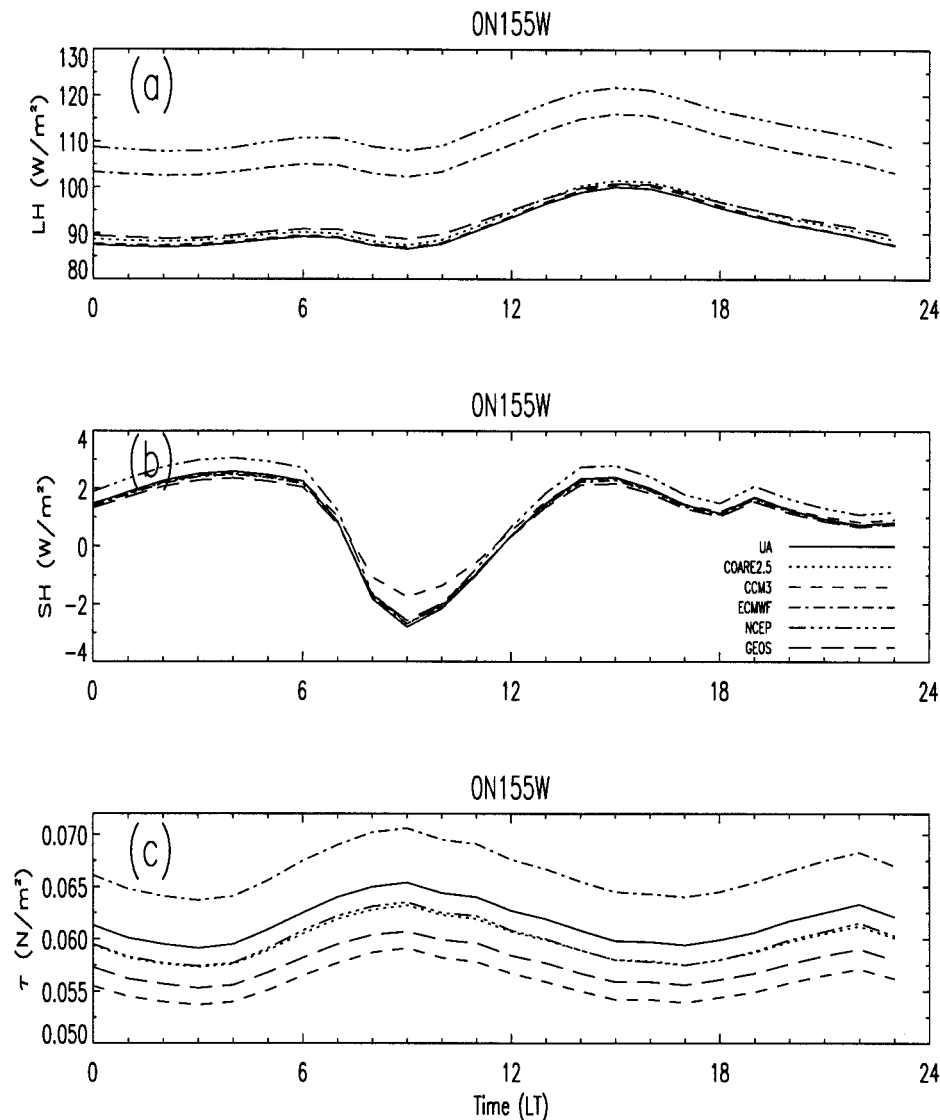


FIG. 6. Diurnal cycles of (a) latent heat flux, (b) sensible heat flux, and (c) wind stress, averaged over the whole observed period at 0° , 155°W . Results using the algorithms of UA (solid lines), COARE 2.5 (dotted lines), CCM3 (short-dashed lines), ECMWF (dot-dashed lines), NCEP (triple-dot-dashed lines), and GEOS (long-dashed lines) are shown.

10^{-3} over the wind speed range of $4\text{--}14\text{ m s}^{-1}$, and DeCosmo et al. (1996) obtained 1.12×10^{-3} for C_{qn} over the range of $4\text{--}18\text{ m s}^{-1}$, and the mean C_{tn} of 1.14×10^{-3} over the range of $6\text{--}23\text{ m s}^{-1}$ (but with only three data points above 18 m s^{-1} wind speed). These observations suggest that the mean value of C_{qn} and C_{tn} is about 1.13×10^{-3} for wind speeds from 4 to 18 m s^{-1} , also consistent with the then consensus value of 1.2×10^{-3} recommended by Smith (1989) and the 1.1×10^{-3} suggested by Garratt (1992). Furthermore, DeCosmo et al. (1996) show that either an increase of C_{qn} by as much as 20% or even a small decrease in C_{qn} over the wind speed range of $5\text{--}18\text{ m s}^{-1}$ cannot be ruled out. On the other hand, these observed neutral exchange

coefficients could be affected by up to 10% due to the use of bulk temperatures (rather than the correct skin temperatures as in our study), the use of 0.98 versus unity in (17), and measurements over the open deep ocean versus shallow water. Hence, Fig. 8a indicates that the NCEP algorithm may overestimate C_{qn} under strong wind conditions. Because C_{dn} in the NCEP algorithm is quite reasonable (see Fig. 8c), (A11) may overestimate z_{oq} . Here C_{qn} from the CCM3 (or COARE 2.5) increases (or decreases) with wind speed, whereas the neutral exchange coefficients from the UA, ECMWF, and GEOS algorithms are close to each other and are nearly constant under strong wind conditions. Though none of these five algorithms can be excluded by avail-

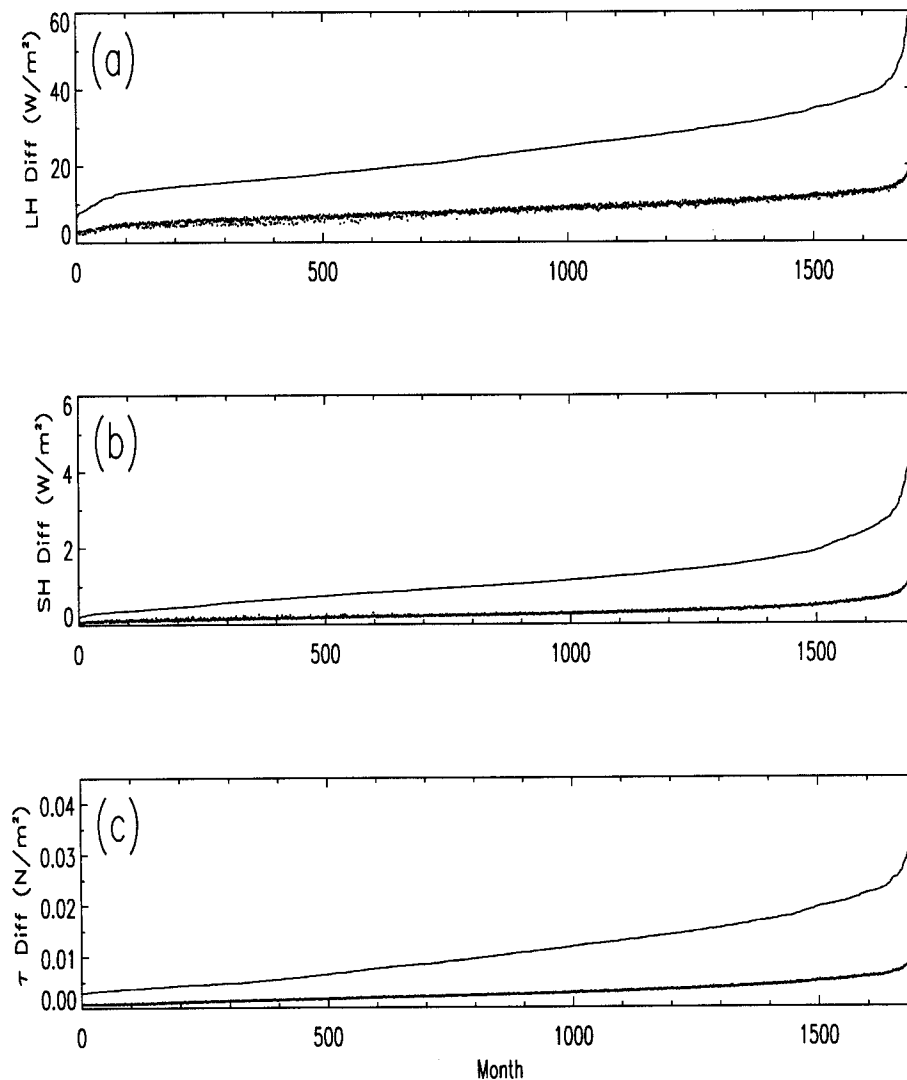


FIG. 7. Maximum difference among monthly mean fluxes computed using the algorithms of UA, COARE 2.5, CCM3, ECMWF, NCEP, and GEOS for all 1694 months of TOGA TAO data (in ascending order for clarity), denoted as the solid line, and the mean absolute deviation of fluxes using these six algorithms from algorithm-averaged flux in each month, denoted as the dots (or the lower curve in each panel). (a) Latent heat flux, (b) sensible heat flux, and (c) wind stress.

able observations, the difference in C_{qn} and C_{tn} between the CCM3 and COARE 2.5 algorithms at larger wind speeds is about 50% of the observed mean value, suggesting the need for future experiments with an emphasis on their trends with wind speed.

Figure 8c shows that values of C_{dn} are in closer agreement than those of C_{qn} or C_{tn} . Furthermore, these values are consistent with observations (e.g., Large and Pond 1982; Garratt 1992; DeCosmo et al. 1996). The differences of up to 20% between algorithms, as shown in Fig. 8c, are not resolvable by available observations.

The CCM3 algorithm uses a significantly smaller z_{ot} under stable atmospheric stratifications than that under unstable conditions [see (A5)] based on Large and Pond (1982). In contrast, none of the other five algorithms

explicitly considers the impact of stability. Hence, the CCM3 algorithm gives significantly different negative values of SH than the others, as shown in Fig. 5b under low SST conditions and in Fig. 6b in the morning. Again, this issue cannot be resolved by available observations but requires future observations.

As mentioned, (A4) for the CCM3 algorithm is problematic under weak wind conditions, and (A11) for the NCEP algorithm is problematic under strong wind conditions. As a possible solution, we replace (A4) by our Eq. (24), and rerun the CCM3 algorithm using the TOGA TAO data. For wind speed between 0 and 0.5 m s^{-1} , the LH value from this modified CCM3 algorithm is 36 W m^{-2} , which is more reasonable than the value of 52 W m^{-2} from the standard CCM3 algorithm (see

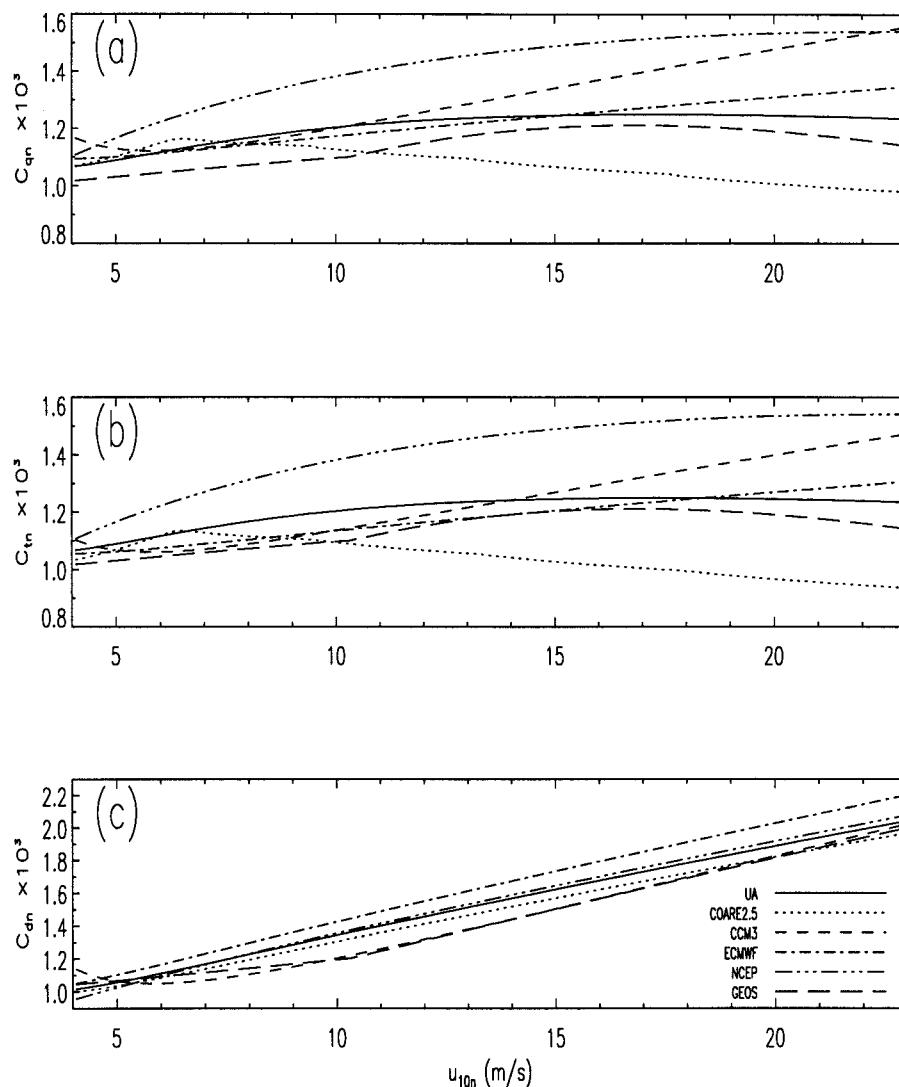


FIG. 8. Neutral exchange coefficients for latent heat in (a), sensible heat in (b), and momentum in (c) as a function of the neutral wind speed at 10-m height. Results using the algorithms of UA (solid lines), COARE 2.5 (dotted lines), CCM3 (short-dashed lines), ECMWF (dot-dashed lines), NCEP (triple-dot-dashed lines), and GEOS (long-dashed lines) are shown.

Fig. 4a). Similarly, we replace (A11) by our Eqs. (25)–(26), and rerun the NCEP algorithm using the TAO data. For wind speed between 15 and 15.5 m s^{-1} , the LH value from this modified NCEP algorithm is 370 W m^{-2} , which is more reasonable than the value of 456 W m^{-2} using the standard NCEP algorithm (see Fig. 4a).

The use of 0.98 versus unity in (17) has a noticeable impact on the computation of surface latent heat flux under strong wind conditions. This factor, which accounts for the vapor pressure reduction over saline (rather than fresh) seawater, is considered in the UA, COARE 2.5, and CCM3 algorithms, but omitted in those of the ECMWF, NCEP, and GEOS. Its impact on global climate modeling was recently addressed by Sud and Walker (1997). As an example, the TOGA TAO data

show that, at a wind speed of 14 m s^{-1} , the average surface humidity [i.e., $q_{\text{sat}}(T_s)$ in (17)] is 21.9 g kg^{-1} so that the humidity difference with a factor of unity versus 0.98 in (17) is 0.44 g kg^{-1} , or about 22% of the surface versus air humidity difference [i.e., $0.98q_{\text{sat}}(T_s) - q_a$] of 2.01 g kg^{-1} . Hence, even though the value of C_{qn} from the ECMWF algorithm at $u_{10m} = 14 \text{ m s}^{-1}$ is slightly smaller than that from the UA algorithm in Fig. 8a, the LH value from ECMWF is about 21% larger than that from UA in Fig. 4a. Therefore, if the ECMWF algorithm were to include the factor of 0.98, LH results under strong wind conditions would be quite close to those from UA in Fig. 4a. More generally, if the factor of 0.98 were considered by the ECMWF, NCEP, and GEOS algorithms, the LH results for all six algorithms

under strong wind conditions in Fig. 4a would be relatively close and proportional to the C_{qn} in Fig. 8a.

6. Conclusions

A bulk aerodynamic algorithm for all stability conditions is derived for the computation of ocean surface fluxes. It uses the standard Monin–Obukhov similarity relations along with a gustiness velocity to account for the contribution of large eddies in the convective boundary layer to surface fluxes. By matching the standard dimensionless scalar (temperature or humidity) gradient (or wind shear) with that under convective conditions (Kader and Yaglom 1990) and with that under very stable conditions (Holtzlag et al. 1990), continuous stability functions $\phi_h(z/L)$ and $\phi_m(z/L)$ are obtained for all stability conditions. The functional forms of roughness lengths for wind, temperature, and humidity (denoted as z_o , z_{ot} , and z_{oq} , respectively) are based on Smith (1988) and Brutsaert (1982) with coefficients determined using the Tropical Oceans Global Atmosphere (TOGA) Coupled Ocean–Atmosphere Response Experiment (COARE) data constrained by other observations under strong wind conditions. A single equation is obtained for z_o (or z_{oq} with $z_{ot} = z_{oq}$), which is valid for the wind speed range from 0 to 18 m s^{-1} .

Intercomparison of six algorithms, including ours (i.e., UA), the COARE algorithm of Fairall et al. (1996a), and those used in the NCAR CCM3, the ECMWF forecast model, the NCEP medium-range forecast model, and the GEOS DAS, shows that the UA and ECMWF algorithms give slightly better fits to roughness lengths than the other four, and the UA and GEOS algorithms give slightly better fits to momentum and latent heat fluxes using the TOGA COARE data. The slightly better fit of the UA algorithm is expected, because the COARE data were used to obtain the coefficients in (24)–(25). Both the TOGA COARE ship data for a few months and the TOGA TAO data from 63 buoys over the tropical Pacific Ocean for several years reveal that the algorithms give significantly different momentum and heat fluxes under very weak or strong wind conditions. For instance, for wind speed between 15 and 15.5 m s^{-1} , the maximum LH difference between algorithms (i.e., between the COARE 2.5 and NCEP algorithms) is calculated to be as large as 180 W m^{-2} compared with a mean value of 360 W m^{-2} from all algorithms. These algorithms agree with each other more closely under moderate wind conditions for which these algorithms were developed. Even for monthly averaged fluxes, the maximum monthly LH, SH, and τ differences between algorithms can be as large as 59 W m^{-2} , 5.9 W m^{-2} , and 0.043 N m^{-2} (or 34%, 22%, and 26% relative to the algorithm-averaged fluxes), respectively, although the mean absolute deviations of LH, SH, and τ using the six algorithms from the algorithm-averaged fluxes in each month are smaller (with the

maximum values being 18 W m^{-2} , 1.5 W m^{-2} , and 0.013 N m^{-2} , respectively).

Using observations reported or reviewed in Large and Pond (1982), Smith (1989), Bradley et al. (1991), Garratt (1992), and DeCosmo et al. (1996), the equation for roughness length for momentum z_o in the CCM3 algorithm would appear to be inappropriate under very weak wind conditions, and so to overestimate latent heat flux. Similarly, the equation for roughness length for heat z_{oq} in the NCEP algorithm appears to be inappropriate under strong wind conditions, and so to overestimate latent heat flux. Our test shows that these problems can be largely avoided by replacing these equations by the corresponding equations in our algorithm. Other differences in roughness lengths (or neutral exchange coefficients) between algorithms cannot be resolved readily from currently available observations. In particular, the trend of neutral exchange coefficients with wind speed under strong wind conditions and the relation of roughness length for temperature z_{ot} with atmospheric stability require further field experiments.

The vapor pressure reduction of 2% over saline seawater (vs freshwater) (e.g., Kraus and Businger 1994) is not considered in the ECMWF, NCEP, and GEOS algorithms. It has a significant impact on the computation of surface latent heat flux under strong wind conditions. For instance, the TOGA TAO data show that the use of unity versus 0.98 in (17) increases LH by about 20% at a wind speed of 14 m s^{-1} .

Acknowledgments. This work was supported by the NOAA OGP under Grant NA66GP0179 and NSF under Grant ATM-9419715. Drs. A. Beljaars, C. W. Fairall, A. Molod, and H.-L. Pan are thanked for providing their subroutines or algorithms. Drs. A. Beljaars, H. M. Helfand, and an anonymous reviewer are also thanked for very helpful comments on the manuscript. The R/V *Moana Wave* data and the TOGA TAO data were obtained via the Internet and were prepared by Dr. C. W. Fairall and the TOGA TAO Office of the Pacific Marine Environmental Laboratory, respectively.

APPENDIX

Algorithms for Intercomparison

Our algorithm (denoted as UA) has been described in section 2, and all others are summarized here. The COARE algorithm (version 2.5), which is an outgrowth of the algorithm of Liu et al. (1979) with several modifications based on the TOGA COARE data analysis, has been described in Fairall et al. (1996a) in detail. The algorithm includes a gustiness velocity to account for the additional flux induced by boundary layer scale variability [with $\beta = 1.2$ in (19) and $z_i = 600 \text{ m}$ in (20)]. Under unstable conditions, the standard Monin–Obukhov similarity relations [i.e., (8) and (12)] are blended with expressions obeying the asymptotic limit

of $\phi_m = \phi_h \sim \zeta^{-1/3}$, but different from (5). Under stable conditions, the value of 4.7 is used instead of 5 in (9) and (13) and without separate treatments for $\zeta > 1$. The roughness lengths for wind, temperature, and humidity are

$$z_o = 0.011 \frac{u_*^2}{g} + 0.11 \frac{\nu}{u_*}, \quad (\text{A1})$$

$$z_{ot} u_* / \nu = a_1 \text{Re}_*^{b_1}, \quad (\text{A2})$$

$$z_{oq} u_* / \nu = a_2 \text{Re}_*^{b_2}, \quad (\text{A3})$$

respectively, with a_1 , a_2 , b_1 , and b_2 taking different values for different ranges of the roughness Reynolds number. The COARE algorithm also considers the contribution of the sensible heat carried by precipitation and the requirement that the net dry mass flux be zero. These terms were turned off in the intercomparison.

The algorithm for the computation of ocean surface fluxes in the NCAR CCM3 uses the standard Monin–Obukhov similarity relations [i.e., (8), (9), (12), and (13)] without special treatments of convective or very stable conditions. Wind speed u is taken as $\max[(u_x^2 + u_y^2)^{1/2}, 1]$ rather than (19). Equations for roughness lengths (Large and Pond 1982) are

$$C_{10n} = k^2 \left/ \left(\ln \frac{10}{z_o} \right)^2 \right. \\ = \frac{0.0027}{u_{10n}} + 0.000142 + 0.0000764 u_{10n}, \quad (\text{A4})$$

where C_{10n} is the neutral drag coefficient at 10-m height, and u_{10n} is the equivalent neutral wind speed at 10-m height with $u_{10n} = u_* / k \ln(10/z_o)$, and

$$z_{ot} = 2.2 \times 10^{-9} \text{ m} \quad \text{for } \zeta > 0,$$

and

$$z_{ot} = 4.9 \times 10^{-5} \text{ m} \quad \text{for } \zeta < 0 \quad (\text{A5})$$

$$z_{oq} = 9.5 \times 10^{-5} \text{ m}. \quad (\text{A6})$$

The algorithm in the ECMWF forecast model (Beljaars 1995a,b) uses (8) and (12) under all unstable conditions with the wind speed defined in (19). Under stable conditions, the profile equations from Holtslag and De Bruin (1988) are used. The factor of 0.98 in (17) is not used. Equations for roughness lengths are

$$z_o = 0.018 \frac{u_*^2}{g} + \frac{1.65 \times 10^{-6}}{u_*}, \quad (\text{A7})$$

$$z_{ot} = \frac{6 \times 10^{-6}}{u_*}, \quad \text{and} \quad (\text{A8})$$

$$z_{oq} = \frac{9.3 \times 10^{-6}}{u_*}. \quad (\text{A9})$$

The algorithm in the NCEP medium range forecast

model uses empirical profile equations (as an extension to the standard Monin–Obukhov similarity relations) for different stability conditions (see the documentation at <http://sgi62.wwb.noaa.gov:8080/web2/tocold.html>). Wind speed u is taken as $\max[(u_x^2 + u_y^2)^{1/2}, 1]$ rather than (19). The factor of 0.98 in (17) is not used. Equations for roughness lengths are

$$z_o = 0.014 \frac{u_*^2}{g}, \quad (\text{A10})$$

$$\ln \frac{z_o}{z_{ot}} = \ln \frac{z_o}{z_{oq}} \\ = \frac{-1.076 + 0.7045 \ln(\text{Re}_*) - 0.05808 (\ln \text{Re}_*)^2}{1 - 0.1954 \ln(\text{Re}_*) + 0.009999 (\ln \text{Re}_*)^2}. \quad (\text{A11})$$

The algorithm in the GEOS DAS (Helfand and Schubert 1995) uses the KEYPS functions (Panofsky and Dutton 1984) under unstable conditions and stability functions of Clarke (1970) under stable conditions. Neither the w_* term in (19) nor the factor of 0.98 in (17) are considered. Equations for roughness lengths are

$$z_o = \frac{a_1}{u_*} + a_2 + a_3 u_* + a_4 u_*^2 + a_5 u_*^3, \quad (\text{A12})$$

where coefficients are determined by an interpolation between the relation of Large and Pond (1981) for moderate to large wind speeds and the relation of Kondo (1975) for weak wind speeds, and

$$\ln \frac{z_o}{z_{ot}} = \ln \frac{z_o}{z_{oq}} = 0.72 (\text{Re}_* - 0.135)^{1/2}. \quad (\text{A13})$$

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