METHODS TO REDUCE BIASES IN WIND SPEEDS FROM SHIPS AND BUOYS

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1. INTRODUCTION

The goal of this study is to develop methods and relationships to convert databases of ship wind speeds to be more homogeneous with databases of buoy wind speeds. Buoy winds have less random observational error than ship winds, and are the standard for validation of numerical-model and remotely-sensed marine data. However the period of record is short (a few decades) compared to that of ship observations which go back to earlier centuries. In this paper we will describe the adjustment and regression methods and results.

2. DATA AND INITIAL PROCESSING

Data from moored Canadian NOMAD buoys were obtained from Canadian Marine Environmental Data Service (MEDS). The database contains hourly reports with fields from all the sensors, including two anemometers, reporting 10 minute means and 8 second peak wind speeds. We analyzed data from 3 NOMAD buoys on the west coast of Canada and 6 from the east coast, from 1980 to 1995 (most initially deployed late 1980s). Gilhousen(1987, G87 hereafter) found that scalar means (reported later in the study period) were about 8% higher than vector means. An experimental study on the west coast found a smaller difference, of about 3% on average (Axys, 1996). The operational buoys reported both averages for some months, and our analysis of that data supported Axys' conclusion (Thomas and Swail, 1999); we therefore used this correction. Most of the MEDS archived meteorological fields were not quality controlled; we attempted to remove all spurious wind speeds. In particular, from 1989 onward, when wind speeds from both anemometers were archived, the wind speed report was not used unless both anemometers were functioning and in agreement.

Ship reports were extracted from the COADS (Comprehensive Ocean Atmosphere Data Set) Release 1a: 1980-95 (Woodruff et al., 1993), within a radius of approximately 120 km of each buoy location. Metadata about each ship was acquired from yearly electronic files of WMO Publication 47 (WMO 1980, with some corrections applied by Kent and Oakley, 1995), and (for Canadian-recruited ships) the Canadian Ship Information System. These sources gave the thermometer and anemometer heights needed to adjust measured ship winds for height. In some cases, unavailable anemometer heights were inferred from platform heights. Typical anemometer heights range from 15 to 40 m, with average heights near 30 m.

Differences in anemometer height are a significant cause of bias, increasing observed wind speeds from sources with high anemometers. Wind speeds were adjusted to a reference level of 10 m, effective neutral, using Walmsley's (1986) method when possible, or a log profile formula if air and sea temperatures weren't available. The log profile assumes neutral atmospheric stability conditions; this assumption will be reasonably good in offshore regions. If we did not have an anemometer height for a ship with measured ship winds, we did not use the winds.

The operational Beaufort equivalent wind scale is meant to give a wind speed equivalent to a 10 m effective neutral wind (U10N), so we did not adjust estimated winds for height. However, various improved equivalent scales have been proposed. We adjust estimated ship wind speeds using Lindau's equivalent scale (Lindau, 1995, 2000). We use both the original estimated wind speed (*UE*) and the estimated, Lindau-adjusted speed (*UEL*) in subsequent regression analyses, since we are interested in assessing the impact of Lindau's equivalent scale on the dataset of estimated ship wind speeds.

We found pairs of ship and buoy reports that were close in time and space (one hour or less apart, and within 120 km). We then applied a quality-control process, flagging ship reports with wind speeds differing greatly from those of neighbouring ships, individual ships whose reported wind speeds differed from those of neighboring buoys in a less-drastic but inconsistent way (determined by interquartile range of the differences), and ships with few reports in the database (N < 15). Table 1 gives the numbers of pairs for each ship wind type (measured and estimated) after the various screening steps have been applied, and the correlation coefficients between the paired values. The table also gives estimates of the observational error variance, which is explained in the next section.

Table 1 Statistics for differences between paired ship and buoy wind speeds, and observational error variance (OEV), for each type of ship wind (*UMA, UE*, and *UEL*), by coast: number of pairs; correlation coefficient; mean, standard deviation and variance of difference in ship buoy wind speeds; total OEV for ship and buoy wind speeds, V_{st} and V_{bt}; buoy/ship total OEV ratio, c_t; and inverse of c_t.

Wind	***East***									***West***								
	N	***r***	$\bar{d}$	***SD***	***V***	V_{st}	V_{bt}	c_t	$1/c_t$	***N***	***r***	$\bar{d}$	***SD***	***V***	V_{st}	V_{bt}	c_t	$1/c_t$
UMA	2759	.792	0.81	2.57	6.59	4.5	2.1	0.47	2.1	7607	.778	0.29	2.49	6.22	4.3	2.1	0.46	2.2
UE	2026	.767	0.70	3.05	9.29	7.2	2.1	0.29	3.4	3065	.748	0.90	3.04	9.25	7.3	2.0	0.27	3.7
UEL		.764	0.78	2.74	7.50	5.4	2.1	0.39	2.6		.748	0.93	2.74	7.52	5.6	2.0	0.35	2.8

3. Analysis Method

3.1 Overview

In order to remove any inhomogeneities remaining after correction for averaging method and measurement height, etc., we develop conversion relationships by regressing buoy (*BU10N*) on ship (*SU10N*) winds in various ways. The regression equation is then used to convert the ship wind speed to a regressed ship wind (*RSW*). Each regression method has a specific purpose or application and gives regressed winds with certain statistical characteristics. We will show the impact on the regressed winds of using each method, and assess which method is most appropriate for climatological purposes. We analyze 3 different types of ship winds: measured, adjusted (*UMA)*; estimated (*UE*); and estimated, Lindau-adjusted (*UEL*). (All buoy winds are *UMA*.)

We regress buoy on ship data because we want an equation to convert ship winds to be more statistically similar to buoy winds. Conventional linear regression (*CON*) (ordinary least squares of Y on X, or OLS(Y|X)), is used to develop a predictive relationship of the mean Y for a given X. This would be a true functional relationship only if the independent variable plotted on the x-axis has no observational error. In our data that is not the case, in fact the random observational error of the ship is larger than that of the buoy. We could regress the ship on buoy data, then invert the resulting equation to get a formula to convert ship winds (*INV* or OLS(X|Y)), but the observational error of the buoy winds also cannot be neglected. These two methods do not treat the data symmetrically: we get different results from each. To account for the observational errors of both the buoy and the ship, we apply an "Errors-in-Variables" (*EIV*) linear regression method, that uses a ratio of the observational error variances to correct the conventional regression parameters. We also apply a geometric mean (GM) regression model. Both the EIV and GM regression models treat each variable symmetrically. This means they are invariant to switching the 2 axes, i.e. we get the same line whether we plot ship on buoy, or plot buoy on ship and invert the regression relation. These methods yield a number of alternative linear conversion relationships for each of 3 sets of ship wind speeds: UMA, UE, and UEL

We found that analyzing each coast separately gives similar regression parameters. However, there are some differences from coast to coast, in the frequency distributions of the reported wind speeds, and in the estimates of observational error variance, so the data from each coast are analyzed separately.

We apply the results of some of the different regression methods to convert the ship winds to regressed ship winds. This is necessary when, after adjusting for height and other quantifiable differences, some inhomogeneties between the ship and buoy wind data sets still remain. We can convert the adjusted ship winds using the regression relationships to attempt to produce a dataset that is homogeneous with the buoy wind dataset. The resulting homogenized datasets could be blended and analysed for temporal trends. The homogenization process should remove a discontinuity with the introduction of buoy winds in last few decades, which would otherwise be present in a time series of marine wind speeds.

We test the effectiveness of the conversion equations at making the ship and buoy data sets homogeneous by comparing the converted ship winds to the adjusted buoy winds (*BU10N*) which we take to be our reference.

We compare descriptive statistics, specific percentiles, and monthly means and standard deviations of the converted wind speed to those of *BU10N.* From this, we choose the conversion methods that best suit our purpose, for estimated and measured ship wind speeds.

3.2 "Errors-in-Variables" Linear Regression (EIV)

In some regressions, the scatter about the line is due primarily to the measurement (observation) process. Types of problems where the true points lie on the line are called functional regression models. When the scatter due to errors in the measurement process is the same from point to point, this condition is called homoscedasticity. This is the classical "error-in-variables" regression model. A non-iterative solution for the slope of the regression line is possible if this ratio of observational error variance of the dependent variable over that of the independent variable, is assumed to be a constant. Lindley(1947) shows the derivation of this method to correct the regression formula for the random observational error of both variables, in order to determine a functional relationship between two variables. He discusses the differences between the functional relationship and the ordinary regression line. Kent et al. (1998) use this method for a comparison of VOS and ERS-1 scatterometer winds, which have significantly different random errors, to determine an unbiased regression. The method is also described in Isobe et al. (1990).

Note that if we assume that the independent variable has zero error, the EIV formula gives the same result as the OLS(Y|X), and if we assume that the dependent variable has zero error, the EIV formula gives the same result as OLS(X|Y). The two lines, from OLS(Y|X) and OLS(X|Y) form lower and upper bounds, respectively, for the slope of the EIV regression line. The EIV regression solution gives the functional relationship between the two variables, i.e. the relationship between the true values, rather than the measured values which contain error. In comparison, an OLS regression line based on the measured values will be biased, and will differ from the functional line expected between true values, because of the errors in the measurements. For example, if two instruments are measuring the same quantity, but one instrument has a much larger measurement error, the OLS regression line will differ from the 1:1 line that would be expected from a regression of the true values. The EIV line should correct for the different errors and give a result close to the 1:1 line, if the two instruments are measuring the same quantity and the estimates of random observational error are correct. When measurement errors are equal, so that the ratio, c, is equal to one, then the EIV formula reduces to the same formula as the orthogonal regression (OR), discussed in the next section.

3.3 Neutral Regressions

There are a class of alternatives to OLS(Y|X), applicable when the intrinsic scatter of the data dominates any errors arising from the measurement process, or when the measurement error is unknown, or we wish to avoid specifying "independent" and "dependent" variables. We look at some of these methods that treat the variables symmetrically. These are sometimes called neutral regressions, or 2-way regressions. One method is the geometric mean (GM) of the OLS(Y|X) and OLS(X|Y) slopes, also called the *reduced* major-axis regression. This method minimizes the sum of the area of the rectangles defined by the data points and the nearest point on the line. Another model gives a line that minimizes the sum of the squares of the perpendicular distances between the data points and the line, called the orthogonal regression (OR) or major-axis regression. These techniques lead to very similar but slightly different regression lines. The formula for the EIV slope parameter reduces to the formula for the OR slope parameter, when the ratio of measurement error variances is assumed to be 1, i.e. when the uncertainties of both sources of data are the same.

Lindau(1995) used the method of cumulative frequencies to derive an improved Beaufort equivalent scale. In this procedure, he sorted both data sets separately in ascending order. Values with the same exceedance probability in their respective distribution are considered to be equivalent. The procedure is identical to orthogonal regression if the relationship is linear, but allows one to detect non-linear relationships also, as they are expected, between Beaufort estimated and measured wind speeds. Lindau wanted to find the true functional relationship between measured and estimated ship winds. Therefore, he ensured that the observational error variances of the two sources of data were equal, by averaging the measured winds over time and the estimated ship winds over space. We followed a similar approach, by finding the equation of the line that fits ranked ship and buoy wind speeds. However, we did not do any averaging to equalize the random observational error. For our purpose, as we discuss below, it may not be necessary to correct for random observational error. When we order the wind speeds from ships and buoy separately, and then match the values quantile for quantile, so that the lowest wind speed reported by a buoy is matched by the lowest reported by a ship, and the highest from each is matched, etc., the ordered matched data pairs exhibit a strongly linear relationship, as seen in the quantile-quantile scatterplots (Fig. 4). We denote the line as QQL. This method is invariant to switching axis. The straight line fit is very close to what we get from the GM regression of the paired data (slopes the same to within 1%). The method of finding the linear relationship between ranked bivariate data seems to be equivalent to the geometric mean regression. This follows because the correlation of the ranked data is very close to 1. The GM regression slope is equal to the OLS regression slope, divided by the correlation coefficient. The slope of the GM line is simply the ratio of sample standard deviations of the Y and X variables. The GM method may be useful if the intent is to produce a data base from ship wind speeds that is statistically similar to that of buoy wind speeds. We do not correct for measurement error when we use this method, because we are interested in the relationship between the reported winds speeds, not the functional relationship between the true winds observed by ships and buoys. By finding a line that matches the ship to the buoy data, quantile by quantile, ship data converted using this relationship will have similar statistical characteristics as the buoy wind data. We use RSGM to denote the ship winds converted using the GM regression parameters. Note that we can also fit the ordered data to a non-linear function. Lindau's scale relating estimated and measured ship wind speeds is non-linear, and a 3^{rd} order polynomial fits it fairly well.

3.4 Determination of Ship and Buoy Random Observational Error Variance (ROEV)

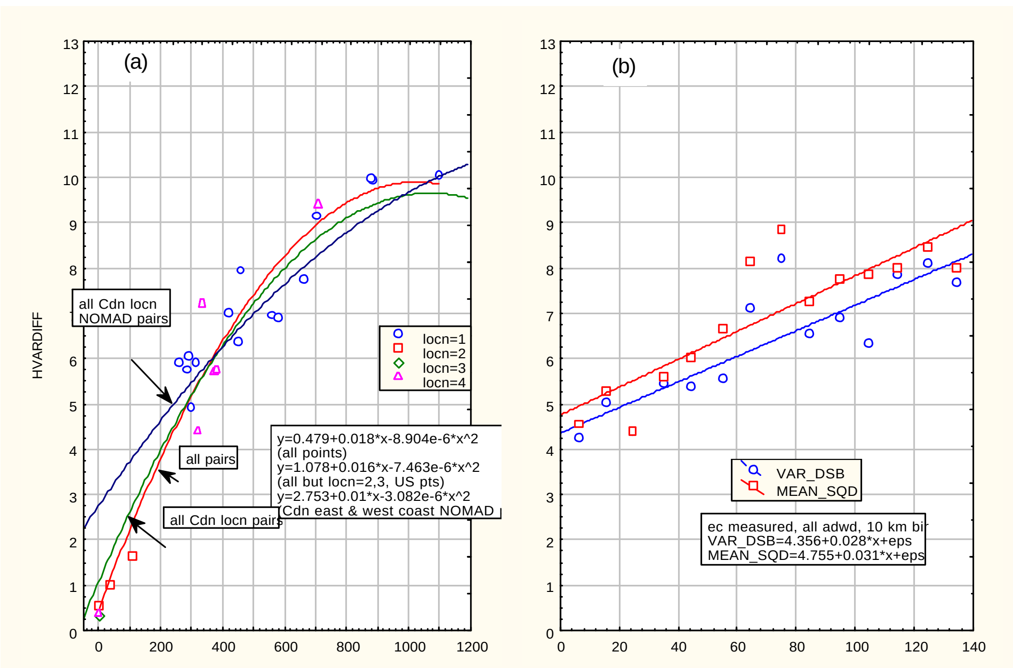

Figure 1 (From TS03) Variograms to determine buoy and ship observational error variance: a) half variance of difference for each buoy-buoy pair, vs separation distance of buoy-buoy pairs, with 2^{nd} order polynomial best fit lines; b) variance of difference for binned differences of east coast measured adjusted ship-buoy pairs vs separation distance, also mean of squared differences for binned differences, with linear best fit lines.

The error variance is the square of the uncertainty, or observational error, associated with each wind speed report. We use an average or "bulk" error variance estimate, in order to apply the EIV regression model. Sources of observational error include: timing within the hour of the observation; anemometer type, calibration, and location (in relation to areas of airflow disturbance over the ship); averaging method or period; effect of wind and waves on the ship; errors in calculation of true wind from the relative wind; rounding artifacts (multiples of 2 and 5, or midpoint of Beaufort intervals); and stage of development of the waves (affecting the observer's estimate of Beaufort equivalent speed). The error or uncertainty of buoy wind speeds comes from similar factors such as the anemometer type and height, and calibration and condition of the instrument (which are very susceptible to damage from icing, for example), averaging method, buoy motion in waves, the effect of wave sheltering or wave breaking on the buoy, etc. Finally, adjusted wind reports would be affected by differences in adjustment method, and in atmospheric stability regime. In every case, some of these factors would cause systematic differences; others would have a random effect only.

We followed the basic approach used by Lindau (1995) to determine the ROEV of the measured and estimated ship wind speeds, except that we worked with variances of differences rather than the mean of squared differences, thus preventing systematic differences from being included in the estimates of ROEV. We use an estimate of error variance for measured, height-adjusted buoy winds, based on buoy-buoy pairs for which half the variance of difference is plotted as a function of distance and interpolated to the origin (see Fig 1a). We determine separate estimates of error variance for *UMA*, *UE*, and *UEL* ship wind speeds in a similar way. We bin the ship and buoy pairs based on separation distance, calculate variance of differences in wind speed for each separation bin, and plot the variance as a linear function of the separation distance. The intercept then gives the combined error variance of the ship and buoy (see Fig 1b). Subtracting the previously determined value for the buoy, yields the ship observational error variance. The method and results are described in more detail in Thomas and Swail (2003, TS03 hereafter, in preparation). Results are compared to those of a study on buoy measurement error (G87) and a study in which the semivariogram method described by Lindau is applied to ship and satellite wind speed data (Kent et al, 1999). Table 1 shows the values we use in this study, which apply specifically to the quality controlled and adjusted data from which they were derived.

4. Regression Results

Table 2 shows linear regression results for UMA, UE, and UEL wind speeds for each coast. The values a0 and a1 are the intercept and slope, respectively, of the best fit regression lines. We can see that for each category of wind and coast, the CON line always has the lowest slope, which is always < 1. The INV line always has the steepest slope, which is always > 1. In fact, we get widely different results from the conventional regression method, depending if we regress buoy on ship winds (CON) or if we regress ship on buoy winds and then invert (*INV*). This is due to the large ship observational error variability. Fig. 2b shows the scatterplot of BU10N on SU10N, for east coast measured winds, and the EIV and GM regression lines, as well as the 1:1 line. The CON and INV lines form the upper and lower bounds for the slopes of the regression lines. The regression lines on the plot cross each other at the same point, defined by the means of the buoy and ship winds speeds for each dataset.

Table 2 Regression coefficients for best fit lines for paired ship and buoy wind speeds, for each type of ship wind (UMA, UE, and UEL). a0 is intercept, a1 is slope.

Wind	***Method***	***East***		***West***	
		a0	***a1***	***a0***	***a1***
UMA	*CON*	1.504	.731	2.080	.729
	INV	-2.222	1.164	-2.082	1.205
	EIV	-.765	.994	-.482	1.022
	GM	-.143	.922	.259	.937
UE	*CON*	2.368	.648	2.436	.633
	INV	-1.659	1.102	-2.117	1.130
	EIV	-.371	.957	-.719	.977
	GM	.620	.845	.487	.846
UEL	*CON*	1.580	.735	1.626	.721
	INV	-3.091	1.260	-3.591	1.290
	EIV	-1.563	1.088	-1.987	1.115
	GM	-.443	.962	-.606	.965

When the error variance ratio is < 1 (buoy OEV < ship OEV), as in our case, the EIV regression line will be closer to the inverse line than to the conventional line. It is bounded by the inverse line and the orthogonal regression line (almost the same as the GM line). Thus, when we regress buoy on ship winds, accounting for observational error through use of the EIV regression, it makes a pronounced difference in the regression line, compared to that of the conventional regression. The EIV line is close to the 1:1 line, particularly for *UMA* winds. It is fairly close for estimated winds (within 4%), but not so close for Lindau-adjusted winds (within about 10%). This means that the functional relationship between buoy and ship UMA winds is about 1 to 1, i.e.. once we adjust for known differences such as anemometer height, and adjust the regression for random observational error, we find that the ships and buoys are measuring approximately the same wind.

Another way to look at this data is using box plots, where the data are binned in different wind speed intervals, as described in Tolman (1998, hereafter T98), and the means or medians for each bin are plotted. The median buoy winds for each ship wind speed bin do follow a linear relationship (not shown). As with the scatter plots, the regression results of the mean or medians of the bins depend on whether buoy winds are binned on ship winds or vice versa. However, the slope of the regression line for the medians is more sensitive to anomalous high wind speeds. The binned analysis must also be corrected for non-zero observational error variance of the independent variable (T98).

The geometric mean regression parameters are given in Table 2. The parameters for the straight line fit to the Q-Q scatterplot of ranked data are the same to within one percent. The GM regression line is midway between that for the CON and INV lines, as shown in Fig. 2b, and the result is symmetric. The lines are much closer to the 1:1 lines than either the CON and INV lines, particularly for UEL winds. The slope is about 0.92 for UMA winds, 0.85 for UE winds, and 0.96 for UEL ship winds (Fig. 3b). If we compare to the corresponding figures of unadjusted measured wind speeds (e.g. Fig 2c and 2d) for west coast measured winds, we see the height adjustment has made quite a difference: the slope of the regression line has increased nearly 25%. As winds increase, SU10N becomes gradually stronger than BU10N. The difference is about 2 m/s for BU10N of 16 m/s.

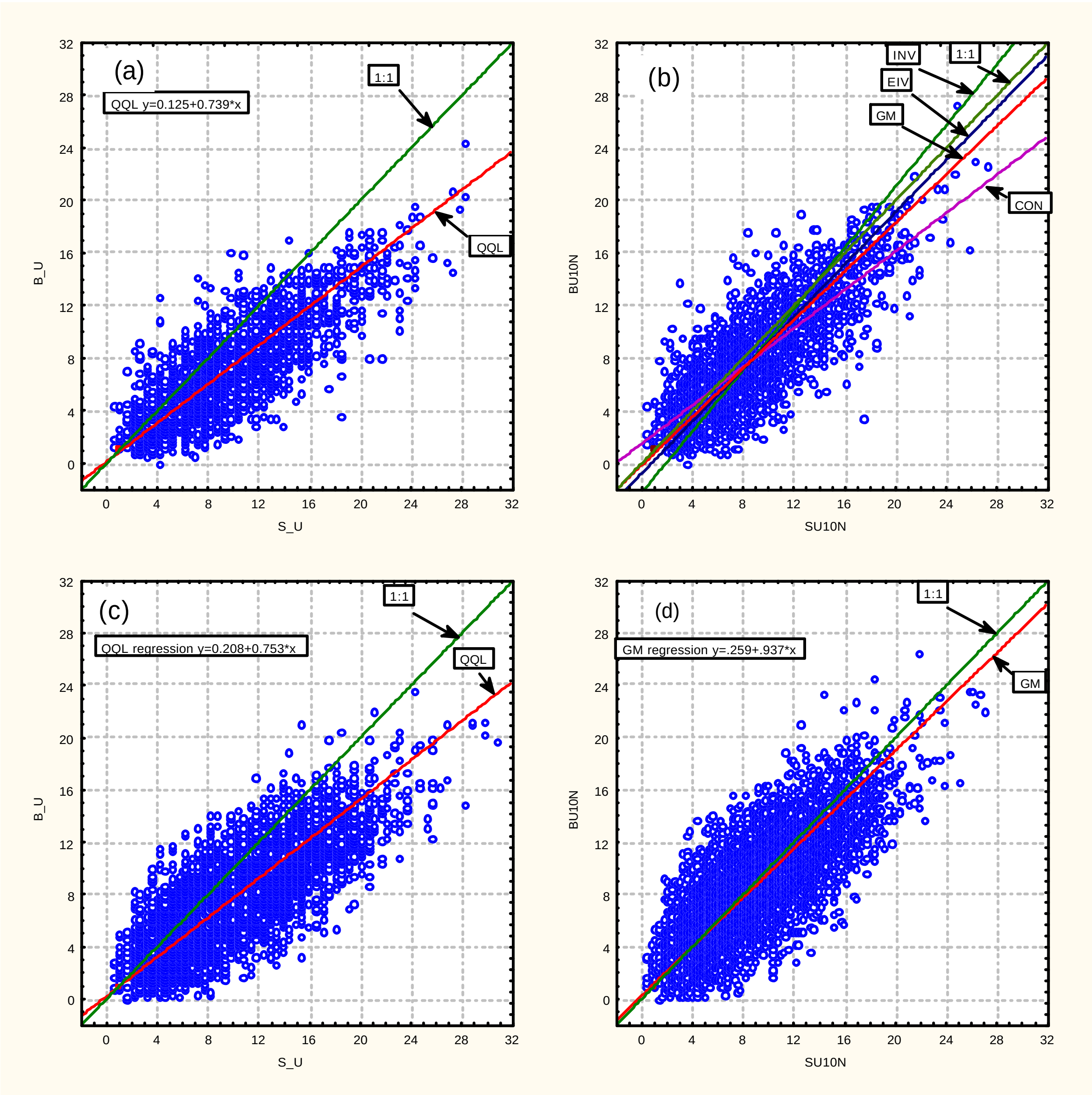

Figure 2 Scatterplots for buoy on measured ship wind speeds, with 1:1 and neutral regression lines a) east coast original, b) east coast BU10N on SU10N also with inverse, EIV, and conventional regression lines, c) west coast original, d) west coast BU10N on SU10N.

In the case of east coast *UMA* winds, the Q-Q plot, Fig. 4a, reveals a fairly linear relationship for most of the dataset of BU10N and SU10N, however at higher winds speeds (SU10N>18 m/s, BU10N>16 m/s i.e. approximately gale force and stronger) the points are slightly off the straight line. This suggests some non-linear effects, causing the strongest SU10N winds to become relatively stronger than the strongest BU10N winds, compared to the linear relationship established for lighter winds. The difference between these points and the QQL line is fairly slight however, only 1-2 m/s. Not shown are the Q-Q scatter plots for west coast UMA winds, or for the UE or UEL winds. The points on the Q-Q scatter plot for west coast UMA winds look consistently linear, with a slope very close to that for the east coast. The Q-Q scatter plots for estimated winds on both coast fit a straight line well (Fig. 4c for east coast), although again there appear to be some nonlinear effects at high wind speeds. A 2nd or 3rd order polynomial fits this slight curve in the line. The corresponding plots for UEL winds (see Fig. 4d for east coast)are fit best by a straight line. Lindau's Beaufort equivalent scale gives a non-linear transformation, that removes the non-linear component from the estimated winds.

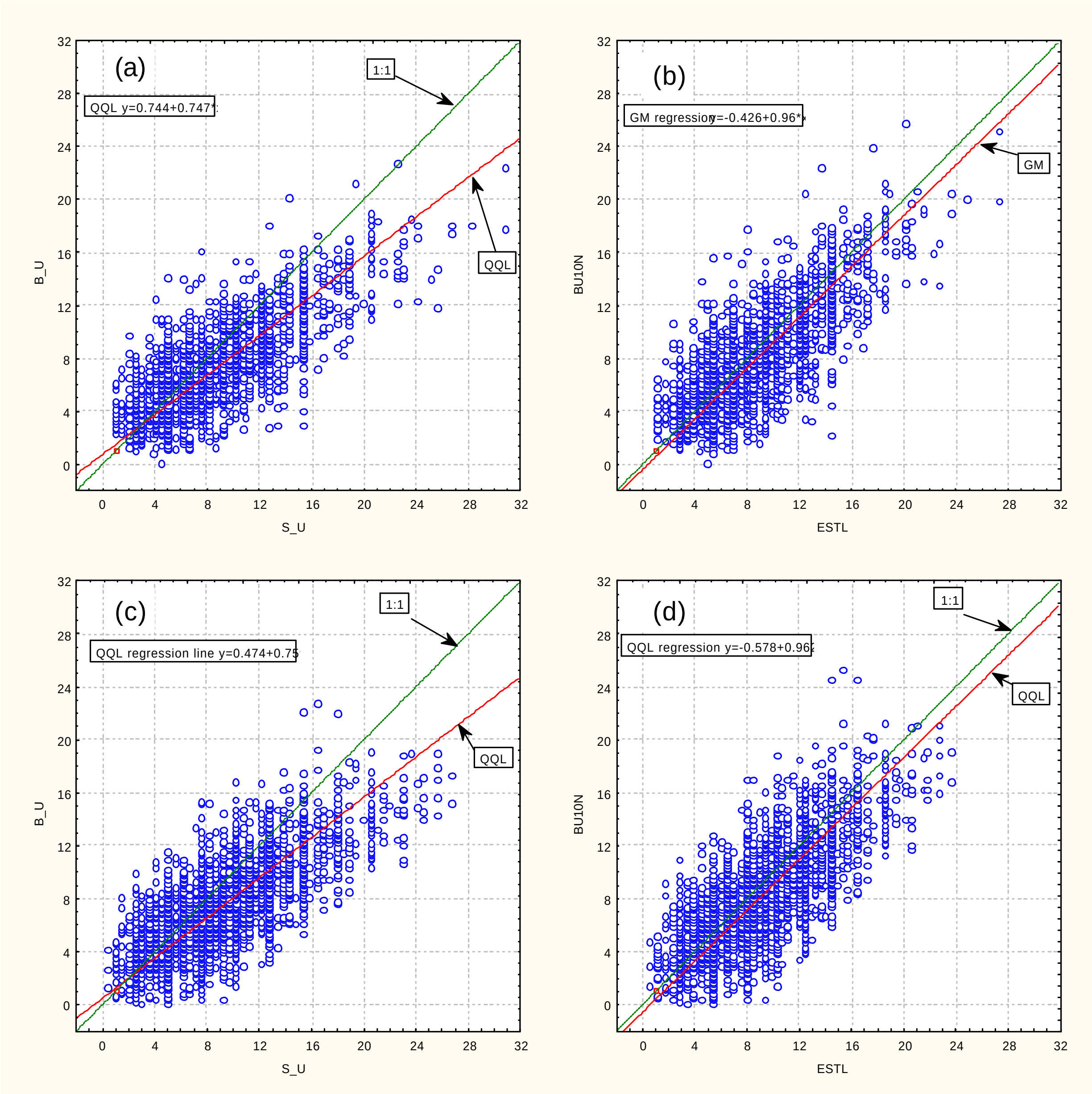

Figure 3 Scatterplots for buoy on estimated ship wind speeds, with 1:1 and neutral regression lines a) east coast original b) east coast BU10N on UEL, c) west coast original, d) west coast BU10N on UEL.

5. Comparison of Original, Adjusted, and Converted Ship and Buoy Wind Speeds

We can assess the impact of the adjustments on the datasets by looking at the change in the frequency distributions. Fig. 5 shows frequency distributions for east coast measured, adjusted and converted winds. The frequency distributions are fitted to the Weibull distribution, which is preferred for wind speeds because it fits the extremes better (Bauer, 1996). However, it seems a little high on the shoulder of the distribution (10-15 m s^{-1}). The Gamma distribution (not shown) seems to fit the data more closely in this region, but it is too high for the extremes.

We can see from Fig. 5a to 5b the impact of the height adjustment. Fig 5a shows that the distribution of original ship winds is more skewed and is shifted to higher values, compared to original buoy winds. Fig 5b shows that the frequency distributions of the height adjusted (and buoy corrected for averaging method) values are much closer. The adjusted ship and buoy wind speed distributions on the west coast show an even stronger agreement than on the east coast. For both coasts, ship winds still show a tendency for stronger winds to be slightly more frequent. On the east coast, ship winds above about 16 m s^{-1} are twice as frequent as buoy winds. The difference is less on the

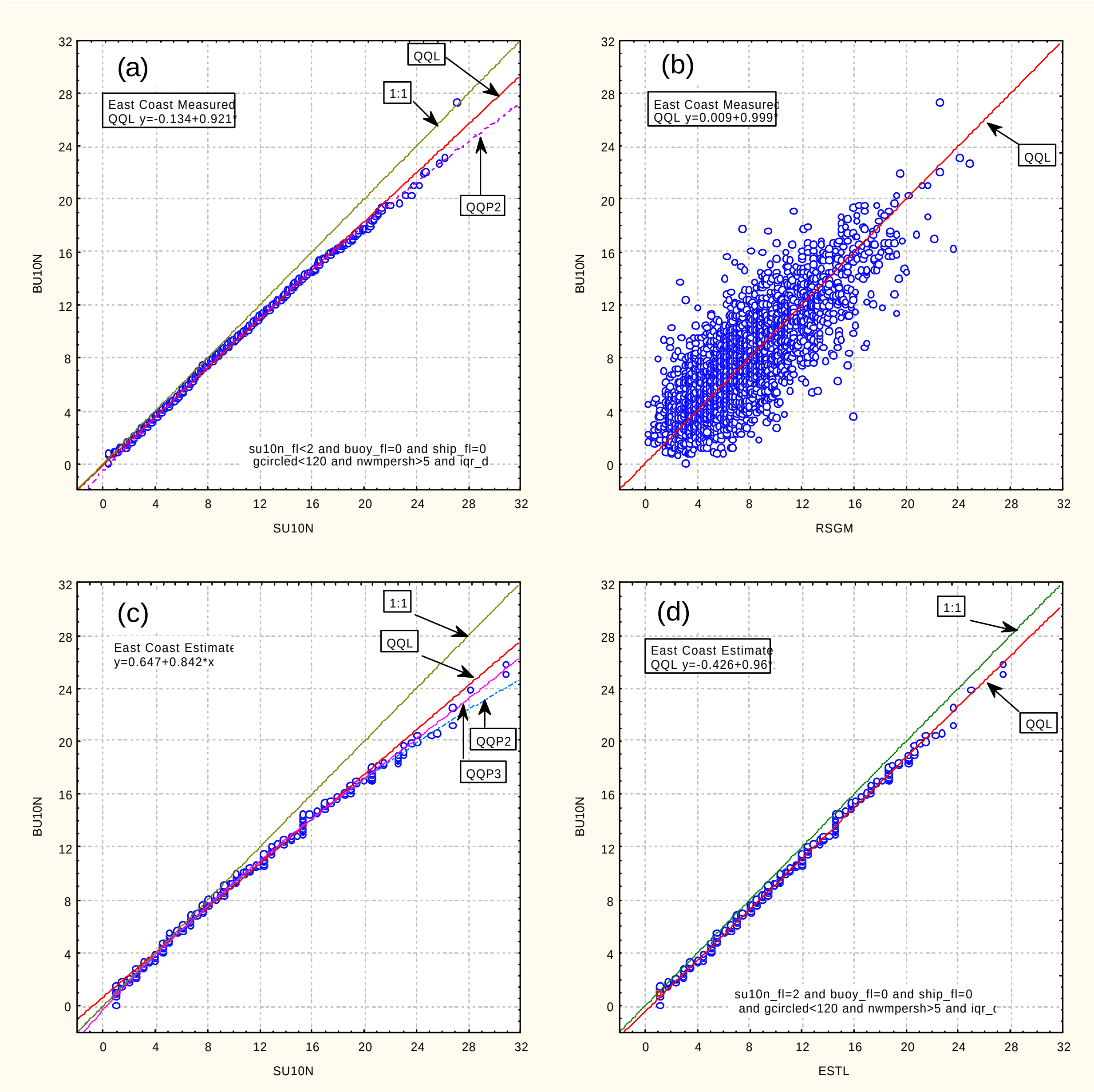

Figure 4 Scatterplots for east coast measured (top) and estimated (bottom) ship and buoy winds a) (Q-Q) scatterplot of BU10N on SU10N measured, with 1:1 line, and linear and 2nd order polynomial regression lines, b) scatterplot of BU10N on RSGM, with QQL regression line, c) Q-Q scatterplot of BU10N on SU10N (original estimated), with 1:1 line, and linear and 2nd and 3rd order polynomial regression lines, and d) Q-Q scatterplot of BU10N on UEL winds, with 1:1 and linear regression line.

west coast. For estimated winds, not shown, Lindau's adjustment brings the distributions closer together, including in the highest winds speeds. Some difference remains; it seems to be slightly greater on the west coast.

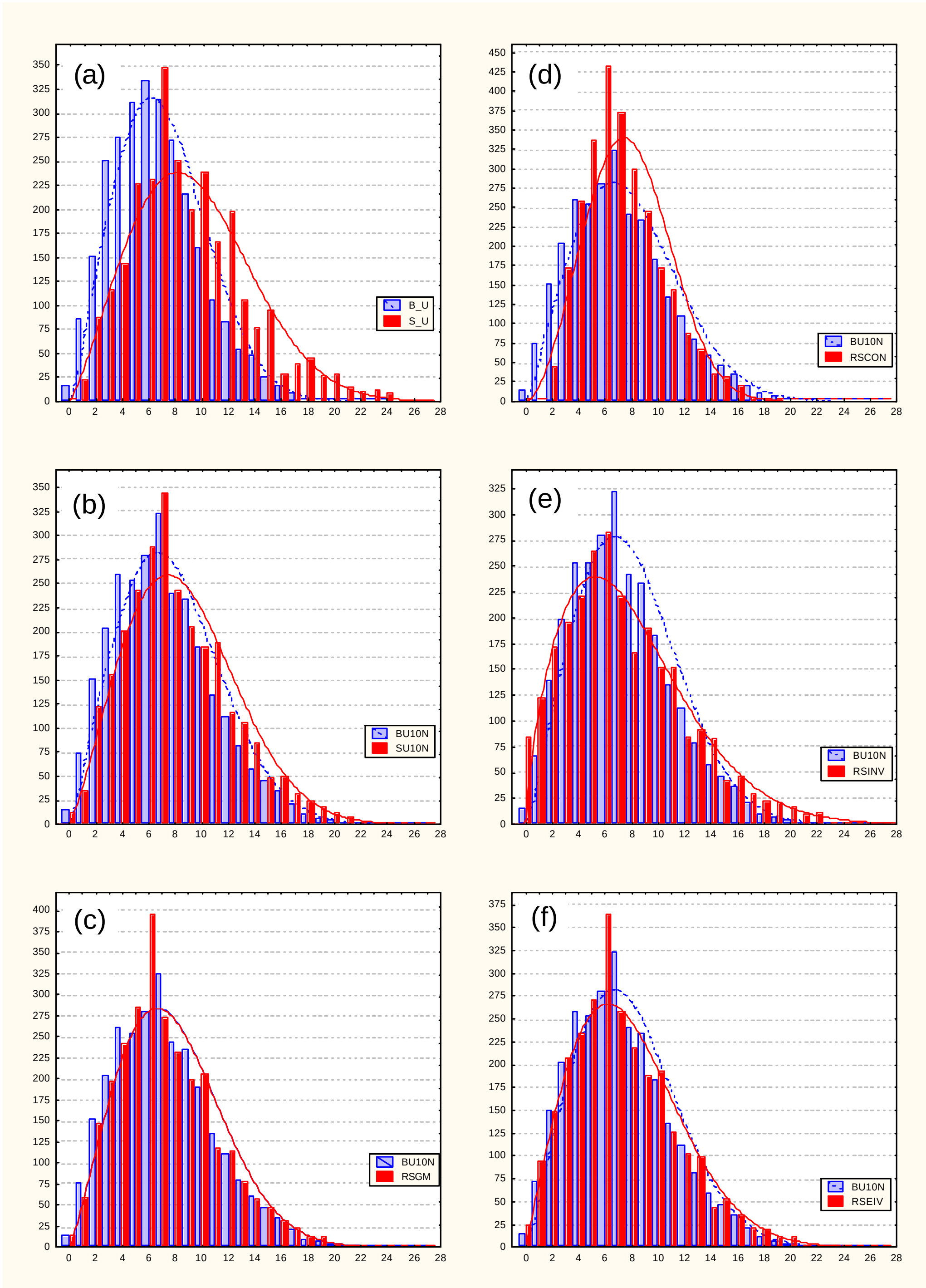

Figure 5 Frequency distributions of east coast measured paired ship and buoy wind speeds, fitted to Weibull distribution a) original buoy and ship b) BU10N and SU10N, c)-f) BU10N and regressed SU10N winds, converted using: c) geometric-mean, d) conventional, e) inverse, and f) EIV regression equations.

Comparison of the frequency distributions of regressed ship winds, to BU10N winds, reveals the effects of different regression equations. The CON regression equation reduces the spread of the ship winds, so that RSCON winds are stronger than BU10N in lighter winds, and weaker than BU10N in stronger winds (see Fig. 5d). This is consistent with the meaning of the conventional regression that gives a prediction for mean values for any given range of wind speed. The INV regression has the opposite effect. It increases the spread of the ship winds (compared to SU10N), so that RSINV winds are relatively greater for strong BU10N, than even the SU10N winds were (see Fig. 5e). Both the EIV and GM conversions give results that are fairly close to that of BU10N (see Fig. 5f and 5c), with RSGM showing the strongest match (slight differences remain at high winds) (see Fig. 5c). Similar patterns occur in the distributions for UE and UEL winds, and for the west coast.

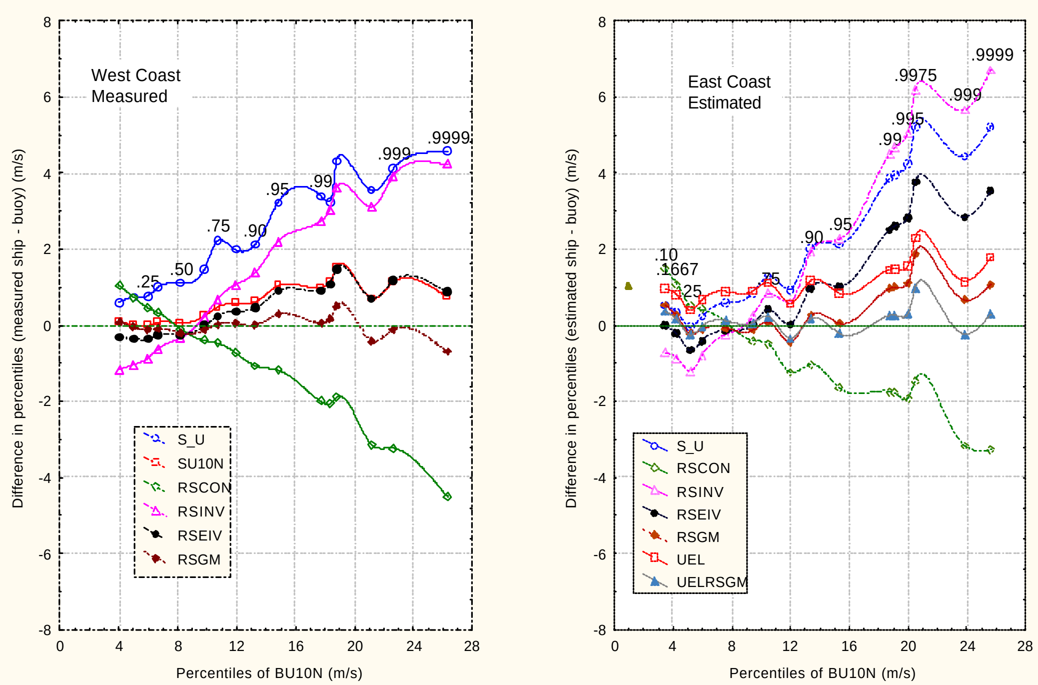

Figure 6 Differences in percentiles (ship - buoy) vs bu10n percentiles, for a) west coast measured, b) east coast estimated. See text for description of original and adjusted and converted ship winds.

We calculated various statistical summaries for the winds, including sextiles, quartiles, and extreme percentiles. Ultimately we want to be able to compare our revised statistics (using the converted ship winds) to existing climatological summaries of marine wind data. Figure 6 shows the difference in percentiles between that of a particular ship wind type and that of BU10N, plotted as a function of BU10N for west coast measured (Fig. 6a) and east coast estimated (Fig. 6b). The percentiles for BU10N are used as the standard. One remarkable feature of these graphs is how much of the full range of wind speeds is higher than the 95th percentile of adjusted buoy winds. This is the range from near gale force and higher. The difference in percentiles gets increasingly large for unadjusted ship winds, with increasing BU10N. For example 99.9th percentile wind speed for BU10N is about 22 m/s, compared to the 99.9th percentile wind speed for original measured ship winds of about 26 m/s. The height adjustment, to SU10N, drops the differences in percentiles substantially, from about 3 m/s by the 95th percentile, to 1 m/s (BU10N 15 m/s). For increasing BU10N, the difference in percentiles with RSCON becomes increasingly negative. The percentiles for RSGM (UMA) are fairly similar to those of BU10N, with differences in percentiles of less than 1 m/s, for the full range of wind speeds of the dataset. The Lindau-scale adjustment for estimated winds, drops the 99th percentile from 4 m/s greater than BU10N, to about 2 m/s. The UELRSGM percentiles show good agreement with the BU10N percentiles, with differences of less than 1 m/s for the full range of values.

We can look at monthly statistics as way to assess the ability of the regression method to give converted ship wind data sets that have a similar amount of seasonal variability as buoy data. This problem is discussed in detail by Lindau (2000). Fig 7 shows 75th percentiles of measured winds on the west coast, for each month. The annual cycle has a minimum in July and a maximum in January. The unadjusted ship values are much higher than all of the converted values and BU10N. The tendency of the CON regression to over-reduce the stronger values shows up particularly over the winter months, where the 75th percentiles of RSCON are lower than the other winds values, just as described by Lindau. The seasonal variation in the range of wind speeds is reduced too much by the CON conversion. We can see that the GM and EIV conversion preserved the same seasonal variation as the BU10N winds, since those are fairly close. The differences in the methods show up more clearly in the higher percentiles during the winter months, and for the lower percentiles in the summer months. The INV conversion increases

the spread of the wind speed distribution in both directions. As a result, the RSINV 25th percentile wind speeds (not shown) are lower than all the other winds, particularly in the summer months (the lowest values). All the methods give fairly similar result for mean monthly conditions, especially months that are not at either end of the annual cycle in wind speed strengths. East coast monthly statistics (not shown) reveal a seasonal cycle with a more extended period of lighter monthly mean winds during the summer, then a more abrupt increase in fall. Monthly statistics for estimated winds (not shown) reveal that Lindau's adjustment actually increases the monthly mean summer winds slightly, compared to the original estimated winds, and reduces the winter monthly means very slightly. The regressed winds have fairly similar monthly means, so the choice of regression method is less important than for the monthly extremes (high and low). The standard deviations of the monthly means show some pronounced differences in the impact of the different regressions. For both coasts, the CON conversion reduces the variance, during every month, compared to the others, while the INV conversion increases the variance. The EIV conversion also increases the variation in the wind speeds to more than what we see in the height adjusted ship winds. The GM conversion gives a variance in the regressed ship winds very similar to that of the adjusted buoy winds.

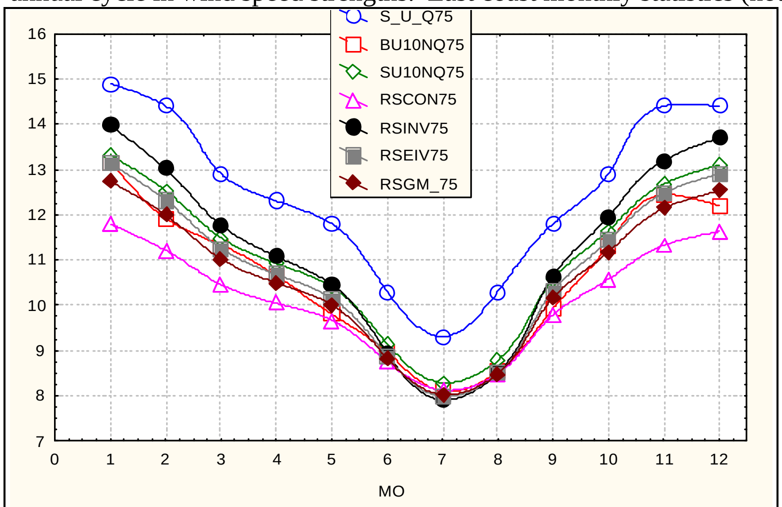

Figure 7 Monthly 75th percentiles (m/s) for west coast measured ship winds, compared to those for BU10N winds, plotted by month.

6. Discussion

The height adjustment of both measured ship and buoy winds makes a large contribution to reducing the differences in the monthly summary statistics.

The EIV model is a simplification of the problem of random observational error, with the assumption that the ratio of random errors is a constant. More sophisticated regression models to deal with observational error that is a function of the variable itself, are described in Feigelson and Babu (1992) and in Ripley and Thompson (1986). TS03 study the dependence of measurement error variance of wind speeds measured (or estimated) by ships and buoys. There does appear to be some dependence of the observational error variance on the wind speed, however more data and analysis is required to quantify this in each case. Separate "bulk" or average measurement error variances, determined for buoy and measured and estimated ship wind speeds, are used here in this study with the EIV regression model. In order to use the EIV method, we have to assume that the ratio of observational error variances of each source is a constant. This may be true, even if the measurement error variance depends on the magnitude of the wind speed, but the analysis in TS03 did not have enough information to show this.

There are small differences in the slopes of the regression lines from coast to coast. The difference is about 2 to 4% for measured winds, only 1% for estimated, with the slopes for the west coast being slightly steeper. There seems to be slightly less bias (west coast ship UMA closer to BU10N). The different tracks and stages of development of the storms on each coast, giving different wind and wave climates, may be a factor.

Also, ship observing practices and vessel characteristics may differ enough to make a difference. The majority of west coast paired ship reports are from tankers, whereas on the east coast more paired reports are from Coast Guard and container ships. The log profile formula was used to adjust a higher proportion of west coast measured winds, which may have slightly over-reduced the winds in unstable situations. Also, we estimated the anemometer height from the platform height for more west coast ships. Regressions of Q-Q scatterplots also allow non-linear fits to the ranked data. There is slightly better agreement between the BU10N data set and east coast UMA ship winds converted using a non-linear regression; the non-linear effects appear at high wind speeds; the effect is not apparent with this dataset of west coast UMA winds. Similarly, it was necessary to use a nonlinear fit to the ranked data, to get regressed estimated winds that agreed as well with BU10N winds, as the UEL winds regressed using linear fit to ranked estimated, Lindau-adjusted data. The Lindau scale is non-linear, and removes the slight non-linearity between buoy and ship winds at high wind speeds. It may be possible to develop some further adjustments to either the buoy or ship winds in these extreme conditions, however these may have little effect on the overall linear relationship between buoy and ship winds determined in this study.

7. Conclusions

The most important step to make ship and buoy data sets more homogeneous is to adjust measured ship and buoy wind speeds from anemometer height to a common reference level of 10 m. Some inhomogeneities do remain in the buoy and ship data sets, even after making corrections for buoy averaging method and adjusting measured winds to a common reference height. To remove remaining inhomogeneities, the ship data can be converted to be more similar to buoy data statistically, by using results of a regression between the ship and buoy data. The best method seems to be to perform a geometric mean regression on the data and use the resulting linear equation on the ship winds. This is effectively a scaling of the ship winds by the ratio of standard deviations of the buoy over that of ship winds. This conversion gave similar frequency distributions, and annual and monthly statistics of converted ship and buoy winds. Some slight differences still remain between the buoy and regressed ship UMA winds above about 16 m/s. Estimated winds can be adjusted either by using the geometric mean regression directly, or adjusting first with Lindau's equivalent scale, then using the geometric mean regression. Use of Lindau's scale first, seems to remove some slightly nonlinear behaviour between buoy and ship winds at high speeds.

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