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USING HIGH FREQUENCY RADAR OBSERVATIONS OF THE OCEAN SURFACE AND OBJECTIVE ANALYSES OF ONSHORE OBSERVATIONS TO ESTIMATE WINDS OVER MONTEREY BAY, CALIFORNIA

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1. Introduction

Winds in coastal areas are both important and difficult to measure. In recent years, radar has been used to determine near-surface ocean currents; several areas are currently instrumented with such radars. One of these is the Monterey Bay region in California where such measurements began in the mid 1990s. Additionally, objective analyses of wind fields have been available from the U. S. Geological Survey for the nearby San Francisco Bay area since before 1999 (Ludwig et al. 1997). These two programs provide the basis for the research described here.

Radar observations of ocean currents are not directly related to winds, but the shear in surface currents results from wind stress at the surface. Current shear can be estimated from radar measurements at multiple frequencies (Meadows, 2002), making it reasonable to consider such data for estimating winds.

Onshore anemometer data archived by the USGS is concentrated around San Francisco Bay, but includes several sites around Monterey Bay that can be used with an objective analysis computer program to estimate winds over the Bay. Thus, we can compare wind fields derived from the two types of data to see how the inclusion of radar estimates of wind affect wind analyses. This paper describes an empirical method for estimating winds from radar observations, and the objective analysis of routine meteorological information. Then, we compare results obtained by the two approaches with observations and each other, exploring how much effect there is when the two data sources are used in tandem.

2. Methods

2.1 Measurement of ocean currents and winds with high-frequency radar

High frequency (HF), or decameter, ground-wave radar is useful for observing near surface currents in the coastal ocean (e.g. Barrick et al. 1985). The radars detect currents, because constructive interference gives returns almost exclusively from a single ocean wavelength (Bragg waves of wave length half that of the radar). Oversimplifying, the radar deduces radial current components from the difference between the radar return's Doppler shift and theoretical wave speed (in the absence of surface current) for the observed ocean wavelength. Effective averaging depth depends on the wavelength, with longer waves "feeling" the current to greater depths. Empirical relationships have been developed between effective current depth and wavelength (Teague et al. 2001). Two radars observing the same area of the ocean, with some straightforward trigonometry, provide estimates of the two dimensional current motion. Here, we use data from two multi-frequency coastal radars (MCR) measuring currents at depths to a few meters below the surface. MCR systems are research tools built by a consortium: University of Michigan, Veridian ERIM International, Stanford University and University of California at Santa Cruz. They operate at 4.8, 6.8, 13.4 and 21.8 Mhz to measure currents at effective depths of 2.5, 1.8, 0.9 and 0.6 m respectively.

Returns from waves moving toward the wind differ from those moving away, causing asymmetry in radar reflectivity that can be used to determine wind direction (but not speed). Among others, Long and Trizna (1973) and Georges et al. (1993) developed methods for using Bragg return signal strength difference (ΔS, dB – receding minus approaching) to estimate wind direction relative to radar line of sight (θ, degrees). We use the relationship developed by Georges et al. (1993) :

$$\left.\begin{array}{c} \theta = 0^\circ \\ \theta = \pm 180\left(\dfrac{24+\Delta S}{48}\right) \\ \theta = 180^\circ \end{array}\right\} \quad for \quad \left\{\begin{array}{c} \Delta S \le -24 \\ -24 < \Delta S < 24 \\ \Delta S \ge 24 \end{array}\right. \qquad (1)$$

Winds toward the radar (θ=180°) or away from it (θ=0°) have no ambiguity, but Equation 1 gives two possibilities for other directions, e.g. when ΔS=0 dB, wind direction will be at right angles to the look direction, either from the right or left. Vesecky et al. (1998), using Eq. 1 with Monterey Bay MCR data demonstrated that this ambiguity can be resolved if two radars view the same area from substantially different directions. They

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estimated directions that generally agreed with surface wind analyses using conventional meteorological data.

Steady-state conditions (admittedly infrequent) produce wind profiles and ocean current profiles that are related to the friction velocity at the surface. According to Meadows (2002), the air friction velocity (u_{*a}) is related to the friction velocity in water (u_{*w}) through the ratio of air/water densities (ρ_a/ρ_w). The equation is:

$$\frac{u_{*w}}{u_{*a}} = \left(\frac{\rho_a}{\rho_w}\right)^{0.5} \approx \left(\frac{1.1}{1025}\right)^{0.5} \approx 0.033 \qquad (2)$$

Seawater density (ρ_w=1025 kg m^{-3}) is used to get the constants in Equation 2, but the result is essentially the same for fresh water. It should be possible to determine u_{*w} from the MCR current profile, then determine u_{*a} from Equation 2. Hasse and Weber (1985) show how wind speed and u_{*a} are related. They use a drag coefficient of 1.3×10^{-3} and showed that the wind speed at 10 m, $u_{10} \approx 28 u_{*a}$. Substituting in Equation 2, then gives

$$u_{10} \approx 840 u_{*w} \quad . \qquad (3)$$

The preceding discussion suggests that there is enough information to estimate wind speed and direction directly from MCR observations, but it has been difficult.

One reason for the difficulties may be the slow response of surface currents to wind changes. We sought a statistical approach that uses MCR information in a way that might account for this slow response of the sea. The approach adopted below uses the MCR vector currents for all effective depths and the Bragg line ratios as a training data set for the method of Partial Least Squares (e.g. StatSoft 2004). The result is an empirical estimation method for speed and direction, derived from in situ buoy measurements that could be tested against a separate 'validation' data set from the same location.

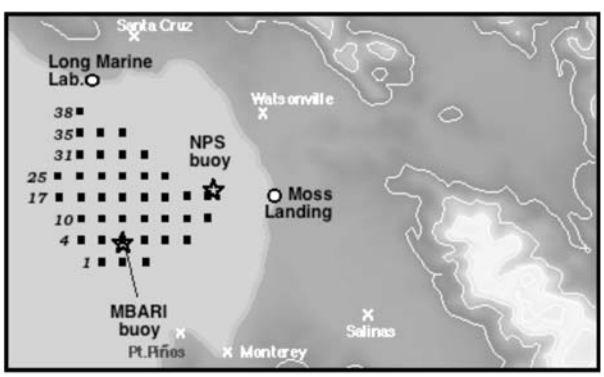

Figure 1 locations of marine labs (❍), M1 and NPS buoys (✩), land stations (**X**), locations used for wind estimates (■); 200 m contours.

Many available radar parameters can be considered for input into a statistical scheme, especially when there are two, four-channel Doppler radar systems in the Monterey Bay area (at Long Marine Laboratory, LML and Moss Landing Marine Laboratory, MLML), as shown in Figure 1. Parameters measured at each range bin for each radar channel are: signal return 1) from approaching waves, 2) from receding waves and 3) Doppler shift from the radial current component. The two radars give 24 primary parameters (3 parameter values × 2 radars × 4 channels) that can be used directly, or converted to ΔS (Eq. 1) and current components (or current speed and direction) at different depths. After some experimentation, the 52 parameters listed in Table 1 were chosen. They include both current measurements and Bragg line ratios; there is considerable redundancy of information, e.g. the current speed and direction is equivalent to U (eastward) and V (northward) components, and the directions relative to look direction come from Equation 1.

Tobias (1995), says this type of problem, with many input variables conveying similar information, and poorly defined relationships with desired parameters, is well suited to Partial Least Squares (PLS) regression. The following brief description is largely based on Tobias (1995) and StatSoft (2004), especially the latter. Ordinary multiple linear regression relates a set of dependent variables **Y** (a matrix of *n* cases by *m* variables) to the independent variables **X** (*n* cases by *p* variables) using a model of the form **Y=XB+E**; **B** is a *p* by *m* matrix of regression coefficients, and **E** is an error matrix with the dimensions of **Y**. This derivation assumes that variable means have been subtracted from each value, and then scaled by the standard deviations to give a set of variables centered on zero, whose ranges of values are approximately equal in magnitude, but unscaled, uncentered variables can beused, and they proved to be. more robust in our application.

TABLE 1 PARAMETERS FOR PLS ESTIMATES

Parameter ID	**Site(s) used**	**Parameter**
1 - 4	MLML	U (northward) component of radial vector – cm s^{-1}
5 - 8	LML	U (northward) component of radial vector – cm s^{-1}
9 - 12	MLML	V (eastward) component of radial vector – cm s^{-1}
13 - 16	LML	V (eastward) component of radial vector – cm s^{-1}
17 - 20	LML & MLML	U (northward) component of current – cm s^{-1}
21 - 24	LML & MLML	V (northward) component of current – cm s^{-1}
25 - 28	MLML	Radial current speed – cm s^{-1}
29 - 32	LML	Radial current speed – cm s^{-1}
33 - 36	LML & MLML	Current speed – cm s^{-1}
37 - 40	LML & MLML	Current direction – degrees
41 - 44	MLML	Line ratio, DS – dB (Eq. 1)
45 - 48	LML	Line ratio, DS – dB (Eq. 1)
49 - 52	MLML	Estimated Wind Direction (°)

There is no inherent reason why ordinary multiple linear regression or principal component analysis (PCA) could not be used, but they require many more data sets than parameters to be effective; we know that many of the 52 variables in Table 1 are correlated and we have only a small data set from which to develop the regression equations, so there is substantial risk that conventional regression will perform well only for the data set from which it has been derived. Even approaches like PCA that eliminate correlation between variables to reduce the number of parameters required to describe the dependent and independent variables need a large data set. PLS overcomes these problems.

According to Statsoft (2004), a new optimal variable set **T** (*n* by *c* matrix) can be derived from linearly weighted combinations of the original predictors (**T**=**XW**). The new predictors **T** are uncorrelated, and **W** is a *p* by *c* weighting matrix, with $c \le p$. In practice, the number of new variables *c* will be fewer than the original number *p* when the number of cases is fewer than the number of variables, or when there is appreciable covariance among variables. Skipping how the weighting matrix **W** is determined, a new linear regression model **Y**=**TQ**+**E** can be derived for the new predictor variables. Here, **Q** is a *c* by *m* matrix of regression coefficients for **T** versus **Y**, and **E** is the error matrix for this regression. Once we have computed **T** and **Q**, a regression equation can be derived with the same form as the original. Then the new model used to estimate wind components is:

$$\mathbf{Y=XB+E} \quad , \tag{4}$$

where **B**=**WQ** is determined from a subset of the data and tested against the remaining cases.

StatSoft (2004) notes that the difference between principal components regression and PLS regression lies in the way that the **T** and **W** matrices are determined. Principal component regression uses the covariances between the *independent* variables, i.e. from the cross-product matrix **X´X**; PLS uses the covariances among *both dependent and independent* variables by working with the matrix **Y´XX´Y**. The prime denotes a transpose matrix. The details of algorithms used for extracting the regression coefficient matrix **B=WQ** are given in StatSoft (2004). Although the form of Equation 4 is essentially the same as that for ordinary multiple regression, PLS regression gives more robust coefficients by using new, uncorrelated intermediate variables in their derivation.

As noted, the PLS algorithm was applied to a subset of data, called the 'training' set. In this case, we used about two-thirds of the available data taken over one month for training. The resulting PLS prediction model was applied to the remaining data. This is a small data set from a single location, so the results must be considered preliminary.

2.2 Objective analysis with the Winds on Critical Streamline Surfaces (WOCSS) methodology

The Winds on Critical Streamline Surfaces (WOCSS) methodology (Ludwig et al. 1991) provides objective analyses of wind observations that account for the fact that stable layers in the atmosphere suppress vertical motions and force air flow around hills and ridges, rather than over them. Briefly, the WOCSS code defines surfaces on which flow should take place, given that there is a maximum height to which the kinetic energy of the wind can lift a parcel of air in a stably stratified atmosphere. The maximum height is based on the critical dividing streamline concept, and assumes that air parcel vertical displacement in complex terrain balances the original kinetic energy of the flow at low altitudes, and the energy required to change altitude in the presence of a buoyant restoring force (see e.g. Sheppard 1956; Hunt and Snyder 1980; McNider et al. 1984). This energy constraint leads to a relationship among potential temperature lapse rate ($d\theta/dz$), the maximum height to which the air can rise (Z_{max}), and the low-altitude wind speed V_0 at the lowest height (z_0) for a particular low surface:

$$Z_{\max} - z_0 = V_0\left(\frac{g}{\bar{T}}\frac{d\theta}{dz}\right) \quad . \tag{5}$$

$\bar{T}$ is the mean temperature between z_0 and $Z_{\mathbf{max}}$, and *g* is the gravitational constant.

The low altitude wind speed V_0 is defined from winds first interpolated to terrain-following surfaces. Equation 5 determines the maximum height for each of a number of flow-following surfaces, which may intersect the terrain when the atmosphere is stable. A second interpolation defines winds on the new surfaces. Then, these "first guess" winds are iteratively adjusted to reduce two-dimensional divergence on the flow surfaces. Winds are set to zero where the flow surfaces intersect the terrain so the iterative adjustments force flow around the terrain obstacles. The code also includes provisions so that the presence of a stable layer at one altitude will influence flow at levels above and below that layer. The method performs well when there is adequate input data (Bridger et al. 1994; Ludwig and Sinton 2000). The stations within the domain used for the WOCSS analyses are marked (×) in Figure 1; stations outside the area were also used, but were weighted less heavily.

3. Observations

3.1 HF radar locations and operation

MCR's are located at the University of California at Santa Cruz's LML and at California State University's MLML (Fig. 1). The Monterey Bay Aquarium Research Institute (MBARI) collects wind speed and direction data from two buoys, one (M1 buoy) is located in the radar coverage area shown in Figure 1. It has gathered data since 1992. These results reported here used data collected at M1 from early December 2000 to early January 2001. Data from a Naval Postgraduate School (NPS) flux buoy (Fig.1) were not used, but are available for later analysis.

Radar data from LML and MLML were processed using beam-forming techniques to yield Doppler spectra that were processed by automated algorithms to get radial currents and the power ratio between the advancing and receding Bragg line peaks (Laws et al. 2000). The parameters in Table 1 were used to get wind estimates at the locations marked by ■ symbols in Figure 1. Signal-to-noise ratio (SNR) must be ≥5 dB from both radars for wind directions to be estimated, so data are not always available from all the locations shown in Figure 1. Generally, there are more usable data from the middle points. Points in Figure 1 are numbered by row, with the point number at the beginning of each row shown in the Figure 1. The number of hours for which estimates could be compared with WOCSS analyses is shown in the histogram of Figure 2. Different shading is used for the bars in the different rows. The number of available cases at any given point depends on simultaneous availability of high SNR radar data and sufficient meteorological information for WOCSS analysis.

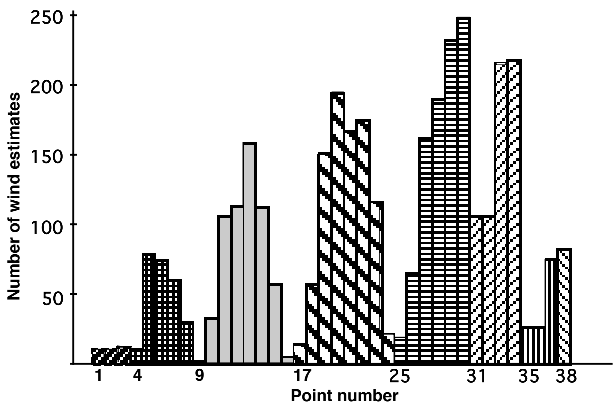

Figure 2 Frequencies of wind estimate availability from the locations shown in Figure 1; each row beginning is identified by its point number.

3.2 Conventional meteorological observations

Inputs required for WOCSS analysis are surface winds and at least one temperature and wind sounding. Soundings are not widely available, either in space or time; we were forced to use the 0000 UTC and 1200 UTC soundings from Oakland, about 100 km north of the center of Monterey Bay. The available surface observations were not ideal, having been collected for the purpose of estimating winds around San Francisco Bay, but there were usually at least a few sites to the south and east of Monterey Bay, as well as the more numerous sites inland and to the north. The dearth of available stations is an important reason for developing other ways to observe winds.

4. Results

The results obtained with the PLS technique are summarized in Figures 3 and 4. Figure 3 shows scatter plots of PLS values of wind speed versus those that were observed. Figure 4 presents the results for direction. In both figures, the training and independent data sets are shown. The results show that multi-frequency HF radar provides good estimates of hourly average winds at the MBARI buoy. Table 2 shows the regression constants and correlation coefficients for the u and v components, and for speed and direction. The correlations are quite high, > 0.7 in all cases. Furthermore, the performance on the independent data is essentially the same as for the training set, which suggests that the method is robust.

Table 2 also shows the same information for estimates based on the WOCSS objective analyses. It is obvious that objective analysis alone does not specify the wind at the MBARI buoy very well. As expected, the estimates are improved when the radar wind values are included among the inputs for the objective analysis. However, the WOCSS analyses with MCR winds are still not as good as those from the MCR alone. The reason for this is that the first guess fields used in the objective analyses are derived from inverse distance (squared) weighted interpolation, which results in considerable smoothing. The wind at any point is heavily influenced by other nearby winds, which may differ from the actual wind at the point. With no terrain features in the bay, iterative adjustments do not significantly change the first guess winds. This artifact also explains the poor estimates at the buoy when WOCSS only uses onshore observations. The winds over land tend to be weaker than over the Bay, resulting in pronounced underestimation of wind speed.

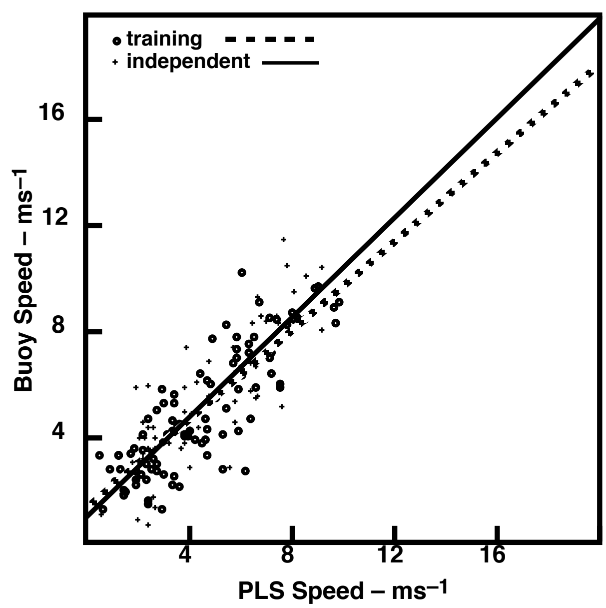

Figure 3 Scatter plots and regression lines of observed wind speed versus PLS estimates for the training and independent data sets.

One of the questions we sought to answer was whether or not the objective analyses would be changed much by the availability of MCR winds. Figures 5 and 6, respectively show the differences in average direction and speed (WOCSS with MCR inputs minus WOCSS without). The direction differences, on average are small, less than ±15° everywhere. West of the Bay, the directions are rotated counterclockwise (CCW) by the MCR observations. The CW rotation near Watsonville suggests that the Monterey Bay winds are usually a little different from those at Watsonville, so there is a change when the interpolation includes the Bay winds.

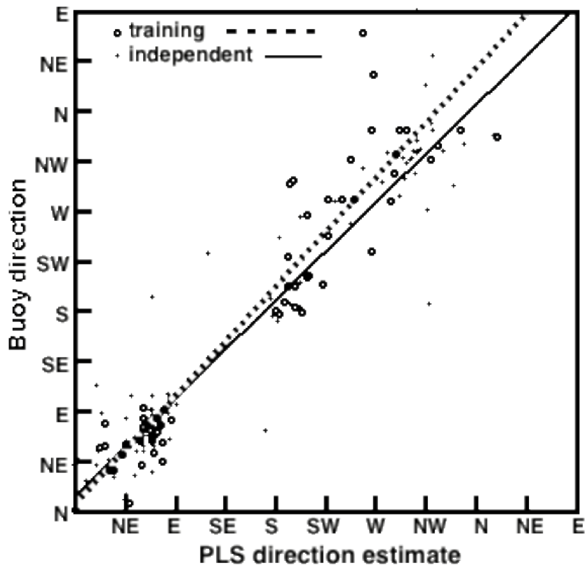

Figure 4 Scatter plots and regression lines of observed wind direction versus PLS estimates for the training and independent data sets.

TABLE 2 Regression parameters and correlations for different wind estimates

Parameter at M1 buoy	Intercept, a	Slope, b	Correlation coefficient
PLS Training set:			
u – m s^{-1}	–0.0	1.00	0.91
v – m s^{-1}	–0.7	0.80	0.72
Speed – m s^{-1}	1.3	0.84	0.85
Direction – °	14.4	0.92	0.95
PLS independent set:			
u – m s^{-1}	–0.2	0.98	0.92
v – m s^{-1}	–0.5	0.98	0.76
Speed – m s^{-1}	1.0	0.94	0.82
Direction – °	3.1	1.02	0.94
WOCSS with MCR:			
u – m s^{-1}	–1.2	0.96	0.85
v – m s^{-1}	–0.7	0.77	0.46
Speed – m s^{-1}	1.3	0.93	0.59
Direction – °	21.1	0.90	0.89
WOCSS without MCR:			
u – m s^{-1}	–3.1	2.28	0.85
v – m s^{-1}	–1.0	1.42	0.37
Speed – m s^{-1}	4.4	0.25	0.08
Direction – °	23.7	0.97	0.80

Figure 6 shows that the availability of MCR winds changes the speeds substantially over that part of Monterey Bay covered by the radar. The MCR wind speeds are as much as 2.5 m s^{-1} greater than what was derived from onshore observations. This is a significant difference. For the most part, the onshore speeds are not much affected. However, it should be noted that throughout the domain, the average wind speeds are increased by the use of MCR winds. This is the result of the aforementioned artifact of inverse distance weighted interpolation. In this case, the presence of numerous observations of higher wind speeds over the bay is felt even at the locations onshore.

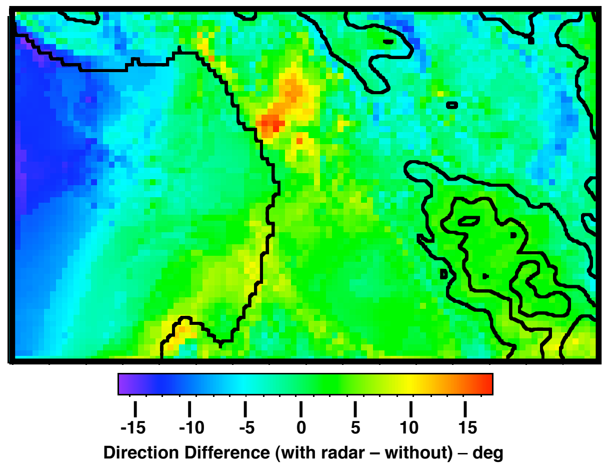

Figure 5 Distribution of the differences in average WOCSS estimates of wind direction with MCR inputs minus those without.

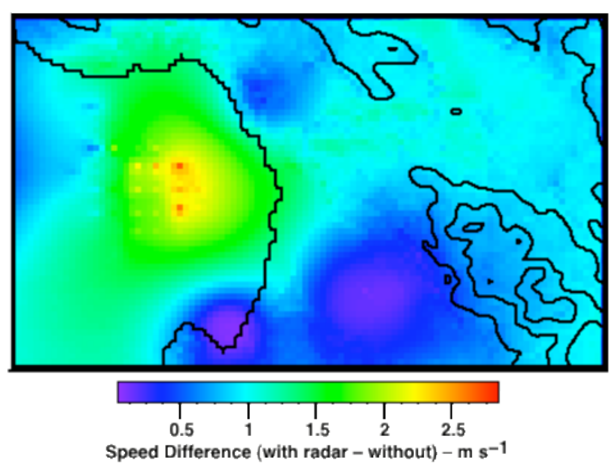

Figure 6 Distribution of the differences in average WOCSS estimates of speed with MCR inputs minus those without.

5. Discussion

The results presented here are preliminary. The PLS method should be applied in other places and to larger data sets. More experimentation should be done with regard to the variables used for the predictions. Regardless of the shortcomings, these results provide strong evidence of the worth of MCR observations for estimating winds. They also provide an incentive to pursue the work further.

Finally, it can be said that the MCR winds do affect objective wind analyses, especially over Monterey Bay. The MCR winds provide information about the higher speeds over the water that would be very difficult to infer in their absence.

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