Applications of oceanic data assimilation

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Abstract

Observational data in the ocean are always limited because of both the technical difficulties and expenses. Consequently, most information on the circulation field is provided by numerical ocean models. Numerical simulation, however, cannot achieve a high level of accuracy because of imperfect estimates of the forcing fields, initial and boundary conditions, and dynamical parameters. To enhance the realism in the simulation, the observed data are often integrated continuously into numerical models in a process called data assimilation. Oceanic data assimilation is somehow different from its counterpart, the atmospheric data assimilation since most of oceanic data acquired are confined to the sea surface. Therefore, the procedure to project sea surface information to the lower layer becomes one of the most difficult problems inherent in implementing oceanic data assimilation.

In the present research, a physical-space statistical analysis system (PSAS) is using to include surface observations in the assimilation. Here we review the PSAS schemes, as an example, in the assimilation of high-frequency (HF) radar-derived surface velocity fields for the Monterey Bay area in California. The model is a fine-resolution, sigma coordinate version of the Blumberg and Mellor (1987) hydrodynamic model. One important issue here is to determine the "blending" of model and observational data using forecast and observation error covariance matrices. Despite a tremendous amount of research done on the estimation of these matrices during recent years, this subject remains open. In this paper, the matrices were derived from estimates of horizontal covariances of HF radar-derived surface velocity and have resulted in some success. In the twin experiment, the assimilation of radar data has significantly improved the model predictions of surface current circulation. Furthermore, in addition to the scheme that only assimilates surface current data into the surface layer of the model, alternative schemes based on dynamical inference methods are implementing for projecting surface information into subsurface layers. The statistical validation of the data assimilation schemes has been tested. The assimilation results are compared with in situ hydrographic data and limited subsurface mooring measurements.

1. Introduction

Data assimilation is an essential component of a coastal ocean prediction system. By assimilating ocean observations, the ocean forecast can be continuously re-initialized. The shore-based HF radar is perhaps the most exciting recent development of coastal ocean monitoring system. It is capable of measuring surface currents in real-time over a 50-km range with a 2-3 km resolution. The new, long-range radar from CODAR may further extend the offshore coverage to 200 km. Such system offers immense potential for use in coastal ocean prediction. The challenge is to find a modeling strategy that can best utilize the HF radar surface current information. One strategy of assimilating HF radar-derived current data into an ocean model is based on the application of a pseudo-shearing stress over the surface layer of the model (Lewis et al. 1998). Their data assimilation technique allows the model to reproduce to some degrees of features observed from CODAR data. However, the approach is a nudging technique, with the nudging coefficient chosen as a solution of a special optimization problem. The observational error covariance matrix as well as the model error prediction covariance matrix were not modeled and taken into account in this previous data assimilation scheme.

For the present study, the surface velocity measurements are assimilating into a hydrodynamic model of the Monterey Bay area using a modification of the Optimum Interpolation scheme that is based on the Physical-space Statistical Analysis System (Cohn et al., 1998). In this case, the error covariance matrices are taken into account in the CODAR surface current data assimilation schemes. The CODAR data are acquired from an observing system deployed along the Monterey Bay area. The surface current data are pre-processing with a dynamically consistent spatial filter (a 33-hour low-pass filter) to remove small-scale, high frequency noises, which must be removed to make the observations more compatible with model dynamics. The model is a fine-resolution, sigma coordinate version of the Princeton Ocean Model (POM, Blumberg and Mellor, 1987) with realistic bottom topography. On the open boundaries, the model is coupled to a larger scale model of the Pacific West Coast (PWC).

In addition to the scheme that only assimilates surface current data into the surface layer of the model which is expecting that the numerical model will transmit information downward through some physical or dynamical manners, alternative data assimilation schemes are also proposed for projecting surface information into subsurface layers. The schemes are based mainly on dynamical inference methods. The statistical validation of the data assimilation schemes has been tested. The simulated velocity fields are also compared with in situ hydrographic data and limited subsurface mooring measurements.

2. Description of the numerical model

The present model based on POM has an orthogonal, curvilinear grid, extending 110 km offshore and 165 km in the alongshore direction (Figure 1). The horizontal resolution is 1-4 km with the maximum resolution in the vicinity of the Monterey Bay. Vertically, the model is characterized realistic bottom topography with 30 vertical sigma levels. This three-dimensional, free surface model is based on the primitive equations for momentum, salt, and heat. For more enhanced description of POM could be referred to Blumberg and Mellor (1987). Cross-shelf open boundaries of the model (northern and southern) are approximately orthogonal to the isobaths of bathymetry in order for the flow to be almost perpendicular to the cross-shelf open boundaries. Furthermore, the model is coupled to a larger scale model of the Pacific West Coast (PWC). The PWC model with a horizontal resolution 1/12° is further coupling to a 1/4° , global Navy Layered Ocean Model (NLOM). A detail description of this model has been given by Shulman et al. (2000).

The model is forced by the 12-hourly FNMOC NOGAPS wind beginning on January 1, 1994. Assimilation of the CODAR current data begins on January 1, 1999 and continues to the end of 1999. The summer period of 1999 from June1 to August 29 are used for analysis and inter-comparison.

3. The data assimilation schemes

3.1 Surface PSAS

The Physical-space Statistical Analysis System (PSAS, Cohn et al., 1998) algorithm first solves the quantity y through a linear system

$$(H P^f H^T + R)\, y \;=\; U^o - H\, U^f \qquad (1)$$

where P^f and R are the forecast error covariance matrix and the observation error covariance matrix, respectively. H is the interpolation operator and the superscript T denotes transpose. U^o represents the observations available at the analysis time and U^f represents the forecast first guess at the model grid point. Then the analyzed state U^a is obtained from the equation

$$U^a \;=\; U^f \;+ P^f H^T y \qquad (2)$$

The error covariance matrixes P^f and R play a major role in the data assimilation schemes described above. They determine the "blending" of model and observational data. In this paper, the forecast error covariance matrix P^f were derived from the estimates of horizontal covariances of the observed HF surface current data while the observation error covariance matrix, R, is given by a diagonal matrix with normalized values. The construction of these covariance functions can be found in Shulman et al (2000). Estimates of the horizontal covariance for CODAR surface velocities are presented on the web site of the ICON project (www.oc.nps.navy.mil/icon).

In addition to the first approach which includes only assimilation into the surface layer of the model, the other approaches based on the dynamical inference method are also proposed to project surface information into the ocean interior. These approaches will be not only to make the data assimilation more effective, but also to adjust the effects of the surface assimilation on the modeled dynamics.

3.2 Subsurface correction based on Ekman spiral theory

According to Equation (2), the corrections for the model surface velocities are:

$$\delta U_s \;=\; U^a - U^f \;=\; (\delta u_s\,,\, \delta v_s) \qquad (3)$$

Correction U_s to the surface model velocity estimated by PSAS can be interpreted as changes to the surface velocity due to the additional (to the existing) wind stress. The Ekman theory (Ekman, 1905) can be applied to estimate this additional wind stress $\delta\tau$ from surface velocity corrections δU_s. The additional (Ekman) has the following form:

$$\delta\tau_x = \rho\,(A_v f/2)^{1/2}\,(\delta u_s - \delta v_s) \qquad (4)$$

$$\delta\tau_y = \rho\,(A_v f/2)^{1/2}\,(\delta u_s + \delta v_s) \qquad (5)$$

Where Av is the eddy viscosity, f is twice the vertical component of the Earth's rotation vector. Using Equations (4), (5) and Ekman theory, we can estimate the corrections to subsurface velocity corresponding to the application of additional wind stress (4)-(5). The corrections to subsurface velocities $\delta U(z) = (\delta u(z)\,,\, \delta v(z))$ will have the following form:

$$\delta u(z) = \exp(-z/D)[\delta u_s \cos(-z/D) - \delta v_s \sin(-z/D)] \qquad (6)$$

$$\delta v(z) = \exp(-z/D)[\delta u_s \sin(-z/D) + \delta v_s \cos(-z/D)] \qquad (7)$$

Where $D = (2A_v/f)^{1/2}$ is the Ekman depth. Subsurface corrections Equations (6)-(7) provide the projection of surface velocity corrections (derived from PSAS) based on

Ekman theory. The results of projection will depend on the value of Av or corresponding D. Note that the use of eddy viscosity Av is dubious and its values vary widely. To maintain model stable and suppress spurious responses, in this study, the constant (throughout the model domain) value of eddy viscosity Av was used. In Section 4, the choice of this value and corresponding value of D are discussed.

4. Data assimilation experiments

In this study, surface currents derived from CODAR/SeaSonde-type instruments were assimilated into the present model.

The model predictions with and without assimilation of CODAR data are compared to currents measured by a 300 kHz RD instruments Acoustic Doppler Current Profiler (ADCP) mounted in a downward-looking configuration on the Monterey Bay Aquarium Research Institute's (MBARI) surface mooring at 122.40° W, 36.67° N, designated M2. The CODAR footprints and location of the M2 station are shown on Figure 2.

On Figure 3, the magnitudes of complex correlation are shown for different values of Ekman depth and corresponding viscosities. The best correlation is observed in the case when $D = 46$ m $(Av = 0.1\ m^2/s)$. Note that the value is in agreement with the typical value (D ~50 m) based on observational evidence of the region (Chereskin, 1995).

5. Discussions and Conclusions

The approach for assimilation of CODAR–derived surface currents is based on application of the Physical–space Statistical Analysis System (PSAS) to estimate the optimal corrections to the model surface velocities. However, effective data assimilation techniques for surface information rely on methods for projecting this information into the interior of the ocean. Unlike other coastal model domains that are confined to the continental shelf and water depths less than 300m, the present model domain includes full–ocean depths exceeding 3000m. It is not expected that variability below the surface layer in the model necessarily correlates with surface velocities. For this reason, we have explored the use of different vertical projection schemes that influence directly only the surface or surface mixed layer. These schemes for vertical projection of the PSAS-derived surface velocity corrections are based on the application of Ekman theory. The performance of data assimilation schemes was judged by correlation between the model currents and ADCP currents at the M2 station (Figure 4).

Comparisons of the magnitudes of complex correlation between model and observed currents, up to 120m, indicate that assimilation of CODAR data according to the Lewis et al. (1998) scheme does not improve the correlation with ADCP currents (Figure 4). This can be explained by the fact that in the Lewis et al. (1998) scheme, the additional pseudo-shearing wind stress is applied only at the locations of the CODAR footprint (which does not include the M2 station). In this case, there are no instantaneous changes/improvements in many model grids (even to the surface velocity), and certainly, there is a delay in transferring information into the subsurface because only wind forcing is corrected.

Assimilation of CODAR data only into the surface layer of the model According to the Shulman et al. (2000) scheme improves the correlation with ADCP currents in the upper 20-30m (Figure 4, curve marked with circles). In the Shulman et al. (2000) scheme, the subsurface projection is delayed by the model adjustment. Also, on Figure 4, correlations are correlations are shown for 6-120m, but the depth of the surface layer of the model is much shallower than 6m (even if depth is equal 3500m, the depth of surface layer will be 3.5m). Therefore, model currents at 6m are not affected immediately by assimilation only into the surface model layer. But the addition of the minimal wind stress (see scheme in Lewis et al., 1998), which conserves the model energy, improves the correlation (Figure 4, curve marked with diamonds) in comparison to the assimilation of CODAR currents only into the model surface layer. And, finally, the significant improvement of subsurface correlation with ADCP data is achieved when the corrections to the surface currents are projected into the subsurface based on Ekman theory (Figure 4, curve marked with squares). This projection of the PSAS-derived surface corrections into the subsurface layers instantaneously affects the subsurface velocity fields.

It is important to understand the dynamic mechanism or mechanisms by which surface velocity information impacts subsurface model currents. The hypothesis is that the primary mechanism is through the horizontal divergence of velocity corrections derived from the PSAS scheme. Our future research will focus on investigation of these dynamic mechanisms and modeling of data assimilation errors and corresponding covariances in the PSAS scheme.

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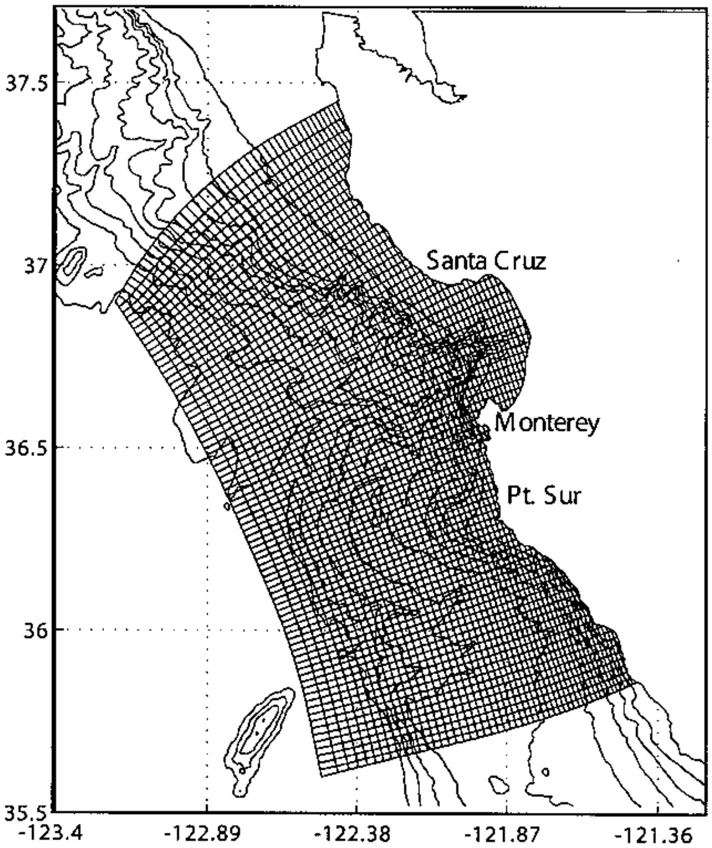

Figure 1. Model grid and bathymetry.

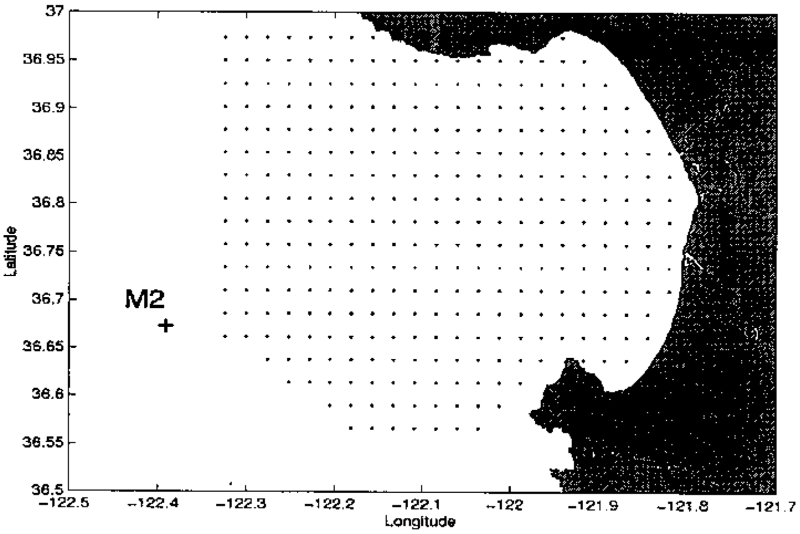

Figure 2. CODAR data footprints and location of M2 mooring.

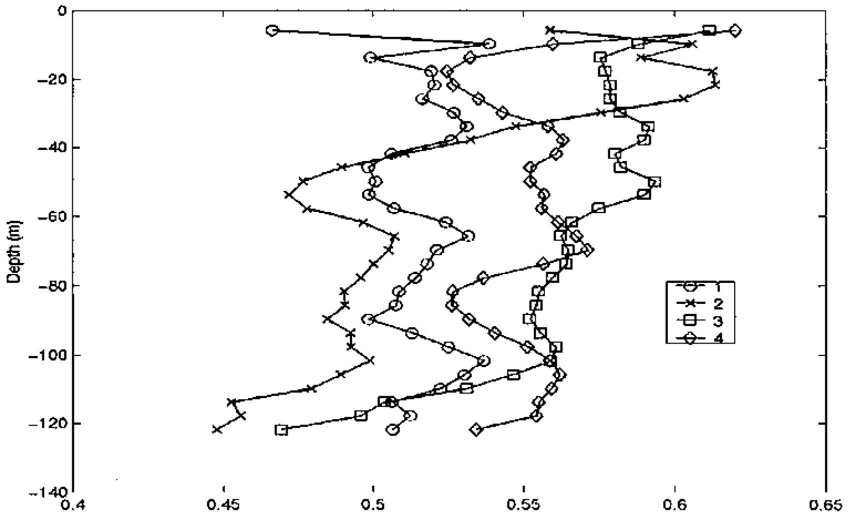

Figure 3. Magnitudes of complex correlation coefficients between the ADCP and model-predicted currents at bouy M2.
1- De = 20m is used in application of the data assimilation scheme (13) - (14);
2 - De = 30m; 3 - De = 46m; 4 - De = 70m

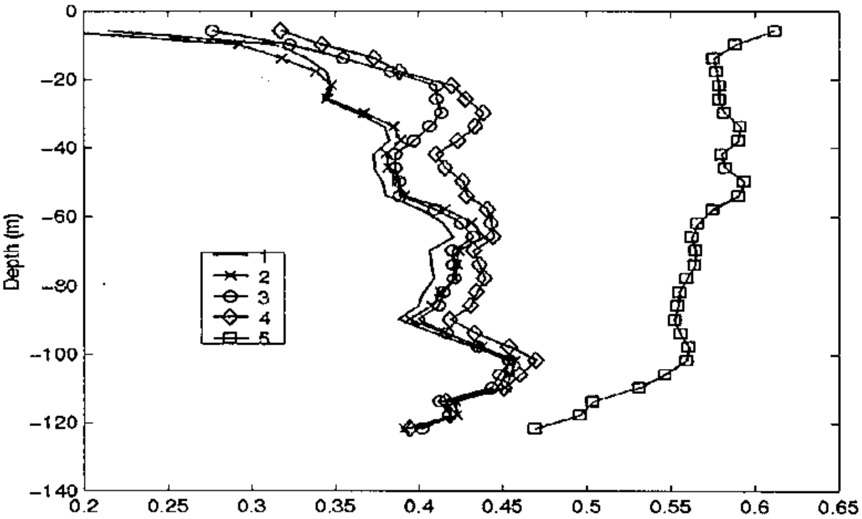

Figure 4. Magnitudes of complex correlation coefficients between the ADCP and model-predicted currents at bouy M2. 1- without data assimilation; 2- with data assimilation according to Lewis et al. (1998); 3 - with assimilation only into the surface layer of the model (Shulman et al., 2000); 4 - with subsurface projection based on energy conservation principle (see section 4.1); 5 - with subsurface projection based on the Ekman theory (see Section 4.2).