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Comparisons of different ensemble schemes for glider data assimilation on West Florida Shelf

Chudong Pan *, Lianyuan Zheng, Robert H. Weisberg, Yonggang Liu, Chad E. Lembke

College of Marine Science, University of South Florida, 140 7th AVE S, St Petersburg, FL 33701, United States

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ABSTRACT

An Ensemble Optimal Interpolation (EnOI) system is built to assimilate underwater profiling glider observations into a West Florida Shelf (WFS) coastal ocean model. The Floating Temporal Window (FTW) technique is incorporated into the EnOI scheme to generate and update associated ensemble members, which are directly extracted from the model output states from previous output cycles. The model performance is validated against independent observations from moorings located near the glider tracks. The EnKF, traditional EnOI and the FTW-EnOI schemes are compared in terms of error covariance evolution and model performance at mooring locations. It is found that all three assimilation schemes provide significant (2–3 times) better fit to the mooring data compared with the free model run. Although the EnKF scheme produces the best results, the FTW-EnOI should be considered as an alternative method given the low computational cost and the flow-dependent information embedded in the algorithm.

1. Introduction

Both ocean models and observations are important sources for oceanographic research. A perfect ocean model, however, does not exist because models are built on various assumptions, use parameterizations of unknown processes and depend on boundary and initial conditions. Ocean observations, on the other hand, are generally sparse in time and space even if they can accurately represent nature. Therefore, a combination of models and observations provides a reasonable strategy for describing ocean processes. With the goal of coordinating observations with models, the Coastal Ocean Monitoring and Prediction System (COMPS) constantly evolves over the years (e.g. Weisberg et al., 2005, 2009) on the West Florida Shelf (WFS). Here we describe recent work toward adding data assimilation to the COMPS WFS coastal ocean model.

The WFS is a broad continental shelf with a gentle slope (Fig. 1(a)). The geometry of the WFS becomes complex due to the decreasing shelf width near the DeSoto Canyon to the northwest, and the barrier of the Florida Key to the south. The WFS circulation is driven by tides, winds, and buoyancy fluxes (e.g. He and Weisberg, 2002; Weisberg et al., 2005; Liu and Weisberg, 2012). Together with the varying topography and the local forcing, the inner shelf becomes a dynamically complex area with the interaction between surface and bottom Ekman layers, and geostrophic interior flow (Weisberg et al., 2005; Liu and Weisberg, 2007; Weisberg et al., 2009). Outside the shelf break, the Gulf of Mexico Loop Current (LC) can sometimes broach the shelf break and further complicates the dynamics and water properties of the inner shelf (e.g. Huh et al., 1981; He and Weisberg, 2003; Weisberg and He, 2003). Although inner shelf observations suggest a seasonal cycle of upwelling circulation in winter and downwelling circulation in summer, synoptic weather fronts affect the inner shelf circulation from time to time, adding complexity to the local water properties (Weisberg et al., 2005).

Because of the dynamical complexity at coastal regions, coastal ocean models inevitably contain forecast uncertainty. To reduce the forecast uncertainty, we need data assimilation systems to constrain the models with coastal observations. Yet it is difficult to apply a data assimilation system to a dynamically complicated area like the WFS. Take the Ensemble Kalman Filter (EnKF) for example. The EnKF has been a popular data assimilation method since Evensen (1994) introduced it to a quasi-geostrophic model. The EnKF gives rise to many "Kalman Filter family members", such as the Ensemble Transform Kalman Filter (ETKF, Bishop and Toth, 1999), the Ensemble Square Root Filters (ESRFs, Tippett et al., 2003) and the Deterministic Ensemble Kalman Filter (DEnKF, Sakov and Oke, 2008). The EnKF algorithm is known to be able to generate flow-dependent and location-dependent background error covariances (e.g. Hamill et al., 2003; Wang et al., 2007; Counillon and Bertino, 2009). The EnKF, however, relies on the dynamic model to generate a state-dependent estimate of the

* Corresponding author. Tel.: +1 727 202 5108/228 342 9236.
E-mail address: panc@mail.usf.edu (C. Pan).

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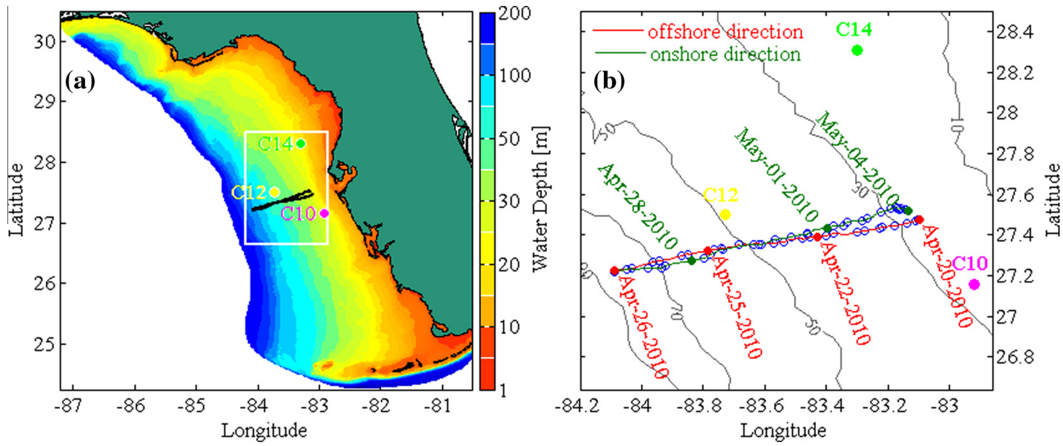

Fig. 1. (a) The WFS coastal ocean model domain and bathymetry of WFS. The purple, yellow and green dots are locations of mooring C10, C12 and C14. The black lines on (a) are locations of glider observations. The area in white rectangular is magnified in (b). The red track in (b) is the trajectory of glider moving offshore from April 20 to April 26, 2010. The green track in (b) is the trajectory of glider moving onshore from April 26 to May 4. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

model error, or the model error covariance. It is unlikely for the EnKF to estimate the correct model error if the model cannot resolve the physical process that is being studied. Therefore, the sophisticated dynamics of the WFS increases the difficulty of the model forecast, and hence the difficulty of the application of the EnKF to the area.

Although EnKF has been one of the major data assimilation schemes in many oceanographic institutions, practical problems still exist for real ocean applications. For example, the computational cost of applying EnKF is high. It is known that to generate an EnKF ensemble with an ensemble size of Ne, one has to run the model Ne times. Hence, the computational cost of EnKF linearly increases with the size of ensemble, which is untenable when a large ensemble size is used on limited computer resources. Another problem is that the forecast ensemble in the EnKF scheme tends to collapse over time. In another word, the ensemble spread, defined as the standard deviation with respect to the ensemble mean, gradually shrinks with time and the model errors keep being underestimated at each assimilation cycle. It follows that the filter puts too much weight on the model and ignores the observations over time. Several solutions have been proposed to avoid ensemble collapse. Anderson and Anderson (1999) suggested that inflating forecast ensemble anomalies by a small amount can effectively increase ensemble spread at each assimilation cycle. Hamill and Snyder (2000) proposed a hybrid 3DVAR-EnKF scheme, which adds static covariance to ensemble error covariance and thereby avoiding ensemble collapse. Similar hybrid schemes have become more and more popular in the last decade (e.g. Wang et al., 2007; Counillon et al., 2009; Yaremchuk et al., 2011). Another solution to reduce ensemble collapse is covariance localization, which was proposed by Houtekamer and Mitchell (2001) and further discussed by Hamill et al. (2001) and Sakov and Bertino (2011). The covariance localization is a procedure where the covariance is multiplied point-by-point with a fifth-order function (Gaspari and Cohn, 1999) which is 1 at the observation point and gradually decreases to 0 when a certain distance is reached. The covariance localization not only effectively reduces spurious long-range covariances when a small ensemble is used (Hamill et al., 2001; Houtekamer and Mitchell, 2001), but also increases the rank of the forecast covariance (Oke et al., 2007), resulting in analysis fields that are better fit to the observations.

A simplified version of the EnKF is the Ensemble Optimal Interpolation (EnOI, Oke et al., 2002, 2005; Evensen, 2003), in which a flow-dependent ensemble is replaced with a static ensemble. That is, the background error covariance is estimated from a prescribed static ensemble and does not change with time. Because the EnOI requires only a single model run and has no risk of ensemble collapse, it became very popular in many operational ocean forecasting systems like the Bluelink Ocean Data Assimilation System (BODAS) at the Bureau of Meteorology (BOM) in Australia (Oke et al., 2008), and the Navy Coupled Ocean Data Assimilation (NCODA) system at Naval Research Laboratory (NRL) in the United States (Cummings, 2005). The disadvantage of EnOI is that the flow-dependent information of the model is not blended into the forecast error covariance, hence the EnOI scheme may miss critical physical information provided by the model.

Recently, Yaremchuk et al. (2011) proposed a hybrid Three Dimensional Variational Data Assimilation (3D-VAR) scheme to assimilate subsurface glider observations into the Navy Coastal Ocean Model (NCOM). In this scheme, the hybrid background error covariance is composed of a static part and a flow-dependent part, whose magnitudes are controlled by a dynamical coefficient. The static part of the hybrid background error covariance is a near-Gaussian function modeled by propagating the diffusion equation. The flow-dependent part is estimated directly from the ensemble of model forecast states, which is similar to EnKF, except that the ensemble is sequential instead of parallel. The application of the hybrid scheme in both twin data experiments and real data experiments resulted in more improvements compared with pure 3D-VAR scheme. Pan et al. (2011) updated the hybrid scheme by adding a "Floating Temporal Window" (FTW) which extracts ensemble members from previous model output states. The FTW technique resolves physical processes caused by rapid changes in external forcing by controlling the appropriate temporal resolution of the ensemble. Yin et al. (2011) also used the FTW approach to generate and update ensembles in the Predictive Ocean Atmosphere Model for Australia (POAMA) EnKF system.

The FTW enables the possibility of incorporating flow-dependent information into the EnOI system. In the present paper, we present a FTW-EnOI system. It is very similar to the traditional EnOI scheme, with the exception of ensemble generation and update. We will compare the FTW-EnOI scheme with both the EnKF and the traditional EnOI. We will show that the FTW-EnOI is capable of producing flow-dependent error covariance, and has the virtues of low computational cost and countering ensemble collapse. The FTW-EnOI can be used as an alternative method of the EnKF when computational resources are limited.