2012-05

Improved statistical prediction of surface currents based on historic HF-radar observations

Paduan, Jeffrey D.; Frolov, Sergey; Cook, Michael; Bellingham, James

Improved statistical prediction of surface currents based on historic HF-radar observations

Jeffrey D. Paduan[1], **Sergey Frolov**[2], **Michael Cook**[1], **James Bellingham**[2]
[1]*Department of Oceanography, Naval Postgraduate School (paduan@nps.edu)*
[2]*Monterey Bay Aquarium Research Institute*

Key words: Surface Currents, HF Radar, Velocity Forecast, Search and Rescue

Abstract: Accurate short-term prediction of surface currents can improve efficiency of search-and-rescue operations, oil-spill response, and marine operations. We developed a linear statistical model for predicting surface currents (up to 48 hours in the future) based on a short time-history of past HF-radar observations (past 48 hours) and an optional forecast of surface winds. Our model used empirical orthogonal functions (EOFs) to capture spatial correlations in the HF-radar data and used a linear autoregression model to predict the temporal dynamics of the EOF coefficients. We tested the developed statistical model using historical observations of surface currents in Monterey Bay, California. The predicted particle trajectories separated from particles advected with HF-radar data at a rate of 4.4 km/day, which represents an improvement over the existing statistical model (drifter separation of 5.5 km/day). We found that the minimal length of the HF-radar data required to train an accurate statistical model was between one and two years, depending on the accuracy desired.

1. Introduction

Surface current mapping by HF radar provides near real time and historical observations of the surface current fields. However, many operations, such as search and rescue and oil spill response, require forecasts of future currents. Two fundamental approaches to such forecasts exist: (1) assimilating HF-radar currents into physics-based models of the ocean circulation (Paduan and Shulman 2004; Breivick and Sætra 2001; Shulman and Paduan 2009), or (2) using empirical models to forecast future currents based on a short time history of past observations (O'Donnell et al. 2012; Garfield et al., 2009; Almeida 2008). In this paper, we present recent results by Frolov et al. (2012) for an empirical method for predicting HF-radar currents based on training using spatial EOF basis functions.

2. Methods

To train and test the developed surface current prediction system, we used a five-year-long dataset (01/01/2006-10/30/2010) of HF-radar currents in Monterey Bay California. Figure 1 shows the configuration of the standard-range HF-radar network in Monterey Bay. The spatial resolution of the dataset was 3 km and the temporal resolution was 1 hour. To fill-in gaps in the current field due to poor radar returns, the HF-radar currents were interpolated using Open Modal Analysis (Kaplan and Lekien, 2007).

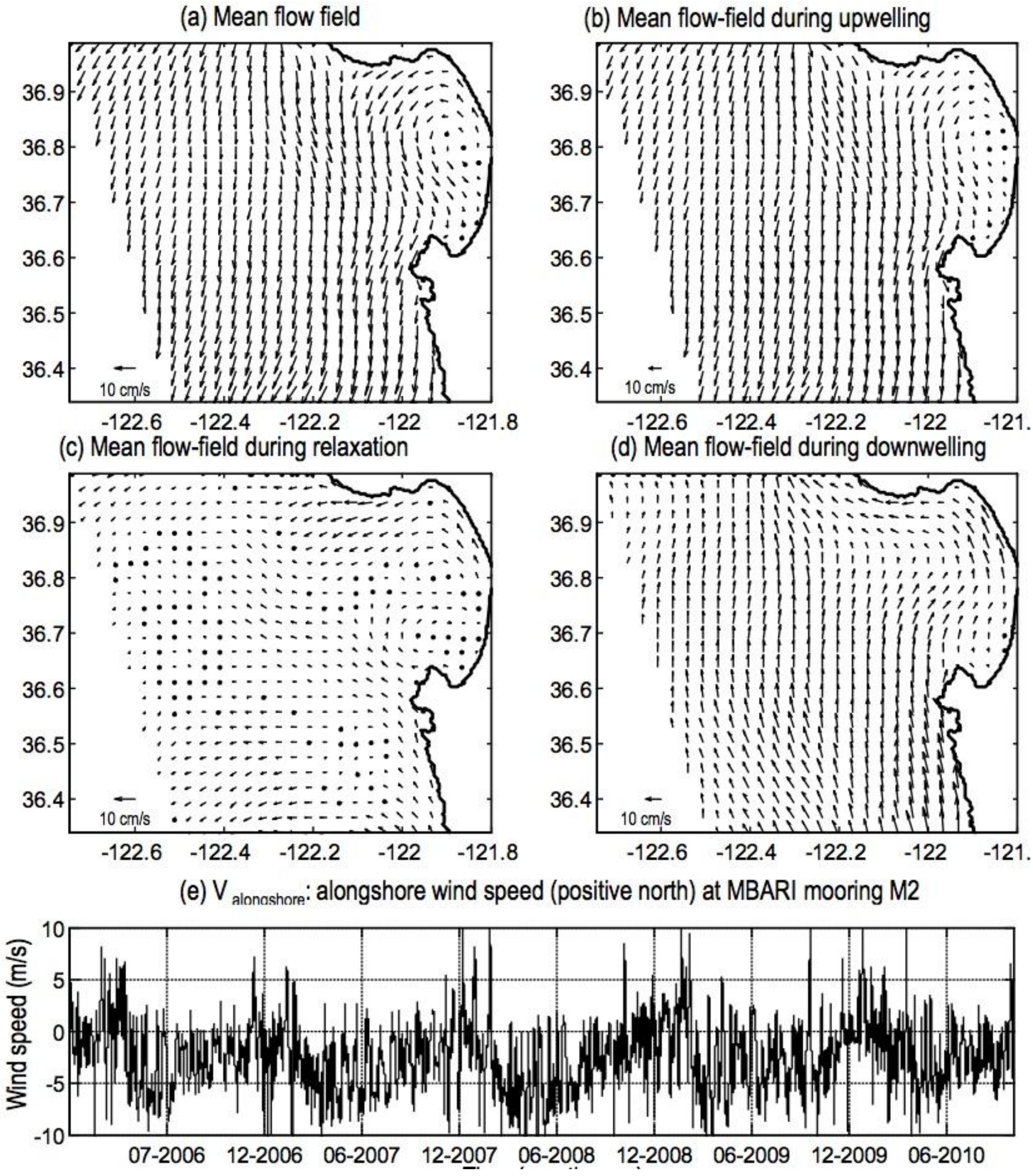

Figure 1. Mean surface current patterns from HF radar mapping data around Monterey Bay, California and the alongshore wind speed measured on a buoy near the offshore edge of the mapping domain. Years 1-4 were used as training data; Year 5 was used as the independent test period.

The linear prediction system was built on the model $x_{k+1} = \hat{x}_{k+1} + \varepsilon \equiv \hat{A}x_k + \hat{B}w_k + \varepsilon$, where k is the time index, x is the stacked grid of u and v velocity components, and w is the set of additional variables, including wind forcing and tidal currents. The dimension of the training set involved with determining the weights $\hat{A}$ and $\hat{B}$ was reduced by representing the surface current patterns by their empirical orthogonal function (EOF) modes as described by Frolov et al. (2012). The solution was obtained using the Netlab© package, which is an open source network training package for Matlab©.

3. Results

A number of experiments were conducted using the four-year training data set and tested using the ten-month independent test period (Figure 1). Cases included with HF radar-derived surface currents only (E-HF), surface currents and wind stress (E-HF-W), and surface currents, wind stress, and tidal currents (E-HF-W-Tide). The critical results are summarized in Figure 2, which shows that the velocity error asymptotes to about 10 cm/sec after several hours. Including wind stress observations in the training data improves the forecasts by about 10%. Frolov et al. (2012) show that the error distributions in time are not uniform. Rather they include episodic peaks associated with wind events. Including wind forcing in the model reduces but does not eliminate those episodic large forecast errors.

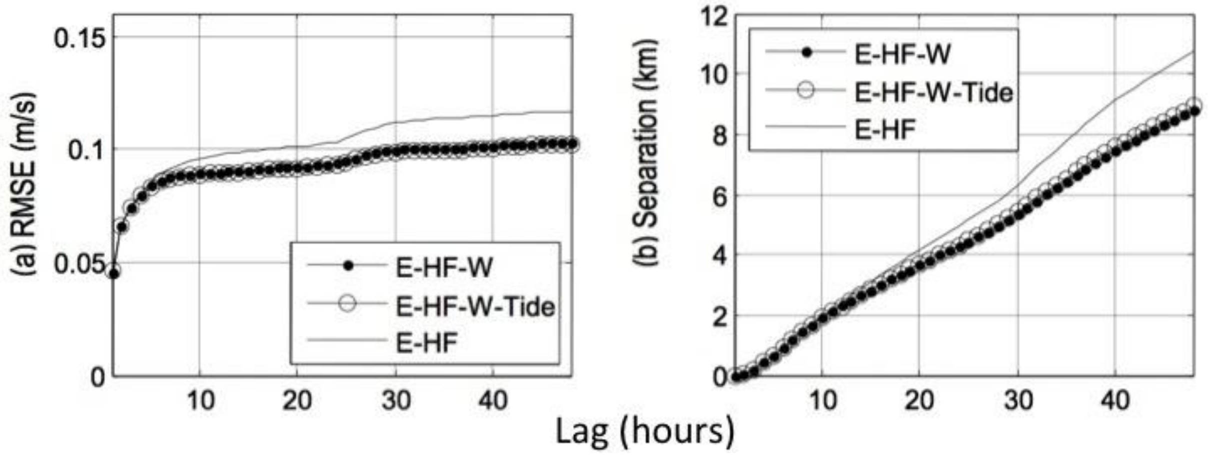

Figure 2. RMS error between predicted and observed velocities (a) and the average separation between observed and predicted trajectories (b) after various time lags.

4. Conclusions and Discussion

The forecast methodology advocated here is predicated upon the existence of available training data from a network of HF radar systems and, if possible, local wind observations. Using the same ten-month test period, the results based on variable training data lengths in the range 0.5 to 4 years were compared. The average 24 hour forecast trajectory position error is shown in Figure 3 for the different training intervals. The forecast accuracy improves with longer training periods, but it does appear that a reasonable plateau is reached after about 2 yr.

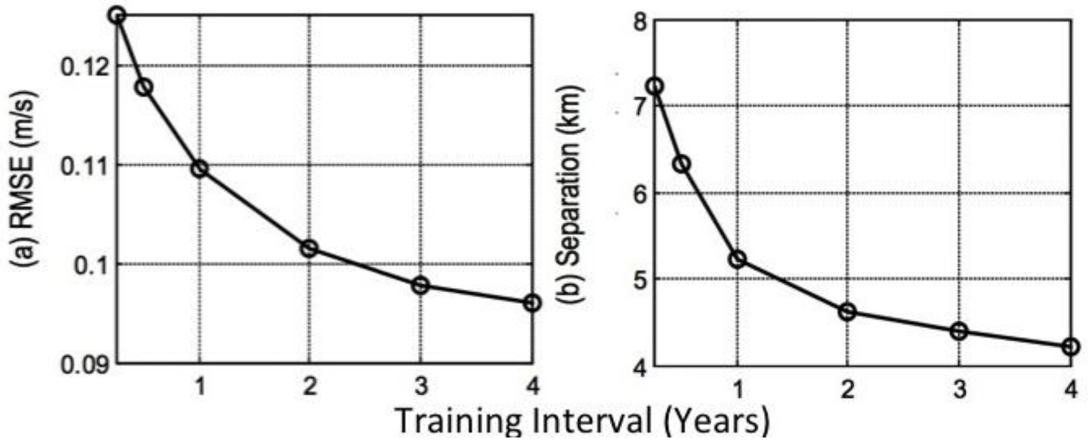

Figure 3. Average velocity (a) and separation (b) error after 24 hours between forecasted and observed surface currents or trajectories for different training intervals.

The use of long-term statistical training techniques with EOF mode dimension reduction is a promising approach to short-term velocity forecasting. In regions such as Monterey Bay where horizontal velocity variations are significant and common, these methods can extract the maximum benefit from the horizontal mapping data provided by HF radar networks.

References

Almeida, F., 2008. The influence of wind on HF radar surface current forecasts. M.S. Thesis, Naval Postgraduate School, Monterey, CA, December, 91 pp.

Breivick, Ø., Ø. Sætra, 2001. Real-time assimilation of HF radar currents into a coastal ocean model. *J. Mar. Sys*., **28**:161-182.

Frolov, S., J. Paduan, and M. Cook, 2012. Improved statistical prediction of surface currents based on historic HF-radar observations. *Ocean Dynamis*, In press.

Garfield N., J.D. Paduan, and C. Ohlmann, 2009. Delivery and Quality Assurance of Short-Term Trajectory Forecasts from HF Radar Observations. Final Report, Project Number: 07-061, The Coastal Response Research Center, Durham, New Hampshire, June, 28 pp.

Kaplan D.M., and F. Lekien, 2007. Spatial interpolation and filtering of surface current data based on open-boundary modal analysis. *J Geophys Res*., **112** (C12). doi:10.1029/2006 JC003984.

O'Donnell J., D. Ullman, C.A. Edwards, T. Fake, and A. Allen, 2012. The Operational Prediction of Circulation and Lagrangian Trajectories in the Coastal Ocean. *Ocean Dynamics*, In press.

Paduan J.D., and I. Shulman, 2004. HF radar data assimilation in the Monterey Bay area. *J Geophys. Res*. **109** (C7). doi:10.1029/2003JC001949.

Shulman I., and J.D. Paduan, 2009. Assimilation of HF radar-derived radials and total currents in the Monterey Bay area. *Deep-Sea Res. II*, **56** (3-5): 149-160. doi:10.1016/j.dsr2.2008.08. 004.