NOTES AND CORRESPONDENCE

Current Patterns on the West Florida Shelf from Joint Self-Organizing Map Analyses of HF Radar and ADCP Data

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(Manuscript received 10 May 2006, in final form 15 August 2006)

ABSTRACT

To assess the spatial structures and temporal evolutions of distinct physical processes on the West Florida Shelf, patterns of ocean current variability are extracted from a joint HF radar and ADCP dataset acquired from August to September 2003 using Self-Organizing Map (SOM) analyses. Three separate ocean–atmosphere frequency bands are considered: semidiurnal, diurnal, and subtidal. The currents in the semidiurnal band are relatively homogeneous in space, barotropic, clockwise polarized, and have a neap-spring modulation consistent with semidiurnal tides. The currents in the diurnal band are less homogeneous, more baroclinic, and clockwise polarized, consistent with a combination of diurnal tides and near-inertial oscillations. The currents in the subtidal frequency band are stronger and with more complex patterns consistent with wind and buoyancy forcing. The SOM is shown to be a useful technique for extracting ocean current patterns with dynamically distinctive spatial and temporal structures sampled by HF radar and supporting in situ measurements.

1. Introduction

High frequency (HF) radars are finding increasing applications for the sampling of surface current patterns at high spatial and temporal resolution (e.g., Barrick 1977; Gurgel et al. 1986; Prandle 1987; Shay et al. 1995, 1998a, 2007; Takeoka et al. 1995; Graber et al. 1996; Paduan and Rosenfeld 1996; Beckenbach and Washburn 2004; Chant et al. 2004; Emery et al. 2004; Kohut et al. 2004; Ullman and Codiga 2004). To improve our understanding of continental shelf processes there exists a need for feature extraction techniques to identify patterns of variability from long surface current image time series so that the underlying physics can be assessed.

Snapshot descriptions (e.g., Shay et al. 1995, 1998a; Kelly et al. 2002; Chant et al. 2004) along with temporal and spatial averaging (Paduan and Rosenfeld 1996; Shen et al. 2000; Nishimoto and Washburn 2002; Ullman and Codiga 2004; Kohut et al. 2004; Roughan et al. 2005) have been applied to obtain characteristic flow patterns from HF radar data. While averaging provides insights, it is generally difficult to define the temporal and spatial scales over which to average, especially on the continental shelf where currents may be anisotropic and nonhomogeneous depending on the processes and time scales (Liu and Weisberg 2005).

Empirical orthogonal function (EOF) analyses are effective for reducing large correlated datasets into a smaller number of patterns ordered by variance reduction (e.g., Klink 1985; Lagerloef and Bernstein 1988; Espinosa-Carreon et al. 2004), and applications to HF radar are given, for example, by Kaihatu et al. (1998), Marmorino et al. (1999), Lipphardt et al. (2000), Beck-
enbach and Washburn (2004), and Kosro (2005). However, a fundamental drawback for HF radar applications is that conventional EOFs require gap-free datasets, which is generally not the case for HF radar. Moreover, through the removal of temporal means, EOFs apply to anomaly fields, and by linearity, EOFs may be of limited use in extracting nonlinear information (Hsieh 2001, 2004).

The Self-Organizing Map (SOM), based on an unsupervised neural network (Kohonen 1982, 2001), is an effective technique for feature extraction and classification. SOM applications among various disciplines (e.g., Kaski et al. 1998; Oja et al. 2003) include climate and meteorology (e.g., Hewitson and Crane 2002; Malmgren and Winter 1999; Cavazos 2000; Hsu et al. 2002; Hong et al. 2004, 2005, 2006) and biological oceanography (e.g., Ainsworth 1999; Ainsworth and Jones 1999; Richardson et al. 2002). SOM analyses have also been applied recently to SST, sea surface height (SSH), winds measured by satellite (Richardson et al. 2003; Risien et al. 2004; Liu et al. 2006a, 2007), and ocean currents measured by moored ADCPs (Liu and Weisberg 2005; Liu et al. 2006b). Some advantages identified for the SOM relative to EOF are that data gaps are accommodated, temporal mean fields are retained, and asymmetric patterns not found in individual EOF modes are extracted by SOM. These previous applications suggest that the SOM may be useful for identifying physical processes detected in HF radar measurements.

As with analysis techniques, all observational techniques have advantages and limitations. High frequency radar, with excellent horizontal coverage, is limited to the surface whereas ADCPs, with excellent vertical coverage, are generally single point measurements horizontally. Neither of these techniques in isolation can properly characterize three-dimensional ocean circulation processes. In combination, however, HF radar and ADCPs provide a powerful system of measurements for describing the ocean circulation (e.g., Paduan and Rosenfeld 1996; Shay et al. 1998b; Chen and Evans 2001; Chant et al. 2004; Ullman and Codiga 2004).

The present paper applies the SOM to isolate key physical processes contained within a joint HF radar and ADCP dataset acquired over the West Florida Shelf (WFS) during the summer of 2003 (Shay et al. 2007). The purposes are twofold. The first is to demonstrate the usefulness of the SOM technique in analyzing such data. The second is to examine patterns of WFS currents in response to wind and tidal forcing and their differences arising from different physical processes. Section 2 briefly introduces the SOM technique and the related terminology. A description of the datasets follows in section 3. The SOM performance and the results are presented in section 4, including patterns associated with semidiurnal, diurnal, and sub-tidal frequency bands. Section 5 then summarizes the results and discusses potential applications for other venues where HF radars are deployed.

2. SOM background

Since the SOM is relatively new to oceanography, a brief introduction to the technique and to the related terminology is given in this section, based on Kohonen (1982, 2001). The SOM performs a nonlinear projection of input data onto a set of units (neural network nodes). Each unit has a weight vector $m_i$, which may be initialized randomly. Here the unit number $i$ varies from 1 to $M$, $M$ being the size of the SOM array. Adjacent units on the grid are called neighbors.

In a sequential training process, each frame of the input time series (referred to as the input vector $x$) is presented to the SOM, and an activation function is calculated based on the Euclidian distance between $m_i$ and $x$. The unit showing the highest activation (i.e., the smallest Euclidian distance) is selected as the “winner,” or the best matching unit (BMU). This process is expressed as

$$c_k = \arg\min_m ||x_t - m_i||$$

where $c_k$ is an index of the SOM winner for data snapshot $k$, and $c$ varies from 1 to $M$. The “arg” denotes “index.” During the training process the weight vector of the winner is moved toward the presented input data by a certain fraction of the Euclidian distance as indicated by a time-decreasing learning rate $\alpha$. Also, the weight vectors of the neighboring units are modified according to a spatial–temporal neighborhood function $h$. The learning rule may be expressed as

$$m_i(t + 1) = m_i(t) + \alpha(t) \cdot h_c(t) \cdot [x(t) - m_i(t)],$$

where $t$ denotes the current learning iteration and $x$ represents the currently presented input pattern. This iterative learning procedure leads to a topologically ordered mapping of the input data. Similar patterns are mapped onto neighboring units, whereas dissimilar patterns are mapped onto units farther apart.

The batch version of the SOM algorithm is computationally more efficient than the sequential version (Vesanto et al. 2000). At each step of the training process, all the input data vectors are simultaneously used to update all the weight vectors. The dataset is partitioned into $M$ groups (by minimum Euclidian distance) and each group is used to update the corresponding weight vector. Updated weight vectors are calculated by
where $\mathbf{x}_j$ is the mean of the $n$ data vectors in group $j$. The $h_i(t)$ denotes the value of the neighborhood function at unit $i$ when the neighborhood function is centered on the unit $i$. In the SOM Toolbox (Vesanto et al. 2000), there are four types of neighborhood functions available—“bubble,” “Gaussian,” “cutgauss,” and “ep” (or Epanechnikov function):

$$h_{ci}(t) = \begin{cases} F(\sigma_t - d_{ci}) & \text{bubble} \\ \exp(-d_{ci}^2/2\sigma_t^2) & \text{Gaussian} \\ \exp(-d_{ci}^2/2\sigma_t^2)F(\sigma_t - d_{ci}) & \text{cutgauss} \\ \max(0, 1-(\sigma_t - d_{ci})^2) & \text{ep} \end{cases}$$

where $\sigma_t$ is the neighborhood radius at time $t$, $d_{ci}$ is the distance between map units $c$ and $i$ on the map grid, and $F$ is a step function

$$F(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$$

The neighborhood radius $\sigma_t$ is either constant or linearly decreasing between specified initial and final values.

Two quantitative measures of mapping quality are average quantization error (QE) and topographic error (TE). The QE is the average distance between each data vector and the weight vector of the BMU. The TE gives the percentage of the data vectors for which the first BMU and the second BMU are not neighboring units. Lower QE and TE values indicate better mapping quality.

3. Observations and data processing

A Wellen Radar (WERA) system (Gurgel et al. 1999) was deployed along the west Florida coast (at Coquina Beach and Venice, Florida) from 23 August to 26 September 2003. Shay et al. (2007) provides a detailed accounting of the deployment (Fig. 1), the WERA data collected, their processing and calibration, and a description of the observed circulation. Here, for ease of visualization, the densely sampled data are subsampled onto a coarser (0.05° in latitude and longitude) rectangular grid by linear interpolation, and only those locations with a 60% or higher data coverage are retained for analysis, inclusive of data gaps. The resultant time series at each grid point are further preconditioned by low-pass filtering (with a 3-h cutoff) the half-hourly samples and then are resampled hourly to be consistent with the ADCP data.

Concurrent ADCP data are from three moorings deployed at the 10-, 20-, and 25-m isobaths offshore of Sarasota, Florida (Fig. 1). The bottom moorings, C11 and C15, housed upward-looking ADCPs, whereas the surface mooring, C10, housed a downward-looking ADCP. Analyses of data from both mooring techniques (upward and downward looking) yielded no significant velocity differences relative to our findings herein. Currents by ADCP are sampled hourly at 0.5-m-depth bins. Upon editing, the ADCP data are resampled by linear interpolation to synchronized hourly, integer meter bins. The near-surface (3-, 4-, and 4-m depths), midlevel (5-, 10-, and 13-m depths), and near-bottom (8-, 17-, and 22-m depths) bins at moorings C15, C11, and C10, respectively, are used for the joint SOM analyses with the WERA data, which have an effective depth of 0.7 m estimated by using the Stewart and Joy (1974) method.

Complimentary datasets include hourly wind data sampled at the C10 surface buoy and at the Venice station (see online at http://www.ndbc.noaa.gov/) and hourly coastal sea level data at St. Petersburg, Florida (see online at http://www.co-ops.nos.noaa.gov/). These data are used to verify some of the dynamical interp-
tations, such as upwelling/downwelling, as revealed in the SOM analyses.

To order the analyses based on process time scales, a rotary spectral analysis performed on both the surface winds and the near-surface velocity data from the C10 buoy are shown in Fig. 2. Both the clockwise and anti-clockwise spectra of the winds and the currents show kinetic energy peaks at semidiurnal, diurnal, and synoptic frequency bands. To examine the ocean processes on these time scales, the velocity data (WERA and ADCP) are filtered in three bands: 6–18, 18–36, and >36 h. If there are gaps in a time series, then the data are treated as several short datasets, filtered separately, and then reconnected with the gaps retained. Thus, while subsets of the overall dataset may contain gaps (i.e., a few missing bins in the HF radar data), the SOM will extract a pattern as long as some data exist. The utility of patterns from gappy portions of the dataset, as with patterns for gap-free portions, may be justified by the relationships between the BMU time series and other dataset time series indicative of the physical processes to which the patterns are attributed (section 4). Gaps that persist for too long in time or over too large an area may render the results unreliable. For this reason we opted to retain only those points for which at least a 60% data return exists, ensuring that none of the gaps are of either long duration or large spatial extent.

4. SOM analyses

Prior to discussing the joint data analyses performed over the semidiurnal, diurnal, and synoptic frequency bands, we must first define the tunable parameter choices required of the analyses. Liu et al. (2006b) offers a practical method for choosing these parameters. The QE monitors the quality of the SOM mapping during the training process. As the average distance between each data vector and the BMU, minimum QE indicates the most accurate representation of the input data. Given a 3 × 4 array (12 patterns), rectangular lattice, “sheet” map shape, linearly initialized weights, and batch training (Liu et al. 2006b), SOM analyses were repeated for differing neighborhood functions and radii, and the resulting average QEs were examined to search for the most accurate SOM mapping. As expected from previous experiments, the ep neighborhood function with a radius of unity provides the best choice. Figure 3 shows the resulting QE convergence for the analyses performed over each of the three frequency bands.

a. Semidiurnal frequency band

The 12 patterns extracted from the 6–18 h bandpass-filtered joint WERA and ADCP dataset are shown in Fig. 4. They are arranged on the SOM such that the
most dissimilar patterns are located the farthest away from each other (e.g., the oppositely positioned patterns 1 and 12 nearly mirror each other). As revealed by the WERA data, the currents are horizontally uniform within the observational domain. The ADCP data further show very little variation with depth, indicating that the semidiurnal currents are predominately barotropic. These results agree with previous findings on the

Fig. 4. (top) The 6–18-h bandpass-filtered St. Petersburg sea level. The (middle) BMU time series and (bottom) characteristic spatial patterns of the 6–18-h bandpass-filtered currents extracted by a $3 \times 4$ SOM. In the SOM, the relative frequency of occurrence of each pattern is shown in the upper left corner of each map. The gray arrows designate the WERA velocity vectors, and the red, blue, and black arrows symbolize the near-surface-, mid-, and near-bottom-level ADCP velocity vectors, respectively.
WFS $M_2$ tide (e.g., Koblinsky 1981; He and Weisberg 2002).

These semidiurnal current patterns may be classified into two categories: patterns with stronger (SOM units 1, 4, 10, 11, 12, 9, and 3) and with weaker (SOM units 2, 5, 6, 7, and 8) currents. Additionally, we see a neap-spring tide modulation in the BMU time series paralleling that of the St. Petersburg tide gauge. For instance, during the spring tide interval from 8 to 13 September, the SOM unit sequence is $3 \rightarrow 2 \rightarrow 1 \rightarrow 4 \rightarrow 10 \rightarrow 11 \rightarrow 12 \rightarrow 9$, consisting of the stronger current patterns, whereas during the neap-tide interval from 1 to 7 September, the weaker current patterns 2, 5, 6, 7, and 8 are more prevalent. In all of these pattern evolution sequences, the semidiurnal tidal currents undergo clockwise rotations consistent with Fig. 2, the previous tidal analyses cited, and the Shay et al. (2007) tidal analyses.

b. Diurnal frequency band

The patterns extracted for the 18-36-h band are shown in Fig. 5. In contrast with the semidiurnal band, these currents are stronger, less horizontally homogeneous, and at times contain large vertical shear. For instance, the SOM units 3, 6, 7, and 10 show that the near-surface and near-bottom currents are out of phase, which is characteristic of a first baroclinic mode near-inertial oscillation. Similar to the semidiurnal band extractions, these diurnal band patterns may be classified into categories with either strong (all of the patterns around the periphery) or weak (the two center patterns) currents. The BMU time series show their evolution. For instance, during the strong current fluctuations (e.g., 10–13 September) the SOM unit sequence is $1 \rightarrow 2 \rightarrow 3 \rightarrow 6 \rightarrow 12 \rightarrow 11 \rightarrow 10 \rightarrow 7 \rightarrow 1$. By contrast, during the weak intervals the sequence is largely $4 \rightarrow 5 \rightarrow 9 \rightarrow 8$. The sense of rotation is clockwise in both cases, but the strong current case shows large vertical shear.

The temporal evolution of the diurnal band current patterns may be explained by a combination of inertial and tidal dynamics. Well-defined but relatively small barotropic diurnal tidal oscillations are documented by He and Weisberg (2002). However, these may be easily masked by larger near-inertial oscillations when the water column is stratified since the local inertial period (26.2 h at mooring C10) is very close to the $K_1$ and $O_1$ tidal periods. For the interval of 29 August through 5 September, the current patterns evolve in the SOM unit sequence $1 \rightarrow 2 \rightarrow 3 \rightarrow 9 \rightarrow 12 \rightarrow 11 \rightarrow 10 \rightarrow 4 \rightarrow 1$ as a mixture of diurnal tides and moderate near-inertial oscillations. The inertial portion of these combined motions appears to be suppressed by the passage of Tropical Storm Henri from 5 to 8 September as the water column de-stratified under strong vertical mixing influence. With restratification after Henri (identified in the near-bottom cooling once the winds switched direction; not shown) and a succession of strong near-inertial variations in wind forcing, we see the appearance of large amplitude, first baroclinic mode near-inertial oscillations in the C10 ADCP data from 10 to 13 September. During this interval, the current patterns evolve in the SOM unit sequence $1 \rightarrow 2 \rightarrow 3 \rightarrow 6 \rightarrow 12 \rightarrow 11 \rightarrow 10 \rightarrow 7 \rightarrow 1$, which differs from the previous weaker current pattern sequence by the replacement of the weak units 9 and 4 with the strong, vertically sheared units 6 and 7. The generation of such large near-inertial motions is consistent with the clockwise polarized spectral peak in wind forcing at a near-inertial period (Fig. 2) and the appearance of such distinctive wind oscillations at the time of a large current response (Fig. 5). Resonance theory (e.g., Rudnick and Weller 1993) predicts such ocean response behavior, and the combined WERA and ADCP data analyses allow for the identification of such near-inertial modulation of the WFS currents.

c. Subtidal frequency band

The SOM extracted patterns for the 36-h low-pass-filtered data are shown in Fig. 6. Compared to those in the semidiurnal and diurnal bands, the subtidal currents are stronger, more horizontally inhomogeneous, and exhibiting of a systematic left-hand rotation with depth, consistent with an Ekman geostrophic circulation response to winds (e.g., Weisberg et al. 2000). Generally, these 12 current patterns may be classified into three groups: upwelling (SOM units 1 and 4), downwelling (SOM units 3, 6, 8, 9, 11, and 12), and transitional patterns (SOM units 2, 5, 7, and 10). The patterns with the largest frequencies of occurrence (for this dataset) are 6 and 4, with occurrences of 24.1% and 16.7%, respectively. Somewhat surprising are the number of patterns with large across-shelf flows (e.g., SOM units 1 and 4), although these may be accounted for by the seemingly opposing flows in the surface and bottom Ekman layers.

The BMU time series together with the winds and sea level data provide a basis for discussing the pattern evolution. Beginning on 28 August when the winds are from the southeast, we see an approximate 6-day interval of along-shelf flow to the northwest (pattern 6) indicative of a summer wind and buoyancy-driven circulation (e.g., Liu and Weisberg 2005; Weisberg et al. 2005). As the winds increase and become more southerly, there is a pattern transition from 6 to 9, 11, and 12, with 12 showing a very strong nearshore jet fed by a large, surface-confined onshore flow. Accompanying
Fig. 5. The (top) hourly winds at Venice. The (second), (third) depth-time plots of the 18–36-h bandpass filtered mooring C10 across- and along-shelf velocity components, respectively. (bottom) Same as those in Fig. 3 but for the 18–36-h bandpass filtered data.
pattern 12 is a rapid rise in sea level. This indicates a mass readjustment that accounts for the nearshore jet being in geostrophic balance with an offshore sloping sea surface. These observations are consistent with a wind-driven downwelling response to the leading edge of Tropical Storm Henri. The trailing edge of Henri brought about a reversal in the winds. The SOM patterns change from 12 to 11, 10, 4, and 1. The first two of
these are transitional states in which the nearshore jet spins down as the coastal sea level drops over a pendulum day, whereas the last two are strong upwelling patterns in response to northwesterly and northeasterly winds. The strong, offshore-directed surface currents revealed by the WERA data in patterns 4 and 1 may be misleading if not combined with the ADCP data, which show alongshore flow at midlevel and onshore flow at depth. During 12–15 September, the winds changed from weak easterly to southeasterly and northeasterly, and the currents evolved from patterns 1→5→8→5.

Despite weak winds, the northward currents in pattern 8 are strong because of a summer buoyancy contribution. During 16–22 September, the winds changed from strong northerly (upwelling favorable) for about 4 days to southeasterly (downwelling favorable). The currents responded to upwelling favorable winds by transitioning through patterns 5→7→4→1. The currents then responded to the downwelling favorable winds by transitioning through patterns 7→2→6→9. We note that these winds and current response patterns (as shown by the BMU time series) are closely related to the coastal sea level variations.

Asymmetries are found between the strongest upwelling (SOM unit 4) and downwelling (SOM unit 12) patterns. First, note that in the downwelling pattern, the coastal jet is largest at the surface near the coast, whereas in the upwelling pattern, the alongshore component of the response is largest at middepth and farther offshore. For example, the middepth current at the 25-m isobath (mooring C10) is stronger than those at 20- and 10-m isobaths (moorings C11 and C15). Second, the cyclonic velocity vector rotation (to the left) with depth near the coast is larger in the upwelling than in the downwelling patterns. These two asymmetric features are consistent with the findings of Liu and Weisberg (2005) and Liu et al. (2006b), and an explanation is given by Weisberg et al. (2000) based on stratification effects on the bottom Ekman layer. There is a difference between the behaviors observed in the aforementioned studies and a third element of asymmetry found here. That is, the currents in the downwelling pattern (12) are stronger than those in the upwelling pattern (4). The explanation may be due to several factors. First, the southerly winds of Tropical Storm Henri during 5–6 September were stronger than the subsequent northerly winds during 9–11 and 16–17 September. Second, the across-shelf temperature structure favors a northward along-shelf flow in summer (Weisberg et al. 1996; Liu and Weisberg 2005; Liu et al. 2006a). Third, the additional baroclinic effects of estuarine freshwater efflux tend to concentrate a downwelling coastal jet closer to the coast than an upwelling coastal jet (e.g., Zheng and Weisberg 2004).

5. Summary and discussion

The SOM was applied to a joint WERA and ADCP dataset on the WFS from 26 August to 23 September 2003. Separate three-dimensional patterns of current variability were extracted for semidiurnal, diurnal, and subtidal frequency bands.

At semidiurnal time scale, current patterns were found to be relatively homogeneous horizontally and uniform vertically, exhibiting clockwise rotation and fortnightly modulation indicative of a barotropic, $M_2$, and $S_2$ tide predominance. While the identification of $M_2$ and $S_2$ tide predominance is not a new observational finding (Koblinsky 1981; Marmorino 1983; He and Weisberg 2002; Shay et al. 2007), the joint analysis of WERA and ADCP data by SOM allows us to better describe the three-dimensional structure and fortnightly modulation.

At diurnal time scale, the patterns were found to be less homogeneous horizontally and more baroclinic vertically. While all such patterns were clockwise polarized, they grouped into two sets—those with relatively large and small amplitudes. The strong current patterns showed pronounced baroclinic structure, whereas the weak current patterns tended to be barotropic. These behaviors may be explained on the basis of near-inertial oscillations under stratified conditions superimposed on barotropic $K_1$ and $O_1$ tides. WFS tidal analysis (He and Weisberg 2002) shows the diurnal constituents to be relatively uniform spatially. This differs from the modulated results shown here due to stratification, allowing for the generation of strong near-inertial oscillations. Unlike near-inertial oscillations identified in many coastal (e.g., Kundu 1976; Shay et al. 1998a) and deep-ocean regions (e.g., Weller 1982), the relatively shallow WFS shows highly modulated near-inertial motions due to variations in stratification.

At subtidal time scales, the current patterns were found to be more complex both horizontally and vertically, and they may be classified into three groups: upwelling, downwelling, and transitional patterns. Large differences in the velocity fields occurred vertically. For both upwelling and downwelling patterns, the velocity vectors were observed to rotate to the left with depth, consistent with an Ekman geostrophic response to wind forcing. Pattern evolution, as shown by the BMU time series, was also consistent with the evolution of the local wind and sea level time series. Similar to previous studies, asymmetries were identified in the upwelling and downwelling patterns. These asymmetries were primarily manifest as more nearshore confined responses.
under downwelling than under upwelling favorable winds.

The SOM is shown to be an effective analysis tool for identifying modulated, nonhomogeneous, anisotropic, three-dimensional coastal ocean current variations observed with high-resolution HF radar and ADCPs. By combining WERA sampled surface current fields with ADCP sampled water column currents, a much more complete representation of the velocity field was obtained when compared with either of these measurement techniques alone. Even in shallow water on a gently sloping shelf it is concluded that rotation and stratification causes three-dimensional, time-dependent current structures that are distinctively different for different physical processes (shown here for tides, near-inertial motions, and weather-induced variability). Sampling and describing such complex space–time structures requires multisensor arrays of instruments for monitoring and various tools for analyses. As a descriptive analysis technique, the SOM is found to be well suited for combining the attributes of HF radar and in situ sensors (ADCPs as used here) to characterize coastal ocean flow fields.

Acknowledgments. Support was given by the Office of Naval Research Grants N00014-98-1-0158 (USF) and N00014-02-1-0972 (RSMAS), the second of these for the Southeast Atlantic Coastal Ocean Observing System (SEACOOS) administered by UNC under Task Order 3-12110-10. The SOM MATLAB Toolbox is by E. Alhoniemi, J. Himberg, J. Parhankangas, and J. Vesan- cato. The success of the seagoing activity at USF is attributed to R. Cole, J. Law, and C. Merz, and J. Donovan, V. Subramanian, and D. Mayer assisted with real-time data acquisition and editing. We similarly acknowledge the UM WERA team efforts by T. Cook, B. Haus, and J. Martinez, and we thank T. Helzel for assistance with the WERA deployment and K.-W. Gurgel for assistance with WERA software and experimental design.

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