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Patterns and dynamics of ocean circulation variability on the West Florida shelf

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Patterns and Dynamics of Ocean Circulation Variability on the West Florida Shelf

by

Yonggang Liu

A dissertation submitted in partial fulfillment of the requirements for the degree of
   Doctor of Philosophy
   College of Marine Science
   University of South Florida

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Keywords: coastal oceanography, continental shelf dynamics, observations, time series, data analysis, neural network, growing hierarchical self-organizing maps

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To my late parents, Xiaofang Chen and Yongxing Liu, and grandparents, Jinfeng Wang and Xinding Liu.
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Note to Reader

The original of this document contains color that is necessary for understanding the data.

The original dissertation is on file with the USF library in Tampa, Florida
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Patterns and Dynamics of Ocean Circulation Variability on the West Florida Shelf

Yonggang Liu

ABSTRACT

Patterns of variability and the dynamics of the ocean circulation on the West Florida Shelf (WFS) are investigated using multi-year, shelf-wide oceanographic observations from moored Acoustic Doppler Current Profiler (ADCP) arrays, hydrographic cruises, High-Frequency (HF) radars, satellites, and coastal tide gauges. Novel neural network techniques, Self-Organizing Map (SOM) and Growing Hierarchical Self-Organizing Maps (GHSOM), are introduced as feature extraction methods in physical oceanography. The SOM is demystified and demonstrated to be a useful feature extraction method in a series of performance evaluations using artificial data sets comprising known patterns. It is then applied to velocity time series from moored ADCP arrays and to a joint HF-radar and ADCP data set, respectively, to extract patterns of ocean current variability, and it is shown to be a useful technique for extracting dynamically consistent ocean current patterns. The extracted characteristic patterns of upwelling/downwelling variability are coherent with the local winds on the synoptic weather time scale, and coherent with both the local winds and the complementary Sea Surface Temperature (SST) patterns on the seasonal time scale. The currents are predominantly southeastward during fall-winter and northwestward during summer. The GHSOM is used to describe the SST seasonal variation. As feature extraction methods, both the SOM and the GHSOM have advantages over the conventional Empirical Orthogonal Function method.

The circulation dynamics are examined, first through depth-averaged momentum balances at selected locations and then via sea surface height (SSH) estimates across the inner shelf. Dominant dynamics of the shelf circulation are diagnosed and a method is
discussed for estimating along-shelf currents from coastal sea level and wind data. Non-
tidal coastal sea level fluctuations are related to both the offshore SSH and the dynamical
responses of the inner shelf to wind and buoyancy forcing. The across-shelf distribution
of the SSH is estimated from the velocity, hydrography, wind, and coastal sea level data.
Subtracting the variability that may be accounted for by inner shelf dynamical responses
yields a residual at the 50 m isobath that compares well with satellite altimetry data. This
suggests the possibility of calibrating satellite SSH data on the continental shelf.
Chapter 1

Introduction

The Continental shelf is a transition region between the coastline and the deep ocean. It is within this coastal ocean region where substantial maritime commerce takes place, where commercial and recreational fisheries are situated, and where many of the environmental concerns occur, such as the disposal of waste materials from land. Knowledge of continental shelf circulation is central to comprehending and predicting the transport and fate of coastal ocean materials and how these impact primary and higher trophic level productivity.

The West Florida Shelf (WFS) is a wide, gently sloping continental shelf located in the eastern Gulf of Mexico. An example of a significant environmental concern that is dependent on the circulation is the episodic, seasonal bloom of red tide. Eventually unveiling the mystery of red tide blooms (e.g., Haddad and Carder 1979; Tester and Steidinger 1997; Vargo et al. 2000; Walsh et al. 2003) will require a comprehensive understanding of the coastal ocean circulation. This dissertation explores the patterns of WFS circulation variability and their related dynamics.

1.1 Background knowledge on the West Florida Shelf circulation

Both observational and model studies show that the WFS circulation is primarily driven by local winds at synoptic time scale (e.g., Mitchum and Sturges 1982; Li and Weisberg 1999a, b), whereas at seasonal time scales it is affected by a combination of the shelf-wide winds, surface heat fluxes, and river runoffs (e.g., Weisberg et al. 1996; Yang and Weisberg 1999; He and Weisberg 2002b, 2003a; Gilbes et al. 1996, 2000). In addition to local forcing the intrusion of the Gulf of Mexico Loop Current and its eddies...
at the shelf slope (e.g., Molinari et al. 1977; Huh et al. 1981; Paluszkiewicz et al. 1983; Vukovich 1988; Sturges 1994; Hetland et al. 1999; Sturges and Leben 2000; He and Weisberg 2003b; Weisberg and He 2003) may also be important forcing factors.

Early knowledge of the WFS circulation was derived from drift bottles (e.g., Tolbert and Salsman 1964), and a seasonality of the surface currents was suggested. Direct current measurements on the WFS using in situ moorings began during 1970s (e.g., Niiler 1976; Price et al. 1978; Mitchum and Sturges 1982; Marmorino 1983a). Most of these observations were over short time periods within a particular season, and seasonal variability of the WFS currents was not known. In 1993, Acoustic Doppler Current Profilers (ADCP) moorings were initiated on the WFS and seasonal variation of the currents was reported based on the records at a single site from October 1993 through January 1995 (Weisberg et al. 1996). Seasonal variation was also suggested by numerical model results (Yang and Weisberg 1999; He and Weisberg 2002b, 2003a). During winter, WFS currents are southeastward, whereas during summer they are northwestward. However, based on the drifters initially deployed only in the northern Gulf of Mexico, Ohlmann and Niiler (2005) recently concluded that a pronounced seasonal cycle did not exist on the WFS. Further clarification of the seasonal variability with an ever evolving data set is therefore needed.

Most previous moorings on the WFS had a limited number of current meter measurements (e.g., Niiler 1976; Price et al. 1976; Mitchum and Sturges 1982; Marmorino, 1983a, b; Weatherly and Thistle 1997), and hence did not offer information on either the spatial patterns or across-shelf structures of the WFS circulation variability. Meyers et al. (2001) described year-long ADCP data at five stations from the 30 m to 300 m isobaths across the WFS. However, with limited sampling across different dynamic regimes the across-shelf structures could not be described. Numerical model results on the WFS did show the across-shelf structures and spatial patterns of the WFS currents (e.g., Li and Weisberg 1999a, b; Weisberg et al. 2000, 2001; He and Weisberg 2002b, 2003a), but they were based on idealized forcing and/or simplified initial conditions. There lacks an observational description of spatial patterns and across-shelf structures of the WFS current variability.
Early observational studies on WFS circulation dynamics focused on shallow water bottom Ekman (e.g., Marmorino 1983a, b) and continental shelf wave theories (Mitchum and Clarke 1986a, b). Observational inferences on WFS momentum balances are limited by the data availability. For instance, Mitchum and Sturges (1982) analyzed three weeks of current meter data from two moorings at the 22 and 44 m isobaths and concluded that the dominant momentum balance in the along-shelf direction was between the wind and bottom stresses, but that in the across-shelf direction had to be assumed to in geostrophic. WFS momentum balances from numerical model results under idealized forcing conditions provide helpful insights to the circulation dynamics (Li and Weisberg 1999a, b; Weisberg et al. 2000, 2001); however, these model results are not yet verified by observations.

1.2 Feature extraction methods

Our world is in an information age. More and more data sets (e.g., from in situ observation, remote sensing, numerical modeling) are available to study oceanography. How to effectively use them is a problem. For example, it is difficult to accurately extract characteristic patterns from long time series. Temporal and spatial averaging are the simplest methods, but it is difficult to define suitable time and length scales over which to average. For example, currents on a continental shelf may exhibit different isotropic or anisotropic behaviors depending on the processes and time scales involved. Thus mean values may be very misleading. The Empirical Orthogonal Function (EOF) technique is widely used in oceanographic and meteorological communities (e.g., Weare et al. 1976; Klink 1985). It separates a data set into a set of orthogonal modes (eigenvectors and principal components). The eigenvectors are often used to describe spatial patterns and the principal components are used to examine the associated temporal variability. However, it requires the data to be gaps-free; moreover, conventional EOF, as a linear method, may not be as useful in extracting nonlinear information (Hsieh 2001). In summary, there is a need for effective feature extraction methods.
1.3 Motivation and objectives

Despite its importance, the WFS circulation has not been widely studied. Many issues remain in question. For example, what are the characteristic current patterns at different time scales? Is the seasonal variation pronounced at all? Any findings on the spatial patterns, across-shelf structures and three-dimensional pictures of the WFS current variability are useful to understand the property transport on the shelf. What is the dominant dynamics of the ocean circulation? Can all the observed physical parameters be explained in terms of dominant coastal ocean dynamics?

Systematic concurrent observations have been performed on the WFS over recent several years, which include monthly hydrographic cruises, shelf-wide ADCP moorings, land-based high-frequency (HF) radar systems, as well coastal tidal gauges and meteorological stations. The acquisitions of these long time series now facilitate a more complete description and diagnostic calculations of WFS based on real observations.

Given the above facts, the goals of my dissertation are to: (1) introduce novel data analysis methods from information science (Kohonen 2001; Dittenbach et al. 2002), Self-Organizing Map (SOM) and Growing Hierarchical Self-Organizing Maps (GHSOM), to physical oceanography community; (2) describe the spatial patterns, across-shelf structures, and three-dimensional views of WFS ocean current variability on different time scales by applying these techniques to different data sets (ADCP and HF radar current data); (3) classify the SST patterns on the WFS; (4) diagnose the dominant dynamics of the shelf circulation in depth-averaged momentum balances at selected locations using a variety of in situ data sets (ADCP currents, winds, water bottom pressure and coastal sea level records, and hydrographic data); (5) estimate SSH variation along a transect across the inner WFS by dynamically examining the ADCP, wind, hydrography and coastal sea level data on the WFS.

Results and conclusions of this work derive from seven peer-reviewed research papers (Liu and Weisberg 2005a, b, 2006; Liu et al. 2006a, b, c; He et al. 2004), which are presented in Chapters 2~7 in this dissertation. Chapter 2 introduces the novel data analysis methods followed by a performance evaluation using artificial data comprising
known patterns. Chapter 3 applies the SOM to the time series of ADCP arrays on the WFS to describe the spatial patterns of the ocean current variability on synoptic, seasonal and inter-annual time scales. Chapter 4 applies the SOM to a joint HF radar and ADCP data set to examine the three-dimensional view of the inner shelf ocean currents on semidiurnal, diurnal and subtidal time scales. Chapter 5 examines patterns of the SST variability from daily satellite data on the WFS using the SOM and GHSOM techniques. Chapter 6 presents depth-averaged momentum balance diagnoses over the synoptic and longer time scales and discusses a method for estimating along-shelf currents from sea level and wind data. Chapter 7 address the factors that cause coastal sea level variability. By subtracting the portion of the sea level variability that can be accounted for by the inner shelf dynamics a residual is arrived at for comparison with mid shelf satellite altimetry data. The analysis suggests a technique for calibrating satellite altimetry data on the continental shelf. Finally, Chapter 8 provides a summary of this dissertation.
Chapter 2

Feature Extraction Methods

2.1 Introduction

Our understanding of ocean processes steadily improves with increasing information: in situ (moored ADCP, temperature, etc.) and remotely-sensed satellite (SST, altimetry, Chl-a, etc.) and radar (surface winds, currents, etc.) data, and numerical model results. However, the percentage of data actually used is low. For instance, it is estimated that less than 5% of all remotely sensed images are ever seen by human eye (Petrou 2004). With the increasing quantity of data there is a need for effective feature extraction methods.

Temporal and spatial averaging are the simplest methods, but it is difficult to define suitable time and length scales over which to average. For example, currents on a continental shelf may exhibit different isotropic or anisotropic behaviors depending on the processes and time scales involved. Thus mean values may be very misleading.

The Empirical Orthogonal Function (EOF) technique is useful in reducing large correlated data sets into a small number of patterns ordered by variance, with wide oceanographic and meteorological applications (e.g., Weare et al. 1976; Klink 1985; Lagerloef and Bernstein 1988). However, conventional EOF, as a linear method, may not be as useful in extracting nonlinear information (Hsieh 2001, 2004).

The SOM, based on an unsupervised neural network (Kohonen 1982, 2001), appears to be an effective method for feature extraction and classification. It maps high dimensional input data onto a low-dimensional (usually 2-d) space while preserving the topological relationships between the input data. Thousands of SOM applications are found amongst various disciplines (Kaski et al. 1998; Oja et al. 2003), including climate
and meteorology (Hewitson and Crane 1994, 2002; Malmgren and Winter 1999; Cavazos 2000; Ambroise et al. 2000; Hsu et al. 2002; Hong et al. 2004, 2005) and biological oceanography (Ainsworth 1999; Ainsworth and Jones 1999; Silulwane et al. 2001; Richardson et al. 2002; Hardman-Mountford et al. 2003). Recent SOM applications include SST and wind pattern extractions from satellite data (Richardson et al. 2003; Risien et al. 2004) and coastal sea level prediction (Ultsch and Röske 2002). All of these applications suggest that the SOM may be useful for meteorological and oceanographic feature extraction. However, for meteorologists and oceanographers unfamiliar with neural network techniques, the SOM remains a “black box,” with associated skepticism.

Early studies on SOM performance evaluation focused on comparisons with other techniques, such as principal component analysis and k-means clustering (Murtagh and Hernandez-Pajares 1995; Kiang and Kumar 2001). In an introduction to the SOM Toolbox (Vesanto et al. 1999, 2000) performance tests were only on the computational requirements of the algorithms, i.e., computing time for different training methods, not on the quality of the mappings or the sensitivity to different SOM parameter choices.

In this Chapter, both the SOM and the Growing Hierarchical Self-Organizing Maps (GHSOM) are introduced to physical oceanographic community. The performance of the SOM in feature extraction is also evaluated. SOM results obtained under various tunable parameter choices and signal-to-noise levels are examined using time series from known patterns. Some of the questions addressed are: does the SOM technique recover known patterns reliably, are any artifacts created, and which parameter choices provide the best results?

The remainder of this chapter is arranged as follows. Section 2.2 briefly summarizes the EOF method. Sections 2.3 and 2.4 introduce the SOM and the GHSOM, respectively. In Section 2.5, both time series of linear progressive wave data and more complex synthetic data are used to train and evaluate the SOM method. Section 2.6 concludes with a summary and discussion.
2.2 Empirical Orthogonal Functions

The EOF is the same as the Principal Component (PC) Analysis (Hotelling 1933) used in the statistics community. It provides a compact description of the spatial and temporal variability of data series in terms of orthogonal functions, or statistical “modes”. In the combined parlance the PCs are the amplitudes, which are functions of time, of their corresponding spatial eigenfunctions, or EOFs. Generally speaking, each mode $n$ has an associated variance, a dimensional spatial pattern $F_n(x)$, and a nondimensional time series $\alpha_n(t)$. Thus, a time series $\hat{T}(x,t)$ may be represented by the EOFs as:

$$\hat{T}(x,t) = \sum_{n=1}^{N} \alpha_n(t) F_n(x)$$  \hspace{1cm} (2.1)

Usually, most of the variance of a spatially distributed series is in the first few orthogonal functions whose patterns may then be linked to possible dynamical mechanisms. Actually, no direct physical or mathematical relationship necessarily exists between the statistical EOFs and any related dynamical modes. The EOF is simply a method for partitioning the variance of a spatially distributed group of concurrent time series. It is called “empirical” to reflect the fact that the eigenfunctions are defined by the covariance structure of the specific data set being analyzed.

2.3 Self-Organizing Map

The SOM is an artificial neural network based on unsupervised learning (Figure 2.1). The SOM performs a nonlinear projection from the input data space to a set of units on a two-dimensional map grid. An illustration of how it works is given in Figure 2.2. Each unit is attached with 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 the Matlab SOM Toolbox (Vesanto et al. 2000) there are three types of training algorithms: sequential, batch and sompak.

In a sequential training process, elements from the high-dimensional input space, referred to as input vectors $x$, are presented to the SOM and the activation of each unit for
the presented input vector is calculated using an activation function. Commonly, the Euclidian distance between the weight vector of the unit and the input vector serves as the activation function. The weight vector of the unit showing the highest activation (i.e. the smallest Euclidian distance) is selected as the “winner” [or best matching unit (BMU)]. This process is expressed as

$$c_k = \arg \min \|x_k - m_i\|$$  \hspace{1cm} (2.2)

where $c_k$ is an index of the "winner" on the SOM for a 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 Euclidean distance as indicated by a time-decreasing learning rate $\alpha$. Also, the weight vectors of the neighboring units are also modified according to a spatial-temporal neighborhood function $h$. The learning rule may be expressed as

$$m_i(t+1) = m_i(t) + \alpha(t) \cdot h_{ij}(t) \cdot [x(t) - m_i(t)],$$  \hspace{1cm} (2.3)

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.

Figure 2.1. Illustration of the neural networks based on the supervised (left) and unsupervised (right) learning algorithms. *Supervised* neural networks are techniques for extracting data input-output relationships and storing those relationships into mathematical equations that can be used for forecasting or decisions-making. *Unsupervised* neural networks are techniques for classifying, organizing and visualizing large data sets.
The batch version of the SOM algorithm is computationally more efficient than the sequential version (Kohonen 1998; Vesanto et al. 1999, 2000). At each step of the training process, all the input data vectors are simultaneously used to update all the weight vectors. The data set 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:

$$\mathbf{m}_j(t+1) = \frac{\sum_{j=1}^{M} n_j h_{ij}(t) \bar{x}_j}{\sum_{j=1}^{M} n_j h_{ij}(t)}$$

where $\bar{x}_j$ is the mean of the $n$ data vectors in group $j$. The $h_{ij}(t)$ denotes the value of the neighborhood function at unit $j$ when the neighborhood function is centered on the unit $i$. In the batch algorithm, the learning rate function $\alpha(t)$ of the sequential algorithm is no longer needed, but like the sequential algorithm the radius of the neighborhood may decrease during the learning process. In the SOM Toolbox, 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

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

[see Vensanto et al. (2000) for the geometries of these neighborhood functions]. The default SOM Toolbox neighborhood function is “gaussian”. The neighborhood radius $\sigma_t$ is either constant or decreases linearly during the iteration process if its initial and final values are given.

The sompak training process is similar, employing C-language programs (Kohonen et al. 1995). Vesanto et al. (1999, 2000) demonstrates that batch training is the fastest of the three algorithms. Our evaluation is therefore based on the batch method
only. The SOM Toolbox version 2.0 can be freely downloaded from the Helsinki University of Technology, Finland: \url{http://www.cis.hut.fi/projects/somtoolbox}.

Figure 2.2. Illustration of how a SOM works. The data time series are arranged to form a big two-dimensional data array such that data at each time step are reshaped to be a row vector. For each time step, the row vector is used to update the weight of the SOM via an unsupervised learning algorithm. This iteration process is called self-organizing. The outcome weight vectors of the SOM nodes are reshaped back to have characteristic data patterns.

2.4 Growing Hierarchical Self-Organizing Map

Despite its wide applications, the SOM analysis has its inherent deficiencies. First, it uses a static network architecture, i.e., the number and arrangement of neural nodes are fixed and have to be defined prior to the training process. Second, hierarchical relations between the input data are difficult to reveal. To address both issues within one framework, a neural network model of the GHSOM was recently introduced (Dittenbach
et al. 2002; Rauber et al. 2002; Dittenbach 2003; Pampalk et al. 2004). The GHSOM is composed of independent SOMs, each is allowed to grow in size during the training process until a quality criterion regarding data representation is met. This growth process is further continued to form a layered architecture such that hierarchical relations between input data are further detailed at lower layers of the neural network. For a cartoon show of the GHSOM, see Figure 2.3.

Figure 2.3 An example of the Hierarchical structure of the GHSOM. All of the four units in the first layer SOM are expanded in the second layer. Only two units in one of the second layer SOMs are further expanded in the third layer.

How does a SOM grow? Prior to the training process a “map” in layer 0 consisting of only one unit is created. This unit’s weight vector is initialized as the mean of all input vectors and its mean quantization error ($MQE$) is computed. The $MQE$ of unit $i$ is computed as

$$MQE_i = \frac{1}{|U_i|} \sum_{k \in U_i} \|x_k - m_i\|, \quad U_i = \{k|c_k = i\}. \quad (2.7)$$

Beneath the layer 0 map a new SOM is created with a size of initially $2 \times 2$ units. The intention is to increase the map size until all data items are represented well. A mean of all $MQE_i$ is obtained as $<MQE>$. The $<MQE>$ is then compared to the $MQE$ in the layer
above, \( <MQE>_{above} \). If the following inequality is fulfilled a new row or column of map units are inserted in the SOM,

\[
<MQE> > \tau_1 \cdot <MQE>_{above}
\]

(2.8)

where \( \tau_1 \) is a user defined parameter. Once the decision is made to insert new units the remaining question is where to do so. In the GHSOM array, the unit \( i \) with the largest \( MQE_i \) is defined as the error unit. Then the most dissimilar adjacent neighbor, i.e., the unit with the largest distance in respect to the model vector, is selected and a new row or column is inserted between these. If the inequality (2.8) is no longer satisfied, the next decision to be made is whether some units should be expanded on the next hierarchical level or not. If the data mapped onto one single unit \( i \) still has a larger variation, i.e.,

\[
MQE_i > \tau_2 \cdot <MQE>_{above}
\]

(2.9)

where \( \tau_2 \) is a user defined parameter, then a new map will be added at a subsequent layer. Generally, the values for \( \tau_1 \) and \( \tau_2 \) are chosen such that \( 1 > \tau_1 >> \tau_2 > 0 \). In the GHSOM Toolbox, \( \tau_1 \) and \( \tau_2 \) are called “breadth”- and “depth”-controlling parameters, respectively. Generally, the smaller the parameter \( \tau_1 \), the larger the SOM arrays will be. The smaller the parameter \( \tau_2 \), the more layers the GHSOM will have in the hierarchy.

The GHSOM MATLAB toolbox, developed jointly by the University of Aberdeen and Vienna University of Technology, Finland, can be freely downloaded at the following website [http://www.oefai.at/~elias.pampalk/ghsom/](http://www.oefai.at/~elias.pampalk/ghsom/). To my knowledge, GHSOM applications have not been found in meteorology or oceanography.

### 2.5 Performance evaluation of the Self-Organizing Map in feature extraction

A series of experiments are designed to evaluate the feature extraction performance of the SOM by using artificial data representative of known patterns. First, a linear progressive wave data set is used. After a brief introduction of the data set, results of a control run are presented to demonstrate the SOM capability in representing progressive wave patterns. Sensitivity studies are then performed by varying map size, lattice structure, initialization, neighborhood function, and random noise level. At last, a more complex data set consisting of multiple patterns is used for evaluation.
2.5.1 Features extracted from linear progressive waves

Linear progressive waves are common to meteorology and oceanography. We specify a sinusoidal pattern in space \( x \) and time \( t \) of the form:

\[
y(x, t) = \sin(kx - \omega t)
\]  

where \( k = \frac{2\pi}{200}, \omega = \frac{2\pi}{50}, x = [1:100], t = [1:200], \) and the amplitude is 1, such that each time step presents a wave of different phase. These data are arranged in a matrix such that each row is a spatial pattern (sine wave) at a given time step.

As an SOM control run, against which to test varying parameters, we use a map size of 3×4, a rectangular lattice, linearly initialized weights, an “ep” neighborhood function with initial and final neighborhood radii of 3 and 1, respectively, and all of these choices will be clarified later. Batch training is performed over 10 iterations, and the results are shown in Figure 2.4.

The original 200 input frames (50 unique sinusoidal patterns repeated four times) are extracted into 12 units (Figure 2.4, top panels). Among these 12 units, numbers 5 and 8 are artifices, because their frequencies of occurrence are zero and their amplitudes are about half of that of the input data. The remaining 10 patterns show equal frequencies of occurrence (10% each of the total input data). From the BMU time series (Figure 2.4, bottom panel) we see the sequence of pattern evolution: 11 → 10 → 7 → 4 → 1 → 2 → 3 → 6 → 9 → 12 → 11 consistent with the phase progression of the synthetic sinusoidal pattern input to the SOM. Further examination of the adjacent SOM units shows a constant phase difference consistent with a progressive sine wave. Wave propagation is in the positive x direction, and the wave amplitude is about 1. Thus the SOM unit pattern extractions and BMU time series provide satisfactory descriptions of the input data set.

The fictitious patterns 5 and 8 are a consequence of the smooth ordered mapping by the SOM that attempts to conserve the input data topology. Consequently, similar patterns are arranged in neighboring regions of the map, whereas dissimilar patterns are mapped further apart. Actually, pattern 1 mirrors pattern 12, pattern 2 mirrors pattern 11, and so on around the SOM. So, both patterns 5 and 8 are topological transitional patterns between the two opposite extremes of the SOM. Since these patterns do not occur in the
input data set their frequency of occurrence is zero. This demonstrates (as we will see again later) that while the SOM technique may produce some spurious patterns, it is capable of distinguishing between fictitious and non-fictitious patterns of a given data set.

Figure 2.4. A 3×4 SOM representation of the linear progressive wave data. The upper 12 panels show the SOM patterns with the frequency of occurrence given at the top of each panel. The lower panel is the BMU time series.

2.5.2 Effects of varying the map size

The training process requires a map size (number of units) specification. Larger map sizes result in more detailed patterns; smaller map sizes result in more general patterns (Vesanto et al. 2000). To test the map size sensitivity, the control run is repeated by changing the map size only, and the results for 2×2 and 4×4 rectangular arrays are shown in Figures 2.5 and 2.6, respectively.
Figure 2.5 Same as Fig 2.4 but for a 2×2 SOM.

The 2×2 array distinguishes four different phases of the sinusoidal function (Figure 2.5). The BMU time series show the wave propagation through the following SOM unit sequence: 3→1→2→4→3, with a π/2 phase angle in between. While some detail is lost in going to smaller map size the systematic phase progression is retained. Far from the smoothing effect of temporal average, the fluctuating nature of the linear wave is picked up in both the space and time domains.

When the map size is increased to 4×4 more detailed patterns (Figure 2.6) are extracted (more sampling in phase space). The progressive wave is represented by 12 different patterns each with π/6 phase difference propagating around the four central null patterns (6, 7, 10, and 11) with zero frequencies of occurrence.

The pattern extracted in each SOM unit is the iterative result of the training process. Hence the amplitude may not be exactly that of the sinusoidal function input to the SOM. Table 2.1 shows the maximum/minimum values obtained for each of the different map sizes that we tested. While generally close to one, they are not necessarily equal to one. Larger map size leads to more accurate results by virtue of less pattern smoothing. However, larger array size results in more patterns so there is a trade off between compressing information into a manageable few patterns and accuracy, as with any technique.
Figure 2.6  Same as Figure 2.4 but for a 4×4 SOM.

Table 2.1.  The minimum and maximum wave amplitudes of the SOM patterns excluding those with zero frequency of occurrence.

<table>
<thead>
<tr>
<th>Map size</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2×2</td>
<td>0.89</td>
<td>0.91</td>
</tr>
<tr>
<td>2×3</td>
<td>0.95</td>
<td>0.97</td>
</tr>
<tr>
<td>3×3</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td>3×4</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>4×4</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>5×5</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>6×6</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>7×7</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>8×8</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>
2.5.3 Sensitivity to map lattice structure

Along with map size, the map lattice and shape must also be specified. The SOM lattice gives the local topology of the map, i.e., the connectivity of the map units. The lattice can be either rectangular or hexagonal in the SOM toolbox (Vesanto et al. 2000). Different shapes may also be chosen: sheet, cylinder or toroid, and for simplicity we only consider the flat sheet here. If instead of the rectangular lattice as in the control run we use a hexagonal lattice we get comparable, but more complex results (not shown). The complication arises since the phase space of the sinusoidal input data pattern is mapped onto a set of SOM units, the number of which does not divide equally into $2\pi$ radians. Hence the frequencies of occurrence of the 10 valid wave patterns are not evenly distributed.

2.5.4 Sensitivity to initialization

The neuron weights may be initialized either randomly or linearly. In random initialization the map weights are initialized with random values in the range of $[\min(x), \max(x)]$. In linear initialization the SOM toolbox initializes the map weights by first performing an EOF decomposition and then linearly interpolating between the first two leading EOFs. The toolbox also provides two quantitative measures of mapping quality: average quantization error (QE) and topographic error (TE). The QE is the average distance between each data vector and the BMU. The TE gives the percentage of the data vectors for which the BMU and the second BMU are not neighboring units. Lower QE and TE values indicate better mapping quality. For comparison with the control run we varied both the initialization methods and the neighborhood functions (and with three sets of neighborhood radii). The QE and TE in these experiments are shown as a function of iteration time in Fig 2.7.

For all neighborhood functions with different radii the QE generally decreases and stabilizes after several training iterations (Figure 2.7, top two rows). For a given neighborhood function and radius, linear initialization leads to shorter QE stabilization
time than random initialization. This linear initialization advantage is increasingly more important with larger, more complex data sets. Also, the QE with linear initialization is slightly less than with random initialization. For all neighborhood functions the TE is also smaller when the linear initialization is used (Figure 2.7, bottom two rows). Linear (versus random) initialization therefore saves iteration time and may provide for better SOM results.

![Figure 2.7](image.png)

Figure 2.7. The QE (top two rows) and TE (bottom two rows) by the four neighborhood functions as a function of iteration number during the SOM batch training process. The top and third rows are for random initialization, and the second and bottom rows are for linear initialization. The left, central and right columns are for initial and final neighborhood radii of [3, 1], [1, 1] and [0.1, 0.01], respectively.

2.5.5 Sensitivity to neighborhood function

The effects of different neighborhood functions and radii on the QE and TE with linear initialization are seen on the second and the bottom rows of Fig 2.7. With larger
neighborhood radii both the “gaussian” and “ep” neighborhood functions give the smallest TE (Fig 2.7j). However, for a given neighborhood radius the “ep” leads to the smallest QE among the four neighborhood functions (Figures 2.7d and 2.7e). For small radii (e.g., $\sigma_t < 0.1$ in Figures 2.7f and 2.7l), both the QE and the TE for different neighborhood functions are the same.

Given these measures we further examine the SOM spatial patterns by changing neighborhood functions from the (“ep”) control run (Figure 2.8). Different neighborhood functions give slightly different wave amplitudes, but they all extract the progressive wave pattern. The “ep” control run is the best since its amplitude is closest to the true value, 1. The “cutgauss” and “bubble” give similar results, whereas the “gaussian” deviates the most. These findings are consistent with the QE results (Figure 2.7d).

![Figure 2.8](image-url)

Figure 2.8. Comparison of SOM results using four different neighborhood functions: “bubble” (bb), “gaussian” (gs), “cutgauss” (cg) and “ep”.

Tests with smaller radii give similar amplitude results, with the control run being the best (Table 2.2). With very small radii, however, all of the neighborhood functions give similar results. The explanation follows from equation (2.5), which shows that the neighborhood functions reduce to a delta function for very small $\sigma_t$ values.
\[ h_{ij} = \begin{cases} 1 & \text{if } c = i \\ 0 & \text{if } c \neq i \end{cases} \] 

such that it is only the weights of the “winner” that are updated in the training process.

Table 2.2. The minimum and maximum wave amplitudes of the SOM patterns from different neighborhood functions.

<table>
<thead>
<tr>
<th>( \sigma_t ) range</th>
<th>“bubble”</th>
<th>“gaussian”</th>
<th>“cutgauss”</th>
<th>“ep”</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>max</td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>[3, 1]</td>
<td>0.82</td>
<td>0.89</td>
<td>0.62</td>
<td>0.78</td>
</tr>
<tr>
<td>[1, 1]</td>
<td>0.86</td>
<td>0.86</td>
<td>0.61</td>
<td>0.77</td>
</tr>
<tr>
<td>[0.1, 0.01]</td>
<td>0.98</td>
<td>0.99</td>
<td>0.98</td>
<td>0.99</td>
</tr>
</tbody>
</table>

The SOM patterns with zero frequency of occurrence are excluded.

2.5.6 Sensitivity to noise

Can the SOM extract known patterns in the presence of random noise? We examine this by adding white noise to the linear progressive wave function. Results are given for a signal-to-noise ratio of 1 (equal variance for signal and noise as shown in Figure 2.9). Comments will also be made for experiments with higher and lower signal-to-noise ratios.

Figure 2.9. Data representation for the case of a sinusoidal function, plus random noise. Superimposed on the original noise-free data (thick line) is a noisy data (thin lines) with a signal-to-noise ratio of one.

Regardless of the neighborhood function employed, Figure 2.10 (which can be compared directly with Figure 2.8) shows that the noise becomes distributed amongst the SOM units. The same progressive waveform is extracted by the SOM, but with some
additive noise. Similar to the noise-free data the QEs are stable after four iterations (not shown) with the “ep” resulting in the smallest QE (the most accurate SOM patterns). When the SOM patterns of Figure 2.8 are subtracted from those of Figure 2.10, the residuals are white noise with variance dependent on the neighborhood functions. The residual (noise) variances are 0.035, 0.026, 0.013, and 0.008 for the “bubble”, “ep”, “cutgauss”, and “gaussian”, respectively. Thus among the four neighborhood functions the “gaussian” gives the smoothest SOM patterns, but at the expense of detail (e.g., the amplitude of the known pattern is least accurate).

Figure 2.10. Same as Figure 2.8 except with random noise (at a signal-to-noise ratio of one) added to the sinusoidal wave data prior to the training processes.

For comparison we perform an EOF analysis on the same noisy data, as shown in Figure 2.11. The first two leading EOF modes account for 26.1% and 25.4% of the variance, respectively. The sum of the two variances is 51.9%, which is close, but not equal, to the true value, 50%. Noise appears in both the EOF spatial and temporal patterns. Here the principal component (PC) time series are normalized to variances of 0.5 (the variance of the noise free data) so that the spatial eigenvectors have the same units as the original data, i.e., the wave amplitudes of the first two EOFs are about 1. Fitting smoothed cosine and sine waves to the first two EOFs, respectively, results in
residual white noise with variances of 0.027 and 0.014, respectively; they are about the same magnitude as those in the SOM patterns. These results indicate that the SOM extracts the known pattern from the noise as well as the EOF.

Figure 2.11. Time domain EOF analysis of the sinusoidal wave data with random noise added (with a signal-to-noise ratio of one). The top three panels are the first three leading mode EOFs (with the variance accounted for by each mode listed on top of each panel). The bottom panel contains the corresponding PC time series. The PC variance is normalized to be 0.5.

Tests with different noise levels of up to 200% of the original data variance (not shown) demonstrate that the SOM remains capable of extracting a known waveform from a noisy data set. The lower the noise level, the smoother the result, but even with 200% noise added, the SOM shows the progressive wave with residual variance amongst units varying between 0.014 and 0.065.

2.5.7 Performance evaluation with more complex patterns

All the above analyses are based on a given repetitive linear progressive wave, and when comparing SOM with EOF neither technique shows a clear advantage in feature extraction. What is the outcome of multiple repetitive patterns? To address this question we constructed a sequence of sine, step, sawtooth, and cosine waves and applied
both SOM and EOF analyses to these. The four input patterns are shown in Figure 2.12. Each of these four spatial patterns is repeated for 50 cycles and these cycles are connected to make up a time series of 200 frames.

![Four unique wave patterns](image)

Figure 2.12. The four unique wave patterns analyzed by SOM and EOF in section 4: (1) sine, (2) step, (3) sawtooth, and (4) cosine functions with amplitudes of 1, 0.8, 1, and 0.5, respectively.

We first use a 2×2 SOM with rectangular lattice structure, a sheet map shape, and linear initialization to extract the four known patterns. Experiments are repeated using all the four neighborhood functions with three sets of neighborhood radii to determine the best results by monitoring QE and TE over the batch training process (Figure 2.13, top two rows). By definition, smaller QE means higher accuracy, and zero QE means that all of the patterns in the input data are completely extracted. In this set of experiments the best result is with an “ep” neighborhood function of initial and final radii of 2 and 1, respectively. The four input patterns are exactly reproduced and with the proper frequencies of occurrence (25%), and the BMU time series further follow the input sequence (Figure 2.14).

While the TE is not the smallest in this case it is an irrelevant measure since it applies to the topological arrangement of the patterns. Since there are only four patterns their arrangement is not important. The TE becomes relevant as more patterns are extracted.

Increasing the map size to 2×3 allows us to investigate the appearance of fictitious patterns when the array size exceeds the number of known patterns. The same procedures are used as above, and the resulting QE and TE are shown in Figure 2.13.
Since fictitious patterns now appear with zero frequency of occurrence, there are more cases for which QE is zero than in the 2×2 SOM. Similarly the TE values are mostly zero. Figure 2.15 shows the SOM result with the “ep” neighborhood function and initial and final radii of 3 and 1, respectively. As in the 2×2 array the four known patterns are extracted (in units 1, 4, 5 and 6), and each with 25% frequency of occurrence. The array contains two fictitious patterns (units 2 and 3), each with zero frequency of occurrence that occur as transitions between the adjacent true patterns, and it is these fictitious patterns that help to minimize the TE. Thus even if we do not know a priori how many unique patterns exist in the input data set, it is safe to use a larger array SOM for feature extraction.

Figure 2.13. The QE (top and third rows) and TE (second and bottom rows) as functions of the SOM training iteration number for different neighborhood functions and radii. The top two rows are for map size of 2×2, and the bottom two rows are for map size of 3×3. The left, central and right columns are for larger ([2, 1] for 2×2 SOM and [3, 1] for 3×3 SOM), medium [1, 1] and small [0.1, 0.01] initial and final neighborhood radii, respectively.
Figure 2.14. A 2x2 SOM representation of the sequential pattern data of Figure 2.12. The upper 4 panels show the SOM patterns with the frequency of occurrence given at the top of each panel. The lower panel is the BMU time series.

Figure 2.15. The same as Figure 2.14 but for a 2×3 SOM.
Results from an EOF analysis on the same data set are shown in Figure 2.16. Of the three leading EOFs none look like the original patterns. Unlike the previous analysis of a simple repetitive waveform the EOF fails to extract the four different patterns presented here. The order in which the patterns are organized is not relevant to the analysis as demonstrated through random permutations of the pattern sequence (not shown). The SOM extracts the patterns while the EOF does not. The only differences between the ordered and random sequence are in the BMU and the PC time series for the SOM and the EOF, respectively.

![Figure 2.16](image)

Figure 2.16. Time domain EOF analysis of the sequential pattern data of Figure 2.12. The top three panels are the first three leading mode EOFs (with the variance accounted for by each mode listed at the top of each panel). The bottom panel gives the corresponding PC time series. The PC variance is normalized to be 0.5.

2.6 Summary and discussions

Both the conventional EOF method and novel neural network techniques, SOM and GHSOM, were introduced as feature extraction methods in meteorology and oceanography. The application of the SOM as a feature extraction technique was demystified by performing sensitivity studies on the tunable parameters of SOM implementation. A series of SOM feature extraction experiments were performed by using artificial data sets comprising known patterns.
The SOM accurately represented a time series of linear progressive sine waves of fixed amplitude, period and wavelength. The following results were found from studies of the sensitivity to the SOM adjustable parameters. (1) A larger map size resulted in slightly more accurate mapping. (2) A rectangular lattice appeared to be preferable for small size SOMs; however, a hexagonal lattice may be useful for larger map sizes. (3) Linear initialization had two advantages over random initialization: less iterations for QE convergence and smaller TE. (4) Among the four neighborhood functions the “ep” type gave the best results (smallest QE and TE). (5) While fictitious patterns appeared in the SOM, they were of no consequence since their frequencies of occurrence were zero.

The following parameter choices are recommended for SOM applications. For a small map size, a suitable SOM configuration is a rectangular neural lattice of "sheet" shape, linear initialization, "ep" neighborhood function, and batch training algorithm. As to the choices of the neighborhood radius and the training iterations, it is practical to monitor QE and TE in a searching process. Minimum QE indicates the most accurate representation of the input data. Minimum TE indicates the best SOM pattern organization such that adjacent to a BMU in the map lattice is the second-BMU. TE is not critical for a small size SOM; however, it may be important for a larger size SOM with increasing data set complexity.

The SOM extracted features from noisy data over a broad range of signal-to-noise ratios. Of the four neighborhood functions, the “ep” gave the most accurate patterns (smallest QE), whereas the “gaussian” gave the smoothest patterns with the lowest noise levels. While noise appeared superimposed upon the SOM units the known patterns were readily identified, and the SOM results were comparable with those by EOF.

As a further test between SOM and EOF, time series were constructed by linking together four unique pattern types. An SOM successfully extracted these four known patterns, whereas an EOF did not. The SOM also allows for data gaps and mean values in the input data (Richardson et al. 2003), making it more convenient to use than the EOF in some cases. On the other hand the EOF, by preserving variance, is capable of exactly reconstructing the data from which it derives by summing over all modes, whereas the
SOM by preserving topology does not provide a convenient way to exactly reproduce the data. So both methods have advantages and disadvantages.

With geophysical applications already made to satellite SST and winds (e.g., Richardson et al. 2003; Liu et al. 2006a), altimetry (e.g., Hardman-Mountford et al. 2003), in situ ADCP (Liu and Weisberg 2005b; Liu et al. 2006b), and gridded atmospheric data (e.g., Cavazos et al. 2002), we anticipate an increased use of the SOM for geophysical feature extractions. Other types of data and analyses amenable to SOM treatments include, but are not limited to, surface currents remotely sensed by HF-radar, climate-related data sets relative to the various identified climate indices, numerical model results, or any geophysical application for which large fields of information (data or models) are available for pattern recognition.
Chapter 3

Spatial Patterns of Ocean Current Variability from Moored ADCP Data
Using the Self-Organizing Map

3.1 Abstract

Patterns of ocean current variability are examined on the WFS by a neural network analysis based on the SOM, using time series of moored velocity data that span the interval October 1998 to September 2001. Three characteristic spatial patterns are extracted in a smoothed 3×4 SOM array with the default parameter choices in the SOM Toolbox (Gaussian neighbourhood function): spatially coherent southeastward and northwestward flow patterns with moderate currents, and a transition pattern of weak currents. On the synoptic weather time scale the variations of these patterns are coherent with the local winds. On the seasonal time scale the variations of the patterns are coherent with both the local winds and complementary SST patterns. The currents are predominantly southeastward during fall-winter months (from October to March) and northwestward during summer months (June through September). The spatial patterns extracted by the (nonlinear) SOM method are asymmetric, a feature that is not captured by the (linear) EOF method. Thus, we find for the synoptic weather and longer time scales: (1) southeastward currents are generally stronger than northwestward currents, (2) the coastal jet axis is located further offshore for southeastward currents than for northwestward currents, and (3) the velocity vector rotations with depth are larger in shallower water when the currents are southeastward relative when the currents are northwestward. With the SOM parameter choices recommended in Chapter 2 for the most accurate mapping, strong current patterns associated with severe weather forcing are
extracted separate from previously identified asymmetric upwelling/downwelling patterns associated with moderate currents and transitional patterns of weak currents.

3.2 Introduction

Most previous observational studies of WFS currents are based on limited current meter measurements, either over short time periods within a particular season or located relatively far offshore (Niiler 1976; Price et al. 1978; Weatherly and Martin 1978; Blaha and Sturges 1981; Mitchum and Sturges 1982; Marmorino 1982, 1983a,b; Mitchum and Clarke 1986a; Halper and Schroeder 1990; Weatherly and Thistle 1997). These studies generally offer little information on either the spatial patterns or the seasonal variability of the water motions over the shelf. Longer records with higher vertical resolution were initiated on the WFS in 1993 using ADCP. Based on velocity data collected at the 47 m isobath from October 1993 through January 1995, a seasonal cycle of the monthly mean currents was hypothesized to be driven by a seasonally varying shelf-wide baroclinic structure along with the winds (Weisberg et al. 1996). More recent and more extensive coverage by ADCP moorings over the inner shelf are available from June 1998 through December 2001, facilitating a systematic analysis of the spatial patterns of ocean current variability, which is the subject of this Chapter. Various analysis techniques are available, including conventional EOF and neural networks. Here we employ both of these techniques and compare their results. The purposes are two fold: (1) to describe the characteristic current patterns and their temporal variations and (2) to demonstrate the usefulness of the SOM Toolbox for such oceanographic applications. The rest of this Chapter is arranged as follows. Section 3.33 describes the data. Linear EOF results are reported in Section 3.4. Applications of nonlinear SOM methods are made in Sections 3.5 and 3.6, respectively, for two sets of SOM parameter choices. Section 3.7 gives a summary and discussions.

3.3 Data

Among the WFS moorings (Figure 3.1), five are bottom-mounted and located between the 10 m to 25 m isobaths, each with an upward looking ADCP measuring the
water column currents at 0.5 m intervals. From the 25 m to 50 m isobaths, there are six surface buoys, each with a downward-looking ADCP, similarly measuring the water column currents. Most of these moorings have been maintained with multiple deployments for more than three years (Fig 3.2), and the period October 1998 through September 2001 selected for analysis has the greatest commonality of data.

Figure 3.1. Map of the West Florida Shelf showing topography (isobaths units in m), acoustic Doppler current profiler (ADCP) moorings, and wind stations. A map of the whole Gulf of Mexico is inserted in the lower right corner, and the square box designates our study area.

Figure 3.2. Time line of the ADCP mooring records. The hatched area shows the time domain of the data on which this study is based.
Near surface, mid-depth, and near bottom velocity data are extracted from each profile so that each of the mooring sites is given equal weight in the analyses. All of the hourly velocity data are then low-pass filtered to eliminate oscillations on time scales shorter than two days, such as tides and inertial motions. The temporal mean and the principal axis currents at these three levels, averaged from October 1998 to September 2001 are shown in Figure 3.3. The mean currents tend to be along isobath and southeastward, and they are much weaker in amplitude than the current fluctuations. The principal axes also tend to align with the isobaths, and the ratios of the minor to major axes of the variance ellipses vary from 0.2 (at the 10 m isobath) to 0.7 (at the 50 m isobath). The ellipse orientations tend to rotate anticlockwise from the surface down to the bottom, with these net angular offsets increasing with increasing water depth.

Figure 3.3. Mean and principal axis currents at the (left) near-surface, (center) mid, and (right) near bottom levels, averaged from 2 day low-pass filtered data from October 1998 through September 2001. Note that the mean currents are much weaker than their deviations.

3.4 EOF patterns

Before performing SOM analyses, we begin with the established technique of time domain EOF. EOF analysis requires the input data to be continuous. CMP2 data is the shortest record, and it is only used to replace the gaps in the CM2 data, as the two
sites are in close proximity. Data gaps in the other records are filled through linear regression from adjacent stations. We perform the analysis by arranging the velocity time series in a two-dimensional array such that each velocity snapshot is in a single row vector and the time series of each velocity component is in a single column. All $u$ components are placed in the first half of the rows followed by all $v$ components. Thus, the input matrix consists of 60 columns ($10$ stations $\times 3$ levels $\times 2$ components) $\times 25585$ rows (hours). The temporal mean values are removed prior to the EOF analysis.

The first EOF mode accounts for 65.0% of the subtidal velocity variance. The eigenvector shows a coherent pattern of along-shelf flows shoreward of the 50 m isobath (Fig 3.4). The currents tend to be along isobath at the mid levels, whereas they tend to turn onshore at the near surface level and offshore at the near bottom level. That is, the current vectors rotate counterclockwise from the surface down to the bottom, and this rotation is more pronounced in deeper water. Thus, relative to the shoreline, for downwelling the horizontal flow field pattern tends to be convergent at the near surface and mid levels, and divergent at the near bottom level, and conversely for upwelling. The alongshore component tends to be largest around the 25 m to 30 m isobaths, indicative of a coastal jet. This is consistent with the coastal jet structure obtained in a constant density numerical model simulation for the WFS (Li and Weisberg 1999a). The associated PC shows the temporal variation of this spatial pattern, which occurs at both synoptic weather and seasonal time scales. In fall-winter (summer) this first mode PC tends to be negative (positive) indicating that the inner shelf currents tend to be southeastward (northwestward). These PC variations are visually coherent with the local winds, suggesting that the local winds are the main driving force for the currents over the inner shelf, and this is consistent with the observed turning in the implied surface and bottom Ekman layers.

The second mode spatial pattern (not shown) consists of northward currents along the 50 m isobath and southward currents near the coast, indicating an inner shelf shear structure. It only accounts for 6.4% of the total variance. Since these patterns contain both the synoptic and seasonal scales, further low-pass filtering does not affect them much (not shown).
Figure 3.4. Time domain empirical orthogonal function (EOF) analysis of the 2 day low-pass filtered currents at the three levels from October 1998 through September 2001. (top) First mode eigenvectors. (middle) First mode PC time series. (bottom) Five day low-pass filtered, daily subsampled winds at Venice station. The first mode EOF accounts for 65.0% of total variance.

3.5 Smoothed SOM patterns

The same data are used for the SOM analysis except that the data gaps are ignored and data from moorings CM2 & CMP2 are treated as two separate time series. Thus, the input matrix consists of 66 columns (11 stations × 3 levels × 2 components) × 25585 rows. Also, the temporal mean values are retained. The size of the SOM array must be specified prior to the training process. After several test runs, an SOM size of 3×4 was selected. This is large enough to represent the characteristic velocity features and small
enough to be visualized and interpreted. The default settings of the SOM parameters in the SOM Toolbox are used, i.e., a hexagonal lattice, “sheet” map shape, linearly initialized weights, batch training, and "gaussian" neighborhood function with initial and final radii of 4 and 1, respectively.

3.5.1 The SOM array

The 3×4 SOM array results are shown in Fig 3.5. The left-hand-side of the array is populated by spatially coherent southeastward currents, while the right-hand-side shows coherent northwestward currents. Similar velocity patterns are located adjacent to one another in this SOM mapping, while dissimilar patterns are at opposite ends of the SOM space, with a continuum of change occurring across the array. For each time frame (spatial snapshot) of the velocity time series, the best-matching unit (BMU), or the “winner”, can be identified according to the minimum Euclidian distance when that frame is compared to the 12 SOM units. Hourly time series of the BMU for the input data is shown in the bottom panel of Figure 3.5. The temporal evolution of the BMU is coarse, as the input velocity data (2-day low-pass filtered) includes both the synoptic and seasonal variations. For a synoptic event, the BMU may switch back and forth between patterns in a matter of days. In order to quantify the representation of each unit, the frequency of occurrence is computed by summing the number of selections of that unit (the BMU) divided by the total record length (the number of input vectors). The relative frequency of occurrence of each unit is shown in the upper-right corner of each map in Figure 3.5. Thus, the SOM unit 1 represents 17.4% of the input (subtidal) currents, showing a pattern with the strongest southeastward currents. Its opposite counterpart, unit 11, represents 17.3% of the data, showing a pattern with the strongest northwestward currents.

3.5.2 Synoptic variability

The synoptic scale variations of the input velocity data from the BMU evolution are better viewed by focusing in on specific time periods. As examples we choose four
representative months (December 1998, August 1999, March 2000 and June 2000), as shown in Figure 3.6 with the BMU plotted along with the wind time series. From the BMU we see the preference for units 1~6 when the local winds are upwelling favorable (directed southward), versus units 10~12 when the winds are downwelling favorable (directed northward). Thus, the SOM units 1~6 represent characteristic upwelling flow patterns, while the units 10~12 represent characteristic downwelling flow patterns. Units 7~9 are transitional patterns. Note that the change of the BMU is highly coherent with the local winds, suggesting that the main driving force for the currents on the inner shelf over the synoptic weather band is the local winds, consistent with the WFS numerical model findings, e.g., He et al. (2004).

We note that the upwelling and downwelling patterns extracted by the SOM are asymmetric (Figure 3.5). The currents in the upwelling patterns are generally stronger than those in the downwelling patterns, and the coastal jet is located around the 25 m to 30 m isobaths in the upwelling patterns, whereas it is located closer to the coast at the shallowest 10 m station in the downwelling patterns. Moreover, the velocity vector rotation with depth differs among the upwelling and downwelling patterns. In the upwelling patterns, the angular offset of about 10° along the 50 m isobath is smaller than the 20° offset at the 10 m isobath, i.e., the rotation increases toward the coast. The downwelling patterns, in contrast, have angular offsets decreasing toward the coast. These asymmetric behaviors cannot be identified in the linear EOF analysis.

3.5.3 Seasonal variability

Although masked by the synoptic variations, the seasonal variations may still be identified in the Figure 3.5 bottom panel. For example, if measured in terms of BMU selectivity, the probability of units 10~12 is low during fall-winter (from November through March), and similarly, the probability of units 1~6 is low during summer (from June to September).

To better describe the seasonal variation, 15-day low-pass filtered velocity data are used as input to the same SOM calculations. Similar to those of the 2-day low-pass
filtered results, the 3×4 SOM shows three sets of flow patterns (Figure 3.7). In the fall-
winter patterns, the currents tend to be southeastward in along-shelf direction with a
coastal jet located around the 30 m isobath. The near bottom currents have obvious
onshore component near shore. In the summer patterns, the currents are weaker.
However, they are northwestward on the inner shelf with a weak current core around the
20–25 m isobaths.

The climatological monthly mean frequencies of occurrence of the three
characteristic sets of patterns in the SOM are shown in the second bottom panel of Figure
3.7. Units 1–6 dominate the winter half year from October through April, with peak
frequency of occurrence in October, and units 10–12 dominate the summer months (June,
July and September). The transition patterns, units 7–9, may occur in all the months, but
with lower frequency of occurrence. Thus, units 1–6 represent the characteristic fall-
winter patterns, whereas units 10–12 represent the characteristic summer patterns.

The climatological monthly mean winds are strong and southward from October
to January, which may partially explain the occurrence of the fall-winter current patterns
during those months (Figure 3.7, bottom panel). The mean winds are northward in June
and July, which may partially explain the presence of the summer patterns in those two
months. The fact that the fall-winter mean winds are much stronger than the summer
mean winds helps to explain the asymmetric strengths of the currents in the fall-winter
and summer seasons.

This SOM representation of the seasonal cycle is consistent with a monthly mean
velocity climatology averaged from October 1998 to September 2001 shown in Figure
3.8. From October through April, the mean currents are southeastward, with the strongest
currents in January. Following a transition in May, the mean currents turn northwestward
from June through September, but with weaker or even southeastward currents in August.
In fall-winter months, the near bottom currents generally have an onshore component on
the inner shelf, and the coastal jet is located around 25–30 m isobaths. In the summer
months (June-July), the coastal jet is located around the 20–25 m isobaths. These
findings compare well with those of the 15-day low-pass filtered SOM results.
Overlaid on these (Figure 3.8) maps is the monthly mean SST climatology, composited using the five-year daily optimum interpolation product from 1998 to 2002 of He et al. (2003). The seasonal variation of the currents is consistent with that of the SST. In winter months, the SST is lower along the coast and higher in the deep ocean area, with a horizontal temperature gradient approximately pointing onshore in the across-shelf direction. This winter SST pattern results in a density-induced baroclinic current flowing along-shelf toward the southeast, which would add constructively with the southeastward wind-driven current. The monthly mean SST gradient is generally not as obvious in summer. However, there is a warm tongue located over the mid shelf in August, which favors a southeastward current on the inner shelf. Recently, Ohlmann and Niiler (2005) found the seasonal cycle of the drifter-derived surface currents on the WFS was not pronounced. Actually, all of their drifters were initially deployed in the northern Gulf of Mexico and no one in the south part of the WFS; Thus, the northwestward currents on the WFS were not adequately resolved.

3.5.4 Inter-annual variability

Our analysis shows that in August, the southward flow patterns outnumber the northward flow patterns (Figure 3.7), consistent with the climatological monthly mean currents (Figure 3.8). This August reversal warrants further study. We calculate the monthly mean frequency of occurrence of the three characteristic patterns, and show the time series in Figure 3.9. Note that since the calculation is based on 35 months, it is not surprising that the values of the frequency of occurrence for individual months are small (<2.5%). We note that the summation of all values in Figure 3.9 equals 100%. In August 1999 both the southward and northward patterns have about the same frequencies of occurrence. In August 2000, the northward patterns outnumber the southward patterns by 0.5% in the frequency of occurrence. However, in August 2001 the southward patterns outnumber the northward patterns by 1.5%. An average of the numbers across these three years results in the preferred southward current pattern. This raises the question on whether the August reversal derives from inter-annual variability as opposed to being a robust feature of the annual cycle.
Figure 3.5. Top 12 panels show a Gaussian smoothed $3 \times 4$ SOM of the 2 day low-pass filtered velocity data at the three levels from October 1998 through September 2001. The relative frequency of occurrence of each pattern is shown in the upper right corner of each map. Bottom panel shows the temporal evolution of the BMU.
Figure 3.6. Time series of the Venice winds and the BMU for the $3 \times 4$ SOM during four separate months: (top to bottom) December 1998, August 1999, March 2000, and June 2000. The wind data were 2 day low-pass filtered and were subsampled at 3 hour intervals.
Figure 3.7. Top 12 panels are the same as Figure 3.5 except for the 15-day low-pass filtered velocity data. Bottom two panels are climatological monthly frequency of occurrence of the three characteristic patterns in the SOM and winds at Venice, Florida, both averaged over 3-year period October 1998 – September 2001.
Figure 3.8. Climatological monthly mean sea surface temperature (SST) superimposed with the currents at the near-surface, mid, and near-bottom levels. The SST data were averaged from 5-year daily maps, 1998–2002; the currents were averaged from 2-day low-pass filtered data, October 1998–September 2001.

Inter-annual variation of the three dominant composite current patterns is seen during these three years. The total frequency of occurrence of the southeastward flow patterns (1–6) during the winter half year (October through March) is 10.8%, 9.2% and 11.2% in 1998–1999, 1999–2000 and 2000–2001, respectively; and that of the northwestward flow patterns (10–12) in summer (June and July) is 3.6%, 3.0% and 2.5% in 1999, 2000 and 2001, respectively. These inter-annual changes may be related to inter-annual variations in either the local (e.g., winds, Figure 3.9), deep-ocean forcing, or some combination thereof (Weisberg et al. 2005). Additional data being collected will
eventually be able to describe these inter-annual variations more clearly, and this highlights the need for long time series as part of the evolving coastal ocean observing systems that are presently under consideration.

Figure 3.9. Monthly mean frequency of occurrence of the three characteristic patterns in the (bottom) SOM and the (top) Venice winds. The wind data were 30-day low-pass filtered and 3-day subsampled.

3.6 The most accurate SOM patterns

Our sensitivity analyses in Chapter 2 suggest that while the SOM is a reliable tool in feature extraction, different controlling parameters may give slightly different results. For example, as regards neighborhood functions the “gaussian” may give the smoothest patterns, whereas the “ep” may give the most accurate mappings. In this Section, the SOM parameters choices follow the suggestions in Chapter 2 for the most accurate mapping, i.e., a rectangular lattice, “sheet” map shape, linearly initialized weights, batch training, and a searching procedure for neighborhood function are used. The SOM experiment is repeated for all the four neighborhood functions with different radius values, and the resulting average QE is examined to search for the most accurate SOM mapping. As expected, the “ep” neighborhood function gives the lowest average QE
among the four types, and when the neighborhood radius shrinks to the very small value, all the QE values converge to that of the “ep” type with the radius of 1. In accordance with Figure 3.10 the SOM result using the “ep” neighborhood function with the radius of 1 and 10 iterations is chosen as the most accurate mapping as given in Figure 3.11.

Figure 3.10. QE as functions of the SOM training process iteration number for the four different neighborhood functions applied to the WFS velocity data. The top, middle and bottom panels are for three different pairs of initial and final neighborhood radii: [3, 1], [1, 1], and [0.1, 0.01], respectively.

Similar to those of the smoothed SOM results, three sets of coherent current patterns are identified: southeastward, transitional and northwestward currents, located in the top, middle and bottom rows of Figure 3.11, respectively. Flow asymmetries are found between the upwelling patterns (4, 7 and 10) and the downwelling pattern (6), i.e., when southeastward currents are compared with northwestward currents the magnitudes are larger, the coastal jet is located further offshore, and the velocity vector rotations with depth are larger in shallower water.

In addition to those of the smoothed SOM results, extreme upwelling and downwelling events, patterns 1 and 3, respectively, are extracted, with maximum current speeds greater than 20 cm/s. These strong current patterns relate to the largest synoptic weather events, with frequencies of occurrence of 1-3%. As seen in the Figure 3.11 bottom panel (note the order of the BMUs on y-axis are rearranged for clarity), the strong
downwelling pattern 3 appears in August through October of each year due to tropical storms and hurricanes; an example is the September 19-22, 1999 tropical storm Harvey event (top panel of Figure 3.12). The strong upwelling pattern 1 appears sporadically in fall and winter due to the passage of the strongest cold fronts and also on the trailing side of tropical storms and hurricanes. Examples of these are the January 21-24, 2001 upwelling event by a winter cold front (bottom panel of Figure 3.12) and the September 14-15, 1999 event by hurricane Floyd (top panel of Figure 3.12). The extreme upwelling and downwelling patterns identified here are less asymmetric than the moderate event patterns previously identified in the smoothed SOM results, especially for the currents in shallowest water. For example, the coastal jet cores for extreme upwelling and downwelling patterns are located around the 30 m isobath and the velocity vector rotations with depth are reduced. This is due to increased mixing with external forcing intensity. An upwelling and downwelling asymmetry is attributed to stratification through the effects of thermal wind on the bottom Ekman layer flows (Weisberg et al. 2001). Extreme weather events cause increased mixing (reduced stratification) and hence a decrease in current response asymmetry.

3.7 Summary and discussions

Both linear EOF and nonlinear neural network (based on the SOM) analyses were employed to examine characteristic patterns of the ocean current variability on the inner WFS, using moored (ADCP) velocity time series that span the three-year interval October 1998 to September 2001. The first mode EOF shows a coherent spatial pattern of along-shelf currents with a coastal jet centered around the 25 m to 30 m isobaths, varying in time (as given by the fluctuating PC time series) on both synoptic and seasonal time scales. These spatial and temporal patterns are such that the currents tend to flow southeastward in winter and northwestward in summer, with an anticlockwise vertical rotation from the surface down to the bottom consistent with Ekman and geostrophic dynamics. Similar current reversals also occur on synoptic scales in response to the wind reversals.
Figure 3.11. Same as Figure 3.5 but for the most accurate SOM mapping. Note the velocity vector scales are different from those in Figure 3.5 and the order of the BMUs on y-axis are rearranged for clarity.
Figure 3.12. Time series of the local winds and the BMU, zoomed in on the bottom panel of Figure 3.11, for September 1999 and January 2001.

A Gaussian smoothed 3×4 SOM array also shows characteristic current patterns. These group into three composite categories: southeastward and northwestward flow patterns with strong currents, and transitional patterns with weak currents. The synoptic, seasonal, and inter-annual variations of these current patterns are shown using different arrangements of the BMU time series. The synoptic variations of the currents are coherent with the local winds. The seasonal variation of the currents is coincident with the variations of both the local winds and the seasonal SST patterns. The currents are dominantly southeastward during fall-winter months (from October to March), and northwestward during summer months (from June through September), although an anomaly occurs in August that may be due to inter-annual variations in winds or deep-ocean influence. The summer currents tend to be weaker than the fall-winter currents.
Both the EOF and SOM techniques are very useful in extracting current patterns. The linear EOF, ordered on variance reduction, form a complete set from which the data may be identically reconstructed. The nonlinear SOM, minimizing Euclidian distance between learned pattern vectors and data vectors, preserves the data topology rather than the variance. While the data may not be identically reconstructed the resulting patterns may be more like the data than any of the leading EOFs. Hence for pattern recognition and description the SOM may have advantage over the EOF.

A significant finding identified herein by the SOM, and not by the EOF, is that the patterns of current variability are asymmetric with respect to upwelling (southeastward) and downwelling (northwestward) flows. At the synoptic weather and longer time scales, the currents in the upwelling patterns are generally stronger than those in the downwelling patterns, and the coastal jet is located around the 25 m to 30 m isobaths in the upwelling patterns, whereas it is located closer to the coast at the shallowest 10 m isobath station in the downwelling patterns. Moreover, the velocity vector rotations with depth differ among the upwelling and downwelling patterns. In the upwelling patterns, the angular offset of about 10º along the 50 m isobath is smaller than the 20º offset at the 10 m isobath, i.e., the rotation increases toward the coast. The downwelling patterns, in contrast, have angular offsets decreasing toward the coast. Similarly, on the seasonal time scale, the currents in the fall-winter (upwelling) patterns are much stronger than those in the summer (downwelling) patterns, but the coastal jet for both of these winter and summer patterns is located around the 20 m to 30 m isobaths. Asymmetry on the seasonal time scale is in part explained by stronger winds in fall-winter than in summer. However, in contrast with the seasonal time scale, the wind reversals at the synoptic time scale are of comparable values. Asymmetry at the synoptic scale has a basis in model simulation as well as in the observations [Weisberg et al., 2001], where under stratified conditions thermal wind effects lead to disproportionately larger responses (in both magnitude and offshore scale) for upwelling favorable winds over downwelling favorable winds.

Another attribute of the SOM is that the temporal mean does not have to be removed prior to the analysis, allowing the output patterns to be visualized in the same
form as the original data. This advantage is not that obvious in our analysis, because the temporal mean currents are much weaker than their deviations. However, it is very useful when the temporal mean values are larger, for instance, in sea surface temperature analyses (Richardson et al. 2003; Chapter 5 of this Dissertation).

Finally, the self-organizing algorithm handles missing data without a priori estimation. From this point of view, the (nonlinear) SOM is more convenient to use than the (linear) EOF.

With the SOM parameter choices recommended in Chapter 2 for the most accurate mapping, strong current patterns associated with severe weather forcing are extracted separate from previously identified asymmetric upwelling/downwelling patterns associated with moderate currents and transitional patterns of weak currents. The extreme upwelling and downwelling patterns identified here are less asymmetric than the moderate event patterns, due to increased mixing with external forcing intensity. This additional finding is attributed to the use of the “ep” neighborhood function, resulting in less smoothing.
Chapter 4

Characteristic Patterns of Ocean Currents from Joint Self-Organizing Map Analyses of HF Radar and ADCP Data

4.1 Abstract

Patterns of ocean current variability are extracted from a joint HF-radar and ADCP data set collected on the WFS from August to September of 2003 using a SOM technique. 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 with 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 dynamically consistent ocean current patterns sampled by HF-radar and other supporting in-situ measurements.

4.2 Introduction

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, 2006; 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). With an ever-increasing
quantity of data, there is a need for effective pattern recognition techniques for extracting characteristic patterns of variability from long time series of surface current maps.

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 often been applied to obtain characteristic flow patterns from HF-radar data. While averaging is useful, it is generally difficult to define suitable time and length scales over which to average, especially on the continental shelf where currents may be anisotropic and nonhomogeneous depending on the processes and time scales involved (Liu and Weisberg 2005b).

EOF analyses are effective for reducing large correlated data sets into a smaller number of patterns ordered by variance, and applications to HF-radar are given, for example, by Kaihatu et al. (1998); Marmorino et al. (1999); Lipphardt et al. (2000); and Beckenbach and Washburn (2004). A drawback for HF-radar applications is that conventional EOFs require gap free data sets, which is generally not the case for HF-radar. Also, by subtracting a temporal mean, EOFs generally yield anomaly fields, and as a linear method EOFs are of limited use in extracting nonlinear information (Hsieh 2001).

The SOM is an effective method for feature extraction and classification (see Chapters 2 and 3). 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 analyzing HF-radar data.

As with analysis techniques, all observational techniques have advantages and limitations. HF-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 provides a three-dimensional view of the ocean circulation. In combination, however, the HF-radar and ADCP attributes provide a powerful system of measurements for describing the ocean circulation (e.g., Paduan and Rosenfeld 1996; Shay et al. 1998b; Shen and Evans 2001; Chant et al. 2004; Ullman and Codiga 2004).
The present paper applies the SOM in analysis of a joint HF-radar and ADCP data set collected on the WFS. The purposes are two-fold. 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. A brief description of the data sets is given in Section 4.3. The SOM performance and the results are presented in Section 4.4, including patterns associated with semidiurnal, diurnal and subtidal frequency bands. Section 4.5 provides a summary and discussion.

4.3 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, respectively) from 23 August through 26 September 2003. Shay et al. (2005) provides a detailed accounting of this deployment (Figure 4.1), the WERA data collected, their processing and calibration, and a description of the observed circulation. Here we decimate the data set onto a coarser (0.05 degree in longitude and latitude) grid by linear interpolation, and we retain only those locations for which a 60% or higher data coverage are provided. Data gaps within this 60% interval are retained as part of the SOM analysis demonstration. The time series at each grid point are further preconditioned by low-pass filtering (with a three-hour cut off) the half-hourly samples and resampling hourly.

Concurrent ADCP data are from three moorings deployed at the 10 m, 20 m and 25 m isobaths offshore of Sarasota, FL (Figure 4.1). 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, middle level and near bottom bins are used for the joint SOM analyses with the WERA data.
Figure 4.1. Map of the West Florida Shelf showing topography (isobaths units in m), WERA coverage (grey area), ADCP moorings (C10, C11 and C15), coastal sea level (St. Petersburg), and wind (Venice and C10) and WERA (Coquina Beach and Venice) stations. A map of the whole Gulf of Mexico is inserted in the upper-left corner, with a square box designating our study area and a thick line showing the track of the tropical storm Henri.

Complimentary data sets include hourly wind data sampled at the C10 surface buoy and at Venice, FL C-MAN station (downloaded from http://www.ndbc.noaa.gov/) and hourly coastal sea level data at St. Petersburg, FL (downloaded from http://www.co-ops.nos.noaa.gov/). These data are used to verify some of the dynamics interpretations, such as upwelling/downwelling, 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 Figure 4.2. Both the clockwise and anticlockwise spectra show kinetic energy peaks at semidiurnal, diurnal and synoptic frequency bands. To examine the ocean processes on these time scales, the velocity data are filtered in three bands: 6 to
18 h, and 18 to 36 h and >36 h using a truncated Fourier transform after applying a 10% cosine taper to the ends. The tapered ends were discarded before further analyses.

![Rotary spectral analyses](image)

**Figure 4.2.** Rotary spectral analyses of the winds at Venice, Florida (top panel) and the near surface currents (ADCP top bin) at mooring C10 (bottom panel). CW and CCW are average kinetic energy density functions associated with the clockwise and counterclockwise components of velocity hodograph ellipse, respectively. The red vertical line in the bottom panel shows the local inertial frequency.

### 4.4 SOM analysis

Prior to discussing the joint data analyses performed over the semidiurnal, diurnal and synoptic frequency bands by SOM, we must first define the tunable parameter choices required of the analyses. Liu et al. (2006b) offer a practical method for choosing among the SOM parameters. The average quantization error (QE) monitors the quality of the SOM mapping during the training process. As the average distance between each data vector and the SOM best-matching unit (BMU), minimum QE indicates the most accurate representation of the input data. Given a 3×4 map size, a rectangular lattice, “sheet” map shape, linearly initialized weights, and batch training as determined to be
most appropriate in Liu et al. (2006b), SOM analyses were repeated for differing neighborhood functions and radii, and the resulting average QE were examined to search for the most accurate SOM mapping. As expected from previous experiments, the “ep” neighborhood function with the radius of 1 provides the best choice. Figure 4.3 shows the resulting QE convergence for the analyses performed over each of the three frequency bands.

Figure 4.3. Normalized QE as a function of iteration number in the batch training process for the SOM analyses of the 36 h low-pass, 18 h~36 h and 6 h~18 h band-pass filtered velocity time series, respectively. All the QE sequences are first subtracted by their own minimum values and then added integers from 0 to 2, individually, so they can be differentiated in one figure.

4.4.1 Semidiurnal frequency band

The 12 coherent patterns extracted from the 6 h to 18 h band-pass filtered joint WERA and ADCP data are shown in Figure 4.4. These patterns are arranged on the SOM in such a way that the most dissimilar patterns are located farthest away from each other, e.g., the opposite patterns of the SOM units 1 and 2 nearly mirror each other. As revealed by the WERA data, the currents are horizontally uniform within this small observational domain. The ADCP data further show very little variation with depth, indicating that the semidiurnal currents are predominately barotropic. These findings agree with previous findings on the WFS $M_2$ tide (e.g., Koblinsky 1981; He and Weisberg 2002a).
These semidiurnal current patterns may be classified into two categories: patterns with stronger (SOM units 1, 4, 10, 11, 12, 9 and 3) and patterns with weaker (SOM units 2, 5, 6, 7 and 8) currents. Additionally we see what appears to be a neap-spring tide modulation in the BMU time series paralleling that at the St. Petersburg tide gauge station. For instance, during the spring tide interval, 8 to 13 Sept, the SOM unit sequence is 3→2→1→4→10→11→12→9, which consists of the generally stronger current patterns, whereas during the neap-tide interval, 1 to 7 Sept, 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 Figure 4.2, the previous tidal analyses cited and Shay et al. (2006) tidal analyses.

4.4.2 Diurnal frequency band

The patterns extracted for the 18 h to 36 h band are shown in Figure 4.5. In contrast with the semidiurnal bands, these currents are stronger, less horizontally homogeneous, and they exhibit large vertical shear. For instance, the SOM units 3, 6, 7, and 10 show near surface and near bottom currents nearly out of phase and characteristic of a gravest (vertical) mode 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 to 13 Sept) the SOM unit sequence is 1→2→3→6→12→11→10→7→1. By contrast, during the weak intervals the pattern sequence is largely 4→5→9→8. In both cases, the sense of rotation is clockwise, but in the strong current case there is larger vertical shear.

The temporal evolution of these stronger or weaker diurnal band currents may be explained in terms of a combination of inertial and tidal dynamics. Well defined, but relatively small, barotropic diurnal tidal oscillations are documented for the study region (He and Weisberg 2002a). 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 periods of the $K_1$ and $O_1$ tides. For the interval 29 Aug through 5 Sept, 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 appear to be suppressed by the passage of the tropical storm Henri during 5 to 8 September as the water column destratified under strong vertical mixing influence. With restratification after Henri, and a succession of strong near-inertial variations in wind forcing, we see the appearance large amplitude, first baroclinic mode near-inertial oscillations in the C10 ADCP data from 10 to 13 Sept. 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 and vertically sheared units 6 and 7. It is the combined analyses of the WERA and the ADCP data that allows for this identification of the near-inertial modulation of the currents within the diurnal frequency band.

4.4.3 Subtidal frequency band

The SOM extracted patterns for the 36 h low-pass filtered data are shown in Figure 4.6. 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 a largely locally Ekman-geostrophic circulation response to winds on the WFS (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 data set) are 6 and 4, with occurrences of 24.1% and 16.7%, respectively. Somewhat surprising are the number of patterns with large cross-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 SOM pattern evolution. Beginning on 28 Aug when the winds are from the southeast, we see an approximate six-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 2005b; 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 near shore jet fed by a large, surface confined onshore flow. Accompanying pattern 12 is a rapid rise in sea level. This indicates a mass readjustment that accounts for the near shore 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 near shore 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 along shore flow at mid level and onshore flow at depth. During 12 to 15 Sept, 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 due to a summer buoyancy contribution. During 16 to 22 Sept, 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
along-shore component of the response is largest at mid depth and farther offshore. Note, for example, that the mid depth current at the 25 m isobath (mooring C10) is stronger than those at 20 m and 10 m isobaths (moorings C11 and C15). Second, the velocity vector cyclonic (to the left) rotation 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 (2005b) 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 the third element of asymmetry found here. The currents in the downwelling pattern (12) are stronger than those in the upwelling pattern (4). The explanation may reside in several factors. First, the southerly winds of tropical storm Henri during 5 to 6 Sept were stronger than the subsequent northerly winds during 9 to 11 and 16 to 17 Sept. Second, the across shelf temperature structure favors a northward along shelf flow in summer (Weisberg et al. 1996; Liu and Weisberg 2005b; Liu et al. 2006a). Third, the baroclinic effects of estuarine fresh water flux, tends to concentrate a downwelling coastal jet closer to the coast than an upwelling coastal jet (e.g., Zheng and Weisberg 2004).

4.5 Summary and discussions

The SOM was applied to a joint WERA and ADCP data set on the WFS from 26 Aug through 23 Sept 2003. Current patterns were extracted and analyzed for semidiurnal, diurnal and subtidal frequency bands. At semidiurnal time scale, current patterns are relatively homogeneous horizontally and uniform vertically, and exhibiting clockwise rotation and fortnightly modulation with time indicative of a barotropic, $M_2$ and $S_2$ tide predominance.

At diurnal time scale, the patterns are less homogeneous horizontally and more baroclinic vertically. While all such patterns are clockwise polarized they group into two sets, those with relatively large and small amplitudes. The strong current patterns show pronounced baroclinic structure, whereas the weak current patterns appear to be more
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.

At subtidal time scales, the current patterns are 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 are observed vertically. For both upwelling and downwelling patterns the velocity vectors rotate to the left with depth, consistent with an Ekman-geostrophic response of the coastal ocean to wind forcing. Pattern evolution, as shown by the BMU time series, is also consistent with the evolution of the local wind and sea level time series. Similar to previous studies asymmetries are identified in the upwelling and downwelling patterns. These asymmetries are manifest primarily as more near shore confined responses under downwelling than under upwelling favorable winds.

By combining the WERA sampled surface current fields with the ADCP sampled water column currents a much more complete representation of the velocity fields is obtained when compared with either of these two methods alone. Relatively strong across shelf oriented surface currents under certain wind conditions quickly adjust with depth in such away as to conserve mass flux and satisfy the Taylor Proudman Theorem, showing that even in shallow water on a very gently sloping shelf the circulation is fully three-dimensional, time dependent and with complex spatial patterns, requiring an integrated multi-sensor array of instruments for monitoring and description. As a descriptive analysis technique, we conclude that the SOM is very well suited for combining the attributes of such HF-radar and fixed sensor arrays in characterizing the coastal ocean flow fields, especially given the ever-increasing quantity of data becoming available.
Figure 4.4. The top panel shows the 6 h to 18 h band-pass filtered St. Petersburg sea level. The second panel (i.e., the BMU time series) and the bottom 12 panels show characteristic temporal and spatial patterns of the 6 h ~ 18 h band-pass filtered currents extracted by a 3×4 SOM. In the SOM, the relative frequency of occurrence of each pattern is shown in the upper-left corner of each map. The grey arrows designate the WERA velocity vectors, and the red, blue and black arrows symbolize the near surface, middle, and near-bottom level ADCP velocity vectors, respectively.
Figure 4.5. The top panel shows the hourly winds at Venice, Florida. The second and third panels are depth-time plots of the 18 h to 36 h band-pass filtered mooring C10 across- and along-shelf velocity components, respectively. The bottom 13 panels are the same as those in Figure 4.3 but for the 18 h to 36 h band-pass filtered data.
Figure 4.6. The top two panels are the 36 h low-pass filtered buoy C10 winds and St. Petersburg sea level, respectively. The bottom 13 panels are the same as those in Figure 4.4 except for the 36 h low-pass filtered data.
Chapter 5

Patterns of Sea Surface Temperature Variability Using Growing Hierarchical Self-Organizing Maps

5.1 Abstract

Neural network analyses based on the SOM and the GHSOM are used to examine patterns of the SST variability on the West Florida Shelf from time series of daily SST maps from 1998 to 2002. Four characteristic SST patterns are extracted in the first layer GHSOM array: winter and summer season patterns, and two transitional patterns. Three of them are further expanded in the second layer, yielding more detailed structures in these seasons. The winter pattern is one of low SST, with isotherms aligned approximately along isobaths. The summer pattern is one of high SST distributed in a horizontally uniform manner. The spring transition includes a mid shelf cold tongue. Similar analyses performed on SST anomaly data provide further details of these seasonally varying patterns. It is demonstrated that the GHSOM analysis is more effective in extracting the inherent SST patterns than the widely-used EOF method. The underlying patterns in a data set can be visualized in the SOM array in the same form as the original data, while they can only be expressed in anomaly form in the EOF analysis. Some important features, such as asymmetric SST anomaly patterns of winter/summer and cold/warm tongues, can be revealed by the SOM array but cannot be identified in the lowest mode EOF patterns. Also, unlike the EOF or SOM techniques, the hierarchical structure in the input data can be extracted by the GHSOM analysis.
5.2 Introduction

The WFS is a broad, gently sloping continental margin influenced by the Gulf of Mexico Loop Current system located seaward of the shelf break (Molinari et al. 1977; Huh et al. 1981; Paluszkiewicz et al. 1983; He and Weisberg 2003b; Weisberg and He 2003) and by local wind and buoyancy forcing, including the fresh water of the Mississippi River generally found at mid-shelf in spring and summer (Gilbes et al. 1996; He and Weisberg 2002b). The shelf circulation is dynamically linked to its varying water properties, and particularly to temperature, which exerts a primary control on density. The close relationship between the shelf water temperature variability and the variability of net surface heat flux and ocean circulation are reported in recent studies (He and Weisberg 2002b, 2003a; Weisberg and He 2003). Thus, a description of the characteristic patterns of SST variability adds to our understanding of the shelf circulation and its air-sea interactions.

A five-year set of daily SST composite maps on the WFS are analyzed using the SOM and the GHSOM techniques. The purposes are two fold: (1) to demonstrate the usefulness of the GHSOM in feature extraction, and (2) to describe the characteristic SST patterns on the WFS and their temporal variations. The rest of this Chapter is arranged as follows. The SST data set is described in Section 5.3. Applications of linear, EOF and nonlinear, GHSOM methods are described in Sections 5.4 and 5.5, respectively. The results are discussed and summarized in Section 5.6.

5.3 Data

A daily, composite SST time series was generated for the WFS by merging SST data from the Advanced Very High Resolution Radiometer and the Tropical Rainfall Measuring Mission Microwave Imager using an optimal interpolation scheme (He et al., 2003). We chose the initial five-year period spanning January 1998 through December 2002 for an analysis here. The data domain is shown in Figure 5.1, which is a little smaller than that of He et al. (2003), focusing more on the WFS. If the data set is
arranged in an \( I \times J \) matrix, where \( I \) and \( J \) are spatial and temporal dimensions, respectively, then a temporal mean SST pattern is expressed as

\[
\bar{T}(x) = \frac{1}{J} \sum_{j=1}^{J} T(x, t_j)
\] (5.1)

and shown in Figure 5.2. The five-year mean pattern shows the warm Loop Current water seaward of the shelf break and the relatively cooler water along the coast near the Florida Big Bend region. The SST gradient points from the southwest to the northeast, with an approximate 30–40° angle deviation from the mean along-isobath direction. This may reflect the combined effects of latitudinal differences in surface heating due to solar radiation and across-shelf differences in water column heating/cooling due to the depth gradient on the shelf.

![Figure 5.1](image)

Figure 5.1   A record-length mean SST map for the five-year period, 1998-2002, overlain on the 20, 50, 100, 200 and 1000 m isobaths for the WFS analysis domain.

Two types of SST anomalies are prepared. The first type, \( \hat{T}(x,t) \), is obtained by subtracting the temporal mean map from the original data

\[
\hat{T}(x,t) = T(x,t) - \bar{T}(x)
\] (5.2)

By further subtracting a time series of spatial mean values, which is expressed as

\[
\ddot{T}(t) = \frac{1}{I} \sum_{i=1}^{I} \hat{T}(x_i,t),
\] (5.3)

a second type SST anomaly, \( \ddot{T}(x,t) \), is obtained as
\[
T(x,t) = T(x,t) - \overline{T}(x) - \overline{T}(t)
\] (5.4)

The spatial mean SST anomaly has higher values in summer and lower values in winter, and the temporal variation is similar to a sine function (Figure 5.2).

Figure 5.2. Time series of the spatial mean SST anomaly for this WFS analysis domain.

Figure 5.3. SST monthly means on the WFS obtained by forming an average for each month over the five-year period, 1998-2002.

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The monthly mean SST patterns, computed over the entire five-year analysis period, show a seasonal variation (Figure 5.3). An across-shelf SST gradient is found in all the winter months, but it is not obvious in the summer months. A spring cold tongue structure that is prominent in April and May is consistent with previous literature (e.g., Weisberg et al. 1996; He and Weisberg 2002b). These SST features will be used for comparison with those derived from linear EOF and nonlinear GHSOM analyses.

5.4 EOF patterns

As in Chapter 3, prior to performing the SOM and GHSOM analyses, we begin with the more established technique of time domain EOF. He et al. (2003) reported EOF results for the first type of SST anomaly defined previously. The first three EOFs of that analysis account for 90.6%, 3.5% and 0.9% of the SST variance, respectively. The dominant first mode represents the seasonal surface heat flux cycle. Note that the strong seasonal variation may hinder our view of other interesting processes. To reduce the impact of the seasonal cycle on the data analysis, the second type of SST anomaly data \( \tilde{T}(x,t) \) are used, wherein both the temporal mean map and the spatial mean SST time series are removed from the original SST. Some previous studies removed the seasonal cycle by fitting each time series to annual and semiannual harmonics and subtracting them from the original data (Espinosa-Carreon et al., 2004). In that way, the amplitude of the harmonics being removed may be different from one point to another on a map. We choose to subtract a time series of spatial mean SST simply because the main purpose of the study is to extract the spatial patterns and it is better not to change the relative values on a SST map. Our EOF results are shown in Figure 5.4. The first mode, although accounting for a smaller percentage of SST variance (59.6%), has a spatial pattern and temporal variation essentially the same as those in He et al. (2003). It represents the seasonal surface heat flux cycle, i.e., the PC time series has an annual periodicity peaking in summer and winter, and the eigenfunction shows two different regimes, the wide WFS and the deep ocean. This is a consequence of water depth and the buffering effect on the temperature by the warm water advection of the Loop Current. Thus, the Loop Current
presents the WFS with a cooling tendency in summer and a warming tendency in winter. The second mode, accounting for 10.8% of the SST variance, reveals a warm/cold tongue pattern on the WFS. The spring cold tongue on the mid WFS is due to the combined baroclinic and barotropic responses of the WFS circulation to the seasonal surface heat and momentum fluxes as described in previous studies (Weisberg et al., 1996; He and Weisberg 2002b; He et al. 2003). The third mode, accounting for 6.4% of the SST variance, reveals a pattern of the shelf break Loop Current eddy. The fourth (and higher) mode revealing smaller spatial structures and higher frequency PC fluctuations are beginning to describe the synoptic scale variability.

Figure 5.4. Eigenfunctions and the associated temporal evolution functions for the first four EOF modes of the SST data. The percent of variance accounted for by each mode is indicated at the upper-right corner of each eigenfunction plot. The labels J, M and S on the abscissa designate the first days of January, May and September, respectively; and similarly on subsequent figures.
5.5 GHSOM mapping of the SST data

In this section, the GHSOM is performed on the original SST data and the SST anomaly data, \( \tilde{T}(x,t) \) and \( \tilde{T}(x,t) \), respectively.

5.5.1 GHSOM analysis of the original SST data

The five-year-long daily SST data are used as input to the GHSOM without any preconditioning. In the application of the GHSOM Toolbox, all the parameters are set to the default values except \( \tau_1 \) and \( \tau_2 \), the breadth- and depth-controlling parameters. Different \((\tau_1, \tau_2)\) values are used to test the GHSOM performance (see Table 5.1). Generally, when smaller \((\tau_1, \tau_2)\) values are chosen there are more nodes, i.e., larger SOM arrays, in the output. A large SOM array identifies a large number of patterns and reveals more detailed structure within the data, whereas a small SOM array identifies fewer, more generalized patterns. We chose the case of \((\tau_1=0.6, \tau_2=0.06)\) to analyze simply because the results have two layers and the SOM arrays are large enough to represent characteristic SST features and small enough to be visualized.

Table 5.1. Total numbers of the SOM units in the GHSOM with different values of controlling parameters. It is the third case (shown in bold type) that is presented.

<table>
<thead>
<tr>
<th>( \tau_1 )</th>
<th>( \tau_2 )</th>
<th>Layer 1 SOM #</th>
<th>Layer 2 SOM #</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.8</td>
<td>0.08</td>
<td>4</td>
<td>4, 0, 0, 4</td>
</tr>
<tr>
<td>0.7</td>
<td>0.07</td>
<td>4</td>
<td>6, 4, 0, 4</td>
</tr>
<tr>
<td><strong>0.6</strong></td>
<td><strong>0.06</strong></td>
<td><strong>4</strong></td>
<td><strong>12, 6, 0, 10</strong></td>
</tr>
<tr>
<td>0.5</td>
<td>0.05</td>
<td>4</td>
<td>30, 15, 18, 55</td>
</tr>
<tr>
<td>0.4</td>
<td>0.04</td>
<td>4</td>
<td>64, 40, 48, 119</td>
</tr>
<tr>
<td>0.3</td>
<td>0.03</td>
<td>6</td>
<td>132, 120, 96, 0, 144, 140</td>
</tr>
<tr>
<td>0.2</td>
<td>0.02</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>0.1</td>
<td>0.01</td>
<td>95</td>
<td>0</td>
</tr>
</tbody>
</table>

The layer 1 GHSOM enables a nonlinear classification of the five-year-long daily SST on the WFS into 4 categories, as shown in the 2×2 SOM array in Figure 5.5. Each unit explains a particular set of SST characteristics. Unit 1 reveals a typical low SST pattern \((16^\circ < \text{SST} < 25^\circ\text{C})\) in which the isotherms are approximately aligned with the isobaths, with the coldest water centered around Florida Big Bend region and with the
warmest water seaward of the shelf break associated with the Loop Current. Unit 4 reveals a high SST pattern (SST > 28°C), with no obvious horizontal temperature gradient. Both units 2 and 3 are transitional patterns between the units 1 and 4 extremes.

Figure 5.5. Layer 1 GHSOM (2×2) for the five-year-long daily SST data on the WFS are in the top four panels. The frequency of occurrence of each pattern is also shown on each map. The BMU time series are shown in the bottom panel.

For each of the five-year-long daily SST maps, a best-matching unit (BMU) can be identified. Time series of the BMU (given by its number, 1-4) show obvious seasonal fluctuations (Figure 5.5, bottom panel). Unit 1 is best-matched in winter, while unit 4 is
best-matched in summer. Unit 2 is best-matched in spring and early winter, and unit 3 in early summer and autumn. The cycle of units 1 → 2 → 3 → 4 → 3 → 2 → 1 therefore takes place in a year. In order to quantify the representation of each unit (1-4), the frequency of occurrence is computed by summing the hits of that unit and dividing by the total record length. The relative frequency of occurrence of each unit is shown in the upper-right corner of each map in Figure 5.5. For example Units 1 and 4 represent 26.3% and 33.7% of all the SST data, respectively. A monthly climatology of the frequency of occurrence during the five years (Figure 5.6) shows that the first pattern appears mostly in January-March, the second in April, November and December, the third in May and October, and the fourth in June-September.

Figure 5.6. Monthly climatology of the frequency of occurrence of the layer 1 GHSOM patterns in Figure 5.5.

Not all units in the first layer grow to the same depth in the GHSOM hierarchy. Only units 1, 2, and 4 are further expanded in a second layer map. The second layer GHSOM grown from unit 1 (winter SST patterns) of the first layer GHSOM (GHSOM 2-1) is shown in Figure 5.7. Different features of the cold coastal water and the warm Loop Current water are classified into the 3×4 SOM array. Unit 2 of this 3×4 second layer has the highest frequency of occurrence (12.9%), showing a typical Loop Current feature seaward of the shelf break. Note that the relative frequency of occurrence here is referred to the total number of hits of unit 1 in the first layer only, i.e., the frequency of occurrences for each of the sublayer SOMs sum to 100%.
Figure 5.7. GHSOM 2-1: Top 12 panels show the layer 2 SOM expanded from pattern 1 of the first layer GHSOM. The relative frequency of occurrence of each pattern is shown in the upper-right corner of each map. Bottom panel shows the BMU temporal evolution.
The second layer GHSOM grown from unit 2 (spring and early winter SST patterns) of the first layer GHSOM (GHSOM 2-2) is shown in Figure 5.8. Specifically, the upper three units (1, 3, and 5) represent spring patterns, while the lower units (2, 4, and 6) represent early winter patterns, and this is evident in the time series of the BMUs (Figure 5.8, bottom panel). The general sequence of the SST variation is units $1 \rightarrow 3 \rightarrow 5$ for the spring evolution and units $6 \rightarrow 4 \rightarrow 2$ for the early winter evolution. The spring cold tongue structure may be identified in units 3 and 5.

![Figure 5.8](image_url)

**Figure 5.8.** GHSOM 2-2: Top 6 panels show the layer 2 SOM expanded from pattern 2 of the first layer GHSOM. The relative frequency of occurrence of each pattern is shown in the upper-right corner of each map. Bottom panel shows the BMU temporal evolution.
The second layer GHSOM grown from unit 4 (summer SST patterns) of the first layer GHSOM (GHSOM 2-4, a $2 \times 5$ array) is shown in Figure 5.9. The peak summer SST patterns are shown in the rhs of the SOM array (units 7~10), while the early and late summer SST patterns are arranged in the lhs (units 1~6). The evolution of the summer SST patterns from early to late summer stages in each year is illustrated in the bottom panel of Figure 5.9. The general characteristic of summer SST is uniformly high temperature. Thus, it is difficult to divide the coastal and the Loop Current waters based on summer SST.

![Figure 5.9](image)

Figure 5.9. GHSOM 2-4: Top 10 panels show the layer 2 SOM expanded from pattern 4 of the first layer GHSOM. The relative frequency of occurrence of each pattern is shown in the upper-right corner of each map. Bottom panel shows temporal evolution of the BMUs.
Figure 5.10. A 4×6 SOM representation of the five-year-long daily SST anomalies. The data are preprocessed by removing the temporal mean map (Figure 5.1). The relative frequency of occurrence of each pattern is shown in the upper-right corner of each map.
5.5.2 GHSOM analysis of the SST anomaly with the temporal mean map removed

Here the SST anomaly \( \tilde{T}(x,t) \) is used as input to the GHSOM analysis. Similar to that in Section 5.5.1, a set of controlling parameters are used to run the GHSOM model, and when \( \tau_1=0.2 \) and \( \tau_2=0.02 \) the GHSOM has only one layer (24 units). This case is chosen to demonstrate the capability of the GHSOM to function as a basic SOM. A 4×6 SOM array of five-year-long daily SST anomalies is shown in Figure 5.10. Similar SST patterns are located adjacent to one another in the SOM mapping, while dissimilar patterns are at the opposite extremes of the SOM space. There is a continuum of change across the SOM array, with the typical summer and winter SST anomaly patterns at the lower-right and upper-left hand corners, respectively, and an annual cycle is obvious in the BMU time series (Figure 5.10, bottom panel). For either peak winter (January ~ February) or peak summer (July ~ August) patterns, the SST anomaly is smaller on the ocean side and larger on the shelf with the largest SST anomaly near the coast of the Florida Big Bend. This result is the same as that from the first EOF mode (Figure 5.4). The spring cold tongue structure may be identified only in unit 5, while the warm tongue structure may be identified in many units (10, 14, and 16).

5.5.3 GHSOM analysis of the SST anomaly with both the temporal mean map and spatial mean time series removed

Here the SST anomaly \( \tilde{T}(x,t) \) is used in the GHSOM model. By removing the time series of spatial mean SST, the strong seasonal variation is reduced, while the relative spatial structure is not altered, i.e., the horizontal SST gradient is not changed. Similar to that in Section 5.5.1, a set of controlling parameters are used to run the GHSOM model. We present the results of \( \tau_1=0.8 \) and \( \tau_2=0.08 \) for the same reason as in Section 5.5.1. The first layer GHSOM is still a 2×2 array representing four categories of the SST anomaly patterns on the WFS (Figure 5.11). Unit 1 reveals a wide warm tongue structure on the shelf, mostly appearing in November as a fall transition (Figure 5.12, bottom panel); in contrast, unit 4 reveals a spring cold tongue structure on the shelf (peaking in April). Unit 2 reveals a pattern with a coastal and deep-ocean contrast in
summer (from June through September). On the other hand, unit 3 shows the reverse of the unit 2 pattern in winter (from January to February). Units 1~4 represent 16.3%, 43.6%, 24.4% and 15.7% of the SST anomaly maps, respectively. Generally, the SST anomaly patterns revealed by the GHSOM may be compared with the first two mode EOFs. Units 2 and 3 resemble the two extremes of the first mode eigenvector with positive and negative weights, respectively; and units 1 and 4 may be ascribed to the second mode EOF with negative and positive weights, respectively. However, the amplitudes of the winter SST anomalies (unit 3) are larger than those of the summer SST anomalies (unit 2). Also, the shapes of the cold and warm tongues are different as shown in units 4 and 1, respectively. These asymmetric phenomena are not identified in the lowest mode EOF results. We note that all the four units may be further expanded in a subsequent layer to reveal more detailed structures, but these are not pursued here.

Figure 5.11. The layer 1 GHSOM (2×2) of the five-year-long daily SST anomalies ($\tau_1=0.8$, $\tau_2=0.08$). The input data are preprocessed by removing both the temporal mean map and a time series of spatial mean values. The relative frequency of occurrence of each pattern is shown in the upper-right corner of each map.
Figure 5.12. Monthly climatology of the frequencies of occurrence of the four characteristic maps in Figure 5.11.

5.6 Summary and discussions

As a data analysis method, the EOF conveniently orders patterns of variability on the basis of variance. However, as a linear method, it may be a suboptimal way of spanning a data space if the system is nonlinear. The nonlinear SOM orders patterns of variability on the basis of topology rather than the variance. A major strength of the SOM is that the underlying patterns in a data set can be visualized in the same form as the original data. Thus, if input data are SST images, then the outputs are SST patterns, not SST anomaly patterns. This is an advantage over the EOF, in which the temporal mean field is removed prior to the analysis. As the SOM output patterns resemble the input format, their qualitative interpretation may be easier than that from the EOF. Also, the SOM is not subject to the symmetry bias of a given EOF mode, such that the SOM patterns may be more realistic than the EOF patterns. As shown in Section 5.5.3, the asymmetric SST anomaly patterns of winter and summer and of the cold and warm tongues revealed by the SOM cannot be identified in the individual EOF patterns. Another advantage of the SOM analysis is that the algorithm is robust in handling missing data, without a priori estimation. Thus, the SOM method can be used to explore incomplete data sets. Moreover, the SOM can be used as a data interpolation technique, estimating missing data from input data that are similar (Hewitson and Crane 2002).

The major advantages of the GHSOM model over the standard SOM are the following. First, the overall training time is reduced since only a necessary number of
units are developed to organize the data at a certain level of detail. Second, the GHSOM uncovers the hierarchical structure of the data, allowing the user to understand and analyze a large amount of data in an exploratory way. Each SOM array in the hierarchy explains a particular set of characteristics of the data. This makes the GHSOM analysis an excellent tool for feature extraction and classification. Third, the size of the SOM array does not have to be specified subjectively before hand; the GHSOM automatically expands in a three-dimensional structure.

Here we used the GHSOM method to extract characteristic patterns of SST variability on the WFS from a time series of daily SST maps that span the five-year interval 1998–2002. Four characteristic SST patterns are extracted in the first layer GHSOM array: characteristic winter and summer patterns, and two transitional patterns. Three of these are further expanded in a second layer, yielding more pattern evolution details. The results show that a seasonal cycle dominates the SST variability on the shelf. Winter SST is characterized by cold water (16ºC < SST < 25ºC) with the isotherms aligned approximately along the isobaths and with the coldest water centered within the Florida Big Bend region and with the warmest water located seaward of shelf break in association with the Loop Current. In contrast, summer SST is characterized by horizontally uniform, warm water (SST > 28ºC) making it difficult to discern shelf from Loop Current waters. The spring transition includes a mid shelf cold tongue.

When the GHSOM analysis is performed on the SST anomaly data (with both the temporal mean map and the time series of spatial mean values removed), four characteristic SST anomaly patterns are also obtained in the first GHSOM layer, representing the SST anomaly patterns in the four seasons. The winter SST anomaly pattern shows the cooling effect of shoaling isobaths on shelf and the warming influence of advection by the Loop Current, while the summer pattern reveals the warming effect of shoaling isobaths on shelf relative to the Loop Current. The spring pattern shows a mid shelf cold tongue, while the fall pattern shows a warm tongue on the shelf. These seasonal patterns, whether extracted from the original data or the anomaly fields, exhibit asymmetries that are not readily apparent in the complementary EOF analysis.
Chapter 6

Momentum Balance Diagnoses

6.1 Abstract

The momentum balance over the WFS is diagnosed using observations of currents, bottom pressures, temperatures, winds, and coastal sea levels, along with hydrographic data from 32 monthly cruises spanning summer 1998 to winter 2001. Over synoptic weather time scales, the depth-averaged across-shelf momentum balance on the inner shelf is essentially geostrophic with smaller contributions from the across-shelf wind stress and other terms. Coherence analyses show that 95% of the acceleration (Coriolis and local) variance may be accounted for by the pressure gradient and friction (surface and bottom) over the synoptic weather band. The balances are more complicated on the outer shelf where the Coriolis, across-shelf bottom pressure gradient and horizontal density gradient terms all have the same magnitude. Over synoptic and longer time scales, the depth-averaged along-shelf momentum balance on the inner shelf is mainly between the wind stress and bottom friction with smaller contributions from the pressure gradient, local acceleration and Coriolis terms. The along-shelf pressure gradient is mainly set up by the local along-shelf wind stress. These balances enable us to estimate the depth-averaged, along-shelf currents on the inner shelf from the winds and coastal sea level or from the winds and across-shelf bottom pressure gradient, or from both. Inferred from these analyses depending on the bottom stress parameterization are a drag coefficient $C_D$ of 2~4×10^{-3} and a resistance coefficient $r$ of 3~6×10^{-4} m/s. The across-shelf sea level gradient may also be inferred from the wind and coastal sea level data. Momentum terms estimated from the observations and those calculated from a numerical model compare well.
Continental shelf momentum balance analyses have been diagnosed from observations for the South Atlantic Bight (Lee et al. 1984, 1989), the Pacific Northwest (Hickey 1984), the Celtic Sea (Thompson and Pugh 1986), and the coastal oceans of northern California (Lentz 1994; Trowbridge and Lentz 1998; Lentz and Trowbridge 2001), North Carolina (Lentz et al. 1999), and New Jersey (Tilburg and Garvine 2003). It is widely accepted that the depth-averaged, across-shelf momentum balance at outer and mid shelf locations is predominantly geostrophic, with the Coriolis force due to the along-shelf currents balancing the across-shelf pressure gradient force (Thompson and Pugh 1986; Brown et al. 1985, 1987; Lee et al. 1984, 1989; Lentz et al. 1999). In the along-shelf direction the momentum balance tends to be frictional. On the Northern Carolina inner shelf the wind stress and pressure gradient are balanced by bottom stress, with flow accelerations becoming increasingly important offshore (Lentz et al. 1999). This is in contrast with the central Southern California Bight, where variations in along-shelf pressure gradient account for a larger fraction of the along-shelf velocity variations than the local wind stress (Hickey et al. 2003).

All continental shelves have their own nuances due to their geometries and boundary currents. The West Florida Shelf (WFS) is broad and gently sloping with the Gulf of Mexico Loop Current at times impinging on the shelf slope (Molinari et al. 1977; Huh et al. 1981; Paluszkieiwicz et al. 1983; Hetland et al. 1999; He and Weisberg 2003b; Weisberg and He 2003), and with the fresh water of the Mississippi River influencing the mid shelf in spring and summer (Gilbes et al. 1996; He and Weisberg 2002b). Previous observational inferences on WFS momentum balances are limited. For instance, Mitchum and Sturges (1982) analyzed three weeks of current meter data from two moorings at the 22 and 44 m isobaths and concluded that the dominant momentum balance in the along-shelf direction is between the wind and bottom stresses.

Li and Weisberg (1999a, b) reported on WFS momentum analyses using a three-dimensional primitive equation model forced by idealized upwelling (and downwelling) favorable winds. When forced by a steady and spatially uniform southeastward along-
shelf wind stress, the vertically integrated across-shelf momentum balance is primarily
geostrophic independent of water depth. The along-shelf momentum balance is
essentially Ekman (a balance between the wind stress and the Coriolis acceleration terms)
over the mid to outer shelf, whereas the balance is between the wind and bottom stresses
near shore. The inner shelf is found to be the region within which the surface and bottom
Ekman layers interact. Offshore of Sarasota, Florida the inner shelf extends out to about
the 50 m isobath. When forced by a steady and spatially uniform offshore wind stress, the
vertically integrated across-shelf momentum balance is depth dependent. The mid to
outer shelf shows an Ekman balance, while on the inner shelf, the Coriolis term decreases
as the pressure gradient term increases, and in the near shore the balance is between the
wind stress and the pressure gradient terms with the Coriolis term playing a secondary
role. In the along-shelf direction, the bottom stress term becomes of increasing
importance with decreasing depth over the inner shelf; on the mid shelf the balance is
primarily Ekman, and further offshore on the shelf slope the local acceleration is
relatively large and spatially variable due to vortex stretching. Additional model
momentum balances under stratified conditions are reported by Weisberg et al. (2000 &
2001). However, these model results are not yet verified by observations.

The acquisition of long time series now facilitate diagnostic calculations of WFS
momentum balances with in-situ data. Hourly time series of velocity, bottom pressures,
bottom temperatures, and winds, along with hydrographic data from 32 monthly cruises
allow us to consider the momentum balances at several locations across the shelf. These
analyses provide further insight into the nature of the WFS dynamics. An overview of the
observations and a description of data processing are given in Section 6.3. The relevant
equations are derived in Section 6.4. Across- and along-shelf momentum balances are
analyzed in Sections 6.5 and 6.6, respectively, and applications are made in Section 6.7.
Bottom friction parameters are estimated in Section 6.8. Comparisons with numerical
model results are made in Section 6.9. Section 6.10 then discusses the results and Section
6.11 provides a summary.
6.3 In-situ observations and data processing

Concurrent programs on the WFS aimed at studying harmful algae blooms and other property variations provided velocity and other data from up to 13 moorings beginning in summer 1998. Figure 6.1 shows the mooring locations and Table 6.1 provides supporting information. There are data from five bottom-mounted moorings (EC5, EC6, EC4, NA1 and NA3) on the inner shelf, each with an upward looking Acoustic Doppler Current Profiler (ADCP) measuring currents over most of the water column at 0.5 m intervals, along with temperature, salinity, and pressure near the bottom. On the outer shelf, there are two subsurface moorings (CM4 and EC1) with upward looking ADCPs located 4 m from the bottom, measuring currents in 5 m intervals over most of water column, along with temperature, salinity, and pressure at the ADCP depth. From the 25 to 50 m isobaths, there are surface buoys (NA2, EC3, EC2, CM2 and CM3) with downward-looking ADCPs measuring currents throughout most of the water column, along with winds at the surface.

Table 6.1. Mooring information.

<table>
<thead>
<tr>
<th>Mooring name</th>
<th>Water depth (m)</th>
<th>Latitude (N)</th>
<th>Longitude (W)</th>
<th>Good bins (m)</th>
<th>Pr. sensor depth (m)</th>
<th>Overall observation period</th>
</tr>
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<td>26° 24.5'</td>
<td>82° 12.5'</td>
<td>3-8</td>
<td>9.5</td>
<td>09/15/1998~08/23/2001</td>
</tr>
<tr>
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<td>27° 17.9'</td>
<td>82° 38.4'</td>
<td>3-8</td>
<td>9.5</td>
<td>07/14/1998~03/17/2002</td>
</tr>
<tr>
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<td>27° 11.2'</td>
<td>82° 47.8'</td>
<td>3-18</td>
<td>19.5</td>
<td>07/13/1998~03/19/2002</td>
</tr>
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<td>82° 56.7'</td>
<td>3-23</td>
<td>24.5</td>
<td>07/13/1998~08/25/2001</td>
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<td>3-23</td>
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<td>82° 54.0'</td>
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<td>26° 45.1'</td>
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</tbody>
</table>

Wind observations are from two NOAA/NDBC stations 42036 and VENF1 (Venice) ([http://www.ndbc.noaa.gov/](http://www.ndbc.noaa.gov/)) and from the USF surface buoys. Hydrographic data are from monthly cruises from June 1998 through December 2001 in which CTD profiles were generally taken along three across-shelf transects, and the station locations relevant to the ADCP moorings are also shown in Figure 6.1. Coastal sea level data at Clearwater and Naples are from the NOAA/NOS ([http://www.co-ops.nos.noaa.gov/](http://www.co-ops.nos.noaa.gov/)).
Figure 6.1. Map of the WFS showing bottom topography, ADCP mooring stations, CTD transect offshore Sarasota, wind and coastal sea level stations. Enlarged inner WFS near Sarasota is shown as an insert map in the upper-left corner. The relative location of the WFS is shown in a Gulf of Mexico map inserted in the upper-right corner.

Editing of the ADCP velocity data consisted of bin mapping to standard depths (by interpolation) and eliminating (side-slope) contaminated data either near the surface (for the bottom-mounted) or near the bottom (for the surface buoys). Principal axes of variance were calculated from depth-averaged, 36-hour low-pass filtered data, and the angles made by the semi-major axes are used to define the along-shelf directions at each of the mooring sites. These generally aligned with the isobaths.
Editing of the bottom pressure data began with inspection to remove the records deemed incorrect due to contamination from sand inundation or battery failures toward the end of deployments. An atmospheric pressure correction was then made using nearby air pressure records. These records were then de-meaned and de-tided by removing the four major tide constituents: M2, S2, K1 and O1, using the Tide Harmonic Analysis Toolbox of Pawlowicz et al. (2002). We then had to contend with trends in some of the deployments. Methods dealing with pressure sensor drift are found in Wearn and Larson (1982) and Harms and Winant (1994). However, fully objective methods for correcting bottom pressure records do not exist (Brown et al. 1987). In our case, with several deployments ranging from two to 14 months duration, we opted for a method of piecewise detrending to eliminate unknown long time interval variations without destroying the synoptic weather band. Instead of detrending an entire deployment, the time series were divided into two or more subsets, and each subset was detrended individually. The length of a subset depended on the data quality. The longest subset was 6 months, while the shortest subset was less than one month. After applying piecewise detrending and 36-hour low-pass filtering, all the bottom pressure records were joined together to form a single long time series for each mooring location.

Each of the bottom pressure sensors also recorded bottom temperature and conductivity. All of the bottom temperature records agreed with the shipboard CTD observations at similar depths. Bio-fouling and in some cases sand contamination degraded the moored salinity data during the later part of each deployment. Rather than attempt to edit these effects we inferred the bottom density from the temperature data. For each mooring location, a linear \( T-\sigma_t \) relationship was obtained by a least squares fit of the near bottom temperature with \( \sigma_t \) from the nearest CTD observation over all of the hydrographic cruises. These \( T-\sigma_t \) relationships were then applied to the bottom temperature time series to derive time series of bottom density for each mooring.

Two wind stress time series were formed for the inner and outer shelves, respectively. For the inner shelf, the NA2 buoy winds were primarily used; when NA2 winds were not available, wind data from buoy EC3 was used instead; when neither NA2 nor EC3 winds were available, an average wind from the other five available records was
used. Similarly, for the outer WFS, an average wind between stations CM2 and CM3 was used, and when neither of these winds was available, an average wind from the other four available records was used instead.

For all of the hourly time series, small gaps of up to a few hours were filled by linear interpolation. For consistency in the across-shelf momentum balances all the hourly time series were piecewise detrended (as with the bottom pressure), de-meaned, and 36-hour low-pass filtered. Current velocity time series were further rotated for across- and along-shelf components according to the current principal axes at individual sites. Wind vectors were converted to an oceanographic direction convention (the direction to which wind is blowing) and then rotated 27º clockwise for across- and along-shelf components. Given these data preparations the across-shelf momentum analyses apply to the time scales of the synoptic weather band. In contrast to the across-shelf momentum balances, since coastal sea level is used instead of the bottom pressure for most of the along-shelf momentum balance calculations, the piecewise detrending is not applied, such that the along-shelf momentum balances also apply to the time scales longer than the synoptic weather band.

6.4 Momentum balance equations

Via the hydrostatic assumption, the pressure at depth $z$ can be computed from bottom pressure $p_b$, water column depth $h$, and internal density structure (Brown et al., 1985)

$$p(z) = p_b - \rho_0 g (z + h) - \int_{-h}^{z} \rho' dz$$  \hspace{1cm} (6.1)

where $g$ is the gravitational acceleration, $\rho_0$ is a reference density, and $\rho(x,y,z,t)$ is a small density anomaly due to spatial and temporal variability, such that $\rho = \rho_0 + \rho(x,y,z,t)$. Here $x$ and $y$ denote the across- and along-shelf directions, respectively, with $x$ positive onshore and $y$ positive northwestward, $z$ denotes the vertical direction, positive upward and zero at the surface. By differentiating equation (6.1) along $x$, and vertically integrating over the water column, the across-shelf pressure gradient is
\[ \left\langle \frac{\partial p}{\partial x} \right\rangle = \frac{1}{H} \int_{-h}^{H} \frac{\partial p}{\partial x} \, dz = \frac{\partial p_b}{\partial x} - \rho_0 g \frac{\partial h}{\partial x} - \frac{g}{H} \int_{-h}^{H} \frac{\partial}{\partial x} \left[ \int_{-h}^{z} \rho' \, dz' \right] \, dz \]  

(6.2)

where \( H = \eta + h \) is the total water depth. The depth-averaged momentum equations, excluding the nonlinear acceleration terms, are

\[ \frac{\partial \bar{u}}{\partial t} - f \bar{v} = -\frac{1}{\rho_0} \left\langle \frac{\partial p}{\partial x} \right\rangle + \frac{\tau_s^x}{\rho_0 H} - \frac{\tau_b^x}{\rho_0 H} \]  

(6.3a)

\[ \frac{\partial \bar{v}}{\partial t} + f \bar{u} = -\frac{1}{\rho_0} \left\langle \frac{\partial p}{\partial y} \right\rangle + \frac{\tau_s^y}{\rho_0 H} - \frac{\tau_b^y}{\rho_0 H} \]  

(6.3b)

where \( (\tau_s^x, \tau_s^y) \) and \( (\tau_b^x, \tau_b^y) \) are the surface and bottom stresses, \( \left\langle \frac{\partial p}{\partial x} \right\rangle \) and \( \left\langle \frac{\partial p}{\partial y} \right\rangle \) are the depth-averaged pressure gradients, \( \bar{u}, \bar{v} \) are depth-averaged velocities, and \( f \) is the Coriolis parameter. Substituting equation (6.2) into equation (6.3a), and removing temporal mean values, leads to the perturbation equation

\[ \frac{\partial \bar{u}}{\partial t} - f \bar{v} = -\frac{1}{\rho_0} \frac{\partial p_b}{\partial x} + \frac{g}{\rho_0 H} \int_{-h}^{H} \frac{\partial}{\partial x} \left[ \int_{-h}^{z} \rho' \, dz' \right] \, dz + \frac{\tau_s^x}{\rho_0 H} - \frac{\tau_b^x}{\rho_0 H} \]  

(6.4)

where all the variables in equation (6.4) are now understood to be deviations from the temporal mean state. Applying Leibniz’s rule to the baroclinic term gives

\[ \frac{\partial \bar{u}}{\partial t} - f \bar{v} = -\frac{1}{\rho_0} \frac{\partial p_b}{\partial x} + \frac{g}{\rho_0 H} \int_{-h}^{H} \frac{\partial \rho'}{\partial x} \, dz' \, dz + \frac{g \rho'_b}{\rho_0} \frac{\partial h}{\partial x} + \frac{\tau_s^y}{\rho_0 H} - \frac{\tau_b^y}{\rho_0 H} \]  

(6.5)

where \( \rho'_b = \rho'(-h) \) is bottom density anomaly. On the left-hand-side (LHS), terms (a) and (b) are the local acceleration and Coriolis terms, respectively. On the right-hand-side (RHS), terms (c)~(g) are bottom pressure gradient, horizontal density gradient, bottom buoyancy, wind stress, and bottom stress terms, respectively. The sum of the first three terms on the RHS, (c)+(d)+(e), is the pressure gradient term.

The bottom buoyancy term arises from the deviation of the seabed from a level reference surface \( \frac{\partial h}{\partial x} \neq 0 \) and can vary through time with \( \rho'_b \) (Thompson and Pugh, 1986). With the bottom slope \( \frac{\partial h}{\partial x} \) between moorings EC4 and EC5 being about 0.5×10^{-3} (10 m/20 km), a \( \rho'_b \) of magnitude 1 kg m^{-3}, results in a bottom buoyancy term of
5 × 10^{-6} \text{ m s}^{-2}, \text{ which, for the latitude of WFS, is equivalent in magnitude to the Coriolis term under a velocity of 7 cm s}^{-1}. \text{ Thus, changes of } \rho'_h \text{ are potentially important and should be monitored if the pressure sensors are sited on a sloping bottom. A similar term, with a different definition of } \rho'_h, \text{ is derived and its significance in calculating bottom velocity transport on continental shelves is addressed by Mellor et al. (1982) and Morison (1991). All of the terms in equation (6.5) are now relatable to the observed variables: velocity \text{ [terms (a), (b) and (g)]}, \text{ bottom pressure [term (c)]}, \text{ CTD data [term (d)]}, \text{ bottom temperature (density) data [term (e)]}, \text{ and winds [term (f)].}

For the along-shelf direction, upon removing the temporal mean values from equation (6.3b), the resulting perturbation equation remains the same form. Near the coast, the along-shelf pressure gradient may be assumed to be constant throughout the water column, and approximated by the along-shelf sea level gradient,

\[ \langle \partial p / \partial y \rangle = \rho_0 g \partial \eta / \partial y, \text{ where } \eta \text{ is sea level.} \]

6.5 Across-shelf momentum balance

6.5.1 Estimation of terms

Since we must differentiate pressure time series between moorings, we define (for consistency) a new velocity time series between adjacent moorings by averaging velocity time series from the two sites, \((\bar{u}_1, \bar{v}_1)\) and \((\bar{u}_2, \bar{v}_2)\), weighted by the water depths, \(h_1\) and \(h_2\), i.e., \((\bar{u}, \bar{v}) = \left( \frac{\bar{u}_1 h_1 + \bar{u}_2 h_2}{h_1 + h_2}, \frac{\bar{v}_1 h_1 + \bar{v}_2 h_2}{h_1 + h_2} \right)\). The local acceleration term \(\partial^2 \eta / \partial t^2\) is computed through forward difference in the time domain. The bottom pressure gradient term can be estimated by using a forward difference \(\partial p_b / \partial x = \Delta p_b / \Delta x\). The horizontal density gradient term can be written as

\[ \frac{g}{\rho_0 H} \int_{-h}^{h} \frac{\partial \rho'}{\partial x} dz' dz = \frac{f}{H} \int_{-h}^{h} v_g(z) dz, \text{ where } \]

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\[ \nu_g(z) = \frac{g}{\rho_0 f} \int_{-h}^{-h} \frac{\partial \rho'}{\partial x} \, dz' \] is the baroclinic geostrophic velocity relative to the bottom. This term can be estimated for each cruise when CTD stations are available near the mooring sites. Time series of bottom density anomalies \( \rho'_b \) at adjacent moorings are averaged to form a new time series of bottom density at the mid-point. For station pair EC5-EC4, EC4-NA1 and CM4-EC1, the bottom slope \( \partial h / \partial x \) is 0.5 \( \times 10^{-3} \), 0.6 \( \times 10^{-3} \), 1.7 \( \times 10^{-3} \), respectively. The bottom buoyancy term can be estimated once these two variables are known. The wind stress is estimated using a neutral drag law (Large and Pond 1981), and the across-shelf component of bottom stress is parameterized by the quadratic form

\[ \tau_b^x = \rho_0 C_D \nu_b \sqrt{u_b^2 + v_b^2}, \]

where \( u_b \) and \( v_b \) are the near bottom velocity components and \( C_D \) is a drag coefficient, taken to be 2.5 \( \times 10^{-3} \) (to be explained in Section 6.8).

6.5.2 Across-shelf momentum balance on the inner shelf

Two diagnostic periods are considered, one for the full record length and the other for the period from February 2001 to March 2002, when the bottom pressure records at both EC4 and EC5 had minimal trends yielding the best quality data subset collected among the deployments. We first examine the Momentum balance on the inner shelf with the best quality data set.

Diagnostic time series of all the across-shelf momentum terms during the February 2001 to March 2002 period are shown in Figure 6.2. The relative magnitude of each term may be measured by the standard deviations (Table 6.2). The standard deviations of the Coriolis and bottom pressure gradient terms are much larger than those of the other terms, suggesting that the across-shelf momentum balance is predominantly geostrophic. This is supported by the high visual correlation between these two terms (Figure 6.2a) and by coherence (Figure 6.3), which is significant with nearly zero phase over the frequency band 0.05 ~ 0.5 cpd.

The standard deviation of the wind stress term is about 0.65 that of the Coriolis term, and the maximum value of the wind stress term has the same magnitude as those of the Coriolis and bottom pressure gradient terms. To compare the wind stress term to the
ageostrophic residual, we subtract the bottom pressure gradient term from the Coriolis term (Figure 6.2b). This ageostrophic momentum term visually resembles the wind stress term, and a coherence analysis (Figure 6.4) demonstrates that the ageostrophic momentum residual can be largely accounted for by the wind stress.

Figure 6.2. Across-shelf momentum balance at 15 m site between the inner shelf moorings EC4 and EC5 from February 2001 to March 2002. Note the scales of the vertical axes differ in different panels for the large and small terms. (a) the Coriolis versus the bottom pressure gradient terms; (b) the ageostrophic residual between the Coriolis and the bottom pressure gradient terms versus the wind stress term; (c) the bottom buoyancy and the bottom stress terms; and (d) the local acceleration term, the residual of the momentum terms except the horizontal density gradient term, versus the horizontal density gradient term calculated from the CTD data.
That the across-shelf wind stress may play an important role in the momentum balance is evident in the 22-24 July 2001 event. The wind stress term has a value of $26 \times 10^{-6}$ m s$^{-2}$ (Figure 6.2b), relative to the bottom pressure gradient term of $-38 \times 10^{-6}$ m s$^{-2}$ and the Coriolis term of $-19 \times 10^{-6}$ m s$^{-2}$ (Figure 6.2a). Thus, the offshore bottom pressure gradient is maintained primarily by the onshore wind stress and secondarily by the Coriolis term, consistent with the Li and Weisberg (1999a, b) findings on the importance of the across-shelf wind stress in their numerical model diagnoses. More recently, the importance of the across-shelf winds as a mechanism for across-shelf transport within the friction-dominated inner shelf was also shown by Tilburg (2003) in a series of two-dimensional simulations.

Table 6.2. Maximum, minimum values and standard deviations ($\sigma$) of the terms in the across-shelf momentum balance (units in $10^{-6}$ m s$^{-2}$).

<table>
<thead>
<tr>
<th></th>
<th>$\frac{\partial u}{\partial t}$</th>
<th>$-fv$</th>
<th>$\frac{1}{\rho_0} \frac{\partial p_b}{\partial x}$</th>
<th>$g \rho_s \frac{\partial h}{\partial x}$</th>
<th>$\frac{\tau^b_x}{\rho_0 H}$</th>
<th>$-\frac{\tau^b_y}{\rho_0 H}$</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC4-EC5 (15 m) max</td>
<td>1.08</td>
<td>22.34</td>
<td>24.97</td>
<td>3.42</td>
<td>24.92</td>
<td>1.70</td>
<td>7.21</td>
</tr>
<tr>
<td>(best quality)  $\sigma$</td>
<td>0.23</td>
<td>5.00</td>
<td>6.66</td>
<td>1.45</td>
<td>3.23</td>
<td>0.29</td>
<td>2.15</td>
</tr>
<tr>
<td>EC4-EC5 (15m) $\sigma$</td>
<td>0.20</td>
<td>4.51</td>
<td>6.17</td>
<td>0.96</td>
<td>2.60</td>
<td>0.24</td>
<td>2.76</td>
</tr>
<tr>
<td>NA1-EC4 (23m) $\sigma$</td>
<td>0.27</td>
<td>4.26</td>
<td>5.63</td>
<td>0.97</td>
<td>1.64</td>
<td>0.22</td>
<td>3.46</td>
</tr>
<tr>
<td>EC1-CM4 (126m)$\sigma$</td>
<td>0.42</td>
<td>5.81</td>
<td>5.24</td>
<td>1.86</td>
<td>0.36</td>
<td>0.06</td>
<td>5.23</td>
</tr>
</tbody>
</table>

Figure 6.3. Cross-spectral analysis between the Coriolis and the bottom pressure gradient terms in the across-shelf momentum equations for the 15 m site between moorings EC4-EC5, February 2001 to March 2002 (the degrees of freedom is measured as 27). (a) Coherence squared (dashed line shows 90% significance level); (b) phase normalized by $\pi$. 93
Figure 6.4. Same as Figure 6.3 except for the wind stress term and the ageostrophic momentum, which is defined as the difference between the Coriolis and the bottom pressure gradient terms.

The remaining terms of diminishing importance are the bottom buoyancy, the bottom stress, and the local acceleration. The standard deviation of the bottom buoyancy term is 0.29 that of the Coriolis term, and both the bottom friction and the local acceleration terms are an order of magnitude smaller than the Coriolis term.

A residual term is computed by summing all the momentum terms except the horizontal density gradient term (Figure 6.2d). If the errors were negligible, the residual term should be accounted for by the horizontal density gradient term. However, the range of the density gradient term estimated from the monthly hydrographic data set (Table 6.3) is much smaller than that of the residual time series, showing that the remaining momentum residual is due to errors rather than the small density gradient term at this shallow (15 m) site (Figure 6.5).

Figure 6.5. Comparison of the across-shelf momentum residual and the density gradient terms estimated from the CTD observations.
Table 6.3. Ranges of the horizontal density gradient term estimated from monthly CTD data (units in $10^{-6}$ m s$^{-2}$).

<table>
<thead>
<tr>
<th>Density term</th>
<th>EC4-EC5 (15 m)</th>
<th>NA1-EC4 (22.5 m)</th>
<th>EC1-CM4 (126 m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>1.7</td>
<td>1.5</td>
<td>24.9</td>
</tr>
<tr>
<td>Minimum</td>
<td>-1.9</td>
<td>-1.8</td>
<td>-8.7</td>
</tr>
</tbody>
</table>

Time domain correlation ($C$) and regression ($R$) coefficients provide an alternate method for examining the contribution of each term to the across-shelf momentum balance. These are given between the bottom pressure gradient term and sums of the other terms in Table 6.4. The values of $C$ and $R$ between the bottom pressure gradient and the Coriolis terms are 0.81 (significant at 95% confidence level) and 0.61, respectively, and when the wind stress is included, $C$ and $R$ increase significantly to 0.93 and 0.88, respectively.

Table 6.4. Correlation and regression analyses of the across-shelf momentum terms.

<table>
<thead>
<tr>
<th>$x(t)$ versus $y(t)$</th>
<th>EC4-EC5 (best qual.)</th>
<th>EC4-EC5 (15 m)</th>
<th>NA1-EC4 (25 m)</th>
<th>EC1-CM4 (126 m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{1}{\rho} \frac{\partial p_h}{\partial x} - f\vec{v}$</td>
<td>0.81 0.61 0.75 0.55 0.73 0.55 0.58 0.64</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$- \frac{1}{\rho} \frac{\partial p_h}{\partial x} - f\vec{v} - \frac{\tau_s^x}{\rho_0 H}$</td>
<td>0.93 0.88 0.88 0.77 0.78 0.67 0.59 0.65</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$- \frac{1}{\rho} \frac{\partial p_h}{\partial x} - f\vec{v} - \frac{\tau_s^x}{\rho_0 H} - \frac{g \rho_0' \frac{\partial h}{\partial x}}{\rho_0}$</td>
<td>0.95 0.95 0.89 0.80 0.79 0.71 0.62 0.76</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$- \frac{1}{\rho} \frac{\partial p_h}{\partial x} - f\vec{v} - \frac{\tau_s^x}{\rho_0 H} - \frac{g \rho_0' \frac{\partial h}{\partial x}}{\rho_0} + \frac{\tau_b^x}{\rho_0 H}$</td>
<td>0.95 0.97 0.89 0.82 0.79 0.73 0.62 0.76</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$- \frac{1}{\rho} \frac{\partial p_h}{\partial x} - f\vec{v} - \frac{\tau_s^x}{\rho_0 H} - \frac{g \rho_0' \frac{\partial h}{\partial x}}{\rho_0} + \frac{\tau_b^x}{\rho_0 H} + \frac{\partial \bar{\tau}}{\partial t}$</td>
<td>0.95 0.98 0.89 0.83 0.80 0.74 0.62 0.76</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$C$: correlation coefficient, all significant at 90% level; $R$: regression coefficient.

In equation (6.5) the LHS (the accelerations) may be regarded as responses to the RHS (the forcing functions of pressure gradient and friction terms) as shown in Figure 6.6. Visually, the acceleration term is dominated by the pressure gradient term and complemented by the friction term. To quantify how much of the variance is accounted for by these forcing terms, a two-input/one-output multiple coherence model is employed.
(Bendat and Pierson 1986). In this statistical model, $x_1(t)$ (pressure gradient term) and $x_2(t)$ (friction term) are two random input variables, and $y(t)$ (acceleration term) is the single random output. The Fourier transform $Y(f)$ of the output is given by

$$Y(f) = H_1(f)X_1(f) + H_2(f)X_2(f) + N(f),$$

where $H_1$ and $H_2$ are the transfer functions between $x_1$, $y$, and $x_2$, $y$, respectively, calculated with the recognition that $x_1$ and $x_2$ may themselves be correlated. $N(f)$ is the Fourier transform of the uncorrelated noise input, and the output is the inverse Fourier transform of $Y(f)$.

![Graphs](image.png)

**Figure 6.6.** Comparison of the across-shelf momentum terms at 15 m site between moorings EC4-EC5, February 2001 to March 2002. (a) acceleration (a sum of the local acceleration and the Coriolis terms); (b) pressure gradient (a sum of the bottom pressure gradient term and the bottom buoyancy term); and (c) friction (a sum of the wind stress and bottom stress terms).

The ordinary coherence between each input and the output, and between the two inputs are shown as a function of frequency (Figure 6.7a). Input 1 is highly coherent with the output over the synoptic weather band ($0.05 \sim 0.5$ cpd), wherein the two inputs are also mutually coherent. The partial coherences for the conditioned input and output variables (by removing the effects of one of the inputs) are higher than the ordinary coherence counterparts, with the pressure gradient values larger than friction values (Figure 6.7b). The multiple coherence gives the combined effects (Figure 6.7c), and this
is about 0.95 over the synoptic weather band. Thus, the combined pressure gradient and friction terms account for 95% of the acceleration variance. We also see that the amplitude of the transfer function $H_1$ is nearly 1, and which $H_2$ has larger variation (also nearly 1) (Figure 6.7d), and the phases between the forcing terms and the response term are close to zero (Figure 6.7e). These findings confirm the validity of the diagnostic equation over the synoptic weather band.

Figure 6.7. Multiple coherence analysis from the two-input/one-output statistic model with the three terms defined in Figure 6.6. Inputs: (1) the pressure gradient term, and (2) the friction term; Output: the acceleration term. (a) Ordinary coherence (dashed line is 90% significance level, the same in (b) and (c)); (b) partial coherence; (c) multiple coherence; (d) amplitude of the transfer function; and (e) phase of the transfer function (unit in $\pi$).
The momentum terms are also estimated using the full-length records. The standard deviations of the individual momentum terms for the station pairs EC4-EC5 and NA1-EC4 are listed in bottom rows of Table 6.2. The standard deviations of the individual terms have similar magnitudes as the corresponding terms in the best quality calculation for EC4-EC5, except for the residual term, which is larger due to longer record length and increased pressure gradient errors. Correlation and regression analyses are performed (Table 6.4), and the same qualitative conclusions are drawn.

The balance for station pair NA1-EC4 is degraded from that of EC4-EC5. This is likely due to the different distance ($\Delta x$) in the finite difference estimate of the bottom pressure gradient [the distance between NA1 and EC4 (~10 km) is half that of EC4/EC5 (~20 km)]. The smaller denominator may amplify the finite difference errors of the bottom pressure gradient. Also, the deeper water location may increase the residual due to the baroclinic effect.

6.5.3 Across-shelf momentum balance on the outer shelf

The outer shelf moorings EC1 and CM4 share the common observation period from 25 June 2000 to 25 June 2001. Like those of the inner shelf, the standard deviations of the Coriolis and the bottom pressure gradient terms are the largest (Table 6.2); in contrast with the inner shelf, the standard deviation of the residual term is as large as the bottom pressure gradient term, and this may be due to increased baroclinic effects with deeper water. From Table 6.3, the horizontal density gradient term estimated from the monthly hydrography near station pair EC1-CM4 ranges from $-8.7 \times 10^{-6}$ to $24.9 \times 10^{-6}$ m s$^{-2}$, with magnitudes similar to the Coriolis and bottom pressure gradient terms (Figure 6.8). Thus, the horizontal density gradient term plays a significant role in the across-shelf momentum balance on the outer WFS. Also, the standard deviation of the bottom buoyancy term ($1.86 \times 10^{-6}$ m s$^{-2}$) is 0.32 that of the Coriolis term and is larger than that on the inner shelf.

The correlation and regression analyses for station pair EC1-CM4 (Table 6.4) are similar to those of the inner shelf station pairs in that each term makes a positive
contribution to the momentum balance; the correlation and regression coefficients are much smaller than those of the inner shelf station pairs, which again is likely due to the horizontal density gradient term not included in the regression analyses.

A residual time series is formed after summing all the terms in (5) except the horizontal density gradient term (Figure 6.8d). The horizontal density gradient term is superimposed as discrete open circles for each cruise. There are usually 5 CTD station pairs between moorings EC1 and CM4, so there are 5 values in each cruise to give a range of the density gradient term. The residual line passes through the circles in most
cases, which indicates the residuals can be accounted for by the horizontal density
gradient term.

The pressure gradient term is composed of the bottom pressure gradient, the
horizontal density gradient and the bottom buoyancy terms; the latter two terms are
directly related to density. Baroclinic adjustment to the currents plays an important role
on the outer shelf, sometimes dominating. It is known that the circulation near the shelf
break is often affected by the deep ocean. For instance, during June-July 2000, the Loop
Current intruded onto the shelf slope (He and Weisberg 2003b), and mooring EC1
recorded strong currents during this event. These findings help to define what is
commonly referred to as the mid and outer shelves. The outer shelf is the region where
deep ocean effects are readily observed in the vicinity of the shelf slope and shelf break.
By virtue of the Taylor–Proudman theorem, however, the shoreward penetration of these
outer shelf responses to deep ocean forcing are limited, so the mid shelf is the region
between the outer shelf and the inner shelf, assuming that the shelf is wide enough to
draw such demarcation.

6.6 Along-shelf momentum balance

6.6.1 Estimation of terms

The local acceleration, the Coriolis, and the wind stress terms can be estimated as
in Section 6.5.1. Our data are insufficient to estimate the vertical structure of the along-
shelf pressure gradient, but since EC5 and EC6 are shallow (10 m) sites, a constant
pressure gradient is assumed throughout the water column. The pressure gradient is
estimated in two ways: (1) using bottom pressure at EC5 and EC6, separated along the
shelf by 108 km, and (2) using coastal sea level at Clearwater and Naples, separated by
229 km. The bottom stress may be parameterized either in a quadratic form,
\[ \tau_b^y = \rho_0 C_D v_b \sqrt{u_b^2 + v_b^2}, \]
or in a linear form,
\[ \tau_b^y = \rho_0 r \sqrt{v_b}, \]
where \( r \) is a resistance coefficient.

We take \( r = 5 \times 10^{-4} \) m/s for the bottom stress estimation at the 10 m sites (to be explained
in Section 6.8).
6.6.2 Standard deviations

The standard deviations of the along-shelf momentum terms from the EC5 and EC6 10 m sites show that the wind stress term is the largest one (Table 6.5), followed by the bottom friction, the pressure gradient, the local acceleration, and the Coriolis terms. The standard deviations of the wind stress and bottom friction terms decrease, while that of the Coriolis term increases, with the increasing water depth because the currents are more isotropic and the across-shelf velocity component is larger in the deeper sites. The wind stress, the bottom friction, and the Coriolis terms all have equal magnitude around a depth of 25~30 m. Further offshore, the standard deviation of the Coriolis term becomes larger than those of the wind stress and the bottom friction terms. At the two 10 m sites, the standard deviation of the residual term is even larger than those of the three small terms. The residual may be attributed to observational and diagnostic errors, although it could also be due to the advection terms that are not estimated.

Table 6.5. Standard deviations of the terms in the along-shelf momentum balance (units in \(10^{-6} \text{ m s}^{-2}\)).

<table>
<thead>
<tr>
<th>Station &amp; water depth</th>
<th>Data length (hours)</th>
<th>Standard deviations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\frac{\partial \tau}{\partial t})</td>
<td>(f u)</td>
</tr>
<tr>
<td>EC5 (10 m)</td>
<td>32272</td>
<td>1.11</td>
</tr>
<tr>
<td>EC6 (10 m)</td>
<td>25578</td>
<td>1.19</td>
</tr>
<tr>
<td>EC4 (20 m)</td>
<td>32274</td>
<td>0.99</td>
</tr>
<tr>
<td>NA1 (25 m)</td>
<td>27336</td>
<td>0.97</td>
</tr>
<tr>
<td>NA2 (25 m)</td>
<td>28227</td>
<td>1.09</td>
</tr>
<tr>
<td>NA3 (25 m)</td>
<td>26377</td>
<td>0.94</td>
</tr>
<tr>
<td>EC3 (30 m)</td>
<td>26951</td>
<td>1.02</td>
</tr>
<tr>
<td>EC2 (50 m)</td>
<td>18472</td>
<td>0.85</td>
</tr>
<tr>
<td>CM4 (78 m)</td>
<td>10638</td>
<td>0.73</td>
</tr>
<tr>
<td>EC1 (162 m)</td>
<td>8759</td>
<td>0.60</td>
</tr>
</tbody>
</table>

The bottom stress term values in the parentheses are calculated with quadratic parameterization \((C_D = 3.2 \times 10^{-3})\).

6.6.3 Correlation and regression analyses

We first assume that the along-shelf wind stress and pressure gradient are the two forcing factors, and the summation of the other momentum terms is the response.
Correlation and regression coefficients between the forcing and the response are calculated for each of these summations (Table 6.6). When the bottom stress term is considered to be the only response, $C$ is significantly high. The local acceleration term contributes positively to the along-shelf momentum balance, while the Coriolis term degrades the balance. We next consider the wind stress to be the only forcing function, with the other terms taken as the responses (Table 6.7). $C$ and $R$ between the bottom friction and the wind stress terms are higher than those between the pressure gradient and the wind stress terms. When both the bottom friction and the pressure gradient terms are considered as the responses, $C$ and $R$ increase significantly. As a response to the wind stress, the pressure gradient is secondary to the bottom friction. Again, the local acceleration term contributes positively to the balance, but the Coriolis term degrades the results. Similar findings are given by Hickey et al. (2003).

Table 6.6. Correlation and regression analyses of the along-shelf momentum balance at the 10 m sites, with both the wind stress and the pressure gradient as forcing.

<table>
<thead>
<tr>
<th>Forcing and response</th>
<th>EC5</th>
<th>EC6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau^a - g \frac{\partial h}{\partial y}$ vs. $\tau^b$</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>$\tau^a - g \frac{\partial h}{\partial y}$ vs. $\tau^b + \bar{\nu}$</td>
<td>0.74</td>
<td>0.80</td>
</tr>
<tr>
<td>$\tau^a - g \frac{\partial h}{\partial y}$ vs. $\tau^b + \bar{u}$</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>$\frac{\tau^a}{\rho_o H} - g \frac{\partial h}{\partial y}$ vs. $\frac{\tau^b}{\rho_o H} + \bar{\nu}$</td>
<td>0.73</td>
<td>0.80</td>
</tr>
</tbody>
</table>

$C$: correlation coefficient, all significant at 90% level; $R$: regression coefficient.

6.6.4 Multiple coherence analysis

Similar to the across-shelf direction we also apply a frequency domain analysis. The two inputs are the along-shelf wind stress and the pressure gradient terms. The output is set to be a sum of the local acceleration, the Coriolis and the bottom stress terms; all derived from the moored velocity records. Velocities from moorings EC5 and
EC6 are averaged to form a new velocity time series for the 10 m isobath. Data from 1 September 1999 to 23 August 2001 are used, and the results are shown in Figure 6.9.

Figure 6.9. Multiple coherence analysis with the two-input/one-output statistic model for the along-shelf momentum balance at the 10 m site between moorings EC5-EC6. Inputs: (1) the along-shelf sea level gradient term, and (2) the along-shelf wind stress term; Output: a sum of the local acceleration, the Coriolis, and the bottom stress terms. (a) Ordinary coherence (dashed line is 90% significance level, the same in (b) and (c)); (b) partial coherence; (c) multiple coherence; (d) amplitude of the transfer function; and (e) phase of the transfer function (units in \( \pi \)).

The pressure gradient input (1) has lower coherence with the output than the wind stress term input (2); but the coherence between the two inputs is high over the synoptic
weather frequency band. The partial coherence between the conditioned input 2 and the output is high, whereas the partial coherence between the conditioned input 1 and the output is smaller. There is a high degree of multiple coherence between the two inputs and the output over the synoptic weather band, with an average value of 0.75. That is to say, over 75% of the “current” variance may be accounted for by the wind stress and pressure gradient terms.

Table 6.7. Correlation and regression analyses of the along-shelf momentum balance at the 10 m sites, with the wind stress term as forcing only.

<table>
<thead>
<tr>
<th>Forcing and response</th>
<th>EC5 C</th>
<th>EC5 R</th>
<th>EC6 C</th>
<th>EC6 R</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{\tau_i^y}{\rho_0 H}$ vs. $\frac{\tau_i^y}{\rho_0 H}$</td>
<td>0.73</td>
<td>0.59</td>
<td>0.75</td>
<td>0.59</td>
</tr>
<tr>
<td>$\frac{\tau_i^y}{\rho_0 H}$ vs. $\frac{\tau_i^y}{\rho_0 H} + \frac{\partial h}{\partial y}$</td>
<td>0.68</td>
<td>0.28</td>
<td>0.67</td>
<td>0.27</td>
</tr>
<tr>
<td>$\frac{\tau_i^y}{\rho_0 H}$ vs. $\frac{\tau_i^y}{\rho_0 H} + \frac{\partial h}{\partial y} - \frac{\partial u}{\partial t}$</td>
<td>0.82</td>
<td>0.87</td>
<td>0.83</td>
<td>0.86</td>
</tr>
<tr>
<td>$\frac{\tau_i^y}{\rho_0 H}$ vs. $\frac{\tau_i^y}{\rho_0 H} + \frac{\partial h}{\partial y} - \frac{\partial v}{\partial t}$</td>
<td>0.81</td>
<td>0.87</td>
<td>0.84</td>
<td>0.88</td>
</tr>
</tbody>
</table>

C: correlation coefficient, all significant at 90% level; R: regression coefficient.

6.6.5 A linear nowcast model for along-shelf velocity

The foregoing statistical results justify the application of a simple dynamic model to nowcast the along-shelf velocity. Following Lentz and Winant (1986) and Hickey et al. (2003), along-shelf wind stress and pressure gradient are used to drive a depth-averaged one-dimensional linear model of the along-shelf currents. Assuming that the Coriolis term is negligible and that the bottom stress is a linear function of depth-averaged velocity $\tau_b^y = \rho_0 r \bar{v}$, equation (6.3b), upon integration in time, provides the depth-averaged along-shelf velocity as
\[
\bar{v}(t) = \bar{v}_0 \exp\left(-\frac{rt}{H}\right) + \int_0^t \tau_x \exp\left[-\frac{r(t-t')}{H}\right]dt' - \int_0^t \frac{1}{\rho_0} \frac{\partial p}{\partial n} \exp\left[-\frac{r(t-t')}{H}\right]dt' 
\]

where \(\bar{v}_0 = \bar{v}(0)\) is the initial condition. \(H/r\) is the frictional adjustment time, and with \(r=5 \times 10^{-4}\) m/s [as in Lentz and Winant (1986) and Hickey et al. (2003)], and \(H=10\) m, the adjustment time is about 6 hours. Thus, the effective integration time is on the order of a pendular day, and the initial condition \(\bar{v}_0\) is relatively unimportant. Since the model is linear, estimates can be made for the wind stress and pressure gradient either alone, or together.

The along-shelf wind stress for the inner shelf, bottom pressure at moorings EC5 and EC6, and sea level records at the Clearwater and Naples coastal stations from 15 December 2000 though 30 April 2001 are used to nowcast the depth-averaged along-shelf currents at the 10 m isobath. The model results are compared with observations in Figure 6.10. The wind stress estimated currents are highly correlated with the observations, but they are overestimated in amplitude. The pressure gradient forced currents are weaker than those estimated by the wind stress, and they are negatively correlated with the observations. When the model is forced by wind stress and along-shelf bottom pressure gradient together, the estimated currents are closer to the observations. Thus, the along-shelf wind stress is the dominant driver, while the pressure gradient is complementary. Calculating the pressure gradient from coastal sea level (as opposed to bottom pressure) improves the results.

The along-shelf wind stress and the pressure gradient terms themselves are negatively correlated (correlation coefficient \(-0.67\sim-0.68\), from Table 6.7). The high coherence between these two terms can also be seen from the previous multiple coherence analyses (Figure 6.9a). Thus, the pressure gradient derives from the local wind, rather than remotely. From this point of view, the WFS is quite different from either the Pacific Northwest Shelf (Hickey 1984) or the central Southern California Bight (Hickey et al. 2003), where the along-shelf pressure gradient is generated primarily non-locally and the pressure gradient disturbances account for a much larger fraction of the along-shelf velocity variance than the local wind stress.
Figure 6.10. Comparisons of the depth-averaged along-shelf velocity estimated with a linear nowcast model along the 10 m isobath and that from the observations at moorings EC5 and EC6 (C: Correlation coefficient, R: Regression coefficient, where $V_{\text{model}} = V_{\text{observation}} \times R + \text{constant}$, same in Figure 6.11). (a) the model is forced by the along-shelf wind stress only; (b) the model is forced by the along-shelf bottom pressure gradient only, with the bottom pressure records from moorings EC5 and EC6; (c) the model is forced by both the along-shelf wind stress and the along-shelf bottom pressure gradient; (d) and (e) are the same as (b) and (c), respectively, except the along-shelf pressure gradient is approximated by the coastal sea level gradient between Clearwater and Naples.
An along-shelf slope of sea level on the WFS was reported by Cragg et al. (1983). In the 4-10 day band this slope was explained by the longshore variation in the width of the shelf, and at lower frequencies it was suggested to be caused by the winds. Also on the WFS, any free continental shelf waves were found to have amplitudes substantially smaller than the wind forced waves (Cragg et al. 1983). In an analytic model of nearshore response to forcing by synoptic scale winds (Mitchum and Clarke 1986a), the along-shelf pressure gradient, while becoming increasingly important offshore, was found to play a small role in driving the along-shelf flow.

The interpretation on the WFS is relatively straightforward. By a classical Ekman-geostrophic spin-up the along-shelf wind generates an along-shelf current over the course of a pendular day (e.g., Weisberg et al. 2000) with bottom stress tending to balance the wind stress. However, owing to the full three dimensional nature of the response an along-shelf pressure gradient also develops that partially counteracts the wind stress. Without provision for the pressure gradient the along-shelf wind response is overestimated. These results are essentially as shown in the model study of Li and Weisberg (1999b).

6.7 Applications of the momentum balances

From the foregoing considerations, is it possible to estimate currents from readily observed variables such as wind and coastal sea level and to provide offshore sea surface height variation from independently observed currents?

6.7.1 Nowcast the depth-averaged along-shelf currents

As already known, the first three dominant terms in the across-shelf momentum balances over the inner shelf are the Coriolis, the pressure gradient, and the wind stress terms. Thus, the depth-averaged along-shelf velocity may also be expressed as

\[
\bar{v} = \frac{1}{\rho_0 f} \frac{\partial p_b}{\partial x} - \frac{\tau^y}{\rho_0 f H}
\]

(6.7)
Figure 6.11. Application of the momentum balances at 15 m site. Upper panel: stack plot of the depth-averaged along-shelf currents from observation (thin lines) versus those (thick lines) estimated from the along-shelf wind stress \( \tau_y \) alone (a) and with the along-shelf sea level gradient \( d\eta/dy \) together (b), or from the across-shelf pressure gradient \( dp/dx \) alone (c) and with the across-shelf wind stress \( \tau_x \) together (d); an average of (b) and (d) gives a better result in (e). Lower panel: stack plot of the across-shelf sea level (pressure) gradient from observations (thin lines) versus those (thick lines) estimated from the along-shelf currents (modelled from \( \tau_y \) and \( d\eta/dy \)) and the across-shelf wind stress \( \tau_x \). (\( C \): Correlation coefficient, \( R \): Regression coefficient).
Based on the bottom pressure data at moorings EC4 and EC5, wind on the inner shelf, and coastal sea level at Naples and Clearwater, the along-shelf velocity is estimated using equations (6.6) and (6.7), respectively. The resistance coefficient is set to be $3.5 \times 10^{-4}$ m/s, and the coastal sea level gradient is down-scaled by a factor of 0.7 to get the along-shelf pressure gradient at the 15 m site. While the along-shelf wind stress tends to over-predict the along-shelf current, especially during strong wind events (Figure 6.11a), the along-shelf pressure gradient helps to eliminate the offset between the estimates and the observations (Figure 6.11b). The across-shelf pressure gradient generally predicts the currents well except for some strong current events (Figure 6.11c), while the across-shelf wind stress improves the current estimation at these peaks (Figure 6.11d). At some peaks (for example, around early August 2001), equation (6.6) overestimates, while equation (6.7) underestimates the velocity (Figure 6.11b&d). An average between these two estimates gives a better nowcast result (Figure 6.11e). During the spin up period, the momentum from the wind stress is not fully exerted on the currents, thus the currents are overestimated if the wind stress is used to drive the along-shelf model [equation (6.6)]. Similarly, the currents are underestimated by the across-shelf model [equation (6.7)] during the spin up period. The real currents lie between these two estimates.

The down-scale factor of 0.7 is used to approximate the along-shelf pressure gradient at the 15 m isobath from the coastal sea level. Hickey (1984) also used a value of 0.7~0.8 on the Pacific Northwest Shelf. As a test of sensitivity we also tried values of 0.9 and 0.5. With 0.9, the estimated currents are weaker ($C=0.76, R=0.88$ in Figure 6.11b), whereas with 0.5, they are stronger ($C=0.82, R=1.07$ in Figure 6.11b). Based on regression coefficient the 0.7 value seems to be approximately correct.

6.7.2 Estimate the across-shelf pressure gradient

By rearranging equation (6.7), we have $\frac{\partial p_b}{\partial x} = \rho_o f \nu + \frac{\tau_x}{H}$, and the across-shelf pressure gradient may be estimated from the depth-averaged along-shelf currents and the across-shelf wind stress. The inner shelf winds and coastal sea level at Clearwater and Naples are used to nowcast the depth-averaged along-shelf currents at 15 m site again.
using equation (6.6) (Figure 6.11b). Both the estimated currents and the observed across-shelf wind stress are further used to calculate the across-shelf pressure gradient. The currents underestimate the across-shelf pressure gradient (Figure 6.11f); the across-shelf wind stress alone explains a part of the across-shelf pressure gradient only during certain major events (Figure 6.11g). Together, the currents and the wind stress reproduce the across-shelf pressure gradient quite well (Figure 6.11h). Over the largely barotropic inner shelf, the sea level gradient approximates the bottom pressure gradient. Thus, the wind and coastal sea level data provide an estimate of the offshore sea surface height variation.

6.8 Estimate of bottom drag and resistance coefficients

The bottom drag coefficient $C_D$ may be estimated by equating the bottom stress term to the residual of the other momentum terms, using the near bottom velocity to fit the bottom stress term. For $x(t) = v_b \sqrt{u_b^2 + v_b^2} / H$ and $y(t) = \frac{\partial\tilde{v}}{\partial t} + f\tilde{u} + g \frac{\partial \eta}{\partial y} - \frac{\tau_y}{\rho_0 H}$, a regression coefficient $C_D$ may be estimated from a least squares fit of the linear system $y(t) = C_D x(t) + b$, where $b$ is a constant. Based on the velocity data obtained at mooring EC5, $C_D$ is estimated to be $3.2 \times 10^{-3}$; however, the velocity data at EC6 yields a $C_D$ of $2.1 \times 10^{-3}$. As an alternate method, $C_D$ may be determined via an empirical search. By using different $C_D$ values, and thus different estimates of the bottom stress term, the along-shelf momentum balance is different. Optimal $C_D$ values may be obtained from the momentum balance in such a way that the $C_D$ either (a) minimizes the mean imbalance squared, (b) maximizes the correlation coefficient between the along-shelf wind stress term (the leading term) and the summation of the other terms, or (c) optimizes the regression between these two terms by setting the regression coefficient equal to 1. Using the velocity data at the 10 m sites (moorings EC5 and EC6) to perform the empirical search yields $C_D$ ranges of $2 \times 10^{-3} \sim 4 \times 10^{-3}$ (Figure 6.12). These values are close to those in Feddersen and Guza (2003). Numerical models on the WFS (Li and Weisberg 1999a; He and Weisberg 2002a; and He et al. 2004) employing the Princeton Ocean Model of Blumberg and Mellor (1987) take the bottom drag coefficient as
\[ C_D = \max \left\{ 2.5 \times 10^{-3}, \left[ \frac{1}{k} \ln \left( 1 + \frac{\sigma_b}{z_0 / H} \right) \right]^{-2} \right\}, \]

where \( k \) is the von Karman constant, \( z_0 \) is the bottom roughness length, \( \sigma_b \) is the \( \sigma \) value of the grid point next to the bottom, and \( H \) is the water depth. Except near shore, the \( C_D \) in these WFS model calculations is generally \( 2.5 \times 10^{-3} \). A similar linear regression is made from the across-shelf momentum balance by assuming the density gradient term is negligible. Using the EC4-EC5 data we arrive at a \( C_D \) value of \( 1.5 \times 10^{-3} \). This value is smaller than those from the along-shelf momentum balance. Since the residual of the much larger terms (the Coriolis and bottom pressure gradient) is likely more error prone, causing \( C_D \) to be underestimated. Thus, \( C_D = 2.5 \times 10^{-3} \) is used for the across-shelf bottom stress estimation, for both the inner and outer shelves.

\[ C_D = \max \left\{ 2.2 \times 10^{-3}, 2.4 \times 10^{-3}, 3.7 \times 10^{-3} \right\}, \]

Figure 6.12. Statistics of the along-shelf momentum terms at the 10 m sites as a function of the bottom drag coefficient \( C_D \). The optimal \( C_D \) values may (a) minimize the mean imbalance squared, where the imbalance is a sum of all the momentum terms, (b) maximize the correlation coefficient, and (c) optimize the regression coefficient (=1) between the along-shelf wind stress and the sum of the other terms. Atop of each panel are the optimal \( C_D \) values estimated from the EC5 and EC6 data alone, and from an average of the EC5 and EC6 data.
Figure 6.13. Statistics of the estimated and observed depth-averaged along-shelf velocity at the 10 m sites as a function of the bottom resistance coefficient $r$: (a) mean squared error, (b) correlation, and (c) regression coefficients. The $r$ values estimated from the EC5 and EC6 data alone, and from an average of the EC5 and EC6 data are listed in the bracket on top of each panel.

The resistance coefficient $r$ may also be estimated. Again, by taking a linear regression of the along-shelf momentum terms, setting $x(t) = \bar{v} / H$ and keeping $y(t)$ the same, $r$ is calculated as $4.1 \times 10^{-4}$ and $4.3 \times 10^{-4}$ m/s, respectively, for the data from EC5 and EC6. If $v_s$ is used instead of $\bar{v}$, these two $r$ values become $3.4 \times 10^{-4}$ and $3.6 \times 10^{-4}$ m/s. These values are larger than those ($1 \times 10^{-4}$~$2 \times 10^{-4}$ m/s) estimated by Mitchum and Sturges (1982), but smaller than the value of $5 \times 10^{-4}$ m/s used by Lentz and Winant (1986), Lentz et al. (1999), and Hickey et al. (2003). As before, empirical search is performed to obtain an optimal $r$. We run a series of model experiments as in section 5.5 in which we vary $r$ from $1 \times 10^{-4}$ to $6 \times 10^{-4}$ m/s, the estimated along-shelf velocities are then compared with the observations. The $r$ values corresponding to the minimum mean square error, the maximum correlation and a regression coefficient of 1 are regarded as the optimal estimates. For any $r$ values larger than $2 \times 10^{-4}$ m/s the mean squared error is
small and the correlation is significantly high (Figure 6.13); the optimal $r$ value for the best regression coefficient is around $5 \times 10^{-4}$ m/s. Chuang and Weisman (1983) used a wide range of $r$ values ($1 \sim 10 \times 10^{-4}$ m/s) in a one-dimensional model on the Louisiana and Texas Shelf. He and Weisberg (2002a) obtained $r$ values of $0.6 \times 10^{-4} \sim 6 \times 10^{-4}$ m/s on the WFS with larger values near shore. Hickey et al. (2003) also found that a much better momentum balance is obtained if larger $r$ value is used. Unless otherwise noted, the value of $5 \times 10^{-4}$ m/s is used in the along-shelf bottom stress parameterization.

6.9 Numerical model results

The Princeton Ocean Model (POM) has been successfully used in the WFS circulation modelling (e.g., Li and Weisberg 1999a, b; He and Weisberg 2002a,b; Weisberg et al. 2001). It is reasonable to assume that outputs from the POM are dynamically consistent. A comparison of the momentum terms estimated from the observations and those calculated from the model results may indicate to what degree the observed and model dynamics agree. This modelling work was originally done by He et al. (2004). Here, it is reconfirmed with an independent study starting with slightly different model domain (Figure 6.14).

An orthogonal curvilinear grid ($81 \times 51$) is used in the horizontal and a sigma coordinate in the vertical (21 layers). Horizontal diffusivities are parameterized according to (Smagorinsky 1963) with a dimension of 0.2. Vertical diffusivities follow the (Mellor and Yamada 1982) level 2.5 closure scheme, and the bottom stress follows a quadratic law using a variable drag coefficient with a minimum value of $2.5 \times 10^{-3}$. A mode splitting technique is employed with external and internal time steps of 24 and 720 s, respectively. The model is initialized at rest with horizontally uniform stratification. Above and below 200 m stratification is based on CTD casts from an April 2001 hydrographic cruise and climatology, respectively. Tidal forcing is excluded, since the tidal mixing associated with the tidal currents is weak in comparison with other sources for mixing (He and Weisberg 2002a). Surface heat flux is set to be zero, as high resolution heat flux data is not available. The only time varying forcing is wind stress. Wind data observed at the
surface moorings and the coastal meteorological stations are converted to wind stress using (Large and Pond 1981) method, and then mapped onto the model grids using an optimal interpolation technique with a de-correlation scale of 300 km. Hourly wind stress is linearly interpolated in time domain to have wind stress field at each time step.

Figure 6.14. Model grids and topography.

The model is run for one month forced by the wind stress in March 2001. Time series of depth-averaged currents, sea surface heights, surface and bottom stresses at the mooring locations are produced hourly as the observations. The major momentum terms are calculated also in the same way as for the observations for the purpose of comparison. Time series of the major momentum terms estimated from the observations and from the model outputs are superimposed in Figure 6.15. The results are almost identical to those by He et al. (2004). For either across-shelf or along-shelf momentum terms, the observations and the model outputs compare well for the dominant terms. The differences of the momentum terms between the data and the model results are due to several factors, including the errors in data retrieval, the deficiency of model parameterizations and the spatial offsets between the mooring point and model grid.
Figure 6.15. Modeled (thin lines) and observed (thick lines) momentum terms in the across (left panels) and along (right panels) shelf directions. $C$ and $R$ are correlation and regression coefficients, respectively.

6.10 Discussions

Errors in the momentum balances derive from the observations, the diagnostic calculations, and the simplified dynamics.

In calculating the depth-averaged currents we must integrate vertically and average horizontally. Data gaps near the surface and bottom must be considered. Experiments performed with either uniform, linear, or no extrapolation of velocity to the surface and bottom gave slightly different results. The case of no extrapolation, i.e., the average of available data only gave better results than an assumed vertical structure. Resolving the near bottom and near surface few meters of the water column would be
beneficial in the future velocity observations. Experiments were also performed with
different horizontal averaging with the best results obtained by a depth weighted average.

The major source of observational error is in the bottom pressure data. For
example, with a distance $\Delta x = 20$ km, $f = 0.66 \times 10^{-4}$ s$^{-1}$ at the latitude of the WFS,
$\rho_0 = 1023$ kg m$^{-3}$, a bottom pressure error of 0.1 dbar (or 100 Pa) translates to an error of
7.3 cm s$^{-1}$ in velocity according to the geostrophic relation $\Delta v = (\rho_0 f)^{-1} \Delta P_b / \Delta x$.
Pressure accuracy was stated to be in 0.15% of full scale range. But the linear trend
(0.02~0.2 bar at moorings EC4, EC5 and EC6) is much larger than this. Wind and bottom
stress parameterizations may also introduce errors. The bottom drag coefficient $C_D$ and
bottom resistance coefficient $r$ are not constant (Grant et al. 1984). Comparing these
values used by various investigators is difficult (Winant and Beardsley 1979; Grant et al.
1984). Moreover, nonlinear parameterizations are more accurate than linear
parameterizations (Feddersen et al. 2000). Errors are also introduced when bottom
temperature alone is used to infer bottom density. Additional density data are required to
better estimate the baroclinic terms.

Advection terms do not appear in our diagnostic momentum equations. Thompson
and Pugh (1986) show that advection is due to the subtidal flow and mean tidal
advection. The Rossby number for the interior circulation is typically $10^{-2}$ and the
subtidal advection can generally be ignored. These findings for the subtidal motions are
consistent with the numerical model results of Li and Weisberg (1999a, b) where the
advection terms were an order of magnitude smaller than the lead momentum balance
terms. Rectification by tidal currents may be a factor where tidal currents are large.
However, on the WFS, the tides are generally weak (He and Weisberg 2002a), so their
effect on the subtidal circulation is thought to be small.

Lentz et al. (1999) consider a wave radiation stress term in a momentum balance
on the North Carolina inner shelf. Radiation stress is found to be important in the across-
shelf momentum balance offshore of the surf zone, in depths at least as great as 13 m, and
such wave forcing is more important than wind forcing in the along-shelf momentum
balance in the surf zone (Feddersen et al. 1998; Lentz et al. 1999). For our case, moorings
EC5 and EC6 are located at the 10 m isobath, but far from the surf zone. Omission of
wave radiation stress in our calculations appears warranted by the relatively weak wave regime of the WFS.

6.11 Summary

Based on multi-year observations of currents, bottom pressures, temperatures, winds, coastal sea levels, and hydrographic data, the depth-averaged momentum balance on the WFS is diagnosed on synoptic and longer time scales. These observational analyses complement previous WFS momentum balance diagnoses performed with numerical models. The following results are presented.

The across-shelf momentum balance on the inner shelf is essentially geostrophic between the Coriolis force due to the along-shelf currents and the across-shelf bottom pressure gradient, as reported elsewhere (Brown et al. 1985, 1987; Lentz et al. 1999, etc). The across-shelf wind stress accounts for most of the variance in the ageostrophic momentum residual. During severe weather events, the across-shelf wind stress may even be the dominant term in the across-shelf momentum balance. This supports model results on the importance of the across-shelf wind stress on the inner shelf (Li and Weisberg 1999a, b; Tilburg 2003). Taking the across-shelf pressure gradient and the friction (surface and bottom) terms as the forcing functions we account for 95% of the variance in the acceleration (Coriolis plus local) on the inner shelf over the synoptic weather band.

The balances are more complicated on the outer shelf where the Coriolis, the across-shelf bottom pressure gradient, and the horizontal density gradient terms all have the same magnitude. The latter term (representing baroclinicity) plays an increasingly important role as the depth and stratification increase. Outer shelf variability is influenced by deep ocean forcing along with the local winds. Such deep ocean forcing, however, is generally limited to the region of the shelf slope and break by virtue of the Taylor-Proudman theorem. If the shelf is wide enough, as is the case for the WFS, then the inner and outer shelf regions are separated by what we refer to as the mid shelf, with these inner, mid, and outer shelf regions all being controlled by different dynamical balances.
The along-shelf momentum balance on the inner shelf is primarily between the wind stress and the bottom stress terms, complemented by the pressure gradient and the Coriolis and local acceleration terms. This result agrees with previous studies (Mitchum and Sturges 1982; Lentz and Winant 1986; Lee et al. 1989; Lentz et al. 1999). It also supports the Li and Weisberg (1999b) finding that the inner shelf is the region of transition from a near shore balance between surface and bottom stress to a mid shelf balance between surface stress and Coriolis force (an Ekman balance).

At synoptic weather and longer time scales, the along-shelf wind stress is the dominant driver of the along-shelf currents on the inner shelf. The bottom friction, pressure gradient, and Coriolis terms are consequences of this. An along-shelf pressure gradient is set up by the local wind stress and acts in opposite to it. It thereby accounts for a smaller fraction of the along-shelf velocity variance than the along-shelf wind stress. These features distinguish the inner WFS from the inner shelf of northern California, where the along-shelf wind stress and pressure gradient tend to be similar in magnitude (Lentz 1994), the Pacific Northwest Shelf, where the along-shelf pressure gradient is primarily of non local origin (Hickey 1984), and the central Southern California Bight where the along-shelf pressure gradient accounts for a much larger fraction of the along-shelf velocity than the local wind stress (Hickey et al. 2003).

It is demonstrated that the depth-averaged, along-shelf currents on the inner shelf may be estimated from the winds and coastal sea level or from the winds and the across-shelf bottom pressure gradient, or from both. The across-shelf sea level gradient on the inner shelf may also be inferred from the wind and coastal sea level data. A simple average of these two approaches provides an improved estimate of the along-shelf currents and the across-shelf sea level gradient.

Inferred from these analyses depending on the bottom stress parameterization are a drag coefficient $C_D$ of $2\sim 4 \times 10^{-3}$ and a resistance coefficient $r$ of $3\sim 6 \times 10^{-4}$ m/s. Momentum terms estimated from the observations and those calculated from a numerical model compare well.
Chapter 7
Ocean Current Structures and Sea Surface Height Estimates
Across the Central West Florida Shelf

7.1 Abstract

The across-shelf structures of the ocean circulation and the associated sea surface height (SSH) variability are examined on the WFS for the three-year interval September 1998 to December 2001. Five sets of characteristic circulation patterns are extracted from two-day, low-pass filtered data using the Self-Organizing Map: extreme upwelling and downwelling structures with strong currents, asymmetric upwelling and downwelling structures with moderate currents, and a set of transitional structures with weak currents. The temporal variations of these structures are coherent with the local winds on synoptic weather time scales. On seasonal time scales they are related to both the local winds and the water density variations. The circulation is predominantly upwelling during fall to spring months (October to April) and downwelling during summer months (June to September). Coastal sea level fluctuations are related to both the dynamical responses of the inner shelf circulation to meteorological forcing and the offshore SSH. On long time scales, the offshore SSH variations appear to dominate, whereas on synoptic weather time scales, the inner shelf wind-driven circulation responses are largest. We estimate the across-shelf distribution of SSH from the velocity, hydrography, wind, and coastal sea level data, and we compare the results with satellite altimetry data, thereby providing a means for calibrating satellite altimetry on the shelf.
7.2 Introduction

Wind driven upwelling and downwelling circulations play important roles in determining coastal ocean water properties (Huyer 1990; Smith 1995). Observational studies of coastal upwelling and downwelling began with across-shelf hydrographic sections, and these were later augmented with velocity data from across-shelf arrays current meters (e.g., Mooers, et al. 1976; Kundu and Allen 1976; Brink et al. 1980, 1983). Determining the across-shelf flow structures within upwelling regions was difficult with individual current meters on moorings since these sampled neither the near surface nor the near bottom regions (Huyer 1990). The introduction of Acoustic Doppler Current Profilers (ADCP) improved on these sampling capabilities, but long time series remain sparse (e.g., Mooers et al. 1976; Kundu and Allen 1976; Murthy and Dunbar 1981; Lentz 2001; Lentz et al. 2003), and across-shelf arrays of ADCPs maintained over several years are rare.

Schematics of coastal upwelling and downwelling structures, e.g., Huyer (1990), suggest asymmetries in the across-shelf structures of the velocity and density fields. Observations of asymmetric behavior are few, however, in part because coastal upwelling receives more attention than coastal downwelling due to its ecological importance (Huyer 1983; Brink 1983; Brink et al. 1983).

Here we consider the across-shelf structure of the circulation on the West Florida Shelf (WFS) and the relationship between the currents and the sea surface height (SSH). The WFS is a wide, gently sloping continental shelf located in the eastern Gulf of Mexico. Weisberg et al. (2005) reviews the circulation observed and modeled over various time scales. Early inferences on the WFS seasonal circulation were from drift bottles (e.g., Tolbert and Salsman 1964). Measurements with in situ moorings began in the 1970s (e.g., Niiler 1976; Price et al. 1978; Weatherly and Martin 1978; Blaha and Sturges 1981; Mitchum and Sturges 1982; Marmorino 1983a, b; Halper and Schroeder 1990; Weatherly and Thistl 1997), but these were mostly of short duration and with limited spatial coverage. Longer duration measurements with ADCPs, first at a single
point (47 m isobath) and then at multiple locations across the shelf began with Weisberg et al. (1996), followed by Siegel (2000) and Meyers et al. (2001). Following these exploratory data sets focus concentrated on the inner shelf for which Liu and Weisberg (2005b) analysed the spatial patterns of current variability from October 1998 through September 2001. The asymmetric upwelling and downwelling responses at synoptic scale identified by Weisberg et al. (2001) were further described, and a coherent seasonal variation was found such that during winter the inner shelf currents tend to be upwelling favorable and southeastward, whereas during summer they are downwelling favorable and northwestward. These across-shelf structures and seasonality were also found in WFS numerical model simulations (e.g., Li and Weisberg 1999a, b; Yang and Weisberg 1999; Weisberg et al. 2000, 2001; He and Weisberg 2002b, 2003a). Recently, however, Ohlmann and Niiler (2005) in their interpretation of surface drifter tracks from northern Gulf of Mexico suggested that a seasonality is not profound on the WFS.

Satellite altimetry provides valuable information on the deep ocean circulation (e.g., Douglas et al., 1987; Fu et al. 1994; Fu and Cheney 1995; Lagerloef et al. 1999). Direct comparisons with in situ measurements of SSH are mostly from the open ocean using sea level records from oil platforms (e.g., Christensen et al. 1994; Ménard et al. 1994; Born et al. 1994; Haines et al. 2003), island tide gauges (e.g., Mitchum 1994, 1998, 2000; Cheney et al. 1994; Verstraete and Park 1995), and GPS buoys (e.g., Bonnefond et al. 2003; Watson et al. 2003), and dynamic height estimates from hydrography (e.g., Cheney et al. 1994; Picaut et al. 1995; Katz et al. 1995; Menkes et al. 1995) and inverted echo sounders (e.g., Picaut et al. 1995; Katz et al. 1995; Teague et al. 1995). In contrast, comparisons with SSH observations near the coast are rare because coastal ocean altimetric observations are not as readily interpretable due to a number of factors (Vignudelli et al. 2005). Complimenting conventional altimetric sensors is a new GPS coastal altimetry technique introduced by Treuhaft et al. (2005). For both the conventional and new techniques the calibration of coastal altimetry requires independent SSH estimations within shallow water environments.

Early observational studies of the WFS sea level response to wind forcing focused on coastal sea level (Marmorino 1982; Cragg et al. 1983). An across-shelf sea level
distribution was examined by Marmorino (1983b) using a tide gauge at Cedar Key, FL, and bottom pressure records from two offshore moorings. Bottom pressure was found to decay offshore, and the across-shelf pressure gradient was used to estimate the along-shelf geostrophic velocity for comparison with the observed currents. However, the baroclinic contribution was omitted and the records were short (< 2.5 months). In a related set of papers Mitchum and Clarke (1986a, b) applied a frictional, wind-forced, barotropic long-wave model to the WFS. The first of these developed an equation for the pressure (sea level) response to along-shelf synoptic wind forcing over a region extending from the coast to where the water depth is three times the Ekman depth in order to provide a boundary condition for the long-wave model. Through comparison made with coastal sea level they suggested that the pressure field (sea level) is controlled by first mode long-waves, consisting of the sum of forced waves evolving with the wind stress and a free wave generated at the Florida Keys, and that a frictional inner shelf correction proportional to along-shelf wind stress is important.

This chapter is an observational study linking the coastal ocean circulation and the SSH and in particular how coastal sea level relates to both the inner shelf and the deeper ocean variations. An SSH equation is derived that takes into account the inner shelf contributions by both the barotropic and baroclinic along-shelf currents and the across-shelf wind stress. The data sets are described in Section 7.3. Section 7.4 provides the SSH equation derivation with respect to the three contribution studied. With the SSH equation related to the velocity, hydrography, local wind stress and coastal sea level, there is a basis for estimating the absolute SSH from these data. Section 7.5 describes the across-shelf structures of the inner shelf currents, and Section 7.6 diagnoses the hydrographic data to give the portion of the across-shelf current structure due to baroclinicity. The results are combined in Section 7.7 to provide an SSH analysis and a comparison with satellite altimetry. The findings are then discussed and summarized in Section 7.8, where the effects of baroclinicity and across-shelf wind stress are shown to be important contributors along with the barotropic currents, and the residual offers a basis for using satellite altimetry on the shelf.
7.3 Data

Five ADCP moorings were maintained between the 10 m and 50 m isobaths offshore of Sarasota, Florida (Figure 7.1) from October 1998 through September 2001. Moorings EC5 and EC4, located at the 10 m and 20 m isobaths, respectively, sampled with bottom-mounted, upward looking ADCPs measuring velocity at 0.5 m intervals from 2 m off the bottom to 2–3 m from the surface. Moorings NA1, EC3 and EC2, located at the 25 m, 30 m, and 50 m isobaths, respectively, sampled with surface buoy-mounted, downward looking ADCPs measuring velocity at either 0.5 m or 1 m intervals from 2–3 m below the surface to 2–3 off the bottom. The velocity data at all of the moorings were sampled hourly.

Figure 7.1. West Florida shelf map showing topography (isobaths in m) and locations of the ADCP, CTD, wind and coastal sea level stations.

Monthly hydrographic data were collected along three WFS transects from June 1998 to December 2001. Here we use data inshore of the 50 m isobath from two transects taken offshore of Tampa Bay and Sarasota, each with 10 CTD stations (Figure 7.1). Figure 7.2 shows the hydrographic sampling relative to the ADCP moorings. Ancillary
data include hourly winds at NDBC Buoy 42036 and Venice, downloaded from the NOAA/NDBC website ([http://www.ndbc.noaa.gov/](http://www.ndbc.noaa.gov/)), hourly sea level at St. Petersburg, downloaded from the NOAA/NOS website ([http://www.co-ops.nos.noaa.gov/](http://www.co-ops.nos.noaa.gov/)), and sea level anomaly data merged from multi-altimetry sensors (Topex/Poseidon or Jason-1 + ERS-1/2 or Envisat), downloaded from the AVISO (Archiving, Validation and Interpretation of Satellite Oceanographic data) website ([http://las.aviso.oceanobs.com/las/servlets/dataset](http://las.aviso.oceanobs.com/las/servlets/dataset)). The sea level anomalies are defined as differences between the observed SSH and the seven-year mean sea level.

Figure 7.2. A timeline diagram showing the concurrent observations of the ADCP (solid lines) and CTD data at Sarasota (crosses) and Tampa Bay (circles) transects.

7.4 Sea surface height equations

Assuming a hydrostatic balance and integrating down from the surface for a right-handed coordinate system with \( z \) positive upward and with atmospheric pressure set equal to zero, the pressure \( p \) at any level \( z \) is

\[
p = \int_z^0 \rho g dz',
\]

where \( \eta \) is the free surface elevation above a zero mean sea surface elevation and \( g \) is the gravitational acceleration. Let the density \( \rho \) consist of a reference value \( (\rho_0) \) and a perturbation \( (\epsilon) \),

\[
\rho = \rho_0 [1 + \epsilon(x, z)],
\]
where $x$ is in the across-shelf coordinate directed, positive onshore. From equations (7.1) and (7.2), the horizontal pressure gradient in the across-shelf direction is

$$\frac{1}{\rho_0} \frac{\partial p}{\partial x} = g \frac{\partial \eta}{\partial x} + g \int_z \eta \frac{\partial \varepsilon(x,z')}{\partial x} dz'. \quad (7.3)$$

The depth-integrated form of equation (7.3), with a partial integration of the second term on the right, yields

$$\frac{1}{\rho_0} \int_{-H}^0 \frac{\partial p}{\partial x} dz = gH \frac{\partial \eta}{\partial x} + gH \int_{-H}^0 (1 + \frac{z}{H}) \frac{\partial \varepsilon(x,z)}{\partial x} dz, \quad (7.4)$$

where $H$ is the bottom depth, and it is assumed that $\eta \ll H$. These derivations may be found in Csanady (1979).

Over synoptic and longer time scales, the dominant terms in the depth-averaged across-shelf momentum balance on the WFS are the Coriolis, the pressure gradient and the wind stress terms (Chapter 6)

$$- f \bar{v} = - \frac{1}{\rho_0 H} \int_{-H}^0 \frac{\partial p}{\partial x} dz + \frac{\tau_s}{\rho_0 H}. \quad (7.5)$$

Substituting the pressure gradient term with equation (7.4), equation (7.5) becomes

$$- f \bar{v} = -g \frac{\partial \eta}{\partial x} - g \int_{-H}^0 (1 + \frac{z}{H}) \frac{\partial \varepsilon(x,z)}{\partial x} dz + \frac{\tau_s}{\rho_0 H}. \quad (7.6)$$

Rearranging equation (7.6) and integrating in the across-shelf direction to solve for $\eta$, the SSH distribution across the shelf, $\eta(x)$, may be expressed as

$$\eta = \eta_0 + \eta_b + \eta_c + \eta_w, \quad (7.7)$$

$$\eta_b = \int_0^x \frac{f \bar{v}}{g} dx, \quad (7.7a)$$

$$\eta_c = -\int_0^x \int_{-H}^0 (1 + \frac{z}{H}) \frac{\partial \varepsilon(x,z)}{\partial x} dz dx, \quad (7.7b)$$

$$\eta_w = \int_0^x \frac{\tau_s}{\rho_0 g H} dx, \quad (7.7c)$$

where $\eta_0$ is the reference sea level at the initial integration point (the 50 m isobath in this paper), $\eta_b$, $\eta_c$ and $\eta_w$ are SSH contributions from the along-shelf depth averaged
(barotropic) and baroclinic currents, and the across-shelf wind stress, respectively, which may be estimated from the observed currents, hydrography and winds across the shelf.

Equation (7.7b) may be written as

$$\eta_c = -\frac{f}{gH} \int_0^z \int_{-H}^0 v_g(x,z) dz dx,$$

(7.8)

where $v_g$ is the relative along-shelf baroclinic geostrophic velocity,

$$v_g = \frac{g}{f} \int_{-z}^0 \frac{\partial e(x,z')}{\partial x} dz'.$$

(7.9)

By definition of the thermal wind relation, $v_g$ is essentially the current vertical shear between two levels. Thus, $v_g$ may be calculated directly from the current vertical profiles. Equation (7.8) provides an alternate method to estimate $\eta_c$ from the along-shelf current vertical shears.

7.5 Across-shelf structure of velocity from the moored ADCPs

7.5.1 EOF results

To focus on the subtidal variability the velocity data are first low-pass filtered using a cut-off of two-day. Five vertical levels extending from the near-surface to the near-bottom are extracted from each profile so that each of the mooring sites is afforded equal weight in the analysis. Since a time domain EOF analysis requires continuous input data the longer data gaps at mooring EC2 are filled by linear regression using data at moorings CM2 or CM3, all located along the same (50 m) isobath. Smaller data gaps in other records are filled through linear regression from adjacent stations. The velocity time series are arranged in a two-dimensional array such that each velocity snapshot is in a single row vector and the time series of each velocity component is in a single column. All $u$ components are placed in the first half the rows followed by all $v$ components. Thus, the input matrix consists of 50 columns (5 stations × 5 levels × 2 components) × 28201 rows (hours), and the temporal mean values are removed prior to the EOF analysis. While the east and north velocity components are used in the EOF analysis (so that the matrix will not be ill-conditioned) the velocity eigenvector is then rotated to the
across- and along-shelf directions for visualization. The along-shelf direction is defined as the direction of the principal axis of the depth-averaged currents for each mooring.

Figure 7.3. First mode eigenvector (top panel) and its principle component (middle panel) from a time domain EOF analysis of 2-day low-pass filtered currents, relative to 30-day low-pass filtered, 3-day sub-sampled winds at Venice, Florida (bottom panel). The across- and along-shelf components are shown as vectors and filled contours, respectively. Positive contour values denote northwestward along-shelf currents.

The first EOF mode accounts for 71.3% of the total subtidal velocity variance. The eigenvector shows a coherent pattern of upwelling/downwelling flows shoreward of the 50 m isobath (Figure 7.3). The along-shelf currents have the same sign across the inner WFS with a current core located at a subsurface level in the vicinity of the 25~30 m isobaths. The across-shelf currents have opposite signs near the surface and the bottom, and these are consistent with the along-shelf current directions according to the
traditional Ekman-geostrophic structure of coastal upwelling/downwelling. The along-shelf velocities are an order of magnitude larger than the across-shelf velocities. The associated PC shows the temporal variation of this across-shelf structure, which occurs at both synoptic and seasonal time scales. In winter (summer) this first mode PC tends to be negative (positive) indicating that the inner shelf currents tend to be upwelling (downwelling). These PC variations are visually coherent with the local winds, suggesting that the local winds are the main driver of the inner shelf currents. These results are consistent with the constant density model results of Li and Weisberg (1999a,b) and their associated definition of the inner shelf.

7.5.2 SOM results

The same data are used for the SOM analysis as in the EOF analysis except that both the data gaps and the temporal mean values are retained. The size of the SOM array must be specified prior to the training process. Similar to those in Liu et al. (2006b,c), the SOM parameters are chosen as follows: a 3×4 map size, rectangular lattice, "sheet" shape, linear initialization, "ep" neighborhood function with a radius of 1, and batch training algorithm.

The current structures extracted by the SOM are shown in the top 12 panels of Figure 7.4. For each frame of the velocity time series, a best-matching unit (BMU) is identified among the 12 SOM units according to the minimum Euclidian distance (Kohonen 2001). Thus, the BMU time series show the temporal variation of these structures (Figure 7.4, bottom panel). To quantify the representation of each unit, a frequency of occurrence is computed by summing the number of times that a given unit is a BMU and dividing by the total record length. The frequency of occurrence of each unit is also shown as a percentage in Figure 7.4. Similar structures on the SOM are organized to be neighboring units and dissimilar structures are located farther away from each other. Thus coherent upwelling, downwelling and transitional structures are found in the upper two rows, the bottom row and the third row of the SOM, respectively.
Figure 7.4. SOM representation of the 2-day low-pass filtered velocity data: the 4×3 SOM (top) and the best-matching unit (BMU) time series (bottom). The across- and along-shelf components are vectors and filled contours, respectively. The relative frequency of occurrence (%) of each pattern is shown in the lower-left corner of each SOM unit.
Among these upwelling and downwelling structures, there are two extreme current patterns, SOM units 9 and 4, respectively, with an along-shelf current core located around the 30 m isobath where the maximum velocity exceeds 26 cm/s. These extreme current patterns correspond to the largest synoptic weather events, with frequencies of occurrence of 1-3%. The strong downwelling structure (SOM unit 4) appears mostly in September-October of each year (Figure 7.4, bottom panel), associated with hurricanes and tropical storms; an example is the 19-22 September 1999 Tropical Storm Harvey event (Figure 7.5, top panel). The strong upwelling structure (SOM unit 9) appears sporadically in fall and winter due to the passage of the strongest extra-tropical cold fronts, and also on the trailing side of tropical storms and hurricanes. Examples of
these are the 21-24 January 2001 upwelling event by a cold front (Figure 7.5, bottom panel), and the 14-15 September 1999 event by Hurricane Floyd (Figure 7.5, top panel).

Except for the two extreme units, flow asymmetries are found between the upwelling (SOM units 1, 2 and 5) and downwelling (SOM units 8 and 12) structures. These asymmetries manifest as follows. First, the along-shelf currents are generally stronger in the upwelling than in the downwelling patterns. Second, the coastal jet has larger across-shelf extent in upwelling than in downwelling, with the current core located at subsurface levels and further offshore (around 25~30 m isobaths) for upwelling flows compared to at surface and near the coast (10 m isobath) for downwelling. Third, while weak, the across-shelf flows have opposite signs near the surface and near the bottom at the 10 m isobath for upwelling, whereas they vanish at the 10 m isobath for downwelling; i.e., a cross-shelf transport for upwelling occurs across the entire inner shelf, whereas it is inhibited in the shallower water (at the 10 m isobath) for downwelling. These asymmetries are consistent with the findings of Weisberg et al. (2001).

The synoptic scale variations are better viewed by zooming in on time. As an example we choose three months (September 1999, March 2000, and January 2001) to verify the SOM representation of these (Figure 7.5). From the BMU time series we see the preference for numbers 9 and 1 and the adjacent units when the local winds are upwelling favorable (directed southward), versus number 4 and 12 and their adjacent units when the winds are downwelling favorable (directed northward). Note that the BMU evolution is coherent with the local winds, consistent with the winds being the main driving force for the currents on the inner shelf over the synoptic weather band.

The same SOM analysis procedure is applied to the 15-day low-pass filtered and daily subsampled velocity data, and the results are shown in Figure 7.6. Similar to those in the subtidal frequency bands, the 12 SOM structures can be classified into three categories according to the along-shelf currents: upwelling (the top two rows of the SOM), downwelling (the bottom row), and transitional (the third row). The climatological monthly mean frequencies of occurrence of the three groups are shown in Figure 7. The upwelling structures dominate the fall through spring months from October through April, with peak frequency of occurrence in November, and the downwelling
structures dominate the summer months (June, July and September). The transitional structures have the highest frequency of occurrence in May. Thus, the upwelling structures represent the characteristic winter flow structures, whereas the downwelling structures represent the characteristic summer structures.

Figure 7.6  Same as Figure 7.4 but for the 15-day low-pass filtered data.
The climatological monthly mean winds are strongest and from the northeast during October through January, which may partially explain the high frequency of occurrence of the winter current structures during these months (Figure 7.7). The mean winds are weak and from the southeast in June and July, which may partially explain the presence of the summer structures in these two months. The fact that the winter mean winds are much stronger than the summer mean winds helps to explain the asymmetric strengths of the along-shelf currents in the winter and summer seasons.

![Climatological monthly mean winds and frequency of occurrence](image)

Figure 7.7  Climatological monthly mean winds (top) and the frequency of occurrence of the three sets of characteristic patterns in the SOM (bottom), averaged over the three year period, Sept. 1998 ~ Dec. 2001.

This SOM representation of the seasonal cycle agrees with the previous results of data analyses and numerical modeling (Weisberg et al. 1996, 2005; He and Weisberg 2002b, 2003a; Liu and Weisberg 2005b; Weisberg et al. 2005). It is also supported by the Hovmoller plots of the near surface currents across the WFS (Figure 7.8). From October through the next March, the surface currents are strong and southeastward. Following a transition in May, the surface currents turn northwestward from June through September. We note that the currents are anomalously southeastward in August 2001, which accounts for the relatively higher frequency of occurrences of the upwelling structures in August in Figure 7.7. Our results are in contrast with statements by Ohlmann and Niiler (2005) who contend that the seasonal variations in the WFS surface currents are not pronounced. We attribute this to insufficient sampling on the WFS currents by the drifters.
Figure 7.8. Hovmoller plot of near surface temperature by CTD sampled along the Tampa Bay transect and 30-day low-pass filtered ADCP near surface currents along the Sarasota transect. Blue triangles indicate the hydrographic cruises. CTD station #1 is closest to shore, and station #10 is at the 50 m isobath.
Further support for the SOM representation of the seasonal variation comes from a six-year climatology of current profiles at our EC4 mooring of longest duration located at the 20 m isobath (Figure 7.9). A two-layer structure is seen in the across-shelf direction with near bottom onshore flow and near surface offshore flow throughout the fall through spring months (October through May), with the strongest upwelling structure during October ~ November. Similarly the along-shelf currents tend to be southeastward from fall to spring and northwestward in summer. The spring transition appears to take longer time than the fall transition, as also evidenced in temperature data (Virmani and Weisberg 2003) and due to convective overturning in fall versus more gradual heating in spring. The six-year velocity profile climatology also corresponds well with the 10-year local wind climatology included in Figure 7.9.

**Figure 7.9.** Climatological means of 20-day low-pass filtered winds (at the NOAA Buoy 42036) and currents (at the EC4 mooring). The wind time series span 1994–2003, and currents span July 1998 through February 2004.
7.6 Across-shelf structure from hydrographic data

Fall/winter and summer across-shelf distributions of the temperature, salinity and baroclinic geostrophic currents are shown in Figure 7.10 for both the Sarasota and Tampa Bay transects. The fall/winter (summer) composites are obtained by averaging the hydrographic data (and the relative geostrophic velocity) from October through March (June through September). The relative geostrophic velocities are first calculated using the hydrographic data in each cruise based on equation (7.9), with zero reference levels at the bottom, and then averaged over the specific months.

In fall/winter the shelf waters are colder and fresher near the coast than offshore. The higher salinity water found offshore tends to move onshore along the bottom and the lower salinity water found near shore tends to move offshore near the surface, indicating an upwelling circulation structure consistent with the along-shelf baroclinic geostrophic currents being directed southeastward. These hydrographic inferences agree with the velocity observations. The baroclinic current core is located between the 25~35 m isobaths (or 45~65 km offshore from the coast) along the Sarasota transect, which has about the same location as those from the SOM. The maximum southeastward baroclinic velocity is 5 cm/s, which is about one third of that from the SOM (unit 1 in Figure 7.6).

In summer, strong stratification is found in the temperature structure due to increased insolation and decreased wind mixing. Surface temperature exceeds 28°C with the highest temperature near the coast, and the downward bowing of the isotherms near the bottom is consistent with a downwelling flow structure. An increase in salinity is due to evaporation, but also noted are lower salinity near surface waters offshore. This is attributed to waters of Mississippi River (and other northern river) origin that regularly flow along the shelf break and mid shelf (e.g., Gilbes et al. 1996; He and Weisberg 2002b) in spring and summer. Nearer to shore the baroclinic currents in summer are weaker and generally northwestward, consistent with the ADCP data.

In summary, seasonal variations of the hydrographic structures are consistent with the observed current structures. The baroclinic current tendency adds constructively to the overall tendency on the seasonal time scale, and the seasonal reversal of the geostrophic currents confirms the conceptual model of Weisberg et al. (1996).
Figure 7.10. Average across-shelf structures of temperature (left column), salinity (central column) and baroclinic geostrophic current (right column) along the Tampa Bay and Sarasota transects during winter (top two rows) and summer (bottom two rows). Zero-velocity levels are set to be on the bottom in the baroclinic geostrophic current calculations. Winter structures averaged from October to March, and summer structures from June through September. The small solid triangles designate CTD locations.

7.7 Across-shelf sea surface height estimates

A method to combine the velocity, hydrography and wind data across the shelf for estimating SSH was proposed in Section 7.4. According to equation (7.8), the across-shelf SSH distribution over synoptic and longer time scales may be estimated from the across-shelf distributions of the along-shelf vertically averaged (barotropic) and baroclinic currents and the across-shelf wind stress.
7.7.1 Time scales longer than 15 days

The depth-averaged currents are obtained from velocity profile data, low-pass filtered to exclude oscillations on time scales shorter than 15 days, subsampled daily and rotated to the along-shelf direction. These barotropic currents at the five mooring sites are integrated in the across-shelf direction from the 50 m isobath to the near shore to produce the \( \eta_b \) contribution to the SSH relative to the 50 m isobath according to equation (7.7a). The \( \eta_b \) values at the six integration points are then linearly interpolated onto 10 locations equally distributed from the 50 m to the 10 m isobaths along the Sarasota transect. We similarly calculated the relative SSH distribution due to the baroclinic currents (\( \eta_c \)) from the monthly hydrographic data according to equation (7.7b). These monthly \( \eta_c \) values are interpolated to form a daily time series for addition to \( \eta_b \). To calculate \( \eta_w \) we begin with 15-day low-pass filtered wind stress vectors, daily subsampled, and rotated 27° clockwise to the across-shelf direction. The across-shelf wind stress component is then used to estimate \( \eta_w \) at the 10 points offshore from Sarasota according to equation (7.7c). The three SSH components (\( \eta_b, \eta_c, \eta_w \)) are then summed together to form a total SSH distribution relative to the 50 m isobath. We note that \( \eta_c \) may also be estimated from the vertical shears of the along-shelf velocity according to equation (7.8). With \( \eta_c \) by hydrography (current shears) denoted by \( \eta_{c1} \) (\( \eta_{c2} \)) the results are shown in Figure 7.11, including each of the individual terms and their sums: \( \eta_1 = \eta_b + \eta_{c1} + \eta_w \); \( \eta_2 = \eta_b + \eta_{c2} + \eta_w \).

Generally, the SSH gradient is directed onshore during fall through spring (October to May) and offshore during summer (June through September). These seasonal SSH variations are consistent with the EOF and SOM velocity analyses. As expected, the depth averaged (barotropic) currents dominate the SSH gradient variations across the inner shelf. The across-shelf wind stress modifies the SSH to a lesser extent, mainly over the shallowest region in winter. The baroclinic currents contribute constructively in the SSH seasonal variation, i.e., \( \eta_c \) values at the coast are lower (higher) than those at the 50 m isobath in winter (summer). We note that \( \eta_c \) values calculated by the two methods do not agree in some months in Figure 7.11. The hydrographic data have higher spatial
resolution in the across-shelf direction, but are sampled monthly and with some months absent data (Figure 7.2), while the current data have higher temporal resolution, but are sparser in space. More observations (with higher resolutions in space and time) would improve the analysis, but the general features are consistent with one another.

The SSH variation in Figure 7.11 are relative to the 50 m isobath. If the absolute SSH at any one of the 10 computation points is known, then the absolute SSH values along the whole transect (10 pints) can be calculated by simply adding back the offset between absolute and relative SSH at that point. The relative SSH at the shallowest computation point ($\eta$) and the coastal sea level at St. Petersburg ($h$) are shown in the top panel of Figure 7.12. Here the coastal sea level is also 15-day low-pass filtered and adjusted for the inverted barometer effect (using the air pressure at Venice, FL).

Assuming that the absolute SSH at that point may be approximated by the adjusted sea level at St. Petersburg, the offset between these two variables ($h-\eta$) can be used to estimate the absolute SSH elsewhere. Assume that this offset is the absolute SSH at the initial integration point (i.e., at the 50 m isobath). We note that despite the two methods for estimating $\eta_1$ and $\eta_2$, the estimated absolute SSH at the 50 m isobath is very similar for both.

The variations at the 50 m isobath are larger. Some of this may be local and due to seasonal steric effect, while some may relate to deeper water steric or dynamic effect. We estimate the local steric effect through the geopotential height $D$ at the 50 m station calculated from the hydrographic data according to

$$D(p_1, p_2) = \frac{1}{g} \int_{p_1}^{p_2} \delta(T, S, p) dp$$

where $p_1$ and $p_2$ are two reference pressure levels, $\delta$, $T$, $S$ and $p$ are specific volume anomaly, temperature, salinity, and pressure, respectively. $D$ is shown against the estimated absolute SSH at the 50 m isobath in Figure 7.12b. The estimated SSH compares well with the geopotential height during the three years, which means a portion of the 50 m SSH variation in the low frequency band is induced locally by the steric height changes on the shelf.
Figure 7.11. SSH estimates relative to that at the 50 m site as a function of time and across-shelf distance ($x$). From top to bottom, the six panels are SSH components due to the barotropic currents ($\eta_b$), the baroclinic currents ($\eta_{c1}$, estimated from the hydrographic data that are designated by the small open circles), and the across-shelf wind stress ($\eta_w$), the total relative SSH ($\eta_1=\eta_b+\eta_{c1}+\eta_w$), the SSH component due to baroclinic currents ($\eta_{c2}$, estimated from the velocity vertical shears), and the total relative SSH ($\eta_2=\eta_b+\eta_{c2}+\eta_w$), respectively. In the across-shelf direction, $x=0$ corresponds to a location of the 50 m isobath, the initial integration point. All the time series are 15-day low-pass filtered except the hydrographic data (and hence $\eta_{c1}$).
Figure 7.12. Comparisons of SSH estimates at the low frequency bands (15-day low-pass filtered). (a) The total relative SSH ($\eta$) estimated at the 10 m isobath and the sea level ($h$) observed at St. Petersburg. Here, $\eta_1$ and $\eta_2$ refer to two types of the total relative SSH where the baroclinic part is estimated from the hydrographic data and from the current vertical shears, respectively. (b) Estimated SSH ($h-\eta$) and the geopotential height ($D$) calculated from the hydrographic data at the 50 m isobath. (c) Estimated SSH ($h-\eta$) and the altimetry SSH anomaly sampled from the 50 m isobath station.

We also compare the absolute SSH estimates at the 50 m isobath with the available satellite altimetry data. We used the gridded sea level anomalies (1/3°x1/3° on a Mercator grid) merged from multi-satellite altimetry sensors (Topex/Poseidon or Jason-1 + ERS-1/2 or Envisat) distributed by AVISO. By sampling a grid point nearest to mooring EC2 (50 m) site, we overlay the SSH anomaly by satellite altimetry on the SSH estimates in Figure 7.12c. The comparison is good. Note the SSH estimates are 15-day low-pass filtered and daily subsampled, and the altimetry time series are sampled in 7-day intervals.
7.7.2 Synoptic time scales

Since the SSH equations are derived from the momentum balance over the synoptic weather and longer time scales, it is informative to check their validity at shorter time scales. By using a two-day low-pass filter on the velocity, sea level, and air pressure time series, and the same integration and interpolation procedures as before we estimate the absolute SSH at the 50 m isobath across the entire subtidal band (Figure 7.13). Since the procedures are linear the results overlay well, and they show the relative variances between the synoptic weather and seasonal time scales.

Figure 7.13. Similar to Figure 7.12c except that both \( h \) and \( \eta_2 \) are 2-day low-pass filtered.

Finally, it is instructive to consider the synoptic weather band by itself by band-pass filtering the time series prior to the SSH estimation procedure. The results are shown in Figure 7.14 for the band of 2-day ~ 15-day. Over a zoomed in period July-December 2001 we see that the 10 m isobath relative SSH estimates are highly correlated with the St. Petersburg sea level, the EC5 (10 m isobath) bottom pressure, and the local winds. This suggests that the wind-driven inner shelf circulation is mainly responsible for the coastal sea level change on the synoptic time scale. We note that the estimated SSH amplitudes are closer to those of the EC5 bottom pressure and smaller than those at the St. Petersburg. This may be explained by the following two factors. First, the St. Petersburg tide gauge is located in Tampa Bay so it experiences additional setup/down by local effects and its location mid-way up the bay. Second, the synoptic scale variation occurring offshore of the 50 m isobath are not taken into account in these estimates. Actually, the absolute SSH at the 50 m isobath, estimated as the difference between the observed absolute \( (h) \) and estimated relative SSH \( (\eta) \) at the EC5 (Figure 7.14, third
panel), is also correlated with the observed coastal sea levels and the winds. The decrease of the SSH amplitudes from the coast (St. Petersburg), offshore to the 10 and 50 m isobaths is consistent with the findings of Mitchum and Clarke (1986a). The fact that the agreement is so good at the EC5 bottom pressure gauge suggest that most of the inner shelf dynamical adjustment does indeed occur inshore of the 50 m isobath, and this is consistent with the model dynamics analysis presented by Li and Weisberg (1999b).

By zooming in on a subset of the analysis Figure 7.14 also shows how the three SSH components are additive to the total relative SSH estimates. For the full record length, the standard deviations of $\eta_b$, $\eta_w$ and $\eta_c$ are 2.6, 1.8 and 1.2 cm, respectively. Thus, among the three dynamical variables, the barotropic currents make the largest contribution to the inner shelf sea level variations, the across-shelf wind stress is the secondary, and the baroclinic currents have the smallest contribution. Cragg et al. (1983) reported that WFS sea level response was a maximum for along-shelf winds, across-shelf winds did not produce sea level fluctuations that were reliably above the noise level. Our analysis shows that the across-shelf winds also play an important role in changing inner shelf SSH, especially during strong weather events (Figure 7.14, bottom panel).

7.8 Summary and discussions

Using velocity profile time series from a moored array across the WFS spanning the interval September 1998 to December 2001, we described the across-shelf structures of the ocean current variability over the inner shelf on the synoptic and longer time scales. From two-day, low-pass filtered data, a coherent wind-driven coastal upwelling/downwelling structure was revealed by the first mode EOF: an along-shelf coastal jet with a current core located around the 25 m ~ 30 m isobaths, and oppositely directed across-shelf flows at the near surface and near bottom levels, consistent Ekman-geostrophic inner shelf dynamics (e.g., Li and Weisberg 1999b; Weisberg et al., 2000). Additional important details are extracted by the SOM: strong upwelling and downwelling flow structures associated with extreme weather forcing, moderate, asymmetric upwelling and downwelling flow structures driven by moderate weather
forcing, and a set of transitional structures with weak currents. The variations of these structures are coherent with local winds on synoptic weather time scales. On seasonal and longer time scales, asymmetric upwelling and downwelling and transitional flow structures were also extracted by the SOM, and their variations are related to both the local winds and the water density distributions. The circulation is predominantly upwelling during fall through spring months (October to April) and downwelling during summer months (June to September). These upwelling/downwelling across-shelf structures provide observational evidence, as well as new insights, to the schematics of coastal upwelling/downwelling regimes of Huyer (1990). They also have important implications for the transports of nutrient and other water property across the shelf.

The coherent seasonal variation of the WFS currents as revealed by the SOM, the supporting Hovmoller plot of the near surface currents, and the six-year climatology of current profiles agrees with previous results of data analysis and numerical modeling (Weisberg et al. 1996; He and Weisberg 2002b, 2003a; Liu and Weisberg 2005; Weisberg et al. 2005). We therefore disagree with the statement of Ohlmann and Niiler (2005) that the seasonal variations of the WFS surface currents are not pronounced, and we attribute this difference in data set interpretation to an insufficient sampling by drifters on the WFS.

On the seasonal and longer time scales, the asymmetry in upwelling/downwelling structures is consistent with an asymmetry in the wind forcing. Winter upwelling favorable winds are much stronger than summer downwelling winds, as shown in Figs. 2, 7 and 9. On the synoptic weather scale, the asymmetry is also due to stratification. Weisberg et al. (2001) using model twin experiments, one with and the other without stratification, explained the observed WFS response asymmetry as a consequence of thermal wind effects on the bottom Ekman layer. Increased mixing for extreme events would therefore tend to mitigate this effect. This synoptic weather scale asymmetry, with larger upwelling than downwelling responses, is consistent with the works of Weatherly and Martin (1978), Trowbridge and Lentz (1991), MacCready and Rhines (1991), and Garrett et al. (1993) when consideration is given to the process of Ekman-geostrophic spin up. With regard to a streamwise vorticity balance, by adding constructively
(destructively) with planetary vorticity tilting by the sheared, along-shelf jet, buoyancy torque enhances (decreases) the dissipation required in the bottom Ekman layer under upwelling (downwelling). The result is a larger upwelling response that extends farther offshore.

WFS circulation is driven by a combination of local and remote forcing (Weisberg and He 2003). Coastal sea level variations can also be apportioned that way, i.e., by the local dynamical response of the inner shelf circulation to local meteorological forcing and by SSH variations occurring farther offshore and as manifest at the 50 m isobath. The local dynamical response can further be partitioned into three parts, i.e., the SSH responses due to the along-shelf depth-averaged (barotropic) currents, the baroclinic currents, and the across-shelf wind stress. On long time scales, the offshore SSH change dominates, and a significant portion of the 50 m isobath SSH variation is due to the local steric height changes, whereas on synoptic weather time scales the inner shelf wind-driven circulation responses are controlling. Among the three dynamical variables, the barotropic currents make the largest contribution to the inner shelf SSH variations, the across-shelf wind stress is the secondary contributor, and the baroclinic currents make the smallest contribution.

On long time scales, the SSH estimated at the 50 m isobath as the residual between the coastal sea level and the inner shelf dynamical responses compared well with satellite altimetry, thus providing a basis for calibrating satellite altimetry on the shelf. On synoptic time scales, the SSH estimates were coherent with the bottom pressure records, coastal sea level, and local winds. So while seasonal SSH variations are largely of offshore origin, at synoptic weather scales these are primarily by the inner shelf dynamical adjustments that occur inshore of the 50 m isobath (Li and Weisberg 1999b).
Figure 7.14. Time series of wind (top panel) and SSH estimates at the synoptic weather bands (2-day ~ 15-day band-pass filtered). The total relative SSH ($\eta$) estimated at the 10 m isobath and the sea level ($h$) observed at St. Petersburg and mooring EC5 (converted from bottom pressure records) are shown in the second panel. The difference between the observed and estimated SSH ($h-\eta$) are shown in the third panel. The three SSH components estimated at the 10 m isobath, due to barotropic currents ($\eta_b$), baroclinic currents ($\eta_c$) and across-shelf wind stress ($\eta_w$), respectively, are shown in the bottom panel.
Chapter 8

Summary

The patterns of ocean circulation variability are described and the circulation dynamics are examined using multi-year, shelf-wide oceanographic data on the WFS. The data sources include multi-year moored ADCP arrays, hydrographic cruises, HF radar, satellite SST and altimetry, surface meteorology, and coastal tide gauges. The goals of my dissertation are to: (1) introduce novel data analysis methods, SOM and GHSOM, from information science to physical oceanography community; (2) describe the spatial patterns, across-shelf structures, and three-dimensional views of WFS ocean current variability on different time scales; (3) classify the SST patterns on the WFS; (4) diagnose the dominant dynamics of the shelf circulation in depth-averaged momentum balances at selected locations; (5) estimate SSH variation along a transect across the inner WFS by dynamically examining the ADCP, wind, hydrography and coastal sea level data on the WFS.

In Chapter 2, the neural network techniques, SOM and GHSOM, are introduced as feature extraction methods in descriptive physical oceanography. A series of experiments are performed to demystify and evaluate the SOM in feature extraction by using artificial data sets comprising known patterns. The SOM accurately represent a time series of linear progressive sine waves of fixed amplitude, period and wavelength. It also extracts features from noisy data over a broad range of signal-to-noise ratios. While noise appeared superimposed upon the SOM units the known patterns are readily identified, and the SOM results are comparable with those by EOF. In a further test between SOM and EOF, using time series constructed by linking together four unique pattern types, an SOM successfully extracts these four known patterns, whereas an EOF
does not. Sensitivity studies are also performed, resulting a set of parameter choices for SOM applications.

In Chapter 3, the SOM is applied to the time series of moored ADCP velocity data that span the interval October 1998 to September 2001 to describe the patterns of ocean current variability on the WFS. Three characteristic spatial patterns are extracted in a smoothed 3×4 SOM array with the default parameter choices in the SOM Toolbox (Gaussian neighbourhood function): spatially coherent southeastward and northwestward flow patterns with moderate currents, and a transition pattern of weak currents. On the synoptic weather time scale the variations of these patterns are coherent with the local winds. On the seasonal time scale the variations of the patterns are coherent with both the local winds and complementary SST patterns. The currents are predominantly southeastward during fall-winter months (from October to March) and northwestward during summer months (June through September).

The spatial patterns extracted by the (nonlinear) SOM method are asymmetric, a feature that is not captured by the (linear) EOF method. Thus, we find for the synoptic weather and longer time scales: (1) southeastward currents are generally stronger than northwestward currents, (2) the coastal jet axis is located further offshore for southeastward currents than for northwestward currents, and (3) the velocity vector rotations with depth are larger in shallower water when the currents are southeastward relative when the currents are northwestward.

In the most accurate SOM mapping with the "ep" neighborhood function, strong current patterns associated with severe weather forcing are extracted separate from previously identified asymmetric upwelling/downwelling patterns associated with moderate currents and transitional patterns of weak currents.

Another SOM feature extraction application is presented in Chapter 4. The patterns of current variability are extracted from a joint HF-radar and ADCP data set collected on the WFS from August to September of 2003. 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 with 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 dynamically consistent ocean current patterns sampled by HF-radar and other supporting in-situ measurements.

In Chapter 5, the GHSOM is used to examine patterns of the SST variability on the West Florida Shelf from time series of daily SST maps from 1998 to 2002. SST seasonal variations are nicely described. The winter pattern is one of low SST, with isotherms aligned approximately along isobaths. The summer pattern is one of high SST distributed in a horizontally uniform manner. The spring transition includes a mid shelf cold tongue. It is demonstrated that the GHSOM analysis is more effective in extracting the inherent SST patterns than the widely-used EOF method. The underlying patterns in a data set can be visualized in the SOM array in the same form as the original data, while they can only be expressed in anomaly form in the EOF analysis. Some important features, such as asymmetric SST anomaly patterns of winter/summer and cold/warm tongues, can be revealed by the SOM array but cannot be identified in the lowest mode EOF patterns. Also, unlike the EOF or SOM techniques, the hierarchical structure in the input data can be extracted by the GHSOM analysis.

In Chapter 6, circulation dynamics are examined by diagnosing the depth-averaged momentum balance on the synoptic and longer time scales, using multi-year observations of velocity, bottom pressure, temperature, wind, coastal sea levels and hydrographic data. The across-shelf momentum balance on the inner shelf is essentially geostrophic between the Coriolis force due to the along-shelf currents and the across-shelf bottom pressure gradient. The across-shelf wind stress accounts for most of the variance in the ageostrophic momentum residual. During severe weather events, the across-shelf wind stress may even be the dominant term in the across-shelf momentum balance. The balances are more complicated on the outer shelf where the Coriolis, the across-shelf bottom pressure gradient, and the horizontal density gradient terms all have the same magnitude. The along-shelf momentum balance on the inner shelf is primarily
between the wind stress and the bottom stress terms, complemented by the pressure
gradient and the Coriolis and local acceleration terms. At synoptic weather and longer
time scales, the along-shelf wind stress is the dominant driver of the along-shelf currents
on the inner shelf. The bottom friction, pressure gradient, and Coriolis terms are
consequences of this. An along-shelf pressure gradient is set up by the local wind stress
and acts in opposite to it. It thereby accounts for a smaller fraction of the along-shelf
velocity variance than the along-shelf wind stress. A method is discussed to estimate the
depth-averaged, along-shelf currents on the inner shelf from the winds and coastal sea
level or from the winds and the across-shelf bottom pressure gradient, or from both.

Finally, in Chapter 7, across-shelf structures of flow variability and circulation
dynamics are further examined by integrating the various observations across the central
WFS for the time interval September 1998 to December 2001.

From the two-day, low-pass filtered velocity data, five sets of characteristic
current structures are extracted by the SOM: strong upwelling and downwelling flow
structures associated with extreme weather forcing, moderate, asymmetric upwelling and
downwelling flow structures driven by moderate weather forcing, and a set of transitional
structures with weak currents. The variations of these structures are coherent with local
winds on synoptic weather time scales. On seasonal and longer time scales, asymmetric
upwelling and downwelling and transitional flow structures are also extracted by the
SOM, and their variations are related to both the local winds and the water density
distributions. The circulation is predominantly upwelling during fall through spring
months (October to April) and downwelling during summer months (June to September).

Non-tidal coastal sea level variations can be attributed to two factors, i.e., local
dynamical response of the inner shelf wind-driven circulation to external forcing and
offshore SSH variation at the 50 m isobath. The local dynamical response can further be
partitioned into three dynamic parts, i.e., the SSH responses due to the along-shelf depth-
averaged (barotropic), baroclinic currents, and the across-shelf wind stress forcing. On
long time scales, the offshore SSH change dominates, and a significant portion of the 50
m isobath SSH variation is due to the local steric height change, whereas on the synoptic
weather time scales, the inner shelf wind-driven circulation responses are controlling.
Among the three dynamical variables, the barotropic currents make the largest contribution to the inner shelf SSH variations, the across-shelf wind stress is the secondary, and the baroclinic currents have the smallest contribution.

The across-shelf distribution of the SSH is estimated from the across-shelf distribution of along-shelf velocity, hydrography, across-shelf wind stress and coastal sea level data. Subtracting the variability that may be accounted for by inner shelf dynamical responses the residual at the 50 m isobath compares well with satellite altimetry data. Thus, this method provides a means for calibrating satellite altimetry on the continental shelf.
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About the Author

Yonggang Liu first received his B.S. degree in Meteorology from Chengdu Institute of Meteorology (Chengdu, China) in July 1993. He then dove into the sea and obtained a M.S. degree in Physical Oceanography from Second Institute of Oceanography, State Oceanic Administration of China (Hangzhou, China) in August 1996. He stayed in Hangzhou for another four years working on the ocean circulation east of the Ryukyu and Taiwan Islands, and in the East and South China Seas. In August 2000, he joined College of Marine Science, University of South Florida to pursue his Ph.D. degree in Physical Oceanography, working on the patterns and dynamics of ocean circulation variability over the West Florida Shelf. He successfully defended his dissertation in November 2005, and is expected to receive his Ph.D. degree in May 2006. His Ph.D. work is compiled into eight research papers (six first-authored) and presented in six international conferences. He is the recipient of Von Rosenstiel Fellowship in 2000. Yonggang Liu can be contacted via email: yliu18@gmail.com.