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Patterns of the loop current system and regions of sea surface height variability in the eastern Gulf of Mexico revealed by the self-organizing maps

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Abstract The Self-Organizing Map (SOM), an unsupervised learning neural network, is employed to extract patterns evinced by the Loop Current (LC) system and to identify regions of sea surface height (SSH) variability in the eastern Gulf of Mexico (GoM) from 23 years (1993–2015) of altimetry data. Spatial patterns are characterized as different LC extensions and different stages in the process of LC eddy shedding. The temporal evolutions and the frequency of occurrences of these patterns are obtained, and the typical trajectories of the LC system progression on the SOM grid are investigated. For an elongated, northwest-extended, or west-positioned LC, it is common for the LC anticyclonic eddy (LCE) to separate and propagate into the western GoM, while an initially separated LCE in close proximity to the west Florida continental slope often reattaches to the LC and develops into an elongated LC, or reduces intensity locally before moving westward as a smaller eddy. Regions of differing SSH variations are also identified using the joint SOM-wavelet analysis. Along the general axis of the LC, SSH exhibits strong variability on time scales of 3 months to 2 years, also with energetic intraseasonal variations, which is consistent with the joint Empirical Orthogonal Function (EOF)-wavelet analysis. In the more peripheral regions, the SSH has a dominant seasonal variation that also projects across the coastal ocean. The SOM, when applied to both space and time domains of the same data, provides a powerful tool for diagnosing ocean processes from such different perspectives.

1. Introduction

The eastern Gulf of Mexico (GoM), with its energetic Loop Current (LC) system, is a unique place for the study of ocean circulation. As a part of the North Atlantic Ocean’s western boundary current, the LC connects the Yucatan Current from the Caribbean Sea with the Florida Current and the Gulf Stream by forming an anticyclonic retroreflecting current with a looping path through the eastern GoM. As the dominant current of the eastern GoM [e.g., Sturges and Lugo-Fernández, 2005], the LC generally penetrates northwestward into the gulf, before shedding an anticyclonic eddy and then retreating back to the south, exhibiting complex phenomena with multiple temporal and spatial scales [e.g., Schmitz et al., 2005; Oey, 2008; Lugo-Fernández and Leben, 2010].

Early LC descriptions, based on limited hydrographic data, yielded only partial spatial patterns [e.g., Leipper, 1970; Maul, 1977; Molinari et al., 1978; Elliott, 1982]. More complete LC patterns had to await simulations by numerical models [e.g., Hurlbut and Thompson, 1980]. It was the applications of satellite remote sensing technologies that led to more reliable and more complete LC system pattern descriptions [e.g., Vukovich et al., 1979; Maul et al., 1985; Jacobs and Leben, 1990]. Satellite altimetry then provided sea surface height (SSH) information useful for ocean circulation studies [e.g., Fu and Chelton, 1984; Willis and Fu, 2008; Chelton et al., 2011]. This is particularly important for the GoM region, where LC pattern contrasts in summer are not evident in satellite sea surface temperature (SST) products, because SST tends to be horizontally uniform in summer months [e.g., Liu et al., 2006a,2011b]. Thus, altimetry data are often used to monitor the LC system [e.g., Leben and Born, 1993; Sturges and Leben, 2000; Leben, 2005; Alvera-Azcarate et al., 2009].

There are also intensive numerical modeling efforts in the GoM (for a review, see Oey et al. [2005]), and some recent models assimilate satellite data ad the model reanalysis products are available to public [e.g., Chassignet et al., 2007]. However, model simulations are subjected to errors originating from initialization and forcing fields, numerical schemes, parameterizations, plus the nonlinearity inherent to geophysical fluid motions. Due to these limitations, model results, even with data assimilation, may not be as accurate as the
satisfy altimetry data themselves. A recent example for the eastern GoM can be seen in Liu et al. [2014]. Thus, satellite altimetry products remain important for studying LC system pattern evolution.

Characterizing the spatial patterns of the complex LC system is challenging. After watching a movie of the LC system derived from altimetry data by Leben [2005], Sturges et al. [2005] commented: “If you wish to obtain a decent understanding of the behavior of the Loop Current, you may want to watch this movie many times.” Even after watching the movie many times, it is difficult to remember the characteristic patterns of the LC system. In practice, snapshots were used to show particular LC patterns for certain case studies [e.g., Hamilton et al., 2011; Liu et al., 2011b; Walker et al., 2011], temporal means are calculated to describe LC climatology [e.g., Vukovich, 2007] and Empirical Orthogonal Functions (EOF) were applied to extract LC anomaly patterns [e.g., Chang and Oey, 2013; Xu et al., 2013].

Here we apply the Self-Organizing Map (SOM) to the LC system. The SOM is an unsupervised learning neural network technique that is useful in feature extraction and pattern recognition for large data sets [e.g., Kohonen, 1988, 2001; Vesanto and Alhoniemi, 2000]. The SOM was introduced to the climate science community as a clustering and pattern recognition method [e.g., Hewitson and Crane, 1994; Ambroise et al., 2000; Cavazos et al., 2002], followed by applications to oceanography [e.g., Richardson et al., 2003; Liu and Weisberg, 2005; Vilbič et al., 2015]. A review of SOM applications in both meteorology and oceanography is provided by Liu and Weisberg [2011].

The SOM, as with any pattern recognition technique, has advantages and disadvantages [e.g., Liu and Weisberg, 2005; Reusch et al., 2005; Liu et al., 2006b; Solidoro et al., 2007]. Whereas it does not preserve variance like the linear EOF, it preserves topology of the data and intuitively orders patterns that are mostly closely matched. For example, Liu and Weisberg [2005] found that the SOM extracted ocean current patterns were more informative and intuitive than the leading mode EOF patterns, i.e., the asymmetric features (in current strength, coastal jet location and velocity vector veering with depth) exhibited by upwelling versus downwelling current patterns extracted by the (nonlinear) SOM were not readily revealed by the (linear) EOF.

As a powerful feature extraction method, the SOM finds wide applications in identifying characteristic ocean current patterns from several types of data sets, including velocity data from an array of moored Acoustic Doppler Current Profilers (ADCP) [e.g., Liu and Weisberg, 2005; 2007], surface currents from high-frequency radars [e.g., Liu et al., 2007b; Mau et al., 2007; Mihanović et al., 2011; Hisaki, 2013; Kalinić et al., 2015], altimetry-derived surface geostrophic currents [e.g., Liu et al., 2008; Tsui and Wu, 2012; Zeng et al., 2015], and outputs from numerical circulation models [e.g., Iskandar et al., 2008; Liu et al., 2009; Jin et al., 2010; Falciери et al., 2014; Williams et al., 2014]. In all of these applications, the SOM was used as a method of classification for characteristic ocean current spatial patterns.

Another SOM application involves the extraction of characteristic temporal patterns from the data and identifying regions with similar variations. An example is provided by Risien et al. [2004] in identifying wind regimes over the Benguela upwelling system. This type of SOM application is also evident in the biological oceanography community such as the identification of regions with patterns expressed by chlorophyll-a, SST, pCO2, etc. [e.g., Saraceno et al., 2006; Hales et al., 2012]. To our knowledge, the use of SOM for temporal patterns in ocean currents from altimetry data has not been explored.

In this paper, we analyze altimetry data in the eastern GoM using the SOM both to extract the spatial patterns of the LC system and to identify regions of sea level variability. The purposes are two-fold: (1) to gain insights on the variability of the LC system and the circulation patterns in the eastern GoM, and (2) to promote both types of SOM applications with the same data set, making the method more useful.

The rest of the paper is arranged as follows. The data are described in section 2. The methodology is introduced in section 3. Section 4 presents results, including a joint EOF-wavelet analysis and dual SOM (space and time) analyses. Discussions and a summary are provided in sections 5 and 6, respectively.

2. Data

Several altimetry-derived products are publicly available for the GoM region, e.g., the Archiving, Validation and Interpretation of Satellite Oceanographic Data (AVISO) gridded product [e.g., Pascual et al., 2006], the Ocean Surface Currents Analyses Real-time (OSCAR) [e.g., Bonjean and Lagerloef, 2002; Johnson et al., 2007;
Both the OSCAR and the GEKCO products incorporated other data sets (e.g., winds), while the AVISO data are purely altimetry. These altimetry-derived products generally have about the same performance in accounting for surface drifter trajectories in hindcast analyses over the eastern GoM region [Liu et al., 2014]. Thus for our purposes here, we choose to use AVISO’s multimission gridded sea level anomaly data produced by the Ssalto/Duacs, with support from the CNES (http://www.aviso.altimetry.fr/duacs/) [e.g., Ducet et al., 2000; Le Traon et al., 2003]. This is a global product with horizontal resolution of 1/3 degree, and temporal resolution of one day. The delayed-time data are used for the period between 1 January 1993 through 23 April 2015, and the near real-time version are used for the recent months (24 April 2015 to 31 December 2015). The near real-time data are usually less accurate then the delayed-time data. However, the recent use of GPS orbits has drastically improved the quality of the near real-time data. The AVISO gridded SLA data are combined with a mean dynamic topography (CNES-CLS09 MDT) [e.g., Rio and Hernandez, 2004; Rio et al., 2011], mean sea surface above geoid, to get absolute SSH. Similarly processed SSH data were previously used in studies of the Caribbean and GoM region [e.g., Alvera-Azcárate et al., 2009; Liu et al., 2014].

In this study, the global SSH data are tailored to the eastern GoM region, within latitude and longitude ranges of [23, 31] degrees north and [92, 81] degrees west, respectively. The daily time series are sub-sampled every three days to reduce the data size. Note that conventional altimetry data are designed mainly for open ocean applications, and for the coastal regions they are not as reliable as in open oceans due to a number of factors [e.g., Cipollini et al., 2008; Vignudelli et al., 2011]. To reduce the effects of the uncertainties of the altimetry data quality in the coastal band, the SSH data in shallow water regions (water depth <100 m) are removed. After these procedures, the resulting SSH data have 1408 valid grid points and 2758 records in time. Locations of the retained grid points are shown as colored squares in Figure 1.

Auxiliary data include tide gauge records and meteorological measurements along the west Florida coast. Hourly tide gauge records at St. Petersburg, FL (Figure 1a) were downloaded from the NOAA website http://tidesandcurrents.noaa.gov/. Hourly air pressure observations were recorded at some of the University of South Florida surface buoys (not shown) and at NOAA/NDBC buoys and C-MAN stations (downloaded from http://www.ndbc.noaa.gov/).

**3. Method**

**3.1. The Dual (Space and Time) SOM Analyses**

The SOM projects high-dimensional input data onto a low dimensional space (usually two-dimensional), while preserving the topology of the input data. The machine learning is accomplished by first choosing a
neuron that most closely matches the presented input data, then determining a neighborhood of excited neurons around the winner, and finally, updating all of the excited neurons. This training process iterates and fine tunes within a preselected number of patterns, and it is called self-organizing. The outcome weight vectors of the SOM nodes can be reshaped back to have characteristic data patterns. More specifics about the SOM can be found in Kohonen [1988, 2001] and Vesanto and Alhoniemi [2000]. A MATLAB Toolbox of the SOM [Vesanto et al., 2000] is freely provided by the Laboratory of Information and Computer Science in the Helsinki University of Technology (http://www.cis.hut.fi/somtoolbox/). Used in this study is the SOM Toolbox version 2.0.

If the input vector is the spatial series (SSH values at the 1048 grid points) at a time (Figure 2), and the iteration is for each time stamp, then the resulting SOM weight vectors contain characteristic spatial patterns of the LC system. By comparing with the extracted spatial patterns, a best matching unit (BMU) can be found for each time stamp of the input time series. The BMU time series indicate the evolution of the characteristic spatial pattern over time. This comprises the first type of SOM application in our study.

If the two-dimensional data matrix is transposed, the input data vector is the time series (the 2758 three hourly SSH values) at a grid point, and the SOM iteration is for each valid grid point (Figure 3). The resulting SOM weight vectors output characteristic SSH time series. For each grid point, we can similarly find a BMU from the extracted time series. The grid points with similar SSH variability (the same BMU) are considered as one group, and the corresponding region can be identified on a map. The SOM in this application classifies temporal variability of the SSH, and finds regions of different SSH variability. This comprises the second type of SOM application in our study.

The SOM has many tunable parameters that control the initialization, iteration, and the final output. This is often the challenging part for SOM users. Liu et al. [2006b] performed an evaluation of the tool with some artificial data composed of known patterns, and did some sensitivity experiments with those tunable parameters. They suggested a set of SOM parameters for practical applications, such as linear initialization, batch training, “ep” (or Epanechnikov function) neighborhood function. We follow the suggestions of Liu et al. [2006b] on SOM parameter choice. The SOM map size is set to be [4 × 4] and [3 × 3] for the type 1 and 2 applications, respectively. These will end up with 16 and 9 units for the spatial and temporal patterns, respectively. Recently, Zeng et al. [2015] applied the SOM to the SSH data of the GoM region, but using only three units [3 × 1] or [1 × 3]. The extracted three patterns show the extension and retraction of the LC process in a highly simplified manner. However, the actual pattern changes are more complex. Thus, we opt with a larger map size, as this will result in more detailed patterns. The determination of the map size is empirical and somehow subjective. Saraceno et al. [2006] used a Hierarchical Ascending Clustering algorithm to reduce the number of SOM units in a more objective way, however, their work was based on a probabilistic version of the SOM, which is different from the one used in this study.
3.2. The Rectified Wavelet Power Spectral Analysis

A continuous wavelet transform may be used to describe a time series in both frequency and time, which is especially useful when the observed variability is modulated. The wavelet analysis method finds wide application in meteorology and oceanography [e.g., Meyers et al., 1993; Lau and Weng, 1995]. A MATLAB Toolbox for wavelet analysis is freely provided by Torrence and Compo [1998] (http://paos.colorado.edu/research/wavelets/), which greatly increased the number of the wavelet users. However, the wavelet power spectrum may be biased toward low frequencies. For a time series composed of sine waves with the same amplitude (i.e., same energy) but different frequencies that wavelet method produces lower spectral peaks for lower frequencies, which is actually expected to be identical peaks if using a Fourier power analysis. We follow the bias rectification proposed by Liu et al. [2007a], i.e., a physically consistent definition of energy for the wavelet power spectrum should be the transform coefficient squared divided by the scale it associates. An example of the MATLAB program is available at http://ocgweb.marine.usf.edu/~liu/wavelet.html.

3.3. Joint SOM-Wavelet Analysis

The characteristic SSH time series extracted by the time domain SOM will be further analyzed for variability in both frequency and time using the wavelet method. The joint SOM-wavelet analysis is similar to that in Risien et al. [2004], but here we use the rectified wavelet power spectral method [Liu et al., 2007a]. The purpose is to diagnose sea level variability over different regions of eastern GoM, and investigate their characteristics in time and frequency domains.

3.4. Joint EOF-Wavelet Analysis

Time domain EOF analysis is often used to obtain dominant modes of variability from a time series of maps [e.g., Thomson and Emery, 2014]. The leading mode eigenvectors contain spatial patterns of anomalies, and their weights are indicated by the associated principal component time series. A Reviewer suggested us to apply an EOF analysis of the SSH data and compare the results with those from the SOM, similar to the work by Liu and Weisberg [2005; 2007]. Here we perform a joint EOF-wavelet analysis, i.e., in addition to the conventional time domain EOF calculations, the principal component time series are analyzed with the rectified wavelet power spectral method [Liu et al., 2007a]. The joint EOF-wavelet analysis results comprise the spatial patterns of the leading EOF modes, their associated principal component time series, and the time-frequency distributions of the rectified wavelet power spectra.

4. Results

First, we show a long-term mean pattern and a standard deviation map of the SSH to get a general view of the sea level distribution in the eastern GoM. Then, we apply the widely known time-domain EOF analysis to the same SSH data sets. Finally, we perform the two types of the SOM analyses. The combination of these analyses results will provide a more complete description of the sea level patterns and variability during the 23 years of altimetry data availability.
4.1. Long-Term Mean Patterns
Long-term mean values are often used to describe a general pattern from a long series of snapshots. The main feature of the long-term mean SSH in the eastern GoM is the LC, intruding northwest into the Gulf (Figure 1a). The mean LC reaches a longitude of 87.5°W to the west, and 26.5°N to the north, with a 45° angle of the general axis. In the mean LC region, the mean SSH values are 60–80 cm, which are about 30 cm higher than those in the peripheral region. Slightly higher SSH values (~40 cm) are seen to the west of the LC in the deep water area of the GoM, however, separate eddies are not identified in the mean SSH field.

Along with the long-term mean map, we calculate the standard deviations of the SSH over the 23 years (Figure 1b). Larger SSH variabilities (standard deviations > 25) are seen in the intruding region of the LC and the region to the west. The largest standard deviations (>30 cm) are located around northwest part of the mean LC. This wide band of large SSH variability mainly corresponds to the region of the LC extension/retraction and the separation and westward propagation of the mesoscale eddies.

The maps of the long-term mean SSH and the standard deviations provide only general information of SSH distributions and variability. Characteristic spatial patterns of the LC system variability cannot be seen from these maps. Characteristic temporal variations of the SSH are not known, either. In the following section, we will explore these features further with the SOM technique.

4.2. Joint EOF-Wavelet Analysis
We apply the joint EOF-wavelet analysis to the altimetry SSH product in the GoM. The analyzed data set is composed of the SSH and the associated surface geostrophic velocity components. The four leading modes of the joint EOF-wavelet analysis results are shown in Figure 4.

The first mode eigenvector shows a large positive SSH anomaly around the northwest edge of the long-term mean LC, sandwiched by two weaker negative SSH anomalies. The second mode eigenvector shows two large neighboring anomalies of different signs in the extension part of the long-term mean LC, with the larger anomaly located more to the southeast. The large anomaly in the second mode is generally weaker and smaller in size than that in the first mode. The first two modes, accounting for 19.6% and 13.8% of the total variance, respectively, show propagating eddy-like SSH anomaly features along the general path of the LC. The rectified wavelet power spectra of the first two principal components show that the SSH anomaly variations are mainly on the intra-seasonal time scales (from 2 months to 1 year).

The third mode EOF, accounting for 9.9% of the total variance, indicates a large SSH anomaly to the north-west of the long-term LC. It compensates the first two modes in reconstructing an elongated LC pattern. It appears less frequently than the patterns in the first two modes, with a time scale of 1–3 years. The fourth mode EOF, accounting for 6.6% of the total variance, shows even weaker and smaller SSH anomalies but still in a propagating wave pattern along the northern edges of the long-term mean LC. These variations generally appear more frequently and have smaller time scales (from 1 month to 1 year).

The EOF spatial patterns of the SSH anomalies are generally consistent with previous EOF analysis results of altimetry SSH data [Chang and Oey, 2013; Xu et al., 2013]. Slightly different results are expected between the current EOF analysis and the previous one because different data are used: (1) Our domain is limited to the GoM region with water depth >100 m, while the previous one included the Caribbean region and all the shallow water areas. (2) The time series lengths are 1993–2015 versus 1993–2010. (3) The variables are (SSH, u, v) versus SSH.

4.3. Self-Organizing Map (SOM) Analyses
4.3.1. Spatial Patterns of the Loop Current System as Revealed by the SOM
Using the SSH and surface geostrophic velocity spatial maps as input vectors (Figure 2), the 4 × 4 SOM extracts 16 patterns of the LC system (Figure 5). These spatial patterns show different LC extensions (retracted or extended northwestward), different stages in the process of LC eddy shedding (anticyclonic eddy separating from the LC and propagating westward), and different patterns of cyclonic rings appearing around the LC. Through the self-organizing process, similar patterns are arranged to be neighboring units (or close to each other) on the SOM, while dissimilar patterns are located far away from each other on the SOM. The units in between are usually transitional patterns. Generally, these patterns can be grouped into five categories listed as follows: The first category of the characteristic patterns are located on the upper-
Figure 4. Time-domain empirical orthogonal function (EOF) analysis results: (top) the first four mode eigenvectors and (bottom) the associated principal component (PC) time series and their rectified wavelet power spectra. The variance accounted for by each mode is also indicated on each plot. The PC variance is normalized to be 0.5. SSH units in cm. Rectified wavelet power spectra are shown as filled contours in base 2 logarithm. The regions of greater than 90% confidence are shown with black contours. Cross-hatched regions on either end indicate the “cone of influence,” where edge effects become important.
Figure 5. (top) Characteristic patterns of the Loop Current systems in the eastern Gulf of Mexico (16 plots) and (bottom) their evolution during 1993–2015 as revealed by a $4 \times 4$ Self-Organizing Map. The frequency of occurrence is given as a percentage number for each pattern. Sea surface heights and surface geostrophic velocities are shown in the maps. The black line designates the 1000 m isobath.
LC. The LCE is either far away from the LC or does not exist at all. The third category of the patterns are located on the upper-right corner of the SOM, showing the LC system with a large anticyclonic eddy that is in the initial stage of the eddy separation or the LC is just pinched off by a meander or cyclonic eddy at a lower latitude from offshore of the southwest Florida shelf break [e.g., Zavala-Hidalgo et al., 2003; Le Henaff et al., 2014]. The LCE is still in close proximity to the West Florida Shelf slope (P9, P13 and P14). The fourth category of the patterns are located on the lower-left corner of the SOM showing the LC system with fully separated LCE (P4, P7 and P8). The LCE is smaller in size, propagating westward, and far away from the West Florida Shelf slope. The fifth category of the patterns are presented in the center of the SOM, showing a northwestward elongated LC system (P6, P7, P10 and P11). Generally, there are more intruded LC patterns than the retracted.

By comparing the 16 patterns with the input data maps, a BMU can be found for each input data vector. Thus, the BMU time series indicate the evolution of the patterns over time or when those patterns occur (Figure 5, bottom). Frequency of occurrence of each pattern can be obtained by dividing the count of the pattern as a BMU by the total record length. The frequency of occurrence of each unit is shown in the upper-left corner of each pattern. Only 23% of the LC realizations have retracted patterns (P12, P15 and P16).

Further examining the zoomed-in BMU time series and the associated SOM patterns, we can see detailed LC system pattern evolution. For example, the BMU time series and the associated spatial patterns (highlighted in colors) in years 2010 and 2011 are shown in Figures 6 and 7, respectively. Year 2010 was of special significance for the GoM because of the Deepwater Horizon oil spill [e.g., Liu et al., 2011a]. The ocean circulation patterns in 2010 were studied using satellite altimetry data by many oceanographers [e.g., Liu et al., 2011b; Hamilton et al., 2011; Walker et al., 2011]. From January through April 2010, the LC grew in size and extended northward into the Gulf, and the patterns changed in sequence P3→P2→P1→P5 around the upper-left corner of the SOM (Figure 6). When the oil spill incident occurred in late April, the LC northern edge was not very far away from the oil spill site, which caused concerns on the potential spreading of the spilled hydrocarbons [e.g., Weisberg, 2011]. In May and early June 2010, the LC slightly retracted southward (P14 and P13), and the LC was pinched from its neck and the LCE intruded onto the west Florida continental slope [e.g., Liu et al., 2011b). From later June through early October 2010, the LCE separated from the main LC, decreased in intensity and size, and propagated westward in the central GoM (P15 and P16). During the rest of the year (October through December), the LC system had a retracted pattern without the LCE (P12), and by the year end the LC gradually grew in size again (P3). Monthly snapshots (12 panels) are often used to describe the evolution of the LC patterns in 2010 [e.g., Weisberg et al., 2014, 2016], in which how long each snapshot persists in time is not known. With the SOM technique, the LC evolution may be summarized with just nine patterns, and when and for how long each pattern persisted are readily seen in the BMU time series (Figure 6). Thus, the SOM provides a concise and informative way to describe the pattern evolution.

Year 2011 was an example of complicated LCE separation process (Figure 7). During the first half of year 2011, the LC system had repeated (three times) LCE separation—reattachment processes in the eastern GoM (P2→P9→P13→P9→P10→P14→P10→P11→P10→P14). Note that these unsuccessful separations were all initiated at the neck of the LC in a eastern location of the LC system. After three times of reattachments, the LC turned to be an elongated shape and extended more to the west in the GoM in early July 2011 (P11). From later July through September 2011, the elongated LC successfully shed an eddy at a western position, and the eddy propagated into the west GoM (P11→P7→P4). From September to October 2011, the LC had a quick growing process (P1→P5→P9). During November and December 2011, another LCE was successfully separated as the LCE reduced its size and intensity while propagating westward (P14→P15).

Another way to view the pattern evolution is to follow the trajectories of the BMU movement on the SOM grid. Again, take years 2010 and 2011 for example (Figure 8). In 2010, the BMU mainly evolved clockwise along the outer SOM units, first in the direction of LC extension (P3→P2→P1→P5→P9), and then in the process of LCE separation and LC retraction (P9→P14→P13→P15→P16→P12). In contrast, the pattern evolution was more complicated in 2011. The LC patterns were back and forth between the units of the upper-right corner, in addition to the path across the SOM grid from the upper-right to the lower-left. This SOM trajectory approach may be convenient for some SOM users in examining certain processes of the time series, but it is hard to see when and for how long each pattern persists. A combination of Figures 6–8 provides a better visualization of the pattern evolution processes.
The complex LC pattern variations were a subject of many previous studies [e.g., Sturges and Leben, 2000; Leben, 2005; Lugo-Fernández, 2007]. Particularly, the intrusion, eddy shedding, and retraction processes of the LC are of interest [e.g., Chang and Oey, 2013; Xu et al., 2013; Lindo-Atichati et al., 2013; Dukhovskoy]...
et al., 2015]. Lugo-Fernández and Leben (2010) found a linear correlation between LC retreat latitude following eddy separation and the subsequent eddy separation period. Alvera-Azcarate et al. (2009) also found a relationship between the intrusion of the LC and the size of the eddies shed from it: larger intrusions tend to trigger smaller eddies. Now that the 23 years of LC patterns are summarized in a very limited number of
SOM units, can we gain some insights from the SOM spatial pattern analysis? As shown in Figure 5, the patterns showing a large size initially separated LCE near the west Florida continental slope (P13 and P14) are located on the upper-right corner of the SOM, while the patterns showing a fully separated and westward propagated LCE (P4, P7 and P8) are located on the lower-left corner of the SOM. For a large LCE initially separated at a lower latitude (pinched at the neck of the LC), it may not directly propagate westward into the central GoM, rather, it may first decay its intensity and then propagate westward into the central Gulf, similar to the process in May–September 2010 (P13→P14→P15→P16, Figure 6), or it may reattach to the LC and form a northwest elongated LC (P10, P11 and P6), similar to the process in February to July 2011 (P13→P9→P10→P14→P10→P11→P10→P14→P11, Figure 7), then a LCE separates from the northwestern part of the LC (P7) and propagate westward, similar to a process in July–September 2011 (P11→P7→P4, Figure 7). Systematically examining the evolution of the yearly BMU time series from 1993 through 2015, we further confirmed these results (Table 1). For a large LCE initially separated at a south or east position (pinched at the neck of the LC) like patterns P13, P14 and P9, in most cases (12 years) it reattached back to the LC in the south to form a larger, elongated or northwest-extended LC (8 years) or separated again and decayed locally and propagated westward as smaller eddies (4 years). Only in three years (1998, 2009 and 2012), such separated LCE directly weakened and reduced its size, then propagated to the west. In contrast, it seems easier for a LCE to separate from an elongated and northwest-extended LC or a LC located at a west position (P6, P10 and P11). Among the 16 years of such LCE separations, 50% separated directly, and 50% reattached to the LC. Only in one year (2014), the separated LCE reattached to the LC and did not separate until the next year. In summary, the characteristic paths of the LC pattern evolution on the SOM can be shown in Figure 9.

**Figure 8.** Trajectory of Best Matching Unit (BMU) evolution on the Self-Organizing Map (SOM) during (a) 2010 and (b) 2011.

4.3.2. Temporal Patterns and Regions of Sea Level Variability as Revealed by the SOM

Using the time series of SSH at each data grid point as an input vector (Figure 3), the (3 × 3) SOM extracts nine different temporal patterns of sea level variability (Figure 10). The mean values and standard deviations of the extracted time series are calculated and listed in the panels, respectively. We see that the sea level variations are arranged in the 3 × 3 SOM in such a way that higher mean sea levels are located in the lower-left corner, and lower mean sea levels are located in the upper-right corner, of the SOM. By comparing the extracted time series with the input data vectors, we can find a BMU for each of the 1048 grid points. This process identifies the regions of sea level variability in the eastern GoM (Figure 11). The regions with large mean SSH values (Figures 10 and 11, R2, R3, R6 and R9) correspond to the long-term mean LC area (Figure 3a), while the regions with small mean SSH values (Figures 10 and 11, R4 and R7) correspond to the peripheral area. This is consistent with the distribution of the long-term mean SSH values in the eastern GoM (Figure 1a). The regions with larger SSH variability are generally in the LC dominated area, however,
the largest variability (R6) is not in the region of the largest mean SSH (R3), rather, it is in a region to the northwest, which is affected by frequent LC extension/retraction and LCE separation/reattachment. The SOM identified regions of sea level variability are confirmed by the long-term mean and standard deviation maps (Figures 1a and 1b). The regions of larger SSH variability are along the general axis of the LC in the eastern GoM, which is roughly consistent with the anomaly patterns revealed by the leading EOFs [Chang and Oey, 2013; Xu et al., 2013].

The rectified wavelet power spectra are shown for the LC active regions (R3 and R9) and the more peripheral regions (R4 and R7), respectively (Figures 12 and 13). Along the general axis of the Loop Current, SSH exhibits strong variability on time scales of 3 months to 2 years, with energetic intraseasonal variations. However, these intraseasonal variations are modulated by interannual changes, especially for the mean LC core region (R3). In the more peripheral regions, the SSH has a dominant seasonal variation, which is quite different from the SSH variations in the LC active regions. Most of these seasonal SSH variations may be contributed from the steric height changes according to an analysis using both hydrographic and altimetry SSH data [e.g., Liu and Weisberg, 2012].

To compare with the sea level variation at a nearby coastal station, we extend the wavelet analysis of the tide gauge record at St. Petersburg, FL [Liu et al., 2007a; Liu and Weisberg, 2012]. The tide gauge is located to the east of the SOM Region 7 across the west Florida continental shelf (Figure 11). We extracted the tide

Table 1. Loop Current Eddy (LCE) Separation and Reattachment During 1993–2015

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<tr>
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*LCE separation started in December of the previous year.

Figure 9. Typical trajectories of Best Matching Unit (BMU) evolution on the Self-Organizing Map (SOM) showing (a) Loop Current (LC) extension process, (b) Loop Current Eddy (LCE) separation from a western location when the LC is in a northwest-southeast elongated shape, and (c) LCE separation at an eastern location in the Gulf of Mexico.
gauge sea level record during identical time period with the altimetry data (January 1993 to August 2015). Prior to a similar wavelet analysis, the tide gauge data are detided for major tides, 48 h lowpass filtered and 12 h subsampled, adjusted for inverted-barometer effect. The rectified wavelet power spectrum is shown in Figure 14. We can see that the dominant SSH seasonal variation in the SOM Region7 also projects across the coastal ocean. However, the energetic sea level variations on synoptic weather time scales (2–20 days) at the coastal tide gauge are not seen in the offshore region (R7). The lack of energetic synoptic weather induced variations in the altimetry over the shelf calls for better altimetry products for coastal applications. On that other hand, we should be cautious in using gridded products for shelf regions. Even though they are called “daily” products, the synoptic variations are largely missing.

5. Discussions of EOF and SOM Analysis Results
Both the time domain EOF and the SOM analyses are performed on the same SSH data set. It would be instructive to compare the results of the two analyses. The EOF is a linear method, it divides the data into a series of orthogonal modes while conserving the variance of the data, however, the SOM is a nonlinear method, it extracts characteristic patterns from the data while preserving topology of the input data. The spatial patterns of the LC system revealed by the EOF are SSH anomalies in the leading mode eigenvectors. They are not as

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**Figure 10.** Characteristic temporal variation of sea surface heights in the nine dynamic regions (R1–R9) as identified by the 3 × 3 Self-Organizing Map. The mean and standard deviation of the SSH time series are listed in the parentheses, respectively.
intuitive as the SOM analysis results, which directly show the characteristic patterns of the LC system and their evolution in time. Adding the EOF anomalies to, or subtracting the anomalies from, the long-term mean map may show some spatial patterns more similar to the real LC patterns, but the features revealed by the limited number the statistically significant leading modes are far less than the abundant spatial patterns extracted by the SOM. It is convenient to examine pattern evolutions as zoomed-in BMU time series with highlighted characteristic maps or as BMU trajectories on the SOM grid, which is particularly useful in process-oriented studies. To achieve this with EOF analysis, one needs to reconstruct the time series from the leading modes [e.g., Chang and Oey, 2013; Xu et al., 2013], which is another step of analysis. The SOM can identify regions of SSH variability and extract their characteristic SSH time series, but the EOF analysis does not have this capability. The EOFs show both larger variations in the LC region and weaker variations in the ambient areas, but with the same weights (principal components). The annual cycles of the SSHs in the peripheral regions are identified by the SOM, but not obvious in the EOF results. However, the intraseasonal variation of the LC system can be obtained by both the EOF and the SOM methods with joint wavelet analysis.

6. Summary
We utilized the neural network method SOM in a new way to analyze the satellite altimetry data in the eastern GoM. The same technique was applied both to the spatial domain to extract characteristic patterns of the LC system and to the time domain to identify regions of sea level variability from the 23 years (1993–2015) of Ssalto/Duacs multimission altimetry data. The SOM revealed rich variability in the eastern GoM, especially along the LC general path, which encompasses a wide range of spatial and temporal scales. The SOM extracted five categories of the spatial patterns of the LC system in the eastern GoM. These patterns show different LC extensions (retracted or extended northwestward), different stages in the process of LCE shedding and propagation. The BMU time series indicate the evolution of these patterns over time or when they occurred in the past, and the frequency of occurrence of a certain pattern gives information on how often the pattern may be seen. Such SOM results may be useful in many other applications. For instance, 2010, the year of the Deepwater Horizon oil spill, was one in which the elongated or northwest
extended LC patterns that could have taken oil to the Florida Keys and beyond were absent after the spill [e.g., Liu et al., 2011b]. Had the spill occurred in other years, then the outcome of oil distribution might have been much different. Hence the SOM extracted spatial patterns could be used in risk analyses for offshore drilling operations.

The temporal evolutions of the SOM patterns as shown by the BMU time series are useful in gaining insights in the LCE separation processes. For an elongated, northwest-extended, or west positioned LC, it is easier for the LCE to separate and propagate into the western GoM, as the separation points are usually at a more northern or western location. In contrast, if the LC main body is still in the eastern GoM, especially in close proximity with, or intruding onto, the west Florida continental slope, the LCE initially separated from the neck of the LC often reattach to the LC and develop into an elongated LC; or it may reduce its intensity locally and then move westward as smaller eddies. Monitoring the separation and westward propagation of mesoscale eddies in the GoM is important for the oil and gas industry because the strong currents associated with these eddies are a threat to offshore drilling activities. While these results are new and interesting, the underlying physical mechanisms remain to be investigated in future studies using more data sets, such

Figure 12. Sea surface height time series in the Loop Current region, (top) Regions 3 and 9 and (bottom) its wavelet power spectrum. The time series are normalized (minus the mean and divided by the standard deviation) prior to wavelet analyses. Rectified wavelet power spectra are shown in base 2 logarithm. The regions of greater than 90% confidence are shown with black contours. Cross-hatched regions on either end indicate the "cone of influence," where edge effects become important.
as three-dimensional velocity and hydrography fields from intensive ocean observations and/or from dependable data assimilative numerical ocean circulation models. The SOM results opened a new topic for future oceanographic studies in the Gulf of Mexico.

When applied to the time domain of the same data set, the SOM identified regions of differing SSH variations. Along the general axis of the LC, SSH exhibits strong variability on time scales of 3 months to 2 years as shown from the rectified wavelet power spectra. The intraseasonal variations are a naturally occurring phenomenon in the LC active region, which was revealed by both the joint SOM-wavelet and the joint EOF-wavelet analyses. In the more peripheral regions, the SSH has a dominant seasonal variation that also projects across the coastal ocean. Identifying regions of variability of environmental variables is an important step toward knowledge-based ocean observing system design with limited funding resources [e.g., Weisberg et al., 2015]. For example, in the case of limited number of buoys to be deployed, one should identify priority areas first and then deploy instruments in different regions of variability, maximizing the benefits of such observing systems [e.g., Liu et al., 2015]. For marine resources management, one also needs to properly identify priority areas for decision-making [e.g., Porter et al., 2015].

**Figure 13.** Same as the Figure 12 but for Regions 4 and 7 (the peripheral regions). Sea surface height time series in (top) Regions 4 and 7 and (bottom) its rectified wavelet power spectrum. Seasonal variation dominates these regions.
The SOM identified regions of SSH variability are consistent with the long-term mean LC patterns and their standard deviations, as well as the anomaly patterns from the joint EOF-wavelet analysis. These regions are also consistent with the SOM extracted spatial patterns and their time evolution. The combined space- and time-domain SOM analyses provide a powerful tool for diagnosing ocean processes from different aspects. To our knowledge, this was the first time for such dual SOM analysis to be performed on a data set. We believe this kind of combined analysis can be applied to many other data sets, especially satellite remote sensing products, and model outputs in the future [e.g., Charantonis et al., 2015]. Such analyses are not limited to geophysical data applications.

References
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LIU ET AL. LOOP CURRENT SYSTEM AS REVEALED BY SOM 2366