Satellite remote sensing of surface oceanic fronts in coastal waters off west–central Florida

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A B S T R A C T
Two algorithms designed to detect deepwater oceanic features and arbitrary edge profiles were tuned to automatically delineate fronts in coastal waters off west–central Florida using satellite-derived sea surface temperature (SST), chlorophyll-a concentration (Chl), normalized water-leaving radiance (nLw), and fluorescence line height (FLH) images during select periods in the spring and fall of 2004 and 2005. The dates correspond to recreational king mackerel, Scromberomorus cavalla, tournaments. A histogram-based algorithm was useful to detect coastal surface SST, nLw, and FLH fronts, specifically. A gradient-based algorithm, with a smaller kernel box of 3 × 3 pixels, best identified nearshore (< 10 m depth) features in Chl images at the mouth of Tampa Bay, but was less effective for fronts farther offshore where gradients were weaker. Local winds and tide levels estimated from a coastal observing buoy, and bathymetric gradients were examined to help understand the factors that influenced front formation and stability. Periods of strong and variable winds led to front movement of up to 10 km per day or dissipation within 2–3 days in over 80% of the fronts detected in SST, Chl, nLw, and FLH imagery. Short episodes of less variable wind velocities typically led to more stable and stationary fronts, within 3–5 km, for up to four days. The occurrence of fronts closely associated with the coastal bathymetry, namely at the 20 m and 30 m isobaths, was significantly higher in the fall SST imagery and in the spring Chl imagery. Fall SST fronts related to bathymetric gradients likely resulted from progressive cooling of the water with depth. Stronger Chl and nLw gradients at the mouths of estuaries in the fall compared to the spring were attributed to increased precipitation and periods of stronger winds or tides. The FLH imagery was most useful in delineating coastal algal blooms. The automatic front detection techniques applied here can be an important tool for resource managers to track coastal oceanographic features daily, over synoptic spatial scales.

1. Introduction
Oceanic fronts are relatively narrow zones of enhanced horizontal gradients of physical, chemical, optical, and/or biological parameters which may have an expression at the ocean’s surface (e.g., see Bowman & Easias, 1978; Le Fèvre, 1986). They mark the boundary between waters of different physical and chemical characteristics, and therefore both water masses near the front may have unique biological characteristics. Fronts can be established through action of wind-driven upwelling, river discharge along the coast, confluence of water masses, tidal friction or a combination of these factors. Their surface expression can be quite apparent or muted, and they may change rapidly or remain stable for some time and over long distances. Some fronts have strong vertical motions on one or both sides, and therefore can have high vertical nutrient fluxes that result in high concentrations of phytoplankton biomass (e.g., Marra et al., 1990). Convergence of water masses also can lead to the accumulation of debris and other materials along fronts, creating surface biological features (e.g., Polovina et al., 2001). Therefore, fronts may exhibit marked gradients in ocean color. However, these may or may not coincide with the surface expression of a thermal front (Bontempi & Yoder, 2004).

Fronts are common in coastal and shelf areas (Pingree & Mardell, 1981; Pingree et al., 1982). On the west Florida shelf (WFS), fronts frequently can be observed in nearshore waters (Schmidt et al., 2001; Hu et al., 2004; Virmani & Weisberg, 2005; Weisberg et al., 2005). Over the mid and outer reaches of the WFS, fronts may occur seasonally or interannually (Gilbes et al., 1996; Del Castillo et al., 2001; Weisberg & He, 2003).

Oceanic front location, duration and intensity have been analyzed by fisheries scientists around the globe to address the hypothesis that fish abundance is higher near fronts due to an increased abundance of
prey (Roffer, 1987; Olson et al., 1994; Lutcavage et al., 2000; Polovina et al., 2001; Schick et al., 2004). Most of this work has focused on shelf and deep waters, but few such studies have been done in coastal waters shallower than about 50 m where front detection may be more difficult due to decreased gradient magnitude, tidal influence, and satellite data limitations (Roffer, 1987; Ullman & Cornillon, 2001; Stegmann & Ullman, 2004).

Identifying, mapping, and studying fronts using traditional ship-based methods is costly and labor intensive, and therefore traditional oceanographic techniques (ships, buoys) are not well suited to study the extent, motion, or persistence of fronts over a large region like the WFS. This is particularly true when manually delineating fronts for commercial and recreational fisheries, and to assist in fisheries and other resource management efforts. The tediousness and manual effort associated with providing a timely map of frontal features to such groups is a primary incentive to develop automated methods for the routine detection of frontal zones based on satellite imagery.

We tested and adapted two independent techniques for automatic detection of surface oceanic fronts in thermal infrared and ocean color satellite imagery for use in the coastal region of the inner WFS, specifically off Tampa Bay, Florida. Local winds and tide levels were analyzed in an attempt to understand the factors that influenced the formation and stability of the fronts detected. Our objectives were 1) to identify where fronts occur along coastal waters off west-central Florida, 2) determine how stable these fronts are, and 3) better understand the physical and biological characteristics of the fronts. Ultimately, this data will be used to identify the relationship between oceanic frontal strength and stability, and recreational king mackerel, Scomberomorus cavalla, tournament catch data (Wall, 2006).

2. Data and methods

2.1. Study area

This study focuses on the inner shelf off west–central Florida, USA, between 28°30′ N, 81°30′ W and 26° N, 84°30′ W (Fig. 1). The region extends approximately 180 km into the Gulf of Mexico from the coast. This area experiences seasonal changes in circulation due to wind, thermal stratification, and fresh water inputs (Schmidt et al., 2001; Hu et al., 2004; Virmani & Weisberg, 2005; Weisberg et al., 2005). These processes generate along- and cross-shelf transport of nutrients (Huh et al., 1981; Weisberg et al., 1996; Sturges & Leben, 2000), which affect plankton growth and distribution, including the occurrence and dispersal of Harmful Algal Blooms (HABs) of the toxic phytoplankton species Karenia brevis (Hu et al., 2004, 2005; Walsh et al., 2006, and references therein).

2.2. In situ data

The frontal analyses conducted for this study were timed to complement recreational fishing tournaments for king mackerel. In 2004, satellite images were processed for three days leading up to and including tournaments held on April 3 and 4; May 1, 2, and 8; October 23 and 30; November 6, 7, and 13. In 2005, dates included the three days leading up to and including the tournaments held on March 26; April 3, 9, 16, 17, 23, and 30; October 15 and 29; November 5, 6, and 12.

Winds and 4 m depth current velocity observations were obtained from buoy-mounted sensors (courtesy of the University of South Florida).
Florida’s Coastal Ocean Monitoring and Prediction System/USF COMPS, Station C10, 27°10′ N, 82°56′ W. For this study, winds that did not vary more than 45° and 5 m s⁻¹ over 24 h were considered to be steady. Similarly, steady currents were defined as those that did not vary more than 45° and 5 cm s⁻¹ over 24 h. The hourly time series of wind and current observations were treated with a 36-hour low-pass filter to help assess the general direction of forces acting on fronts over scales of the order of a day.

Tide level observations were obtained with a sea level gauge located in Tampa Bay off St. Petersburg, FL (courtesy of the NOAA National Ocean Service, Station 8726520, 27° 46′ N, 82° 38′ W). Tidal forces were strongest due to new or full moon phases during April 5 and 19; May 4 and 19; October 14 and 28, and November 12 and 26 in 2004, and April 8 and 24; October 3 and 17, and November 2 and 16 in 2005 (USNO, 2005). The gradient magnitude of fronts located within 20 km of the mouths of the estuaries on days within 24 h of a new or full moon (spring tide) or strong (>8 m s⁻¹) winds were compared with the gradient near the estuaries on days just prior and after these events to help understand the influence of possible increased estuarine flow, due to tidal or local wind forcing.

2.3. Satellite data

Infrared (IR) and visible – 1.0 km² pixel resolution satellite images were obtained by the USF Institute for Marine Remote Sensing (IMaRS; http://imars.usf.edu) from the NOAA Advanced Very High Resolution Radiometer (AVHRR) on polar orbiting environmental satellites NOAA-12, NOAA-15, and NOAA-17, and NASA’s Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra and Aqua satellites. Chlorophyll-a concentration (Chl), a proxy for water clarity, and normalized water-leaving radiance at 443 nm (nLw,443), a proxy for water clarity, were derived from MODIS/Aqua and ORBIMAGE’s Sea-viewing Wide Field-of-View Sensor (SeaWiFS). Solar-stimulated fluorescence line height (FLH) data were derived from MODIS as well. In total, 468 MODIS and AVHRR IR images and 90 MODIS and SeaWiFS ocean color images were used to analyze the surface ocean features for the three days leading up to and including the tournament days. Because IR images were collected from three separate AVHRR sensors and two MODIS sensors, there was substantially better coverage for each of the dates of interest. Ocean spectral reflectance imagery was available for less than half of the days for which SST data were available.

SeaWiFS and MODIS/Aqua images were processed using the NASA software SeaDas (version 4.8). Briefly, atmospheric effects were removed from the calibrated at-sensor radiance to obtain the spectral nLw, which represents the normalized ocean-reflected light for incident light, i.e. accounting for variations in solar/viewing geometry, atmosphere, and time. Then, a band-ratio bio-optical inversion algorithm was applied to estimate Chl (O’Reilly et al., 2000). The MODIS data products also included solar stimulated phytoplankton FLH, which may be a more accurate index for Chl in optically complex waters where high concentrations of land-derived colored dissolved organic matter occur (Hu et al., 2005, 2006).

Sea surface temperature (SST) was derived from AVHRR and MODIS IR data using the TeraScan and SeaDas software packages, respectively, and a Multi-Channel Sea Surface Temperature (MCST) algorithm. AVHRR images were navigated manually for proper geometric registration and then correction, and then a ±3-day median filter was applied to help remove pixels where SST values were contaminated with cloud effects. Daily SST composites were derived by averaging cloud-filtered images from MODIS and AVHRR passes prior to approximately 2200 Greenwich Mean Time (GTM), when the king mackerel tournaments typically ended. Daily MODIS and SeaWiFS ocean color composites with the least cloud cover and image banding (Seemann et al., 2003) were derived from the individual satellite passes. Composites with <50% cloud cover were only incor-

orated when no better data coverage was available. To enhance the detection of gradients in the images, the SST composite data were linearly rescaled from the 256-color image to the minimum and maximum SST values present in the region of interest, and the ocean color data were log-transformed.

Prior to applying an algorithm to delineate fronts, three iterative 3×3 pixel median filters were applied to remove noise and enhance the frontal features. The consecutive filters showed little loss of large oceanographic frontal features, yet small (less than approximately 15 pixels) fragmented fronts were deleted. The filters also appeared to enhance front detection, led to the identification of what appeared to be longer fronts by linking neighboring features, and minimized the detection of noise or false fronts.

The wind data collected at the buoy were supplemented with NASA’s Quick Scatterometer (QuikSCAT) satellite-derived wind data obtained from NASA’s Jet Propulsion Lab.

2.4. Frontal detection

A variety of algorithms exist to automatically detect oceanographic fronts from satellite imagery. These algorithms range from using simple statistics to characterize the gradient (Van Woert, 1982; Cornillon & Watts, 1987) to more complex methods such as a cluster-shade technique (Holley & Pecknough, 1989), semivariogram analysis (Franklin et al., 1996; Diehl et al., 2002), histogram analysis (Cayula & Cornillon, 1992, 1995; Saraceno et al., 2005), and entropic histogram analysis based on the Jensen–Shannon divergence (Vázquez et al., 1999). In this paper, an edge describes the algorithm’s mathematical distinction of populations in the satellite data and a front describes the verified edge in the context of oceanographic features.

The histogram analysis developed by Cayula and Cornillon (1992, 1995) detects thermal fronts and ignores false fronts or frontal features not identified by in situ observations with good skill (Mavor & Bisagni, 2001; Ullman & Cornillon, 2001; Belkin & Cornillon, 2004). A comparative study of the cluster-shade technique and the single image edge detection (SIED) histogram analysis by Cayula et al. (1991) found the performance of the SIED to be superior. Since the histogram method (Cayula & Cornillon, 1992; Cayula & Cornillon, 1995) has been successfully applied to detect gradients in satellite-derived Chl images for the Long Island Sound (Stegmann & Ullman, 2004) and in nLw images in the South Atlantic Bight (Bontempi & Yoder, 2004), it was used in this study.

In addition to the Cayula and Cornillon (1992) SIED method, the “Canny method” developed by Canny (1986) was also tested for applicability to the imagery. The Canny method has not been as widely used as the Cayula and Cornillon algorithm with regards to the application of oceanographic satellite data (Castelao et al., 2006) and it remains to be applied to coastal ecosystems. Here we use it primarily to identify and examine fronts in the Chl satellite images. Due to the smaller kernel box used in the Canny method, it was expected to be more effective than the SIED algorithm in detecting fronts near the coast, namely off the mouth of Tampa Bay.

We modified these algorithms to enhance their performance to detect weak fronts in coastal waters off west–central Florida as follows:

2.4.1. Cayula and Cornillon (1992) algorithm

An edge is represented as the line that separates two populations of pixels that contribute to a bi-modal histogram distribution within a specific area of an image. The gradient or distance between the two modes in geophysical units (°C, mg Chl m⁻³, etc.) determines the strength of the edge; the farther away the modes, the greater the difference in the mean values of the populations and thus the larger the gradient.

This algorithm initiates with a cloud detection mechanism so that an artificial edge is not drawn around data gaps created by a cloud or land mask. Then, a histogram is computed within a moving
window with a choice of either 64×64, 32×32 or 16×16 pixels. Due to relatively weak ocean surface gradients found on the inner WFS, in addition to the default 32×32 pixel moving window, a 16×16 pixel moving window was applied to detect weaker, smaller fronts.

In the original Cayula and Cornillon (1992) algorithm, an edge is identified if the following requirements are met: the ratio of the between-population variance to the within-population variance in the bi-modal histogram is greater than 0.76; and the difference between the mean values of the two populations in the histogram is greater than three digital counts. To compensate for the decreased algorithm sensitivity with smaller window sizes (D. Ullman, University of Rhode Island, USA, pers. comm.), the ratio of variance between the two populations to the variance within the populations was changed from the default 0.76 to 0.72 for this study.

A cohesion algorithm is then applied which distinguishes between the two populations. “High cohesion” predicts that pixels near an edge, surrounding pixels are likely to belong to the same population. For each detected edge, this algorithm creates a spatial segmentation between the two populations to verify the existence of a true front based on the cohesion of the surrounding gradients.

The final step applies a contour-following function to link adjacent edge pixels, eliminate weak, typically false, edges, and remove isolated edge pixels. Contours extend and connect isolated edge pixels by selecting the neighboring edge pixel that least changes the direction of the contour. This is statistically determined by calculating the ratio of gradients (the sum of gradient vectors to the sum of the absolute gradient vectors within a 3×3 pixel window, centered at the last contour pixel). If the ratio is greater than 0.90, then the edge pixel in the 3×3 pixel window is added to the contour. However, contours less than 10 pixels long are removed.

Two additional changes were made to the original method. First, the minimum length for a valid front was increased from 10 to 20 pixels. This increased the spatial range in which front segments are considered part of the same feature. Second, the threshold of the ratio of gradients was changed from 0.90 to 0.95 to increase the coherence between the fronts. Since long, jagged fronts are often the result from noise and not true thermal fronts (Cayula & Cornillon, 1992), the results of the changes in the contour-following function appear to produce more realistic fronts.

The Cayula and Cornillon (1992) algorithm with the above adjustments was applied to the SST, \(nLw\), 443, and FLH daily composite imagery. The algorithm was coded in FORTRAN but embedded in the Interactive Data Language (IDL; Research Systems Inc.) software for processing.

### 2.4.2. Canny (1986) algorithm

The Canny method for edge detection consists of four steps. First, a Gaussian filter is applied to smooth the image. The size of the filter mask depends on the standard deviation of the Gaussian filter, sigma. In this study, a sigma value of 1.0, corresponding to a 7×7 pixel mask, was used. Second, the edge gradient (strength and direction) for each pixel was computed using a 3×3 pixel window in the smoothed image. Third, the edges which contain two or more adjacent pixels in the gradient image were traced by only one pixel. In this process, the edge pixel with the strongest gradient magnitude remains. Fourth, hysteresis (double) thresholding is applied to determine the significance of the edge gradient. Chains of edge pixels gradients with magnitudes below the lower gradient threshold are removed. Edge pixel gradient magnitudes above the lower threshold and connected through a chain to any edge pixel gradient with a magnitude above the upper gradient threshold remain. In this study, thresholds of 0.05 and 0.08 were applied to identify inshore CHL fronts (after logarithmic transformation) without increasing the detection of noise. These threshold values were determined through trial and error. Values were adjusted until the results showed little to no noise (clouds, land, or banding) interfered with the process of detecting sharp oceanographic gradients. The Canny algorithm was implemented using Matlab® software (Mathworks, Inc.).

Both front detection algorithms described above were also applied to a digital bathymetry grid of the inner WFS interpolated to ~ 90 m² resolution (Divins & Metzger, 2005) to identify areas of depth gradients. This analysis sought to understand the role of these areas in the genesis and stability of the fronts.

The final frontal images were remapped in the standard North American Datum 1983 projection for spatial analysis. This was carried out using ArcGIS (Environmental Systems Research Institute / ESRI™).

In summary, the adjusted Cayula and Cornillon (1992) algorithm was applied to daily composite SST, \(nLw\), 443, and FLH satellite data and, after comparing the results of both algorithms, the Canny method was applied to daily composite CHL satellite data.

### 2.5. Front analysis

Stable fronts were determined by examining the frontal pixels present on the fishing tournament day and located within ~ 3 km (3 pixels) for up to three days prior. This distance was predefined by the radius of inertial motion (He & Weisberg, 2002) and the Rossby radius of deformation (Y. Liu, University of South Florida, USA, pers. comm.) for this region. The number of pixels identified as the same front in the images before and including the tournament was divided by the number of frontal pixels in the tournament day image. This represented the fraction (or percentage) of frontal pixels detected on the tournament day that were stable for up to three days before.

The gradient field was calculated by applying a gradient magnitude equation on each original daily composite (without filtered, rescaled or stretched data):

\[
\text{Gradient magnitude (GM)} = \sqrt{(\partial T/\partial x)^2 + (\partial T/\partial y)^2},
\]

where \(\partial T\) equals the change in the parameter value (SST in °C, CHL in mg m⁻³, and \(nLw\), 443 and FLH in mW cm⁻² μm⁻¹ sr⁻¹) in the horizontal (x) and vertical (y) direction; \(\partial x\) and \(\partial y\) was 3 pixels. The fronts detected as described above were then overlaid onto the gradient image, and the gradient magnitude surrounding the daily and sustained front pixels were determined for each tournament day.

Eq. (1) was also used to identify the presence of false fronts detected by the front detection algorithms. A false frontal pixel is identified in the frontal image if it does not spatially coincide with a gradient pixel (where GM > 0.02) within the gradient image. The percentages of false frontal pixels in each image were calculated for the four parameters to help determine the accuracy of the front detection algorithms.

The spatial relationship between the fronts and isolines was determined by calculating the number of frontal pixels in each composite image that were within 1 km of the NOAA bathymetry contours (NOAA, 2000) from 10 m to 50 m in 10 meter increments. This number was normalized by the total number of frontal pixels in that image and then multiplied by 100 to identify the percentage of frontal pixels closely associated with the coastal isolobes. These fronts were considered bathymetry fronts. Isolated, single frontal pixels near an isobath were not considered bathymetry fronts. The percentage of bathymetry fronts identified in each image for each parameter was compared by season using an ANOVA and boxplot analysis. The spatial analysis was carried out in ArcGIS developed by ESRI™.

### 3. Results

#### 3.1. Winds and currents

Atmospheric fronts and wind changes were observed in the meteorological data throughout the study period (Fig. 2). While wind
Fig. 2. 2004 wind velocity data for (a) April, (b) May, (c) October, and (d) November. 2004 current velocity data for (e) April, (f) May, (g) October, and (h) November. 2005 wind velocity data for (i) April, (k) October (note the change in scale), and (l) November. 2005 current velocity data for (j) April. Arrows indicate tournament dates.
direction was predominantly to the south (either southward, south-eastward or southwestward) during all study periods, hourly winds typically oscillated more than 45° and over 5 m s\(^{-1}\) over 24 h. Indeed, we did not observe steady winds throughout any consecutive four-day period associated with the tournaments. Instead, wind directions that changed greater than 90° per day were recorded on 79% of the four-day tournament periods. The remaining 21% of the tournament periods recorded less variable but unsteady wind velocities. In April 2004, the mean wind direction over the three days leading up to and including the tournaments held that month was southeastward (Fig. 2a). In May 2004 (Fig. 2b), October 2004 (Fig. 2c), November 2004 (Fig. 2d), April 2005 (Fig. 2i), October 2005 (Fig. 2k), and November 2005 (Fig. 2l), winds were more likely to blow south-southwestward. Steady winds occurred only on November 6, 2004. However, wind strength was greater than 8 m s\(^{-1}\) on this date and variable during the three days prior.

With few exceptions, current direction and speed mostly followed the wind direction, within 90° to the right due to Ekman transport and speed (Fig. 2e–h, j). Gaps in wind data collected at the buoy occurred from November 16 to 30, 2004, April 1 to 4, 2005, and November 24 to 30, 2005. No current data were available for May 14 to May 31, 2004, October and November 2005.

3.2. Front detection algorithms

A comparison of the original and adjusted thresholds applied to the Cayula and Cornillon (1992) front detection algorithm for an SST daily composite image is shown in Fig. 3. The adjusted algorithm...
with the 32×32 pixel box detects more fronts for this study area, and the 16×16 pixel box results identifies weaker fronts. The mean Gradient Magnitude (GM) obtained using the 32×32 pixel box compared to the 16×16 pixel box for the SST and nLw 443 images was 0.03 °C km⁻¹ and 0.04 mW cm⁻² μm⁻¹ sr⁻¹ km⁻¹ higher, respectively. The difference for the FLH imagery was negligible (2.3 E⁻⁴ mW cm⁻² μm⁻¹ sr⁻¹ per km).

The results of the two front detection methods applied to Chl data are compared in Fig. 4. The Canny method detected more fronts in nearshore waters around the estuaries and to the north of Tampa Bay (Fig. 4a). While the Cayula and Cornillon (1992) algorithm identified offshore Chl fronts, it also seems to delineate fronts where strong gradients are not visually apparent, therefore possibly falsely identifying fronts or visual illusion effects within the image (Fig. 4b).

The addition of the 16×16 pixel box results in the Cayula and Cornillon (1992) algorithm did not significantly increase the percentage of falsely identified thermal fronts compared to using only the 32×32 pixel box result (Student’s t-test, p>0.05). Mean percentages of falsely identified front pixels using the adjusted Cayula and Cornillon (1992) algorithm thresholds for SST, nLw 443, and FLH data were 0.60±0.40%, N=19; 1.28±1.38%, N=18; and 0.05±0.06%, N=4, respectively. Using the Canny method, a mean of 1.41±1.45%, N=18, for the Chl frontal pixels were falsely identified. Differences in sample size per parameter result from limited data available on tournament

![Image](image_url)
days. This indicates that the frontal detection methods do not identify a significant amount of false frontal pixels.

3.3. Bathymetric gradients

Although the WFS is typically characterized as gently sloping, areas of transition in the bathymetry (steep gradients) were identified with the adjusted Cayula and Cornillon (1992) algorithm (Fig. 5a) and with the Canny method (Fig. 5b). The spatial gradient analyses (not shown) show relatively sharp gradients near the 20 m, 30 m, and 40 m isobaths between Tampa Bay and Charlotte Harbor. The association of these isobaths to the detected bathymetric fronts is best identified for the adjusted Cayula and Cornillon (1992) algorithm results (see Fig. 5a). Another sharp gradient was detected north of 28° N near the 10 m isobath.

3.4. Oceanic fronts

In spring 2004 and 2005, thermal fronts traced the outline of a cold-water tongue that originated in the north and extended along the inner shelf south of Charlotte Harbor (Fig. 6a shows an example of the spring thermal front pattern). This feature corresponds to the predominant southward wind and current direction. Thermal fronts detected in the fall of 2004 and 2005 show an alongshore pattern, parallel to bathymetric contours of the inner WFS (Fig. 6b shows an example of the fall thermal front pattern). Therefore, the fall SST fronts seemed to be preferentially aligned with coastal bathymetric contours relative to spring SST fronts. Indeed, chains of thermal frontal pixels were more likely to occur within 1 km of the 10 m, 20 m, and 30 m isobaths in the fall than the spring (ANOVA, $p \ll 0.01$, significant).

Fig. 7. NLw fronts detected on (a) April 3, 2004 as an example of spring and (b) November 6, 2004 as an example of fall. White lines delineate fronts. The 20 m, 30 m, and 40 m isobaths are outlined in black. Areas of black represent the landmask or clouds.

Fig. 8. Chl fronts (white lines) on (a) April 3, 2004 as an example of spring and (b) November 6, 2004 as an example of fall. The 20 m, 30 m, and 40 m isobaths are outlined in black. Areas of black represent the land mask or clouds.
In general, $n_{\text{Lw}443}$ fronts were not related to the bathymetry in either season for either year ($p > 0.05$) (Fig. 7). However, increased $n_{\text{Lw}443}$ values and gradients located approximately along the 10 m isobath near the north coast of 28° N appeared to be more pronounced during spring 2004 and 2005 images compared to fall 2004 and 2005. Conversely, frontal gradient magnitudes within 20 km of the mouth of the estuaries were significantly higher in fall 2004 and 2005 compared to spring 2004 and 2005 for images within 24 h of a recorded spring tide or strong winds (ANOVA, $p < 0.01$, $p < 0.05$, respectively).

The strongest fronts detected in spring 2004 Chl images were largely shoreward of the 20 m isobath (Fig. 8a). In contrast, fall 2004 Chl images show strong gradients both near the mouth of the estuaries and farther offshore on the shelf (Fig. 8b). These offshore fronts form along the edge of river plume waters that spread seaward from the coast (Hu et al., 2004, 2005). In this image, the stronger gradients near the mouth of the estuaries coincided with strong ($>8$ m s$^{-1}$) south-westward winds. Chl gradient magnitudes for fronts located within 20 km of the estuaries’ mouths were significantly higher for all fall images, compared to all spring Chl images, within 24 h of a spring tide or strong winds (ANOVA, $p < 0.01$ or $p < 0.05$, respectively). Conversely, spring 2004 Chl data had significantly more fronts within 1 km of the 20 m and 30 m bathymetric gradients than in fall 2004 (ANOVA, $p < 0.01$). Significantly more fronts were identified coinciding with the 30 m bathymetric gradient in the spring 2005 Chl data than in fall 2005 (ANOVA, $p < 0.01$).

Harmful algal blooms were present off central Florida in 2005 from January through at least November (Hu et al., 2006). The frontal detection algorithms applied to the $n_{\text{Lw}443}$, Chl, and FLH fall 2005 data were effective in outlining the boundaries of water masses, some of which were confirmed to contain high counts of HAB organisms (Fig. 9). Fall 2005 $n_{\text{Lw}443}$ and Chl fronts traced the boundaries of a high Chl patch ($>5$ mg m$^{-3}$) up to 70 km off the coast of the Charlotte Harbor area (Fig. 9, left and middle panel). FLH images more clearly differentiated between chlorophyll patches and river plumes along the coast (Fig. 9, right panel). On average, approximately 50% of the fronts identified in the FLH images were located near or on the 10 m, 20 m, or 30 m isobaths.

Fronts were displaced up to 10 km over a 24 hour period when winds speeds were greater than 8 m s$^{-1}$ and currents were greater than 10 cm s$^{-1}$ between April 2 to 4, 2004, April 2 to 3, 2005, and 29 to 30, 2005. Fig. 10 shows the displacement of thermal fronts from April 2 to 3, 2005. The tip of the cold tongue identified by the westernmost arrow moved ~10 km southward. The temporally consistent fronts were displaced only small distances, between 3 and 5 km, on October 29 to 30, 2004 and October 28 to 29, 2005, under weaker ($<8$ m s$^{-1}$) and less variable wind velocities (Fig. 11). Similar frontal displacement was observed for the ocean color data (not shown).

3.5. Stable oceanic fronts

Frontal pixels stable for at least three days or more leading up to a tournament in SST, $n_{\text{Lw}443}$, Chl, and FLH fields were identified on all tournament dates where consecutive data were available. However, they represented only a small fraction of all frontal pixels identified on each tournament day, specifically ~18 ± 14% SST, ~25 ± 13% $n_{\text{Lw}443}$, ~25 ± 18% Chl, and ~17 ± 11% FLH pixels (Table 1).

Fig. 12 shows the combined stable frontal pixels in the spring (black lines) and fall (blue lines) identified for the 19 tournament days during 2004 and 2005 for SST, $n_{\text{Lw}443}$, and Chl. Stable fall 2005 FLH frontal pixels are shown in blue. The stable gradients in SST and Chl were typically located some 30 to 50 km off the coast, and roughly followed the change in steepness of the shelf bathymetry near the 20 m and 30 m isobaths. The $n_{\text{Lw}443}$ showed fronts throughout the inner shelf in both seasons, while only a few, small stable fronts were seen in the FLH product. No significant difference was found between the gradient magnitudes around the stable frontal pixels compared to the gradient magnitudes around the frontal pixels found on any individual day for any of the four parameters (ANOVA, $p > 0.05$).

4. Discussion

The Cayula and Cornillon (1992) algorithm has previously been applied to lake or shelf-break environments. Here we tested it for mapping coastal fronts in inner shelf waters off the west coast of Florida. We found that the algorithm, after tuning several parameters, was useful to detect coastal surface thermal, water clarity, and fluorescence fronts. The Canny method better identified nearshore features (<10 m depth), specifically at the mouth of Tampa Bay, but was less effective for offshore detection. We suspect this to be due to the smaller kernel box (3 × 3) applied in the Canny method compared to...
the Cayula and Cornillon (1992) histogram algorithm (32×32 or 16×16 kernel box). The smaller box size allows the Canny method to detect fronts near the coast by calculating gradients closer to the land mask. The histogram algorithm works better offshore likely because it is more sensitive to smaller gradients. Although the Canny method was originally developed for arbitrary edge profiles, it shows promise for future applications when studying coastal Chl fronts from satellite data.

How accurately do these methods identify fronts? In the open ocean, frontal features can range from a few hundred meters to tens or even thousands of kilometers. In the WFS, fronts tend to be small, on the order of less than 50 km, and may be weaker than some major oceanic fronts due to the geomorphology of the shelf. Because of the lack of concurrent field oceanographic data, visual inspection of the imagery was used to validate the automated detection and demarcation of fronts. Images were visually analyzed to confirm that fronts were identified and traced by the algorithms where color gradients were observed. We also verified that they were consistent with features detected in the days prior as a means to ensure that the feature or gradient was not an anomaly or an error. On average, less than 2% of frontal pixels were identified as false, which supports the viability of these methods to accurately detect coastal surface oceanic fronts.

Using ocean color imagery collected by the Coastal Zone Color Scanner (CZCS) and IR data collected with the AVHRR, Gilbes et al. (1996) identified a tongue-shaped plume of cold, high chlorophyll water (affectionately called the “green river”) that forms every spring over the middle of the WFS, extending from Cape San Blas. Virmani and Weisberg (2003) then described a process that would lead to the formation of this plume. Similarly, a tongue-shaped pool of cold water is identified in the spring SST frontal images (see Fig. 6a). However, the

Fig. 10. Sea surface temperature fronts detected on (a) April 2, 2005 and (b) April 3, 2005. The arrows on the images correspond to regions of frontal displacement, dissipation or establishment. Areas of black represent the land mask or clouds.

Fig. 11. Sea surface temperature fronts detected on (a) October 28, 2005 and (b) October 29, 2005. The arrows indicate regions where fronts showed little change or movement over 48 h. Areas of black represent the land mask or clouds.
exact association of the observed coastal cold water plumes to the ‘green river’ is unknown.

In the fall, while the interior of the Gulf is still warm, storms cool the coastal waters and eventually shelf waters (Virmani & Weisberg, 2003). This may be the cause for many of the fall SST frontal data that were found along the coastline and bathymetry. However, some warm pools of water on the southern shelf define cross-shelf fronts in the late fall. River plumes and red tides likewise frequently showed cross-isobath fronts.

Different products derived from ocean color data show different frontal features (see Figs. 7–9). The default Chl algorithm is based on a ratio between one of the blue bands and a green band (O’Reilly et al., 1998; Carder, Chen, Lee, Hawes, & Kamykowski, 1999). Hence, if the spectral reflectance due to a constituent (e.g., suspended sediments, shallow bottom) is relatively flat between blue and green, or if a constituent other than Chl absorbs strongly in the blue (such as color dissolved organic matter/CDOM), the Chl product will show different patterns from the FLH data.

Fig. 8 illustrates the influence of bottom reflectance and river/estuary plumes on the Chl estimates. In the fall Chl image, high concentrations and fronts are identified near the mouths of the estuaries and along the coast, specifically north of 28° N, which is a shallow sandy area. These increased plume gradients are likely due to the combined effect of

![Image](attachment:image_url)
What contributed to the lack of persistence of fronts on the WFS? Highly variable winds and current velocities were observed throughout the study period. These forces resulted in an ~80% loss of surface oceanic SST, Chl, $nLw_{443}$, and FLH fronts that had been present over the previous 48 to 72 h. This supports Franks and Walstad (1997) who found that wind events alter the shape and intensity of the Chl patches near fronts, and wind direction largely dictates the future patch characteristics. However, while some fronts may move 10 km over a 24 hour period, they may retain similar biomass levels.

Approximately 20% of the SST, Chl, $nLw_{443}$, and FLH fronts were stable and showed less movement and dissipation. Some features within the October 29, 2005 SST and the April 4, 2004 Chl imagery will be discussed here for illustration purposes. These SST and Chl images contained 32.9% and 28.4% of stable front pixels, respectively. October 29, 2005 and the three days prior recorded weaker ($<$ 8 m s$^{-1}$) and less variable wind velocities resulting in lessened frontal movement and dissipation. The stable SST fronts on this day, specifically north of 28° N, approximately followed the 10 m isobath. April 4, 2004 and the three days prior recorded wind changes from northeastward to southeastward, though speed remained near 5 m s$^{-1}$. Despite the change in wind direction, stable Chl fronts stretching down the 10 m and 20 m isobaths from north of 28° N nearly to the mouth of Charlotte Harbor were observed. These areas coincide with the sharper bathymetric gradients identified in the frontal bathymetry analysis. Thus, physical and biological water-column processes are related to bottom topographic features, such as slopes, ridges, and canyons (Huh et al., 2006).

\[\begin{array}{c}
\text{cells/liter} \\
\text{NOT PRESENT} \\
\text{PRESENT (1,000 cells or less)} \\
\text{VERY LOWa (>1,000 to <5,000)} \\
\text{VERY LOWb (5,000 to 10,000)} \\
\text{LOWa (>10,000 to <50,000)} \\
\text{LOWb (50,000 to <100,000)} \\
\text{MEDIUM (100,000 to <1,000,000)} \\
\text{HIGH (>1,000,000)}
\end{array}\]

**Fig. 13.** *Karenia brevis* in situ counts from November 7–9, 2005 reported by FWRI. Arrows indicate patches of observed extreme HABs.
The maps of stable fronts and bathymetric gradients, and the relationship observed between the local wind, bottom topography, and the genesis and duration of coastal fronts provides valuable information for defining ecosystem relationships in this area. This is likely to help improve our understanding of the influence of the environment on surrounding living marine organisms. Specifically, these observations provide the foundation for an analysis of recreational king mackerel catch data collected during tournaments in the context of environmental observations. More broadly, these results help fisheries researchers and management personnel by providing likely locations where species of interest may aggregate and contribute to defining predator–prey relationships. Additionally, they may improve the ability of scientists to track and perhaps even predict the accumulation and movement of HABs along the WFS by identifying areas most susceptible to increased frontal duration.

5. Conclusion

Oceanic fronts over the inner WFS were detected and delineated using automated computer image processing techniques applied to four remotely-sensed parameters, namely SST, CHL, nL443, and FLH. Thresholds of the Cayula and Cornillon (1992) front detection algorithm were tuned to improve detection of the local coastal fronts. The Cayula and Cornillon (1992) algorithm appeared to identify CHL fronts better than the Cayula and Cornillon (1992) algorithm, particularly closer to shore. Strong and variable winds recorded throughout the study period resulted in front movement upwards of 10 km per day and led to over 80% of fronts dissipating within 2–3 days. During short episodes of less variable wind velocities, about 20% of the fronts were spatially sustained within 5 km for periods of up to four days. From the front detection results, significant spatial associations were identified between seasonal frontal features, bathymetric gradients, and tidal flux. Fall SST fronts and spring CHL fronts were coupled with the coastal bathymetry, particularly the 20 m and 30 m isobaths between the estuaries. Spring SST, and fall CHL and nL443 fronts were more strongly influenced by plumes and tidal periods. We attribute this result to the coastal tongue-shaped pool of cold water in the spring, and enhanced ebb and flow from spring tides in combination with increased precipitation and heat flux in the fall. FLH data delineated HAB boundaries most effectively compared to the other ocean color parameters because of the negligible influence from the bottom and CDOM on the near infrared wavelengths.

Despite the limitations due to cloud cover and uncertainties inherent in the satellite data products, combined with appropriate frontal detection algorithms, remote sensing data provided valuable information on the front location, duration, and intensity, as well as on the linkages between physical processes and biological characteristics of the WFS.

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