# Retrievals of sea surface temperature fronts from SAR imagery

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[1] We present a new methodology to identify SST fronts of the Gulf Stream, using linear relationships between sea surface temperature (SST) gradients, and curl and divergence of wind stress fields, derived from high resolution (1 km) SAR data. The new approach uses a composite metric determined from the wind stress divergence and curl fields from individual SAR images. Multi-stage spatial filtering, Wiener and Gaussian low-pass filters, and a statisticallybased high pass spatial filter are applied to the derived wind stress curl and divergence fields. Results are significantly improved by restricting SAR imagery to cases where wind speed is less than 12 m/s, thus removing strong wind shear fronts. The method is demonstrated with SAR images of the Gulf Stream and has potential to be applied in near real time operations. The advantages of SAR imagery over optical sensors are its independence of cloud or night-time conditions and high accuracy. Citation: Kuang, H., W. Perrie, T. Xie, B. Zhang, and W. Chen (2012), Retrievals of sea surface temperature fronts from SAR imagery, Geophys. Res. Lett., 39, L10607, doi:10.1029/2012GL051288.

## 1. Introduction

[2] The Gulf Stream is a strong poleward warm current in the western Atlantic with a large transfer of heat from the ocean to the atmosphere, affecting the entire troposphere. It is associated with strong sea surface temperature (SST) gradients. Sea surface thermal fronts interact with the atmosphere through atmospheric boundary layer forcing, and are crucial for weather forecasting, climate monitoring and upper ocean dynamics. It is well known that warming and deepening of the atmospheric boundary layer causes increased low-level cloudiness over the warm downwind side of SST fronts. This makes it difficult to retrieve the position of sea surface thermal fronts in cloud-covered days from satellite-borne optical sensors such as the MODerate Resolution Imaging Spectroradiometer (MODIS) or Advanced Very High Resolution Radiometer (AVHRR).

[3] Satellite-borne Synthetic Aperture Radar (SAR) images are independent of clouds, night-time, or most weather conditions and are unbiased except in heavy rain. SAR is sensitive to interactions of wind with the ocean surface. The tilting and redistribution of the short waves caused by wind

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stress variations, which may be associated with sea surface thermal fronts, are characteristic patterns that are identifiable in SAR imagery. *Nghiem et al.* [2000] found a difference of more than 5 dB in normalized radar cross section (NRCS) backscatter data, for the  $\sim 9^{\circ}$ C SST difference that typically occurs across the Gulf Stream. Thus, Gulf Stream features are detectable by SAR.

[4] Recent studies found a coupling between wind stress and the SST response to the local heat fluxes and marine weather [Sikora et al., 1995; Song et al., 2006; O'Neill et al., 2010]. It is suggested that, not only are variations in the wind stress important factors in the study of air-sea interactions in the Gulf Stream region, but that the wind stress curl and divergence fields are linearly related to the crosswind and downwind components of the SST gradients, respectively [Chelton et al. 2004, O'Neill et al., 2010; Jones et al., 2012]. In this formulation, the acceleration of the winds flowing across the Gulf Stream, is the dominant cause for wind stress divergence, whereas wind stress curl is partially due to the atmospheric response and partially due to the ocean currents; the latter may increase or reduce the stress, if the wind blows against, or with, the surface currents, respectively [Small et al., 2008]. Using these linear relationships between SST gradients and wind stress variations, Xie et al. [2010] proposed a method for detecting Gulf Stream thermal fronts, based on the minimization of a functional of the wind stress curl and wind stress divergence, derived from SAR data. Their method was limited by numerical noise and speckle artefacts in SAR images; verification was limited by time discrepancies between collocated SST and SAR images, and the shifting Gulf Stream.

[5] The objective of this study is to determine an improved methodology to provide accurate high-resolution identification of Gulf Stream thermal frontal features. Our approach is based on curl and divergence fields of the wind stress, calculated at high-resolution (1 km) from individual SAR images. Section 2 describes the data. Section 3 describes the multi-step spatial filter, and related conditions for identification of SST fronts in SAR images. Section 4 gives retrieved results from SAR images, in comparison with SST images, and section 5 provides the conclusions.

# 2. Data

[6] The focus of this study is RADARSAT-2 ScanSAR imagery of the Gulf Stream region from 75°W to 55°W longitude, and from 35°N to 46°N latitude. These are wide swath SAR images, 300 km  $\times$  300 km, with 25 m  $\times$  25 m pixels, in VV polarization mode. Wind directions are provided by QuikSCAT L3 data with 0.25° resolution, from the Physical Oceanography Distributed Active Archive Center (PODAAC, ftp://podaac-ftp.jpl.nasa.gov/allData/quikscat/L3/jpl/). AVHRR and MODIS blended SST data are used to verify candidate thermal fronts, derived from SAR retrievals.

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## 2.1. Wind Direction

[7] Because SAR only obtains backscatter using single look geometry, additional information about the wind direction is needed to retrieve surface wind speed. In this study, we use nearly simultaneous QuikSCAT swaths to assign wind directions to the SAR images. At 25 km resolution, daily QuikSCAT wind vectors are coarser than the processed 1-km scale of the SAR images. To obtain high resolution wind vectors from RADARSAT-2 images, we first average the SAR data from the original 25 m pixel spacing to 1 km, and then we linearly interpolate the wind directions to the geographic position of each 1-km scale unit. where *T* represents SST,  $\vec{\tau}$  is wind stress, *a* and *c* are local along-wind (or downwind) and crosswind coordinates, respectively, and  $\vec{k}$  is a vertical unit vector. Stronger SST gradients in the downwind direction (hereafter  $(\nabla T)_a$ ) have stronger dependence on wind stress divergence, whereas stronger SST gradients in the crosswind direction (hereafter  $(\nabla T)_c$ ) have stronger dependence on wind stress curl. For SAR-derived wind stress, we combine these relations and use *Xie et al.*'s [2010] minimization condition,

$$|\nabla T|_{\min} = bA \tag{3}$$

where A is denoted the Wind Stress Perturbation (WSP) coefficient, defined by

$$A = \sqrt{\left\{ \left[ \overline{(\nabla \times \vec{\tau})_p} - \overline{(\nabla \times \vec{\tau})_n} \right] / \left[ \overline{(\nabla \cdot \vec{\tau})_p} - \overline{(\nabla \cdot \vec{\tau})_n} \right] \right\}^2 |\nabla \cdot \vec{\tau}|^2 + |\nabla \times \vec{\tau}|^2} \tag{4}$$

#### 2.2. Wind Stress

[8] The dependence of VV-polarization C-band backscatter on surface wind vectors and viewing geometry is summarized in geophysical model functions, the most popular of which are CMOD4 and the newly developed CMOD5. CMOD5 is more reliable over a wider wind speed scale, and CMOD5.N [*Hersbach*, 2008, 2010] works best with RADARSAT-2 data [*Zhang et al*, 2011]. Here, we use the SAR backscatter (NRCS-VV), incidence angle at the pixel of interest, wind direction from QuikSCAT, and CMOD5.N to compute the associated wind speed at 1 km resolution. The algorithms of *Liu et al.* [1996] and *Xu and Scott* [2008] are used to derive the 10 m neutral wind field, from which we calculate the wind stress, curl and divergence of wind stress, at 1 km resolution.

### 2.3. Sea Surface Temperature

[9] To validate the identity of detected SST fronts derived from SAR images, we use MODIS and AVHRR SST data. These data were blended, sometimes over several days, to minimize cloud contamination. Since the daily position of the Gulf Stream can change by as much as 30 km/day, whereas rings can move 4–5 km/day, it is not always possible to have exact correspondences between SAR and SST maps. Therefore, comparisons are between snapshots of cmscale ocean surface roughness features, and averaged SST maps.

# 3. Methodology

[10] O'Neill et al. [2003, 2010], Chelton et al. [2004] and Maloney and Chelton [2006] suggest that SST gradients can be decomposed into downwind and cross wind components, and that gradients of these components are linearly related to the wind stress divergence and curl fields, respectively. We use curvilinear coordinates to write

$$\frac{\partial T}{\partial a} \propto (\nabla \cdot \vec{\tau}) \tag{1}$$

$$\frac{\partial T}{\partial c} \propto (\nabla \times \vec{\tau}) \cdot \vec{k} \tag{2}$$

which must be minimized in order for bA to represent a SST gradient. Here, p and n denote elements whose values are positive and negative, respectively, '-' denotes the mean value, and b is assumed to be constant in a given SAR image. An example of this methodology is given in Figures 1a(i)–1c(iii), showing the SAR image on May 22, 2009, the SAR-derived SST thermal fronts, and a collocated SST image 5 hours before.

[11] The linear relations between wind stress variations and SST gradients suggested by *O'Neill et al.* [2003] and *Chelton et al.* [2004] were derived from 4-year averaged 25-km resolution QuikSCAT data. In practice, sea state, orography and ocean currents can introduce biases and noise into wind speed retrievals from SAR imagery, as shown in Figure 1a(iii), which vary temporally and spatially [*Hersbach* 2010]. Thus, it is important to determine the conditions where *Xie et al.*'s [2010] method can reliably detect gradient SST components from SAR imagery.

#### **3.1. Local Coordinates**

[12] Once the wind stress curl field  $(\nabla \times \vec{\tau})$  is constructed, the prominent candidate features for potential SST thermal fronts become obvious. Using a few points on these potential SST thermal fronts, a local curvilinear coordinate system (LCS) (Chris Jones, personal communication, 2012) is constructed on the SAR-derived wind stress curl and divergence  $(\nabla \cdot \vec{\tau})$  fields, and also on the gradient SST field, as shown in Figure 1b. Thus,  $\nabla \times \vec{\tau}$ ,  $\nabla \cdot \vec{\tau}$  and gradient SST fields are projected onto respective LCS grids, using nearest neighbor interpolation to produce the local along-wind gradient SST, denoted  $(\nabla T)_a$ , local crosswind gradient SST, denoted  $(\nabla T)_c$ , local  $\nabla \times \vec{\tau}$ , and local  $\nabla \cdot \vec{\tau}$ . Analysis of relations among these components will elucidate the spatial scales and conditions whereby  $\nabla \times \vec{\tau}$  and  $\nabla \cdot \vec{\tau}$  can act as indicators to detect SST thermal fronts.

## 3.2. Multi-step Spatial Filter

[13] In order to retrieve thermal fronts from SAR imagery, we only consider dominant features of the divergence  $\nabla \cdot \vec{\tau}$  and curl  $\nabla \times \vec{\tau}$  wind stress fields, after performing spatial high-pass filtering. Therefore, to eliminate noise, we use



**Figure 1.** (a(i)) SAR image at 22:11:34 UTC on May 22, 2009, (a(ii)) co-located SST image at 17:46:48 UTC on May 22, 2009, (a(iii)) detected SAR-derived results by *Xie et al.* [2010], and (a(iv)) SAR-retrieved thermal fronts from the new methodology. Illustration of the methodology to extract parameters of selected features in LCS. The RADARSAT-2 image was obtained at 22:10:58 UTC on April 28, 2009. Gradient SST data was extracted from MODIS data at 2:06:17 UTC on April 29, 2009, 4 hours after the SAR image: (b(i)) gradient SST in crosswind direction, (b(ii)) gradient SST in along wind direction, (b(iii)) curl from SAR, and (b(iv)) divergence from SAR. Wind speed scale is indicated. Wind speed range is between 4.8 m/s and 8.3 m/s.



**Figure 2.** Plots of extracted wind stress variations and gradient SST components, showing: (a) wind stress curl to cross wind gradient SST, and (b) wind stress divergence to along wind gradient SST. The correlation coefficient is 0.9 in Figure 2a and 0.93 in Figure 2b.

SAR data, averaged to 1 km resolution, and we select only the features satisfying the following relations,

$$|\nabla \cdot \vec{\tau}| > \overline{|\nabla \cdot \vec{\tau}|} + std(|\nabla \cdot \vec{\tau}|)$$
(5)

$$|\nabla \times \vec{\tau}| > \overline{|\nabla \times \vec{\tau}|} + std(|\nabla \times \vec{\tau}|) \tag{6}$$

where, as before, '-' denotes the spatial mean value over a given SAR image. The wind field used in this study is directly retrieved from the SAR normalized radar cross section (NRCS), averaged to 1 km resolution. Because it is inevitable that there are speckles and noise in the curl and divergence fields, we use a combination of Gaussian low-pass filters and Wiener filters to suppress these effects and smooth the curl and divergence fields before they are processed with equations (5) and (6). A Gaussian filter is used because it does not generate numerical noise near the low-pass cut-off scale.

[14] In observations of the Gulf Stream, SST thermal fronts have some degree of continuity. Therefore, in the SAR images, potential SST fronts cannot be isolated pixels, SST spikes, clumps, or isolated local features. This is relevant to the SAR-derived filtered  $\nabla \cdot \vec{\tau}$  and  $\nabla \times \vec{\tau}$  fields that are used to identify the main potential SST thermal fronts, and then represented with LCS grids. Thus, for any given grid node on a potential SST thermal front, the 8 nearest pixel neighbours are identified; continuity requires that at least 1 of the 8 nearest pixel neighbours also reside on the SST thermal front. By performing this evaluation of the SAR image, the linear extent and overall configuration of a potential SST thermal front is established. This approach determines whether a potential feature is large enough to warrant further investigation, or not.

## 3.3. Conditions for SST Fronts

[15] Mesoscale SST fronts in the Gulf Stream should be continuous linear features that are at least 5 km in length, as

a basic condition [*Sikora and Ufermann*, 2004]. They should be linear, not clumps. However, from an analysis of 41 SAR images and related collocated, almost co-temporal, SST images, we found that actual retrievals of SST fronts from SAR imagery required length scales in excess of 30 km. Although we experimented with other possible scales, for example 5, 10, 20, 40 and 50 km, we found that the 30 km length scale gives optimal results. If the length scale is assumed too large, then too many of the SAR –derived features are eliminated, whereas if it is too small then we fail to eliminate noise. The 30 km scale was also used as the length threshold for detection of SST fronts by *Jones et al.* [2012].

[16] After eliminating weak signals by equations (5) and (6), and short strong signals (<30 km, spikes, or clumps) in the wind stress divergence and curl fields, we obtained the results shown in Figure 1a(iv), for the SAR image at 22:11:34 UTC on May 22, 2009. The main SST thermal fronts are present in the analyzed SAR image. However, although speckles and noise are removed from the SAR-derived curl and divergence fields by the filtering and the length conditions invoked here, additional SST thermal gradient features are also lost. The retrieved wind speed of this example is between 3 m/s to 11 m/s, which is important; wind stress retrieval from SAR is not reliable if winds are too weak, whereas if winds are too strong competing processes can dominate over the linear relations between  $\nabla \cdot \vec{\tau}$ ,  $\nabla \times \vec{\tau}$  and SST thermal fronts. The next section presents further discussion of restrictions on wind speed, to remove wind shear fronts and other noise.

## 4. SAR Imagery Results

### 4.1. Feature Analysis

[17] To reduce noise, 9 pairs of RADARSAT-2 SAR images and collocated SST images were selected, between October 2008 and May 2009. These data pairs were selected because (1) there are no large areas where the backscatter is lower than the instrument noise level in the SAR images; (2) the time discrepancy between SAR and SST imaging is not greater than 15 hours; (3) there are few clouds over the Gulf Stream North Wall region in the SST images. From these 9 data pairs, 29 sets of sub-images were selected, collocating blended SST thermal front features and corresponding SAR features. For these 29 pairs, the mean local divergence and curl wind stress fields, as well as the local gradient SST components, were extracted for the LCS grid domains.

[18] The LCS grids were constructed along fronts, as depicted in Figure 1b. Each front was first interpolated to have a regular resolution spacing of 1 km along its length. Cross front transects, with the same spacing, were then constructed at each point along the front. Each transect was made normal to the front, at the point of intersection, and extended to a distance of 5 km to either side. For each of the 29 sub-image pairs, the change in wind speed across the SAR-derived thermal front was required to be consistent with change in wind speed across the SST front in the corresponding SST image. Thus, for example when wind blows from the cold side to the warm side in the SST subimage, it should increase, which should also occur for the thermal front in the associated SAR-derived wind stress subimage [Chelton et al., 2004]. This is also a condition in our methodology.



**Figure 3.** Detection of the location of SST thermal fronts from variation in wind stress divergence and curl fields from SAR (black), overlapped on blended SST data (background image): (a) 22:06:58 UTC on 25 Oct. 2008 with MODIS data 15 hours earlier, (b) 22:27:58 UTC on 07 March 2009 with blended SST data 6 hours earlier, (c) 10:50:47 UTC on 11 Apr. 2009 with 3 days averaged SST data, and (d) 22:10:58 UTC on 28 Apr. 2009 with blended SST data 4 hours later.

[19] Figure 1b is an example of extracted parameters. The RADARSAT-2 image used in this example was obtained at 22:10:58 UTC on April 28, 2009. Gradient SST data was extracted from MODIS data at 2:06:17 UTC on April 29, 4 hours after the SAR image. Because of the time discrepancy between SST and SAR images, a small shift occurred between selected fronts in the SST image and the SAR-derived wind field. This example is in qualitative agreement with equations (1) and (2); the along-wind SST gradient varies as the divergence, whereas the crosswind SST gradient varies as the curl.

[20] To explore these relations further, we correlated the LCS-averaged local crosswind and along-wind gradients of SST,  $(\overline{\nabla T})_c$  and  $(\overline{\nabla T})_a$  respectively, as functions of local wind stress divergence  $\overline{\nabla \cdot \vec{\tau}}$  and in curl  $\overline{\nabla \times \vec{\tau} \cdot \vec{k}}$  in Figures 2a and 2b, respectively. When the SAR-retrieved wind speed is below 12 m/s, the correlation coefficients exceed 0.9 in Figure 2, for extracted parameters and the regressed linear functions. Therefore, the proportionalities of

 $(\overline{\nabla T})_a$  to  $\overline{\nabla \cdot \vec{\tau}}$ , and  $(\overline{\nabla T})_c$  to  $\nabla \times \vec{\tau} \cdot \vec{k}$  suggested in equations (1) and (2) are reliable, when SAR-derived winds obey the appropriate conditions.

[21] This wind speed restriction is consistent with the fact that when wind speeds exceed 12 m/s, large waves begin to form, foam crests become more extensive, sea spray begins to form, affecting air-sea heat exchanges [*Perrie et al.*, 2005], and significant wave heights may exceed 3.5 m for fully developed conditions [*Pierson and Moskowitz*, 1964]. Thus, SAR imaging mechanisms and the relations for SSTs and the marine boundary layer become nonlinear. In such relatively high sea states, it is not possible to retrieve SST thermal fronts from SAR, because of competing air-sea processes at the sea surface.

## 4.2. Multi-step Filtering

[22] We applied a multi-stage spatial filter to the SARderived curl and divergence wind stress fields before they were used to construct the thermal front function A, in equations (1)–(4). This approach separately selects relatively strong crosswind and downwind signatures, and removes small-scale discrete features. Moreover, we do not use the ratios of wind stress curl  $|(\nabla \times \vec{\tau})|$  and divergence  $|(\nabla \cdot \vec{\tau})|$ to the SST gradient components, required by *Xie et al.*'s [2010] approach. The latter was based on the assumption that the coupling coefficients for the relations between downwind and crosswind SST gradients and divergence and curl wind stress are constants, for any given SAR image.

[23] After spatial filtering, continuous SST thermal front features with high winds (>12 m/s) were removed. We retained only those that have wind speed changes across SAR-derived thermal fronts that are consistent with wind changes across the corresponding SST fronts. Filtering the wind stress divergence and curl fields separately is better than filtering function A directly, because spurious features in A can be continuous for lengths that exceed 30 km. However, when the filter is separately applied to the curl and divergence fields, then only the dominant SST thermal front signatures are retained. Finally, only linear features are retained, no clumps.

[24] We applied the proposed retrieval methodology to 45 SAR images in the Gulf Stream region. Since it is difficult to find collocated, cloud-free, single-pass SST images from MODIS and AVHRR data, some cases use 3-day or 7-day averaged SST data to validate the location of the detected SST front features. Figure 3 shows the detection results for 4 of these cases, with detected thermal fronts from SAR (black), overlaid on SST features. Because of the shift of the Gulf Stream, there is some inaccuracy in the averaged, blended SST images.

[25] Results indicate that although our method cannot detect all the thermal fronts, for these 4 cases, more than 95% of the SAR-detected fronts in each case are thermal fronts. Overall, it is clear that there is not a complete correspondence between the blended SST front features in Figure 3 and the SAR-derived thermal fronts. This may be due to some very strong, small scale ( $\sim 1$  km) features in the SAR images, which can distort the intensity. Moreover, noise is not completely removed, because spurious features related to competing ocean processes can also have continuous lengths that exceed 30 km. However, when filtering is applied to the curl and divergence fields, most of the strongest thermal front signatures are retained. There are some SST fronts that cannot be retrieved because of limitations in the SAR data, for example, high winds or heavy rain. However, the thermal gradient features that we retrieved from SAR are more evident, cleaner and more precise than those resulting from the minimization methodology of *Xie* et al. [2010].

# 5. Summary

[26] A high-resolution methodology is presented to retrieve SST thermal fronts from SAR imagery, using linear statistical relationships between variations in 1-km scale features of the SAR-derived wind stress divergence and curl fields, and SST gradients from optical sensors. Our results represent an improvement over previous SAR studies, because small-scale, weak features in divergence and curl wind stress fields are removed before they are used in detection of the thermal fronts. [27] By analysis of the extracted mean parameters of gradient SST components and wind stress variations, we found that the proposed method is effective when retrieved wind speeds are between 3 m/s to 12 m/s. Besides the cases presented in Figure 3, we verified the results with an additional 41 RADARSAT-2 images acquired at dual-polarization (VV, VH) image mode in the Gulf Stream region. Results suggest that the proposed method works well. Because larger temperature gradients occur during winter than during summer, the SST-induced surface wind stress response over the Gulf Stream is stronger during winter. Thus, cases collected in late winter and early spring tend to result in better retrieval results than those occurring during late summer.

[28] SAR images of sea surface thermal fronts induced by variations in wind stress have different polarimetric characteristics for different polarimetric channels. The ocean surface backscatter for SAR images in VV- and HH-polarization modes is a function of wind speed and direction, and radar incidence angle [*Zhang et al.*, 2011, 2012]. In low to moderate sea states, the cross-polarization (VH, HV) backscatter is much smaller than in co-polarization (HH, VV), and not sensitive to radar incidence angle or wind direction, but depends linearly on wind speed, even in hurricanes [*Zhang and Perrie*, 2012].

[29] In this study we used QuikSCAT wind directions to retrieve wind speed from SAR images which has 25 km resolution. Since SAR has been shown to provide accurate vector winds, on the order  $\pm 1.5$  m/s, for speeds of 3–25 m/s, and for directions, on the order  $\pm 20^{\circ}$ , at high (1 km) resolution [*Zhang et al.*, 2012], it is important for ongoing research to retrieve vector winds directly from SAR images. This will effectively simplify the process, especially data collection. We also need to develop more robust filtering and analysis methods to produce cleaner results, and avoid loss of information when the thermal front signals are weak and competing ocean processes are present.

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## References

- Chelton, D. B., M. G. Schlax, M. H. Freilich, and R. F. Milliff (2004), Satellite measurements reveal persistent small-scale features in ocean winds, *Science*, 303, 978, doi:10.1126/science.1091901.
- Hersbach, H. (2008), COMD5.N: A C-band geophysical model function for equivalent neural wind, *Tech. Memo. 554*, Eur. Cent. for Medium-Range Weather Forecasts, Reading, U. K.
- Hersbach, H. (2010), Comparison of C-band scatterometer CMOD5.N equivalent neural winds with ECMWF, J. Atmos. Oceanic Technol., 27, 721–736.
- Jones, C. T., T. Sikora, P. W. Vachon, and J. Wolfe (2012), Towards automated identifications of sea-surface temperature front signatures in Radarsat-2 images, J. Atmos. Oceanic Technol., 29, 89–102, doi:10.1175/ JTECH-D-11-00088.1.
- Liu, W. T., W. Tang, and R. Atlas (1996), Responses of the tropical Pacific to wind forcing as observed by spaceborne sensors and simulated by an ocean general circulation model, *J. Geophys. Res.*, 101, 16,345–16,359, doi:10.1029/96JC01347.
- Maloney, D. M., and D. B. Chelton (2006), An assessment of the sea surface temperature influence on surface wind stress in numerical weather prediction and climate models, J. Clim., 19, 2743–2762, doi:10.1175/ JCLI3728.1.

- Nghiem, S. V., F. K. Li, E. J. Walsh, and S. H. Lou (2000), Radar backscatter across the Gulf Stream sea surface temperature front, *IEEE Trans. Geosci. Remote Sens.*, 38, 926–941, doi:10.1109/36.841975.
- O'Neill, L. W., D. B. Chelton, and S. K. Esbensen (2003), Observations of SST-induced perturbations of the wind stress field over the Southern Ocean on seasonal timescales, *J. Clim.*, *16*, 2340–2354, doi:10.1175/ 2780.1.
- O'Neill, L. W., S. Esbensen, N. Thum, R. M. Samelson, and D. B. Chelton (2010), Dynamical analysis of the boundary layer and surface wind responses to mesoscale SST perturbations, *J. Clim.*, 23, 559–581, doi:10.1175/2009JCLI2662.1.
- Perrie, W., E. L. Andreas, W. Zhang, W. Li, J. Gyakum, and R. McTaggart-Cowan (2005), Impact of sea spray on rapidly intensifying cyclones at midlatitudes, *J. Atmos. Sci.*, 62, 1867–1883, doi:10.1175/JAS3436.1.
  Pierson, W., and L. Moskowitz (1964), A proposed spectral form for fully
- Pierson, W., and L. Moskowitz (1964), A proposed spectral form for fully developed wind seas based on the similarity theory of S. A. Kitaigorodskii, *J. Geophys. Res.*, 69, 5181–5190, doi:10.1029/JZ069i024p05181.
- Sikora, T. D., and S. Ufermann (2004), Marine atmospheric boundary layer cellular convection and longitudinal roll vortices, in *Synthetic Aperture Radar Marine User's Manual*, edited by C. R. Jackson and J. R. Apel, pp. 321–330, NOAA, Silver Spring, Md. [Available at www.sarusersmanual.com.]
- Sikora, T. D., G. S. Young, R. C. Beal, and J. B. Edson (1995), Use of spaceborne synthetic aperture radar imagery of the sea surface in

detecting the presence and structure of the convective marine atmospheric boundary layer, *Mon. Weather Rev.*, *123*, 3623–3632, doi:10.1175/1520-0493(1995)123<3623:UOSSAR>2.0.CO;2.

- Small, R. J., S. P. deSzoeke, S. P. Xie, and L. W. O'Neill (2008), Air-sea interaction over ocean fronts and eddies, *Dyn. Atmos. Oceans*, 45, 274–319, doi:10.1016/j.dynatmoce.2008.01.001.
- Song, Q., P. Cornillon, and T. Hara (2006), Surface wind response to oceanic fronts, J. Geophys. Res., 111, C12006, doi:10.1029/2006JC003680.
- Xie, T., W. Perrie, and W. Chen (2010), Gulf Stream thermal fronts detected by synthetic aperture radar, *Geophys. Res. Lett.*, *37*, L06601, doi:10.1029/2009GL041972.
- Xu, Y., and R. B. Scott (2008), Subtleties in forcing eddy resolving ocean models with satellite wind data, *Ocean Modell.*, 20, 240–251, doi:10.1016/ j.ocemod.2007.09.003.
- Zhang, B., and W. Perrie (2012), Cross-polarized synthetic aperture radar: A new potential measurement technique for hurricanes, *Bull. Am. Meteorol. Soc.*, in press.
- Zhang, B., W. Perrie, and Y. He (2011), Wind speed retrieval from RADARSAR-2 quad-polarization images using a new polarization ratio model, J. Geophys. Res., 116, C08008, doi:10.1029/2010/C00522.
- Zhang, B., W. Perrie, P. W. Vachon, X. Li, and W. G. Pichel (2012), Ocean vector winds retrieval from C-band fully polarimetric SAR measurements, *IEEE Trans. Geosci. Remote Sens.*, in press.