Inferring Marine Atmospheric Boundary Layer Properties from Spectral Characteristics of Satellite-Borne SAR Imagery

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ABSTRACT

For the commonly observed range of air–sea temperature difference and surface wind speed, the static stability of the atmospheric surface layer can have a significant effect on the mean surface stress and its turbulence-scale horizontal variability. While traditional satellite-borne scatterometers have insufficient horizontal resolution to map this turbulence-scale horizontal variability, satellite-borne synthetic aperture radars (SAR) can. This paper explores the potential for applying existing boundary layer similarity theories to these SAR-derived maps of turbulence-scale horizontal variability in air–sea stress.

Two potential approaches for deriving boundary layer turbulence and stability statistics from SAR backscatter imagery are considered. The first approach employs Monin–Obukhov similarity theory, mixed layer similarity theory, and a SAR-based estimate of the atmospheric boundary layer depth to relate the ratio of the mean and standard deviation of the SAR-derived wind speed field to the stability of the atmospheric surface layer and the convective scale velocity of the atmospheric mixed layer. The second approach addresses these same goals by application of mixed layer similarity theory for the inertial subrange of the SAR-derived wind speed spectra. In both approaches, the resulting quantitative estimates of Monin–Obukhov and mixed layer scaling parameters are then used to make a stability correction to the SAR-derived wind speed and to estimate the surface buoyancy flux.

The impact of operational and theoretical constraints on the practical utility of these two approaches is considered in depth. Calibration and resolution issues are found to impose wind speed limits on the approaches’ applicability. The sensitivity of the two approaches’ results to uncertainty in their nondimensional parameters is also discussed.

1. Introduction

Backscatter variability within synthetic aperture radar (SAR) imagery of the sea surface depends strongly on the magnitude of that part of the surface wave height spectrum having scales comparable to the SAR wavelength (e.g., Lehner et al. 1998). Because the magnitude of these surface waves is affected by both oceanographic and atmospheric phenomena, SAR imagery of the sea surface routinely depicts manifestations of both oceanographic and atmospheric phenomena (Vesecky and Stewart 1982). Among the oceanographic phenomena frequently observed in SAR images are wave–current interactions (Thompson 1985), sea surface slicks (Nilsson and Tildesley 1995), surface gravity waves (Rufenach et al. 1991), and internal waves (see the Joint Canada–U.S. Ocean Wave Investigation Project and SAR Internal Wave Signatures Experiment special issue of the Journal of Geophysical Research, 1988, Vol. 93, No. 10–11, 12 217–14 164). Commonly detected atmospheric phenomena include boundary layer convection (Sikora et al. 1995; Mourad 1996, 1999; Zecchetto et al. 1998), convective storms (Atlas 1994; Atlas et al. 1995), and a wide variety of other mesoscale circulations forced by coastal topography or sea surface temperature gradients (e.g., Beal et al. 1997; Lehner et al. 1998).

Kilometer-scale atmospheric boundary layer convect-
Fig. 1. ERS-1 synthetic aperture radar wind speed image taken at 1538 UTC 17 Jun 1993. Pixel size is 150 m × 150 m so the 256 × 256 pixel image does not extend the full width of the ERS-1 radar swath.

Convective boundary layer convection is a common phenomena, forming via buoyant production of turbulence kinetic energy wherever the sea surface virtual potential temperature exceeds that of the lower atmosphere (Stull 1988). The Comprehensive Ocean–Atmosphere Data Set (COADS, available from Lamont-Doherty Earth Observatory at Columbia University via http://ingrid.ldgo.columbia.edu:80/SOURCES/OBERHUBER/) shows this condition to be met in the climatological mean for a significant fraction of the world’s oceanic regions. The resulting atmospheric boundary layer convection takes the form of either two-dimensional rolls (e.g., LeMone 1973; Brown 1980; Mourad 1996; Mourad and Walter 1996; Wackerman et al. 1996) or three-dimensional cells (e.g., Kropfi and Hildebrand 1980; Young 1988b; Schmidt and Schumann 1989; Schumann and Moeng 1991; Zecchetto et al. 1998). Theory (Deardorff 1970; Küttner 1971; Brown 1980) and observations (Woodcock 1975; Mourad 1996, 1999; Mourad and Walter 1996; Zecchetto et al. 1998) suggest that two-dimensional rolls are much more common during high wind conditions while three-dimensional cells are the expected form under low wind conditions. Deardorff (1976) in particular provides a theoretical interpretation for the observational evidence (Woodcock 1975) that both wind speed and air–sea temperature difference are important in determining which form of boundary layer convection exists. These authors found that greater air–sea temperature difference increases the likelihood of three-dimensional cells occurring for a given wind speed.

Both forms of boundary layer convection are important targets for high-resolution SAR-based meteorology. Three-dimensional convective cells are of interest because their scale and intensity can be used to quantitatively diagnose boundary layer depth \( Z_L \) (Sikora et al. 1997; Zecchetto et al. 1998) and a wide range of turbulence statistics including the surface buoyancy flux \( B \) (Young and Kristensen 1992). Figure 1 shows an example of three-dimensional cells imaged by European Remote Sensing Satellite-1 (ERS-1) orbit 10047 off the east coast of North America at 1538 UTC 17 June 1993 during the Second High Resolution Remote Sensing (HI-RES 2) project. A similar case in the Mediterranean Sea was captured at much higher resolution by Zec-
wavenumbers around 0.002 rad m$^{-2}$ and the mesoscale inertial subrange occurring at smaller wavenumbers.

The inertial subrange of the atmospheric turbulence spectrum is being resolved in the form of these boundary layer convective structures.

The inertial subrange of the atmospheric turbulence spectrum can also be manifested in SAR imagery of the sea surface as can be seen in the SAR-derived wind speed spectrum shown in Fig. 2. The inertial subrange of the atmospheric turbulence spectrum also provides quantitative information that can be used to diagnose the atmospheric boundary layer scaling parameters and, hence, a wide range of turbulence statistics (Kaimal et al. 1976; Young 1988a). It is plausible, therefore, that high-resolution SARs could be used to diagnose turbulence statistics of a three-dimensional cellular convective boundary layer via either of these two approaches. This paper explores the issues associated with such an attempt.

FIG. 2. Unfiltered average cross-wind spectra for the image block shown in Fig. 1. The microscale peak is located at wavenumbers around 0.005 rad m$^{-1}$ and the microscale inertial subrange is centered on a wavenumber of 0.01 rad m$^{-1}$. The spectral gap is located at wavenumbers around 0.001 rad m$^{-1}$ with the mesoscale inertial subrange occurring at smaller wavenumbers. The speckle contribution can be seen at wavenumbers around 0.002 rad m$^{-1}$.

Because atmospheric boundary layer convection frequently occurs in the same time and place as the common SAR-observed oceanographic phenomena, quantitative analysis requires separation of their signatures. Scale separation via simple bandpass filtering is not sufficient as the horizontal scales associated with many oceanographic features overlap the small-scale end of the atmospheric turbulence spectrum. While bandpass filtering cannot separate the two families of phenomena, Fourier transformations of SAR imagery does offer a promising alternative via analytic models of the atmospheric turbulence spectra and noise spectra as discussed in depth in section 2a.

A key element in the quantitative analysis of atmospheric phenomena in SAR imagery is the assumption that SAR backscatter can be quantitatively transformed to surface wind speed. This conversion requires that backscatter be related to the amplitude of part of the surface wave spectrum, that amplitude be related to the surface stress (Keller et al. 1992), and that surface stress be related to the wind speed relative to the moving sea surface (e.g., Wissman 1992; Stoffelen and Anderson 1993). This so-called current relative wind speed is the resulting derived parameter because that component of the true wind vector that matches the surface current in magnitude and direction exerts no stress on the sea surface (Fairall et al. 1996). Most such scatterometer algorithms define a semiempirical relationship between backscatter power and neutral, 10-m, current relative wind speed (Fetterer et al. 1998; Wackerman et al. 1996). Such scatterometer algorithms as CMOD4, IFREMER, and the Wismann model have been successfully applied to SAR imagery at mesoscale resolutions (e.g., Fetterer et al. 1998; Wackerman et al. 1996) and at resolutions small enough to resolve boundary layer convective elements (e.g., Zecchetto et al. 1998; Lehner et al. 1998). Thus, in contrast to conventional satellite-borne scatterometers, satellite-borne SARs can resolve the horizontal variability in backscatter on the 100-m and kilometer scale that results from boundary layer turbulence (Mourad 1996; Sikora et al. 1997; Zecchetto et al. 1998). The small-scale limit of applicability for such scatterometer models will be explored in depth in section 3b.

The modeled relationship between wind speed and backscatter depends strongly on the look direction of the scatterometer with respect to the wind direction (e.g., Figs. 6 and 7 in Lehner et al. 1998). Conventional scatterometers determine the wind direction by measuring the backscattered power from different look directions using multiple antennas. Because current satellite-borne SARs provide only one look angle but much higher horizontal resolution, we use instead a spectral technique analogous to that of Zecchetto et al. (1998) to determine the wind direction.

The neutral, current relative wind determined in this empirical manner may then be related to the surface stress ($\tau$) through a drag-law-type similarity relationship (e.g., Keller et al. 1989, 1992; Fairall et al. 1996). While the true relationship between $\tau$ and wind speed is known to depend on the static stability of the surface layer (e.g., Garratt 1977; Smith 1988; Fairall et al. 1996), the neutral drag formulation is appropriate for backing stress out of scatterometer algorithm wind estimates because of the implicit use of that formulation in their forward models.

Standard fluid dynamic similarity theories provide the means of converting the resulting SAR-derived estimates of turbulence-scale stress variability into esti-
mates of surface layer stability and other boundary layer properties. Monin–Obukhov similarity theory relates a wide variety of atmospheric surface layer turbulence statistics to the static stability of the surface layer (e.g., Monin and Obukhov 1954; Businger et al. 1971; Panofsky and Dutton 1984; Fairall et al. 1996). Mixed-layer similarity theory plays the same role in the remainder of the convective (unstable) atmospheric boundary layer (Deardorff 1970; Kaimal et al. 1976; Young 1988a). Such schemes have been widely used to derive difficult to measure surface layer properties from others that are more easily sensed. For example, the standard bulk aerodynamic approach for calculating surface fluxes (e.g., Panofsky and Dutton 1984; Fairall et al. 1996) iterates the Monin–Obukhov relationships between stability, wind speed, air–sea temperature and humidity differences, and surface fluxes to obtain estimates of the stability and fluxes from the other parameters. Another application iterates these equations to obtain estimates of the stability from anemometer records via the mean and standard deviation of the wind speed (Young and Kristensen 1992). The approach discussed in section 2b using SAR-derived wind speed and its variance is a closely equivalent problem, although somewhat more complex.

An alternative iterative approach using the inertial subrange similarity theories of Kaimal et al. (1976) to estimate the mixed-layer convective scale velocity is described in section 2c. This quantity can, in turn, be combined with SAR-derived estimates of the boundary layer depth (Sikora et al. 1997) to calculate the surface buoyancy flux $B$ (Deardorff 1970) and thus the atmospheric boundary layer stability (Fairall et al. 1996).

These approaches offer the possibility of remotely sensing a wide variety of surface-layer and mixed-layer properties. The surface-layer stability estimate can be used with Monin–Obukhov similarity formulas to derive profiles of the wind speed and turbulence intensity in the surface layer and to make a stability correction to the SAR-derived wind speed. Moreover, surface-layer stability estimates have applications to a number of remote sensing problems including microwave ducting and scintillation (Paulus 1985; Musson-Genon et al. 1992; Babin et al. 1997). Likewise, mixed-layer similarity can be combined with the $B$ and $Z$ estimates to derive profiles of turbulence intensity through the depth of the convective atmospheric boundary layer (e.g., Kaimal et al. 1976; Young 1988a). Thus, a number of very useful applications exist if the SAR-derived stability estimates are sufficiently robust.

2. Approaches

As a preliminary step, the SAR backscatter image (e.g., Fig. 1) is converted to neutral wind speed using a CMOD4-like scatterometer algorithm (referred to simply as CMOD) (Thompson and Beal 1998; Stoffelen and Anderson 1993) mentioned above and discussed in section 3a. The CMOD scatterometer algorithm combines the relation between backscatter intensity and surface roughness, that between surface roughness length ($z_0$) and $\tau$, and that between $\tau$ and the neutral, current relative, 10-m wind speed into a semiempirical formulation. The latter relation is assumed in CMOD to be the drag law for a surface layer with neutral stability (i.e., the CMOD empirical relationship was originally derived for near-neutral conditions).

a. Filtering

SAR backscatter imagery captures the signatures not only of atmospheric turbulence, but also of larger-scale atmospheric phenomena (Freilich and Chelton 1986) and a host of oceanographic phenomena including swell (Hasselmann and Hasselmann 1991; Hasselmann et al. 1985). Thus, removal of the effects of these phenomena from a SAR image is an essential precursor to successful application of the turbulence analysis approaches described in sections 2b,c. Filtering of some sort is needed for this removal process. The filtering must not, however, distort the turbulence spectra if the two analysis approaches described in sections 2b,c are to yield useful results. Thus, a spectral modeling approach is suggested that makes use of the information provided by existing boundary layer similarity theories for the turbulence spectra of the horizontal wind speed components (e.g., Kaimal et al. 1972; Kaimal et al. 1976; Stull 1988; Young 1987; Nucciarone and Young 1991) to remove the contribution of mesoscale wind variations and small-scale noise. If ocean swell is detected in the image or spectra (Hasselmann and Hasselmann 1991; Hasselmann et al. 1985), the analysis may have to be aborted at this stage for reasons discussed in section 3a.

The classic boundary layer turbulence spectrum under convective conditions contains significant power at mesoscale and longer wavelengths (Freilich and Chelton 1986; Lilly 1989) followed by a spectral gap at smaller wavelengths (Nucciarone and Young 1991) and a microscale peak associated with the dominant convective eddies at wavelengths of 100 m to a few kilometers (Kaimal et al. 1976; Young 1987; Sikora et al. 1997). For three-dimensional convective cells, the wavelength of this microscale peak has been found to be approximately 1.5 times the boundary layer depth (Kaimal et al. 1976; Young 1987). At scales between the spectral gap and the microscale peak, the spectrum follows a $k^4$ power law (e.g., Kaimal et al. 1972; Young 1987), while at scales smaller than the microscale peak, the energy falls off following the Kolmogoroff $k^{-5/3}$ power law of three-dimensional inertial subrange turbulence. The same power law dependence frequently exists in the mesoscale as well, due in that case to two-dimensional inertial subrange turbulence (Lilly 1989).

SAR-derived turbulence spectra can be contaminated by both the mesoscale atmospheric wind variance described above and small-scale noise. This small-scale
noise is frequently called speckle in the literature. Speckle is thought to be caused by the tilting of Bragg scattering features by the longer waves and by undersampling of relatively rare, high-backscatter features of the surface wave pattern (D. Thompson, The Johns Hopkins University, 1999, personal communication). The $k^1$ power law dependence of speckle power calculated from more heavily contaminated images (not shown) supports this hypothesis. The evidence of wind speed dependence of the speckle contribution to the spectrum presented in section 3a also suggests that this interpretation of speckle may be valid as windier conditions would produce more longwave tilting of Bragg scatterers and more wave breaking events. Because power laws are known for the spectral contribution of each of the relevant phenomena, removal of the mesoscale and speckle contributions from SAR-derived wind speed spectra can be approached via spectral modeling.

The spectrum of horizontal wind at wavelengths longer than the microscale peak reflects the sum of a $k^{-5/3}$ mesoscale contribution and a $k^1$ microscale contribution. The spectral gap is located at the scale where both phenomena contribute equally to the spectral power. One approach to removing the mesoscale contribution is to fit a $k^1$ power law to that subrange between the spectral gap and the microscale peak where mesoscale contamination is negligible. The longer wavelength spectral estimates are then replaced via extrapolation of this power law following the model of Kaimal et al. (1972). If an uncontaminated $k^1$ subrange does not exist, it is doubtful whether the contribution of the microscale turbulence to the SAR-derived wind speed spectrum is significant enough to support either of the approaches described in sections 2b,c as this condition results from the microscale peak being lost in the short wavelength tail of the mesoscale spectrum.

The spectrum of horizontal wind at wavelengths shorter than the microscale peak reflects the sum of a $k^{-5/3}$ microscale inertial subrange contribution and a $k^1$ speckle (noise) contribution. Both the slightly contaminated low wind spectra shown in Fig. 2 and moderately contaminated high wind spectra (not shown) can be fit well by the sum of these two power laws. By fitting this model to slightly or moderately contaminated data, the inertial subrange turbulence contribution to the spectrum can be separated from the speckle (noise) contribution. If the speckle dominates the entire inertial subrange, however, it is unlikely that the contribution of the microscale turbulence can be retrieved with sufficient accuracy to support either of the approaches described in sections 2b,c.

Indeed, the degree of speckle contamination appears to impose one of the most restrictive bounds on the range of meteorological conditions to which these two approaches might be applied. This bound and its relationship to other constraints on these approaches will be discussed in section 3a. The need to rotate the SAR image into natural coordinates (alongwind and crosswind) before filtering via these spectral models is discussed in section 2c. The rotation itself contributes to the noise that must subsequently be removed via the spectral model described above. It should be noted that the use of SAR imagery for meteorological analysis may become impossible in the presence of significant oceanographic signatures with scales corresponding to the microscale peak or microscale inertial subrange (i.e., approximately 100 m to 10 km).

The impact of these procedures on a sample (lightly contaminated) spectrum can be seen by comparing Fig. 2 (unfiltered) with Fig. 3 (filtered as described above). The spectrum in Fig. 2 was obtained by averaging the 256 cross-wind spectra obtained from the 256 by 256 pixel (38.4 km by 38.4 km) image shown in Fig. 1. The filtering has removed the mesoscale contribution and the speckle contribution while leaving the microscale peak and microscale inertial subrange essentially unchanged from the unfiltered spectra shown in Fig. 2.

b. Variance approach

Because similarity relationships exist between boundary layer stability and the surface stress variability, the potential exists for estimating boundary layer stability and other turbulence parameters from turbulence-scale SAR-derived neutral, current relative, 10-m wind speed maps such as those created by the filtering approach described in section 2a. Table 1 outlines the steps in this approach. Two iterative loops are required. The first loop determines the neutral drag coefficient, the roughness length, and the stress pattern. The second loop determines the true, diabatic drag coefficient, the surface-layer stability, and the stability correction to the SAR-derived current relative, 10-m wind speed.

To begin the first of these two iterative loops, the image average of the neutral, current relative, 10-m wind speed ($\overline{V}$) is used to recover the surface stress and the friction velocity ($u_*$) via
Table 1. Data flow and sequence of equations for the variance approach to estimating boundary layer stability from SAR imagery. The equation number is provided for the source of each input variable and for the destination of each output variable. The equation numbers of input variables originating outside each loop are in boldface as are those for output variables destined for use outside the loop.

<table>
<thead>
<tr>
<th>Equation no.</th>
<th>Input variables</th>
<th>Provide by equation no.</th>
<th>Output variables</th>
<th>Supplies equation no.</th>
<th>Loop name</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>( C_{dc} )</td>
<td>FFT</td>
<td></td>
<td></td>
<td>No loop</td>
</tr>
<tr>
<td>1</td>
<td>( u_a )</td>
<td>CMOD, 2</td>
<td>( Z_s )</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>( z_0 )</td>
<td>1</td>
<td>( \tau )</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>( \sigma_s )</td>
<td>4</td>
<td>( u_a )</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>( Z_s, \sigma_s, u_a )</td>
<td>0, 9, 1</td>
<td>( \sigma_s )</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>( x )</td>
<td>7</td>
<td>( \psi_m )</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>( u_a, L )</td>
<td>1, 9</td>
<td></td>
<td></td>
<td>No loop</td>
</tr>
<tr>
<td>7</td>
<td></td>
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<tr>
<td>8</td>
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</tbody>
</table>

\[
\tau = u_a^2 = C_{dc} \bar{V}^2, \quad (1)
\]

where \( C_{dc} \), the neutral stability drag coefficient, is found from the log wind law (Fairall et al. 1996)

\[
C_{dc} = \left[ \frac{k}{\ln \left( \frac{z}{z_0} \right)} \right]^2 \quad (2)
\]

and the Charnock relation (Smith 1988)

\[
z_0 = \frac{0.011 u_a^2}{g} + \frac{0.11 v}{u_a}, \quad (3)
\]

where \( k \) is von Kármán’s constant (e.g., section 3a and Fairall et al. 1996), \( z \) is the 10-m nominal level of the CMOD winds, \( g \) is the acceleration gravity, and \( \nu \) is the kinematic viscosity of air calculated according to the formula of Fairall et al. (1996). Concerning the calculation of \( \nu \), if the wind speed is greater than about 12 m s\(^{-1}\), a wind speed–dependent formulation for the first constant should be used in place of the fixed value of 0.011. Because this trio of equations is transcendental in \( u_a \) and \( z_0 \), it is solved iteratively (loop 1, Table 1), with 10 iterations sufficing for adequate convergence. The resulting values of \( z_0 \) and \( u_a \) are used in the second iterative loop (described below and outlined as loop 2, Table 1) wherein Monin–Obukhov and mixed-layer similarity theories are used to relate wind speed variance to the surface-layer stability.

Thus, the above set of equations can be used to recover \( \tau \) from the CMOD wind estimates. The \( \tau \) field recovered in this manner depends only on the relation between backscatter and \( z_0 \) and that between \( z_0 \) and \( \tau \) as captured in the CMOD scatterometer equation. This \( \tau \) field has the same horizontal resolution as the original SAR backscatter field and serves as the basic input field for the following iterative Monin–Obukhov and mixed-layer similarity algorithm, which is used for diagnosing surface-layer stability and making stability corrections to the CMOD wind speed estimates. This SAR-derived \( \tau \) field is held invariant throughout the second iterative loop. The \( u_a \) used in this second loop is calculated from the mean of this \( \tau \) field via (1). The \( z_0 \) for momentum transfer is calculated via the Charnock relation given in (3). As with the first loop in this approach, the data flow and sequence of equations for this second loop is outlined in Table 1.

The steps within this variance-based algorithm’s second iterative loop are as follows. First the wind speed field is recomputed from the stress field using a formula derived from the diabatic drag law of Monin–Obukhov similarity theory (Panofsky and Dutton 1984; Fairall et al. 1996):

\[
s = \sqrt{\frac{\tau}{C_d}}, \quad (4)
\]

where \( s \) is the wind speed and \( C_d \) is the diabatic drag coefficient derived from the current stability estimate via a flux–profile relation (Businger et al. 1971; Panofsky and Dutton 1984), which is based on Monin–Obukhov similarity,

\[
C_d = \left[ \frac{k}{\ln \left( \frac{z}{z_0} \right) - \psi_m} \right]^2, \quad (5)
\]

where \( \psi_m \) is defined as

\[
\psi_m = \ln \left[ \left( 1 + \frac{x^2}{2} \right)^2 - 2 \tan^{-1}(x) + \frac{\pi}{2} \right], \quad (6)
\]

where \( x \) is defined as

\[
x = \left( 1 + 16 \frac{z}{L} \right)^{1/4}, \quad (7)
\]

where \( L \) is the Obukhov length, a measure of surface layer stability. On the first pass through the iterative loop, \( L \) is approximated as negative infinity, which is equivalent to the neutral stratification assumed in CMOD. On subsequent passes through the iterative loop, \( L \) is refined as described next.

In each pass through the iterative loop, refined esti-
mates of $L$ are obtained from the refined estimates of the stability-corrected wind speed field produced by (4). The key formula in this process is the relationship between surface wind gustiness and $\tau$. This relation [derived by solving the upper equation in Fig. 7.5 of Panofsky and Dutton (1984) for $L$] is expressed as a similarity formula relating $L$; $Z_i$, the standard deviation of the along-mean flow wind component ($\sigma_u$); and $u_w$:

$$L = -\frac{Z_i}{\left(\frac{\sigma_u}{u_w}\right)^2 - 4\sqrt{0.6}},$$

(8)

where $Z_i$ is obtained from the SAR backscatter spectra by the method of Sikora et al. (1997) for cases with three-dimensional convection. Equation (8) is based on both Monin–Obukhov similarity and mixed-layer similarity because gustiness in the surface-layer wind speed depends on both surface-layer and mixed-layer processes.

The value of $\sigma_u$ required in (8) is obtained from the mean ($\bar{u}$) and standard deviation ($\sigma_u$) of the wind speed field that was derived via (4). Thus, both of these statistics are calculated for a region much larger than a single SAR pixel. In the example presented in this paper, a $256 \times 256$ array of 150-m pixels is used, so a single value each for the mean wind speed and wind speed standard deviation is derived from an area of 1475 km$^2$.

The physical basis for determining the subimage size needed for calculation of these wind field statistics is discussed in detail in section 3. The relationship between $\sigma_u$ and $\sigma_f$ is a regime-dependent weighted average of simple empirical functions fit to the results of Monte Carlo simulations superimposing random bivariate normal (i.e., $u$ and $v$) gusts on a mean wind:

$$\sigma_v = \begin{cases} \sigma_u, & \text{for } \frac{\sigma_u}{s} < 0.20, \\ 0.785 - \left(0.0522 - \frac{\sigma_u}{s}\right), & \text{for } \frac{\sigma_u}{s} > 0.35, \end{cases}$$

(9)

and where $\sigma_v$ is a linearly weighted average of these two formula for gust ratios between these two regimes. Because (8) relates only to the turbulent (submesoscale) component of wind, larger-scale atmospheric signatures, oceanographic signatures, and speckle must be avoided or eliminated via the analytic spectral modeling approach described in section 2a.

As is generally observed with iterative solutions of the Monin–Obukhov equations, convergence is rapid and not strongly dependent on the proximity of the final solution to the neutral stratification assumed at the outset. In practice, 10 iterations are generally sufficient to ensure convergence. The results presented in section 3 are based on a conservative implementation that uses 14 iterations through the loop.

As a useful by-product of this analysis, $B$ can be obtained by solving the formal definition of $L$ for that quantity (Panofsky and Dutton 1984; Fairall et al. 1996):

$$B = \frac{u_w T_v}{L \rho g},$$

(10)

where $T_v$ is the surface virtual temperature in absolute units. Use of the remotely sensed sea surface temperature in place of $T_v$ will result in at most a few percent error in the $B$ estimate. The value of $B$ is not required in the iterative loop but can be used, in combination with $Z_i$, to calculate the convective scale velocity of the mixed layer [$w_m$; Deardorff (1970)]. Given the $w_m$, $B$, and $Z_i$, standard formulas based on mixed-layer similarity theory can be used to estimate the profiles of many turbulence statistics (e.g., Kaimal et al. 1976; Young 1988a).

c. Inertial subrange approach

A similar iterative approach could potentially be used to find the mixed-layer scaling parameters from the horizontal one-dimensional spectra of the SAR backscatter field. This approach is based on the mixed-layer similarity findings that $Z_i$ is $\frac{2}{3}$ the wavelength of the microscale peak in the turbulence spectrum for convective boundary layers of the three-dimensional cellular form (Kaimal et al. 1976) and that the power in the inertial subrange of the wind speed spectrum depends only on wavelength, $Z_i$, and $w_m$ (Kaimal et al. 1976; Young 1987). Thus, by analyzing the SAR-derived wind speed spectrum, estimates of both $Z_i$ (Sikora et al. 1997; Zecchetto et al. 1998) and $w_m$ may be obtained. The value of $Z_i$, found in this way depends only on the shape of the spectrum and is not sensitive to the calibration accuracy of the backscatter–wind speed relationship. In contrast, $w_m$ depends on the amplitude of the spectrum and so requires an accurate transformation of backscatter to wind speed. Moreover, the SAR-derived wind speed must be corrected for the effect of surface layer stability on this relationship. Thus, the inertial subrange approach contains an iterative stability correction loop similar to that used in the variance approach described above. The data flow and sequence of equations in this loop (number 3) is outlined in Table 2.

The first step in this inertial subrange approach is the calculation of one-dimensional horizontal spectra from the SAR-derived CMOD wind field. Because shear effects can distort the alongwind spectra (Nicholls and Readings 1981; Mann 1998), broadening the microscale peak to the point where $Z_i$ is difficult to determine with precision, the cross-wind spectra are used. The wind speed image is, therefore, first rotated until one axis is aligned with the surface wind direction. The wind direction can be derived from SAR imagery via the method of Zecchetto et al. (1998) for low wind speeds or
that of Wackerman et al. (1996) for high wind speeds. Alternatively another source of wind direction information could be used. After image reorientation, the mean cross-wind spectrum is computed. Filtering based on analytic spectral models as described in section 2a is then used to eliminate all nonturbulence contributions to this spectrum as was done in the variance approach. The resulting spectrum has a single clearly defined peak for unstable boundary layers. The value of $Z_i$ is computed by multiplying the wavelength of this peak by $\frac{2}{3}$, the scale factor for three-dimensional convection (Sikora et al. 1997). The inertial subrange is also clearly defined for a range of wavelengths extending down from this microscale peak. Provided the SAR has adequate resolution and speckle is not an uncorrectable problem, the power in at least the larger-scale portions of the inertial subrange spectra) by iterating the following steps. First, provided the SAR has adequate resolution and speckle is not an uncorrectable problem, the power in at least the larger-scale portions of the inertial subrange can be computed. The power in this part of the spectrum can be combined with $Z_i$ to find $w_a$ via a rearrangement of the mixed-layer similarity version of the Kolmogoroff inertial subrange formula (Kaimal et al. 1976; Young 1987):

$$w_a = \left[ \frac{4}{3} \frac{\alpha_k \Psi^{2/3}}{S(k)} \right]^{1/2},$$

(11)

where $S(k)$ is the spectral power density at wavenumber $k$, $\alpha_k$ is the Kolmogoroff inertial subrange spectral constant for wind speed [approximately 0.55; Dyer and Hicks (1982)], and $\Psi$ is the nondimensional dissipation rate [approximately 0.6; Kaimal et al. (1976)]. The effect of uncertainty in these constants will be discussed in sections 3a,b. Equation (11) is applied to as many inertial subrange wavelengths as possible. The results are averaged to minimize the effect of scatter in spectral estimates.

The resulting average value of $w_a$ is then corrected for the effects of stability on the relationship between SAR backscatter and wind speed (and hence the inertial subrange spectra) by iterating the following steps. First, the definition of $w_a$ is inverted to find $B$:

$$B = -\frac{w_a^2 T_a}{gZ_i},$$

(12)

Then $L$ is computed from a rearranged form of (10). Then $L$ is substituted into (7) and that result for $x$ into (6) to yield $\psi_w$. The stability correction factor for the SAR-derived CMOD winds is then calculated as the square root of the ratio of the neutral drag coefficient to the true diabatic drag coefficient,

$$\frac{C_{dn}}{C_d} = 1 - \left( \frac{w_a \sqrt{C_{dn}}}{k} \right)^2,$$

(13)

and the CMOD wind speeds are multiplied by this correction factor. The value of $C_{dn}$ used in this equation comes from loop 1 of Table 1. Finally, the spectral power density is likewise corrected for stability effects by the square of this factor and the result used to recompute $w_a$. Convergence of this iteration is rapid with 10 cycles being more than sufficient for practical applications.

This inertial subrange approach diagnoses the same quantities as the variance approach ($w_a$, $B$, $L$, and the stability correction factor for wind speed) but is quasi-independent of that approach as it uses a portion of the wind speed spectrum that contributes a relatively small fraction of the total turbulence-scale variance of wind speed. Thus, the two approaches provide at least a partial check on each other. Sensitivity tests and experimental comparisons with in situ observations of these quantities will be used in the next section to provide another assessment of their performance.

3. Discussion

a. Constraints

Both geophysical processes and radar design parameters limit the meteorological conditions to which the two approaches proposed above might reasonably be applied. Any application of these approaches should, therefore, only be undertaken after consideration of the constraints discussed below.

Calibration of the radar backscatter is of primary importance in quantitative meteorological interpretation of SAR imagery (Lehner et al. 1998). Calibration errors of only a few decibels can have a serious impact on the derived winds (e.g., Fig. 3 of Keller et al. 1989) and, hence, on the turbulence statistics derived from them.

Table 2. Data flow and sequence of equations for the inertial subrange approach to estimating boundary layer stability from SAR imagery. Columns and boldface conventions are the same as for Table 1.

<table>
<thead>
<tr>
<th>Equation no.</th>
<th>Input variables</th>
<th>Provided by equation no.</th>
<th>Output variables</th>
<th>Provided to equation no.</th>
<th>Loop name</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$\lambda_{max}$</td>
<td>FFT</td>
<td>$Z_i$</td>
<td>8</td>
<td>No loop</td>
</tr>
<tr>
<td>11</td>
<td>$Z_i$, spectral power</td>
<td>0, FFT</td>
<td>$w_a$</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>$w_a$, $Z_i$</td>
<td>11, 0</td>
<td>$B$</td>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>$u_u$, $B$</td>
<td>7, 12</td>
<td>$L$</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>$L$</td>
<td>10</td>
<td>$x$</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>$x$</td>
<td>7</td>
<td>$\psi_w$</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>13</td>
<td>$\psi_w$, $C_{dn}$</td>
<td>6, 1</td>
<td>$C_{dn}C_d$</td>
<td>Spectral power</td>
<td>3</td>
</tr>
</tbody>
</table>
measurable return. If the turbulence-induced lulls in the wind speed fall below that threshold, the turbulence statistics, including the spectra, become contaminated and so should not be used in the two approaches outlined above. If this speed floor clipping is minor enough in a particular image, its effects on the variance approach could, in theory, be avoided by fitting a normal distribution to the remaining wind speed estimates and computing the mean and variance from that distribution instead of directly from the SAR-derived wind field. For most recent SARs, the speed floor problem occurs only at very low wind speeds on the order of 1 m s\(^{-1}\). Some operational space-borne SARs have shown saturation problems because the onboard analog to digital converters have too little dynamic range [i.e., too few bits, Lehner et al. (1998)]. If wind speeds reach the value at which saturation occurs (approximately gale force), neither of the approaches outlined above would yield meaningful results. In practice, small-scale noise (speckle) becomes a problem before this limiting wind speed is reached.

SAR observations discussed in Lehner et al. (1998) and early experience with the two approaches outlined above suggest that the growth of small-scale noise at high wind speeds imposes one of the primary limits on the range of meteorological conditions to which they may be applied. Figure 2 shows the contribution of such noise to the small-scale end of the SAR-derived wind speed spectrum for a low wind (\(\sim 2 \text{ m s}^{-1}\)) case. Other images (not shown) with higher wind speeds had higher noise floors. As this noise floor increases, so does the wavelength at which it begins dominating the SAR-derived wind speed spectrum. Thus, while Zecchetto et al. (1998) had no trouble resolving the energy containing part of the turbulence spectrum in a low wind (low noise) regime (3.8 m s\(^{-1}\)), Lehner et al. (1998) present data that indicates a major noise contribution for wave-lengths of 400 m or less in a high wind regime (15 m s\(^{-1}\)). To fully quantify this relationship between speckle noise intensity and wind speed, it will be necessary to analyze the SAR-derived wind speed spectra from imagery taken in a wide range of conditions. Given such a formula and the mixed-layer theory for turbulence spectra, it would be possible to compute the stability-dependent limiting wind speeds for the two analysis approaches outlined in section 2.

The applicability of these two approaches is also contingent on the SAR-detectable wave field being in equilibrium with the pixel-scale wind field, that is, that the scatterometer algorithm be appropriate at the minimum resolution required for the analysis. Investigations of this limit using in situ observations have been hindered by the difficulty in making statistically robust comparisons between time averages and space averages in a moving, chaotic turbulence field. Such averages are not comparable, in theory, unless extended to cover the full range of turbulence scales, as borne out by the observational results of Keller et al. (1989), Vachon and Dobson (1996), and Wackerman (1996). Until another area-sampling remote sensing device, perhaps Doppler lidar, is deployed in perfect synchronicity with a SAR overpass, comparisons in the spectral domain must be used to avoid these averaging problems.

The key observational evidence for the successful application of scatterometer algorithms at scales below a kilometer is the existence, under appropriate meteorological conditions, of a \(-5/3\) spectral slope in that part of the inertial subrange of three-dimensional turbulence resolved by the SAR imagery. Figure 2 shows this power law relationship to hold down to scales at which the turbulence spectra sinks below the noise floor associated with speckle.

The key theoretical argument for SAR resolution of wind features at subkilometer scales is that the response time of the Bragg-scattering waves from a C-band, moderate incidence angle SAR is on the order of 1–5 s for winds speeds of a few to 10 m s\(^{-1}\). This response time is obtained as the reciprocal of the result of the gravity–capillary wave growth rate equation [e.g., Eq. (1) in Plant 1982]. This wave response time can be converted into a minimum useful pixel size by using wind speed in the classic time–distance–rate formula. For wind speeds of a few meters per second as examined in the example presented below and in Zecchetto et al. (1998), this minimum stress-resolving (and thus wind resolving) pixel size would be 15 m. Thus, it is not surprising that Zecchetto et al. (1998) were able to resolve wind driven burst and sweep turbulence events 120 m long using a 4.4 m \(\times\) 4.4 m pixel, C-band SAR.

The impact of wave age and the wavy boundary layer on the validity of scatterometer algorithms and Monin–Obukhov similarity should also be considered. Hristov et al. (1998) show a sharp change in the turbulence behavior between wind driven seas and swell, with the critical wave age (\(U_{\text{cr}}/C_{\text{p}}\)) being 0.9. Donelen et al. (1997) demonstrate that this effect extends into negative values of wave age as well, albeit with a change of sign. The success of CMOD4 and similar scatterometer algorithms (Wackerman et al. 1996; Fetterer et al. 1998; Lehner et al. 1998; Stoffelen 1998) suggest that these problems do not pose a significant operational constraint in most cases. Nonetheless, the two-dimensional spectra of SAR backscatter should be examined to determine the wavelength and orientation of any swell present and its wave age computed before attempting to use the analysis approaches described in section 2.

As with all applications of similarity theory, the approaches outlined in section 2 require robust estimates of turbulence statistics. The large eddy simulation results of, for example, Moeng (1984) suggest that area averaging over a domain with sides equal to several times the boundary depth yields repeatable turbulence statistics. Recent studies use domain sides equal to at least 10 boundary layer depths for even greater robustness. The latter criterion is applied in the example presented in section 3c.
b. Sensitivity

The next step in exploring the usefulness of the two approaches outlined in section 2 is to quantify their sensitivity to uncertainties in both their input parameters and their internal similarity constants. In order to quantify the potential errors of the variance approach under the full range of stability conditions commonly observed at sea, we conducted sensitivity tests in which we specified those quantities that would, in operational use, be derived from SAR imagery: \( Z_i \), the mean backscatter intensity, and the standard deviation of the backscatter. The sensitivity tests were conducted with five representative boundary layer depths: 0.5, 0.8, 1.0, 1.2, and 2.0 km. The 1.0-km case serves as a baseline, the 0.8- and 1.2-km cases are based on the reported errors in SAR-based \( Z_i \) estimates (Sikora et al. 1997), and the 0.5- and 2.0-km cases represent the range of error likely if one were forced to use a climatological value of \( Z_i \) instead of an observed value. For each boundary layer depth, the variance algorithm was run for 100 situations reflecting all possible combinations of 10 values of mean backscatter and 10 values of backscatter standard deviation. Two aspects of the variance approach’s behavior are of particular interest: the importance of the stability correction to the SAR-derived wind speed, and the sensitivity of the output parameters to uncertainty in \( Z_i \). The former quantifies the potential usefulness of this approach and the latter its robustness.

The influence of surface layer static stability on the relationship between wind speed and \( \tau \) is, of course, most significant at very low wind speeds (Keller et al. 1989). To avoid giving an exaggerated impression of the significance of this effect on scatterometry at typical wind speeds, we will limit our sensitivity discussion to a single moderate value of 8 m s\(^{-1}\). Likewise, the discussion will be limited to the stability range bounded by \( B \) values of 0.0 and 0.5 K m s\(^{-1}\). The former is representative of air that has come to equilibrium with the underlying ocean surface while the latter is reasonable for a cold-air outbreak over warm water. For brevity, the stability effect on each variable discussed will reflect all possible combinations of 10 values of mean backscatter and 10 values of backscatter standard deviation. Two aspects of the variance approach’s behavior are of particular interest: the importance of the stability correction to the SAR-derived wind speed, and the sensitivity of the output parameters to uncertainty in \( Z_i \). The former quantifies the potential usefulness of this approach and the latter its robustness.

The impact of stability on the ratio of mean backscatter to mean wind speed for this pair of conditions is approximately 18%. The effect of uncertainty in \( Z_i \) is an order of magnitude less than that of the stability correction. Thus, the correction of SAR-derived wind speeds for the stability effect is robust even in the face of gross uncertainty in the boundary layer depth.

Although the stability-corrected SAR-derived winds discussed above are very insensitive to errors in the input \( Z_i \), \( L \) and \( B \) are not. Both exhibit fractional errors almost as large as the fractional error in \( Z_i \). The relationship between fractional error in \( Z_i \) and that in \( B \) is positive and nearly linear while that for \( L \) is negative and significantly nonlinear. Thus, quantitatively accurate estimates of \( L \) and \( B \) can only be obtained from SAR imagery if equally accurate estimates of \( Z_i \) are available. Given the uncertainties associated with standard bulk aerodynamic estimates of the \( L \) and \( B \) from in situ observations (Fairall et al. 1996), the SAR-based variance approach described above could be competitive if the \( Z_i \) error estimates of Sikora et al. (1997) are universally valid. They should therefore be verified on a larger dataset.

The results of the variance approach are also sensitive to values of the similarity constants used in its equations. Von Kármán’s constant has been estimated by various authors to range from 0.35 to over 0.4 (Panofsky and Dutton 1984; Bergmann 1998). Bergmann provides a review of the sources of experimental error responsible for this scatter and presents a theoretical argument for \( k \) being truly constant with a value of \( 1/\epsilon \) (i.e., 0.3678). Because the other constants in the similarity formulas of section 2 are the product of tuning against observational data under an assumed value of \( k \), care must be taken to adjust the other parameters appropriately if one uses a value \( k \) other than that assumed in their development. Because \( z_0 \) appears in the other equations only inside a log function, any uncertainty in the empirical constants of the Charnock relation propagates only weakly into the other parameters. The Monin–Obukhov and mixed-layer similarity formulas used in the variance approach are rife with empirical constants. All of these constants have an unreported degree of uncertainty that is probably on the same order as the measurement error in \( k \).

The inertial subrange approach also includes two similarity constants with a degree of uncertainty, \( \alpha_i \) and \( \Psi \). Dyer and Hicks (1982) review the results of several field experiments and find ±5% scatter in reported values of the Kolmogoroff constant. A review of Fig. 4 in Kaimal et al. (1976) suggests a similar degree of variability in the \( \Psi \). In neither case is this uncertainty a major problem when finding \( w_+ \) because it depends on the square root of \( \alpha_i \) and the cube root of the \( \Psi \). Both \( B \) and \( L \) are, in contrast, at least linearly sensitive to uncertainties in these two constants as both depend on the cube of \( w_+ \).

Because the highly successful (e.g., Fairall et al. 1996) inertial-dissipation approach for in situ measurement of surface-layer fluxes depends on these same spectral constants, this degree of uncertainty appears unlikely to cause major difficulties. Edson and Fairall (1998) explore the limits of these assumptions using in situ observations taken at sea.

Given the number of somewhat uncertain similarity constants involved in these two approaches, the propagation of error discussed above is by no means deci-
sive. Comparison of the results obtained using different sets of these equations (i.e., the variance and inertial subrange approaches) provides a somewhat more definitive test. Moreover, shortcomings uncovered in such a test can highlight key sensitivities in the approaches. Ultimately, testing against a large set of in situ observations is needed to provide a solid estimate of error levels in the approaches described herein. Both of these types of testing are employed in the next section although the number of available cases is severely limited by lack of coordinated in situ observations of the convective marine atmospheric boundary layer (CMABL) in field projects to date.

c. Example

As an example analysis, these two SAR-based approaches for estimating \( w^* \), \( L \), wind speed stability correction, and \( B \) were applied to one of the few SAR images for which high quality in situ observations are available for all of these parameters. This analysis was conducted using a \( 3 \times 3 \) array of 256 \( \times \) 256 pixel ERS-1 images, of which Fig. 1 is the lower center image. Pixel size is 150 m, sufficient to resolve the larger-scale portions of the inertial subrange of the wind speed spectrum (Fig. 2). Here, \( L \) was observed from the USNS \textit{Bartlett} near the north border of the nine-image array while the \textit{R/V Columbus Iselin} launched an atmospheric sounding for determining \( Z_1 \) in another of the images. These in situ observations can also be used to compute \( L \) and \( w^* \).

While carefully selected to provide a nearly ideal case, this \( 3 \times 3 \) array of images illustrates the potential problems with quantitative analysis of SAR imagery caused by the noise floor and the minimum sensitivity of the SAR. Because this HI-RES 2 case featured mean current relative wind speeds between 1 and 2 m s\(^{-1} \), the SAR sensitivity threshold was encountered in some pixels. To detect this problem, histograms of the pixel values of wind speed should be examined before quantitative analysis is undertaken of a SAR image. An image uncontaminated by low wind thresholding will have wind speed values with an approximately normal distribution as do the three most southeasterly images in the \( 3 \times 3 \) array. The images to their northwest in the array exhibit progressively greater degrees of histogram clipping in response to the southeast to northwest decrease in mean wind speed across the image array. Images whose histograms exhibit clipped low-speed tails and/or spikes at their low-speed ends should not be analyzed via the two approaches described above. The testing using this image array is therefore confined to the three images in the southeast corner of the array.

The results of the inertial subrange approach applied to the cross-wind spectra for the three minimally clipped images are shown in Table 3. The values for the three images are in general agreement with each other but show a trend toward weaker \( B \), less unstable \( L \), and lower \( w^* \) in the north and west as expected from the orientation of the sea surface isotherms in the imaged region. Thus, the approach diagnoses the greatest instability over the warmest water. A quantitative intercomparison of the results of the two approaches will assess the degree to which their depictions of this mesoscale gradient agree.

### 1) APPROACH INTERCOMPARISON

The results of application of both the inertial subrange and variance approaches to the three unclipped Gulf Stream images are compared below. Two summary statistics are presented for each of these intercomparisons. First, the ratio of the results of the inertial subrange approach to those of the variance approach is computed for each of the three images in the sample and this ratio is averaged over the three-image sample to arrive at an estimate of the interapproach bias (\( \mu \)). Second, the standard deviation of this ratio (\( \sigma \)) is computed across the three-image sample described above to quantify the degree of interimage variability in the interapproach bias. Comparisons yielding both \( \mu \) near 1.0 and \( \sigma \) near 0.0 indicate that two approaches are giving essentially the same results for all three images in the sample. In contrast, good \( \mu \) in association with poor \( \sigma \) would indicate scatter and, hence, unreliability, in one or both of the approaches. Likewise, good \( \sigma \) in association with poor \( \mu \) would indicate that both approaches are possibly reliable but that one or both suffer from a calibration

<table>
<thead>
<tr>
<th>Variable</th>
<th>Subimage</th>
<th>West</th>
<th>Middle</th>
<th>North</th>
<th>Approach ( \mu )</th>
<th>Comparison ( \sigma )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Z_1 ) (m)</td>
<td></td>
<td>800</td>
<td>850</td>
<td>850</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>( w^* ) (m s(^{-1} ))</td>
<td></td>
<td>0.43</td>
<td>0.52</td>
<td>0.50</td>
<td>1.008</td>
<td>0.027</td>
</tr>
<tr>
<td>Stability correction</td>
<td></td>
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<td>0.86</td>
<td>0.86</td>
<td>0.999</td>
<td>0.004</td>
</tr>
<tr>
<td>( B ) (K m s(^{-1} ))</td>
<td></td>
<td>0.0031</td>
<td>0.0049</td>
<td>0.0044</td>
<td>1.021</td>
<td>0.078</td>
</tr>
<tr>
<td>( L ) (m)</td>
<td></td>
<td>4.6</td>
<td>3.0</td>
<td>3.0</td>
<td>0.978</td>
<td>0.076</td>
</tr>
<tr>
<td>Wind speed (m s(^{-1} ))</td>
<td></td>
<td>1.58</td>
<td>1.57</td>
<td>1.52</td>
<td>0.999</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Table 3. Results from the inertial subrange approach for the west, middle, and north subimages are shown in the first three data columns. The fourth data column shows the mean interapproach bias for these three subimages while the fifth data column shows a measure of the associated interapproach standard scatter.
problem caused by uncertainties in the similarity constants as discussed in section 3a.

Agreement between the two approaches is striking (Table 3). Bias and scatter are both less than one would expect from bulk aerodynamic analysis of in situ observations (Fairall et al. 1996), perhaps reflecting the much larger sample of eddies in a two-dimensional SAR-derived wind field than in a one-dimensional time series of in situ observations. The degree of interapproach agreement observed with this set of SAR images suggests that the similarity constants used in the approaches may be more mutually consistent than previously assumed. It is quite possible that the scatter noted in values of these constants derived from in situ measurements results in part from the greater undersampling problems associated with one-dimensional time series (Lenschow and Stankov 1986). Taken together, these mean bias and scatter results suggest that, applied to cross-wind spectra from suitable images, both the inertial subrange and variance approaches may prove capable of providing repeatable and potentially well-calibrated estimates of $w_u$, $B$, $L$, and the stability correction to wind speed for those convective marine atmospheric boundary layers with three-dimensional cells.

2) COMPARISON WITH IN SITU OBSERVATIONS

The intensive in situ observational efforts of the HI-RES 2 project provide a rare opportunity for comparison with turbulence analyses of a coincident SAR image. SAR-estimated atmospheric boundary layer depth in the three unclipped images discussed above ranged from 800 to 850 m over the warmest waters of the Gulf Stream. The in situ sounding launched over these warm waters obtained a boundary layer depth of 930 m.

Computing $w_u$ from the observed $Z_i$ and the average of all available in situ observations of $B$ in the Gulf Stream’s unstable atmospheric boundary layer within an hour of the overpass time yielded a value of $0.27 \text{ m s}^{-1}$. The inertial subrange (variance) approach’s values range from 0.43 to 0.52 ($0.42$ to $0.52 \text{ m s}^{-1}$). The USNS Bartlett’s position during this time was in a southwest to northeast band of cooler waters displaced across the Gulf Stream from the analyzed images. Thus, its somewhat lower values of $w_u$ continues the cross–Gulf Stream spatial trend observed between the three SAR images.

The comparison of SAR-derived $B$ estimates with USNS Bartlett observations is less enlightening as the in situ observations for this period are $0.00063 \pm 0.00087 \text{ K m s}^{-1}$ compared with $0.0031$ to $0.0049 \text{ K m s}^{-1}$ for the inertial subrange approach and $0.0028$ to $0.0049 \text{ K m s}^{-1}$ for the variance approach. The SAR-observed cross–Gulf Stream mesoscale trend in $B$ is even greater than that in $w_u$, so quantitative comparison with the laterally displaced in situ observations is difficult.

The SAR-derived current relative wind speed for this case is ranges from 1.4 to 1.6 m s$^{-1}$ across the image array for both approaches. The USNS Bartlett reported current relative winds of approximately 1.5 m s$^{-1}$ as well when it traversed the convective region. The multihour time difference between the most nearly collocated in situ observations and the SAR overpass make this agreement less definitive than it might appear at first glance.

The SAR-based estimates of the $u_w$ corresponding to the USNS Bartlett’s in situ observations range from 0.056 to 0.058 m s$^{-1}$ compared with the in situ value of $0.060 \pm 0.027 \text{ m s}^{-1}$. Thus, the SAR-based estimates are well within the range of scatter of the in situ observations. Combining the mean $u_w$ and $B$ values from the USNS Bartlett’s in situ observations yields an estimate of −25 m for L compared with −3.0 to −4.6 m for the corresponding inertial subrange estimates and −2.9 to −5.1 m for the variance approach. Again, reflecting the ship’s displacement toward cooler water relative to that observed by these SAR images, $B$ and $L$ showed the poorest agreement in this comparison with in situ observations.

4. Conclusions

Two diagnostic approaches for quantifying convective boundary layer turbulence using quasi-independent ranges of the SAR-derived surface wind speed spectrum are presented and the limits of their potential utility explored. Both approaches depend on classic similarity theories for the turbulence statistics of the three-dimensional convection common in unstable boundary layers under light wind situations. One approach uses similarity formulas relating the turbulence-scale wind speed variance to marine atmospheric boundary layer stability while the other uses the inertial subrange spectral similarity formula to diagnose $w_u$. The sensitivity of their results to uncertainties in the input parameters and similarity constants is analyzed as are the geophysical and design constraints on their applicability. Some of the results of this analysis are illustrated by an example interapproach comparison using a set of SAR images of the Gulf Stream. Finally, example results obtained using the two approaches are compared with in situ turbulence observations from the HI-RES 2 project.

Sensitivity tests using artificially generated backscatter fields in the variance approach demonstrate that the static stability of the atmospheric surface layer can easily require an order 10% correction to scatterometer wind speed estimates under relatively common at-sea conditions. This result was confirmed with the runs using actual SAR images and in situ observations from the HI-RES 2 project. The sensitivity tests also demonstrate that both the variance approach and inertial subrange approach have the potential to robustly determine this correction even in the face of gross uncertainty in the input value of $Z_i$. In contrast, the two approaches’ quantitative estimates of $B$ and $L$ are subject to ap-
proximately the same relative error as the input value of boundary layer depth. For three-dimensional convective cells, the Sikora et al. (1997) algorithm offers the possibility of obtaining, from the SAR backscatter field, $Z$, estimates with sufficient accuracy for meaningful flux and stability calculations.

Uncertainty in the numerous similarity constants employed in the two approaches requires that they be tested both against each other and against in situ observations. The methods for conducting such a test are demonstrated on a HI-RES 2 case. For this nearly ideal case, results from the two approaches are in good agreement (i.e., minor interapproach biases and little scatter). Both approaches did a generally credible job of estimating the surface wind speed, $w_*$, and the stability correction to wind speed observed by the HI-RES 2 ships. The SAR-derived $Z$, estimates also agreed to within 10% with the corresponding in situ observation. Only $B$ and $L$ proved difficult to verify with useful accuracy due to the in situ observations being displaced across the sea surface temperature gradient from the available CMABL imagery. These results were expected because $w_*$ has a lower-order dependence on the air–sea temperature difference than do $B$ and $L$. These results suggest that both the inertial subrange and variance approaches may, under favorable conditions, have the potential to provide repeatable and well-calibrated estimates of $w_*$, $B$, and the stability correction to wind speed for convective marine atmospheric boundary layers.

Several meteorological, oceanographic, or instrument conditions can limit the applicability of these approaches. In conditions of high wind (i.e., near-neutral stratifications as quantified by large absolute values of $L$), the wind speed variance and inertial subrange behavior vary little with $w_*$. Thus, both approaches return highly uncertain values under these conditions. Both approaches are, however, able to detect the onset of near neutrality, generating appropriately large values of $L$ in response. Thus, failure of the approaches is readily detectable. Under these conditions, the CMOD wind speed does not require correction for stability because that correction goes to zero as the stability approaches neutral. Moreover, CMOD and similar scatterometer algorithms suffer from their own high wind limit as the relationship between wind speed and backscatter weakens. High winds are also associated with increased noise (speckle) dominance of the small-scale part of the SAR backscatter spectrum. This rising noise floor sets a very real upper limit on the wind speeds to which these two approaches might be applied. A wind field that varies below the sensitivity threshold of the SAR or above its analog to digital saturation point also invalidates these two approaches.

Stable conditions likewise foil these approaches. The variance approach has proven reliable in detecting such conditions based on the sharp decline in the ratio of wind speed variance to $u_*$ as stability increases. Thus, stable conditions generate imaginary results from (8), providing a rather easy to use error detection criterion. Even under appropriate wind speed and stability conditions, however, oceanographic signatures can contaminate the SAR-derived wind spectra to such a degree that the wind speed variance spectra cannot be quantitatively analyzed.

Horizontal resolution of a SAR is another design parameter that is critical to the implementation of these two approaches. It must be on the order of 100 m or better to resolve enough of the wind speed spectrum. The inertial subrange approach in particular requires high resolution. Thus, along with the meteorological and oceanographic constraints, sensitivity and horizontal resolution of future SARs will determine the long-term utility of the approaches described herein.

The potential applications of these approaches are numerous enough that efforts should be made to collect more definitive verification data by means of SAR overpasses and collection of atmospheric soundings in conjunction with existing air–sea interaction experiments. Careful coordination of all platforms will be required to obtain the necessary in situ soundings and turbulence measurements in the appropriate atmospheric conditions during the SAR overpasses. These measurements should be made in convective boundary layers across a broad range of wind speeds and surface-layer stabilities. The tropical oceans would provide one convenient setting for such an observational effort.

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