Stable Boundary Layer in Complex Terrain. Part I: Linking Fluxes and Intermittency to an Average Stability Index

LUIZ E. MEDEIROS* AND DAVID R. FITZJARRALD
Atmospheric Sciences Research Center, University at Albany, State University of New York, Albany, New York

(Manuscript received 11 November 2013, in final form 5 June 2014)

ABSTRACT
Average heat and momentum fluxes observed by a network of surface stations during the Hudson Valley Ambient Meteorology Study (HVAMS) were found as functions of a spatially representative bulk Richardson number $R_i$. Preferential sites were identified for the occurrence of strong turbulence under mesoscale stability conditions common to all stations. Locally sensed turbulence intermittency depends on the mesoscale flow stability. Nearly continuous turbulence with few long-lived intermittent events occurs when $R_i < R_{ic}$, the critical gradient Richardson number. Less-continuous mixing associated with a larger number of events occurs when $R_{ic} < R_i < 5$, with the weakest turbulence and fewer events observed for $R_i > R_{ic}$. It was found that the need to allow for extra mixing above the conventional critical bulk Richardson number in numerical weather prediction models is primarily a consequence of spatial averaging in a heterogeneous landscape and is secondarily the result of turbulence above $R_{ic}$ at locations with “nonideal fetch.”

1. Introduction
Understanding of mixing processes occurring in the stable boundary layer (SBL) lags behind that for the convective boundary layer (Fernando and Weil 2010). The 100–200-m-thick SBL, which often forms in early evening over land, exhibits intermittent and spatially localized mixing events (Mahrt 1999). It remains a challenge to predict minimum temperatures and to estimate SBL properties in realistic patchy landscapes, which properties are critical information for both predicting nocturnal pollutant concentrations and minimum temperatures relevant to agriculture. A related challenge is determining the turbulent fluxes of scalars (such as temperature, carbon dioxide, and water vapor) and momentum in stable conditions (Howell and Sun 1999; Acevedo et al. 2006).

Numerical weather prediction (NWP) models require surface momentum, sensible heat, and latent heat fluxes; dispersion models need information on turbulent intensities; and ecological models depend on fluxes of key trace gases. Most often, such information is not directly available and one must relate fluxes and variances to simpler characteristics of the flow, a process that is known as the parameterization problem. In the atmospheric surface layer, this process is commonly accomplished through similarity relationships, the most common being the Monin–Obukhov (MO) similarity hypothesis.

The MO similarity “universal” flux-gradient relationships express the stability dependence of shear flows. They were found by making careful observations in homogeneous terrain (e.g., Wyngaard 2010). A common way to quantify stability without using directly measured fluxes is to employ the gradient Richardson number $R_i = (g/\theta_{ref}) \partial \theta / \partial z (\partial U / \partial z)^2$ (where $\theta_{ref}$ is a reference temperature, $\partial \theta / \partial z$ is the potential temperature gradient, and $\partial U / \partial z$ is the mean wind shear) or, more simply, a bulk Richardson number $R_{br}$, substituting finite differences for derivatives. Both theory and selected local field observations confirm the idea of a critical gradient Richardson number $R_{ic} \approx 1/4$ (e.g., Miles 1961; Howard 1961; Ohya et al. 2008), which is a maximum limit beyond which turbulent activity is unsustainable. Difficulties arise in the too-common situation in which the MO rules are applied for situations outside their bounds of validity, for example,
for grid cells with inhomogeneous terrain, for grid cells with appreciable advection, or under very stable conditions. Moreover, reduced nocturnal turbulent intensities diminish the spatial coherence of turbulent events, a consequence of which is that large variability may arise even in a reasonably small area, with portions of it remaining connected to the upper boundary layer and other portions disconnected and responding to local forcing. Mahrt (2014) states bluntly that “patching existing similarity theory does not seem useful for the very stable boundary layer.” Therefore, even if both the connected and disconnected regions individually follow similarity scaling, it does not follow that the same scaling applies to relate the averaged statistical moments to the average stability state of the region (Mahrt 1987). One consequence of this mismatch is the need to allow models to force significant mixing in conditions for which the grid-averaged $Ri_{\text{m}}$ mismatch is the need to allow models to force significant (Salmond and McKendry 2002; AF2003) and in the spatially discontinuous, both in the horizontal plane this line of investigation. It has been carefully tested observationally; here we continue data from single stations (Acevedo et al. 2006), NWP methods used to estimate fluxes under conditions of vertical direction (Mahrt and Vickers 2002). Whereas attenuates such differences such that a gridcell $Ri_{b} > Ri_{\text{cr}}$ has been justified by noting that unresolved subgrid surface heterogeneity causes turbulence to be localized spatially (McCabe and Brown 2007).

Landscape heterogeneities force spatial differences in local profiles, and the spatial averaging process likely attenuates such differences such that a gridcell $Ri_{b} > Ri_{\text{cr}}$. The aim of this paper is to determine whether spatial averaging accounts for the need to allow fluxes at “supercritical” $Ri_{b}$. Apart from Acevedo and Fitzjarrald (2001, 2003, hereinafter AF2003) this hypothesis has not been carefully tested observationally; here we continue this line of investigation.

At night, turbulence is often temporally sporadic and spatially discontinuous, both in the horizontal plane (Salmond and McKendry 2002; AF2003) and in the vertical direction (Mahrt and Vickers 2002). Whereas methods used to estimate fluxes under conditions of intermittent turbulence are better suited to studies of data from single stations (Acevedo et al. 2006), NWP modeling involves grid cells that are much larger than the representative area of a single station. Problems with describing the SBL are reflected by persistent difficulties to parameterize conditions in NWP models; under very stable conditions, intermittent surface-layer turbulence is poorly resolved (Fernando and Weil 2010). In some cases, models produce too much cooling (Viterbo et al. 1999); in others, too thick of a turbulent layer is predicted (McCabe and Brown 2007). This problem arises because models assume continuous turbulence close to the ground. In the typical approach, surface fluxes are found using first-order closure schemes (e.g., McCabe and Brown 2007), and the diffusion coefficients are usually functions of a bulk Richardson number. As stability functions are used to adjust the turbulent diffusion coefficients for momentum $K_{m}$ and heat $K_{h}$ in the subgrid turbulence parameterizations (e.g., Delage 1997; Mahrt 1987), one must allow mixing even for grid cells with $Ri_{b} > Ri_{\text{cr}}$. In practice, stability functions with “long tailed” (e.g., Louis et al. 1981) distributions are used, allowing for the effects of infrequent extreme-mixing events at supercritical grid-averaged $Ri_{b}$. An alternative is not to allow mixing under these conditions; then a function that decays rapidly with increasing $Ri_{b}$ (“short tailed” or “sharp”; King et al. 2001) is preferred.

Without these empirical corrections for which observational or theoretical support is limited, models often provide poor estimates of minimum temperatures and SBL thickness, which in turn affects the predicted life cycles of a variety of phenomena, including the predicted evolution of low pressure systems and nocturnal low-level jet characteristics (Steeneveld et al. 2008). The short-tailed distributions produce insufficient mixing, which leads to a weakly turbulent, shallow, and cold SBL with insufficient drag. This result further leads to excessively deep and long-lived low pressure systems. As an alternative, long-tailed distributions allow more mixing and produce a warmer SBL with more drag, and this result leads to better estimates of low temperatures and time durations of cyclonic systems. Because of increased mixing, however, the simulated SBL is deeper (Svensson and Holtslag 2009) and any low-level jet that is produced is weaker and at a higher altitude than is typically observed. In the aggregate, these problems also limit the ability of such models to forecast dispersion of contaminants in the SBL.

Our research question is, How are the mesoscale background conditions related to the network-averaged fluxes and to turbulent intermittency? We use direct measurements of turbulence from fast-response sensors to ask whether accounting for spatial inhomogeneity offers a physical explanation for the high $Ri_{b}$ mixing. In Part II (Medeiros and Fitzjarrald 2013, manuscript submitted to J. Appl. Meteor. Climatol.), we seek geometrical properties of the landscape that can be used to predict the locations and intensity of this mixing.

Our empirical method seeks a connection between the current model-tuning approaches for nocturnal mixing and real landscape properties. We do not address here the issue of what causes intermittent and localized turbulence.

To quantify how intermittent and localized turbulence causes the spatially averaged flux to depart from that observed at individual stations, we identify turbulent mixing periods that are responsible for an appreciable part of the nocturnal fluxes. In a two-step process we search first for periods with abrupt changes in the average of the square vertical velocity $w^{2}$, taken to signify the beginning of periods with turbulence. In the second
step, a threshold is applied to \((w^2)^{1/2}\) to identify calm and turbulent periods, characterizing the latter as an intermittent turbulent breakdown episode. Then we combine features of the background state (e.g., wind speed, temperature difference between bottom and top of the SBL, and the SBL thickness) to express a regional bulk Richardson number \(Ri_{br}\) that is linked to station-network-average turbulent activity.

2. Data

Data come from the Hudson Valley Meteorological Study (HVAMS). The intensive observational period (IOP) began in mid-September of 2003 and ended on 31 October 2003. HVAMS featured the deployment (Fig. 1) of nine Integrated Surface Flux System (ISFS) stations from the National Center for Atmospheric Research (NCAR), the Mobile Integrated Sounding Unit (MIPS) from the University of Alabama in Huntsville, the University of Wyoming King Air instrumented aircraft, and additional radiosonde launches at the National Weather Service (NWS) Forecast Office in Albany, New York. Stations that were not part of the IOP deployment but are used in the long-term data analysis for the HVAMS project include the NWS Automatic Surface Observing Systems (ASOS) at Albany and Poughkeepsie, New York, and five conventional surface weather observation stations (H1–H5) deployed as part of the long-term HVAMS effort. On 16 October 2003 a flux tower was added to the flux-station network. The project continued with the weather stations and flux tower in operation for the following three years.

The study region, the area within the rectangle in Fig. 1, located between the cities of Poughkeepsie and Albany, corresponds to a north–south extension from 42.8° to 41.8°N, with an east–west extension from 73.4° to 74.3°W. The region corresponds to an area of approximately 70 km \(\times\) 118 km, approximately that of a typical grid cell in most atmosphere–land components of climate models (1° longitude \(\times\) 1° latitude; Hurrell et al. 2013). Laser ceilometer observations from the ASOS station at Albany International Airport (ALB; Fig. 1) were used to estimate...
the cloud-cover fraction. At Kingston–Ulster Airport (M; Fig. 1) the University of Alabama MIPS system (Knupp et al. 2000) included a 915-MHz Doppler radar wind profiler. The University of Wyoming King Air aircraft equipped with diverse meteorological sensors made several “close approaches” to the local airports during dusk and dawn (8, 1, CC, 4, and M; Fig. 1). Sensors used on this aircraft are detailed online (http://www.atmos.uwyo.edu/n2uw/users/capabilities.shtml).

After the IOP, all ISFS stations and the MIPS facility (M; Fig. 1) were removed. Station H1 was moved from its original site to the station-4 site, H4 was moved to the station-6 site, and H3 was moved to Schodack State Island Park (S), where there was previously no station. Data from this long-term observation period (LTOP) from 2005 and 2006 are used here.

3. Intermittent events and turbulent fluxes in stable conditions

To identify intermittent turbulent events and estimate fluxes, we use fast-response data (10 Hz) that are block averaged to 1 Hz from 3D-sonic anemometers at the flux stations. The 1-Hz data were obtained by performing block averages at every 10 consecutive data points. All analyses reported here are based on 1-Hz data. Detailed comparisons showed that using the averaged data yields only a 10% difference in estimated fluxes, insufficient to alter any of the conclusions reached here. Turbulent fluxes and turbulent events reported here refer to the nocturnal period, defined as the period between the local sunrise and sunset times. During the HVAMS IOP, the nocturnal period was between 2300 and 1100 UT. The momentum flux $\rho w'U'$ and sensible heat flux $\rho c_p w'T'$ were determined using the eddy-covariance method, where $\rho$ is the air density (1.2 kg m$^{-3}$), $c_p$ is the specific heat at constant pressure (1004 J kg$^{-1}$ K$^{-1}$), $U$ is the horizontal wind speed, $w$ is the vertical velocity, and $T$ is the sonic anemometer–derived temperature. Perturbations of velocity and temperature ($U' = U - \overline{U}, w' = w - \overline{w}$, and $T' = T - \overline{T}$) were found by removing a 15-min running mean. We estimated fluxes for variable time intervals for which turbulence was considered stationary. (Further details about the interval choice follow.) Although the sonic temperature also depends slightly on humidity fluctuations (an error of up to 10%; Liu et al. 2001), this too does not affect our conclusions; we seek only indicators of turbulence activity.

Events

Periods of sustained turbulence are found using an arbitrary, but objective, technique (Howell 1995). These periods are found by performing a Haar transform on the vertical-velocity second statistical moment $w^2$ and selecting intervals for which its average value is approximately constant. The Haar wavelet transform $HT$ is defined by

$$HT = \frac{1}{2m} \left( \sum_{i=1}^{m} w_{i+j}^2 - \sum_{i=1}^{m} w_{i-m+j}^2 \right),$$  \hspace{1cm} (1)

where $m$ is a function of a chosen time window $\tau_h$ and sampling frequency $f$ (1 Hz), with $m = \tau_h / f$; for this analysis, $\tau_h = 20$ min. Here, $N$ is the total number of points in a chosen interval and $i$ is the $i$th velocity element. We modified the method of Howell (1995) to search for abrupt changes in $w^2$. The algorithm evaluates local maxima in the Haar wavelet transform of $w^2$ for a fixed-time interval scale $\tau_h$ in which $\overline{w^2}$ is calculated.

The consequence of this choice is discussed below. By default, the beginning and end of the time series mark abrupt changes. A period with constant $\overline{w^2}$ in the time series of $w^2$ corresponds to a time interval between two adjacent maxima in the Haar transform, and this period is usually larger than $\tau_h$. This period is designated here by $\tau$ and is used to calculate the fluxes and the statistical parameter $\sigma_w = (\overline{w^2})^{1/2}$. If more than two maxima are identified in the HT for a time interval $\tau$ that is shorter than $\tau_h$, only the larger maximum is kept (Howell 1995). Little difference was observed using the square of the vertical velocity perturbation $w^2$ in place of $w^2$. Each approach resulted in near-constant $[N^{-1} \sum_{i=1}^{N} (w - \overline{w})^2]^{1/2}$ and $\overline{(w^2)}^{1/2}$, with similar period lengths and timing of occurrence. Figure 2 presents the time series of $w$ for some flux stations (e.g., stations 1, 3, 5, and 7) during one IOP night. In a test of sensitivity (result not shown), the shorter time windows $\tau_h$ identified more changes in the time series than did the longer ones. This occurred because 1) in larger time windows the shorter distance allowed between two maxima is larger and 2) turbulence bursts with shorter duration than the $\tau_h$, which can produce temporary high values of $w^2$ and therefore higher $\overline{w^2}$, are greatly attenuated in longer time windows, which can cause misidentification of the beginning and ending time of the burst.

The key objective here is to find periods that have sufficient mixing to affect SBL development and its thermodynamic properties. Seeking periods $\tau$ with nearly constant $\overline{w^2}$ was designed to guarantee approximate turbulent stationarity. We believe that the magnitude of the $\sigma_w$ alone is sufficient to identify turbulent periods that contribute to the bulk momentum flux and sensible heat flux exchanges between the surface and the atmosphere. We perform a second screening to find which periods have $\sigma_w \geq$ threshold $\sigma_{th}$. The threshold chosen, $\sigma_{th} = 0.1$ m s$^{-1}$, was based on the finding that
fluxes for periods with $\sigma_w \leq \sigma_{th}$ did not contribute significantly to the overall average momentum and heat fluxes during the entire HVAMS campaign. The term periods of increased turbulence will be reserved to describe those periods that satisfied the threshold condition, and the term period will describe the periods in general that were or were not so classified.

To identify a turbulent event, contiguous periods of increased turbulence ($\sigma_w \geq 0.1 \text{ m s}^{-1}$) are considered to be a single event (see, e.g., station 7 between 0410 and 0450 UT; Fig. 2). If during a given night all periods had $\sigma_w \geq 0.1 \text{ m s}^{-1}$, then the entire night is counted as a single event. At the other extreme, if all of the periods had $\sigma_w < 0.1 \text{ m s}^{-1}$, then we designate zero events for that night. For nights with more than one event, there must be more than one period of increased turbulence followed by a period of weak turbulence. Shaded regions in Fig. 2 represent turbulent events because they have $\sigma_w > \sigma_{th}$. In Fig. 3, periods with $\sigma_w \leq \sigma_{th}$ had contributed little to the momentum and heat flux. An appreciable flux contribution appears only for periods with $\sigma_w \geq \sigma_{th}$. Considering periods up to $\sigma_w = 1\text{ m s}^{-1}$
means that the contributions from nearly all important periods enter in the average flux calculation.

The periods outside the shaded regions are periods of weak turbulence or vanishing turbulence and do not count for events. Stations with more events per night are more intermittent. On the case-study night, stations 3 and 6 experienced the most intermittency (6 and 5 events, respectively) while stations 1 and 5 were the least intermittent (3 events and 1 event). Note that station 5 was the most turbulent. Some events happen abruptly and are easily identified, such as those at station 7, whereas at other stations turbulence increases slowly and is harder to identify, such as that seen at station 1 between 0000 and 0200 UT.

FIG. 3. Cumulative average momentum flux (solid lines) and heat flux (dotted lines) during the entire HVAMS campaign as function of a variable threshold $\sigma_{th}$. The x axis indicates an upper-limit value for $\sigma_w$ of the periods. So, for example, the flux average value on the y axis corresponding to $\sigma_{th} = 0.1 \text{ ms}^{-1}$ represents the contribution of periods for which $\sigma_w \leq \sigma_{th}$. The vertical dotted line shows the chosen threshold $\sigma_{th} = 0.1 \text{ m s}^{-1}$; below this value no flux is observed. The flux stations (left) 1, 3, 5, 7, and 9 and (right) 2, 4, 6, 8, and 10 are shown from top to bottom.
Short time windows \( (\tau_h) \) are more sensitive to abrupt changes in the \( w^2 \), allowing for better identification of the edges of events. The disadvantage is that single events can be identified as multiple events if the combined action of the Howell method and threshold screening fails to identify consecutive periods of increased turbulence as part of single events. Even if this occurs, the amount of flux added in the extra events does not significantly affect the nocturnal flux totals (Fig. 4). Overall average fluxes had a small variation among the different time windows tested (Fig. 4). For momentum flux a maximum difference of 22\% was observed, and for heat flux a maximum difference of 8\% was observed. The running-mean time window \( (\tau_r) \) had even smaller impact in the fluxes: for momentum the maximum observed difference was 3\%, and for heat it was 9\%. The chosen time intervals of 20 and 15 min, respectively, for \( \tau_h \) and \( \tau_r \) do not significantly impact the values of the fluxes.

The length of \( \tau_h \) does not affect the results of our study of intermittency since the same rules are applied to identify the intermittent events at different stations; the choice only affects the counting of events. Because the rules are uniform, any shifting in the number of events per night should be approximately the same at all stations.

4. Local stability

In this section we present analysis of the local bulk Richardson number \( R_{ibl} \) and local fluxes. The \( R_{ibl} \) of stations 1–9 were obtained from the temperature difference \( \Delta \theta \) and height difference \( \Delta z \) between 2 and 7 m above ground level (AGL), with the wind speed taken at 7 m and assumed to vanish at the surface. For station 10 we used the 12- and 3-m tower wind and temperature profile levels to compute \( R_{ibl} \). The fluxes used corresponded to periods of increased turbulence (or intermittent events with \( \sigma_u > \sigma_u^* \); black dots in Fig. 5) and calm periods (\( \sigma_u < \sigma_u^* \); light-gray dots in Fig. 5).

Fluxes showed a better relationship with \( R_{ibl} \) during periods of increased turbulence, in the sense that they increase in magnitude with decreasing \( R_{ibl} \) and in the sense that there exists a clear point (a critical \( R_{ibl} \) value) at which turbulence shuts off. This occurs probably because turbulence is well defined during such periods (Fig. 5). For heat flux there exists a less clearly defined

---

**Fig. 4.** Nocturnal momentum (black lines) flux and heat flux (gray lines) vs time-window length (min) for station 10 during November 2003. The thick black line and thick gray line with open squares are, respectively, momentum and heat fluxes using a 15-min running-mean filter. Other running-mean filter intervals (10, 20, and 30 min) are shown for comparison.
critical value as well. At most stations (1, 2, 3, 4, 5, 6, and 7) the heat flux magnitude first increases before decreasing with decreasing $R_{ibl}$. This behavior of the heat flux is consistent with what was found by Luhar et al. (2009, their Fig. 4a). At very small values of $R_{ibl}$ the vertical gradient of potential temperature should be at a minimum and the associated heat flux should be small in magnitude. On the other hand, at large values of $R_{ibl}$ the heat flux must vanish because turbulence is suppressed. So, the maximum negative values for heat flux should happen between these two regimes of stability.

We found that the local area fluxes are distinct in the sense that they overlap at different regions of the cloud of points (small gray points in Fig. 5). This clearly illustrates the consequence that different local landscapes have on roughness length at the nonideal HVAMS sites. HVAMS stations were located in clearings of variable size, with the nearest obstacles (usually trees) at distances...
varying between 10 and more than 100 m. We employed the concept of transmission factor that was developed by Fujita and Wakimoto (1982) to assess station exposure; the transmission factor depends on wind direction and is defined as the ratio between the local mean wind and the maximum network-average wind. Stations 8, 9, and 10 were the most exposed; 1, 2, 3, 4, 5, and 6 were moderately sheltered; and 7 was the most sheltered [the details are in Part II (Medeiros and Fitzjarrald 2013, manuscript submitted to J. Appl. Meteor. Climatol.)].

HVAMS local fluxes overall tended to vanish when $R\text{ib}_h \approx R\text{icr}$. At most-sheltered station 7, 13% of the maximum heat flux for the $R\text{ib}_h > R\text{icr}$ range is still observed. We suspect that the locally observed turbulence might not be entirely related to the local wind and temperature profiles.

Most periods of increased turbulence lay to the left of the $R\text{icr}$ value, indicating that the approach outlined in the events section of section 3 to identify intermittent turbulent events is adequate. Figure 5 demonstrates that the network of flux stations is capable of measuring turbulence, in spite of any exposure deficiencies.

5. Regional bulk Richardson number—$R\text{ib}_b$

Here we develop a regional $R\text{ib}_b$ ($R\text{ib}_b$).

$$R\text{ib}_b = \frac{(g/\theta']_x)\Delta\theta/\Delta z}{(\Delta U/\Delta z)^2},$$

(2)

that represents regionally the background flow affecting the HVAMS network. Here, $\theta_x$ is a reference potential temperature, $g$ is the acceleration of gravity (9.81 m s$^{-2}$), and $\Delta\theta$ and $\Delta U$ are respectively the potential temperature and wind speed difference between two levels. We assume that the entire HVAMS region is exposed to a common background flow and that a criterion like $R\text{ib}_b$ is adequate to evaluate the dynamic stability of the region.

A difficulty is finding representative vertical temperature and wind gradients ($\Delta\theta/\Delta z$; $\Delta U/\Delta z$). We do not have detailed vertical wind and temperature profiles that are continuous in time to determine

$$\frac{\Delta \chi}{\Delta z} = \frac{1}{\tau} \int_0^\tau \left[ \int_0^{h(t)} \chi_{\text{SBL}}(t) - \chi(t, z) \right] dz \right] dt,$$

(3)

where $\chi = U$ or $\theta$, $h$ is the height of the stable boundary layer, and the subscript SBL refers to the top of the layer. We use a bulk-layer model to address this difficulty (Fig. 6). We consider only the stability of the layer at the end of the night, when the SBL carries the cumulative effects of the nighttime turbulent exchanges, advective cooling, and radiative cooling.

We chose wind speed and temperature at SBL top to represent the upper boundary wind and temperature (Figs. 6a,c,e,g), assume the wind speed at the ground to be zero, and use the network minimum temperature as the lower boundary temperature. We suppose these represent the most stable pockets of air, whereas the maximum temperatures represent sites most likely connected to the overlying flow. The upper-air temperature and wind were determined using the early morning (1200 UT) ALB sounding and wind profiler data at the level just above the point at which $\Delta\theta/\Delta z \sim 0$ (Fig. 6a) or at the level just below the first significant potential temperature jump (Fig. 6e). The SBL height $h$ was defined by the elevation difference between the point at which the vertical derivative of the potential temperature approached zero (Fig. 6d) or between the point just below the first potential temperature jump and the average network elevation (Fig. 6h), fixed at 89 m above sea level. Accordingly, only one $R\text{ib}_b$ value was available nightly. The idealized $\theta$-profile schematics depicted in Figs. 6d and 6h represent the two most common situations.

The areawide mean temperature represents an intermediate situation. AF2003 and Medeiros and Fitzjarrald (2013, manuscript submitted to J. Appl. Meteor. Climatol.) suggested that sheltered sites amid concave topography potentially have less turbulence than relatively exposed ones with convex surface.

A practical difficulty with using the maximum temperature at the lower boundary is that often the layer appears as convective (result not shown). This occurs when the temperature of the warmest station is very close to the temperature at the top of the SBL and a small difference reverses the sign of $\Delta\theta$ across the layer. Also, under clear sky and light winds the warmest station also tends to be in higher terrain, making $\Delta\theta$ represent the temperature difference referenced to the uppermost part of the SBL. Accordingly, when we use the coldest temperature of the network to represent the low-elevation sites, $\Delta\theta$ is never negative. The key point is that our regional $R\text{ib}_b$ represents the maximum level of stability that can be found over the region.

6. Results

a. Network-averaged fluxes as a function of $R\text{ib}_b$

Because $\Delta z$ was based on the SBL height obtained at the end of the night, the thickness of the SBL carries cumulative influences of nocturnal fluxes; thus,
a nocturnal average of the fluxes is most suitable for comparison. We obtained Ri_br for 35 out of 50 nights during the IOP, these being nights for which data needed to obtain Ri_br were available. For this subset, relevant ranges were Δz: [55, 523] m; Δθ: [2, 17] K; and ΔU: [1, 15] m s⁻¹.

Network-average momentum and heat fluxes have moderate dependence on Ri_br for 0 < Ri_br < 45. Both momentum and heat fluxes became more negative with decreasing Ri_br. Nonetheless, for sensible heat flux the least stable data point does not follow the overall

FIG. 6. Vertical potential temperature θ profiles (solid line with circles—all surface stations; thick dashed line—1200 UT Albany sounding; dotted line—aircraft) on (a) 6 and (c) 8 Oct. (b),(f) The wind barbs for all surface stations (“Network”) two sounding levels (“ALB sounding”). The surface station θ and wind refer to 2-h average before 1200 UT. The aircraft profile was made at 1124 UT 6 Oct and at 1200 UT 8 Oct. The gray thick line indicates the height of the SBL. (c),(g) Time–height sections of wind speed and direction obtained by the MIPS wind profiler during the same nights of (a) and (e), respectively. Also shown are schematics of an idealized bulk model layer when (d) ∂θ/∂z decreases with elevation and/or (h) when there is a jump in the θ profile. The h is the height of the SBL, and Δθ is the potential temperature difference between the surface and a level just above h (see section 5 for details). The energy needed to mix the bulk layer is drawn from the kinetic energy of the mean flow within or above it.
tendency of decreasing flux with decreasing stability (Fig. 7).

Aircraft profiles (times signs in Fig. 7), available for only seven nights, are used as a complementary alternative to relate the network fluxes to $R_{ibr}$. For these data, $R_{ibr}$ was found from spatial averages of direct wind and the upper-SBL $\theta$ measured in the early morning during close approaches at the five local airports described above. Note that the lower-level $\theta$ still comes from its network minimum. Most of the bulk Richardson numbers calculated from the aircraft data lay within the set of other $R_{ibr}$ points, supporting the idea that $R_{ibr}$ is a representative estimate of regional-flow stability.

We compared predicted momentum flux and sensible heat flux obtained by empirical relation with the network-average fluxes. The predicted fluxes were obtained from a formulation given in McCabe and Brown (2007) and Louis (1979).
\[ \overline{w'x'} = -f^2 \left( \frac{\Delta U}{\Delta z} \right) \left( \frac{\Delta x}{\Delta z} \right) f_a(R_{ibr}), \]  

(4)

where \( l \) = mixing length, \( \chi = U \) or \( \theta \), \( f = \) stability function, and \( \alpha = \) stability function type. Here we use four different types of stability functions: two from the work of McCabe and Brown (2007), which are referred to as sharp (adapted from King et al. 2001) or as “long”; one from Delage (1997), which is referred to as “Delage97,” and one from Louis et al. (1981), which is referred to as “Louis81.” The formulas for the first three are

\[
\begin{align*}
    f_{\text{sharp}} &= \frac{(1 - 5R_{ibr})^2}{2} & \text{for } 0 < R_{ibr} < 0.1 \\
    f_{\text{long}} &= \frac{1}{1 + 10R_{ibr}} & \text{and} \\
    f_{\text{Delage97}} &= \frac{1}{(1 + 12R_{ibr})^2}.
\end{align*}
\]

(5, 6, 7)

Equations (5), (6), and (7) are taken to be equally valid for momentum and sensible heat fluxes, but for the case of Louis81 there are different stability functions for momentum and sensible heat fluxes:

\[
\begin{align*}
    f_{\text{Louis81}} &= \begin{cases} 
        \frac{10R_{ibr}}{\sqrt{1 + 5R_{ibr}}} & \text{momentum} \\
        \frac{1 + 15R_{ibr}}{\sqrt{1 + 5R_{ibr}}} & \text{heat}
    \end{cases}
\end{align*}
\]

(8)

The most restrictive stability functions, sharp and Delage97, underestimate observed fluxes for lower \( R_{ibr} \) values more than do the long and Louis81 functions. For weakly stable conditions, using the former two functions yields fluxes closer to measured values while the latter two overestimate. Predicted momentum fluxes using sharp and Delage97 functions are closer to measured values only for \( R_{ibr} < \frac{1}{4} \). For sensible heat flux, predicted values are closer to the measurements when \( R_{ibr} < 1 \). For more stable conditions (\( R_{ibr} > 1 \)), either function underestimates momentum and sensible heat fluxes. The long and Louis81 forms predict momentum fluxes closer to those observed for \( \frac{1}{2} < R_{ibr} < 3 \). For \( R_{ibr} \) values outside this range, these two forms overestimate and underestimate, respectively. Sensible heat flux values predicted using the long-form approach overestimates for \( R_{ibr} > 3 \). Louis81 yields fluxes close to observed only for \( R_{ibr} \approx 2 \); below and above this limit, it overestimates and underestimates, respectively.

AF2003, using a network of 26 stations spread over an area covering 30 km x 30 km of a heterogeneous landscape near Albany, found that a stability function (Louis 1979) with the same format as Delage97 (but with a different constant) always underpredicted sensible and latent fluxes as compared with observed areal averages. AF2003, having no direct flux measurements, used the MO approach to estimate fluxes.

We compared local observed and predicted fluxes using Louis81 (Table 1); results are similar to those of Poulos and Burns (2003; hereinafter PB2003). The main difference between the current work and PB2003 is the value of the constant in the flux relation (ours is \( \approx 0.01 \) and PB2003 is \( \approx 0.003 \)). This difference causes the predicted curves to be displaced to larger \( R_{ib} \). Note that we did not adjust any relation for wind or temperature gradient in terms of \( R_{ib} \) because there were more data. The difference between maximum and minimum predicted fluxes is smaller than the difference between observed flux and Louis81-predicted fluxes at almost all stations for all levels of stability. The relative difference between predicted fluxes diminishes with increasing stability. Overall, the empirical stability functions perform better for momentum than for heat. For \( R_{ib} > 2 \), all empirical relations underestimate the flux, as occurred for network-averaged momentum and heat fluxes when using sharp, Delage97, and Louis81 (Fig. 7). At intermediate stability \( \frac{1}{4} < R_{ib} < 2 \), results are practically identical, except at station 8 where the predicted fluxes overestimate. For weak stability \( \frac{1}{2} < R_{ib} \), the predicted fluxes are underestimates at stations 4, 5, and 7 and overestimates for the rest.

PB2003 showed that both Louis81 and Delage97 stability functions predict vanishing heat fluxes for \( R_{ib} > 2 \) and \( R_{ib} \geq 1 \), respectively. For momentum flux, PB2003...
found that Louis81 closely reproduced the observed values but that Delage97 underestimated them. For the range $0.1 < \text{Ri}_{\text{br}} \leq 1$, both methods overestimate the sensible heat flux. For $\text{Ri}_{\text{br}} < 0.5$, they overestimate the momentum flux. Our results agree with PB2003 that fluxes are underestimated under strongly stable conditions, but for weakly stable conditions we observed underestimates for some stations and overestimates for others. Therefore, adjusting stability functions to improve the flux prediction at a specific location does not necessarily improve the flux prediction at others.

When considering only nights with $\text{Ri}_{\text{br}} > 2$, the network-average momentum and heat fluxes are respectively $-0.012 \text{ kg m}^{-1} \text{s}^{-2}$ and $-4.32 \text{ W m}^{-2}$, but the contribution of local fluxes when the stability is found to be supercritical explains only 6% and 8% of the missing network momentum and heat fluxes, respectively. Therefore, improving the prediction of local flux will only slightly improve the prediction of regional fluxes, because most of the missing fluxes still come from the fact that spatial averaging of wind and temperature profiles eliminates the contribution of local stations at subcritical stability conditions that have outsized flux contributions to network averages. The spatial distribution of local stabilities in terms of the regional stability (Fig. 8) indicates that local stabilities span subcritical and supercritical values of $\text{Ri}_{\text{br}}$ range.

We conclude that there is an appreciable network-average flux when $\text{Ri}_{\text{br}} > \text{Ri}_{\text{cr}}$, justifying the usage of stability functions that allow mixing for $\text{Ri}_{\text{br}} > \frac{1}{4}$. Thus, observations demonstrate that the $\text{Ri}_{\text{cr}} = \frac{1}{4}$ cutoff for turbulence is not suitable for spatially averaged fluxes in heterogeneous terrain.

### b. Spatial distribution of fluxes

Spatial heterogeneity forces local stability (Fig. 8) and local fluxes (Fig. 9) to be heterogeneous across the landscape. Under the same background-flow conditions ($\text{Ri}_{\text{br}}$), different stations have different heat (Fig. 9) and momentum (result not shown) exchanges. There are preferential sites for occurrence of mixing, “hot spots” within a grid cell, as Mahrt (1987) hypothesized and AF2003 demonstrated with observations. Stations 5, 10, 4, and 6 dominate the regional nocturnal turbulent exchange. Each site has distinct characteristics (exposure, slope, surface concavity, and elevation), factors that influence local turbulence activity. Local mixing ceases when the local Richardson number $\text{Ri}_{\text{br}}$ becomes supercritical (Fig. 5). It is often the case that, at the dominant mixing stations, $\text{Ri}_{\text{br}}$ is subcritical nearly all night, whereas, at the ones that have lesser exchanges, $\text{Ri}_{\text{br}}$ is supercritical for much of the night. A real step to improve estimates of surface fluxes in grid cells with a heterogeneous sub-grid surface would be to identify the sites that maintain

### Table 1. Comparison between locally measured fluxes and fluxes predicted using Eqs. (4) and (8); $M_p =$ measured momentum flux, $M_p =$ predicted momentum flux, $M_{\text{max}} =$ maximum predicted momentum flux, $M_{\text{min}} =$ minimum predicted momentum flux, $H_p =$ measured heat flux, $H_p =$ predicted heat flux, $H_{\text{max}} =$ maximum predicted heat flux, and $H_{\text{min}} =$ minimum predicted heat flux.

<table>
<thead>
<tr>
<th>Range</th>
<th>Station</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$10^{-3} &lt; \text{Ri}_{\text{br}} \leq 1/4$</td>
<td>$100 \times \frac{1}{N} \sum_{i=1}^{N} [M_p(i) - M_m(i)]/\frac{1}{N} \sum_{i=1}^{N} M_m(i)$</td>
<td>28</td>
<td>7</td>
<td>53</td>
<td>-34</td>
<td>-30</td>
<td>-24</td>
<td>-67</td>
<td>146</td>
<td>84</td>
<td>63</td>
</tr>
<tr>
<td>$1/4 &lt; \text{Ri}_{\text{br}} \leq 2$</td>
<td>$100 \times \frac{1}{N} \sum_{i=1}^{N} [M_p(i) - M_m(i)]/\frac{1}{N} \sum_{i=1}^{N} M_m(i)$</td>
<td>-86</td>
<td>-24</td>
<td>-78</td>
<td>-73</td>
<td>-88</td>
<td>-92</td>
<td>-90</td>
<td>4</td>
<td>-126</td>
<td>-10</td>
</tr>
<tr>
<td>$2 &lt; \text{Ri}_{\text{br}}$</td>
<td>$100 \times \frac{1}{N} \sum_{i=1}^{N} [M_p(i) - M_m(i)]/\frac{1}{N} \sum_{i=1}^{N} M_m(i)$</td>
<td>-99</td>
<td>-213</td>
<td>-99</td>
<td>-99</td>
<td>-100</td>
<td>-100</td>
<td>-99</td>
<td>-112</td>
<td>-102</td>
<td>-6</td>
</tr>
</tbody>
</table>

| $10^{-3} < \text{Ri}_{\text{br}} \leq 1/4$ | $100 \times \frac{1}{N} \sum_{i=1}^{N} [H_p(i) - H_m(i)]/\frac{1}{N} \sum_{i=1}^{N} H_m(i)$ | 117 | 28 | 51 | -34 | -4 | 366 | -75 | 215 | 135 | 9 |
| $1/4 < \text{Ri}_{\text{br}} \leq 2$ | $100 \times \frac{1}{N} \sum_{i=1}^{N} [H_p(i) - H_m(i)]/\frac{1}{N} \sum_{i=1}^{N} H_m(i)$ | -69 | -80 | -85 | -80 | -49 | -132 | -90 | 8 | -156 | -18 |
| $2 < \text{Ri}_{\text{br}}$ | $100 \times \frac{1}{N} \sum_{i=1}^{N} [H_p(i) - H_m(i)]/\frac{1}{N} \sum_{i=1}^{N} H_m(i)$ | -99 | -99 | -100 | -99 | -102 | -99 | -99 | -104 | -98 | -1 |

| $10^{-3} < \text{Ri}_{\text{br}} \leq 1/4$ | $100 \times \frac{1}{N} \sum_{i=1}^{N} [H_p(i) - H_m(i)]/\frac{1}{N} \sum_{i=1}^{N} H_m(i)$ | -55 | -35 | -45 | -18 | -21 | -168 | -14 | -76 | -64 | -28 |
| $1/4 < \text{Ri}_{\text{br}} \leq 2$ | $100 \times \frac{1}{N} \sum_{i=1}^{N} [H_p(i) - H_m(i)]/\frac{1}{N} \sum_{i=1}^{N} H_m(i)$ | -66 | -45 | -32 | -42 | -99 | 66 | -20 | -266 | 123 | -153 |
| $2 < \text{Ri}_{\text{br}}$ | $100 \times \frac{1}{N} \sum_{i=1}^{N} [H_p(i) - H_m(i)]/\frac{1}{N} \sum_{i=1}^{N} H_m(i)$ | -4 | -5 | 2 | -6 | 13 | -4 | -3 | 23 | 10 | -10 |
Ribl and relate their local landscape characteristics to mixing. In Part II (Medeiros and Fitzjarrald 2013, manuscript submitted to J. Appl. Meteor. Climatol.), we address two questions: 1) What influence does each surface characteristic have on turbulence? and 2) Under what circumstances does one particular site dominate?

c. Turbulent fluxes and intermittency over the longer term

In this section we analyze data from the HVAMS LTOP, considering data from the single flux tower (station 10), five standard weather stations, and regular radiosonde observation from the Albany NWS Forecast Office. From the five weather stations, 1-min-average temperature, wind, and pressure data are used. Turbulence data from the flux tower cover a period of approximately 3 years; for the weather stations, a longer period of record is available but only two years were used so as to assure data overlap. [See section 2.1.3 of chapter 2 and appendix A.1 of Medeiros (2011) for more experimental-array details and operational periods.]

The longer-period LTOP record allows examination of background-flow influences on local turbulence. Again, we use Ribr to evaluate the background-flow state. In the ideal situation, we would need the same flux-station network used before to obtain the regionally average fluxes, but in the LTOP our only flux data are at station 10. Although we are fixed to one landscape type, we argue that having years of data leads to adequate natural variability in Ribr. The aim here is to develop a climatological description of the boundary layer structure on stable nights, determining conditions favorable for nocturnal mixing events at a site representative of a Hudson Valley clearing for a period of approximately 2 years.

1) VARIATIONS OF LOCAL TURBULENCE WITH MESOSCALE FLOW STATE

The technique used earlier (events section of section 3) was applied during the LTOP for station-10 data to identify the intermittent turbulent events and to obtain the nocturnal fluxes and the dependence of momentum and sensible heat fluxes on Ribr (Fig. 10). Both fluxes become more negative with decreasing Ribr, and for Ribr > Ricr there is still appreciable flux. The much longer data record reinforces results presented in section 6a. The small momentum flux for Ribr ≈ 0.5 (Fig. 10) seems anomalous. We
have no clear explanation for this behavior, but we speculate that it is a consequence of the bin averaging.

The number of events per night at station 10 is smallest under weakly stable flow ($R_{ibr} < R_{ibc}$), largest in the range $R_{icr} \leq R_{ibr} \leq 5$, and intermediate for $R_{ibr} > 5$ (Fig. 11). Here, in addition to the number of events per night, we also want to quantify the portion of the nighttime that is filled with turbulence. For such, we use an intermittency index $\zeta$, which varies between 0 and 1, defined as 1 minus the ratio of the sum of the duration of all intermittent events to the whole nighttime duration:

$$\zeta = 1 - \frac{\sum_{k=1}^{N} d_k}{\tau_N},$$

where $d_k$ is the duration of the $k$th turbulent event within a night, $N$ is the total number of events occurring during the night, and $\tau_N$ is the nocturnal duration. The higher the value of $\zeta$ is, the less the nocturnal period is turbulent (see right axis of Fig. 11). A value of $\zeta = 0$ indicates continuous nocturnal turbulence; $\zeta = 1$ denotes a completely quiescent night.

We define intermittency as the number of events per night. Kondo et al. (1978) defined intermittency by the ratio of time that the flow was considered to be turbulent over a 30-min period using a $\sigma_T$ threshold calculated over 30 s. This method can miss events when $\sigma_T$ is small because of weak vertical temperature gradients. In our approach we avoid this pitfall by using a measure related to turbulent activity ($w^2$). In general, the Kondo et al. (1978) event durations ($<30\text{ min}$) were smaller than those found in the work presented here.

In the range $R_{ibr} \approx R_{icr}$ approximately 80% of the nighttime is turbulent; for $R_{ibr} > 5$ only 60% of the nighttime is turbulent. This result agrees with that of
Doran (2004) who, using a local $Ri_b$, showed that the fraction of time with turbulence within a 1-h period increases with decreasing stability. Combining this information with the number of events per night shows that the turbulence is more continuous at low $Ri_b$ than at high $Ri_b$, indicating that in the $Ri_b < Ri_{cr}$ regime turbulence tends to be strong (higher fluxes) and continuous during a few long-duration events (1.7 events per night), whereas for $Ri_{cr} < Ri_b < 5$ intermittent turbulence with several turbulence breakdowns (2.6 events per night) is characteristic. For $Ri_b > 5$, there is also intermittent turbulence but fewer, short-lived events (2.1 events per night) were observed. At this extreme the fluxes are weak.

2) COMPARISON BETWEEN REGIONAL AND LOCAL $Ri_b$ OBTAINED DURING IOP AND LTOP

In Fig. 12 we present the distributions of regional and local Richardson numbers for the IOP and LTOP. Although there are many more nights during the LTOP than in the IOP, most of the cases in both LTOP (Fig. 12b) and IOP (Fig. 12a) lay in the range $0.1 < Ri_b < 100$. Results from the LTOP show a wider distribution that includes very weakly and very strongly stable cases. There is good agreement between the results found in both periods, however. To be specific, there is significant turbulence for $Ri_b > Ri_{cr}$ (Figs. 7 and 10). The distribution for the IOP appears to be bimodal, but we believe it is an artifact of the small sample (33 cases). Future work that examines more nocturnal cases will help us to determine whether it eventually approaches a normal distribution.

Depending on the stability of the background flow ($Ri_{br}$), different landscape types lead to local flows that respond differently to the regional stability (Fig. 8). If there were no spatial inhomogeneities, changes in the local flow would mirror those of the background. If the background flow were fixed over a heterogeneous landscape, any spatial difference may be uniquely related to spatial landscape variation. The long-term record focuses attention primarily on changes in the background flow (Figs. 10, 11). During the IOP, there were changes in the background flow (Fig. 7) as well, but our analysis focused on differences in landscape texture near individual stations (Fig. 9). In comparing Fig. 12a with Fig. 12d, it is clear that the range of variability of both regional $Ri_b (Ri_{br})$ and local $Ri_b (Ri_{bl})$ is similar. Note that because $Ri_{br}$ and $Ri_{bl}$ were obtained in a different manner ($Ri_{br}$...
used the bulk $\Delta \theta$, $\Delta U$, and $h$, whereas $Ri_B$ used the local temperature and wind profiles with a much smaller fixed height), the $Ri_B$ distribution is biased toward larger values of $Ri_B$. In comparing Fig. 12c with Fig. 12d, we note that local-flow states found at a single station under the influences of a wide range of background-flow states are not as diverse in terms of stability as those found over 10 different IOP stations under the influence of a narrower range of background-flow states. Thus, under a wide range of background-flow conditions local landscape can limit the range of local-flow stabilities achievable at a station. Overall, we conclude that what was observed temporally in terms of regional-flow state in approximately 2 years is comparable to what is observed spatially with robust sampling in terms of local flow in just 1.5 months.

7. Summary

The background flow, controlled by the horizontal mesoscale pressure gradient and regional cloud cover, forces nocturnal surface-layer turbulence. In regional average, we find that there is no critical $Ri_B$ to serve as a sharp turbulence cutoff. We demonstrated that mixing during regionally supercritical conditions is an observational consequence of spatial averaging, reflecting the influence of a few “not-so-cold spots” (e.g., stations 4, 5, 6, and 10) of mixing (AF2003). These few stations characterize sites that dominate regional momentum and heat transfers. Although turbulence does not vanish for any value of $Ri_B$, it decreases with increasing $Ri_B$. Even for conditions with no average mesoscale pressure gradient, turbulence can still be generated locally by drainage flows or other small-scale circulations induced by slope or land-cover contrasts. Our detailed observational study is consistent with Mahrt (1987), who opined that spatial heterogeneity leads the local $Ri_B$ to differ from the $Ri_B$ determined from the area-averaged wind and temperature profiles (Fig. 8). The area-averaged $Ri_B$ tended to be smaller than the profile-averaged $Ri_B$, causing the fluxes in models that use the latter approach to be underestimated; extra mixing has to be allowed in the models. Mahrt’s work, however, was based on a hypothetical distribution of $Ri_B$ within a grid-size model, whereas the current results are based on observed
spatial-averaged network fluxes, local observed Ri_{br}, and regionally determined Ri_{br}; this latter value is based on properties of the bulk SBL.

The so-called sharp and Delage97 stability functions have similar performance for predicting network-average fluxes. For momentum, the inferred values only approached observations for weak stability (Ri_{br} < \frac{1}{4}), otherwise underestimating. For heat, they approached observations when Ri_{br} < 1, otherwise underestimating. The Louis81 function performed similarly for momentum and heat, overestimating when Ri_{br} < 1 and underestimating when Ri_{br} > 2. Its predicted fluxes approached the observed flux only in the range 1 < Ri_{br} < 2. For the so-called long function, the situation was similar for momentum but different for heat. Its predicted heat flux approached the observed for very stable conditions (Ri_{br} > 3), elsewhere overestimating. We conclude that long and Louis81 are better for momentum; for heat, sharp and Delage97 are better for weak stability and long is better for strong stability.

We showed that local mixing (as a function of the momentum and sensible heat fluxes, the number of intermittent events, and the intermittency index) responds to the mesoscale background flow. The local landscape imposes limits on the range of stability observed at a single site, however. During the long-term observational period, when a more diverse set of background-flow conditions was encountered, the range of local-flow stabilities at station 10 was not as diverse as was found locally across the network of flux stations during IOP.

Another interesting result is how intermittency responds to the background-flow stability. The nighttime filled with turbulence, quantified by the intermittency index, decreases with increasing Ri_{br}, but the number of intermittent events per night shows a more complex behavior. It increases first in the range 0 \leq Ri_{br} \leq 2 and decreases thereafter, reflecting effects of strong stability. When the intermittency index is combined with number of events, it shows that turbulence tends to be more continuous at low Ri_{br} (Ri_{br} \leq \frac{1}{4}), with few intermittent events that may last more than one-half of the night. At high Ri_{br}, turbulence is more intermittent, with a high number of intermittent events that last much less than one-half of a nighttime period.

These results provide observational support for the necessity of mixing at high Ri_{br}, first introduced pragmatically by modelers. For future work, a denser network of stations covering a wider range of landscapes, and deeper vertical wind and temperature profiles taken at different locations, would provide a better estimate of

**Fig. 12. Probability distributions of (top) Ri_{br} and (bottom) Ri_{bl} in the (a),(c) LTOP and (b),(d) IOP.**
Ri_{\text{sg}}. In Part II (Medeiros and Fitzjarrald 2013, manuscript submitted to *J. Appl. Meteor. Climatol*), we examine how site sheltering and topographic shape influence nocturnal mixing processes.

**Acknowledgments.** Author L. E. Medeiros acknowledges financial support from the Brazilian agency Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) under Grant 2152045 and the Fulbright Institute of International Education (IIE) under Grant 15053195 during the first four years of graduate studies at University at Albany, State University of New York (SUNYA). HVAMS was supported by NSF Grant ATM0313718 (coprincipal investigators D. R. Fitzjarrald and J. M. Freedman) during 2003–06. Work since that time by Fitzjarrald has been supported by the SUNYA Atmospheric Sciences Research Center. Special thanks are given to Jessica Neiles, project assistant during the intensive field phase, and SUNYA undergraduate students at the time Kim Sutkevich, Jason Herb, and Aaron Feinberg who also assisted during the field operations. We thank the teams from University of Wyoming, (especially Larry Oolman and pilot Tom Drew), the University of Alabama in Huntsville MIPS team, and the NCAR Atmospheric Technology Division team (Steve Oncley, Kurt Knudson, Tony Delany, and Tom Horst). Of particular relevance to this paper and its companion, we single out Tom Horst’s recommendation that we apply to use all nine ISFS flux stations. We needed that insight.

**REFERENCES**


