Measurements of Boundary Layer Profiles with In Situ Sensors and Doppler Lidar

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ABSTRACT

A new in situ measurement system and lidar processing algorithms were developed for improved measurements of boundary layer profiles. The first comparisons of simultaneous Doppler lidar–derived profiles of the key turbulence statistics of the two orthogonal horizontal velocity components (longitudinal and transverse) are presented. The instrument requirements for accurate observations of stably stratified turbulence were determined. A region of stably stratified low turbulence with constant gradients of temperature and velocity was observed above the nocturnal boundary layer using high-rate sensors. The important turbulence parameters were estimated, and turbulence spectra were consistent with new theoretical descriptions of stratified turbulence. The impact of removing the larger-scale velocity features in Doppler lidar estimates of turbulent velocity variance and length scales was investigated. The Doppler lidar–derived estimates of energy dissipation rate $\epsilon$ were found to be insensitive to spatial filtering of the large-scale atmospheric processes. The in situ and lidar-derived profiles were compared for the stable boundary layer in a suburban environment.

1. Introduction

Measuring and modeling of the boundary layer is challenging, especially for the nighttime stable boundary layer (SBL). In particular, high-quality in situ measurements of profiles of mean and turbulent statistics of the nighttime SBL are logistically difficult using instrumented towers or instrumented research aircraft (Tjernström 1993). A suite of fast response turbulence sensors attached to a tethered system can operate effectively under these nighttime conditions. The Tethered Lifting System (TLS) was developed for the 1999 Cooperative Atmosphere–Surface Exchange Study (CASES-99) field campaign (Poulos et al. 2002) by the Cooperative Institute for Research in Environmental Sciences (CIRES) at the University of Colorado (Balsley et al. 1998, 2003, 2006) and modified for measurements in the open spaces of the Washington, D.C., area (Frehlich et al. 2006) to provide high-resolution in situ profiles of the SBL.

High-resolution in situ measurements are able to resolve unusual features in the temperature, velocity, and turbulence structure of the boundary layer, the residual layer, and the free atmosphere. An ideal example is given in Fig. 8 of Frehlich et al. (2006), where the height of a well-defined mixing layer coincides with a small layer of cooler air, which could only be resolved with the TLS in situ sensors. The high-resolution velocity and temperature data provide unique measurements of the turbulent structure of stable regions, which are difficult to mimic in the laboratory, especially the low-turbulence regions above the SBL. This offers a unique opportunity to verify new turbulent scaling laws for stably stratified flows (Smyth and Moum 2000a,b; Werne and Fritts 1999, 2001; Riley and de Bruyn Kops 2003; Lindborg 2006). TLS measurements of a stably stratified boundary layer are presented and compared with the new theoretical predictions. Critical instrumentation issues are identified for accurate measurements of small-scale turbulence in these low-turbulence regimes.

layer. For solid-state lidars, the lidar pulse is well approximated by a Gaussian shape and the critical parameters can be determined from the monitor pulse (Frehlich et al. 1994), and the effects of the spatial filtering of the radial velocity by the pulse can then be corrected (Banakh and Smalikho 1997; Frehlich 1997; Frehlich et al. 1998, 2006; Davies et al. 2004; Smalikho et al. 2005) to produce reliable estimates of turbulent statistics. This correction is possible when the lidar pulse parameters are stable and when the mean Doppler radial velocity estimates are given by a convolution of the instantaneous radial velocity with an effective pulse range–weighting function (Banakh and Smalikho 1997; Frehlich 1997). Accurate corrections for the pulse smoothing from other Doppler lidar systems, such as CO₂ Doppler lidars, would be possible if these conditions are met (see Post and Cupp 1990; Pearson and Rye 1992). In some cases, such as measurements in the convective boundary layer (Lothon et al. 2006), the effects of the spatial smoothing can be ignored if the range gate is smaller than the length scale of the turbulence. Measurements of hazardous turbulence conditions around airports are also feasible with careful processing of the lidar data (Chan 2006). However, for low-turbulence conditions, especially the stable boundary layer, careful corrections for the pulse smoothing and the radial velocity estimation error is required for accurate turbulence estimates (Frehlich and Cormann 2002; Frehlich et al. 2006). In addition, the statistical accuracy of the estimates is improved by scanning over a three-dimensional volume with well-chosen scanning geometries. Recent interest in the effects of atmospheric turbulence on wind energy generation requires more reliable measurements of turbulence profiles in the SBL (Fritts 2005; Banta et al. 2006; Kelley et al. 2006). Recently, profiles of turbulence for the transverse velocity component have been developed based on the variations of the radial velocity as a function of the arc distance along an azimuth scan (Frehlich et al. 2006). A new lidar processing algorithm is presented for profiles of the turbulence statistics of the longitudinal velocity component (radial velocity component in the radial direction), which provides simultaneous profiles of the key turbulence statistics of two orthogonal horizontal components over a three-dimensional volume with vertical resolution sufficient for stable boundary layer studies.

High spatial and temporal resolution TLS measurements of the small-scale turbulence statistics have also determined the spatial intermittency in the SBL, which is the essence of Kolmogorov’s refined similarity theory (Kolmogorov 1962) and also provides the required input for rigorous error analysis (i.e., the statistical accuracy of turbulent estimates that are one source of self-correlation in many formulations of similarity theory such as Monin–Obukhov similarity theory; Klipp and Mahrt 2004; Baas et al. 2006). In addition, the separation of the atmospheric variables into a turbulent component and a mean or slowly variable component can be ill posed, especially for statistics such as variances and fluxes for challenging conditions such as stable boundary layers (Kaimal and Finnigan 1994; Mahrt 1998; Vickers and Mahrt 2003) and larger-scale forcing such as with a density current and a frontal passage (Piper and Lundquist 2004). The standard analysis technique for these situations is selecting a suitable averaging interval to define the mean and turbulent quantities for both in situ observations (Kaimal and Finnigan 1994; Mahrt 1998; Vickers and Mahrt 2003) and remotely sensed measurements such as Doppler lidar (Banta et al. 2003, 2006). The optimal choice of the averaging time is difficult to quantify when there is no obvious scale separation between the forcing mechanisms and turbulence. The effects of the larger mesoscale forcing on convective boundary layer turbulence has been identified from the Boreas campaign where no well-defined length scale was observed in the spatial spectra and hence there is no clear separation between small-scale turbulence and large-scale forcing (Lenschow and Sun 2007).

Mesoscale models use parameterizations of the boundary layer that are challenging for the SBL (Roth 2000; Zilitinkevich and Baklanov 2002; Sorbjan 2006; Esau and Zilitinkevich 2006; Mauritsen and Svensson 2007; Zilitinkevich et al. 2007). Large-eddy simulations (LESs) are being used to investigate NWP model parameterization in neutral and stably stratified flows (Esau and Zilitinkevich 2006); however, the numerical requirements for stable boundary layers are challenging (Saiki et al. 2000; Sullivan et al. 2003). Better measurements of the SBL is required to advance the LES and NWP modeling effort, especially a consistent measurement and definition of boundary layer height (Roth 2000; Seibert et al. 2000; Zilitinkevich and Baklanov 2002; Balsley et al. 2006; Zilitinkevich et al. 2007).

Advanced data assimilation techniques are based on statistics of total observation error, which include the observation sampling error or “error of representativeness” resulting from the mismatch of the observation spatial average and the effective model spatial average (Frehlich 2001b, 2006; Frehlich and Sharman 2004). Improvements in next-generation models and data assimilation will require observations that more closely match the spatial average of the models and observations that provide estimates of the turbulence statistics that define the observation sampling error. New Doppl-
ler lidar scanning and processing algorithms were employed in Washington, D.C., to extract such spatially averaged mean and turbulence profiles of velocity (Frehlich et al. 2006). These results are extended to provide a more complete description of the boundary layer velocity statistics.

To address these diverse issues of atmospheric measurements, the paper is structured as follows: in section 2, we present an analysis of the instrumental requirements for accurate in situ measurements of stably stratified turbulence and comparisons of recent results to theoretical predictions; section 3 discusses a new Doppler lidar analysis technique for producing higher vertical resolution estimates of the radial velocity statistics; and section 4 focuses on the first simultaneous comparisons of Doppler lidar derived profiles of the three key turbulence statistics (i.e., energy dissipation rate $\epsilon$, velocity variance $\sigma^2$, and outer scale of turbulence $L_o$) for the two horizontal velocity components (longitudinal and transverse) and the key instrumental and data processing issues for these measurements such as the impact of spatially filtering the radial velocity estimates to remove large-scale atmospheric processes. The paper concludes with a summary and discussion.

2. In situ TLS measurements

The TLS was developed for a variety of atmospheric measurements with a focus on measurements of the small-scale turbulence (Balsley et al. 1998, 2003, 2006; Muschinski et al. 2001). Temperature measurements are produced with a new low-frequency response solid-state temperature sensor and a high-frequency response fine cold-wire sensor. Low-frequency velocity measurements are made using a new two-axis sonic anemometer vaned into the wind and a high-frequency response fine hot-wire sensor. The temperature is calibrated to an absolute accuracy of better than 0.5 $K$ and the accuracy of the linear calibration constant was better than 2%. The velocity is calibrated to an absolute accuracy of better than 0.5 m s$^{-1}$ and the accuracy of the slope of the calibration curve is better than 5% (Frehlich et al. 2003).

Small-scale turbulence statistics can be estimated from the temporal spectrum of along-stream velocity (i.e., the longitudinal component) and temperature assuming that Taylor’s frozen flow hypothesis is valid (Taylor 1938; Wyngaard and Clifford 1977; Hill 1996) and assuming that the small-scale turbulence is locally homogeneous and isotropic (Frehlich et al. 2003). Then, the spatial spectrum of longitudinal velocity $E_l(k)$ at high wavenumber $k$ can be written as (Monin and Yaglom 1975, p. 354)

$$E_l(k) = \nu^{5/4} \epsilon^{1/4} \phi_l(k, \eta) = C_2 \epsilon 2^{3/5} k^{-5/3} g(\beta \eta^2 k^2),$$

where $\nu$ is the kinematic viscosity, $\epsilon$ is the energy dissipation rate,

$$\eta = \nu^{3/4} \epsilon^{1/4}$$

is the Kolmogorov microscale, $C_2$ is the Kolmogorov constant, and the universal function is $\phi_l(x) = C_3 x^{-5/2} g(\beta x^2)$ (see Frehlich et al. 2003; Azizyan et al. 1989), and

$$g(x) = (1 + x) \exp(-x) - \frac{11}{6} x^{5/6} \left(1 + \frac{6}{11} x\right) \Gamma(1/6, x),$$

where

$$\Gamma(a, x) = \int_x^\infty t^{a-1} \exp(-t) \, dt$$

is the incomplete gamma function. The constant $\beta = 2.955$ 18 is based on the required normalization for the Kolmogorov constant $C_2 = 0.4977$. The velocity spectrum $E_l(k)$ is only a function of the energy dissipation rate $\epsilon$ and the kinematic viscosity of air $\nu$. This result relies on the universal scaling of high Reynolds number turbulence.

A direct estimate of $\epsilon$ for homogeneous and isotropic turbulence is (Monin and Yaglom 1975, p. 56)

$$\epsilon = 15 \nu \int_0^{\infty} k^2 E_l(k) \, dk,$$

which indicates that turbulent energy is dissipated by viscous forces at the high-wavenumber region (small spatial scales). We define the function $P(k)$ as

$$P(y) = \frac{15 \nu}{\epsilon} \int_0^{y^\eta} x^2 E_l(x) \, dx,$$

which defines the fraction of the energy dissipation rate produced from wavenumber less than $k = y/\eta$. The functions $g(\beta \eta^2 k^2)$ and $P(\eta k)$ are shown in Fig. 1. The median wavenumber for energy dissipation rate is $k \approx 0.2/\eta$ and the 10% wavenumber $k_{10}$ (10% on the energy dissipation rate is produced from wavenumber less than $k_{10}$ is $k_{10} \approx 0.05/\eta$. Since $\eta \approx 0.005$ m, $k_{10} \approx 10$ m$^{-1}$, and the small scales define the energy dissipation rate and therefore high-resolution, in situ measurements are required to resolve these scales for a direct estimate of $\epsilon$.

The small-scale spatial spectrum of the along-stream temperature fluctuations can be written as

$$E_T(k) = 0.073 \, 084 \, 6 C_7^2 k^{-5/3} h(l_o k),$$

where
where $C_T^2$ is the temperature structure constant;

$$l_0 = 5.797 \times 84 \chi^{3/4} \epsilon^{1/4}$$

(8)

is the temperature inner scale; $\chi$ is the thermal diffusivity of air; and

$$h(x) = (1 + 2.07x + 0.23567x^2) \exp(-x)$$

$$+ 0.006 888 89x^{5/3} \Gamma(1/3, x)$$

(9)

describes the Hill bump (Hill 1978). This result also relies on the universal scaling of high Reynolds number turbulence.

The temporal spectra are written in terms of the spatial spectra using the mean velocity $U$ to scale temporal frequency $f$ to spatial frequency $k$ (i.e., $k = 2\pi f/U$; Frehlich et al. 2003). Then,

$$S_T(f) = \frac{2\pi}{U} E_T(2\pi f/U) \quad \text{and}$$

$$S_u(f) = \frac{2\pi}{U} E_u(2\pi f/U).$$

(10)

(11)

The best spectral estimate of $\epsilon$ and $C_T^2$ are produced using the maximum likelihood algorithm with the temporal spectra $S_u(f)$ and $S_T(f)$, respectively, assuming Taylor’s frozen hypothesis is valid (Frehlich et al. 2003).

The TLS can be either operated at a constant altitude or in profiling mode by slowly ascending and descending at a rate of approximately 0.5–1.0 m s$^{-1}$, which provides similar resolution to the moving carriage of the Boulder Atmospheric Observatory (BAO) tower (Gossard and Frisch 1987). To better evaluate the high-wavenumber region of the temperature and velocity spectrum for low-turbulence conditions in stable regions, the hot-wire and cold-wire electronics and data acquisition system were modified and the sampling rate increased to 1 kHz to produce direct estimates of small-scale turbulence statistics such as $\epsilon$ in Eq. (5).

An example of along-stream velocity data $U(t)$ from a low-turbulence region above the stable boundary layer (see Fig. 7, region A from 148- to 168-m altitude) is shown in Fig. 2 as well as the corresponding spectra and theoretical best-fit model with $\epsilon = 1.03 \times 10^{-5}$ m$^2$ s$^{-3}$ using Eqs. (11) and (1) with only the good spectral data away from the obvious interference peaks. The error in the estimates of $\epsilon$ is approximately 10% based on the $\chi^2$ statistics of the useful spectral estimates in the frequency interval of 0.2–220 Hz. Note that a direct estimate of $\epsilon$ using Eq. (5) is not possible because of the interference, however, there is good agreement at the high frequencies above the interference indicating a direct measurement is possible with improved sensors. Also shown in Fig. 2 is the best-fit straight line and the $\pm 10\%$ deviation in the slope about the best fit to indicate a measure of the statistical accuracy of the gradient.
Fig. 3. The high-rate potential temperature $\Theta(t)$ vs time and the average temperature spectrum $S_f(f)$ for the low-turbulence region above the stable boundary layer (see Figs. 2 and 7). The best-fit spectral model in Eq. (10) plus sensor noise is shown as a dashed line. The best-fit potential temperature gradient and the ±10% deviation are shown as solid and dashed lines, respectively. The $f_{OZ}$ is also indicated.

$S = (\partial U/\partial z) = -0.0157 \text{ s}^{-1}$, where the altitude $z$ is determined from a GPS sensor. The descend rate is 0.833 m s$^{-1}$ and therefore the vertical and horizontal measurement region is 20 and 220 m, respectively. There is an obvious wave with a small amplitude of approximately 0.1 m s$^{-1}$ and the standard deviation of the velocity about the best-fit line is $\sigma_u = 0.051 \text{ m s}^{-1}$ and the length scale of the velocity fluctuations is defined (e.g., Monin and Yaglom 1975, p. 198) as $L_u = \sigma_u^2/\epsilon \approx 12.8 \text{ m}$.

The calibrated temperature $T$ is converted to potential temperature by

$$\Theta = (T + 273.15)(P_o/P)^{0.285 \cdot 714},$$

(12)

where $T$ is temperature in C, $P_o$ is the reference pressure at the surface, and $P$ is the pressure at the measurement height. An example of potential temperature data from the same low-turbulence region as in Fig. 2 is shown in Fig. 3 as well as the corresponding spectra and theoretical best-fit model with $C_T^2 = 8.13 \times 10^{-6} \text{ K}^2 \text{ m}^{-2/3}$. The gradient of potential temperature is $\partial \Theta/\partial z = 0.0073 \text{ K m}^{-1}$ and is clearly bounded by the ±10% deviations around the best-fit line. Detector noise and interference from the nearby sonic anemometer (vibrational noise induced in the high gain electronics) dominates the high-frequency region of the spectrum. The best-fit model includes the 1/f noise from the sensor, which appears at frequencies above 30 Hz. For this example, there is sufficient uncontaminated spectral power at lower frequencies to extract an accurate estimate of $C_T^2$ with an error of approximately 10% based on the $\chi^2$ statistics of the spectral estimates in the frequency interval of 0.2–30 Hz. Other physical parameters are $\nu = 2.606 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$, $\eta = 0.0064 \text{ m}$, $U = 9.15 \text{ m s}^{-1}$, and the average temperature is $T = 26.4 \text{ C}$.

The high-rate turbulence measurements are essential for investigating the turbulence parameters predicted by direct numerical simulations (DNS) of stably stratified turbulence (Werne and Fritts 1999, 2001; Gibbon-Wilde et al. 2000; Riley and de Bruyn Kops 2003; Herbert and de Bruyn Kops 2006) with a constant potential temperature gradient and constant velocity gradient. The critical parameter regime is defined by the Brunt–Väisälä frequency $N = (g/\Theta)(\partial \Theta/\partial z)^{1/2} = 0.0151 \text{ s}^{-1}$, the Ozmidov scale $L_{OZ} = (\epsilon N^2)^{1/2} = 1.73 \text{ m}$, the Ozmidov frequency corresponding to $L_{OZ}$ (i.e., $f_{OZ} = U/L_{OZ} = 5.26 \text{ Hz}$), the gradient Richardson number $R_g = N^2/S^2 = 0.92$, the buoyancy Reynolds number $R_b = \epsilon/(\nu N^2) = 1747$, the Reynolds number $R_e = \sigma_u L_u/\nu = 24963$, and the local Froude number $F_h = \sigma_u/(NL_u) = 0.26$. Since the buoyancy Reynolds number $R_b$ is larger than 1000, the calculations of energy dissipation rate $\epsilon$ from the velocity spectrum assuming isotropy of the small scales is valid (Smyth and Moum 2000b).

The recent theories of stably stratified turbulence in low Froude number ($F_h < 1$) predict a −5/3 spectral slope for frequencies less than the Ozmidov frequency (Riley and de Bruyn Kops 2003; Lindborg 2006). This is clearly shown in Figs. 2 and 3 for both the velocity and the temperature field. Since the sensor moves a vertical distance of approximately 0.9 m for a horizontal sampling distance of 10 m, there is little contribution from the fluctuations in the vertical direction since the vertical turbulence length scale is approximately $L_u = L_n F_h = 3.4 \text{ m}$ (Lindborg 2006). Also note that the Richardson number of approximately 1 supports the recent interpretation of the Richardson number in stratified flows (Majda and Shefter 1998). These turbulence structures are most likely the manifestation of the decay phase of some earlier larger-scale instability (e.g., a Kelvin–Helmholtz instability). Identifying the exact nature of the instability is not feasible with the limited data.

There are several formulations for expressing the energy dissipation rate $\epsilon$ in terms of $C_T^2$ for well-defined
turbulent layers in the steady state, especially in the radar literature (Gossard and Frisch 1987; Bertin et al. 1997):

$$\varepsilon = \left[ \gamma N^2 C_T^2 / (d\Theta/dz)^2 \right]^{3/2},$$

where $\gamma$ varies from approximately 0.8 to 2. The estimates of $\varepsilon$ based on the measurements in Figs. 3 and 4 for this range of $\gamma$ vary from $1.46 \times 10^{-7}$ to $5.76 \times 10^{-7}$ m$^2$ s$^{-3}$, which is inconsistent with the measured value of $\varepsilon = 1.26 \times 10^{-5}$ m$^2$ s$^{-3}$. This turbulent regime is known to have large scatter in predictions of $\varepsilon$ from $C_T^2$ and local gradients (Bertin et al. 1997).

3. Doppler lidar measurements

The Doppler lidar used in this study is a 2-$\mu$m eye-safe WindTracer lidar manufactured by Coherent Technologies, Inc. (CTI; Henderson et al. 1991, 1993). The lidar parameters are a Gaussian pulse width $\Delta T = 66.0$ m (full width at half maximum), a range-gate length $\Delta p = 72.0$ m, the effective range resolution $\Delta R = 85.8$ m (Banakh and Smalikho 1997), an azimuth scan rate of $2.5^\circ$ s$^{-1}$, a pulse repetition frequency (PRF) of 500 Hz, a measurement time per radial velocity profile $T = 0.2$ s using 100 lidar pulses per profile, and the azimuth spacing $\Delta \phi = 0.5^\circ$. The scanning geometry is similar to the operations at Washington, D.C. (Frehlich et al. 2006) and a top view is shown in Fig. 4 along with the local buildings and the location of the TLS in the open space between the residential buildings in Lafayette, Colorado. The azimuth angle $\phi$ varied from 40$^\circ$ to 85$^\circ$ to focus on the open space. The elevation angle varied from $-0.8^\circ$ to $24^\circ$ to provide useful profiles in both nighttime and daytime conditions (see also Frehlich et al. 2006). The lidar was approximately 20 m above the flat open space region. Range-gate distances from 420 to 2508 m were used for all the lidar analysis and the average transverse dimensions of the lidar sensing volume for each radial velocity estimate is $\Delta h \approx 1464 \sin 0.5^\circ = 12.8$ m, which is much less than the effective range resolution $\Delta R = 85.8$ m and the assumption of zero $\Delta h$ is valid (Frehlich and Cornman 2002).

The field campaign covered a 1-week period from 7 to 13 June 2006 and TLS data was only collected from 2300 to 0600 LT because of Federal Aviation Administration (FAA) restrictions. High daytime temperatures existed for most of this period and therefore all the nighttime data was statically stable because of radiative cooling.

Profiles of wind speed and direction are produced by a best fit to the radial velocity as a function of azimuth angle for a given fixed elevation angle and range-gate distance and combining all the estimates occupying a height interval of dimensions of 10 m (Browning and Wexler 1968; Frehlich et al. 2006). The turbulence component of the radial velocity is defined as the deviations of the radial velocity from the best-fit model for each range gate (see Fig. 3 of Frehlich et al. 2006). To investigate the effects of filtering the data to remove the
large-scale processes, the turbulent velocity fluctuations are produced by subtracting a polynomial fit of order \( M \) as a function of azimuth for each range gate.

Unbiased estimates of the turbulence statistics of the velocity field can be produced from structure functions of the Doppler lidar radial velocities if 1) a universal description of the structure functions are known a priori (e.g., a von Kármán model), 2) the effects of the spatial averaging by the finite extent of the lidar pulse and processing algorithms are included in the analysis, and 3) the contribution from the estimation error in the radial velocities is removed, which is essential for the low-turbulence regimes (Frehlich and Cornman 2002; Frehlich et al. 2006). Two versions of the structure function method will be employed: the structure functions with the separation variable \( s \) along range (i.e., longitudinal velocity statistics) and with the separation variable \( s \) based on the azimuth angle separation (i.e., transverse velocity statistics). Both processing techniques correct for the effects of the spatial averaging by the lidar pulse using standard deconvolution algorithms (Banakh and Smalikho 1997; Frehlich et al. 1998, 2006; Frehlich and Cornman 2002; Smalikho et al. 2005).

The azimuth structure function technique provides turbulence profiles with a vertical resolution of (Frehlich et al. 2006)

\[
\Delta z_{\text{turb}} = \Delta R \sin \theta,
\]

where \( \Delta R \) is the effective range resolution of the radial velocity estimates and \( \theta \) is the lidar elevation angle. Profiles of the transverse turbulent statistics are produced by processing all the data within a given altitude bin. An example of the average azimuth structure function, the corrected structure function, the best-fit von Kármán model, and the best-fit lidar structure function model is shown in Fig. 5 from the time period 0523–0540 UTC 7 June 2006 for raw data (no spatial filtering) and a fourth-order polynomial filter (\( M = 4 \)). Range gates with an altitude inside the 80–90-m height interval were processed for elevation angles up to 6°. Therefore, the largest vertical resolution is \( \Delta z_{\text{turb}} = 15 \) m. The average correction to the structure functions from the radial velocity estimation error is \( 2 \sigma^2 = 0.004 \) \( \text{m}^2 \text{s}^{-2} \) and therefore \( \sigma_{\epsilon} = 0.0449 \) \( \text{m} \text{s}^{-1} \) is the average estimation error determined with the covariance technique (Frehlich 2001a; Frehlich et al. 2006) applied to the azimuth structure function for each range gate. The raw data (no filtering) indicates a large turbulent length scale of \( L_{00} = 748 \) m and the filtered data has a much lower length scale and lower standard deviation of \( \sigma_{\epsilon} \). However, the estimates of \( \epsilon \), the energy dissipation rate that defines the small-scale turbulence, are independent of the filtering. Similar results were produced for filter order from 1 to 4.

Lidar-derived profiles of the turbulent statistics (i.e., \( \sigma_{\epsilon}, \epsilon_{\text{turb}}, \) and \( L_{00} \)) for the radial velocity (i.e., longitudinal component) have been produced for a fixed lidar beam using the time-averaged radial velocity to define the mean and turbulent components (Frehlich et al. 1998). These profiles have a poor vertical resolution of \( \approx 200 \) m, which is suitable for convective boundary layer studies but not for stable boundary layers research. The longitudinal and transverse turbulence parameters were estimated simultaneously using data from a zero elevation angle azimuth scan and using the definition of turbulence as the fluctuation about the best-fit model (Frehlich et al. 2006, their Fig. 4). Since the domain was statistically homogeneous, large lags in the radial direction were possible and isotropic statistics were observed. These results will now be extended to produce simultaneous profiles of the longitudinal and transverse turbulence parameters.

The vertical resolution of the lidar-derived estimates of longitudinal velocity statistics is (Frehlich et al. 2006)

\[
\Delta z_{\text{turb}} = (R_{\text{max}} - R_{\text{min}} + \Delta R) \sin \theta,
\]

where \( R_{\text{min}} \) and \( R_{\text{max}} \) are the minimum and maximum range-gate distances, respectively, for the given altitude region. To improve the vertical resolution for SBL measurements, the elevation angle, the number of
range gates \((R_{\text{max}} - R_{\text{min}})\) and the range-resolution \(\Delta R\) for a given altitude region must be made as small as possible. Therefore, for new lidar-derived profiles of the longitudinal velocity statistics, we restrict the analysis domain to elevation angles from 0° to 4° and select \(R_{\text{max}} - R_{\text{min}} = 360\) m for a maximum vertical resolution of \(\Delta z_{\text{turb}} \approx 30\) m. An example of the radial or longitudinal velocity structure functions \(D_{u}(s)\), the corrected structure functions, the best-fit von Kármán model, and the best-fit lidar structure function model for the same altitude and range region as in Fig. 5 is shown in Fig. 6. The correction for the estimation error of the radial velocity is based on the temporal covariance of the velocity differences between range-gate pairs (Frehlich and Cornman 2002) and \(\sigma_{c} \approx 0.047\) m s\(^{-1}\). The longitudinal turbulence parameters are approximately equal to the transverse parameters of Fig. 5, indicating approximately isotropic horizontal velocity statistics. The estimate of \(\epsilon_u = 1.32 \times 10^{-5}\) m\(^2\) s\(^{-3}\) for the spatially filtered data is noticeably lower than the estimate \(\epsilon_u = 1.72 \times 10^{-5}\) m\(^2\) s\(^{-3}\) from the raw data indicating more sensitivity to the large-scale features than the azimuth technique. However, the spatially filtered estimates are in good agreement for both techniques, which may provide more accurate information on isotropy, especially for \(\epsilon\). A shorter pulse length and shorter processing range gate is required to resolve the turbulent structures. However, since the estimation error is inversely proportional to the pulse width, the correction for the estimation error then becomes more difficult in the low-turbulence regions because a larger fraction of the structure functions at small spacings is produced from the estimation error contribution (see Fig. 5 in the current paper and Frehlich and Cornman 2002).

4. Measurements of atmospheric profiles

Lidar-derived profiles of wind speed and turbulence are produced by processing the structure functions using data contained in a selected 10-m height interval as shown in Figs. 5 and 6 (see also Frehlich et al. 2006). The effective vertical resolution is then approximately 35 m for the longitudinal method and 20 m for the azimuth method. An example of 1-s TLS data (0.83-m vertical resolution) and lidar-derived profiles using the azimuth structure function technique is shown in Fig. 7 for the time period 0523–0540 UTC 7 June 2006. The roughness sublayer is clearly visible as enhanced turbulence and enhanced relative humidity in the first 50 m. Above the roughness sublayer is a region of lower turbulence (lidar derived \(\epsilon \approx 10^{-5}\) m\(^2\) s\(^{-3}\)) up to the mixing height \(H \approx 120\) m defined as the large drop in small-scale turbulence \(\epsilon\) at the maximum gradient in potential temperature (see Balsley et al. 2006). These conditions are challenging for remote sensing estimates of turbulence because the velocity estimates must have a very small estimation error. The lidar-derived profiles of \(\epsilon\) from the raw data and with spatial filtering are approximately equal for most of the profile. However, the length scale \(L_{0}\) and standard deviation \(\sigma\) are sensitive to the spatial filtering. Note the large variations or “small-scale intermittency” of the high-resolution TLS estimates of \(\epsilon\) and \(C_{T}^{2}\), which is typical of fully developed turbulence and is dominated by the intrinsic atmospheric processes and not the estimation error of approximately 10%–15% (Frehlich et al. 2004). There are also large differences between the TLS and lidar-derived \(\epsilon\) profiles, which reflects the large variability of the small-scale turbulence in the stable boundary layer, which has been observed previously with sodar and frequency-modulated continuous-wave (FMCW) radar (Gossard and Frisch 1987; Eaton et al. 1995).

A comparison of the turbulence statistics for the transverse velocity (i.e., the azimuth structure functions) and the longitudinal velocity (i.e., the radial velocity structure functions) is shown in Fig. 8 for the raw lidar velocity estimates and the spatially filtered velocity estimates. The estimates of \(\epsilon\) agree in the height interval from 50 to 120 m, which indicates a region of approximately isotropic small-scale turbulence. This interval also has similar estimates of \(\sigma\) for the raw and
filtered lidar data. The length scales have larger variability, indicating the difficulty in defining a valid length scale for these intermittent turbulent processes with larger-scale forcing or gravity waves. There are regions with approximately equal length scales for the same spatial filtering (e.g., around 80–120 m).

The lower-altitude region below 50 m is the most challenging since the turbulence outer-scale \( L_0 \) is small and therefore the effects of the spatial filtering by the lidar pulse are larger. In this regime, a shorter lidar pulse is desirable as well as extending the theoretical turbulence model to include anisotropy of the velocity field (e.g., Lenschow and Kristensen 1988). Variations in surface altitude and surface roughness from the suburban location (see Fig. 4) can also introduce anisotropy in the velocity statistics.

5. Summary and discussion

New measurements of atmospheric profiles are produced using in situ sensors and Doppler lidar processing algorithms with a focus on studies of the stable boundary layer (SBL). The low-turbulence conditions in and above the SBL are challenging conditions for high-rate turbulence measurements because a low noise floor with no interference is required. These stably stratified regions are ideally suited for investigations of turbulence processes since they contain many regions of approximately constant gradient of velocity and temperature (Figs. 2 and 3), which are the subject of many theoretical studies. For many of the regions investigated in this preliminary study, the temperature gradients are statistically more reliable than the velocity gradients because they typically have weaker wave contributions (Figs. 2 and 3). The small-scale velocity and temperature turbulence consists of regions of stably stratified turbulence with a low Froude number and a large inertial range scaling \( f^{-5/3} \) both below and above the Ozmidov frequency \( f_OZ \) (Riley and de Bruyn Kops 2003; Lindborg 2006). The gradient Richardson number is on the order of unity, which supports the hypothesis that turbulence-scaling laws are valid when the Richardson number is larger than 0.25 (Majda and Shefter 1998; Strang and Fernando 2001; Balsley et al. 2003, 2006) and are important for NWP model parameterization in stable conditions (Sorbjan 2006; Esau and Zilitinkevich 2006; Mauritsen and Svensson 2007). Reliable estimates of the energy dissipation rate \( \epsilon \) and the temperature structure constant \( C_T^2 \) can be produced from the one-dimensional spectra assuming universal scaling of high Reynolds number turbulence and assuming Taylor’s frozen assumption [see Eqs. (1) and (7)]. However, improvements in the sensors and electronics to remove interference and reduce the detector noise are required to produce accurate direct estimates.
of the small-scale statistics like $\varepsilon$ [see Fig. 1 and Eq. (5)]. These in situ sensors can provide high-quality turbulence and local mean quantities and statistical accuracy can be improved using multiple sensors and a slower ascent/descent rate. In addition, the statistical description of small-scale intermittency (Frehlich et al. 2004) is required for better error analysis to fully evaluate theoretical predictions (Riley and de Bruyn Kops 2003; Lindborg 2006) of stably stratified turbulence, which requires many key turbulence parameters (e.g., $N$, $F_h$, $Rc$, $Rb$, $Rf$, $L_{OZ}$, $\varepsilon$, and $C_2^T$). Since the stably stratified free atmosphere above the boundary layer may be predominantly populated with the decay stage of various instabilities (Kelvin–Helmholtz, Taylor–Green, propagating and ducted wave instabilities, etc), fundamental turbulence-scaling laws can be extracted from this type of data and the results may be valid for all similar dimensionless parameter regimes such as the upper troposphere and stratosphere (Lindborg 2006). There are still fundamental questions regarding the definition of local gradients since waves can modulate both the background fields and the small-scale turbulence, especially when convective instabilities are produced (Meillier et al. 2008).

Lidar-derived profiles of wind speed, direction, and turbulence were produced as a spatial average over a suburban location using two methods: the azimuth structure function and the radial structure function. The azimuth technique senses the velocity component transverse to the structure function separation variable, has the highest vertical resolution, and is most sensitive to the smaller scales of turbulence since the lidar sensing volume is much smaller in the direction transverse to the lidar beam than the radial or longitudinal direction (see Figs. 5 and 6). Turbulent total kinetic energy (TKE) is defined as the variance of all three of the turbulent velocity components, which usually employs a time average or space average to separate the turbulent fluctuations from the background mean quantities and has been related to the longitudinal velocity variance $\sigma_u^2$ by Banta et al. (2006). Spatially average lidar-derived turbulence profiles were determined with the
raw lidar radial velocity estimates and with a spatial filter produced from a higher-order polynomial fit to the radial velocity as a function of the lidar beam azimuth for each range gate and fixed elevation angle. The estimates of energy dissipation rate $\epsilon$ from the azimuth structure function method were similar over the altitude region of well-defined turbulence for both the raw data and the spatially filtered data (see Figs. 5 and 7). This implies that the exact shape of the turbulence model used in the best fit has little effect on the estimates of $\epsilon$. More high-quality verification data that samples the same space–time region is required to verify this hypothesis. The radial structure function method is not as robust for these conditions because the effects of the smoothing of the velocity field by the lidar pulse in the radial direction is more extreme as shown in Fig. 6. A shorter pulse is required to better resolve the turbulent eddies in the inertial range. However, even with the large corrections for the pulse smoothing, the estimates of $\epsilon$ from the radial structure function method are in good agreement with the azimuth structure function method in the upper region of the SBL (i.e., from 50 to 120 m, for both raw data and filtered data; Fig. 8). The estimates of velocity standard deviation $\sigma$ (related to TKE) and the turbulence length scale $L_0$ are not well defined for the higher altitudes above the SBL because of larger-scale atmospheric processes. A spatial filter that removes the larger-scale radial velocity components does produce well-behaved profiles but the results are a function of the amount of the spatial filtering. This is a fundamental issue, which is critical for in situ tower measurements (Vickers and Mahrt 2003) and now lidar-derived turbulence algorithms (Banta et al. 2006), especially for the SBL. Another challenge is the characterization of the low-turbulence regions above the SBL where accurate corrections for the estimation error of the radial velocities is more important (see Figs. 5 and 6 in the current paper; Frehlich 2001a; Frehlich and Corman 2002; Frehlich et al. 2006). Improvements in lidar design and processing algorithms should resolve the complex features of the roughness sublayer and the low-turbulence area of the stably stratified free atmosphere (see Figs. 7 and 8).

The high-resolution TLS data displays large vertical variability in the small-scale turbulence statistics $\epsilon$ and $C_T^2$ compared with the spatially averaged lidar-derived profiles. However, the location of the mixing height is still clearly observed as a drop in $\epsilon$ at approximately 120 m. The lidar-derived profiles of $\epsilon$ also indicate a noticeable drop in $\epsilon$ at the same altitude. More research is required to provide the most robust statistical description of the atmospheric turbulence profiles for the SBL. For NWP applications, the spatially averaged lidar profiles are more representative of the inherent spatial average of the NWP model and therefore provide smaller total observation error than rawinsondes and in situ data, which is a critical requirement for advanced data assimilation (Frehlich 2001b, 2006; Frehlich and Sharman 2004). This may be most critical for NWP model parameterization, which are essentially based on gradients of the model variables or Richardson number (Sorbian 2006; Mauritsen and Svensson 2007) and better parameterizations may require data with a similar spatial average as the NWP model. Recent and future advances in high-resolution remote measurements of temperature with Raman lidar (Behrendt et al. 2004) may produce spatially averaged profiles of mean and turbulent statistics of the temperature field using similar algorithms as for the velocity turbulence profiles from Doppler lidar. Will the Richardson number profile from in situ data agree with a spatially averaged profile from a Doppler lidar and a Raman temperature lidar? These fundamental questions can be answered with improvements in both in situ and remote sensing techniques.

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