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### Key Points:

- We estimate errors in atmospheric measurements from Uncrewed aircraft systems (UAS) platforms using the relaxed filtering method
- Uncertainties in wind speed, wind direction, and potential temperature can be significant over typical averaging periods
- We propose sampling strategies that mitigate errors in UAS measurements

### Supporting Information:

Supporting Information may be found in the online version of this article.

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## How Representative Are Uncrewed Aircraft System Measurements of the Convective Boundary Layer?

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**Abstract** Uncrewed aircraft systems (UAS) demonstrate significant potential for filling data gaps in the atmospheric boundary layer. However, the extent to which UAS observations—typically vertical profiles taken over 15 min—are representative of the boundary layer as a whole remains poorly characterized. Using large eddy simulations (LES) of the daytime convective boundary layer (CBL), we quantify random errors in UAS measurements that occur due to insufficient statistical convergence of the time average to the true ensemble mean. Random errors in first-order moments increase as the CBL becomes increasingly unstable, and are largest near the surface for most quantities. Errors are on the order of 2–6 m s<sup>−1</sup> for wind speed, 15–60° for wind direction, 0.2–3 K for potential temperature, and 0.1–1 g kg<sup>−1</sup> for specific humidity, with errors in turbulent fluxes on the order of 50%–100%. Sampling strategies that mitigate random errors are discussed in light of our results.

**Plain Language Summary** Atmospheric measurements from instrumented uncrewed aircraft systems (UAS or “drones”) can provide data from portions of the lowest 1–2 km of the atmosphere that are difficult to sample using other methods. These data have great potential for addressing fundamental research questions and for improving weather forecasts. However, because vertical profiles from UAS data are typically collected over ~15 min at a fixed horizontal location, it is not well understood how well these data represent mean properties of the lower atmosphere. Using high-resolution large eddy simulations of the lower atmosphere, together with an error estimation technique, we quantify errors in UAS measurements as a function of height and atmospheric stability. Errors in wind speed and direction, temperature, and humidity are found to be appreciable over typical averaging periods, which diminishes the usefulness of UAS data for research and forecasting. We propose strategies for UAS sampling that minimize these errors.

## 1. Introduction

Measurements of the lower atmosphere from uncrewed aerial systems (UAS) have risen in popularity in recent years, given the potential of these systems for filling data gaps in the atmospheric boundary layer (ABL; Chilson et al., 2019; Houston et al., 2021; Pinto et al., 2021). Tower-based instruments are typically confined to the lowest  $\mathcal{O}(10$  m) of the ABL, making in situ observations in the convective mixed layer and entrainment zone difficult to obtain. While operational radiosondes can provide routine vertical profiles of atmospheric state variables throughout the troposphere and lower stratosphere, these observations are typically collected twice per day (with the exception of targeted field campaigns) and their spatial resolution within the boundary layer is limited. In contrast to radiosondes, UAS are reusable and have significantly improved spatial resolution, while being capable of measuring the same variables (i.e., temperature, humidity, wind speed, and direction) with comparable accuracy (Bell et al., 2020). Measurements from UAS platforms have been featured prominently in a number of recent field campaigns, including the Verifications of the Origins of Rotation in Tornadoes Experiment Southeast (VORTEX-SE; Dumas et al., 2016, 2017), the Innovative Strategies for Observations in the Arctic Atmospheric Boundary Layer experiment (Greene et al., 2022; Kral et al., 2018, 2021), the Lower Atmospheric Profiling Studies at Elevation—A Remotely Piloted Aircraft Team Experiment (LAPSE-RATE; Boer, Diehl, et al., 2020; Boer, Houston, et al., 2020), the TRacking Aerosol Convection interactions ExpeRiment (TRACER; Lappin et al., 2024), and the Propagation, Evolution, and Rotation in Linear Storms (PERiLS; Kosiba et al., 2024).

Investigators have used UAS data to estimate sensible heat fluxes (Lee et al., 2017), and to assess the validity of gradient-based scaling in the stable boundary layer (Greene et al., 2022). Other authors have envisioned the possibility of a “3D mesonet,” where a spatially-distributed mesoscale network of UAS observations would

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provide continual observations of atmospheric state variables throughout the depth of the ABL (Chilson et al., 2019), which could be used to address fundamental research questions and inform operational forecasting. Researchers have also highlighted the potential improvements to numerical weather prediction (Flagg et al., 2018; Jensen et al., 2021, 2022) and dispersion modeling (Ngan et al., 2023) when UAS observations are assimilated.

Despite the promise of UAS data for research, operational forecasting, and assimilation into numerical weather prediction models, the extent to which UAS observations are representative of the mean state of the daytime convective boundary layer (CBL) remains largely unexplored. Vertical profiles from rotary-wing UAS are typically collected over a period of  $\sim 15$  min with the maximum flight time determined by UAS battery life. Note that while fixed-wing UAS platforms have also been developed for atmospheric observations, we focus herein on rotary-wing UAS which are ideal for vertical profiling of the ABL at high spatial and temporal resolution. An important decision when designing flight strategies for vertical profiling with rotary-wing UAS is its ascent rate. This is typically set within the range of  $1\text{--}4\text{ m s}^{-1}$  (e.g., Greene et al., 2022; Lappin et al., 2024; Pillar-Little et al., 2021; Segales et al., 2020) depending on the application, and data are then processed into altitude bins ranging from 3 to 10 m high. Herein we consider an ascent rate of  $3\text{ m s}^{-1}$  and altitude bins of 5 m for first-order statistics (cf. Lappin et al., 2024), which corresponds to an averaging time of 1.67 s per bin. For second-order moments, we consider an 1800 s averaging period, which is conventional for turbulent flux measurements, due to the large magnitude of errors in these quantities. However, we note that such a long averaging period is not currently possible, due to the current limitations of rotary-wing UAS battery life. Because UAS observations are typically averaged over relatively short time periods (i.e., seconds), they are subject to insufficient convergence of time averages to the true ensemble mean by the ergodic hypothesis. In the ABL literature, these types of errors are referred to as “random errors” (Dias et al., 2018; Greene & Salesky, 2023; Lenschow et al., 1994; Lumley & Panofsky, 1964; Salesky et al., 2012), and have been analyzed in the context of in situ turbulent flux measurements (Dias et al., 2018; Lenschow et al., 1994; Salesky et al., 2012) and UAS measurements under stably stratified conditions (Greene & Salesky, 2023).

In this letter, we address the research question of “How representative are UAS measurements of the CBL?” Using the framework of random error analysis, we investigate the extent to which vertical profiles of atmospheric variables collected from UAS platforms are representative of the true ensemble mean ABL state. We performed a suite of large eddy simulations (LES) spanning weakly to moderately convective conditions to generate emulated UAS observations, then applied the relaxed filtering method (RFM; Dias et al., 2018) to estimate the random errors in first- and second-order moments. Random errors are analyzed as a function of dimensionless height ( $z/z_i$ ) and global stability ( $-z_i/L$ ). Informed by our results, we discuss UAS sampling strategies for the CBL that can mitigate these random errors.

## 2. Methods

### 2.1. Large Eddy Simulations

We performed a suite of LES of the daytime CBL, which provides data to serve as the basis for random error analysis. The LES code employed herein solves the low-pass filtered equations for momentum ( $\rho \tilde{u}_i$ ), potential temperature ( $\tilde{\theta}$ ), and specific humidity ( $\tilde{q}$ ), and includes the effects of Coriolis and buoyancy, subject to appropriate boundary conditions. Our suite of simulations is configured similar to those in our prior work (Salesky & Anderson, 2018; Salesky et al., 2017). By independently varying the forcings: geostrophic wind  $U_g$  and kinematic surface heat flux  $H_0/\rho c_p = \overline{w'\theta'}_0$ , we are able to attain a suite of simulations with global stabilities of  $-z_i/L = 1.3, 3.9, 9.5$  and  $25.0$ , which correspond to weakly to moderately convective conditions. Here  $z_i$  is the CBL depth and  $L = -u_*^3 \Theta_0 / \kappa g \overline{w'\theta'}_0$  is the Obukhov length, where  $u_*$  is the friction velocity,  $\Theta_0$  is a reference potential temperature, and  $\kappa$  is the von Kármán constant. Simulations were performed on a  $L_x L_y L_z = 12 \times 12 \times 2\text{ km}$  domain discretized with a  $N = n_x n_y n_z = 256^3$  grid, over 6 hr physical time with averages calculated over the last hour. Notably, the LES output allows us to examine both 3D volumetric fields, as well as emulated profiles captured by a “virtual UAS” as it ascends from the surface to the top of the ABL. For further details of the LES code and suite of simulations, the reader is referred to the Text S1 and Figure S1 in Supporting Information S1.

## 2.2. Random Error Estimation

Random errors in turbulence statistics in the ABL occur due to insufficient convergence of temporal or spatial averages to the true ensemble mean by the ergodic hypothesis. In practice, maximum possible averaging times for in situ tower-based observations are typically limited to  $T = 30\text{--}60$  min in the ABL due to the inherent non-stationarity associated with the diurnal cycle (Lenschow et al., 1994; Salesky et al., 2012). However, maximum averaging times for UAS are much more limited (on the order of seconds) due to battery life limitations. Reynolds-averaged turbulent statistics are formally defined in terms of the ensemble mean; thus insufficient averaging (in time or space) will lead to errors due to lack of statistical convergence. For a variable of interest  $f$  with ensemble mean  $\langle f \rangle$  and time average  $\bar{f}$ , the random error can be defined in terms of the error variance (Lumley & Panofsky, 1964), that is, the variance of the ensemble of time averages relative to the true ensemble mean:

$$\sigma_{\bar{f}}^2 = \langle [\langle f \rangle - \bar{f}]^2 \rangle \quad (1)$$

Here  $\sigma_{\bar{f}}$  can be interpreted as the standard deviation of the time-average of  $f$ ; thus estimation of random errors can allow one to quantify uncertainty in temporally- or spatially-averaged ABL turbulence statistics. It is also useful to introduce the relative random error

$$\epsilon_f = \frac{\sigma_{\bar{f}}}{|\bar{f}|}, \quad (2)$$

which can be formed by normalizing  $\sigma_{\bar{f}}$  by the magnitude of  $\bar{f}$  and is typically reported as a percentage (%) error. While a number of methods have been proposed for estimating random errors (Lenschow et al., 1994; Lumley & Panofsky, 1964), these typically require estimation of the integral timescale  $\mathcal{T}_f$ , which is sensitive to the method used to estimate it, and may not always exist (Dias et al., 2018; Salesky et al., 2012). In order to avoid estimation of  $\mathcal{T}_f$ , we estimate random errors using the relaxed filtering method (RFM; Dias et al., 2018), where one low-pass filters a turbulent variable of interest at multiple temporal or spatial scales, fits a power law to the error variance as a function of scale, and evaluates it at the averaging time (or length) to obtain a random error estimate. The relative random error  $\epsilon_f$  in a variable of interest  $f$  can be calculated as:

$$\epsilon_f(L_{avg}, z) = \sigma_{\bar{f}}(L_{avg}, z) / \langle f(z) \rangle \quad (3)$$

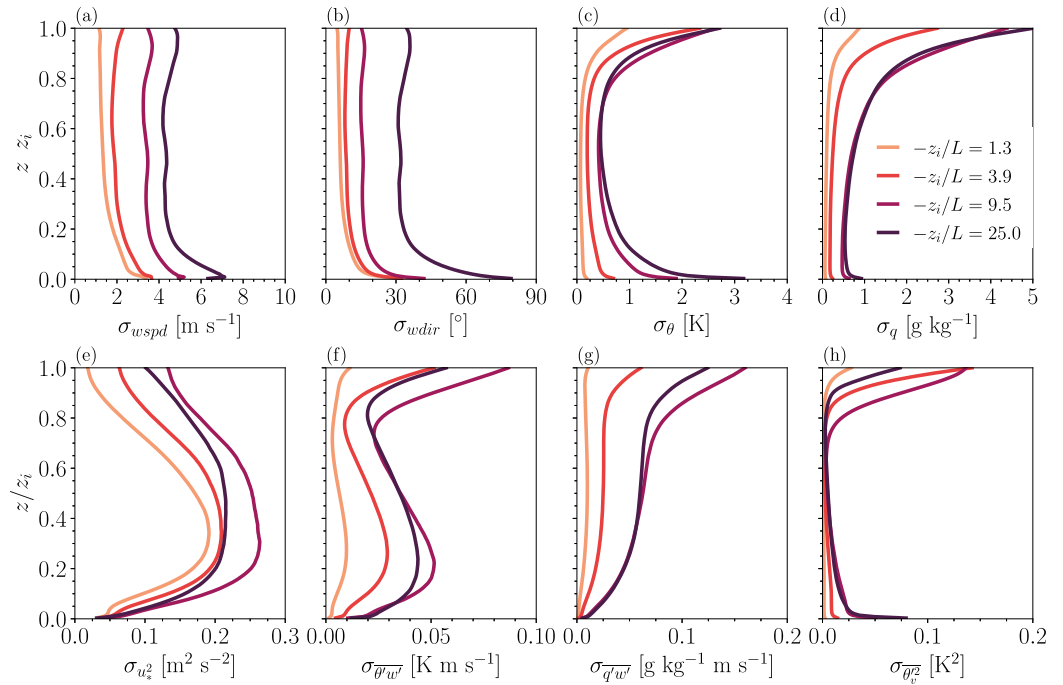
$$= [\langle f'^2(z) \rangle C_f(z) L_{avg}^{-p(z)}]^{1/2} / \langle f(z) \rangle, \quad (4)$$

where  $C_f(z)$  and  $p(z)$  are respectively a height-dependent coefficient and exponent obtained from the RFM, and  $L_{avg}$  is the spatial averaging length. Further details about the RFM and application to our LES output are provided in Text S2 in Supporting Information S1.

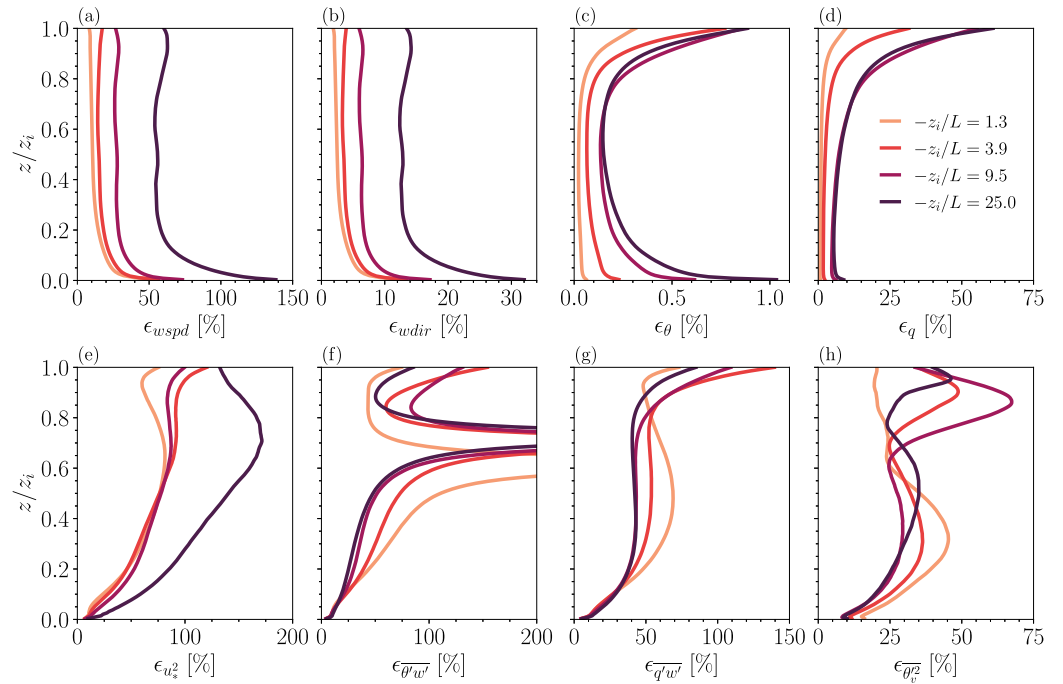
## 3. Results

### 3.1. Random Errors

Random errors in first- and second-order moments were estimated from LES output using the RFM, and are displayed in Figures 1 and 2. In order to facilitate clearer interpretation of our results, random errors are presented in dimensional form in Figure 1 and as a percentage relative error in Figure 2. Errors in first- and second-order moments are displayed in Figures 1 and 2 in panels (a)–(d) and (e)–(h), respectively as a function of global stability ( $-z_i/L$ ) and dimensionless height ( $z/z_i$ ). While observations from UAS platforms are routinely used to calculate first-order moments, it is also instructive to consider errors in turbulent fluxes, as new techniques for calculating fluxes from UAS data become increasingly feasible (Wildmann & Wetz, 2022). Note that for these analyses, we consider averaging times of 1.67 and 1800 s for first- and second-order moments, respectively. This longer averaging period for second-order moments corresponds to a best case scenario, where UAS could sample at a given height for extended period of time in order to converge statistics. However, we note that such long averaging times are not currently possible given UAS battery life.



**Figure 1.** Profiles of dimensional random errors in first- and second-order quantities as a function of dimensionless height ( $z/z_i$ ) and global stability ( $-z_i/L$ ). Panels correspond to random errors in mean (a) wind speed, (b) wind direction, (c) potential temperature, (d) specific humidity, (e) kinematic momentum flux, (f) kinematic heat flux, (g) kinematic humidity flux, and (h) virtual potential temperature variance.



**Figure 2.** As in Figure 1 but for relative random errors [%] in first- and second-order quantities as a function of dimensionless height ( $z/z_i$ ) and global stability ( $-z_i/L$ ). Panels correspond to relative random errors in mean (a) wind speed, (b) wind direction, (c) potential temperature, (d) specific humidity, (e) kinematic momentum flux, (f) kinematic heat flux, (g) kinematic humidity flux, and (h) virtual potential temperature variance.

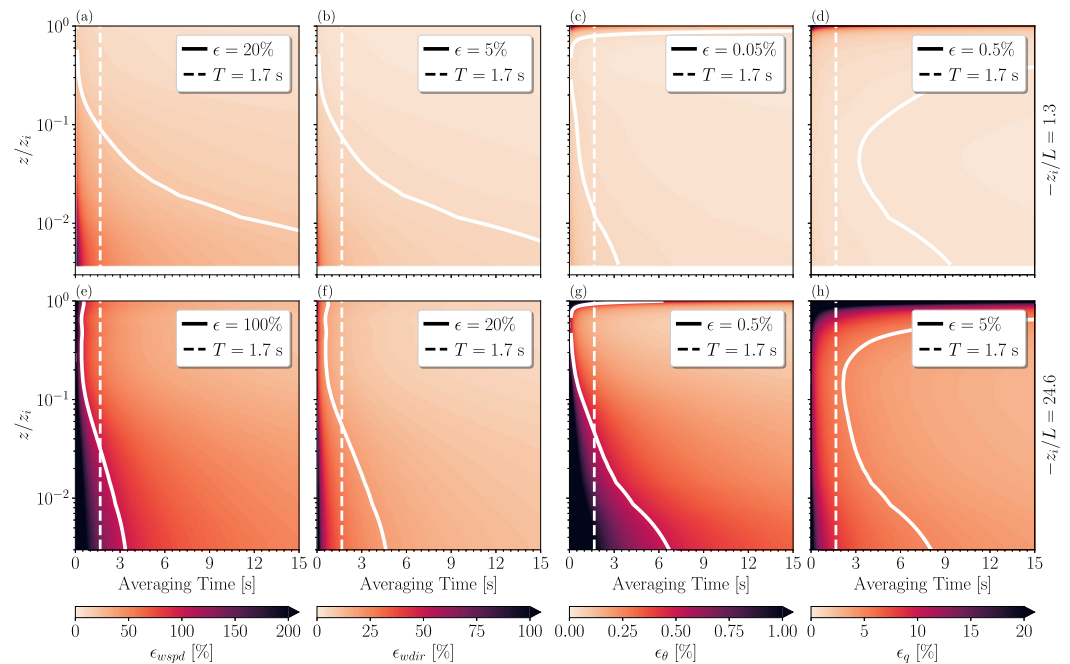
One can see from Figures 1 and 2 that errors in mean wind speed (panel (a)) range from approximately  $2\text{--}5\text{ m s}^{-1}$ , while errors in wind direction (panel (b)), range from  $10$  to  $40^\circ$ . Both attain their maximum values in the atmospheric surface layer (i.e.,  $z/z_i \leq 0.15$ ), and increase with increasing global instability ( $-z_i/L$ ). Errors in potential temperature (panel (c)) range from approximately  $0.2\text{--}0.5\text{ K}$  in the mixed layer, but are larger both in the surface layer and in the entrainment zone, where they range from  $0.2$  to  $3.0\text{ K}$ . As with wind speed, errors in  $\theta$  increase with increasing  $-z_i/L$ . Errors in specific humidity (panel (d)) range from approximately  $0.2\text{--}1\text{ g kg}^{-1}$  in the surface layer and mixed layer (also increasing with  $-z_i/L$ ), and increase in the entrainment zone. Even though these random errors may seem relatively small in some cases, it is important to emphasize that variations in boundary layer temperature and moisture on the order of  $1\text{ K}$  and  $1\text{ g kg}^{-1}$ , respectively, can be large enough to determine whether or not convection initiation occurs (Crook, 1996). Consequently, the magnitude of these random errors may make deep convection initiation difficult to diagnose from UAS observations, particularly for more highly convective (large  $-z_i/L$ ) conditions.

Random errors in second-order moments are displayed in Figures 1 and 2, panels (e)–(h). Here one can see that typical errors in the kinematic momentum flux (panel (e)) are on the order of  $0.1\text{--}0.2\text{ m}^2\text{ s}^{-2}$  (i.e.,  $50\%\text{--}100\%$ ), increase with increasing  $-z_i/L$ , and attain their maximum value in the convective mixed layer. For the kinematic heat flux, random errors range from  $0.01$  to  $0.05\text{ K m s}^{-1}$ , or  $20\%\text{--}100\%$  (panel (f)). Again, the random errors increase with increasing  $-z_i/L$ . The errors in the kinematic specific humidity flux range from approximately  $0.01\text{--}0.05\text{ g kg}^{-1}\text{ m s}^{-1}$ , or on the order of  $40\%\text{--}70\%$  (panel (g)). Finally, errors in the virtual potential temperature variance (panel (h)) are on the order of  $0.01\text{--}0.05\text{ K}^2$ , or  $20\%\text{--}50\%$  relative error. Thus, while UAS platforms may seem promising for measurement of turbulence statistics throughout the depth of the CBL, data collected over typical averaging periods may result in unacceptably large values of random errors in the fluxes or variances for many applications. Moreover, the averaging times ( $T = 1800\text{ s}$ ) that we consider herein are highly optimistic for UAS measurements. If random errors would be estimated using a realistic averaging time, such as what is used operationally (e.g.  $T = 1.67\text{ s}$ ), errors in second-order moments would increase by several orders of magnitude. A discussion of optimal sampling strategies from UAS that mitigate random errors follows; however, we first consider how random errors vary as a function of averaging time and whether constant ascent rates are an optimal measurement strategy.

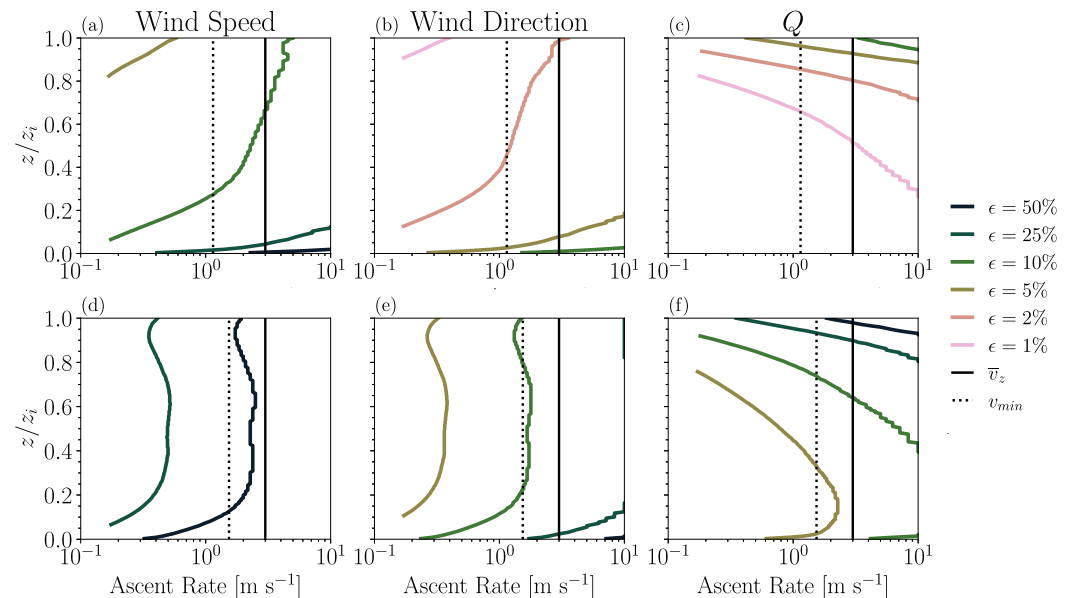
### 3.2. Averaging Times and Optimal Ascent Rates

Because the random errors are found to be both height- and stability-dependent, it is evident that employing constant ascent rates for UAS measurements in the CBL will result in larger random errors near the ground for first-order moments. In Figure 3 we consider the more general case of how random errors vary as a function of averaging time and height, for weakly convective ( $-z_i/L = 1.3$ ) and moderately convective ( $-z_i/L = 24.6$ ) conditions in panels (a)–(d) and (e)–(h), respectively. One can see that the averaging times required to maintain the same level [%] of relative random error increase significantly near the ground (i.e.,  $z/z_i \leq 0.1$ ), requiring averaging times greatly exceeding  $T = 1.67\text{ s}$  used during typical UAS operations. As a result, there is a tradeoff between profiling the entire depth of the CBL during a  $\sim 15$  minute UAS flight and averaging long enough to reduce measurement uncertainty to an acceptable level. As we observed previously from Figures 1 and 2, random errors in first-order moments increase with  $-z_i/L$ ; thus the required averaging time to maintain a constant % random error becomes larger as the CBL becomes increasingly convective. Furthermore, random errors are larger in kinematic quantities than in thermodynamic quantities for the same averaging period; thus, significantly larger averaging periods are needed to sample wind speed and direction with the same relative random error as potential temperature and specific humidity.

In order to further illustrate this point, in Figure 4, we display the minimum UAS ascent rates one would have to use to achieve a specified value of random error in wind speed, wind direction, and specific humidity for a given height and stability. Because UAS operations (ascent rates, flight plans, etc.) can be fully determined by the end user with modern autopilot systems, it is possible for UAS to ascend at a variable, altitude-dependent rate in order to ensure that random errors remain quasi-constant throughout the depth of the boundary layer. In Figure 4, each colored curve corresponds to the value of relative random error denoted in the legend, the solid black vertical line corresponds to an ascent rate of  $3\text{ m s}^{-1}$  (utilized by the University of Oklahoma CopterSonde, Segales et al., 2020), and the dashed vertical line corresponds to the minimum constant ascent velocity that would allow one to sample the entire depth of the CBL within the span of a typical UAS battery life.



**Figure 3.** Contours of relative random error  $\epsilon$  [%] as a function of averaging time and dimensionless height ( $z/z_i$ ). Panels (a)–(d) correspond to weakly convective conditions ( $-z_i/L = 1.3$ ), while panels (e)–(h) correspond to moderately convective conditions ( $-z_i/L = 24.6$ ). Plots show errors in (a), (e) mean wind speed, (b), (f) wind direction, (c), (g) potential temperature, and (d), (h) mean specific humidity. In each panel, the dashed vertical line corresponds to an averaging time of 1.67 s (corresponding to the typical value employed for Uncrewed aircraft systems data processing), while the white curves correspond to the magnitude of relative error specified in the legend.



**Figure 4.** Minimum ascent rates for Uncrewed aircraft systems (UAS) to achieve a specified level of random error as a function of dimensionless height ( $z/z_i$ ). Panels (a)–(c) are displayed for weakly convective ( $-z_i/L = 1.3$ ) conditions, while panels (d)–(f) are displayed for highly convective ( $-z_i/L = 24.6$ ) conditions. Optimal ascent rates are depicted for (a), (d) wind speed, (b), (e) wind direction, and (c), (f) specific humidity. In each panel the solid vertical line corresponds to the mean ascent velocity ( $\bar{v}_z = 3$  m s<sup>-1</sup>) typically used for the CopterSonde, while the dashed vertical line ( $v_{min}$ ) corresponds to the minimum ascent rate that would allow one to profile the entire convective boundary layer within a typical UAS battery life of 15 min (i.e.,  $v_{min} = z_i/15$  min).

One can see that the minimum required ascent rate varies significantly with altitude, stability, and the variable of interest. For example, if one wanted to achieve wind speed measurements with less than 10% random error for weakly convective conditions (panel (a)), an ascent rate of 20–30 cm s<sup>−1</sup> would be required in the atmospheric surface layer. While these low ascent rates are possible with UAS, they preclude sampling of the entire depth of the CBL within nominal UAS battery life. For more highly convective conditions (panel (d)), the outlook is worse; using the same ascent rates of 20–30 cm s<sup>−1</sup> would result in larger random errors (25% or greater). For other variables (e.g., specific humidity in panels (c) and (f)) one could use a larger ascent rate in the surface layer, but would have to decrease the ascent rate in the upper mixed layer and entrainment zone to ensure quasi-constant random error as a function of height.

#### 4. Discussion and Conclusions

Using a suite of LES of the CBL, spanning weakly to moderately convective conditions, we estimated random errors in first- and second-order moments of turbulence statistics for typical UAS sampling strategies. Random errors were found to be on the order of 2–6 m s<sup>−1</sup> for wind speed, 15–60° for wind direction, 0.2–3 K for potential temperature, and 0.1–1.0 g kg<sup>−1</sup> for specific humidity. The relative errors in wind speed and direction were larger than those in potential temperature and specific humidity, indicating that UAS are more reliable for measurements of thermodynamic quantities than for kinematic quantities in the CBL. Errors in the turbulent fluxes of momentum, heat, and humidity were found to be much larger than those in first-order moments, that is, on the order of 50%–100%. Furthermore, errors in second-order moments were estimated for an averaging time of  $T = 1800$  s; errors in second-order moments from a 15 min flight with an averaging time of several seconds would be larger by several orders of magnitude. Errors in all quantities considered were found to increase with global stability ( $-z_i/L$ ); thus one should be particularly cautious when using UAS data collected under high surface heat flux/weak wind conditions. In addition, random errors vary with height and were found to be larger in the surface layer (for wind speed, wind direction, and potential temperature) and entrainment zone (for potential temperature and specific humidity) than in the mixed layer. Based on our analysis, we have the following specific recommendations for UAS measurements in the CBL:

1. Because random errors are larger in the surface layer and entrainment zone, using slower ascent rates for UAS when sampling these regions of the flow would be advantageous for reducing the uncertainty in measurements.
2. Whenever possible, it would be beneficial to couple UAS observations with those from other platforms. Tower-based instrumentation can provide measurements in the surface layer with longer averaging times (e.g.,  $T = 30$ –60 min) and consequently lower values of random errors. Remote sensing instruments which operate continuously, such as Doppler lidar, can also provide observations of wind speed and direction which can be averaged over longer periods.
3. If multiple UAS are available, one could perform vertical profiling at multiple horizontal locations and perform both ensemble and temporal averaging. If one adopts this approach, UAS ideally would be separated by at least twice the integral lengthscale of the variable of interest in order to ensure that measurements from each UAS are statistically independent. Note that this approach requires one to assume that the flow is horizontally homogeneous.
4. As opposed to the typical approach of adopting a constant ascent rate when collecting vertical profiles, it may be more beneficial to adopt a “zoom and hover” strategy where a UAS ascends rapidly to an altitude of interest, hovers there (e.g. for 30–60 s) to collect a longer timeseries, and then ascends rapidly to the next altitude of interest. This could either be done with a fixed distance (e.g. 50 or 100 m) between vertical sampling locations, or with variable spacing if one desires higher spatial resolution in specific regions of the CBL. Another strategy for random error mitigation would be to collect data both while ascending and descending from two or more flights (e.g., during the same 30 min period), and then conduct both temporal and ensemble averaging. This approach has been implemented previously (Greene et al., 2022), albeit only using data from ascending flights.
5. Due to the magnitude of random errors in second-order moments (50% or greater with an averaging period of  $T = 1800$  s), turbulent flux measurements from UAS platforms, just like any in situ eddy covariance method, have significant uncertainty associated with them in the CBL. Moreover, it is challenging to obtain reliable, high-frequency measurements of vertical velocity  $w$  from multirotor UAS, although current work in this area may make this a possibility in the future (e.g., Wildmann & Wetz, 2022). Currently, accurate flux measurements would require ensemble averaging from multiple UAS sampling for extended periods at a given height and/or by compositing multiple subsequent UAS flights, as discussed in the previous point.

This study focuses on errors that arise in turbulence measurements in the CBL based on fundamental issues surrounding the estimation of statistics from stochastic spatiotemporal data. Specifically, we examine properties of random errors due to insufficient convergence of the sample temporal average to the true ensemble mean. We emphasize that these errors are distinct from other sources of measurement error including instrument bias and dynamic response, and the total measurement uncertainty will include contributions from sensor static and dynamic performance characteristics in addition to random errors. The parameter space considered herein encompasses global stabilities ranging from near-neutral ( $-z_i/L = 1.3$ ) to moderately convective ( $-z_i/L = 25.0$ ) conditions. Although we also planned to perform the error analysis for the free convective limit ( $-z_i/L \sim 1000$ ), Taylor's frozen flow hypothesis is questionable in this limit due to the low wind speeds ( $\bar{U} \sim \mathcal{O}(1 \text{ m s}^{-1})$ ), therefore we omitted these stabilities from our present analysis.

Other approaches to characterizing measurement uncertainty in UAS observations exist, such as recent work on the Wind via Optimal Estimation (WINDoe) technique (Gebauer & Bell, 2024). This method is based on Bayes' theorem and uses a similar approach to the Tropospheric Remotely Observed Profiling via optimal estimation retrieval method (Turner & Blumberg, 2018; Turner & Löhnert, 2014) used for thermodynamic profilers. While the WINDoe uncertainties do not have the same interpretation as the random errors addressed herein, it provides another approach for characterizing measurement uncertainty from UAS platforms and demonstrates that errors in mean wind profiles derived from UAS can be significant over typical averaging periods.

Novel UAS sampling strategies, such as measurements from UAS swarms (Wetz et al., 2023) that provide simultaneous, spatially-distributed data, can provide unique insights on the structure of the atmospheric boundary layer. This type of observational strategy would be ideal for direct comparison against numerical simulations. Future investigations to design sampling techniques and assess measurement uncertainty using LES may prove fruitful to the design of experiments and interpretation of data.

## Data Availability Statement

Postprocessed large-eddy simulation data used for the generation of figures in this study are available with open access in a Zenodo repository described by Greene et al. (2024).

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