Response to reviewer:

We greatly appreciate the reviewer's recognition of the value and significance of the present study, as well as the very valuable comments on the paper. We have addressed the comments carefully as detailed below. The original comments are in black italic and our replies in black normal font, we also put the revised paragraph in blue after each reply to show the changes.

The manuscript entitled "A Correction Algorithm for Rotor-Induced Airflow and Flight Attitude Changes during Three-Dimensional Wind Speed Measurements Made from a Rotary Unmanned Aerial Vehicle" presents a novel algorithm designed to improve UAV-based wind measurements obtained through direct techniques using flow sensors. This topic is of high scientific relevance, as drone-based wind measurements can help address observational gaps within the planetary boundary layer. Furthermore, the manuscript aligns well with the scope of Atmospheric Measurement Techniques. However, I believe the manuscript requires further revisions before it is suitable for publication. Below, I have outlined my specific comments and suggestions for improvement.

Reviewer Comments:

1. In line 57, the manuscript states that indirect wind velocity estimates do not reflect flight conditions. Given extensive research on improving these methods, clarifying their specific drawbacks compared to direct measurements with airflow sensors would benefit readers.

Response: Thank you for your valuable suggestions. We have further clarified the drawbacks of indirect wind speed measurements on UAVs in Lines 54-65 of the revised manuscript, as detailed below:

"While these methods offer advantages of operational simplicity and cost-effectiveness, their core principle relies on inversely estimating wind speed through dynamic parameters such as thrust, attitude angles, and flight velocity (Crowe et al., 2020; Donnell et al., 2018; Sikkel et al., 2016; Simma et al., 2020). However, their accuracy is critically dependent on both the measurement precision of inertial measurement unit (IMU) and the computational reliability of inversion algorithms. Specifically, inherent noise interference in IMU sensors (e.g., gyroscope drift and accelerometer vibration noise) (Neumann and Bartholmai, 2015), combined with uncertainties in parameter configuration within inversion algorithms (Bonin et al., 2013), can lead to significant deviations in wind speed estimations. Furthermore, these methods typically assume constant aerodynamic parameters for UAVs, an assumption that often fails to hold in practical complex wind field environments (Bonin et al., 2013)."

2. In line 85, the manuscript notes that wind tunnel tests can improve the accuracy of airspeed-UAV motion relationships but are limited by high costs and errors from airflow reflections. However, it lacks references supporting evidence of these errors. Please include any relevant references.

Response: Thank you very much for your reminder. We have added the following supporting references in Line 100 (corresponding to Line 85 in the original manuscript) of the revised manuscript.

"While effective in determining numerical relationships, the method is limited by the high cost of wind tunnel experiments (Dao et al., 2023), and more importantly, by the additional errors introduced by reflected airflows from the wind tunnel walls and ground (Haleem, 2021; Pettersson and Rizzi, 2008), as well as the same issues of full simulations of real UAV rotor speed and attitude changes during flight."

3. In line 169, the manuscript mentions simulation parameters but does not specify the CFD framework beyond stating it is a built-in SolidWorks simulation. Clarifying the CFD framework and comparing its advantages and disadvantages in performance when compared to alternatives like Ansys Fluent would benefit the reader.

Response: We sincerely appreciate the reviewer's valuable feedback regarding the clarification of the CFD framework. We have provided a detailed specification of the simulation methodology in the revised manuscript (Section 2.1.2, Lines 144-165):

"2.1.2 Simulation Tool

The CFD simulations were conducted using SolidWorks Flow Simulation 2022, a pressure-based finite volume solver employing a fully coupled turbulence modeling approach. It employs an adaptive Cartesian mesh approach for three-dimensional solid meshing, with the governing equations being the Navier-Stokes equations for simulating the interaction of fluids, and the turbulence model utilizing the standard k-ε two-equation model (Jonuskaite, 2017).

The selection of SolidWorks Flow Simulation was driven by its seamless integration with CAD geometries, which eliminated potential errors associated with STL file conversions for our complex multi-rotor UAV design. Additionally, its wall functions for boundary layers effectively resolve gradient variations in boundary layers around rotating blades, reducing trial and error related to near-wall settings. The built-in solver convergence adopts a phased approach to multiple variant scenarios, decreasing the need for re-runs caused by insufficient convergence and thereby conserving computational costs. Its unique turbulence model automatically determines flow regimes (laminar, transitional, and turbulent), ensuring shorter turbulence model setup times while maintaining enhanced model accuracy (Azmi et al., 2017; Ramya et al., 2015).

While ANSYS Fluent offers advanced transient turbulence models (e.g., DES/LES), its computational cost for equivalent spatial resolution was typically higher than SolidWorks (Afaq and Ahmad, 2023). Given our need to simulate over 100 operational scenarios, SolidWorks' balance of engineering accuracy and computational tractability was deemed optimal for deriving empirical correction algorithm."

4. In line 181, the manuscript models the fluid as air with both turbulent and laminar flow, assuming a turbulence intensity of 0.1% and a length scale of 0.012 m. Given that atmospheric turbulence intensity ranges from 1% to 20% and length scales vary from sub-centimeter to kilometers, clarifying these assumptions would help the reader understand the limitations of the simulation results.

Response: We sincerely appreciate the reviewer's insightful comment regarding the turbulence parameters used in our CFD simulations. Below, we clarify the rationale behind our choices and explicitly address the limitations introduced by these assumptions:

1) Rationale for turbulence intensity (0.1%):

The selected turbulence intensity (0.1%) aims to isolate the rotor-induced flow dynamics from background atmospheric turbulence. Since the primary focus of this study is to characterize the systematic bias caused by the UAV rotor itself (rather than external atmospheric fluctuations), a low turbulence intensity was adopted to minimize confounding effects.

2) Turbulence length scale (0.012 m):

The turbulence length scale was chosen based on the characteristic geometry of the miniature three-dimensional ultrasonic anemometer (frame width ~0.01 m). This ensures that local vortices around the sensor are adequately captured.

We have explained the rationale for setting these parameters in Lines 223-228 of Section 2.4 in the revised manuscript, as shown below:

"The fluid was modeled as air with characteristics of turbulent and laminar flow. To isolate the rotor-induced flow dynamics from background atmospheric turbulence, a turbulence intensity of 0.1% and a turbulence length scale of 0.012 m were set. This low turbulence intensity minimizes confounding effects from ambient atmospheric fluctuations, while the length scale corresponds to the anemometer frame width (~0.01 m) to resolve rotor-generated eddies. These assumptions prioritize the systematic bias correction for rotor-induced airflow."

Additionally, we fully acknowledge that the selected parameters do not represent the full spectrum of atmospheric turbulence. Our current results are most applicable to low-turbulence environments (e.g., open fields at dawn). Therefore, we have further supplemented the limitations of the parameter settings in this study in Section 3.6 (Lines 504-530) of the revised manuscript, as shown below:

"3.6 Discussion on the Limitations of the Algorithm

The current development of algorithms based on idealized steady-state CFD simulations relies on two key assumptions: low environmental turbulence intensity (0.1%) and turbulence length scales dominated by anemometer geometric parameters (0.012 meters). While this idealized setup effectively isolates rotor-induced flow distortion, its turbulence characteristics fundamentally differ from natural atmospheric conditions. However, it is crucial to emphasize that the algorithm's applicability under turbulent conditions remains valid. This is because rotor-induced wind speed deviations exhibit systemic long-time-scale characteristics, whereas atmospheric turbulence primarily affects measurement accuracy through random fluctuations in wind speed and direction with instantaneous nature. This temporal-scale distinction enables our correction algorithm to effectively eliminate systemic biases while minimizing the impact of transient turbulence effects. Nevertheless, it should be noted that under stable atmospheric conditions (low wind speeds) as discussed in Sec. 3.5 or extreme weather scenarios, such airflow environments may disrupt the stable manoeuvrability of UAV rotors or obscure the systemic drainage effects of rotors, potentially leading to a nonlinear degradation in algorithm accuracy.

In addition, another limitation of our study is the assumption of a smooth surface in CFD simulations, which does not fully capture the impact of surface roughness on wind speed variations near the ground. In reality, surface roughness elements (e.g., vegetation, buildings, or terrain irregularities) alter the wind profile, increasing turbulence and wind shear in the atmospheric surface layer. This effect is particularly relevant for UAV-based wind measurements at low altitudes.

To further enhance the correction algorithm's applicability under diverse environmental conditions, future research will focus on the following aspects: conducting sensitivity studies under different turbulence intensity conditions, implementing supplementary correction modules specifically targeting atmospheric turbulence, and incorporating surface roughness length parameters in future CFD simulations. Although atmospheric turbulence presents significant challenges for UAV-based wind measurements, the correction framework established in this study has demonstrated its effectiveness in improving measurement accuracy across diverse meteorological conditions, thereby laying a critical foundation for developing reliable UAV-based wind measurement systems."

5. In line 236, the manuscript states that the wind speed at the anemometer location is minimally influenced by the UAV rotos. However, the results in Figure 9 show a significant change in measurements of wind speed and direction when the correction derived from simulation results is applied to field measurements. In fact, this change is greater than the change observed when correcting aircraft motion alone. The manuscript should address this discrepancy in results.

Response: We sincerely appreciate the reviewer's thoughtful observation regarding the apparent discrepancy between the statement in Line 236 (referring to Figure 5 (corresponding to Figure 3 in the original manuscript)) and the results presented in Figure 11 (corresponding to Figure 9 in the original manuscript). Below, we provide detailed clarification to address this concern:

1) Fundamental differences in context between Figure 5 and Figure 11

The CFD simulations in Figure 5 focus on a specific tailwind scenario to illustrate the spatial distribution of rotor-induced airflow under idealized conditions. In this static simulation, the anemometer is positioned outside the core downwash region (directly beneath and laterally above the rotors), resulting in minimal direct interference from rotor-induced airflow. This supports the claim that, in this controlled scenario, the measured wind speed at the anemometer location approximates the true airspeed.

In contrast, the field observations in Figure 11 involve dynamic and complex real-world conditions, including UAV motion and attitude variations, real-time adjustments in rotor thrust, and atmospheric turbulence. These factors amplify the interaction between rotor-induced airflow and ambient wind, even when the anemometer is not within the primary downwash zone. For instance, during UAV maneuvers, transient rotor thrust fluctuations (e.g., due to stabilization or turbulence response) can perturb the local airflow field dynamically, indirectly affecting the anemometer's measurements.

2) Significance of the correction algorithm in field observations

In Figure 11, the corrected wind speed exhibits significant fluctuation amplitudes, reflecting the algorithm's simultaneous resolution of three coupled issues: errors introduced by the UAV's own motion and attitude changes (e.g., anemometer alignment deviations caused by attitude tilt) and the dynamic effects of rotor airflow on the local flow field. Although CFD simulations (Figure 5) indicate minimal direct influence of the rotors on the anemometer in static downwind scenarios, during actual flight, rotor thrust continuously varies due to attitude adjustments or turbulence responses. This indirectly alters the flow field structure around the anemometer, leading to persistent low-frequency deviations. For example, during UAV roll maneuvers, differences in thrust between the rotors on both sides may induce asymmetric distribution of local airflow, thereby affecting anemometer measurements.

3) Simulation and field results

The CFD results (Figure 5) establish a foundational understanding of rotor-induced airflow patterns under controlled conditions. However, the field results (Figure 11) reflect the algorithm's necessity in addressing cumulative errors arising from the interplay of UAV motion, attitude changes and rotor-induced airflow. The larger correction magnitude in field data highlights that even subtle rotor-induced perturbations, when combined with UAV attitude changes, can lead to significant measurement biases. This underscores the algorithm's practical value in real-world applications, where isolated CFD scenarios do not fully capture the complexity of airborne wind measurements.

In response to the reviewer's valuable feedback, we have already updated the manuscript to clarify the relationship between the CFD simulations (Figure 5) and field observations (Figure 11). Specifically, we added the following description in Lines 303-308 of Section 3.1.

"These simulation results show that the flow field around the UAV varies significantly depending on both the presence/absence of wind and its directional characteristics, and the anemometer experiences different levels of interference accordingly. Thus, accurately quantifying the interference of the UAV rotors on the anemometer is essential. However, in practical application scenarios, it is also necessary to comprehensively consider additional airflow disturbances induced by the UAV's own motion and attitude fluctuations, and to develop corresponding dynamic compensation algorithms."

6. In line 236, the manuscript asserts that the wind speed at the anemometer location is minimally affected by the UAV rotors. However, the results presented in Figure 9 show a noticeable alteration in both wind speed and direction when the correction derived from simulation results is applied to the field measurements. Notably, this change is more pronounced than the adjustment observed when only correcting for aircraft motion. The manuscript should thoroughly address this discrepancy and provide a clearer explanation for the observed differences in the results.

Response: We appreciate the reviewers' insightful feedback. This comment aligns with the issue raised in Comment 5, for which we have already provided a detailed explanation in response to Comment 5. Additionally, further clarifications have been incorporated into the revised manuscript in Section 3.1, Lines 303-308. The specific details are as follows.

"These simulation results show that the flow field around the UAV varies significantly depending on both the presence/absence of wind and its directional characteristics, and the anemometer experiences different levels of interference accordingly. Thus, accurately quantifying the interference of the UAV rotors on the anemometer is essential. However, in practical application scenarios, it is also necessary to comprehensively consider additional airflow disturbances induced by the UAV's own motion and attitude fluctuations, and to develop corresponding dynamic compensation algorithms."

7. In the caption of Figure 9, it is mentioned that UAV measurements were first averaged using a 10-second sliding window before calculating 5-second averages. However, the rationale for applying a 10-second sliding average prior to computing the 5-second average is unclear. Given that moving averages can smooth out real wind fluctuations, further clarification on the necessity and impact of this approach would be beneficial to the reader.

Response: We sincerely appreciate the reviewer's insightful question regarding the rationale behind applying a 10 s sliding window prior to computing 5 s averages in Figure 11 (corresponding to Figure 9 in the original manuscript). This approach was carefully designed to address two key challenges in the UAV-based wind measurement system, and we provide the following clarifications:

The raw wind measurements from the UAV (before correction) inherently contain high-frequency fluctuations caused by rotor-induced turbulence and rapid attitude changes. These perturbations occur at sub-second timescales, which are unrelated to atmospheric wind variability. A 10 s sliding window was selected based on spectral analysis of the raw data, as it effectively suppresses noise about 0.1 Hz while preserving the signal trends relevant to atmospheric motions. This step ensures comparability with the meteorological tower's 5 s data, which inherently lacks such high-frequency artifacts due to its stable mounting and calibrated anemometers.

After noise reduction via the 10 s sliding average, we calculated non-overlapping 5 s averages to exactly match the temporal resolution of the meteorological tower measurements (5 s discrete outputs). This two-step averaging ensures both datasets share identical timestamps and statistical representativeness, enabling a fair comparison between the $\mathbf{V_T}$ and $\mathbf{V_R}$.

Furthermore, we have made the following modifications to the title of Figure 11 in the revised manuscript:

"Figure 11: Comparison of wind speed and wind direction time series for $\mathbf{V_R}$, $\mathbf{V_O}$, and $\mathbf{V_T}$. (a) Comparison of wind speed time series for $\mathbf{V_R}$, $\mathbf{V_O}$, and $\mathbf{V_T}$. (b) Comparison of wind direction time series for $\mathbf{V_R}$, $\mathbf{V_O}$, and $\mathbf{V_T}$. (Note: The meteorological tower measured wind data at 5 s intervals, while the UAV-based measured and corrected wind data were processed with a 10 s sliding average to suppress rotor-induced high-frequency noise, followed by 5 s non-overlapping averaging to align temporally with the tower's 5 s output interval.)"

8. In line 393, it is mentioned that a UAV was flown around a meteorological tower in a box pattern. However, the manuscript does not provide any information on the commanded flight speed during these experiments. Including this detail would be highly valuable for the reader, as the UAV's operating speed is a crucial parameter for understanding the validation results.

Response: We sincerely appreciate the reviewer's perceptive suggestion. In the revised manuscript, we have supplemented the commanded flight speed information in Section 3.5, Lines 457-461, as shown below.

"The UAV flew around the tower in a box flight path at a horizontal distance of about 10 m away from the tower, at all three heights. During these flights, the UAV maintained a commanded horizontal speed of approximately 5 m/s, a value selected as a compromise between achieving sufficient spatial sampling resolution and maintaining stable flight attitude control."

9.The validation results presented in Figure 9 show large errors in wind speed and wind direction estimates while operating in low wind conditions. A more thorough discussion of these errors would strengthen the contribution of this manuscript. Moreover, understanding the limitations of the presented algorithms would help the growing community of scientists using UAV-based algorithms for wind sensing assess the impact of this algorithm.

Response: We sincerely thank the reviewers for their constructive feedback regarding the observation errors under low wind speed conditions. In the revised manuscript, we have expanded the discussion in Section 3.5 (Lines 484-486) as follows to further clarify the reasons for the algorithm's mediocre performance under low wind speeds:

"The mediocre performance of $\mathbf{V_R}$ under low wind speeds may originate from the disruption of stable maneuverability in drone rotors caused by low wind speeds, which in turn leads to the failure of the correction algorithm based on CFD steady-state simulations."

In addition, we have also pointed out the corresponding limitations of this algorithm in Section 3.6, Lines 506-532:

"3.6 Discussion on the Limitations of the Algorithm

The current development of algorithms based on idealized steady-state CFD simulations relies on two key assumptions: low environmental turbulence intensity (0.1%) and turbulence length scales dominated by anemometer geometric parameters (0.012 meters). While this idealized setup effectively isolates rotor-induced flow distortion, its turbulence characteristics fundamentally differ from natural atmospheric conditions. However, it is crucial to emphasize that the algorithm's applicability under turbulent conditions remains valid. This is because rotor-induced wind speed deviations exhibit systemic long-time-scale characteristics, whereas atmospheric turbulence primarily affects measurement accuracy through random fluctuations in wind speed and direction with instantaneous nature. This temporal-scale distinction enables our correction algorithm to effectively eliminate systemic biases while minimizing the impact of transient turbulence effects. Nevertheless, it should be noted that under stable atmospheric conditions (low wind speeds) as discussed in Sec. 3.5 or extreme weather scenarios, such airflow environments may disrupt the stable manoeuvrability of UAV rotors or obscure the systemic drainage effects of rotors, potentially leading to a nonlinear degradation in algorithm accuracy.

In addition, another limitation of our study is the assumption of a smooth surface in CFD simulations, which does not fully capture the impact of surface roughness on wind speed variations near the ground. In reality, surface roughness elements (e.g., vegetation, buildings, or terrain irregularities) alter the wind profile, increasing turbulence and wind shear in the atmospheric surface layer. This effect is particularly relevant for UAV-based wind measurements at low altitudes.

To further enhance the correction algorithm's applicability under diverse environmental conditions, future research will focus on the following aspects: conducting sensitivity studies under different turbulence intensity conditions, implementing supplementary correction modules specifically targeting atmospheric turbulence, and incorporating surface roughness length parameters in future CFD simulations. Although atmospheric turbulence presents significant challenges for UAV-based wind measurements, the correction framework established in this study has demonstrated its effectiveness in improving measurement accuracy across diverse meteorological conditions, thereby laying a critical foundation for developing reliable UAV-based wind measurement systems."

10. The validation results presented in Figure 9 reveal significant errors in wind speed and direction estimates, particularly under low wind conditions. A more comprehensive discussion of these errors would strengthen the manuscript by offering deeper insights into the algorithm's performance. For instance, exploring the correlation between VO , VR, and VT could provide valuable context, especially given the critical role of accurate wind fluctuation estimates in turbulence measurements. Furthermore, a clearer examination of the algorithm's limitations would greatly benefit the growing community of scientists employing UAV-based wind sensing algorithms, helping them better evaluate its potential impact and applicability.

Response: We thank the reviewer for their careful comment. This comment is similar to Comment 9, and we have revised the manuscript accordingly based on the previous feedback. These revisions are also applicable to the current comment.