



Supplement of

Wind estimation based on flight dynamics of unmanned aerial vehicle: influencing variables and its environmental application

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S1. Estimation of UAV rotor thrusts

UAV rotor speeds are important parameters for wind estimation using machine learning algorithms. Direct measurement of rotor speeds is challenging; however, rotor thrusts, which can be roughly estimated from the flight command values issued by the UAV controller, can serve as proxies. For the quadcopter used in this study (DJI M300 RTK), the four rotor thrusts (R_1 to R_4) can be estimated as follows:

$$\begin{bmatrix} R_1 \text{ thrust} \\ R_2 \text{ thrust} \\ R_3 \text{ thrust} \\ R_4 \text{ thrust} \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 1 & 1 & 1 & -1 \\ 1 & -1 & 1 & 1 \\ 1 & -1 & -1 & -1 \\ 1 & 1 & -1 & 1 \end{bmatrix} \begin{bmatrix} T \\ M_x \\ M_y \\ M_z \end{bmatrix}$$

where T denotes total lift (throttle), M_x , M_y , and M_z are the roll (aileron), pitch (elevator), and yaw (rudder) moments. The values of T , M_x , M_y , and M_z can be obtained from the UAV flight log file.

It should be noted that using flight command values issued by the UAV controller to estimate thrust may introduce significant uncertainty. Future studies applying a machine learning approach for wind estimation should therefore seek to incorporate actual rotor thrust or rotor speed data to improve accuracy.

Table S1 Fitting coefficients a_{M,η_r} and b_{M,η_r} for the UAV inclination-wind speed relationships.

Payload configuration	Relative wind direction	Coefficient $a_{M,\eta}$	Coefficient $b_{M,\eta}$	R^2	
Default setting	M _o	0°	2.29	0.71	0.987
	M _o	45°	2.99	0.58	0.964
	M _o	90°	1.94	0.82	0.949
	M _o	180°	0.57	1.23	0.977
	M _o	225°	0.53	1.21	0.985
	M _o	270°	0.58	1.22	0.986
Additional front-top payload	M _{o+f}	0°	2.80	0.71	0.976
	M _{o+f}	45°	3.43	0.56	0.849
	M _{o+f}	90°	2.27	0.79	0.951
	M _{o+f}	180°	0.57	1.32	0.987
	M _{o+f}	225°	0.59	1.22	0.991
	M _{o+f}	270°	0.65	1.22	0.985
Additional central-top payload	M _{o+m}	0°	2.94	0.74	0.942
	M _{o+m}	45°	3.52	0.59	0.881
	M _{o+m}	90°	1.77	0.92	0.937
	M _{o+m}	180°	0.45	1.40	0.967
	M _{o+m}	225°	0.41	1.38	0.981
	M _{o+m}	270°	0.49	1.42	0.990

*: The fitting algorithm for these coefficients is: $V_{wind,M,\eta_r} = a_{M,\eta_r} \cdot \Psi^{b_{M,\eta_r}}$, where V_{wind,M,η_r} is the wind speed and Ψ is the UAV inclination angle.

Table S2 Fitting coefficients k and b for wind sensor calibrations under various flight conditions*.

Payload configuration		Relative wind direction	k	b	R^2
Default setting	M _o	0°	0.98	1.51	0.994
	M _o	45°	1.14	1.19	0.993
	M _o	90°	0.84	0.42	0.988
	M _o	180°	1.01	0.52	0.985
	M _o	225°	1.19	1.36	0.994
	M _o	270°	0.92	0.40	0.973
Additional front-top payload	M _{o+f}	0°	0.99	0.95	0.988
	M _{o+f}	45°	1.09	0.38	0.993
	M _{o+f}	90°	0.98	0.0036	0.995
	M _{o+f}	180°	1.01	0.55	0.990
	M _{o+f}	225°	1.09	0.89	0.991
	M _{o+f}	270°	1.02	-0.17	0.992
Additional central-top payload	M _{o+m}	0°	0.88	1.28	0.991
	M _{o+m}	45°	1.05	0.81	0.977
	M _{o+m}	90°	0.83	0.54	0.995
	M _{o+m}	180°	0.96	0.68	0.978
	M _{o+m}	225°	1.14	0.97	0.990
	M _{o+m}	270°	0.79	0.24	0.982

*: The fitting algorithm for these coefficients is: $V_{reference} = kV_{measured} + b$, where $V_{reference}$ is the input wind speed from the wind wall and $V_{measured}$ is the wind speed measured by the onboard sensor.

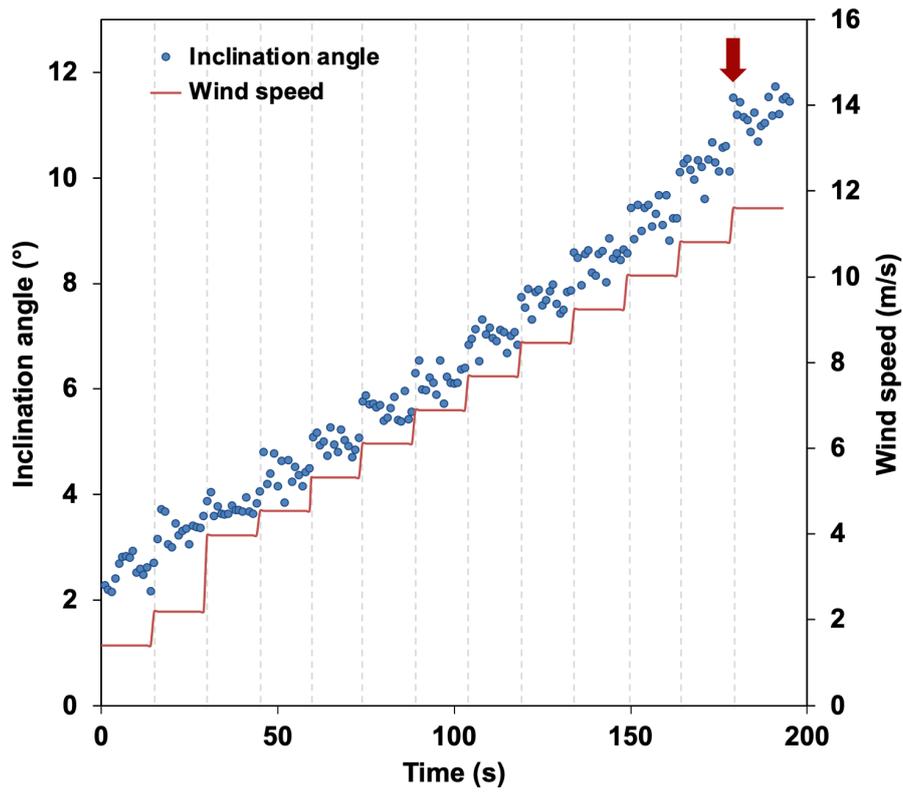


Figure S1 UAV attitude response to a step change in wind speed. The red arrow indicates an example of this behavior, showing a step increase in wind speed from 10.8 m/s to 11.6 m/s. In response, the UAV inclination angle rose immediately from 10.1° to 11.4° and stabilized at the new level.

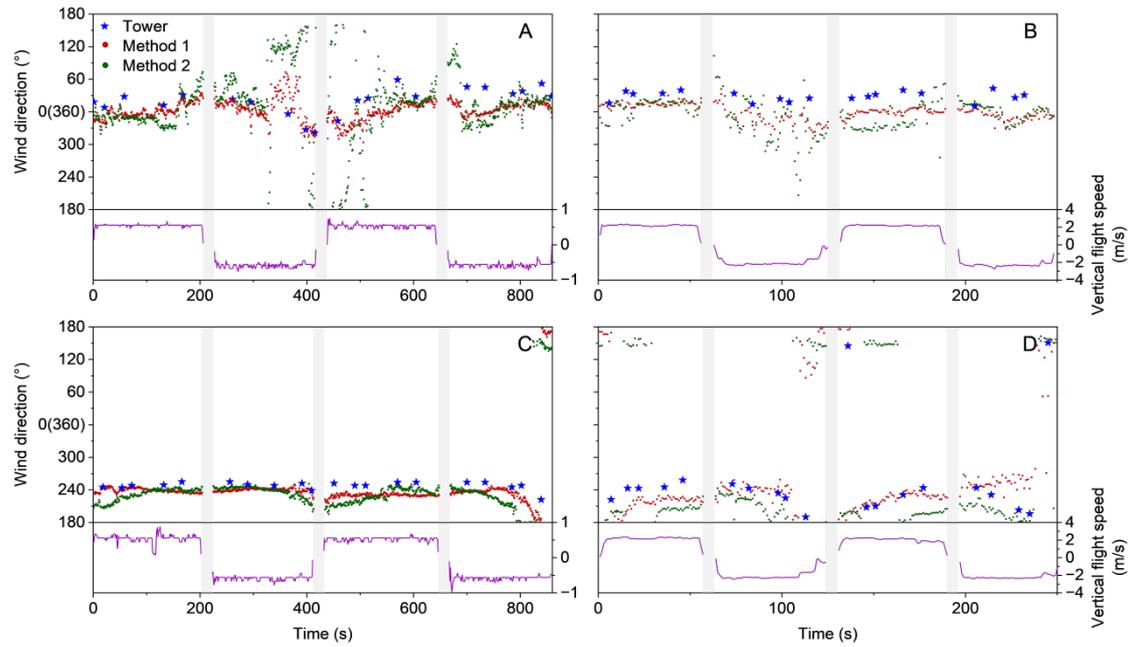


Figure S2 Comparison between UAV-based wind direction estimates and reference measurements from the meteorological observation tower during vertical flight operations: ascending and descending at 0.5 m/s (A) and 2 m/s (B) with default payload, and at 0.5 m/s (C) and 2 m/s (D) with additional front-top payload. Gray shaded areas indicate hovering periods.

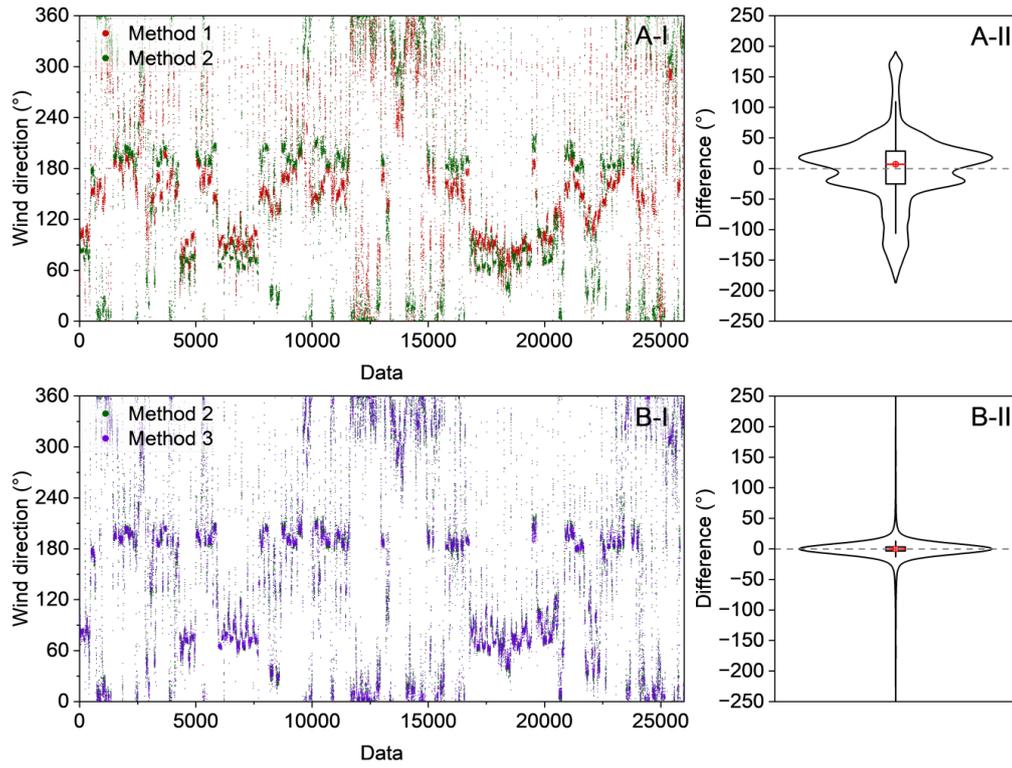


Figure S3 UAV-based wind direction estimation and deviation analysis comparing methods 1 versus 2 (A-I, A-II) and methods 2 versus 3 (B-I, B-II) from the field observation campaign.

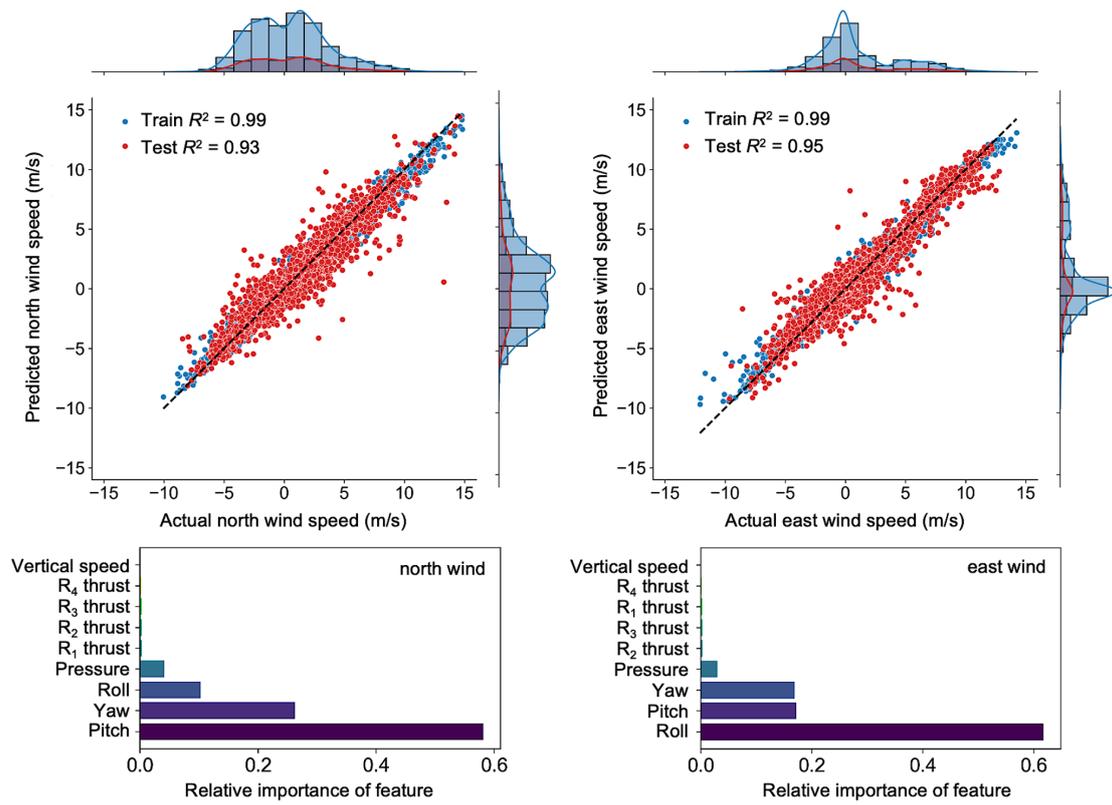


Figure S4 Performance of wind estimation using machine learning algorithms for hovering flights. The wind components are separated into northward and eastward winds for better visualization. The RMSE values are 0.9 m/s and 0.8 m/s for the northward and eastward wind predictions, respectively.

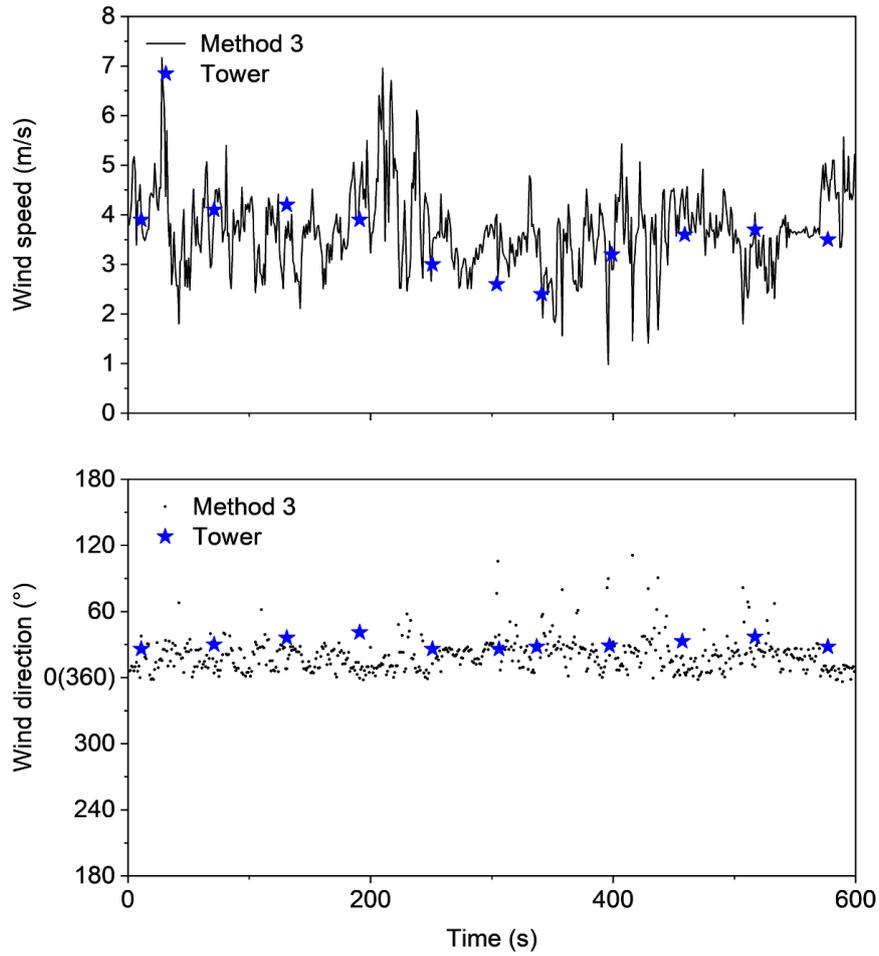


Figure S5 Comparison between UAV-attitude-based wind speed estimates using machine learning algorithms (method 3) and reference measurements from the meteorological observation tower during hovering flight operations.

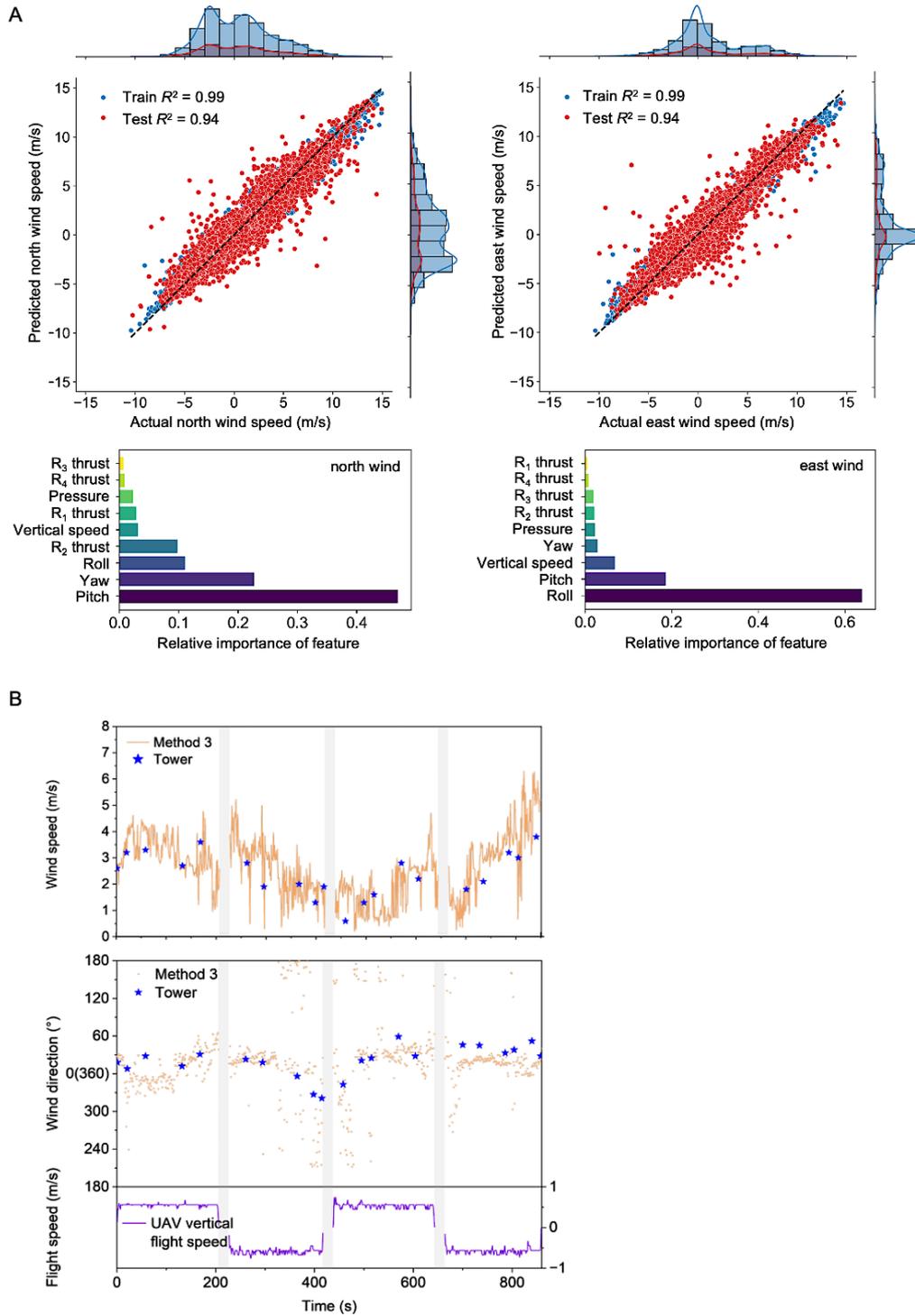


Figure S6 (A) Performance of wind estimation using machine learning algorithms for vertical flights. The wind components are separated into northward and eastward winds for better visualization. The RMSE values are 0.9 m/s and 0.8 m/s for the northward and eastward wind predictions, respectively. (B) Comparison between UAV-attitude-based wind speed estimates using machine learning algorithms (method 3) and reference measurements from the meteorological observation tower during vertical flight operations.