

JHTDB-wind: a web-accessible large-eddy simulation database of a wind farm with virtual sensor querying

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1 **Abstract.** This manuscript introduces JHTDB-wind (<https://turbulence.idies.jhu.edu/datasets/windfarms>), a publicly accessible
2 database containing large-eddy simulation (LES) data from wind farms. Building on the framework of the Johns Hopkins
3 Turbulence Database (JHTDB), which hosts direct numerical and some large-eddy simulation datasets of canonical turbulent
4 flows, JHTDB-wind stores the full space-time (4D) history of the flow and provides users the ability to access and query
5 the data via a web-based virtual sensor interface. The initial dataset comprises LES results from a large wind farm with
6 6×10 turbines, modeled using a filtered actuator line method, under conventionally neutral atmospheric conditions. This
7 data comprises one hour of flow field data (velocity, pressure, potential temperature, and others, approximately 15TB) and
8 wind turbine data—including both turbine-level operational quantities and blade-level aerodynamic quantities (approximately
9 1.3TB)—stored in Zarr and Parquet formats, respectively. Data retrieval is facilitated by the Giverny Python package, allowing
10 remote users to query the database in Python or Matlab (C and Fortran support are available for flow field data). This paper
11 details the simulation setup and demonstrates data access through examples that analyze wind farm flow structures and turbine
12 performance. The framework is extensible to future datasets, including the JHTDB-wind diurnal cycle simulation analyzed in
13 Xiao et al. (2025).

14 1 Introduction

15 Eddy-resolving simulations of atmospheric boundary layer phenomena (Porté-Agel et al., 2000; Bou-Zeid et al., 2004; Kumar
16 et al., 2006) and of wind farms in particular (Calaf et al., 2010; Meyers and Meneveau, 2012; Gebraad et al., 2016; Stevens
17 and Meneveau, 2017; Zhang et al., 2023) have significantly advanced our understanding of the complex, multi-scale, and

18 multi-physics processes involved. Large Eddy Simulations (LES) offer high spatial and temporal resolution, capturing the
19 dynamics of relatively small and fast turbulent eddies (Churchfield et al., 2012; Chatelain et al., 2013; Yang et al., 2021; Li
20 et al., 2022). While the range of resolved scales in LES is constrained by computational resources, the number of LES grid-
21 points in typical simulations continues to increase. However, data handling and post-processing capabilities have not kept pace
22 with the resulting rapid increase in data volumes. For instance, a single LES of turbulent flow outputting five field variables
23 (e.g., the three velocity components, potential temperature and pressure) on $2,048^3$ spatial grid points and integrated over,
24 say, 10^4 time-steps (McWilliams et al., 1994; Alexakis et al., 2024), can generate Petabytes (PB) of data. As a result, most
25 studies store only a few selected snapshots and rely heavily on pre-defined run-time diagnostics when time-resolved analysis
26 is required. This approach reduces storage requirements but limits the ability to revisit data when new questions and concepts
27 arise, often necessitating costly recomputation. Furthermore, certain analyses —such as backward-in-time particle tracking
28 from an extreme dissipation event—cannot be performed without the full temporal data.

29 To address these challenges, modern database technologies have increasingly been applied to preserve and store data from
30 simulation-based turbulence research (Perlman et al., 2007; Zhang et al., 2018; Chung et al., 2022; Duraisamy et al., 2019).
31 One example is the Johns Hopkins Turbulence Database (JHTDB, <https://turbulence.idies.jhu.edu>), an open-access platform
32 supported by the National Science Foundation (Perlman et al., 2007; Li et al., 2008). JHTDB enables researchers to interact with
33 easily accessible, large-scale simulation data. The system currently hosts more than 1 PB of DNS data for canonical, turbulent
34 flows of fundamental interest (over 2 PB if counting warm backup copies), including 6 space-time resolved data sets and
35 several others with a few snapshots available. Some LES datasets of stably stratified atmospheric turbulence are also included
36 in JHTDB. Through web-service-based tools, users can query the database using a “virtual sensors” interface, specifying spatial
37 and temporal locations for which the system returns properly interpolated field or derivative values (Li et al., 2008; Yu et al.,
38 2012). A hallmark of the platform is that it allows users to access only the specific subsets of the data they require, eliminating
39 the need to download massive datasets or manage complex file formats. This approach has significantly broadened access to
40 high-fidelity eddy-resolving simulation data and has contributed to democratizing high-performance computational turbulence
41 research. To date, JHTDB data have been used in research reported in over 400 peer-reviewed journal articles.

42 At the same time, with the growing global demand for renewable energy continuing to rise, enhancing wind energy efficiency
43 has become a key priority. As wind turbines grow larger and wind farms expand in scale, their interactions with the atmospheric
44 boundary layer (ABL) become increasingly complex—particularly with respect to wake dynamics, energy extraction, and
45 the redistribution of momentum within the flow. LES of large wind turbines have emerged as a crucial complement to field
46 measurements, enabling researchers to explore flow-turbine interactions in detail and to develop engineering models that inform
47 turbine placement strategies and improve wind farm efficiency. For example, Calaf et al. (2010) used LES with periodic
48 boundary conditions to study the performance of “infinite” arrays of wind turbines under neutrally-stratified conditions. Abkar
49 and Porté-Agel (2013, 2014) examined how wind farm density and free-atmosphere stability influence kinetic energy fluxes
50 in a conventionally neutral boundary layer (CNBL) - defined as neutrally-stratified surface layers capped by stably-stratified
51 free atmospheres (Zilitinkevich et al., 2002). Allaerts and Meyers (2015) explored the effect of capping inversion profile on
52 wind farm performance. Numerous additional LES-based studies have further advanced the field (Yang et al., 2014; Aitken

et al., 2014; Martínez-Tossas et al., 2015; Stevens et al., 2018; Gharaati et al., 2022, 2024; Aiyer et al., 2024), highlighting the continued value of high-resolution simulation tools for understanding and optimizing wind energy systems.

These simulations, like many previous numerical studies of large-scale wind farms, generate extensive datasets. However, access to these data often remains restricted to the original researchers who conducted the simulations. The data (typically 4D space-time fields of velocity, temperature, etc.) are ephemeral: they must be analyzed in real-time during the simulation, or, at best, a limited number of snapshots are stored for post-processing, while the large majority of the data is discarded. As demonstrated in the case of the JHTDB database, providing access to the full time-history of a simulation could provide substantial benefits for the broader wind energy research community. The value of open access to time-resolved numerical datasets is now being recognized beyond fluid dynamics, particularly in the fields of Geosciences. For example, the recently released NOW-23 dataset (Bodini et al., 2023) comprises a full year of Weather Research and Forecasting (WRF) model simulations of off-shore wind conditions over several expansive (100's km) U.S. coastal regions, offering valuable data for wind farm developers. However, no equivalent open-access LES datasets currently exist at smaller scales that explicitly include wind turbine effects—datasets that would be highly valuable for researchers focused on wake interactions, turbine siting, and wind farm optimization. More in general, the lack of data sharing in the wind energy sector has been recognized to hinder technical progress and leads to missed opportunities for improving the efficiency of energy markets (Kusiak, 2016)

To begin addressing the need for open access to LES wind farm data, we construct JHTDB-wind (see <https://turbulence.idies.jhu.edu/datasets/windfarms>, Zhu et al. ((2025))), a publicly accessible turbulence database built on the JHTDB framework. This paper presents the dataset by detailing the simulation methodology (Section 2), and flow configuration—specifically, a CNBL interacting with a 60-turbine wind farm using National Renewable Energy Laboratory (NREL) 5MW reference turbines. Here, CNBL is chosen because it is a less complicated atmospheric state, observed in nature (Liu and Stevens, 2022), for example, during the transition period after sunset or on cloudy days with powerful winds (Allaerts and Meyers, 2017; Liu et al., 2024). Simulation parameters are described in Section 3. The construction of the database system is described in Section 4, followed by an overview of representative data access methods based on the JHTDB virtual sensor method, illustrated here via Python examples (Section 5). Conclusions are summarized in Section 6. Further documentation is available directly on the database website.

2 Large-eddy simulation framework

In this study, we use the open source LES code LESGO (<https://lesgo.me.jhu.edu>) as a numerical solver to simulate ABL flows and its interactions with wind turbines (Calaf et al., 2010; Stevens and Meneveau, 2017; Martinez et al., 2017; Stevens et al., 2018; Shapiro et al., 2018, 2020; Gharaati et al., 2022; Narasimhan et al., 2022, 2024a, b, c; Gharaati et al., 2024; Ayala et al., 2024). The model represents all variables on a three-dimensional Cartesian grid, with x , y , and z denoting the streamwise, spanwise, and vertical directions, respectively. In index notation, these are expressed as x_i where $i = 1, 2, 3$. The corresponding velocities are denoted by u_i , or also with u , v , and w for its x , y , and z -direction components, respectively.

85 2.1 Governing equations and numerical methods

86 The turbulent flow is simulated by solving the filtered Navier-Stokes equations in their rotational form with Boussinesq thermal
87 forcing and Coriolis effects, along with the transport equation for the potential temperature field. The governing equations
88 include the filtered mass conservation,

$$89 \quad \frac{\partial \tilde{u}_i}{\partial x_i} = 0, \quad (1)$$

90 the filtered momentum conservation,

$$91 \quad \frac{\partial \tilde{u}_i}{\partial t} + \tilde{u}_j \left(\frac{\partial \tilde{u}_i}{\partial x_j} - \frac{\partial \tilde{u}_j}{\partial x_i} \right) = -\frac{\partial \tilde{p}^*}{\partial x_i} + \frac{g}{\theta_0} (\tilde{\theta} - \theta_0) \delta_{i3} - \frac{\partial \tau_{ij}^{\text{SGS},d}}{\partial x_j} - f_i + f_c (\tilde{u}_2 - V_g) \delta_{i1} - f_c (\tilde{u}_1 - U_g) \delta_{i2}, \quad (2)$$

92 and the filtered heat conservation,

$$93 \quad \frac{\partial \tilde{\theta}}{\partial t} + \tilde{u}_j \frac{\partial \tilde{\theta}}{\partial x_j} = -\frac{\partial \Pi_j}{\partial x_j}. \quad (3)$$

94 Here, the tilde indicates filtering at the LES grid scale $\tilde{\Delta} = \sqrt[3]{\Delta x \Delta y \Delta z}$; ρ is the density of air; $\tau_{ij}^{\text{SGS}} = \widetilde{u_i u_j} - \tilde{u}_i \tilde{u}_j$ is the
95 unresolved subgrid-scale (SGS) stress tensor, and $\tau_{ij}^{\text{SGS},d} = \tau_{ij}^{\text{SGS}} - \delta_{ij} \tau_{kk}^{\text{SGS}}/3$ is the deviatoric (trace-free) part of τ_{ij}^{SGS} , where
96 δ_{ij} is the Kronecker delta; $\tilde{p}^* = \tilde{p}/\rho + \tilde{u}_k \tilde{u}_k/2 + \tau_{kk}^{\text{SGS}}/3$ is the pseudo pressure, where $\tilde{p}$ is the resolved pressure; $g = 9.81 \text{ m/s}^2$ is
97 the gravitational acceleration; θ_0 is the reference potential temperature scale; and f_i is the distributed body force for modeling
98 the turbine-induced aerodynamic forces on the air flow (see §2.3). In the present study, $\tau_{ij}^{\text{SGS},d}$ is parameterized using the
99 Lilly-Smagorinsky eddy-viscosity type model (Smagorinsky, 1963; Lilly, 1966), i.e., $\tau_{ij}^{\text{SGS},d} = -2\nu_{\text{SGS}} \tilde{S}_{ij} = -2(C_s \tilde{\Delta})^2 |\tilde{S}| \tilde{S}_{ij}$,
100 where $\tilde{S}_{ij} = 0.5(\partial \tilde{u}_i/\partial x_j + \partial \tilde{u}_j/\partial x_i)$ is the resolved strain-rate tensor, $|\tilde{S}| = \sqrt{2\tilde{S}_{ij}\tilde{S}_{ij}}$ is the strain-rate magnitude, and $\nu_{\text{SGS}} =$
101 $(C_s \tilde{\Delta})^2 |\tilde{S}|$ is the modeled SGS eddy viscosity. The coefficient C_s is dynamically determined using the Lagrangian-averaged
102 scale-dependent dynamic model (Bou-Zeid et al., 2005), which has been successfully applied in several prior LES studies
103 of wind turbine wake flows (Calaf et al., 2010; Stevens and Meneveau, 2017; Martinez et al., 2017; Stevens et al., 2018;
104 Narasimhan et al., 2022; Gharaati et al., 2022; Narasimhan et al., 2024a; Gharaati et al., 2024). In Eq. 3, the term $\Pi_j =$
105 $\widetilde{u_j \theta} - \tilde{u}_j \tilde{\theta}$ is the SGS heat flux whose eddy diffusivity (κ_{SGS}) is determined from $\kappa_{\text{SGS}} = Pr_{\text{SGS}}^{-1} \nu_{\text{SGS}}$, where the SGS Prandtl
106 number of $Pr_{\text{SGS}} = 1$ (Narasimhan et al., 2022) is prescribed.

107 The atmospheric boundary layer flow is driven by a geostrophic wind whose pressure gradient is given by $-\nabla P_\infty/\rho =$
108 $(f_c V_g, -f_c U_g)$. Here, $f_c = 2\Omega \sin \phi = 10^{-4} \text{ s}^{-1}$ is the Coriolis parameter corresponding to a mid-latitude position (specifically
109 to $\phi = 43.44^\circ$ with Earth's rotation rate $\Omega = 7.27 \times 10^{-5} \text{ rad/s}$). The quantities U_g, V_g are the geostrophic wind velocity com-
110 ponents along the x and y directions, respectively, with magnitude $G = \sqrt{U_g^2 + V_g^2}$, and directed at an angle of α_G relative to
111 the x direction such that $U_g = G \cos \alpha_G$, $V_g = G \sin \alpha_G$. At each timestep, a proportional-integral (PI) controller is utilized to
112 control the direction of the geostrophic wind such that the wind flows in the streamwise direction with zero wind veer at the
113 hub height (Sescu and Meneveau, 2014; Narasimhan et al., 2022).

114 LESGO uses a Fourier-series-based pseudo-spectral method based on collocated grids for the spatial discretizations in the
115 horizontal (x and y) directions, and a second-order central-difference method based on staggered grids in the vertical (z)

direction. The 3/2-rule is used to eliminate the aliasing error associated with the pseudo-spectral discretization of the nonlinear convective terms. The simulation is advanced in time using a fractional-step method. First, the velocity field is advanced in time by integrating Eq. (2) using the second-order Adams-Bashforth scheme to obtain a predicted velocity field. Then a pressure Poisson equation is constructed based on the divergence-free constraint Eq. (1) for the new time step and is solved to obtain the pseudo-pressure field. Lastly, the predicted velocity field is projected to the divergence-free space using the gradient of the pseudo pressure to obtain the velocity field for the new time step. The above fractional steps are repeated at every time step in LES to advance the flow field in time. More details of the numerical schemes used in the LESGO solver can be found in the original references (Albertson, 1996; Albertson and Parlange, 1999).

2.2 Boundary conditions

In the x (nominally the streamwise) direction, inflow–outflow boundary conditions are applied using the concurrent precursor simulation approach (Stevens et al., 2014). Specifically, a separate precursor domain without wind turbines is simulated to generate realistic turbulent inflow conditions, which are then imposed at the inlet of the wind farm domain. To ensure periodicity, a fringe region is introduced at the end of the wind farm domain where the outflow is gradually forced to match the inflow from the mapped region in the precursor domain. More details of the inflow-outflow conditions implemented in the current pseudo-spectral solver are provided in Stevens et al. (2014). Additionally, the simulation in the precursor domain uses a shifted periodic boundary condition where the flow field in a spanwise shifting region is shifted to prevent persistent spanwise locking of large-scale turbulent structures (Munters et al., 2016). Following the recommendation in Munters et al. (2016) a shift of $L_{y\text{-shift}} = 0.25L_z$ is used in this study, where L_z is the domain height. In the spanwise (y) direction, periodic boundary conditions are used. In the vertical (z) direction, the ground surface boundary condition is specified in both the precursor and wind turbine domains using the Monin-Obukov Similarity Theory (MOST)-based equilibrium surface flux modeling (Monin and Obukhov, 1954). The components of local surface shear stress are computed as a function of the prescribed roughness length according to

$$\tau_{i,3|\text{surf}} = -u_*^2 \frac{\widehat{u}_i}{\sqrt{\widehat{u}^2 + \widehat{v}^2}}, \quad i = 1, 2; \quad \text{and} \quad u_* = \kappa \frac{\sqrt{\widehat{u}^2(0.5\Delta z) + \widehat{v}^2(0.5\Delta z)}}{\ln(0.5\Delta z/z_0)}. \quad (4)$$

Here, $\kappa = 0.41$ is the von Kármán constant, z_0 is the prescribed roughness length, the friction velocity u_* is expressed in terms of the horizontal velocity $(\widehat{u}, \widehat{v})$ at the first grid-point ($z_1 = 0.5\Delta z$), filtered at twice the grid resolution, $\widehat{\Delta} = 2\widetilde{\Delta}$ (Bou-Zeid et al., 2005). Since we simulate conventionally neutral conditions, the surface heat flux is set to zero, and thus no stability correction terms (as used in Xiao et al. (2025)) are included. At the top of the domain, a stress-free boundary condition is imposed. A sponge or Rayleigh-damping layer (Durrán and Klemp, 1983) is included approaching the top boundary, ranging from $0.75L_z$ to L_z , with a sponge inverse relaxation time-scale (frequency) parameter of 3.9×10^{-3} 1/s. In this layer, a damping body force with a cosine profile is applied to suppress the reflection of gravity waves.

Henceforth, the $(\tilde{\cdot})$ notation for LES-filtered field variables (e.g., velocity $\tilde{u}_i$, temperature $\tilde{\theta}$) will be omitted for brevity. All subsequent variables should be interpreted as implicitly filtered quantities obtained from the LES solution, governed by the equations presented in this Section.

2.3 Wind turbine representation

The aerodynamic forces exerted by wind turbines on the airflow are modeled through the distributed body force term f_i in the momentum transport equations (Eq. 2). During the initial spin-up phase, we employ an actuator disk model (ADM) on a coarse grid for computational efficiency, with the thrust force magnitude calculated as $f = \frac{\pi}{8} \rho C'_T \langle u_T \rangle_d^2 D^2$ (Calaf et al., 2010; Howland et al., 2016). Here, ρ is the air density, $\langle u_T \rangle_d$ is the local wind velocity averaged over the rotor disk, D is the diameter of the wind turbine, and C'_T is the local thrust coefficient (set to a common value $C'_T = 1.33$). We recall (Calaf et al., 2010) that C'_T is based on the disk-averaged velocity $\langle u_T \rangle_d$ which, unlike the far-upstream velocity U_∞ , is immediately available in LES.

After the spin-up simulation converges to quasi-steady behavior, the grid is refined to its final resolution, and the actuator line model (ALM) is adopted (Sørensen and Shen, 2002; Troldborg, 2009; Jha et al., 2014; Martínez-Tossas et al., 2015). In ALM, each turbine blade is represented by a collection of actuator points along a line, where forces are applied according to the velocity field and the angle of attack. The forces per unit width at every actuator point are computed as

$$\mathbf{f}_{\text{alm}} = 0.5 \rho c |\mathbf{V}_{\text{rel}}|^2 (C_L \mathbf{e}_L + C_D \mathbf{e}_D), \quad (5)$$

where c is the airfoil chord length, $|\mathbf{V}_{\text{rel}}|$ is the magnitude of the relative velocity of the upwind flow to the turbine blade, C_L and C_D are lift and drag coefficients obtained from tabulated airfoil data, and $\mathbf{e}_L$ and $\mathbf{e}_D$ are unit vectors along the direction of the lift and drag forces at each actuator point, respectively. These forces are then smeared using a Gaussian kernel to project them into the computational LES grid:

$$\eta_\varepsilon = \frac{1}{\varepsilon^3 \pi^{3/2}} e^{-r^2/\varepsilon^2} \quad (6)$$

where r is the distance from the grid point to the actuator point, and ε denotes the width of the kernel. The kernel width is chosen to be at least $\varepsilon = 2(\Delta_x \Delta_y \Delta_z)^{1/3}$, as recommended to avoid numerical instabilities (Troldborg, 2009; Martínez-Tossas et al., 2015).

The accuracy of the ALM can be sensitive to grid resolution and the choice of ε . The optimal ε_{opt} needed to resolve the induced velocities is typically much smaller than the ε used to avoid numerical instabilities (Martínez-Tossas et al., 2017). To address this challenge, we use the generalized filtered lifting line theory correction to accurately represent the blade aerodynamics (Martínez-Tossas and Meneveau, 2019; Martínez-Tossas et al., 2024), including the shedding of unresolved vorticity leading to missing induced velocities at the blade. The correction accounts for subgrid-scale induced velocity that would be obtained by using an optimal ε_{opt} by estimating its contribution and adding it to the resolved velocity in the LES. With the correction, the ALM provides consistent blade loading predictions across varying grid resolutions.

The NREL 5 MW baseline wind turbine (Jonkman, 2009) is adopted as our reference model. It is a widely-used benchmark model developed by NREL to standardize research on wind technologies. The turbine has a diameter of $D = 126\text{m}$, three

178 blades, and a hub height at elevation $z_h = 90$ m. It reaches a rated electrical power output of 5 MW at a rated wind speed
 179 of approximately 11.4 m/s. Its rotor blades utilize the DU (Delft University) and NACA (National Advisory Committee for
 180 Aeronautics) series airfoil profiles optimized for aerodynamic efficiency, structural integrity, and minimal fatigue loads, making
 181 the NREL 5 MW turbine an essential tool for evaluating wind turbine performance, control strategies, structural design, and
 182 offshore platform dynamics.

183 The dataset employs fixed but row-dependent rotor angular velocities determined through an initialization procedure. Initial-
 184 ization begins with all turbines operating at $TSR=7.5$ (near-optimal for NREL 5MW turbines). In this initialization simulation,
 185 the angular velocity Ω for each turbine is then computed dynamically using:

$$186 \quad \Omega = TSR \times \frac{1.087 U_d}{(1-a)R}, \quad (7)$$

187 where U_d is the disk-averaged velocity; the numerator incorporates an empirical 8.7% correction factor for LES filter-scale
 188 effects ($\varepsilon = 16$ m), validated through single-turbine laminar inflow tests; the induction factor a derives from rotor geometry
 189 (blade number $N_b = 3$, radius $R = 63$ m, and chord $c = 3\text{--}4$ m) and local inflow angle ϕ via:

$$190 \quad a = \frac{1}{(4 \sin^2 \phi) / (\sigma_r C_n) + 1}, \quad (8)$$

191 with rotor solidity $\sigma_r = N_b c / (\pi R)$ and force coefficient $C_n = C_L \cos \phi + C_D \sin \phi$. After approximately 30 minutes of simulation,
 192 the angular velocity Ω for each turbine is averaged within its respective row, which serves as the fixed operational values for
 193 the subsequent database simulations.

194 We also note that LESGO's ALM implementation includes detailed turbine operation control methods, such as pitching the
 195 blades (feathering) during region III operations, e.g. above rated conditions. In the current simulation we chose to operate all
 196 turbines exclusively at optimal tip-speed ratio, "region II" (also without including regions 1.5 and 2.5). This choice was made
 197 in order to avoid the need to store additional data relating to blade pitch (curtailment) and other complex turbine control actions.
 198 Since this practice deviates slightly from the reference NREL-5MW nameplate data, we refer to the turbine in our simulations
 199 as the NREL-5MW+ turbine. Indeed, the front turbines are allowed to rotate slightly faster than the maximum rotation rate of
 200 the original NREL-5MW reference turbine.

201 **3 Simulation parameters**

202 We simulate turbulent flow through a 10×6 array of NREL-5MW+ turbines (with diameter $D = 126$ m) in a $28.224 \times 3.78 \times$
 203 2 km^3 domain, equally split between precursor and wind farm subdomains (each $112D = 14.112 \text{ km}$ long). Figure 1 displays
 204 the domain dimensions. The precursor domain includes the region denoted as P of length $5L_x/8$, mapping region P_M ($L_x/8$),
 205 and spanwise shifting region P_S ($L_x/8$). The wind farm domain features $14D$ of upstream buffer zone, $63D$ turbine region, $21D$
 206 downstream wake recovery region (these three regions combined are denoted as W), and $14D$ outflow fringe region (W_F). The
 207 turbines are spaced $7D$ (streamwise) and $5D$ (spanwise), with lateral boundaries $2.5D$ from the outermost turbines. Note that the
 208 fringe region W_F , as well as the mapping (P_M) and spanwise shifting (P_S) regions, have a length of $L_x/8$, and the mapping region

209 P_M extends from $5L_x/8$ to $3L_x/4$. Vertically, a 0.5 km Rayleigh damping sponge layer (denoted as R) is located between 1.5 and
 210 2 km (see Figure 1). We adopt $\theta_0 = 263.5$ K as the reference potential temperature, consistent with the value chosen in studies
 211 by Gadde and Stevens (2021) and our prior simulations of SBL and CNBL flows reported in Narasimhan et al. (2024a). This
 212 reference temperature was inspired by observations from the Beaufort Sea Arctic Stratus Experiment (BASE) and simulations
 213 by Kosović and Curry (2000). While the value of θ_0 is relatively low, it serves primarily as a relative additive reference that
 214 does not significantly affect the simulated flow dynamics or the physical interpretation of the results. For example, if we used
 215 273K, it would change the implied thermal expansion coefficient in our Boussinesq approximation only by about 3%.

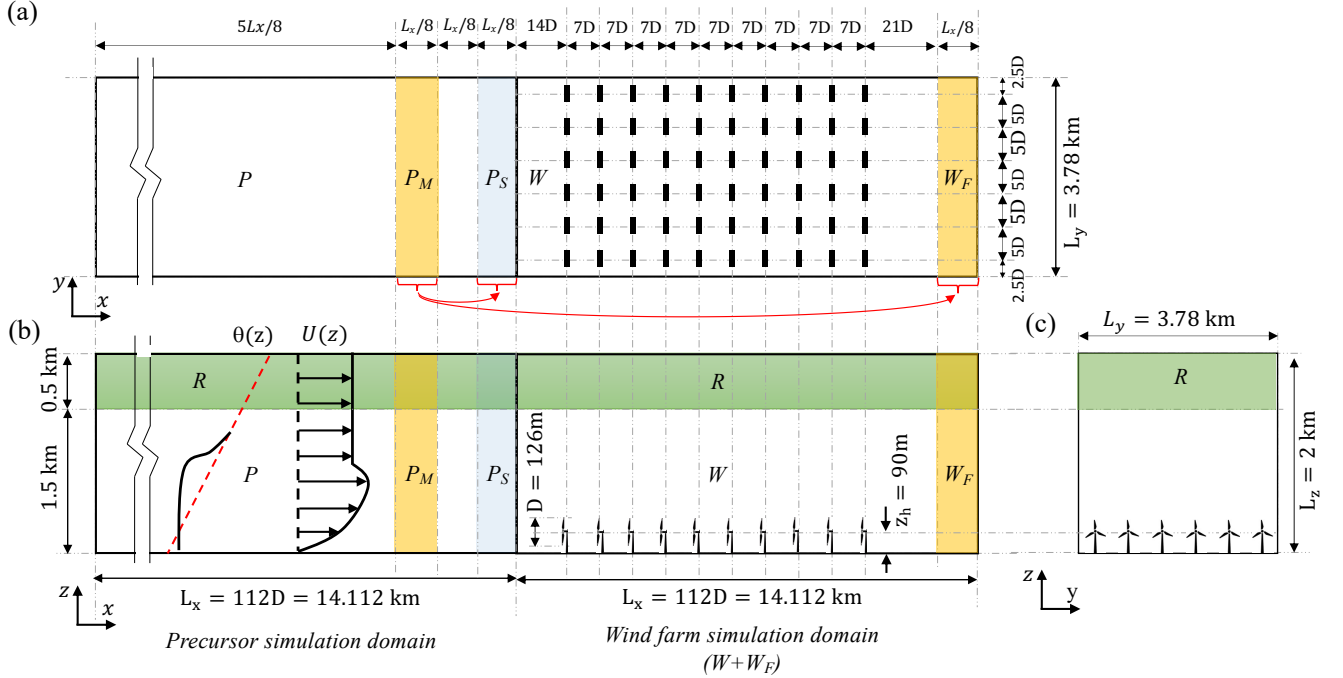


Figure 1. Schematic representation of the computational simulation domain (not to scale), showing: (a) top view (x - y plane), (b) side view (x - z plane) and (c) front view (y - z plane). The precursor computational domain consists of the regions denoted as “ P ”, the precursor mapping region “ P_M ”, and the precursor spanwise shifting region “ P_S ”. The wind farm computational domain includes the wind farm region “ W ” and the fringe region “ W_F ” near the outlet. Both precursor and windfarm computational domains include a Rayleigh damping region at the top (region “ R ”). The turbine diameter $D = 126$ m and hub height $z_h = 90$ m are also marked.

216 The turbulent flow is driven by a constant geostrophic wind speed $G = 15$ m/s at $\alpha_g \approx -22.5^\circ$ to the x direction, with
 217 the angle controlled by a PI controller ($K_p = 10$, $K_i = 0.5$) to align hub-height mean wind velocity with the x -axis in the
 218 conventionally neutral boundary layer (Sescu and Meneveau, 2014; Narasimhan et al., 2022). The surface has roughness length
 219 $z_0 = 0.1$ m and reference potential temperature $\theta_0 = 263.5$ K. Initial conditions set $U_g = 15$ m/s (streamwise) and $V_g = 0$ m/s
 220 (spanwise), perturbed by random noise, while potential temperature decreases from 265 K at the surface with a 1 K/km lapse
 221 rate, including random perturbations below 1 km.

222 The numerical simulation is conducted in three consecutive phases to ensure proper flow development and statistical con-
 223 vergence.

- 224 – Phase 1: Coarse-resolution ADM spin-up: A 10-hour simulation using the ADM is performed to establish a quasi-
 225 stationary atmospheric boundary layer and wind farm wake field. This phase leverages the computational efficiency of
 226 ADM, which approximates turbine forces without resolving actuator line-level aerodynamics.
- 227 – Phase 2: Fine-resolution ALM convergence. A 1-hour simulation using the actuator line model at finer spatial res-
 228 olution transitions the flow from ADM-averaged to ALM-resolved turbine representation. Besides the turbine model
 229 update, two additional changes are introduced in this phase: (i) the time-stepping scheme is switched from a constant
 230 Courant–Friedrichs–Lewy (CFL) number of 0.0625 to a fixed time step of $\Delta t = 0.025$ s. This adjustment has negligi-
 231 ble impact on the results because, under these simulation conditions, $CFL = 0.0625$ corresponds to $\Delta t \approx 0.03$ s. The
 232 slightly more restrictive $\Delta t = 0.025$ s maintains numerical stability while preserving solution accuracy. (ii) The rotor
 233 control changes from a fixed tip-speed ratio ($TSR = 7.5$) to fixed rotor angular velocities that vary across turbine rows,
 234 as tabulated in Table 1. This adjustment has a negligible impact on the results because the prescribed angular velocities
 235 closely match the values achieved under $TSR = 7.5$ conditions (see the calculation method in Section 2.3), ensuring
 236 nearly identical rotor dynamics.
- 237 – Phase 3: Fine-resolution simulation for database construction. A final 1-hour simulation is carried out to collect high-
 238 fidelity flow and turbine data. Flow field variables are recorded every 20 LES time steps (i.e., every 0.5 s) on a filtered
 239 and subsampled spatial grid (every other grid point in the x – y plane), while wind turbine data—both integral and blade-
 240 resolved—are stored at every LES time step (0.025 s). Note that we purposefully operate the NREL-5MW+ turbine in
 241 “region II” during the simulation time, in order to avoid having to choose and document additional controller actions.
 242 As a result, during some times some of the turbines operate “above rated conditions” but maintaining self-consistent
 243 aerodynamic behavior of the blades and air-flow.

Table 1. Rotor speed for each row of turbines.

Row No.	1	2	3	4	5	6	7	8	9	10
Ω (rad/s)	1.33	1.02	1.04	1.07	1.09	1.09	1.09	1.09	1.09	1.10

244 The three phases of the simulation are illustrated through the time history of the boundary layer height $z_i = h_{ABL}$ and the
 245 geostrophic wind angle shown in Figure 2.

Table 2. Three consecutive phases and computational domain parameters

Phase	Grid level	Turbine model	Domain size $2L_x \times L_y \times L_z$ (km $\times$ km $\times$ km)	Number of grid points $2N_x \times N_y \times N_z$	Spatial resolution $\Delta x \times \Delta y \times \Delta z$ (m $\times$ m $\times$ m)	Time grid CFL or Δt (- or s)
1	Coarse	ADM	$2 \times 14.112 \times 3.78 \times 2$	$2 \times 512 \times 192 \times 400$	$27.56 \times 19.69 \times 5$	CFL=0.0625
2	Fine	ALM TSR=7.5	$2 \times 14.112 \times 3.78 \times 2$	$2 \times 1,536 \times 384 \times 400$	$9.19 \times 9.84 \times 5$	CFL=0.0625
		ALM $\Omega = \text{const}$				$\Delta t = 0.025$ s
3	Fine	ALM $\Omega = \text{const}$	Simulation with			
			$2 \times 14.112 \times 3.78 \times 2$	$2 \times 1,536 \times 384 \times 400$	$9.19 \times 9.84 \times 5$	$\Delta t = 0.025$ s
			Sampling over/with			
			$(10.584 + 12.348) \times 3.78 \times 2$	$(576 + 672) \times 192 \times 400$	$18.38 \times 19.68 \times 5$	$\Delta t = 0.5$ s

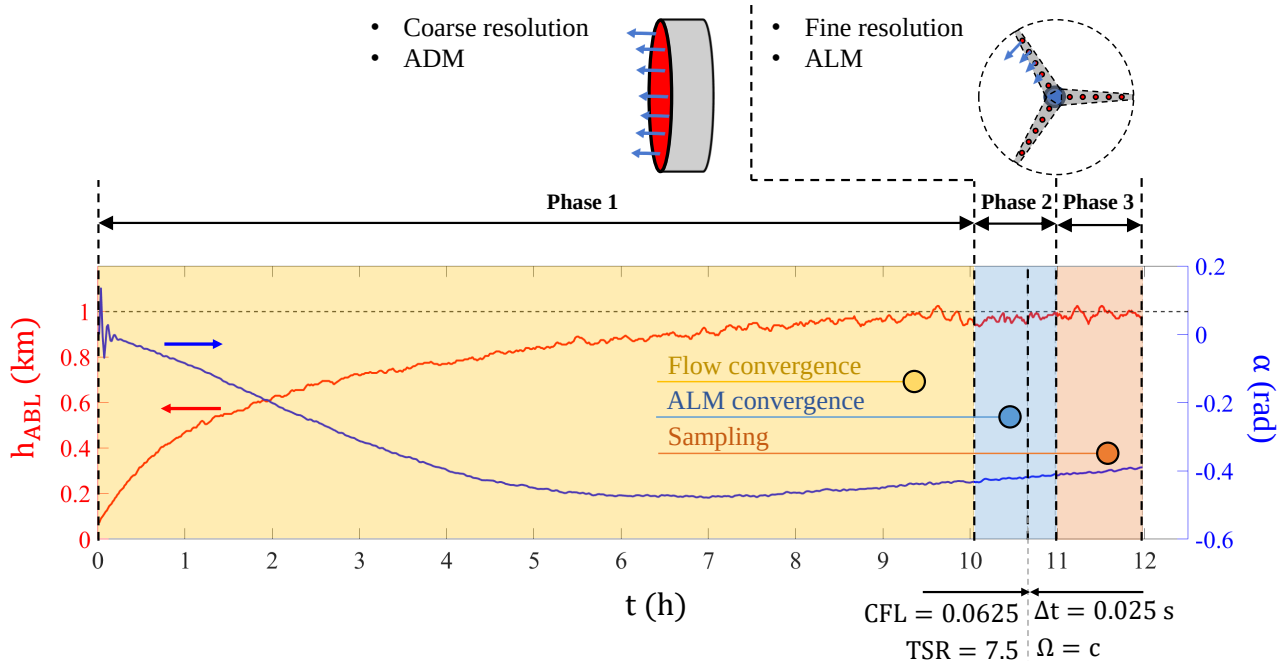


Figure 2. Time history of boundary layer height $z_i = h_{ABL}$, and geostrophic wind angle α , indicating the three simulation phases (phase 1: Coarse-resolution ADM spin-up, phase 2: Fine-resolution ALM convergence, and phase 3: Fine-resolution simulation for database construction).

247 The LES data from the final 1-hour sampling period are systematically ingested into the database and organized into two pri-
 248 mary data types: (i) flow field data, consisting of 4D space-time fields (3D spatial + temporal) captured across both simulation
 249 domains (precursor and wind farm domains), providing complete spatiotemporal information about the atmospheric flow; and
 250 (ii) turbine data, which are further subdivided into two subtypes. The first subtype is turbine integral operational data, com-
 251 prising time histories of turbine power and thrust. The second subtype is turbine blade data, which includes time histories of
 252 aerodynamic quantities sampled at each discrete actuator point along each blade.

253 4.1 Flow field data

254 4.1.1 Domain of the dataset

255 As described in Section 3, the LES is conducted in the domain of dimensions $2 \times 14.112 \times 3.78 \times 2 \text{ km}^3$ (see Table 2). When
 256 compiling the database, we exclude numerically imposed auxiliary regions: the precursor spanwise shifting region P_S (final
 257 $L_x/4$ of the precursor domain) and the wind farm fringe region W_F (final $L_x/8$ of the wind farm domain), as visualized in
 258 Fig. 1. These regions serve purely numerical functions (periodicity enforcement and inflow recycling, respectively) without
 259 contributing to physical flow dynamics of interest. The resulting database domain has the extents of $(10.584 + 12.348) \times$
 260 $3.78 \times 2 \text{ km}^3$, as shown in Fig. 3. The top 0.5km sponge region is kept in the database for simplicity of data management and
 261 possible interest.

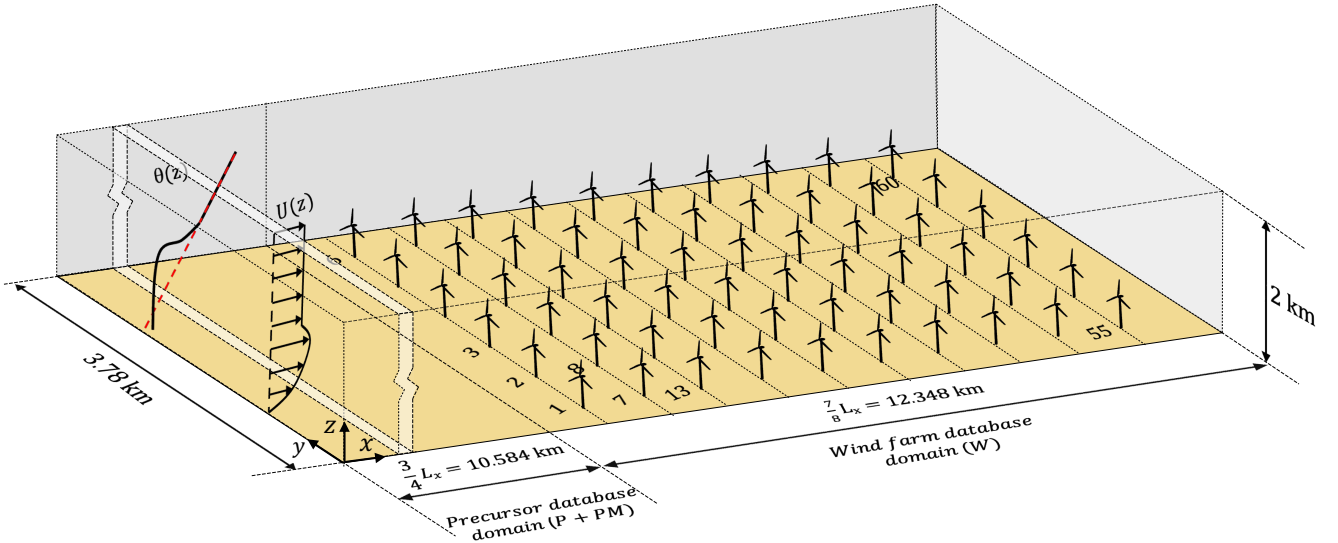


Figure 3. Schematic representation of the database domain (not to scale). This is the physical domain available in the database, merging the precursor domain ($P + P_M$) up to the end of the mapping region at $3/4 L_x$, with the windfarm domain (W) and excluding the fringe region (W_F). Turbines are numbered from 1 to 60 as shown. The domain dimensions are $(10.584 + 12.348) \times 3.78 \times 2 \text{ km}^3$.

262 4.1.2 Spatial resolution of the dataset

263 To minimize storage, we applied spectral filtering on x - y planes for flow field data by truncating Fourier modes above $\kappa_{\max}/2$,
264 where $\kappa_{\max} = \pi/\Delta_{\text{LES}}$ is the LES cutoff wavenumber. The filtered fields were then subsampled at every alternate grid point
265 in the x and y directions, maintaining the original vertical (z) resolution. This approach reduces the dataset size by 75% while
266 maintaining fidelity in capturing the dynamically significant larger-scale flow structures and turbine wake interactions. Thus
267 that the flow field data has a grid size of $(576 + 672) \times 192 \times 400$.

268 4.1.3 Temporal resolution of the dataset

269 Field data are stored at intervals of 0.5 s (every 20 LES steps of 0.025 s), ensuring that fluid parcels advected at the maximum
270 geostrophic speed (15 m/s) travel less than the horizontal grid spacing ($\Delta x \approx 9.19$ m) between snapshots. Although rotor blade
271 tips move across several vertical grid spacings during this interval, the corresponding rotor force field is smooth (Gaussian
272 filtered at scale $\varepsilon = 16m > 2\sqrt[3]{\Delta x \Delta y \Delta z}$), ensuring that the storage frequency of 0.5s remains appropriate. Over the 1-hour
273 simulation period (i.e., 3,600 seconds, the simulation advances through $3,600/0.025=144,000$ LES time steps, with flow fields
274 stored at $144,000/20 = 7,200$ consecutive snapshots).

275 4.1.4 Final structure of the dataset

276 Consequently, the final stored data dimensions are $n_x \times n_y \times n_z \times n_t = 1,248 \times 192 \times 400 \times 7,200$. At each stored time step, six
277 spatial fields are recorded: the three velocity components $u(x, y, z, t)$, $v(x, y, z, t)$, and $w(x, y, z, t)$; the (kinematic) pressure field
278 $p(x, y, z, t)/\rho = p^*(x, y, z, t) - u_k u_k/2$ (the SGS stress trace is not available and is anyhow negligible); the potential temperature
279 field

280 These 4D field variables are stored using the Zarr format (Miles and et al., 2023). In Zarr-based storage, data are organized
281 into chunks, the smallest units retrieved during a query. To ensure efficient data access, chunk sizes must be large enough to
282 support common operations, such as differentiations and interpolations, that typically require access to a three-dimensional
283 neighborhood around the query point, while remaining small enough to avoid excessive memory usage. Based on extensive
284 testing and prior experience with other JHTDB datasets, a chunk size of 64^3 grid points provides optimal retrieval speeds
285 and performance for typical data access modalities. We chose a similar chunk size but shaped according to $52 \times 64 \times 80$ so
286 that an integer multiple of the chunk size in each direction fits into the stored domain size. The total amount of data stored is
287 about 15 Terabytes. These flow field data can be queried using `getData(...)` calls from analysis programs such as Python,
288 MATLAB, Fortran, or C, in the same manner as with other turbulence datasets available through JHTDB.

Table 3. Summary of flow field variables.

No.	Name of variable	Name in dataset	Symbol	Unit	Data size $n_x \times n_y \times n_z \times n_t$	Data resolution $\Delta x \times \Delta y \times \Delta z \times \Delta t$ (m $\times$ m $\times$ m $\times$ s)
1	Streamwise velocity	velocity	u	m/s	$1,248 \times 192 \times 400 \times 7,200$	$18.38 \times 19.68 \times 5 \times 0.5$
2	Spanwise velocity		v			
3	Vertical velocity		w			
4	Potential temperature deviation	temperature	θ'	K or C		
5	Pressure (kinematic)	pressure	p	m^2/s^2		
6	SGS eddy viscosity	eddyviscosity	ν_{SGS}	m^2/s		
7	Turbine streamwise force (kinematic)	force	f_x	m/s^2	$871 \times 384 \times 40 \times 7,200$	$9.19 \times 9.84 \times 5 \times 0.5$
8	Turbine spanwise force (kinematic)		f_y			
9	Turbine vertical force (kinematic)		f_z			

4.2 Wind turbine data

4.2.1 Turbine-level data

The turbine-level data are integral quantities characteristic of each turbine operation, which are derived from the actuator line modeling. This dataset includes high-fidelity time histories of power output, thrust force, and rotor angular velocity, sampled at $\Delta t = 0.025\text{s}$ for all 60 turbines, as summarized in Table 4. In the present dataset, the angular velocity is held constant in time, but for other datasets (e.g. Xiao et al. (2025)), this is not generally the case. For each variable, the dataset consists of 144,000 rows and 2 columns, where the first column represents time and the second column contains the corresponding values of the recorded variable. The turbine data are stored in files using the Parquet format, which facilitates efficient access and querying from various programming languages. Turbine-level data can be accessed using the `getTurbineData(...)` function call from analysis environments such as Python or MATLAB.

Note that unlike field data that are all stored in kinematic (density-independent) units, force and power data require specifying air density. The value used in the simulations to evaluate forces is $\rho_{\text{air}} = 1.23\text{ kg}/\text{m}^3$.

4.2.2 Blade-level data

In addition to the integral quantities characteristic of each turbine's operation, more detailed information is captured along each turbine blade to enable blade-resolved aerodynamic analysis. This fine-grained dataset allows users to investigate the local aerodynamic behavior of blades under unsteady inflow conditions, which is critical for understanding load distributions,

Table 4. Summary of turbine-level variables. Each dataset is an $n_t \times 2$ matrix, where n_t is the number of time steps. Columns 1 and 2 represent time and measured values, respectively.

No.	Name of variable	Name in dataset	Symbol	Unit	Data size $n_t \times 2$	Data resolution Δt (s)
1	Power	power	P	W	144,000 $\times$ 2	0.025
2	Thrust force	thrust	F_t	N		
3	Rotor angular velocity	RotSpeed	Ω	rad/s		

305 fatigue effects, and control optimization strategies. The turbine blade-level dataset includes high-fidelity time histories sampled
 306 at 0.025 s for all 180 blades in the wind farm (60 turbines $\times$ 3 blades each), with aerodynamic and geometric quantities sampled
 307 at 100 discrete actuator line points along the blade span. As summarized in Table 5, a total of 19 variables are sampled and
 308 stored, with each variable written to a separate file. For each variable, the dataset has dimensions of 144,000 $\times$ 3 rows and 103
 309 columns. Each time step includes three rows corresponding to the three blades of a turbine, resulting in a total of 144,000 $\times$ 3
 310 rows. Vertically, the first column represents time in seconds, the second column specifies the turbine number, and the third
 311 column denotes the blade number (blades can be identified by the time-histories of the individual ALM point positions). The
 312 remaining 100 columns contain the values of the selected variables at each of the 100 actuator points from the blade root to tip.
 313 Similar as turbine-level data, blade-level data are stored as Parquet files, allowing efficient access across multiple programming
 314 environments. Blade-level data can be accessed using the `getBladeData(...)` function call from analysis environments
 315 such as Python or MATLAB.

Table 5. Summary of blade-level variables. Each dataset is an $(n_t \times 3) \times 103$ matrix, where n_t is the number of time steps and 3 represents the turbine blades. Columns 1-3 represent time, turbine number, and columns 4-103 store aerodynamic measurements at 100 discrete locations along each blade.

No.	Name of variable	Name in dataset	Symbol	Unit	Data size $(n_t \times 3) \times (n_\ell + 3)$	Data resolution $\Delta t \times \Delta \ell$ (s $\times$ m)
1	ALM point x-position	xPos	P_x	m	$(144,000 \times 3) \times (100 + 3)$	0.025×0.615
2	ALM point y-position	yPos	P_y			
3	ALM point z-position	zPos	P_z			
4	Perturbation velocity at LES resolution, component 1	uy_LES1	$u'_{y,LES1}$	m/s		
5	Perturbation velocity at LES resolution, component 2	uy_LES2	$u'_{y,LES2}$			
6	Perturbation velocity at optimal resolution (0.25c), component 1	uy_opt1	$u'_{y,opt}$			
7	Perturbation velocity at optimal resolution (0.25c), component 2	uy_opt2	$u'_{y,opt}$			
8	Perturbation velocity correction $u'_{y,opt} - u'_{y,LES}$, component 1	du1	$\Delta u'_{y,1}$			
9	Perturbation velocity correction $u'_{y,opt} - u'_{y,LES}$, component 2	du2	$\Delta u'_{y,2}$			
10	Angle of attack	alpha	α	rad		
11	Lift coefficient	Cl	C_L	-		
12	Drag coefficient	Cd	C_D			
13	Lift force per unit length	lift	F_L/ℓ	N/m		
14	Drag force per unit length	drag	F_D/ℓ			
15	Local relative velocity magnitude	Vmag	V_{mag}	m/s		
16	Axial component of the local relative velocity in blade-oriented coordinates	Vaxial	V_{axi}			
17	Tangential component of the local relative velocity in blade-oriented coordinates	Vtangential	V_{tan}			
18	Axial component of the local force	axialForce	F_{axi}	N		
19	Tangential component of the local force	tangentialForce	F_{tan}			

317 5.1 Flow field data

318 A defining feature of the JHTDB database system (Li et al., 2008) is its low entry barrier for data usage, enabling users to
 319 efficiently explore large-scale simulation datasets through Web Services and the virtual sensor methodology. The JHTDB-
 320 wind system adopts the same approach, allowing access to wind farm data using these established tools. Users can develop
 321 analysis scripts or notebooks in familiar programming languages such as Python and Matlab (as well Fortran and C) to run
 322 them remotely on their own machines or on SciServer, a cloud service dedicated to running code close to the data. Within these
 323 analysis environments, users specify space-time arrays by defining spatial locations (e.g., along a line, across a surface, within
 324 a subvolume, or scattered arbitrarily) and corresponding time instances, i.e. users specify the positions of virtual sensor arrays.
 325 These space-time arrays are then passed to the predefined function, `getData(...)`, which returns interpolated values of
 326 the selected variables at defined coordinates. This framework enables targeted, on-demand data access without the need to
 327 download large volumes of raw simulation output.

328 Figures 4 and 5 display contour plots of flow field variables at the turbine hub height ($z = z_h = 90\text{m}$) for the precursor and
 329 wind farm domains, respectively.

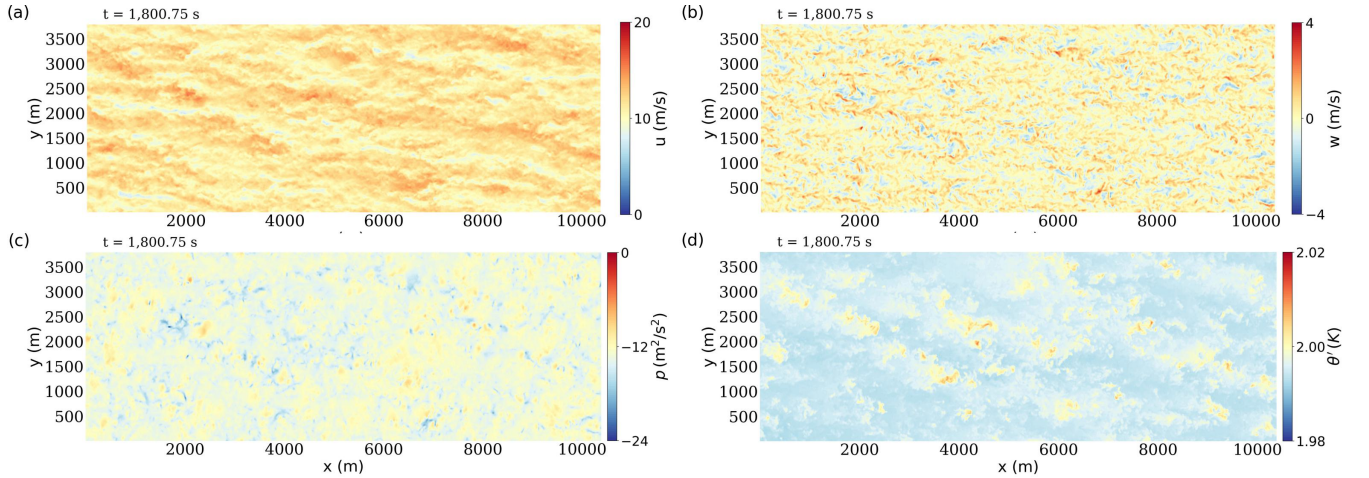


Figure 4. Contour plots of instantaneous flow field variables in the precursor domain between $x = 0\text{m}$ and $x = 10,381.875\text{m}$. (a) the streamwise velocity, (b) the vertical velocity, (c) the pressure, and (d) the potential temperature deviation.

330 Fig. 6 presents Python code snippets that demonstrate how to query the JHTDB-wind database to extract snapshots of
 331 velocity, pressure, and potential temperature fields at a specific time, approximately in the middle of the stored 1-hour dataset,
 332 namely at $t = 1,800.75\text{s}$. As a first step, an array “*points*” is populated with spatial coordinates that define a 2D plane: in this
 333 case, an equally spaced grid of 950×200 points in the x and y directions at a constant height $z = z_h = 90\text{m}$. These query
 334 points typically do not coincide with the actual simulation grid points, and users are not required to know the grid layout to

335 access the data. The JHTDB-wind interface provides interpolated field values based on a user-specified interpolation method.
 336 Supported options include no interpolation (it returns the value at the nearest grid point), Lagrange Polynomials of order 4,
 337 6, or 8, and several spline interpolation methods (Li et al., 2008; Graham et al., 2016). In this example, we use 8th-order
 338 Lagrange polynomial interpolation in space. Similarly, if the requested time does not coincide with a stored timestep, temporal
 339 interpolation is applied using third-order Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) method (Li et al., 2008).
 340 This user-friendly data access model eliminates the need for downloading and parsing simulation files. Instead, the Python
 341 API returns arrays with the queried field variables, which can then be visualized directly within a Jupyter notebook (or Matlab
 342 code). This approach was used to generate Figs. 4 and 5. It is important to note that the full one-hour dataset (comprising
 343 14,400 timesteps) is available for analysis, allowing users to query any time between $t = 0$ and $t = 3,600$ s. For example, Fig.
 344 7 shows a hub-height snapshot over the entire domain at time $t = 2,505$ s.

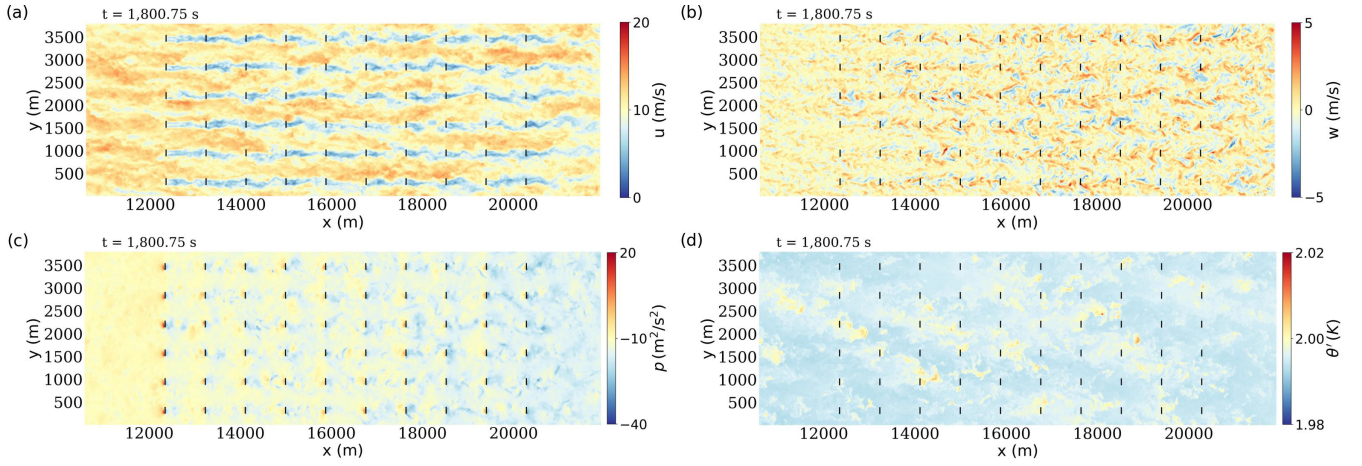


Figure 5. Contour plots of instantaneous snapshots of field variables in the wind farm domain between $x = 10,584$ m and $x = 21,921.375$ m. (a) the streamwise velocity, (b) the vertical velocity, (c) the pressure, and (d) the potential temperature deviation. The black solid lines represent the location of wind turbines.

345 Similar queries can be made for the values, spatial gradients, and Hessians (second-order derivatives) of all variables listed
 346 in Table 3. For example, Fig. 8(a) and (b) show x -component of the turbine force-field f_x and the x -direction gradient of
 347 the pressure field ($\partial p / \partial x$), respectively, on a $y - z$ plane intersecting Row 1 (Turbines #1 - #6) at $x = 12,348$ m (1764 m
 348 downstream of the wind farm domain), at time $t = 1000.013$ s. Fig. 8(c) and (d) present similar results on a plane intersecting
 349 Row 9 (Turbines #49 - #54) at $x = 19,404$ m (8,820m downstream of the wind farm domain) at another time $t = 2,000.67$ s.
 350 These plots were generated using the Python code shown in Fig. 9. In these examples, the queried times are intentionally chosen
 351 not to coincide with the stored simulation time steps, demonstrating the temporal interpolation capabilities of JHTDB-wind.

352 Next, we provide examples of computed mean vertical profiles of fundamental flow quantities within the precursor domain,
 353 which features standard conventionally neutral atmospheric conditions. Figure 10 shows vertical profiles of horizontal- and
 354 time-averaged mean velocities, subgrid-scale eddy viscosity, and deviations in potential temperature, all obtained by averag-

```

"""
initialize getData parameters (except time and points)
"""
variable1, variable2, variable3, temporal_method, spatial_method, spatial_operator = 'velocity', 'pressure', 'temperature', 'pchip', 'lag8', 'field'

"""
initialize getData times and points
"""
time, nx, ny, n_points = 1800.75, 950, 200, 950 * 200

x_start, x_end, y_start, y_end = 10584, 21921.375, 0, 3789
x_points, y_points, z_points = np.linspace(x_start, x_end, nx, dtype=np.float64), np.linspace(y_start, y_end, ny, dtype=np.float64), 90
points = np.array([[x, y, z_points] for x in x_points for y in y_points], dtype=np.float64)

"""
use the tools and processing gizmos.
"""
# process interpolation/differentiation of points.
result1 = getData(dataset, variable1, time, temporal_method, spatial_method, spatial_operator, points)
result2 = getData(dataset, variable2, time, temporal_method, spatial_method, spatial_operator, points)
result3 = getData(dataset, variable3, time, temporal_method, spatial_method, spatial_operator, points)

```

Figure 6. Python code snippet used to obtain the data to generate the Fig. 5.

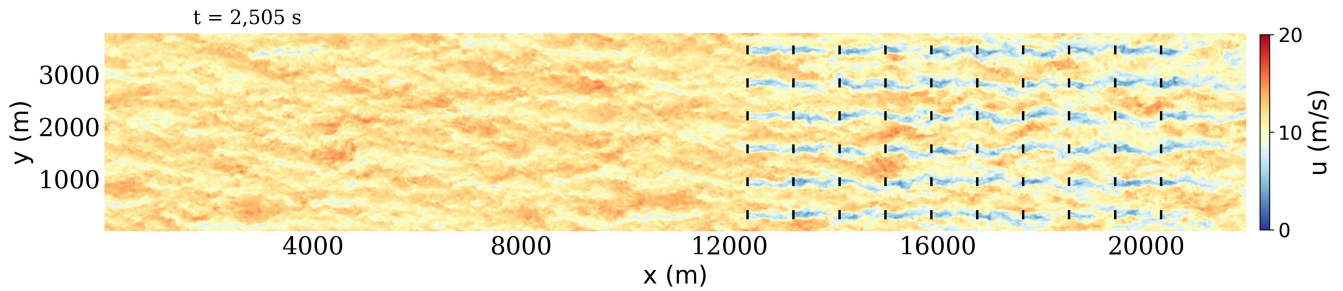


Figure 7. Contour plot of instantaneous snapshot of streamwise velocity in the entire database domain, ranging from $x = 0$ to $x = 22,913.625$ m, at time $t = 2,505$ s. As before, the black solid lines represent the location of wind turbines.

ing in the horizontal directions and over time. The data used to produce these profiles is retrieved using the virtual sensor
framework, and an example code snippet demonstrating this process is shown in Figure 11.

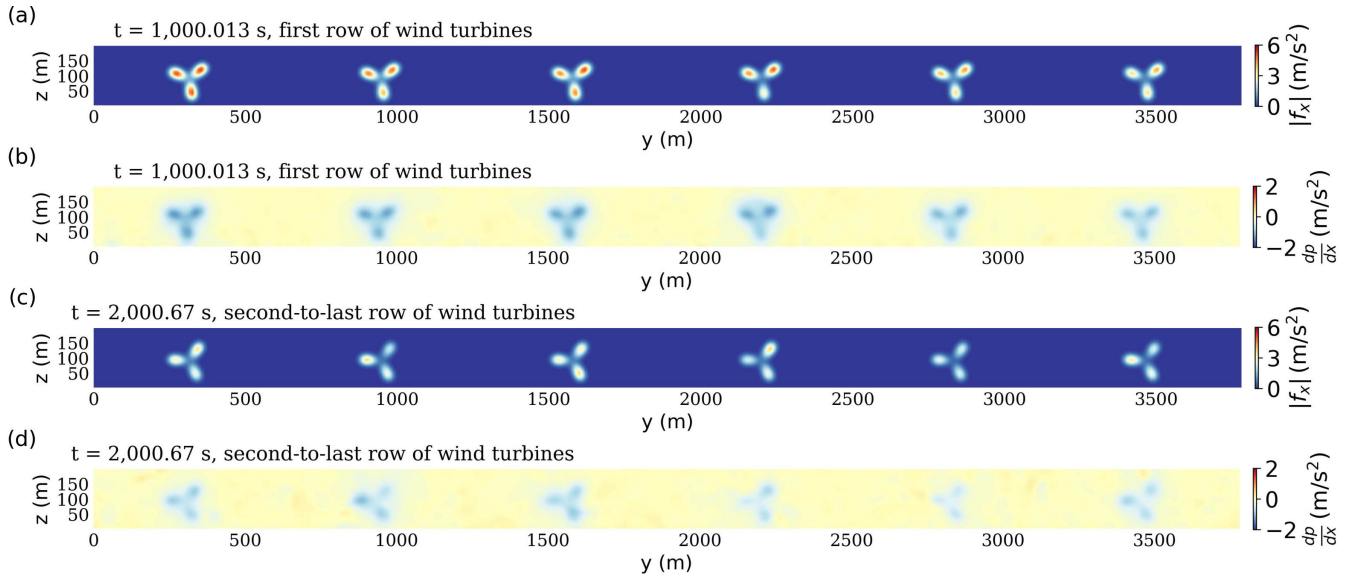


Figure 8. Instantaneous contours of x-direction turbine force (as projected onto the LES grid using Gaussian smoothing as part of the ALM method) in $y-z$ planes at (a) Row 1 ($x = 12,348$ m) and between the relevant vertical range $z \in [2.5, 200]$ m, and (b) Row 9 ($x = 19,404$ m). Panels (c) and (d) show the x-direction pressure gradient distributions on the same planes, coincident with the turbines.

```

"""
initialize getData parameters (except time and points)
"""
variable1, variable2, temporal_method, spatial_method1, spatial_method2, spatial_operator1, spatial_operator2 = 'force', 'pressure', 'none', 'none', 'fd4lag4', 'field', 'gradient'

"""
initialize getData times and points
"""
time1, time2, ny, nz, n_points = 1000.013, 2000.67, 384, 40, 384 * 40

y_start, y_end, z_start, z_end = 0, 3780, 2.5, 197.5

"""
first row of wind turbines locates 12348 m downstream of inlet.
second-to-last row of wind turbines locates 19404 m downstream of inlet.
"""
x_points1, y_points1, z_points1 = 12348, np.linspace(y_start, y_end, ny, dtype=np.float64), np.linspace(z_start, z_end, nz, dtype=np.float64)
points1 = np.array([[x_points1, y, z] for y in y_points1 for z in z_points1], dtype=np.float64)
x_points2, y_points2, z_points2 = 19404, np.linspace(y_start, y_end, ny, dtype=np.float64), np.linspace(z_start, z_end, nz, dtype=np.float64)
points2 = np.array([[x_points2, y, z] for y in y_points2 for z in z_points2], dtype=np.float64)

"""
use the tools and processing gizmos.
"""
# process interpolation/differentiation of points.
result_force1 = getData(dataset, variable1, time1, temporal_method, spatial_method1, spatial_operator1, points1)
result_force2 = getData(dataset, variable1, time2, temporal_method, spatial_method1, spatial_operator1, points2)
result_pressure1 = getData(dataset, variable2, time1, temporal_method, spatial_method2, spatial_operator2, points1)
result_pressure2 = getData(dataset, variable2, time2, temporal_method, spatial_method2, spatial_operator2, points2)

```

Figure 9. Python code snippet used to obtain the data to generate the Fig. 8.

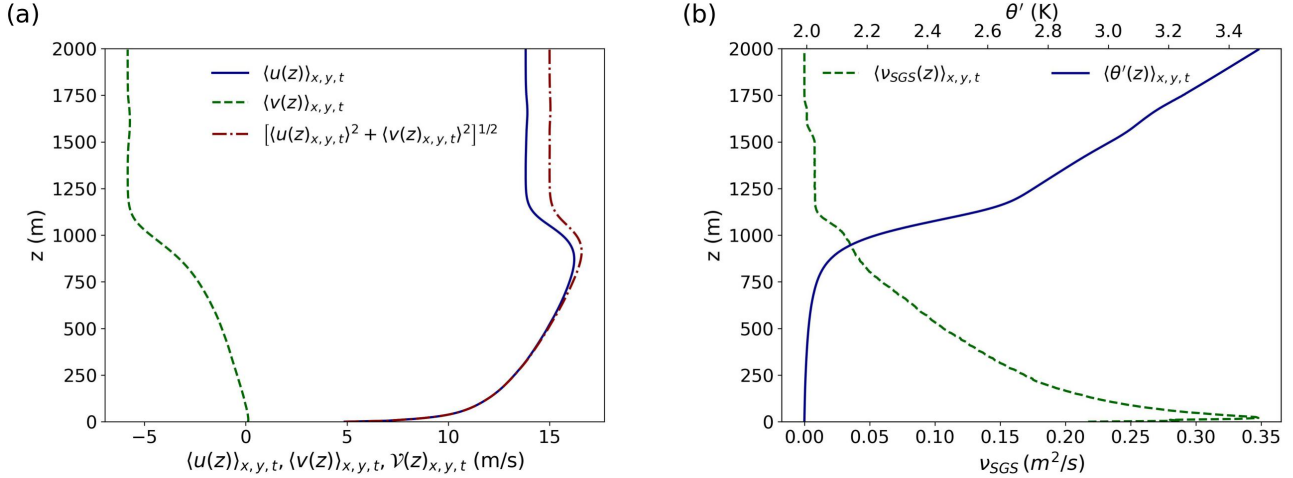


Figure 10. Vertical profiles of horizontal- and time-averaged (a) velocities $\langle u(z) \rangle_{x,y,t}$, $\langle v(z) \rangle_{x,y,t}$ and velocity magnitude $\mathcal{V}(z)_{x,y,t} = [\langle u(z)_{x,y,t}^2 + \langle v(z)_{x,y,t}^2 \rangle]^{1/2}$, (b, bottom axis) subgrid-scale eddy viscosity $\langle v_{SGS}(z) \rangle_{x,y,t}$ used in the LES as a result of the Lagrangian scale-dependent dynamic model, (b, top axis) potential temperature deviation $\langle \theta'(z) \rangle_{x,y,t}$ (i.e., the deviations from a reference temperature $\theta_0 = 263.5$ K).

```

"""
Initialize getData parameters (except time and points)
"""
variable, temporal_method, spatial_method, spatial_operator = 'velocity', 'pchip', 'lag8', 'field'

"""
Initialize getData times and points
"""
time1, time2, time3, time4, nx, ny, nz = 900, 1800, 2700, 3598.5, 200, 100, 100

x_start, x_end, y_start, y_end, z_start, z_end = 0, 10584, 0, 3780, 2.5, 1997.5
x_points, y_points, z_points = np.linspace(x_start, x_end, nx, dtype=np.float64), np.linspace(y_start, y_end, ny, dtype=np.float64), np.linspace(z_start, z_end, nz, dtype=np.float64)
points = np.array([x, y, z] for x in x_points for y in y_points for z in z_points), dtype=np.float64)

"""
use the tools and processing gizmos.
"""
# Process interpolation/differentiation of points
result1 = getData(dataset, variable, time1, temporal_method, spatial_method, spatial_operator, points)
result2 = getData(dataset, variable, time2, temporal_method, spatial_method, spatial_operator, points)
result3 = getData(dataset, variable, time3, temporal_method, spatial_method, spatial_operator, points)
result4 = getData(dataset, variable, time4, temporal_method, spatial_method, spatial_operator, points)

# Calculate the average
average_result = [
    (v1 + v2 + v3 + v4) / 4
    for v1, v2, v3, v4 in zip(result1, result2, result3, result4)
]

```

Figure 11. Python code snippet used to obtain the data to generate vertical profiles of $\langle u(z) \rangle_{x,y,t}$: for the 250 heights z between $z = 0.7$ m and $z = 2,000$ m separated by 8 m, we query data on a regular mesh (not necessarily coinciding with stored grid points). For statistical convergence, we average over 4 times covering the entire hour ($t = 900; 1,800; 2,700; 3,600$) s.

5.2 Wind turbine data

Wind turbine data, including both the turbine-level and blade-level data, are considerably smaller than the 4D flow fields, and one possibility would have been to allow users to download them directly as files. However, such an approach would require

361 users to identify specific files, understand naming conventions, and handle formatting, posing a barrier to seamless integration
 362 with flow field queries. To maintain consistency and usability across the platform, we adopt a similar virtual sensor data
 363 access paradigm used for the flow field data. Two dedicated query functions are developed: `getTurbineData(...)` for
 364 turbine-level quantities and `getBladeData(...)` for blade-resolved data. For `getTurbineData(...)`, users specify
 365 the turbine number (ranging from 1 and 60) and desired time instances. For `getBladeData(...)`, both turbine and blade
 366 numbers need to be specified, along with an array of actuator point indices (1 to 100) and times at which the data are requested.
 367 Linear interpolation in time is supported to provide values between stored simulation steps.

368 As an example, Fig. 12 show a time series of total power generated by the wind farm (a), as well as by the first and second-
 369 to-last row of 6 turbines (b). The code snippet specifying the `getTurbineData(...)` call is shown in Fig. 13. Similar calls
 370 can be made to extract any of the turbine specific variables listed in 4.

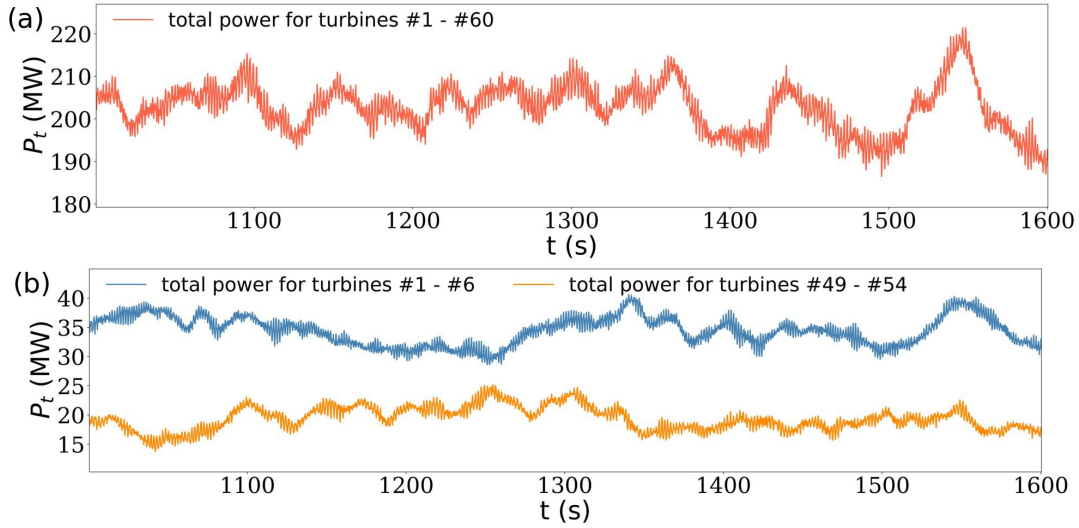


Figure 12. Time evolution of power from turbines during the 10-minute time interval $t \in [1000.33, 1600.33]$ s. (a) shows the total power from the entire wind farm, while (b) shows the power for the turbines in Row 1 (i.e., Turbines #1-#6) and in Row 9 (i.e., Turbines #49-#54).

371 Next, we illustrate the use of `getBladeData(...)` in Fig. 14, showing time histories of the lift and drag coefficients
 372 (a), as well as the lift coefficient as function of blade angle (b), computed according to $\zeta(t) = \arctan[z(t) - z_h]/(x(t) - x_T)$,
 373 during a shorter time period of 60 seconds. The results shown are for a particular turbine and blade (Turbine #28 in the central
 374 portion of the wind farm and blade #3, the latter being an arbitrary choice, of course). The Python code snippet shown in Fig.
 375 14 illustrates how the call to `getBladeData(...)` is made, and again, the queried data are simply plotted as a time-
 376 series plot as part of the same code. Using a similar approach, variable data can be extracted along turbine blades and further
 377 processed to compute higher-order statistics. Figure 16 shows axial force, tangential force, drag and lift coefficients for an
 378 upstream turbine (Turbine #1, blade #1) and a downstream turbine (Turbine #60, blade #1) at a specific time of $t = 1,500$ s.
 379 Any of the variables listed in Table 5 can be similarly queried (also in Matlab).


```

"""
Initialize getTurbineData parameters
"""
turbines = list(range(1, 61))
turbine_variable = 'power'

"""
Initialize time array, below shows the one from 1000.33 s to 1600.33 s and the time interval is 0.025s
"""
time_start, time_end, dt = 1000.33, 1600.33, 0.025
ntime = int((time_end - time_start) / dt)
turbine_times = np.linspace(time_start, time_end, ntime, dtype=np.float64)

"""
use the tools and processing gizmos.
"""
# process turbine data.
turbine_result = getTurbineData(dataset, turbines, turbine_variable, turbine_times)

```

Figure 13. Python code snippet illustrating the use of the function `getTurbineData(...)` as part of a loop over all turbines in the wind farm, and subsequent summation to evaluate time-series of total power used to generate Fig. 12(a).

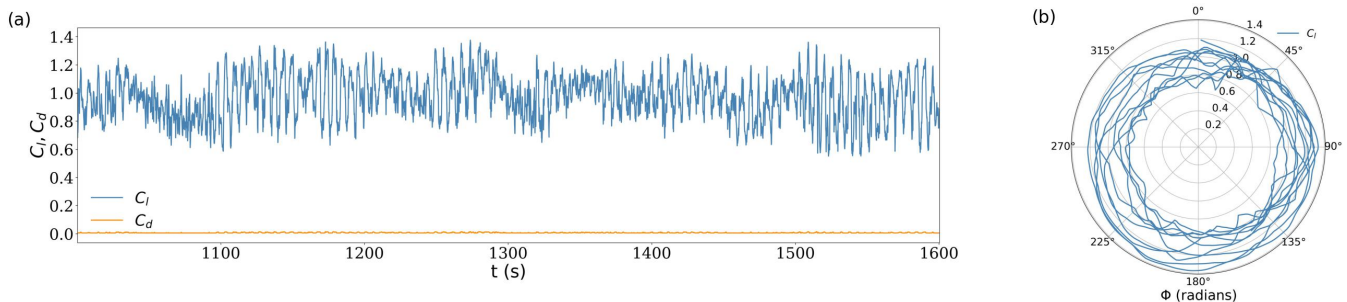


Figure 14. (a) Time evolution of lift and drag coefficients on an ALM point 80% along the span of blade #3 for Turbine # 28. (b) Polar plot of lift coefficient for that point as a function of blade angle along its rotation. With a fixed Ω of (1.09 rad/s) for this turbine (obtained via a call to `getTurbineData(...)`), there are around 10.5 revolutions within the 60 seconds queried.

380 6 Conclusions

381 In this paper, we have introduced JHTDB-wind, hosting datasets from high-fidelity LES simulations of wind farms. We extend
382 the standard “virtual sensors” data access methods (Li et al., 2008; Yu et al., 2012; Graham et al., 2016) that have been success-
383 fully used for democratizing access to more fundamental turbulence datasets. Besides velocity, pressure, potential temperature,
384 and SGS eddy-viscosity fields, JHTDB-wind adds full 4D (space-time) data on aerodynamic turbine force distributions as
385 seen by the flow as well as time series of turbine and actuator line specific aerodynamic data along each of the turbine blades,
386 modeled using ALM. We explain the simulation details and provide background on the numerical method and flow parameters,
387 and provide detailed examples and explanations of the user-friendly data access methodologies. It is hoped that these data will
388 provide useful insights about the complex fluid dynamic processes occurring in wind farms.

389 We realize that in generating a dataset for a representative conventionally neutral boundary layer case, with a relatively
390 large wind farm with 60 turbines, many other choices could have been made (flow parameters, turbine model and control
391 scheme, usage of a particular LES numerical code, numerical resolution, and so on). We anticipate that different members of
392 the community would have made different choices, and we look forward to conversations about how to further improve such

```

"""
initialize getBladeData parameters
"""
turbines, blades, blade_variable1, blade_variable2 = [28], [3], 'Cl', 'Cd'

"""
initialize time array, below shows the one from 1000.33 s to 1600.33 s and the time interval is 0.025s
"""
time_start, time_end, dt = 1000.33, 1600.33, 0.025
ntime = int((time_end - time_start) / dt)
blade_times = np.linspace(time_start, time_end, ntime, dtype=np.float64)
blade_actuator_points = [80]

"""
use the tools and processing gizmos.
"""
# process blade data.
blade_result1 = getBladeData(dataset, turbines, blades, blade_variable1, blade_times, blade_actuator_points)
blade_result2 = getBladeData(dataset, turbines, blades, blade_variable2, blade_times, blade_actuator_points)

```

Figure 15. Python code snippet used to obtain the data to generate Fig. 14.

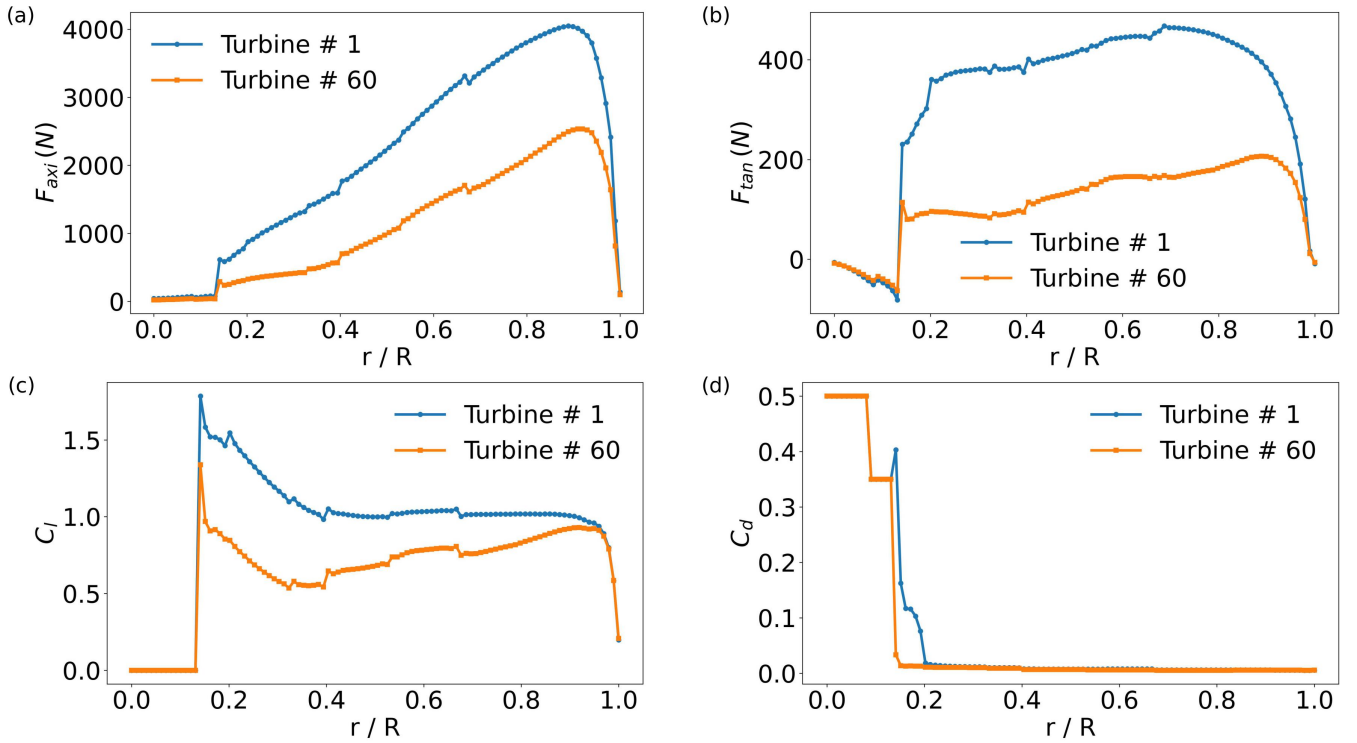


Figure 16. Distributions of ALM quantities along the turbine blade at a specific time ($t = 1,500$ s for two turbines (Turbine #1, blade #1; blue lines; Turbine #60, blade # 1, orange lines): (a) Axial component of the local force (on each $\Delta\ell = 0.615$ m segment), (b) Tangential component of the local force (on each $\Delta\ell = 0.615$ m segment), (c) Lift coefficient, (d) Drag coefficient.

393 datasets. We believe, however, that the case selected is representative of CNBL wind farm dynamics that have been studied by
394 many others before, with a well-tested numerical code. Hence, the authors hope that the data can be of some use and interest
395 to researchers in wind energy.

396 As a final note, we have additionally prepared a second dataset for JHTDB-wind featuring an 8-turbine wind farm over a
397 full diurnal cycle, capturing both strongly stable and unstable atmospheric boundary layer regimes at different times of the day
398 and night (Xiao et al., 2025).

399 7 Code and data availability

400 The wind farm data is available at the JHTDB-wind website at <https://turbulence.idies.jhu.edu/datasets/windfarms> (see also its
401 DOI: <https://doi.org/10.26144/D8ES-FC15>). Various modes of data access are provided (Zhu et al., (2025): (i) Single-point
402 queries of flow field variables using a browser interface at <https://turbulence.idies.jhu.edu/database/query>. (ii) Multiple point
403 queries up to 4096 points at a time: downloading DEMO codes (Python or Matlab) at <https://turbulence.idies.jhu.edu/database/>
404 wind and executing the DEMO code on user’s own platforms. Users can then edit the DEMO codes to select different points
405 and times to query desired data. Default DEMO codes provided are set up for accessing the diurnal cycle wind farm dataset.
406 To access the conventionally neutral dataset, users can change the “*dataset*” variable to “*nbl_windfarm*” and select times to the
407 range between 0 and 3600 seconds.

408 *Author contributions.* XZ performed the simulations, generated the majority of the data, and assisted in document and figure preparation,
409 and detailed proof-reading. SX performed the majority of the data transformation into Zarr and Parquet formats, worked on testing data
410 access methods, and generated many of the figures. GN developed the thermal stratification and initialization methods in the LES code.
411 LAMT developed and implemented the generalized ALM method in the LES code. MS and HY developed the Giverny backend software
412 and Python/Matlab data access codes. GL directed the SciServer and zarr format optimization. AS designed the storage architecture. DG
413 participated in data interpretation and analysis and manuscript editing. CM participated in simulation and database design, data interpretation
414 and analysis, and document preparation and proof-reading.

415 *Competing interests.* We declare no competing interests.

416 *Acknowledgements.* The authors are grateful to IDIES staff for support in the creation of the JHTDB-wind database, as well as to Dr. Ned
417 Patton for insightful comments regarding the simulations and data, and to Prof. Ben Schafer for his steadfast support and encouragement
418 of JHTDB-wind. The project was made possible by a seed grant from the Ralph O’Connor Sustainable Energy Institute Research Initiative
419 (ROSEI) at JHU, and by NSF grant #2034111 as well a joint NSF-DOE grant # 2401013. The JHTDB project is supported by NSF (CSSI-
420 2103874) and the Institute for Data Intensive Engineering and Science (IDIES) and its staff. We are grateful for the high-performance
421 computing (HPC) resources and assistance received from both Cheyenne (doi:10.5065/D6RX99HX), made available by NCAR’s CISL and
422 sponsored by the NSF, and the Advanced Research Computing at Hopkins (ARCH) core facility (rockfish.jhu.edu), supported by the NSF
423 under grant OAC1920103.

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 549 Data at multiple points (up to 4096 at a time) can be accessed by downloading the DEMO codes (Python or Matlab) at <https://turbulence.idies.jhu.edu/database/wind> and executing the DEMO code on user’s own platforms. Users can then edit the DEMO codes to select
 550 different points and times to query desired data. The default DEMO codes are set up for accessing the diurnal cycle wind farm dataset. To
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