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Assessment of Wind-Farm-Atmosphere Interactions at the Sørilige Nordsjø II Large Offshore Wind Farm: A Comparative LES and Analytical Wake Study

Mostafa Bakhoday Paskyabi^{1,2,3}  | Xu Ning^{1,2}

¹Geophysical Institute, University of Bergen, Bergen, Norway | ²Bergen Offshore Wind Centre (BOW), University of Bergen, Bergen, Norway | ³Bjerknes Centre for Climate Research, Geophysical Institute, University of Bergen, Bergen, Norway

Correspondence: Mostafa Bakhoday Paskyabi (mostafa.bakhoday-paskyabi@uib.no)

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ABSTRACT

Sørilige Nordsjø II (SNII) is a planned large-scale offshore wind farm in the Southern Norwegian North Sea near the Danish border, with phased development targeting a total installed capacity of up to 3 GW. For projects of this scale, site assessments are typically performed using computationally efficient analytical models. However, these models—often calibrated using data from smaller, sub-gigawatt wind farms—lack the fidelity to represent the complex flow physics in large offshore parks. In particular, they fail to account for the two-way interaction between extensive wind farms and the thermally stratified atmospheric boundary layer, which significantly influences wake behavior and overall energy yield. This study investigates the boundary layer dynamics within the SNII wind farm, focusing on wake behavior and its coupling with the overlying free atmosphere under stable, neutral, and unstable stratification. We conduct a detailed energy/momentum budget analysis to identify dominant energy sources and sinks that govern wind farm performance. A high-resolution large-eddy simulation (LES) is performed for a representative subdomain of the SNII site, consisting of 120 floating wind turbines, each rated at 15 MW. The LES results are benchmarked against three analytical wake models—TurboPark, Niayifar and Porté-Agel, and Bastankhah and Porté-Agel—all of which use Gaussian wake formulations, with turbulence effects explicitly incorporated only in the Niayifar and Porté-Agel and TurboPark models. The comparison reveals power prediction discrepancies ranging from less than 1% to over 56% between the LES and the analytical models, with the smallest differences under neutral conditions, moderate discrepancies in the unstable case (up to 31%), and the largest deviations under stable stratification. Energy budget diagnostics suggest that these differences stem from the wake models' omission of critical physical mechanisms, including geostrophic forcing, pressure-gradient-driven energy input, and turbulent energy dissipation. Finally, downscaling the wind farm configuration in this study from 120 turbines (1.8 GW) to a 1.5-GW layout with 100 turbines—consistent with the planned Phase I capacity—results in only a modest reduction in total energy yield. Across all atmospheric stability regimes and wake models, the reduced layout maintains comparable or slightly improved capacity factors due to diminished wake losses, particularly under neutral and stable conditions where wake interactions are strongest. For example, in the TurboPark model, the capacity factor under unstable conditions increases from 61.4% to 62.1%, while under stable conditions it increases from 72.9% to 73.3% after downsizing. This study suggests that incorporating key physical processes into site design analyses and wake models, combined with strategic layout optimization, can improve predictive accuracy, enhance per-turbine efficiency, and reduce wake losses under varying

Abbreviations: CFD, computational fluid dynamics; LES, large eddy simulation; PALM, parallelized large eddy simulation model; SNII, Sørilige Nordsjø II.

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environmental conditions, providing a viable pathway to optimize early-phase deployment of next-generation offshore wind farms like SNII with minimal loss of total power output.

1 | Introduction

Offshore wind is increasingly recognized as a cornerstone for achieving national and international climate targets, with rapid expansion expected over the coming decades. The North Sea, with its consistently high wind resources and shallow waters, is particularly well suited for large-scale offshore wind development and currently hosts over 70% of Europe's offshore capacity. The European Union, the United Kingdom, and Norway collectively aim to install around 262 GW of offshore capacity in the North Sea—comparable to the entire onshore wind capacity currently operating across Europe [1, 2]. Based on present-day offshore technology, such as the Hywind Tampen project (11 turbines, 88 MW), this goal would correspond to approximately 340 Hywind Tampen-scale developments on the Norwegian continental shelf by 2040 and around 3000 installations across the North Sea by 2050 [3]. In Norway, the first licensing round for offshore wind has already concluded for the Sørlige Nordsjø II (SN II) and Utsira North (UN) areas, marking the first step toward the national target of awarding 30 GW by 2040 through subsequent tender rounds [4].

At gigawatt-scale capacities, the flow through and around offshore wind farms can differ substantially from that in smaller, sub-gigawatt projects. Numerical studies have demonstrated that large wind farms can induce mesoscale atmospheric responses, including counterclockwise wind direction shifts within the wake and vertical displacement of the inversion layer above the farm [5–7]. These large-scale flow modifications highlight a key source of uncertainty in wind farm power production, namely, its strong sensitivity to prevailing atmospheric conditions. In particular, energy entrainment from the overlying atmosphere into turbine wakes plays a dominant role in governing overall farm efficiency. Consequently, a detailed understanding of the interactions between the atmospheric boundary layer (ABL), offshore processes such as ocean gravity waves [8], and wind farms is essential for accurate power prediction and optimized wind farm design.

Previous studies have investigated offshore wind farm wakes in the North Sea within the framework of the WIPAFF (Wind Park Far Field) project, which combines aircraft observations, satellite measurements, and mesoscale modeling to examine the far-field impacts of large offshore wind farms. Emeis et al. [9] highlighted the unique characteristics of the marine atmospheric boundary layer, emphasizing that low turbulence intensity and stable stratification can lead to exceptionally long wake structures. Aircraft observations from the WIPAFF campaign further revealed that wakes from large offshore wind farms may extend tens of kilometers downstream, particularly under stable conditions [10], and have been used to assess the performance of engineering wake models against real atmospheric measurements [11]. In addition, mesoscale simulations coupled with observational data have provided insights into the evolution of turbulent kinetic energy (TKE) and its role in wake recovery processes [12]. While these studies offer valuable observational and mesoscale perspectives, the underlying microscale flow dynamics governing turbulence transport, energy exchange, and momentum redistribution within large wind

farms remain insufficiently resolved. Addressing these processes requires modeling approaches capable of capturing both the large-scale atmospheric forcing and the small-scale turbulence structures within the ABL. Among the available methods, large-eddy simulation (LES) provides a particularly powerful framework, as it explicitly resolves the dominant turbulent motions while maintaining a tractable computational cost compared to fully resolved computational fluid dynamics approaches. As such, LES serves as a critical tool for bridging the gap between mesoscale observations and microscale flow physics, enabling improved representation of wake dynamics, energy entrainment, and their implications for wind farm performance and design.

Large-eddy simulation offers a distinct advantage in wind farm studies by resolving temporal fluctuations and capturing the dominant, large-scale flow structures in the ABL, while representing smaller, unresolved turbulence through subgrid-scale (SGS) parameterizations. This enables LES to accurately model the complex flow dynamics within and around wind farms. Previous LES investigations [5, 7, 8, 13, 14] have demonstrated substantial differences in flow fields and kinetic energy budgets between sub-gigawatt and multi-gigawatt-scale wind farms. Such growing body of LES-based research has revealed a range of intricate phenomena, including inversion layer displacement, gravity-wave-induced pressure gradients, flow blockage, Coriolis-force-related wind direction shifts, and wind-wave interactions under stable atmospheric conditions. These processes are often highly site-specific and complex, influenced by factors such as coastal proximity, land-sea interactions, and deep-ocean dynamics [15, 16]. Importantly, such effects cannot be adequately represented by fast-running analytical wake models, which under varying stability conditions can yield significant errors in power output predictions. Consequently, LES studies of large wind farms, when compared directly against analytical model results, provide a critical pathway for refining and tuning future analytical wake model formulations.

For large planned offshore wind farms such as SNII, no detailed LES studies have yet compared results with analytical wake models, and the complex interactions between the farm and the marine atmospheric boundary layer remain largely unexplored. To address this gap, we perform high-fidelity LES of a 1.8 GW (and 1.5 GW, Section 5.2) wind farm—matching the planned capacity of SNII Phase I—and systematically evaluate the results against three widely used engineering wake models: the Niayifar-Porté-Agel (NP) model [17], the TurboPark model [18], and the Bastankhah-Porté-Agel (BP) model [19]. These models were selected because they all employ a Gaussian wake profile; while NP and TurboPark explicitly incorporate turbulence effects, the BP model is included as the widely used baseline Gaussian model. Differences in column-integrated power production between LES and engineering models are quantified, with the LES results further interpreted through an energy and momentum budget analysis. To complement the benchmark case studies under three atmospheric stability regimes, the engineering wake models are applied in long-term (11-year) simulations to evaluate typical wake flow effects across a range of

atmospheric conditions. Given the absence of a finalized project layout, a regular array rotated relative to the site geometry and prevailing southwesterly inflow is adopted as a controlled reference, allowing robust exploration of flow dynamics and wake variability that informs future design choices for such large scale offshore wind projects.

The paper is organized as follows: Section 2 describes the study site and dataset. Section 3 outlines the LES configuration and the engineering wake model setup. Section 4 presents the results, while Section 5 discusses model sensitivity to farm layout and the implications of downscaling from a 1.8- to a 1.5-GW configuration. Section 6 summarizes the main findings and conclusions.

2 | Study Site: SNII Subdomain, Wind, and Stability Data

Sørlige Nordsjø II, located about 140 km off Norway's southern coast, spans 2591 km² with water depths of 53–70 m, allowing deployment of both floating and bottom-fixed offshore wind turbines, see Figure 1a. Opened for development in 2020, SNII is planned to host up to 3 GW of installed capacity [20, 21]. Its strategic location near mainland Europe supports future cross-border grid connections, promoting energy security and economic viability.

This study employs 11 years (2014–2024) of hourly data from both ERA5 reanalysis [22] and the Norwegian hindcast archive (NORA3) [23]—each based on numerical weather

prediction models—to characterize the metocean conditions at the SNII site.

Figure 1a illustrates the geographic location of SNII, where black markers denote the positions of 120 floating wind turbines, each rated at 15 MW [24], corresponding to 1.8 GW. For alignment with the planned Phase I capacity of 1.5 GW, the farm is downsized in the simulations to 100 turbines (Section 5.2). To simplify the simulation setup and reduce the computational cost of LES, the configuration shown in Figure 1 was chosen to exploit geometric symmetry and to promote stronger wake interactions under the prevailing southwesterly wind direction, thereby enabling a more detailed analysis. Although this simplification aids interpretation, it is acknowledged that optimal, non-uniform layouts could influence flow interactions and overall performance. Figure 1b presents the climatological wind rose for the SNII site, constructed from 11 years of hourly NORA3 data at 150-m height. The diagram illustrates both mean wind direction and wind speed distributions within the turbine's operational range, spanning from the typical cut-in speed of 4 m s⁻¹ to more than the cut-out speed of 25 m s⁻¹. The dominant wind directions are southwesterly, followed by northwesterly, with occurrences showing a pronounced peak near 245°, indicating the prevailing inflow direction at this offshore site.

3 | Methodology

This section consists of three components: (1) stability classification from ERA5 data, (2) high-fidelity simulations using PALM [25], and (3) low-fidelity predictions with PyWake [26].

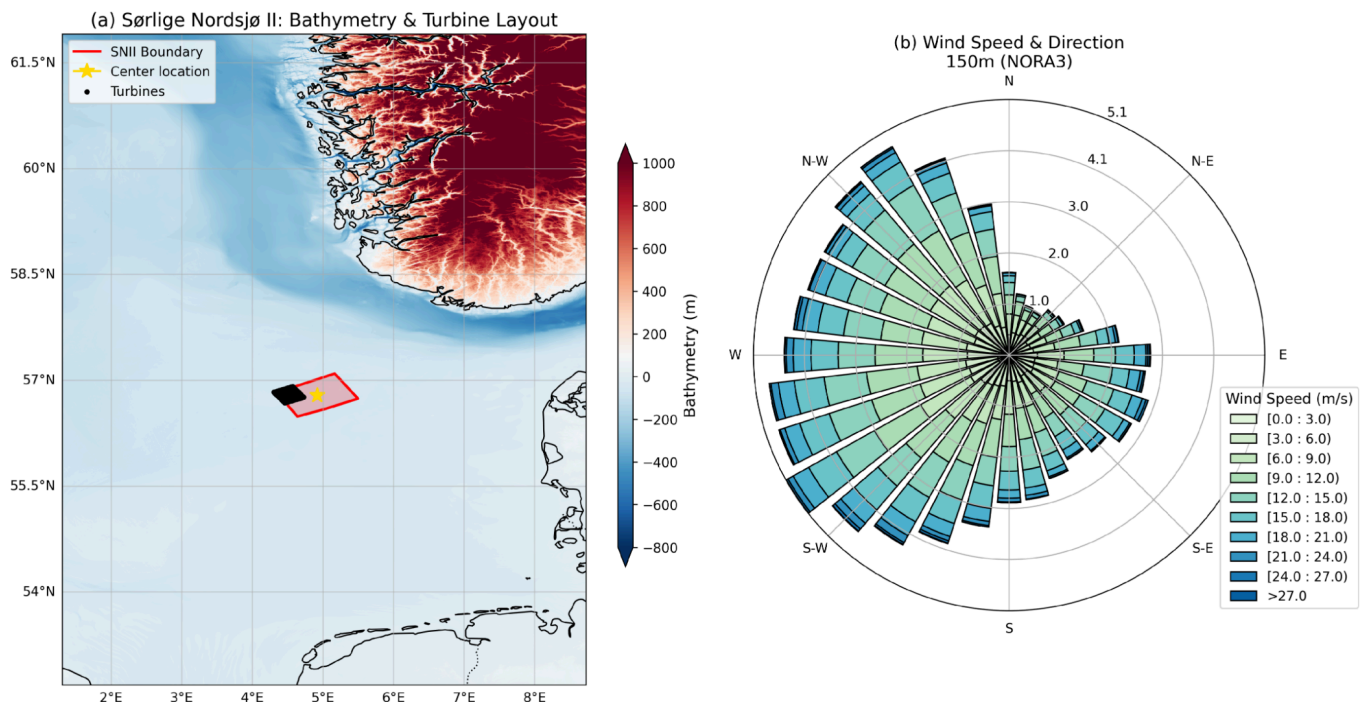


FIGURE 1 | (a) The Sørlige Nordsjø II (SNII) offshore wind farm domain, highlighted in red, along with the modeled study site comprising 120 floating wind turbines rated at 15 MW each, totaling an installed capacity of 1.8 GW (black markers). The gold star indicates the geographic center of the domain, from which wind and turbulence data are extracted for subsequent analysis; and (b) Wind rose diagram based on NORA3 reanalysis data at 150 m above mean sea level, averaged over the period 2014–2024, illustrating the prevailing wind directions and wind speed distribution at the study location.

3.1 | Atmospheric Stability Conditions

Accounting for atmospheric stability is essential for accurate wind resource assessment and for evaluating structural loads on offshore wind turbines. Stability directly influences key flow characteristics such as vertical wind profiles, turbulence intensity, and wake behavior—particularly relevant for modern offshore turbines, whose hub heights often extend beyond the surface layer and into the full atmospheric boundary layer.

To characterize near-surface atmospheric stability, we employ the Monin-Obukhov Similarity Theory (MOST), which relates surface-layer turbulence to both mechanical shear and thermal buoyancy. The core parameter in this framework is the Monin-Obukhov length L , or equivalently the dimensionless stability parameter $\zeta = \frac{z}{L}$. The Monin-Obukhov length L is defined as

$$L = -\frac{u_*^3 \theta_0}{\kappa g w' \theta'}, \quad (1)$$

where u_* is the friction velocity, θ_0 the mean potential temperature, $\kappa \approx 0.4$ the von Kármán constant, g gravitational acceleration, and $w' \theta'$ the kinematic surface heat flux [27].

TABLE 1 | Stability classification based on Monin–Obukhov length L .

Stability class	Range of L (m)
Very stable	$0 \leq L < 200$
Stable	$200 \leq L < 1000$
Near neutral	$ L \geq 1000$
Unstable	$-1000 < L \leq -200$
Very unstable	$-200 < L \leq 0$

The sign and magnitude of the Monin-Obukhov length L determine the atmospheric stability regime. Specifically, $L > 0$ corresponds to stable conditions, $L < 0$ indicates unstable (convective) conditions, and $|L| \rightarrow \infty$ theoretically represents near-neutral stability. For practical classification, the stability regime is categorized into five classes as shown in Table 1.

In this study, the Monin-Obukhov length is estimated using ERA5 reanalysis data, which provides hourly resolved meteorological variables such as 10-m wind speed, 2-m air temperature, and surface heat flux. See Appendix A2. These inputs enable classification of atmospheric conditions into stable, neutral, or unstable regimes over offshore domains, offering a synoptic-scale characterization of boundary layer stability with relevance to wind energy performance assessments.

Figure 2a presents a pie chart illustrating the distribution of atmospheric stability conditions at the SNII site. The majority of the time is characterized by *very unstable* conditions, 35.8% of cases, followed by *unstable* stratification, which occurs in approximately 21.6% of cases. *Stable* conditions represent about 15.3% of the total observations. Figure 2b displays the monthly frequency of each stability regime over an 11-year period from 2014 to 2024, providing insight into the seasonal variability of atmospheric stability at the site. Over the 11-year period, no clear intra-annual pattern is observed for predominantly unstable conditions. However, a noticeable decrease in the occurrence of very stable conditions is evident during the winter months.

Stability conditions were derived from ERA5, which provides all variables required to calculate the Monin-Obukhov length L and shows good agreement with NORA3 at hub height. Based on these ERA5-derived stability classes, Figure 3 presents wind roses constructed from the full NORA3 time series of wind speed and direction at 150 m, without additional filtering. The results indicate that southwesterly winds (200° – 270°) dominate under stable and neutral conditions, while unstable periods are more frequently associated with northwesterly to northerly flows (280° – 320°), with occasional contributions from the northeast.

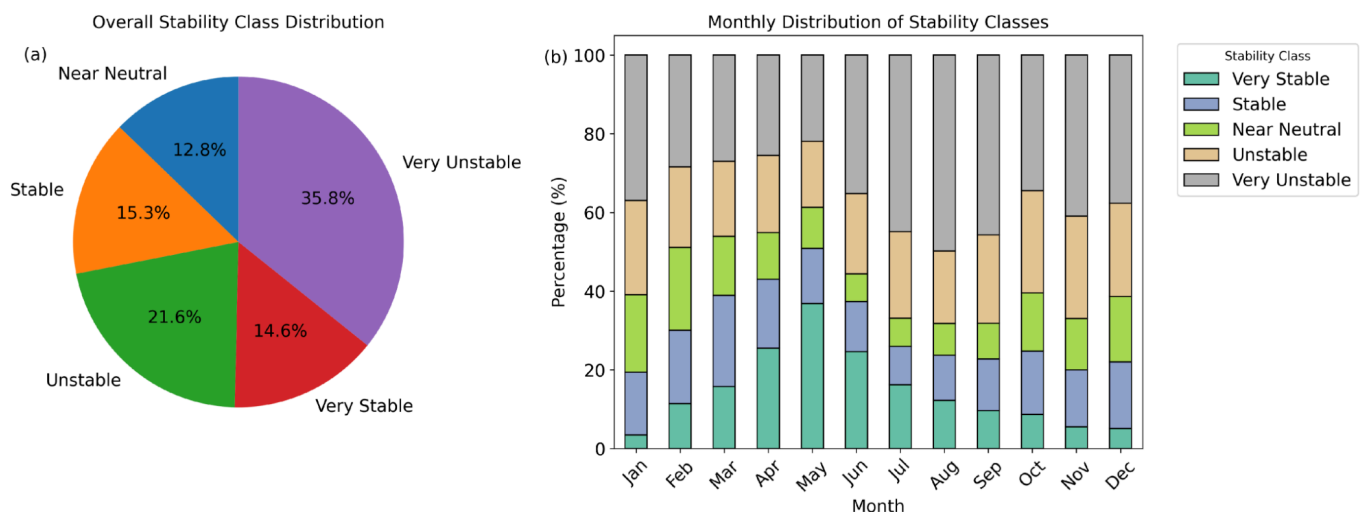


FIGURE 2 | (a) Percentage occurrence of each of the five atmospheric stability classes defined in Table 1 and (b) monthly frequency distribution of stability classes over an 11-year period (2014–2024), based on Monin-Obukhov length (L) derived from ERA5 reanalysis data.

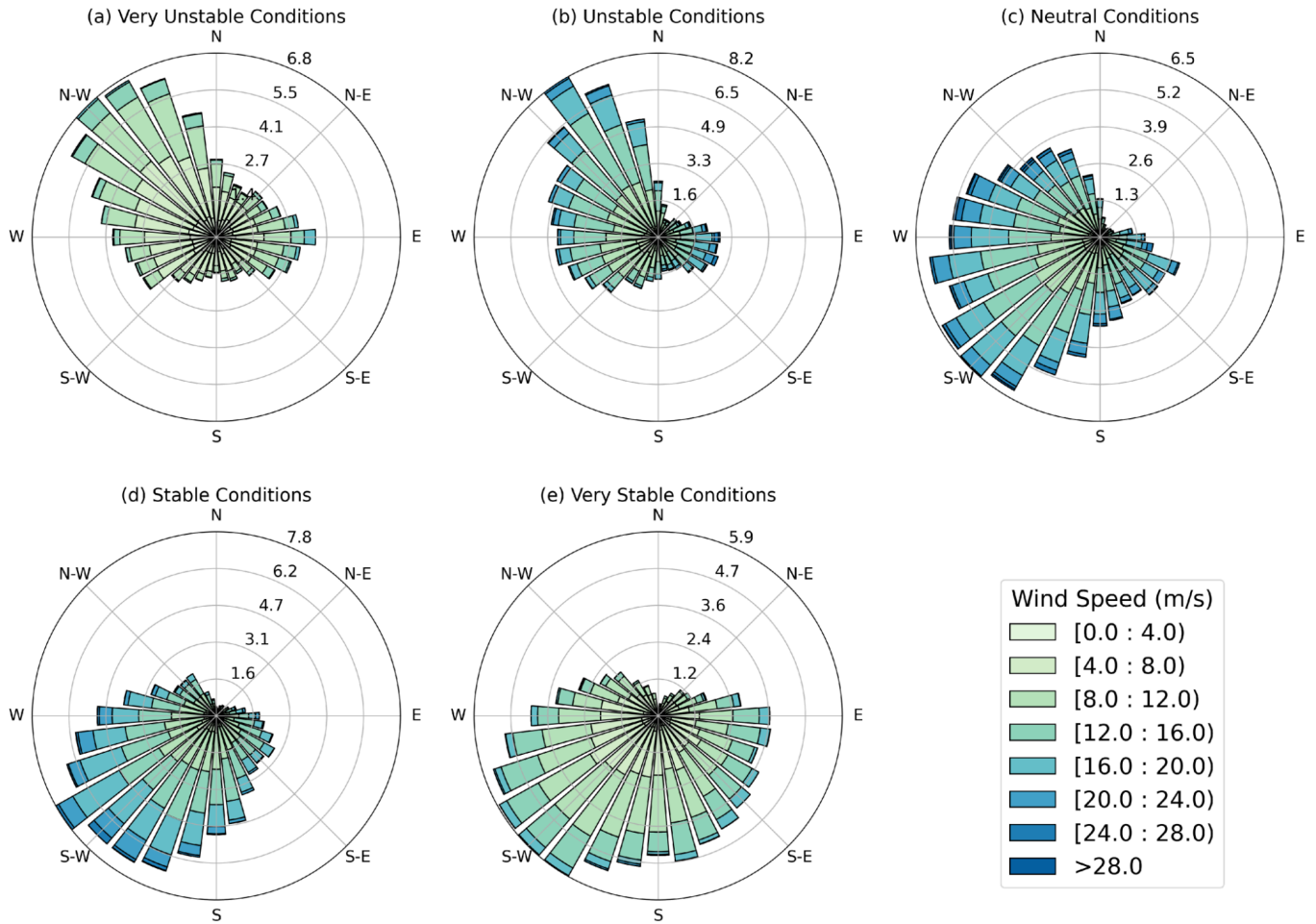


FIGURE 3 | Polar histograms of mean wind speed at 150 m above sea level (ASL), based on NORA3 data, are presented for different atmospheric stability regimes classified using the Monin-Obukhov parameter derived from ERA5 reanalysis: (a) very unstable, (b) unstable, (c) neutral, (d) stable, and (e) very stable conditions.

3.2 | High-Fidelity Model Experiments

3.2.1 | PALM Model

The high-resolution flow simulations in this study are performed using the Parallelized Large-Eddy Simulation Model (PALM), developed at the Institute of Meteorology and Climatology, Leibniz Universität Hannover [25]. PALM solves the non-hydrostatic, incompressible Navier-Stokes equations under the Boussinesq approximation. The filtered governing equations for mass, momentum, and potential temperature are as follows:

$$\frac{\partial \tilde{u}_j}{\partial x_j} = 0 \quad (2)$$

$$\begin{aligned} \frac{\partial \tilde{u}_i}{\partial t} = & -\frac{\partial(\tilde{u}_i \tilde{u}_j)}{\partial x_j} - \epsilon_{ijk} f_j \tilde{u}_k + \epsilon_{i3j} f_3 u_{gj} \\ & - \frac{1}{\rho_0} \frac{\partial \pi^*}{\partial x_i} + g \frac{\tilde{\theta} - \langle \tilde{\theta} \rangle}{\langle \tilde{\theta} \rangle} \delta_{i3} - \frac{\partial}{\partial x_j} \left(\overline{u_i'' u_j''} - \frac{2}{3} e \delta_{ij} \right) + d_i, \end{aligned} \quad (3)$$

$$\frac{\partial \tilde{\theta}}{\partial t} = -\frac{\partial(\tilde{u}_j \tilde{\theta})}{\partial x_j} - \frac{\partial}{\partial x_j} \left(\overline{u_j'' \theta''} \right), \quad (4)$$

where variables marked with a tilde are filtered at the grid scale, $\tilde{u}_i$ is the filtered velocity component, $\tilde{\theta}$ is the filtered potential temperature, and π^* is the modified perturbation pressure, defined as $\pi^* = p + \frac{2}{3} \rho_0 e$, where $e = \frac{1}{2} \overline{u_i'' u_i''}$ is the subgrid-scale (SGS) turbulent kinetic energy. The Coriolis term involves $f_i = (0, 2\Omega \cos \phi, 2\Omega \sin \phi)$, with Earth's angular velocity $\Omega = 7.29 \times 10^{-5}$ rad/s and geographical latitude ϕ . The terms u_{gj} denote geostrophic wind components, and d_i represents turbine-induced body forces.

The SGS turbulence is parameterized using a 1.5-order closure scheme originally proposed by Deardorff [28]. The computational domain uses a structured Arakawa C-grid with equidistant horizontal spacing and vertical grid stretching is applied above the boundary layer, increasing the spacing up to a maximum of $\Delta z_{\max} = 200$ m to reduce computational cost, since turbulence does not need to be resolved in this region. To prevent gravity wave reflection at the domain top, Rayleigh damping is applied above the height $z_{rd} = 4.5$ km using a damping coefficient $f_{rd} = 0.01/\Delta t$, where Δt is the time step. Angular brackets in Equation (4) denote horizontal averaging. It is noted that the vertical domain height, topped with the Rayleigh damping layer, was selected to ensure that wind-farm-induced gravity

waves and boundary layer dynamics are not affected by artificial reflections.

Wind turbines are modeled using the actuator disc method with rotation (ADM-R), which accounts for both axial momentum extraction and the addition of angular momentum to simulate wake rotation. The turbine control strategy for the IEA-15 MW reference turbine is implemented within the PALM Wind Turbine Model (WTM) using the baseline architecture described by Jonkman et al. [29]. The simulation utilizes the standard PALM control mechanisms for speed, pitch, and yaw, with no additional modifications to the underlying source code. To adapt the baseline controller to the IEA-15 MW specifications, the parameters were calibrated to follow the constructor's power curve and rated setpoints. The control logic operates across distinct atmospheric regimes: In the sub-rated region, a generator torque controller regulates rotor speed to optimize power extraction, while above the rated wind speed, a collective blade pitch controller maintains rated power by adjusting the aerodynamic load. Furthermore, each turbine is equipped with an active yaw control system—implemented following Storey et al. [30] and Steinfeld et al. [31]—which ensures the rotor disk remains aligned with the incoming wind direction to maximize aerodynamic efficiency and minimize wake skewing. All three control mechanisms were active throughout the simulations to capture the dynamic response of the turbine to the turbulent atmospheric boundary layer.

3.2.2 | Precursor Runs

A series of precursor simulations, conducted without wind turbines, were carried out to establish steady-state marine atmospheric boundary layer (MABL) conditions. The resulting flow fields are used both as the initial state and as inflow boundary conditions for the main wind farm simulations. All simulation cases employ the same computational domain, grid configuration, and lateral periodic boundary conditions, differing only in their thermodynamic initialization and imposed surface thermal forcing; see Table 2.

The domain spans $L_x = 4584$ m in the streamwise x direction and $L_y = 3048$ m in the spanwise y direction, with a uniform horizontal grid spacing of $\Delta x = \Delta y = 24$ m. Vertically, the grid

is uniformly spaced at $\Delta z = 20$ m up to a height of 500 m. Above this level, a geometric stretching is applied with a growth factor of 1.05, yielding a total of 96 vertical levels and a maximum domain height of approximately 9.1 km.

Periodic (cyclic) boundary conditions are applied laterally in the precursor simulations. To ensure numerical consistency and physical realism, the vertical grid structure and Rayleigh damping configuration are kept identical to those in the main simulations. This setup allows for seamless transition of turbulence structures and gravity wave behavior between precursor and main simulations.

Three atmospheric stratification regimes are considered (see Figure 4): neutral, convective, and stable. The idealized truly neutral boundary layer (NEU) is defined by a constant potential temperature of $\bar{\theta} = 300$ K. The convective boundary layer (CVT) is generated through continuous surface heating at a rate of 0.02 K/h, promoting enhanced turbulent mixing. In contrast, the stable boundary layer (STB) is initiated by applying surface cooling of -0.2 K/h following a 44-h spin-up period to ensure the decay of inertial oscillations. We use the same spin-up duration for all stability cases.

The wind farm layout is rotated so that it is oriented normal to the x -axis. For each stability regime, a precursor simulation is performed using wind speeds within the $7\text{--}8\text{ m s}^{-1}$ range, which corresponds to the most frequently observed wind speed for the respective wind-direction and wind speed sectors (see Table 3) as derived from the wind roses in Figure 3. To ensure representative and steady-state inflow at hub height, the geostrophic wind components are iteratively adjusted to match target values extracted from NORA3 (Table 3). The wind shear exponent α was estimated for each stability case using a non-linear least-squares regression. The power-law profile, $u(z) = \bar{u}_h(z/z_{hub})^\alpha$, was fitted to the NORA3 wind speed data across the rotor-equivalent height range ($z \in [30, 270]$ m), where z_{hub} is the reference hub height of 150 m. The turbulence intensity (TI) at hub height is estimated from NORA3 subgrid-scale turbulence kinetic energy (TKE) using the relation:

$$TI = \frac{\sqrt{\frac{2}{3} \text{TKE}}}{\bar{u}_h}, \quad (5)$$

TABLE 2 | Thermodynamic initialization and surface forcing used in the precursor simulations for the neutral (NEU), convective (CVT), and stable (STB) cases.

Parameter	NEU	CVT	STB
Initial potential-temperature profile Surface potential temperature	$\theta = 300$ K	$\theta = 283$ K	$\theta = 283$ K
Capping inversion	Not imposed	Not imposed	Not imposed
Onset height of lapse rate	N/A	1000 m	0 m
Free-atmosphere lapse rate	N/A	0.35 K / 100 m	0.35 K / 100 m
Surface thermal forcing	None	+0.02 K h ⁻¹	-0.20 K h ⁻¹
Surface heating/cooling period	N/A	From simulation start	44 h
Roughness length	0.0002 m	0.0002 m	0.0002 m

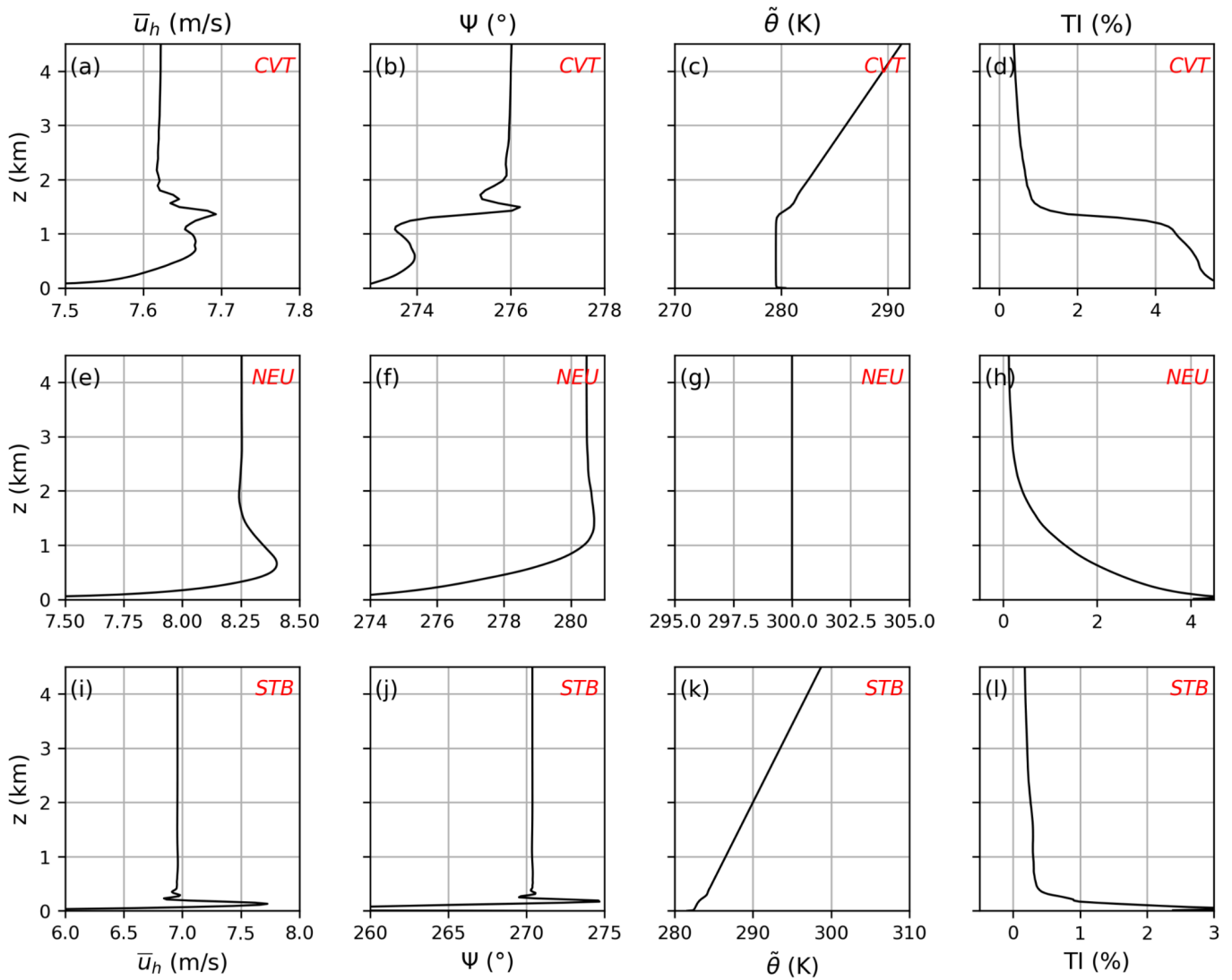


FIGURE 4 | Vertically resolved profiles of (a, e, i) horizontal wind speed $\bar{u}_h = \sqrt{\bar{u}^2 + \bar{v}^2}$, (b, f, j) wind direction Ψ (measured clockwise), (c, g, k) potential temperature $\bar{\theta}$, and (d, h, l) turbulence intensity (TI), shown for three distinct atmospheric stability regimes: convective (CVT; a–d), neutral (e–h), and stable (i–l). Each profile represents a horizontal average across the full precursor simulation domain and a temporal average over the final 4 h of the simulation period.

where $\bar{u}_h$ is the mean wind speed at z_{hub} . Based on the resolved-scale variances of the velocity components ($\overline{u'^2}$, $\overline{v'^2}$, $\overline{w'^2}$) and the mean SGS turbulent kinetic energy $\bar{e}$, the total TKE is calculated as

$$\text{TKE} = \frac{1}{2}(\overline{u'^2} + \overline{v'^2} + \overline{w'^2}) + \bar{e}. \quad (6)$$

Equations (5) and (6) are also used to compute TI and TKE, respectively, based on output from the PALM model. Primes in Equation (6) represent fluctuations from the time-averaged flow, for example, $u' = \tilde{u} - \bar{u}$.

It should be noted that the neutral case presented here represents a truly neutral boundary layer (i.e., NEU). While this serves as a fundamental benchmark for isolating momentum-driven induction, real-world offshore conditions often manifest as conventionally neutral boundary layers (CNBLs), where a neutral layer is capped by a stably stratified free atmosphere. In a CNBL,

the presence of a capping inversion and stable stratification aloft can trigger gravity-wave excitations and limit the vertical entrainment of momentum into the farm [13]. Consequently, the blockage effects observed in our NEU case may be considered conservative; in a CNBL, the interaction between the farm and the atmospheric capping layer can lead to significantly higher pressure perturbations and further reductions in farm-wide efficiency [32].

3.2.3 | Main Runs

The flow fields in the main simulations build directly upon the instantaneous flow field of the last time step of prerun simulation, maintaining the same vertical resolution while expanding the horizontal domain to fully encompass the wind farm and its downstream wake development (it is larger than the precursor domain). The wind farm is centrally placed within the domain

in a square layout of side length $L_F \approx 19$ km. The domain includes upstream and downstream zones with nominal size L_F and $1.4L_F$, respectively, and lateral padding of approximately

TABLE 3 | Atmospheric parameters and geostrophic wind components for the three stability experiments, derived from NORA3 as target data for the selected wind-direction sectors with wind speeds in the range $7\text{--}8\text{ m s}^{-1}$.

Parameter	Neutral	Convective	Stable
Wind Speed [m/s]	7.95	7.64	7.62
Wind Direction [deg]	245.7	246.6	243.0
Turbulence Intensity at Hub Height [%]	3.79	5.59	1.25
Shear Exponent α	0.063	0.024	0.043
Monin-Obukhov Length L_{MO} [m]	∞	-172.7	63.5
Geostrophic Wind u_g [m/s]	8.116	7.58	6.959
Geostrophic Wind v_g [m/s]	-1.500	-0.8	-0.048

Note: Here, wind directions are in the meteorological “from” convention.

$0.9L_F$ from the domain boundaries (see Figure 5). A reference wind turbine with a rated capacity of 15 MW and a rotor diameter of 240 m, based on the IEA 15 MW design [24], is employed in this study. The wind turbines are positioned in a uniform grid layout, oriented perpendicular to the prevailing south-westerly wind direction (see black markers in Figure 1a). The spacing between turbines is approximately 8.5 rotor diameters ($8.5D$) in the streamwise and approximately 7 rotor diameters ($7D$) spanwise directions, yielding an installed power density of approximately 4.38 W/m^2 .

Cyclic (periodic) boundary conditions are applied along the lateral (north–south) boundaries, while a radiation boundary condition is imposed at the domain outlet to allow for wave energy dissipation. At the inlet, time-averaged velocity and potential temperature profiles from the prerun simulations are applied, ensuring a dynamically consistent initialization. To preserve turbulent characteristics at the inflow, fluctuations (e.g., in velocity and temperature) are extracted from within the domain at a specified location $x = 6.1\text{ km}$ (recycling plane) and mapped back to the inlet ($x = 0$). To avoid artificial streamwise streaks, these turbulent fields are not reinserted at the same lateral position y , but are instead shifted by a small offset y_{shift} , promoting a more realistic and homogeneous inflow [6, 25]. In our configuration, setting $y_{\text{shift}} = 3$ displaces the left and right boundaries by three subdomain lengths along the y -axis. Moreover, in this

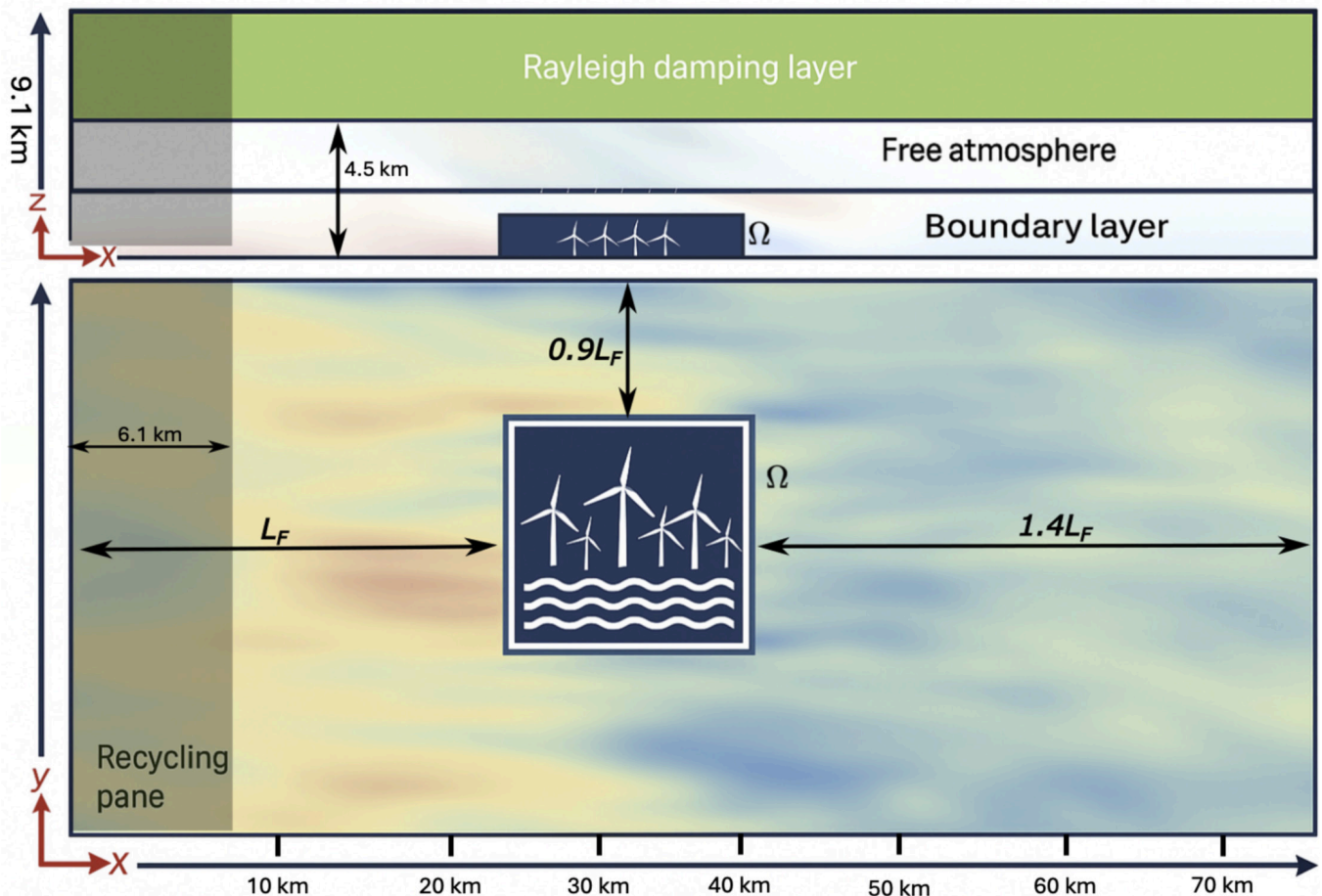


FIGURE 5 | (a) Vertical cross-section (side view) of the computational domain in the x - z plane, and (b) horizontal layout (top view) in the x - y plane. All dimensions are given in kilometers.

recycling zone, a Rayleigh damping layer of width 6.1 km is applied to the potential temperature field to suppress spurious wave reflections induced by wind farm perturbations.

It is worthy to mention that the adopted grid resolution (24 m × 24 m × 20 m) represents a strategic compromise between resolving energy-containing wake scales and the high computational cost of multi-GW farm simulations. While the stable condition ideally requires finer discretization to resolve small-scale turbulent structures and sharp vertical gradients, true grid convergence in the STB remains an open challenge in LES [33, 34]; research indicates that second-order statistics often fail to reach independence even at very fine resolutions on the order of 1 m [35]. Our chosen resolution is consistent with recent large-scale offshore studies using PALM in the North Sea [6], where it has been shown to effectively capture macroscopic wind shear and farm-scale induction. We acknowledge that this resolution may lead to a slight underestimation of turbulent mixing and enhanced numerical diffusion in stable conditions, potentially making the predicted wake recovery more conservative. However, for the primary objective of this study—benchmarking the large-scale wake dynamics and efficiency against analytical engineering models—this discretization sufficiently resolves the dominant flow features and momentum fluxes across the 240 m rotor diameters.

3.3 | Momentum and Energy Budgets

In this study, we employ both momentum and kinetic energy budget analyses to gain a comprehensive understanding of wind farm flow dynamics and farm-atmosphere interactions, capturing the driving forces of the flow as well as the processes of energy conversion and dissipation within the MABL.

3.3.1 | The Kinetic Energy Budget

The mean kinetic energy consists of the kinetic energy of the mean flow (KEM), $\bar{E}_k$, and the TKE:

$$\bar{E}_k = \bar{E} + e = \frac{1}{2} (\bar{u}_i \bar{u}_i + \overline{u'_i u'_i}), \quad (7)$$

where the prime denotes the turbulent component, $e = 0.5 \overline{u'_i u'_i}$, see Equation (6). The conservation equation for the mean kinetic energy can be derived by multiplying the momentum equation with u_i and taking the time average:

$$\begin{aligned} \frac{\partial \bar{E}_k}{\partial t} = & \underbrace{-\frac{\partial}{\partial x_k} (\bar{u}_k \bar{E}_k)}_{\mathcal{A}: \text{Advection}} + \underbrace{-\frac{\partial}{\partial x_k} (\overline{u'_i u'_k} \bar{u}_i)}_{\mathcal{T}_1: \text{Resolved stress transport}} + \underbrace{-\frac{\partial}{\partial x_k} (\tau_{ki} \bar{u}_i)}_{\mathcal{T}_2: \text{SGS stress transport}} \\ & + \underbrace{-\frac{\partial}{\partial x_k} (\overline{u'_k e})}_{\mathcal{T}_3: \text{TKE transport}} + \underbrace{-\frac{\partial}{\partial x_k} (\overline{u'_i \pi'^*})}_{\mathcal{T}_4: \text{Pressure transport}} + \underbrace{-\frac{1}{\rho_a} \bar{u}_i \frac{\partial \bar{\pi}^*}{\partial x_i}}_{\mathcal{P}: \text{Mean pressure work}} \\ & + \underbrace{g \frac{\bar{T} - T_0}{T_0} \bar{w}}_{\mathcal{B}: \text{Buoyancy production}} + \underbrace{-\tau_{ki} \frac{\partial \bar{u}_i}{\partial x_k}}_{\mathcal{D}: \text{Dissipation}} + \underbrace{\bar{u}_i d_i}_{\mathcal{F}: \text{Wind turbine sink}} \\ & + \underbrace{-\bar{u} f_3 v_g + \bar{v} f_3 u_g}_{\mathcal{G}: \text{Geostrophic forcing}} \end{aligned} \quad (8)$$

The left-hand side of Equation (8) represents the temporal rate of change of the mean kinetic energy $\bar{E}_k$. The right-hand side consists of 10 terms, each with a distinct physical interpretation [36]. The groupings are defined as follows:

- $\mathcal{A}$: Divergence of kinetic energy advection.
- $\mathcal{T}$: Turbulent transport of kinetic energy, further divided into: $\mathcal{T}_1$: Transport of KEM by resolved turbulent stresses, $\mathcal{T}_2$: Transport of KEM by SGS stresses, $\mathcal{T}_3$: Transport of TKE by resolved turbulent stresses, and $\mathcal{T}_4$: Transport of TKE by perturbation pressure fluctuations.
- $\mathcal{P}$: Energy input due to mean perturbation pressure gradients.
- $\mathcal{B}$: Energy input from buoyancy forces.
- $\mathcal{D}$: Dissipation via the SGS turbulence model.
- $\mathcal{F}$: Energy sink due to wind turbine drag.
- $\mathcal{G}$: Energy input from geostrophic forcing.

3.3.2 | The Momentum Budget

The momentum budget analysis involves integrating the stream-wise component of the Reynolds-averaged momentum equation over a defined control volume Ω and evaluating each momentum source and sink term. The integral form of the budget is expressed as

$$\begin{aligned} \int_{\Omega} \frac{\partial \bar{u}}{\partial t} d\Omega = & \underbrace{- \int_{\Omega} \left(\frac{\partial \bar{u}^2}{\partial x} + \frac{\partial \bar{v} \bar{u}}{\partial y} + \frac{\partial \bar{w} \bar{u}}{\partial z} \right) d\Omega}_{\mathcal{A}^M: \text{Mean momentum advection}} \\ & - \underbrace{\int_{\Omega} \frac{1}{\rho} \frac{\partial \bar{\pi}^*}{\partial x} d\Omega}_{\mathcal{P}^M: \text{Pressure gradient force}} + \underbrace{\int_{\Omega} f(\bar{v} - v_g) d\Omega}_{\mathcal{G}^M: \text{Geostrophic forcing}} \\ & + \underbrace{\int_{\Omega} \left(\frac{\partial \tau_{t,11}}{\partial x} + \frac{\partial \tau_{t,12}}{\partial y} + \frac{\partial \tau_{t,13}}{\partial z} \right) d\Omega}_{\mathcal{T}^M: \text{Turbulent momentum flux}} \\ & + \underbrace{\int_{\Omega} d_1 d\Omega}_{\mathcal{F}^M: \text{Wind turbine-induced momentum sink}} \end{aligned} \quad (9)$$

Here, the overbar $\bar{\cdot}$ denotes a Reynolds-averaged quantity. The physical interpretation of each term in the momentum budget, for the entire wind farm domain Ω extending vertically from the ocean surface to a height of 360 m, is as follows:

- $\mathcal{A}^M$: Mean momentum advection.
- $\mathcal{P}^M$: Pressure gradient force.
- $\mathcal{G}^M$: Geostrophic forcing (including Coriolis and geostrophic pressure gradient contributions).
- $\mathcal{T}^M$: Turbulent momentum flux, where $\tau_{t,11}$, $\tau_{t,12}$, $\tau_{t,13}$ are the turbulent (subgrid-scale) fluxes of streamwise momentum in the x -, y -, and z -directions, respectively.

- $\mathcal{F}^M$: Wind turbine-induced momentum sink, where d_1 denotes the turbine body-force contribution in the streamwise x -direction.

3.4 | Low-Fidelity Modeling: PyWake

High-fidelity simulations of wind farm flows, such as those conducted using the PALM model system (as discussed in Section 3.2), offer detailed resolution of the flow field around individual turbines. However, this level of precision comes at a high computational cost. As a more practical alternative, analytical models are commonly used to represent wake effects and wake-wake interactions across the wind farm. Although they are less accurate than high-fidelity approaches, their simplicity and significantly lower computational demands make them especially valuable for tasks like wind farm optimization and preliminary design studies.

In this study, we utilize three wake models that share a common foundation based on a Gaussian-shaped velocity deficit profile. The Niayifar-Porté-Agel (NP) model [17] and the Turbulence Optimized Park (TurboPark) model [18] include a turbulence-intensity-dependent wake expansion rate, while the original Bastankhah-Porté-Agel (BP) model [19] represents the baseline Gaussian formulation without explicit TI dependence.

The BP model adopts a Gaussian-shaped velocity deficit profile that conserves momentum and more accurately represents the wake flow than earlier top-hat models, and it serves as the basis for various analytical wake models. The NP model applies linear superposition of wake deficits, conserving momentum. It accounts for turbine-induced turbulence based on the method of Crespo and Hernández [37], assuming a TI range of 7%–14% and considering only the nearest upstream turbine for wake interactions. In contrast, the TurboPark model uses quadratic superposition to conserve kinetic energy, incorporates turbulence modeling from Frandsen [38], and aggregates contributions from all upstream turbines using a TKE-preserving method.

Simulations were performed using PyWake [26], with meteorological inputs including a hub-height wind speed, ambient TI, and a wind direction, and the shear exponent at hub height, all obtained from NORA3. Turbine-specific data such as thrust and power coefficients, rotor diameter, and hub height were sourced from Gaertner et al. [24].

4 | Results

4.1 | PALM LES Results

Figure 6a,d,g presents the mean horizontal wind speed at hub height for all stability regimes, illustrating the influence of atmospheric stratification on wake dynamics. Under

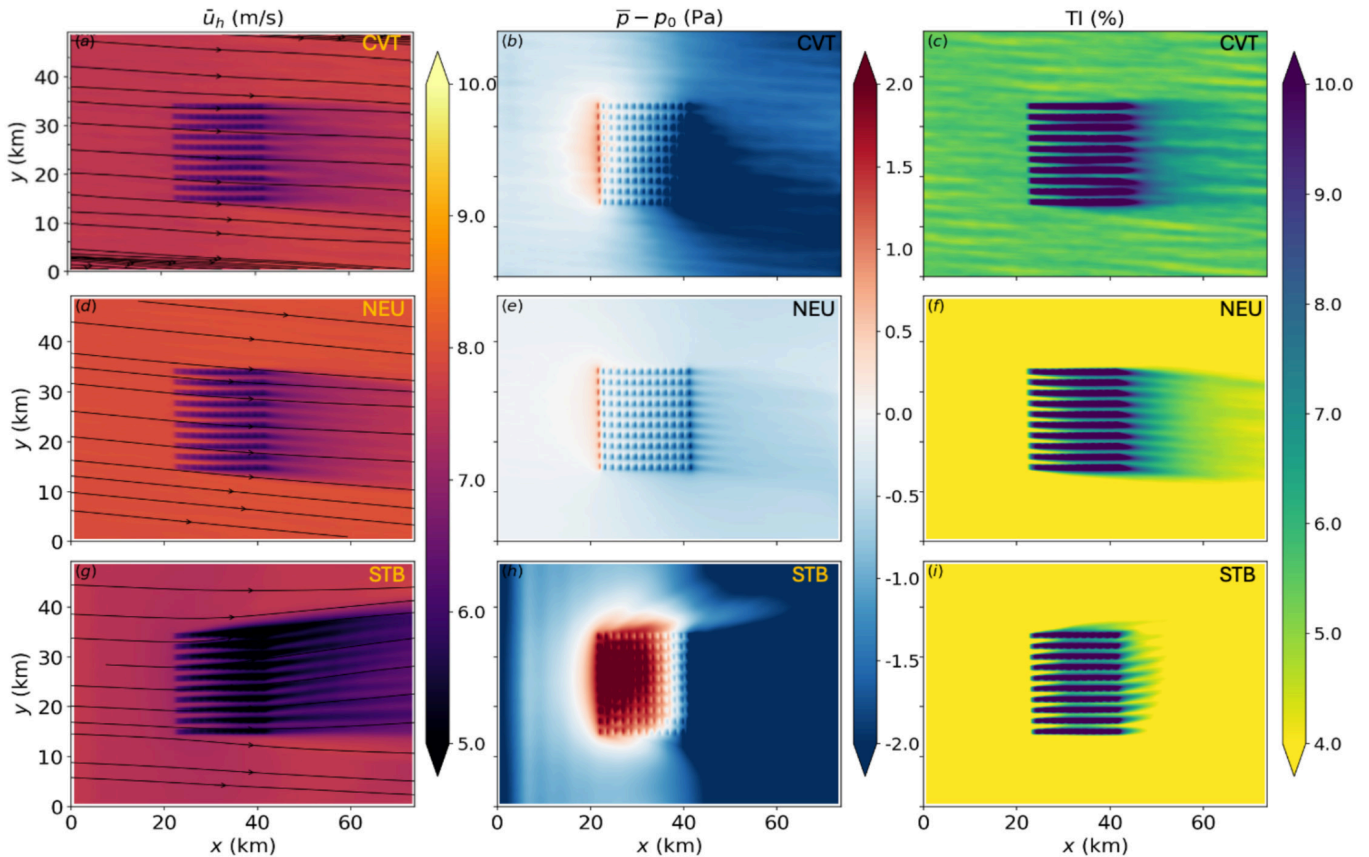


FIGURE 6 | (a, d, g) Mean horizontal wind speed $\bar{u}_h$ at hub height across all three stability conditions, (b, e, h) corresponding horizontal pressure perturbations at hub height, and (c, f, i) mean TI at hub height, estimated using Equation (5). Note that wind directions use the meteorological “from” convention; PALM outputs are in a Cartesian grid (x east, y north).

convective and neutral conditions, deeper boundary layers enhance turbulent mixing, facilitating faster wake recovery (see also Figure 7). Conversely, stable stratification suppresses turbulence, resulting in longer and more persistent wakes. Figure 6b,e,h illustrates how wind farms can modify pressure gradients within the boundary layer due to the generation of stationary gravity waves in the stably stratified free atmosphere and displacement of the inversion layer. These gravity-wave-induced pressure variations lead to upstream flow blockage, characterized by increased perturbation pressure, up to approximately more than 2 Pa, compared to the undisturbed inflow. This results in a reduction in wind speed and turbine performance, even at the first row of turbines. Additionally, the pressure distribution across the wind farm becomes asymmetric, with elevated pressure upstream and lower pressure in the wake. In our simulations, the wake exhibits a counterclockwise turning relative to the inflow wind direction, consistent with the other studies [6]. This rotation is primarily attributed to the reduction in wind speed within the wake, which diminishes the Coriolis force and thereby shifts the balance of forces toward a deflection in the direction of the pressure gradient, as also reported in previous studies [13, 39]. The farm-induced pressure gradient and background wind veering aloft under stable stratification may still modulate the wake orientation, but our results suggest that their contribution

to the rotation is secondary compared to the Coriolis-related mechanism. While the ambient boundary layer (BL) height strongly influences the rate of wake recovery via TKE fluxes, the growth of the wind-farm-induced internal boundary layer (IBL) is also strongly modulated by atmospheric stability and the presence of a capping inversion. Figure 6c,f,i shows the TI at hub height, illustrating these effects. In the convective case (CVT), strong turbulent mixing and efficient momentum entrainment from aloft promote rapid IBL growth and wake recovery, with streaks of elevated TI persisting for 30–40 km downstream. However, the capping inversion still limits the vertical extent of such growth, in some convective cases, preventing the IBL from expanding into the free atmosphere. In the neutral case (NEU), although TKE levels are lower than in CVT, the absence of a strong capping inversion allows the IBL to grow beyond the initial BL height, accompanied by an upward displacement of the BL top—indicating momentum input from the free atmosphere. In contrast, the stable case exhibits significantly lower turbulence intensity both within and beyond the wind farm, with elevated TI levels persisting only a few kilometers downstream (Figure 6i). This behavior is a physical characteristic of stable boundary layer dynamics. In the STB regime, a shallow inversion layer interacts directly with the turbine layer; while it is locally lifted over the wind farm due to turbine-induced momentum deficit

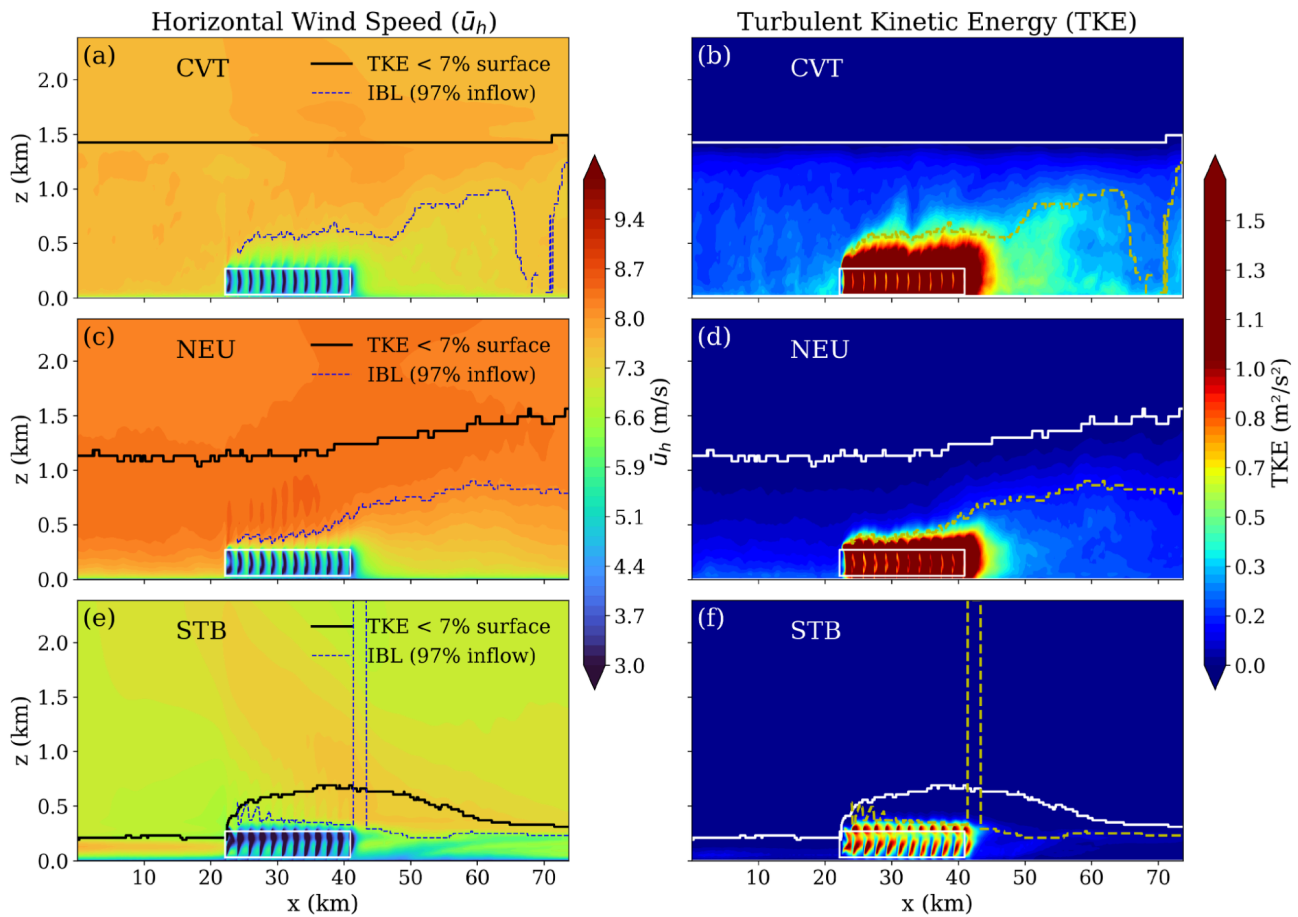


FIGURE 7 | Vertical cross-sections at $y = 34$ km showing (a, c, e) the mean horizontal wind speed $\bar{u}_h$ and (b, d, f) the turbulent kinetic energy (TKE) for three atmospheric stability conditions. The inversion layer height z_i is defined as the altitude where TKE falls below 7% of its near-surface value (within the first 50 m). The internal boundary layer (IBL) is identified where the wind speed reaches 97% of the inflow at each height. The extent of the wind farms is also indicated.

and turbulence production, it is subsequently restored downstream by strong stable stratification. This process effectively constrains both vertical wake expansion and IBL growth. Furthermore, because turbulence production is buoyancy-suppressed, the vertical entrainment of momentum from the flow aloft—the primary driver for wake recovery—is significantly weakened. Consequently, the wake remains narrow and vertically constrained, causing the velocity deficit to persist over much longer downstream distances despite the rapid decay of TI (Figure 6g,i). We acknowledge that the relatively coarse grid resolution may contribute to an underestimation of small-scale turbulent structures in the STB, potentially resulting in a faster TI decay than would be captured at higher resolutions. However, the qualitative trend of suppressed turbulence coupled with a slow, constrained wake recovery is physically representative of stable atmospheric conditions. Overall, instability and weak capping favor deeper mixing and faster recovery, whereas strong, low-lying inversions severely limit the vertical development of wind-farm wakes.

To assess the influence of atmospheric stability on downstream flow and TKE, we examine the evolution of both the background BL and the wind-farm-induced IBL. Turbine-induced momentum extraction at the wind farm entrance reduces horizontal wind speed, leading to upward flow deflection and vertical momentum transport. Here, the inversion layer height is defined where TKE falls below 7% of its surface value, while the IBL height is identified where the time-averaged horizontal wind speed reaches 97% of the plane-averaged inflow at that level. Alternative criteria exist—for instance, Wu and Porté-Agel [40] use a 99% threshold. In all three cases, the IBL height stays near or below 1.5 km; however, under convective conditions, it can reach the inversion layer within tens of kilometers downstream

[6]. Within the wind farm, however, the IBL remains shallow and highly perturbed.

Figure 8 presents vertical cross-sections of perturbation pressure, computed as deviations from the inflow profile to highlight flow-induced disturbances. The data have been time- and spanwise-averaged to isolate coherent features. These patterns reveal signatures of stationary inertial gravity waves, characterized by phase lines tilted upstream—an indication of upward wave energy propagation. The alignment between perturbation pressure and vertical velocity fields (shown in Figure 9c for the STB case) confirms that the two are in phase, consistent with gravity-wave dynamics. Gravity-wave signatures are strongest under stable conditions, where the stratified boundary layer acts as an efficient waveguide. The low capping inversion reflects part of the farm-induced wave energy, enhancing upward energy transfer and producing pronounced oscillations aloft. In contrast, buoyancy-driven turbulence in the CVT case increases mixing and damps coherence, so waves still form where turbine momentum extraction creates localized divergence-convergence, but their amplitude and organization are weaker. In the NEU case, the absence of stratification and a capping inversion removes the restoring force; farm-induced vertical forcing is simply mixed away rather than oscillating, leaving little organized wave motion. Collectively, the results indicate the ordering STB > CVT in wave prominence, governed by the interplay of stratification, inversion height, and turbulence-mediated mixing.

Further analysis of Figure 8a–c reveals the presence of three distinct gravity wave modes, distinguished by their inclination angles. Near the leading edge of the farm, the first mode shows steep, nearly vertical phase lines; above the farm, the second mode appears with more horizontally inclined lines; and in the

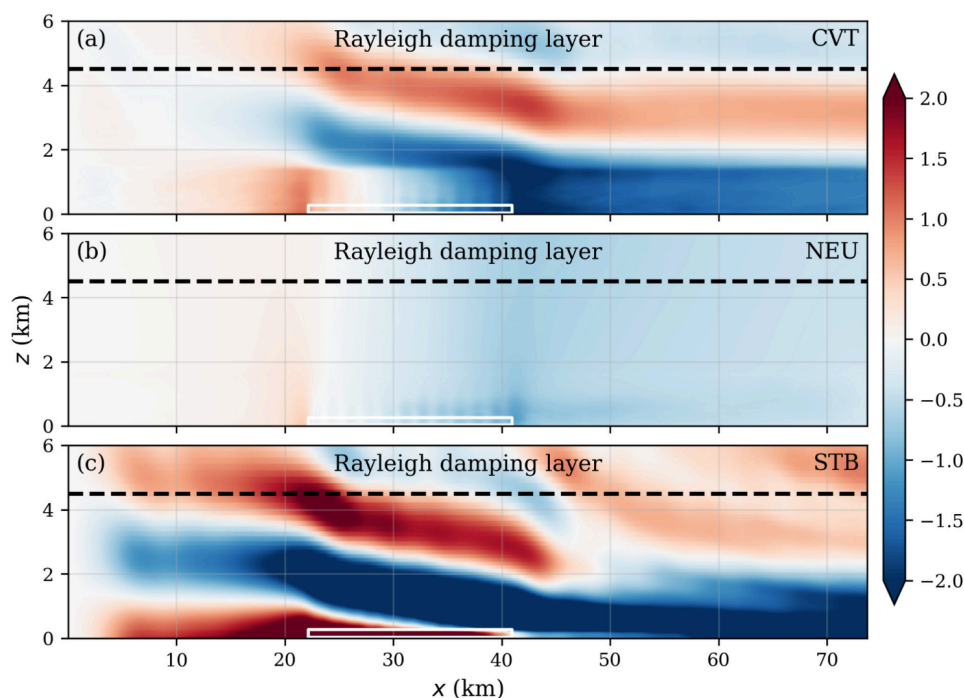


FIGURE 8 | Vertical cross-section of mean pressure perturbations along the wind farm centerline, shown as deviations from the corresponding inflow pressure at each height (p_0), for three stability cases: (a) convective, (b) neutral, and (c) stable conditions.

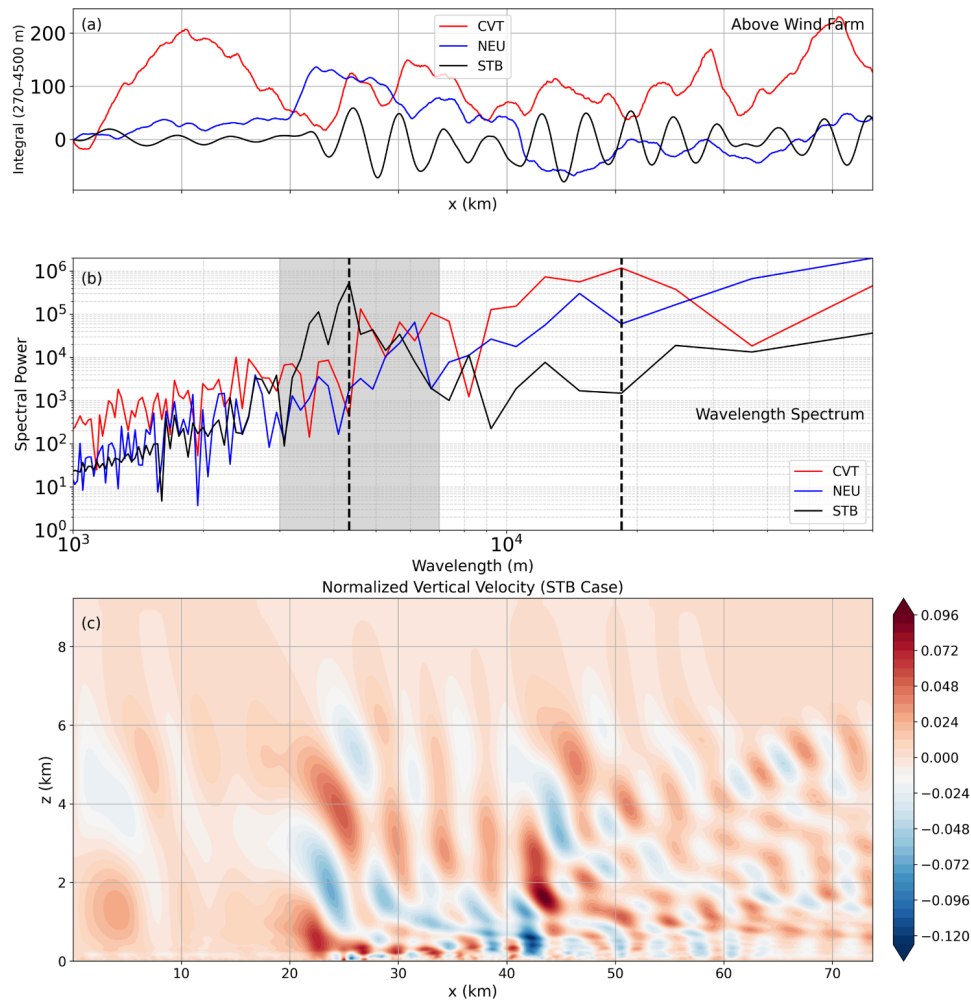


FIGURE 9 | (a) Vertically integrated vertical wind velocity ($\bar{w}$) above 270 m over the wind farm, used to investigate the characteristics of internally generated gravity waves under different atmospheric stability conditions; (b) the corresponding wavenumber spectrum of the vertically integrated $\bar{w}$, illustrating the dominant gravity wave modes; and (c) the vertical velocity anomaly for the stable condition.

wake region, the third mode exhibits nearly horizontal phase lines, often coupled with finer structures near the surface—especially under stable stratification [7]. These wave patterns are strongly influenced by the structure of the inversion layer, which behaves analogously to terrain in stratified flows. Sharp transitions in inversion height near the leading edge generate the first wave mode, while broader hill- and valley-shaped features downstream give rise to the second and third modes. The relatively flat and asymmetric shape of the inversion layer may explain the observed linear pressure gradients across the wind farm, rather than the more sinusoidal distributions typical of ideal gravity wave behavior [36]. Additionally, an adverse pressure gradient (increasing pressure in the streamwise direction) develops upstream of the wind farm in both CVT and STB cases. The associated pressure buildup leads to flow deceleration, in line with Bernoulli's principle, and contributes to blockage. This upstream pressure buildup appears more pronounced under stable conditions and is likely modulated by the presence of gravity waves [41]. Downstream, the associated favorable pressure gradient may aid wake recovery. In contrast, the NEU case shows only a modest pressure increase upstream, attributable to purely hydrodynamic interactions rather than wave-driven effects.

It is worth to mention that in Figure 8a, no anomalous pressure perturbations or wave reflections are observed at the damping layer interface. Furthermore, the localized pressure drop observed behind the wind farm in unstable conditions (Figure 6) is interpreted as a physical response to momentum extraction under a constrained boundary layer. Unlike the neutral case, the convective boundary layer is capped by a distinct inversion layer that limits vertical momentum replenishment, forcing a more pronounced pressure adjustment in the wake region. This setup is consistent with, or more conservative than, heights used in similar LES studies [6].

The spatial pattern of vertical velocity anomalies w' (vertical velocity minus the undisturbed inflow w), integrated over the height range of 270–4500 m, clearly exhibits oscillatory behavior indicative of gravity wave activity. Among the three stability regimes, the stable case shows the most pronounced and coherent wave structure (see also Figure 9c), as evidenced by strong undulations in the integrated signal. Using a zero-crossing analysis over the domain $x = 20$ –42 km, we estimate a dominant horizontal wavelength of approximately 4134 m for STB, which aligns closely with the 4336.9 m wavelength

obtained from the spectral peak in the wavenumber analysis (Figure 9b). This consistency between time-averaged spatial patterns and spectral content reinforces the interpretation that the oscillations are caused by stationary gravity waves propagating through the stably stratified atmosphere, triggered by momentum extraction within the wind farm. In contrast, the CVT case also shows detectable oscillations, with a wavelength of approximately 4848 m (zero-crossing) and 4608 m (spectrum), though with lower amplitude and coherence than in STB, possibly due to competing buoyancy-driven turbulence that disrupts wave formation. For the neutral case, no clear zero-crossing wavelength could be extracted, and the spectral energy is more diffuse, suggesting a lack of organized wave motion in the absence of stratification.

4.1.1 | Energy Budget

Figure 10 presents the kinetic energy (KE) budgets within a control volume encompassing the entire wind farm for three different atmospheric stability regimes: convective, neutral, and stable. The terms in Equation (8) have been converted from units of $\text{W} \cdot \rho^{-1}$ to megawatts (MW) per turbine for clearer interpretation. For all cases, the budgets are balanced, with total energy sources matching total sinks: 5.19 MW for CVT, 6.34 MW for NEU, and 4.26 MW for STB.

Under CVT conditions, losses are strongly dominated by turbine-induced surface friction, $\mathcal{F}$, due to wind turbines ($\sim 71\%$ of the sink budget; Table 4), with additional contributions from dissipation and vertical advection. The main energy input comes from stream-wise advection ($\mathcal{A}_x = \sim 34\%$), vertical transport ($\sim 25\%$), and pressure work ($\sim 22\%$). In addition, buoyancy provides a direct source of kinetic energy ($\sim 4\%$), while geostrophic forcing contributes modestly ($\sim 9\%$).

In the NEU case, turbine-induced friction again dominates the sinks ($\sim 60\%$), but vertical advection, dissipation, and a non-negligible residual ($\sim 15\%$) also contribute. Sources are more

TABLE 4 | Kinetic energy budget terms (in MW per turbine) and their percentage contributions under different atmospheric stability conditions: Convective (CVT), Neutral (NEU), and Stable (STB).

Term	CVT	NEU	STB
Source terms			
$\mathcal{A}_x$	1.775 (34.2%)	3.292 (51.9%)	2.859 (67.2%)
$\mathcal{A}_y$	—	0.055 (0.9%)	—
$\mathcal{T}_y$	0.005 (0.1%)	0.008 (0.1%)	0.001 (0.0%)
$\mathcal{T}_z$	1.279 (24.6%)	1.999 (31.5%)	0.201 (4.7%)
$\mathcal{P}$	1.161 (22.4%)	0.409 (6.5%)	0.825 (19.4%)
$\mathcal{B}$	0.222 (4.3%)	0.000 (0.0%)	—
$\mathcal{G}$	0.485 (9.3%)	0.578 (9.1%)	0.371 (8.7%)
Sink terms			
$\mathcal{A}_y$	0.133 (2.6%)	—	0.395 (9.3%)
$\mathcal{A}_z$	0.507 (9.8%)	0.931 (14.7%)	0.502 (11.8%)
$\mathcal{T}_x$	0.152 (2.9%)	0.062 (1.0%)	0.028 (0.7%)
$D + R$	0.453	1.526	0.985
$\mathcal{B}$	—	—	0.225 (5.3%)
$\mathcal{F}$	3.682 (70.9%)	3.822 (60.3%)	2.122 (49.8%)
Total source	5.19 MW	6.34 MW	4.26 MW
Total sink	5.19 MW	6.34 MW	4.26 MW

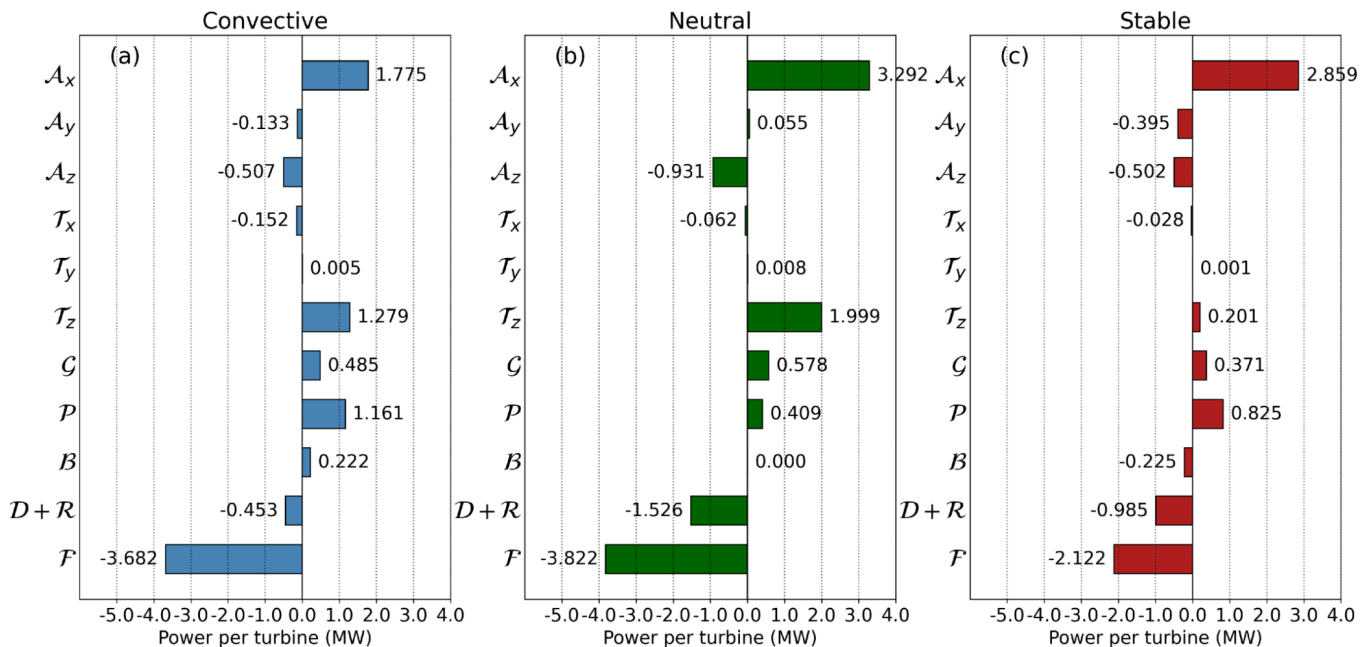


FIGURE 10 | Mean kinetic energy budget terms averaged over the wind farm control volume for different atmospheric stability conditions: (a) convective, (b) neutral, and (c) stable. All terms are defined in Equation (8).

evenly distributed than in CVT, with stream-wise advection ($\sim 52\%$) and vertical transport ($\sim 32\%$) leading, complemented by pressure work, geostrophic forcing ($\sim 9\%$), and weak cross-wind inflow. This overall balance indicates that under neutral conditions the boundary layer remains steadier and better organized than under convective conditions, which are more turbulent and disrupted.

Under STB conditions, the overall fluxes are smallest. Friction by farm is again the leading sink ($\sim 50\%$), but advection, dissipation, buoyancy, and the residual (together $\sim 40\%$) play stronger relative roles than in CVT or NEU. On the source side, stream-wise advection dominates overwhelmingly ($\sim 67\%$), with only modest contributions from pressure work ($\sim 19\%$), geostrophic forcing ($\sim 9\%$), and weak vertical transport. This highlights the suppression of vertical exchange and the stronger reliance on horizontal transport when stratification is stable.

Interestingly, the total advective energy loss is largely unaffected by the south/north boundaries, as the additional outflow through these boundaries is offset by a reduction in $\mathcal{A}_z$. The lateral energy loss $\mathcal{A}_y$ arises from transverse flow divergence within the wind farm. Minor variations in incoming wind speed across the lateral boundaries—induced by wake effects and wind-farm-driven deceleration near the recycling plane—contribute to this divergence. These dynamics also produce subtle directional shifts at the northwestern and southwestern corners of the farm, associated with horizontal flow deflection and wake

contraction. Because the background wind conditions differ between cases, the absolute magnitudes in Table 4 should not be compared directly. Instead, the emphasis is on the *characteristic pathways* and *relative behavior* of the energy-budget terms, which reveal systematic differences between CVT, NEU, and STB regimes.

4.1.2 | Momentum Budget

Figure 11 presents the vertically integrated momentum budget terms within the control volume encompassing the wind farm, with integration performed from the surface up to 360-m height. The plots illustrate the spatial distribution of advection and vertical turbulent momentum fluxes across the wind farm area for three atmospheric stability regimes. Overall, pronounced variations are observed along the y-direction near the western boundary, and along the northern boundary in the CVT case (i.e., Figure 11b). These areas correspond to regions of higher turbine power production. In the NEU case, an increase in meridional momentum advection ($\mathcal{A}_y^M$) is evident along the northern edge extending eastward, while in the stable case, a localized enhancement of vertical turbulent momentum flux ($\mathcal{T}_z^M$) appears in the eastern corner (Figure 11h). In the STB case, this increase is largely linked to faster wake recovery behind the wind farm, which induces a compensating downward motion of the airflow above to satisfy mass continuity. This downward motion correlates with the reduction (negative values) in $\mathcal{A}_x^M$ observed for the last column. These

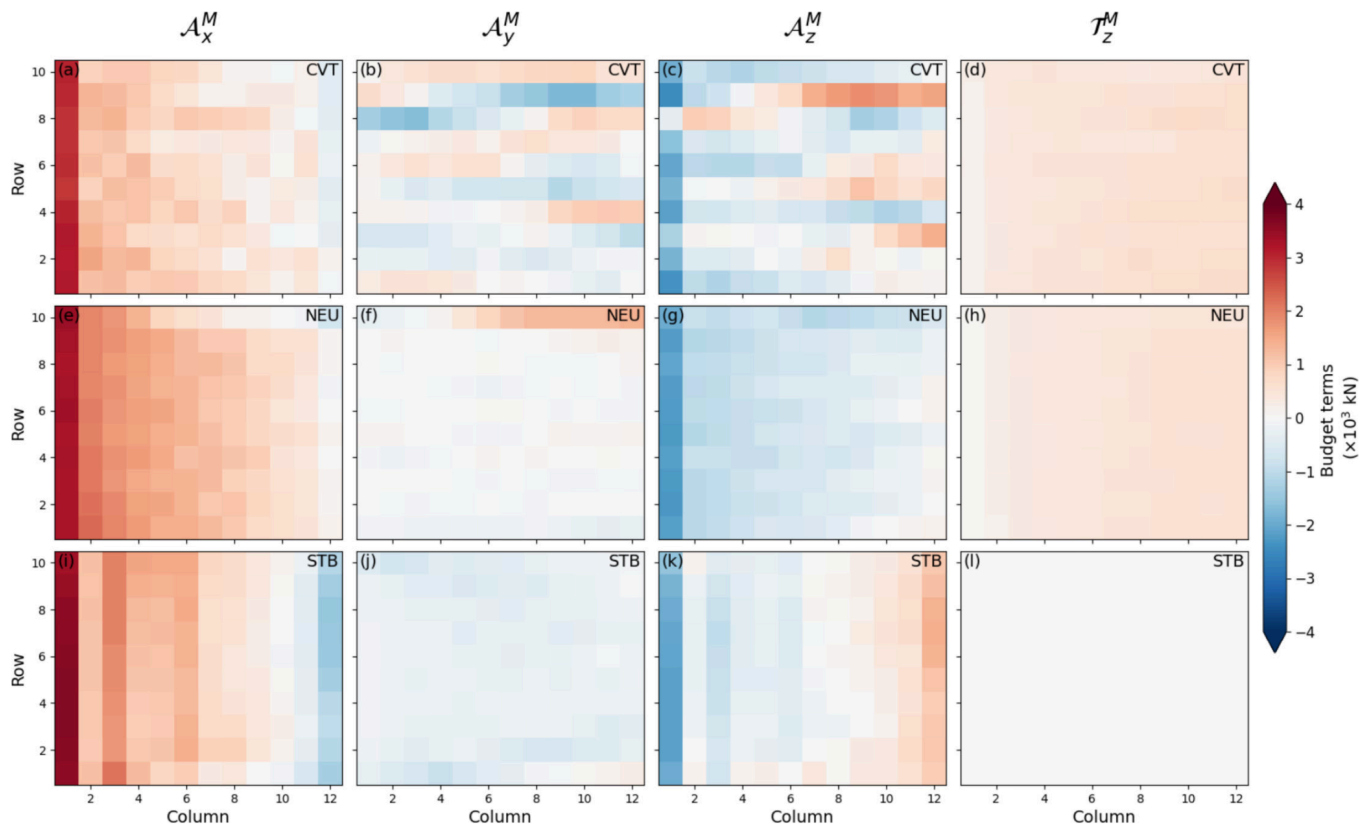


FIGURE 11 | Momentum budgets within the control volume encompassing the entire wind farm under varying stability and wind conditions. The budget terms include mean momentum advection through the west/east ($\mathcal{A}_x^M$), south/north ($\mathcal{A}_y^M$), and bottom/top ($\mathcal{A}_z^M$) boundaries, as well as turbulent momentum fluxes through the bottom and top boundaries ($\mathcal{T}_z^M$).

patterns are further influenced by spatial variations in wind direction across the farm and by elevated TI near the downstream boundary. In the central and western sectors, the wind is more aligned with turbine rows, causing downstream turbines to experience full wake conditions. Conversely, at the corners of the farm, the wind direction deviates slightly (see Figure 6d,g), reducing wake overlap and increasing turbine power output. This in turn leads to a more pronounced difference between the inflow and outflow momentum across control volume boundaries—particularly affecting $\mathcal{A}_x^M$. In convective conditions, vertical transport of momentum is enhanced due to strong buoyancy-driven turbulence. This leads to efficient mixing between the lower and upper layers of the atmosphere, effectively replenishing momentum in the turbine region and often reducing wake effects, as observed in Figure 11d. In neutral conditions (Figure 11h), vertical mixing is mainly driven by wind shear, resulting in moderate momentum exchange and a more balanced flow structure. In stable conditions (Figure 11l), turbulence is suppressed by atmospheric stratification, which limits vertical mixing. This leads to weak vertical momentum transport and slower wake recovery downstream of the turbines.

Figure 12 illustrates the column-wise distribution of the momentum budget terms along the streamwise x -direction, as computed by Equation (9), for 12 consecutive columns of a wind farm under three distinct atmospheric stability regimes. Across all conditions, the maximum momentum exchange occurs at the leading edge (first column), where wind turbines are subjected to the strongest forces. This peak is predominantly governed by a strong negative momentum sink induced by turbine drag, which is largely balanced by upstream mean advection.

In the CVT case, a non-negligible secondary contribution from the geostrophic forcing partially offsets the turbine-induced momentum loss, while contributions from other terms, such as pressure gradient and turbulent transport, remain minimal at the front. In the upstream region of the farm, mean advection constitutes the principal momentum source; however, its magnitude declines sharply after the first column, indicating rapid momentum redistribution due to flow deceleration and wake development. The pressure gradient term, while secondary in magnitude, exhibits contrasting behaviors across stability regimes: It remains subdued throughout most of the farm under NEU conditions, but increases in magnitude further downstream under both stable and convective regimes, suggesting enhanced pressure recovery mechanisms or flow acceleration induced by thermal stratification.

Turbulent momentum transport, especially under neutral conditions, exhibits a downstream intensification pattern, highlighting the progressive role of turbulent mixing in momentum redistribution deeper into the wind farm. This underscores the evolving balance of forcing terms and the complexity of flow adjustment mechanisms driven by turbine-atmosphere interactions under varying thermal stratification.

4.1.3 | Power and Efficiency

Figure 13 presents the wind turbine electrical power output, aerodynamic efficiency, and total aerodynamic (thrust and torque) loads as simulated by PALM under three distinct atmospheric stability conditions. The results in Figure 13a,e,i reveal

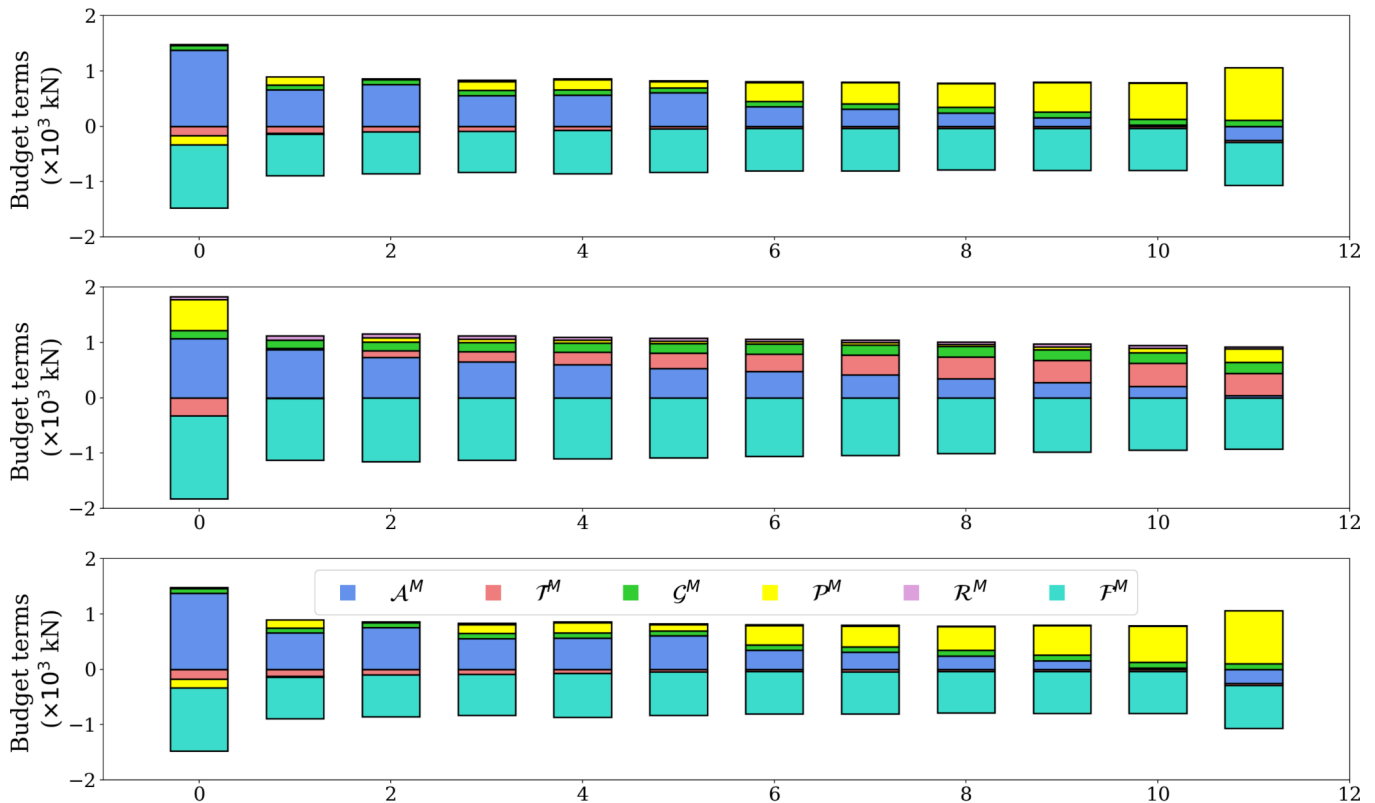


FIGURE 12 | Momentum budget terms averaged over each turbine column for three atmospheric stability conditions: (a) convective (CVT), (b) neutral (NEU), and (c) stable (STB).

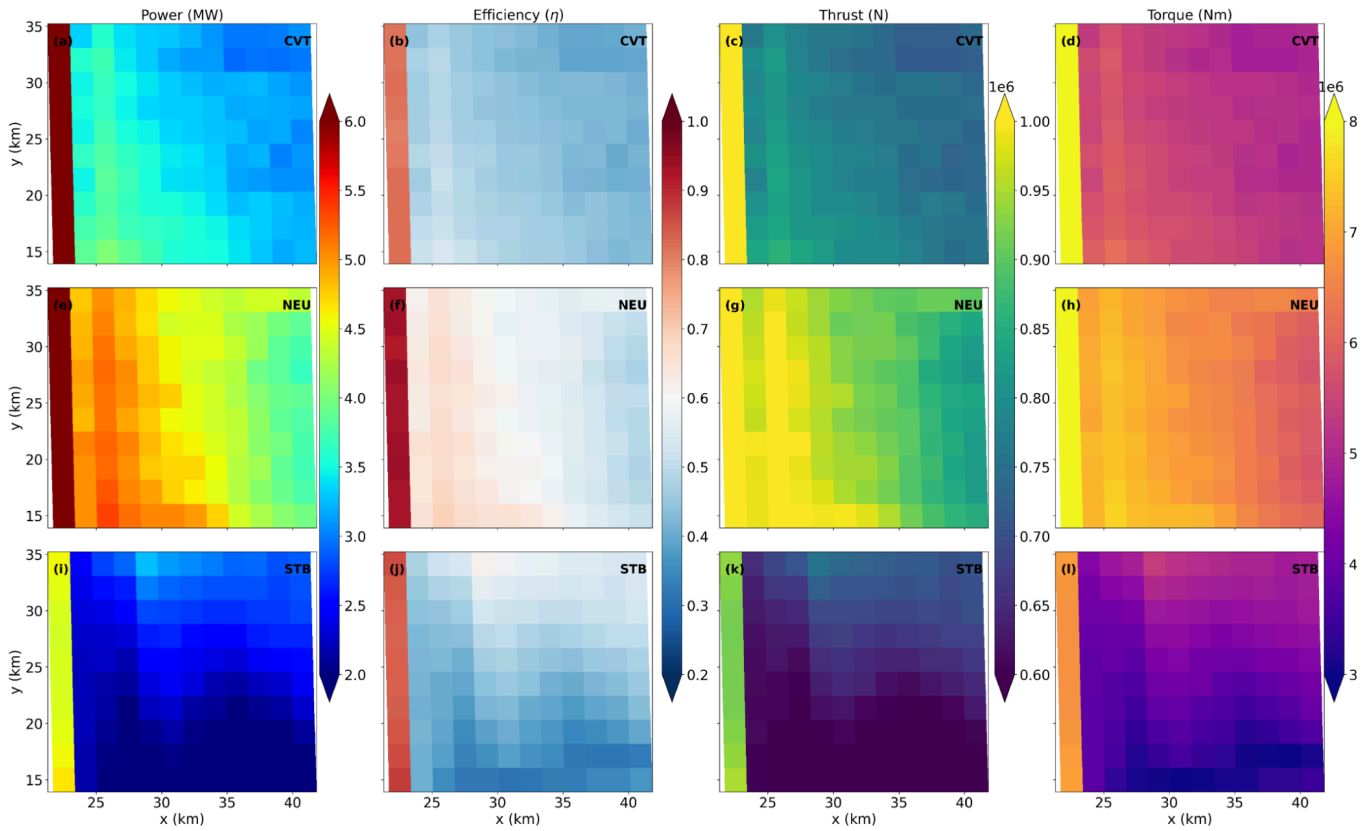


FIGURE 13 | Spatial distribution of wind turbine and wind farm performance metrics from the LES simulations under three atmospheric stability conditions: convective (top row), neutral (middle row), and stable (bottom row). (a, e, i): Turbine-level electrical power output. (b, f, j): Wind farm efficiency, η_{wf} from results of PALM. (c, g, k): Aerodynamic thrust load distributions across the wind farm. (d, h, l): Aerodynamic torque load distributions across the wind farm.

substantial qualitative differences in power distribution across the wind farm depending on the stability regime. Under convective conditions, turbine power output varies gradually along both rows and columns, indicating a relatively gradual reduction of power within the farm caused by vigorous vertical mixing, less velocity deficit (more uniform flow regimes within the farm area), and less pronounced blockage effects. In contrast, during neutral and especially stable stratification, a clear front-to-back gradient emerges: Turbines located in the front rows (in the first column) generate significantly more power than those situated deeper within the farm. This trend is most pronounced for the downstream turbines—those in the southeast under STB conditions and in the northeast under NEU conditions. The first column exhibits the highest power production, largely due to blockage and upstream pressure effects (as illustrated in Figure 6). However, even within the interior columns, substantial power fluctuations are observed, reflecting spatial heterogeneity in wind direction and wake exposure across the farm. In the CVT case, the lowest production occurs in the northeastern corner, where highly row-aligned inflow winds (Figure 6a) lead to strong cumulative wake shadowing from multiple upstream rows. In the STB case, a clear north–south asymmetry emerges, with turbines in the southern sector producing less than those in the north. This pattern results from strong wake deflection under stable stratification, which steers the wake southward (Figure 6i), thereby reducing wake overlap in the northern sector while intensifying it in the south.

TABLE 5 | Wind farm performance and efficiency metrics for different stability cases.

Case	Avg power/turbine (MW)	Total power (MW)	Efficiency (rated, %)	Efficiency (ref, %)
CVT	3.65	437.83	24.32	58.46
NEU	4.65	558.28	31.02	64.12
STB	2.46	295.17	16.40	54.62

Note: The wind farm efficiency is computed using two reference values: the rated power $P_{rated} = 15$ MW, and the isolated turbine power P_{ref} , representing undisturbed inflow conditions.

Figure 13b,f,j displays the turbine-level efficiency η_{wt} , while Table 5 reports the farm-level efficiency η_{wf} . To provide a true free-stream baseline, we normalize the power by an isolated turbine reference power, P_{ref} , obtained from standalone simulations conducted for each stability condition. These reference main runs utilize the identical precursor wind fields for each stability case, but are executed in a domain three times the size of the precursor to ensure the absence of global blockage or induction effects [32]. In these reference runs, a single turbine is positioned near the center of the domain to ensure undisturbed inflow conditions. For additional context, we also report

efficiencies relative to the rated turbine power, $P_{\text{rated}} = 15$ MW. The reference-normalized efficiencies are defined as

$$\eta_{\text{wf}} = \frac{P_{\text{wf}}}{n_{\text{wt}} P_{\text{ref}}}, \quad \eta_{\text{wt}} = \frac{P_{\text{wt}}}{P_{\text{ref}}}, \quad (10)$$

where P_{wf} is the total farm power, n_{wt} is the number of turbines, and P_{wt} is the power of an individual turbine. By using P_{ref} as the denominator, η_{wt} specifically quantifies the performance reduction of each turbine due to wake effects and farm-induced blockage relative to an undisturbed, isolated operation in the same atmospheric conditions. For comparison with a capacity-factor-like metric, we also report $\eta_{\text{rated}} = P_{\text{wf}}/(n_{\text{wt}} P_{\text{rated}})$. Unlike metrics normalized by front-row turbines, this approach ensures that the efficiency calculation is not influenced by local induction or global blockage that can depress front-row power.

Based on Table 5 and Figure 13b,f,j, the highest wind farm efficiency is observed under neutral condition, reaching approximately 31.0% relative to the rated power and 64.1% relative to the isolated turbine reference power. While convective condition benefits from buoyancy-driven turbulence and enhanced mixing, the farm-level efficiency in this regime ($\eta_{\text{wf}} \approx 58.5\%$) is lower than in the neutral case, likely due to the higher baseline turbulence intensity of the inflow among other players. In the STB case, the farm attains its lowest performance, reaching only 16.4% of its rated capacity and 54.6% relative to the isolated reference power. This reduction is driven by stable stratification, which suppresses turbulent kinetic energy and limits the vertical entrainment of high-momentum air from aloft. Consequently, wakes recover slowly and downstream turbines operate within deeper velocity deficits over longer fetches, significantly amplifying cumulative wake losses. Stable conditions also enhance global blockage effects, which can reduce inflow speeds even for the first row of turbines. As shown in Figure 13j, while favorable pressure gradients may help redistribute energy downstream [13], the overall efficiency remains significantly below the neutral case (Figure 13f).

Figure 13c,g,k and d,h,l map the rotor-integrated aerodynamic thrust and torque, respectively, for the three stability regimes and should be read alongside the power and efficiency fields. In convective inflow, enhanced mixing accelerates wake recovery, so many downstream turbines see improved inflow: Farm power and η_{wf} rise broadly, while loads increase more moderately. In the neutral case, shear-driven entrainment results in intermediate performance. Power and efficiency exhibit pronounced spatial gradients as they decline with depth into the wind farm, while load patterns closely follow this downstream evolution without the severe wake persistence, observed under stable conditions. In the stable case, suppressed mixing sustains wake deficits and farm-scale blockage: Downstream turbines exhibit the lowest power and efficiency yet still carry non-trivial aerodynamic loads, highlighting a regime where energy yield is poor but fatigue-relevant loading persists. See Appendix B. Overall, the load maps co-vary with power and efficiency but are less sensitive; interpreting them together reveals where turbines operate near optimal performance versus pitch-regulated states (most likely for the front-row turbines), and identifies stability-dependent risk zones (especially in stable, deep-wake regions).

4.2 | Cross-Comparison of Models

Figure 14 compares column-averaged turbine power output from PALM with three engineering wake models. In the CVT case (Figure 14a), PALM predicts a first-column average power of about 6.2 MW, noticeably higher than all engineering models (which lie near 5.3–5.4 MW). From the second column onward, PALM shows a sharp reduction to ~ 3.5 MW due to strong wake effects. Interestingly, the third column exhibits a modest recovery to ~ 5.1 MW, reflecting partial wake exposure of some turbines, before gradually declining further downstream. In terms of total farm output, PALM yields 437.8 MW, whereas NP and TurboPark underestimate by 6.3% and 15.1%, respectively, and BP underpredicts by more than 30%. Among the engineering models, NP aligns most closely with PALM throughout the array, while TurboPark initially underestimates power but converges toward PALM values in the far wake. BP, by contrast, departs substantially from both PALM and the other models, consistently underpredicting power and failing to converge downstream.

Under NEU conditions (Figure 14b), PALM shows a sharp drop in power output at the second column, reflecting the onset of cumulative wake effects from the first-column turbines (first-column average ~ 7.2 MW). Further downstream, however, the column-averaged power levels off, indicating a quasi-stationary regime. The total farm power in PALM is 558.3 MW, and here all three engineering models perform better, with TurboPark deviating by less than 1%, NP by $\sim 5\%$, and BP by $\sim 4\%$. NP provides the closest column-by-column agreement with PALM.

The STB case (Figure 14c) highlights a distinct behavior. In the first column, PALM predicts a relatively low average power of ~ 4.4 MW, whereas all three engineering models predict higher values (5.5–5.7 MW), reflecting their inappropriate or missing representation of global blockage, the assumption of horizontally homogeneous inflow, and a limited ability to capture inversion-induced shear and suppressed turbulent mixing. Beyond the second column, however, NP and TurboPark converge toward PALM and reproduce the nearly stationary behavior observed downstream. In terms of total farm output, PALM predicts 295.2 MW, whereas NP and TurboPark strongly overestimate (by 34% and 21%, respectively), while BP severely underpredicts (128.6 MW, or a 56% deficit). BP thus fails to converge to PALM values, maintaining a large persistent bias despite a stationary profile shape.

Taken together, these comparisons illustrate how LES (PALM) captures stability-dependent flow and wake dynamics that simplified models approximate with varying fidelity. NP and TurboPark generally reproduce PALM trends, especially downstream, whereas BP exhibits the largest deviations across all regimes. The stability-dependent differences reinforce the interpretation from PALM that convective and neutral conditions sustain cumulative wake growth without reaching equilibrium, while stable stratification enables a quasi-fully developed state over a shorter fetch due to suppressed turbulent entrainment.

Table 6 along with Figure 14 illustrates that model performance varies notably with atmospheric stability: While analytical

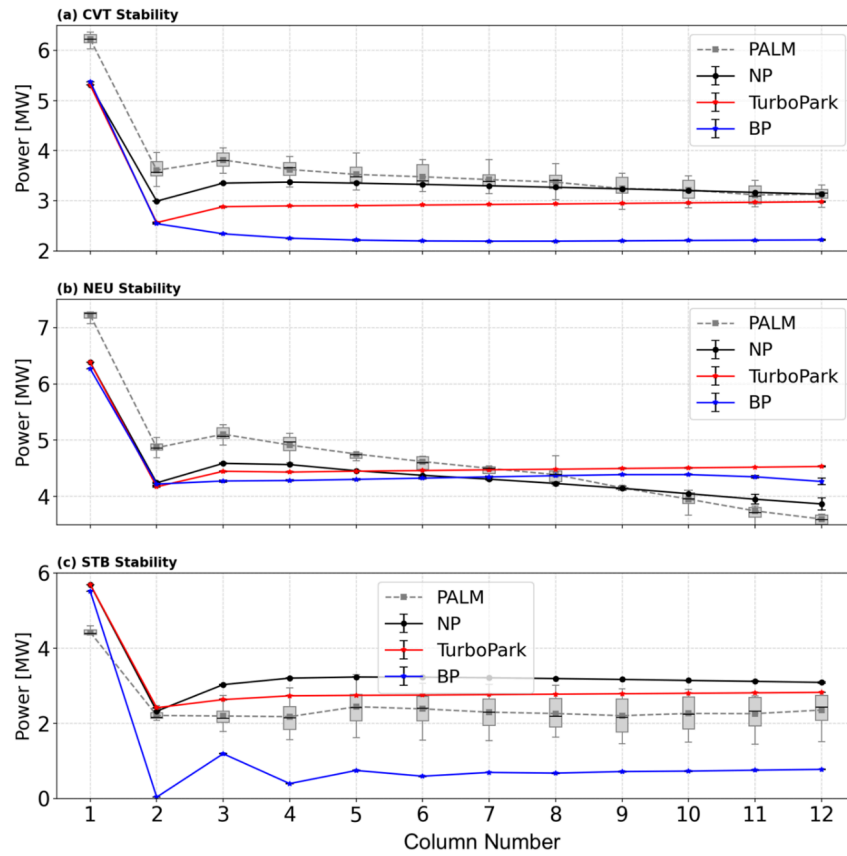


FIGURE 14 | Wind turbine power predictions from the LES model PALM, the Niayifar and Porté-Agel (NP) model, the TurboPark model, and BP. Markers indicate the average power per turbine column (column-wise mean), while error bars show the minimum and maximum power values within each column. Results are presented for different atmospheric stability conditions: (a) convective (CVT), (b) neutral (NEU), and (c) stable (STB). In all PyWake model simulations, the reference wind speed, wind direction, turbulence intensity, and shear exponent used in the wake models are based on the LES inflow conditions at hub height.

TABLE 6 | Total predicted wind farm power output (in MW) for each model and stability case.

Case	Model	Total power (MW)	Δ (MW)	Δ (%)
CVT	PALM	437.83	—	—
	NP	410.12	+27.70	6.3%
	TurboPark	371.88	+65.95	15.1%
	BP	301.54	+136.29	31.1%
NEU	PALM	558.28	—	—
	NP	531.75	+26.53	4.8%
	TurboPark	553.70	+4.59	0.8%
	BP	537.97	+20.31	3.6%
STB	PALM	295.17	—	—
	NP	396.82	−101.65	34.4%
	TurboPark	357.81	−62.64	21.2%
	BP	128.62	+166.55	56.4%

Note: Discrepancies (Δ) are relative to the PALM (LES) simulation results. Positive Δ indicates underprediction, negative Δ indicates overprediction.

models closely match PALM predictions under neutral conditions (discrepancies $< 1\%$), they tend to underestimate or overestimate total power in unstable and stable cases, with maximum deviations exceeding 56% in the latter.

4.3 | PyWake Decadal Results

To assess long-term wake effects—following the comparison between fast-running engineering models and PALM—we examine wake losses across stability classes using 11 years of hub-height wind data. We employ two complementary, normalization-consistent metrics:

$$\text{WakeLoss}_{\text{total}} = 100 \frac{P_{\text{no-wake}} - P_{\text{wake}}}{P_{\text{no-wake}}}, \quad (11)$$

where $P_{\text{no-wake}}$ is the farm power under a no-wake baseline and P_{wake} is the corresponding waked farm power. Normalizing by the baseline power is standard and avoids inflation of percentages at high losses.

For above equation, the power data are extracted at hub height for 15MW turbines located at the geographical center of the SNII site (the golden star in Figure 1a). We use the regular

turbine layout defined earlier for the full 1800 MW wind farm. It is important to note that the results are also applicable to the park's initial phase (i.e., 1500 MW capacity), as the dominant (southwesterly) wind direction allows the exclusion of the last two turbine columns without significantly affecting the wake characteristics (see Section 5.2).

Figure 15 shows total wake losses (%) from three PyWake models across stability classes (very unstable to very stable). The engineering runs are driven by NORA3-derived data of hub-height wind speed/direction, shear, and turbulence intensity; therefore the magnitudes should be read as conditional on this inflow description. The results are sensitive to (i) the farm layout, (ii) environmental variability (spatial inhomogeneity, ambient TI, shear), (iii) uncertainty in the Monin-Obukhov stability classification, and (iv) the choice of inflow dataset. Substituting a different inflow and environmental data (e.g. ERA5, a WRF downscale, or site LiDAR/met-mast) would change the inflow statistics—especially TI—and thus the absolute wake-loss values, with the strongest impact on TI-dependent models (NP, TurboPark); BP is comparatively less sensitive. Accordingly, the values reported here are NORA3-driven estimates; repeating the analysis with another inflow may shift magnitudes while preserving the qualitative ordering across stability classes. Where feasible, calibrating TI to site measurements or bracketing it via a TI-sensitivity band is recommended.

For the BP model, the strongest wake losses are observed under very stable conditions (up to 22.8%), while the smallest occur under neutral conditions (around 8%–9%). One possible

explanation is the relatively high frequency of (very) unstable conditions in the North Sea—accounting for roughly 50% of all cases over the 11-year period—combined with the non-optimized farm layout. However, because wake losses are also strongly influenced by wind direction and speed, it is difficult to attribute the observed patterns solely to atmospheric stability in the present aggregated analysis. Similar trends are nonetheless seen across all models, with the smallest wake losses consistently occurring under neutral stability conditions. To support a better understanding of the statistical variation in the internal wake losses at the SNII site, the percentage occurrence of each stability class—based on hub-height conditions at the center of the farm—is as follows: Very Unstable: 28.71%, Unstable: 20.49%, Neutral: 15.39%, Stable: 18.73%, Very Stable: 16.68%.

TABLE 7 | Wind-farm performance and efficiency across stability classes, computed with the TurboPark engineering model.

Case	Avg power (MW/turbine)	Total power (MW)	Efficiency (P_{rated})	Efficiency (P_{ref})
CVT	11.24	1348.66	74.93%	88.45%
NEU	12.30	1476.01	82.00%	91.24%
STB	11.70	1413.34	78.52%	89.36

Note: Efficiencies using (i) a front-row reference turbine power P_{ref} and (ii) the rated power $P_{\text{rated}} = 15$ MW per turbine.

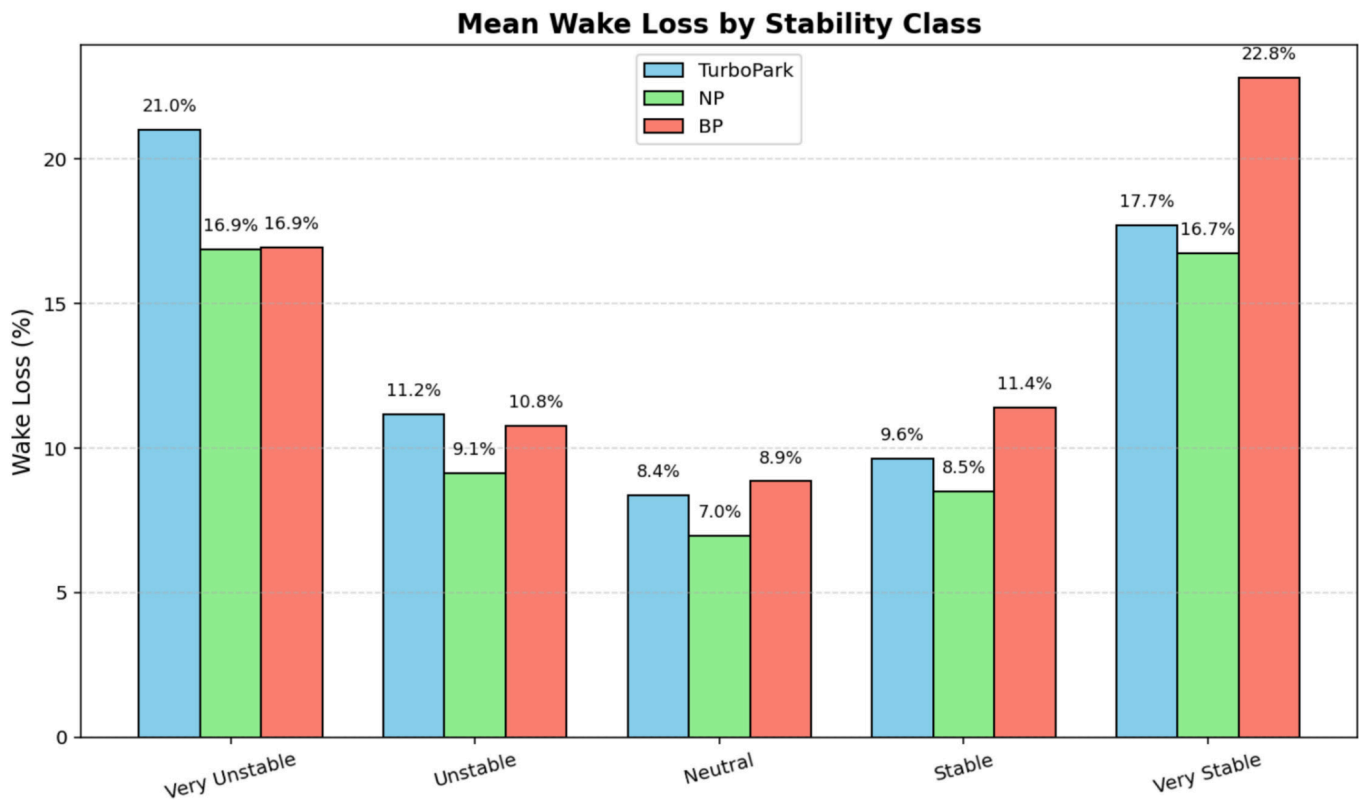


FIGURE 15 | Comparison of mean wake losses across five atmospheric stability classes—Very Unstable, Unstable, Neutral, Stable, and Very Stable—as predicted by three engineering wake models: (1) the NP model, (2) the TurboPark model, and (3) the original BP model. Wake loss is expressed as the relative reduction in total farm power compared to a dynamic no-wake reference. The figure highlights the sensitivity of each model to atmospheric stability and turbulence-induced wake recovery.

Table 7 reports park performance from the TurboPark model. The neutral case attains the highest output (12.30MW/turbine; 1476.01MW), followed by stable, with unstable lowest (11.24MW/turbine; 1348.66MW). The efficiency relative to the rated power, η_{rated} , is effectively a case-specific capacity factor (CVT: 74.93%, NEU: 82.00%, STB: 78.52%), which conflates resource strength (wind speed, shear) with wake impacts. By contrast, normalizing by a front-row reference turbine, η_{wf} , largely removes the ambient resource level at that state and highlights internal wake interactions. An internal wake-loss metric yields $\sim 11.55\%$ (CVT), 8.76% (NEU), and 10.64% (STB). It is noted that using P_{rated} to infer a “wake loss” is not appropriate: η_{rated} is a capacity factor that also depends on the instantaneous wind regime and turbine operating state. The P_{ref} -based metric better isolates within-farm wake effects, though it is slightly

conservative because the front row can already be affected by global blockage (making P_{ref} lower and thus η_{wf} higher), see also Equation (10).

Physically, convective turbulence accelerates vertical entrainment and wake recovery, so downstream turbines see less velocity deficit and the farm maintains a high fraction of the front-row reference power. Neutral flow recovers more slowly (higher internal losses), while stable stratification suppresses mixing and amplifies farm-scale blockage, producing the largest cumulative wake penalties. These trends are consistent with LES diagnostics and prior studies: Stability controls the balance between turbine extraction and atmospheric replenishment, with convective conditions favoring faster recovery and stable conditions prolonging wake deficits.

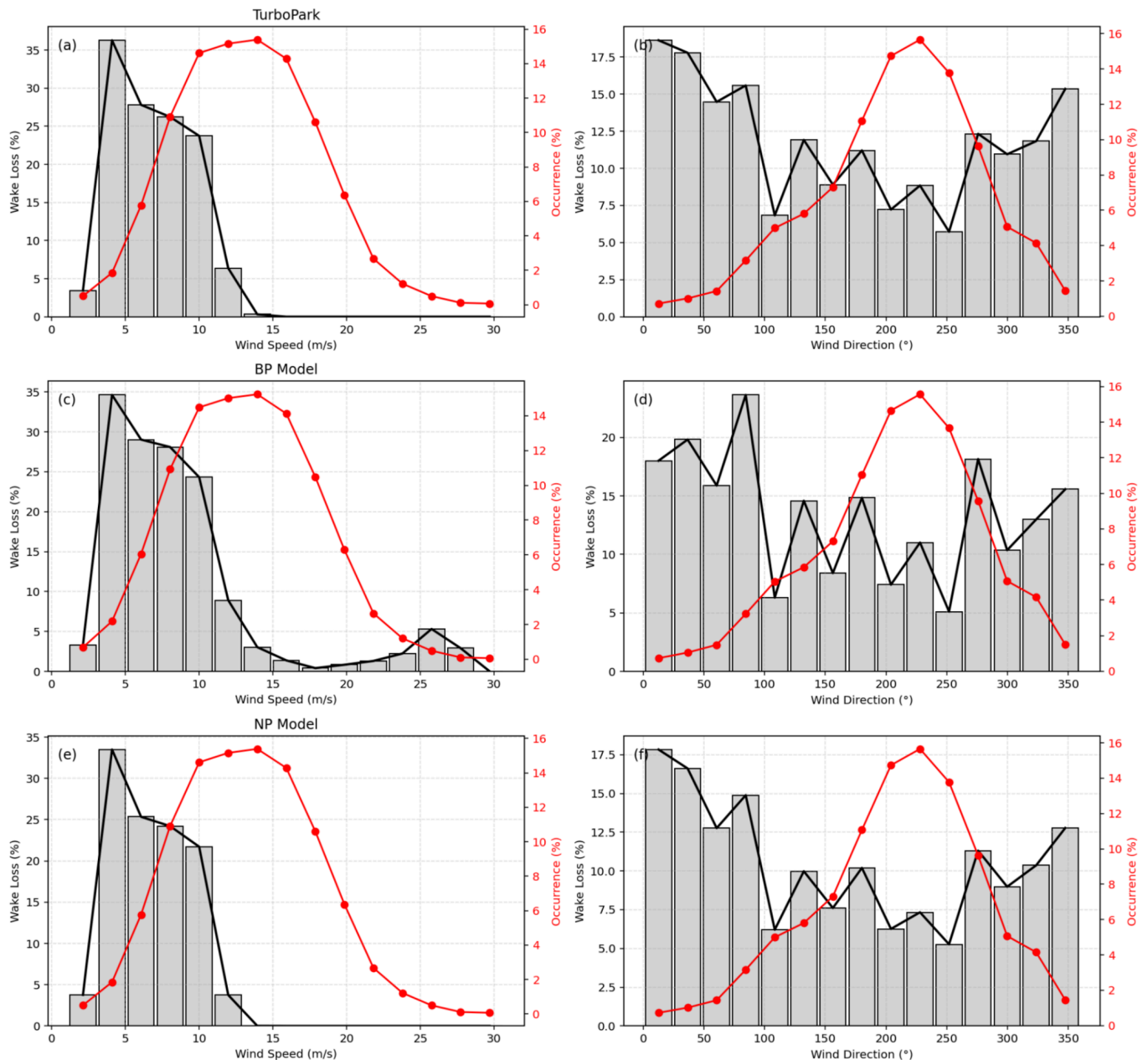


FIGURE 16 | Results from different engineering model simulations showing internal wake loss (%) as a function of wind speed and wind direction under stable atmospheric conditions: (a, b) TurboPark; (c, d) BP; and (e, f) NP. Red contours indicate the joint frequency of wind speed and wind direction, while black lines show internal wake loss values plotted at the midpoints of each bin.

Figure 16 shows the variation of the total wake losses with wind speed and wind direction for three fast-running engineering wake models under stable atmospheric conditions. All three models—TurboPark, NP, and BP—exhibit differences in predicted wake losses, primarily due to how each model represents turbulence and its interaction with atmospheric stability. These discrepancies highlight the critical role of turbulence modeling, particularly the treatment of TI, in wake loss estimation. The sensitivity of wake losses to wind direction varies across the models, with the BP model consistently predicting higher losses across a broad range of directions (Figure 16d), with the highest frequency of wind occurrence observed between 200° and 250° as indicated by the red curve (right-hand axis, wind frequency). This behavior is expected, as the BP model does not account for ambient TI in its wake expansion formulation. As a result, wake recovery is limited under stable, low-TI conditions, and wake effects persist further downstream. A notable difference also emerges in the wake loss distribution with respect to wind speed. The BP model predicts non-negligible wake losses even at wind speeds above 15 ms^{-1} under stable conditions, whereas NP and TurboPark do not. This discrepancy may be related again to

the fundamental differences in how the models handle turbulence and wake—wake interactions: While BP assumes a fixed wake expansion regardless of TI, both NP and TurboPark dynamically adjust wake recovery based on turbulence levels. In PyWake the turbine follows a static power curve with a rated (flat) plateau; pitch-control dynamics are not simulated. At high wind speeds this plateau can *mask* some of the wake impact in percentage terms: If both the no-wake and waked operating points lie on the flat segment, a given wind-speed deficit yields only a small power change. If, however, the wake shifts a turbine off the plateau (from just above rated to just below), the power drop is pronounced. Under stable (low-TI) conditions, NP and TurboPark predict slower wake expansion and more persistent deficits; thus, whether the observed fractional loss appears small at high wind may depend on the operating point relative to the plateau. Spatially, losses concentrate in the farm interior where wake overlap is strongest and are smaller near the edges (cf. Figures 14 and 17a,d,g).

So far, we have examined the multi-year variability of total wake losses. To gain a deeper understanding of which atmospheric conditions are most critical in inducing larger wake losses,

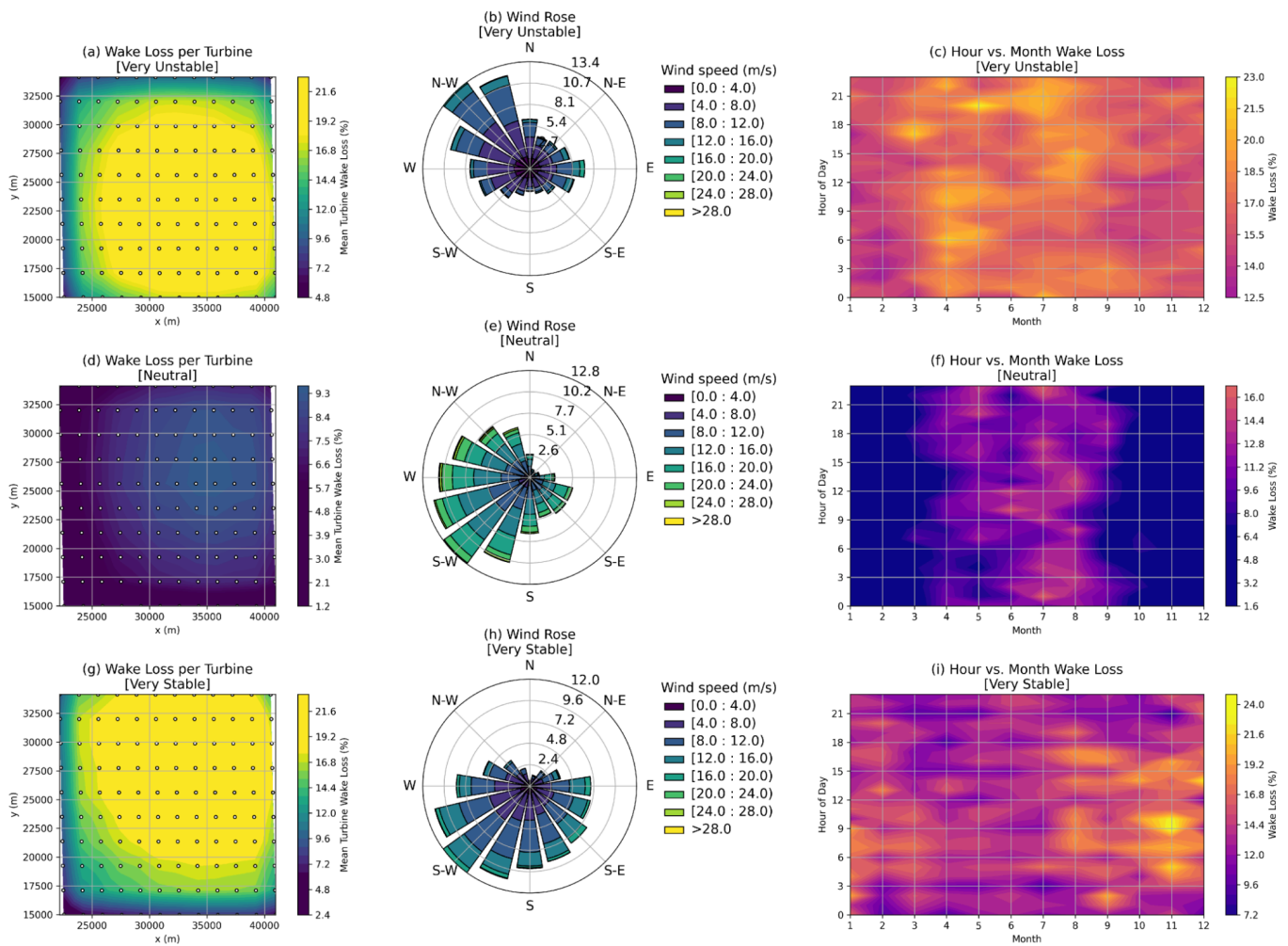


FIGURE 17 | (a, d, g) Eleven-year averaged internal wake losses from the TurboPark simulation in PyWake under three atmospheric stability conditions: very unstable (top), neutral (middle), and very stable (bottom). (b, e, h) Polar histograms showing the mean wind speed at 150 m above sea level, based on 11 years of wind data for each stability regime. (c, f, i) Corresponding hourly and monthly variations of spatially averaged internal wake losses.

we analyze their behavior on both space and time (hourly and monthly timescales). In Figure 17, the wake loss outputs of the TurboPark wake model are presented for three atmospheric stability regimes: very unstable, neutral, and very stable. Significant differences are evident in the qualitative spatial distribution of wake losses across these regimes. Under very unstable conditions, where the dominant wind direction is from the northwest (Figure 17a,b), the flow and wake fields vary noticeably along both turbine rows and columns. Lower wake losses are observed at turbines located on the northwestern boundary, while larger losses occur toward the southeastern edge of the wind farm, compared to the inner turbines. For both neutral and very stable conditions (Figure 17d,g), with dominant winds from the southwest (Figure 17e,h), larger wake losses are concentrated in the downstream turbines—particularly those in the northeastern section of the wind farm. This behavior arises partly from the linear superposition method applied to the velocity deficit and is also influenced by the turbulence modeling approach used in the NP model. The greatest intra-row and intra-column variations are found under very stable conditions (Figure 17g). In the upstream turbine columns, the highest power output and lowest wake losses are recorded at the southwestern-most turbines.

The hourly variation in wake losses is more pronounced under very unstable and neutral conditions, whereas stable conditions exhibit a clearer seasonal pattern. A distinct seasonal peak in wake losses under stable conditions occurs in November and

December, while summer and autumn show significantly lower wake impacts. This pattern aligns with the increased frequency and strength of atmospheric stability during late autumn and early winter, when surface cooling, low TI, moderate wind speeds, and extended nighttime periods suppress vertical mixing and delay wake recovery—resulting in more persistent and intense wake effects. Under neutral conditions, higher wake losses are consistently observed during the summer months, across nearly all hours of the day. This is primarily driven by lower wind speeds during summer, which lead to elevated thrust coefficients and thus stronger wake effects. In contrast, very unstable conditions show a broader temporal distribution, with elevated wake losses occurring across a wider range of months and throughout much of the daytime period.

5 | Discussion

5.1 | Sensitivity of the Convective PALM Results to the Change in Wind Speed/Direction

We restrict the additional PALM sensitivity experiment to the convective case for three scientific reasons and one practical constraint. *First*, CVT (with very-unstable conditions) dominates the site climatology (Figure 2). *Second*, CVT exhibits the strongest divergence between PALM and the engineering models in the upstream array (first five columns; Figure 14),

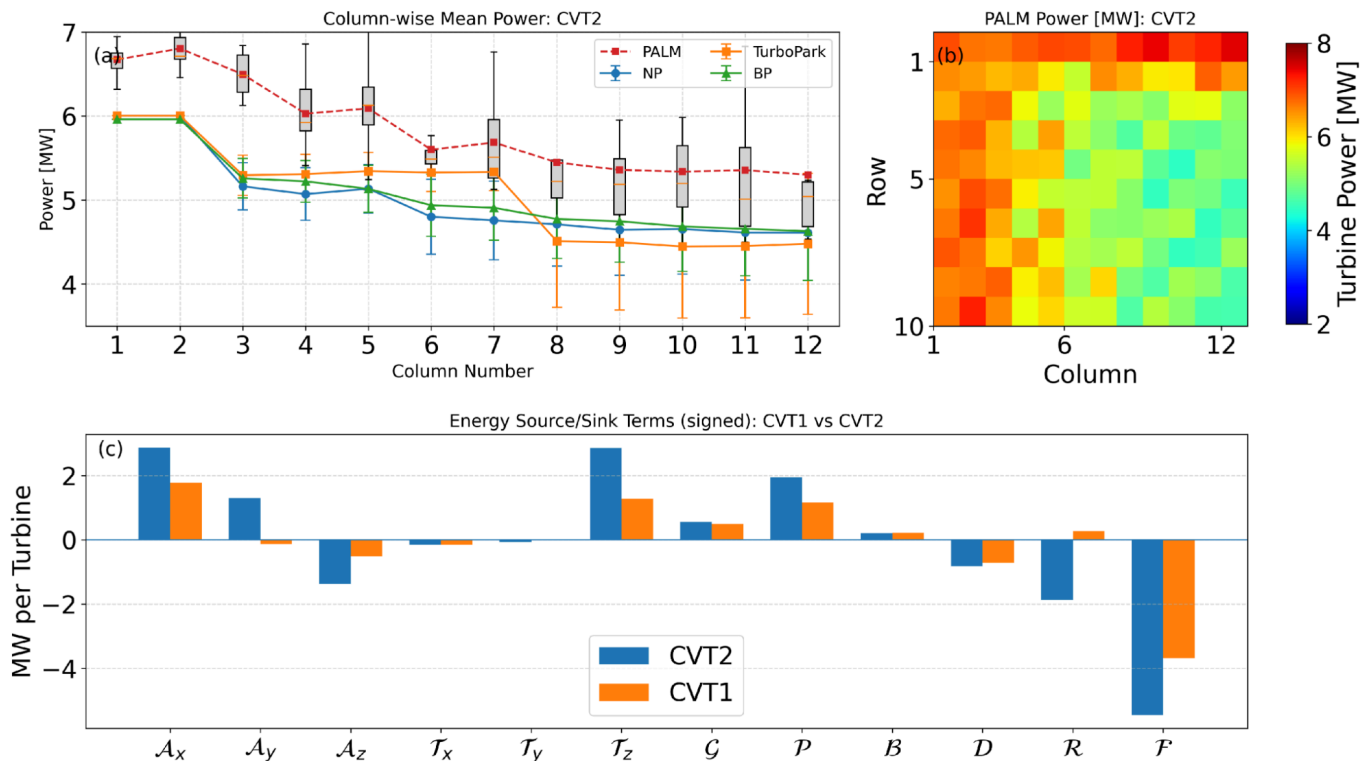


FIGURE 18 | Wind turbine power predictions from three PyWake simulations—TurboPark, NP, and BP—alongside PALM model results, based on slightly different wind speed and wind direction conditions than those in Figure 14. Markers represent the mean power output per turbine column (column-wise average), and error bars indicate the minimum and maximum power values within each column. Results are presented for convective atmospheric stability regimes: (a, b) convective case for new experiment (CVT2), and (c) comparison of control-volume kinetic-energy budget terms (sources vs. sinks) for the original convective case (CVT1) and the new convective case (CVT2); bars show contributions in MW (sources positive, sinks negative). In all PyWake simulations, the reference wind speed, wind direction, turbulence intensity, and shear exponent used in the wake models are based on inflow conditions at hub height from the LES model.

providing the most stringent fidelity test. *Third*, the mechanism probed—small inflow direction/speed changes effectively staggering the layout relative to the wind—is geometric rather than somewhat regime-specific; repeating it for NEU/STB may not change the qualitative conclusion. *Fourth*, given the close NEU-PALM agreement and the high computational cost of additional LES, extending this test to NEU/STB would be computationally prohibitive for limited added insight. We therefore concentrate resources on CVT.

Figure 18a shows the column-wise mean turbine power from PALM for the convective, more misaligned-inflow case (CVT2) at 7.82 m s^{-1} and meteorological wind direction 305.4° (from), alongside predictions from the three engineering wake models. The averaging follows the same column-wise integration used in Figure 14b. Across all columns, PALM (CVT2) yields systematically higher power than the engineering models, which cluster closely and exhibit similar column-wise patterns; the spatial variability in PALM most closely resembles TurboPark. In contrast, the engineering models—despite identical inflow—the TurboPark model shows notable deviations for columns 5 and 7 with other two engineering models due to their wake formulations: different superposition rules (linear vs. quadratic) and turbulence-intensity-dependent wake growth/recovery (NP, TurboPark) versus TI-independent expansion (in BP), as highlighted in Figure 14a. Relative to the original CVT run (CVT1) in Figure 14, the PALM-model bias is larger in CVT2, and the gap does not diminish toward the downstream columns (i.e., no convergence with increasing farm size).

Relative to the original convective run (CVT1), the new convective case (CVT2) delivers a step-change in performance: Total farm power increases from 437.83 to 608.77 MW and the average wake loss drops from 53.28% to 14.90%. In the PALM fields (Figure 18b), CVT2 exhibits peak production along the northern and western edges under the prevailing 305.4° inflow, with the largest deficits confined to the downstream portion of the farm—consistent with cumulative wake build-up and a weaker farm-scale blockage. By contrast, in CVT1 (Figure 13a), the first column dominates output and flow deflection/blockage are more pronounced. The mechanism is twofold. First, the inflow rotates from 273.3° (CVT1 after rotation) to 305.4° (CVT2), which effectively staggers the array relative to the wind and reduces wake-overlap depth. Second, the slightly higher wind speed and shear in CVT2 enhance lateral supply and vertical entrainment, as reflected by stronger pressure-work and transport pathways and a less severe upstream pressure build-up (i.e., a milder pressure anti-symmetrical dipole across the farm). Together these changes curtail cumulative wake amplification, yielding the observed doubling of total power and the reduction in wake losses from $\sim 53\%$ to $\sim 15\%$.

Figure 18c shows that the total kinetic-energy budget (sources, equal to sinks) nearly doubles from 5.192 to 9.739 MW when moving from CVT1 (orange) to CVT2 (blue). This jump mirrors the performance gain (total farm power $437.83 \rightarrow 608.77 \text{ MW}$) and the reduction in wake loss. The increase in source power is driven by a coherent shift in the dominant source pathways: (i) stronger streamwise advection $\mathcal{A}_x$ (+1.09 MW), (ii) a flip

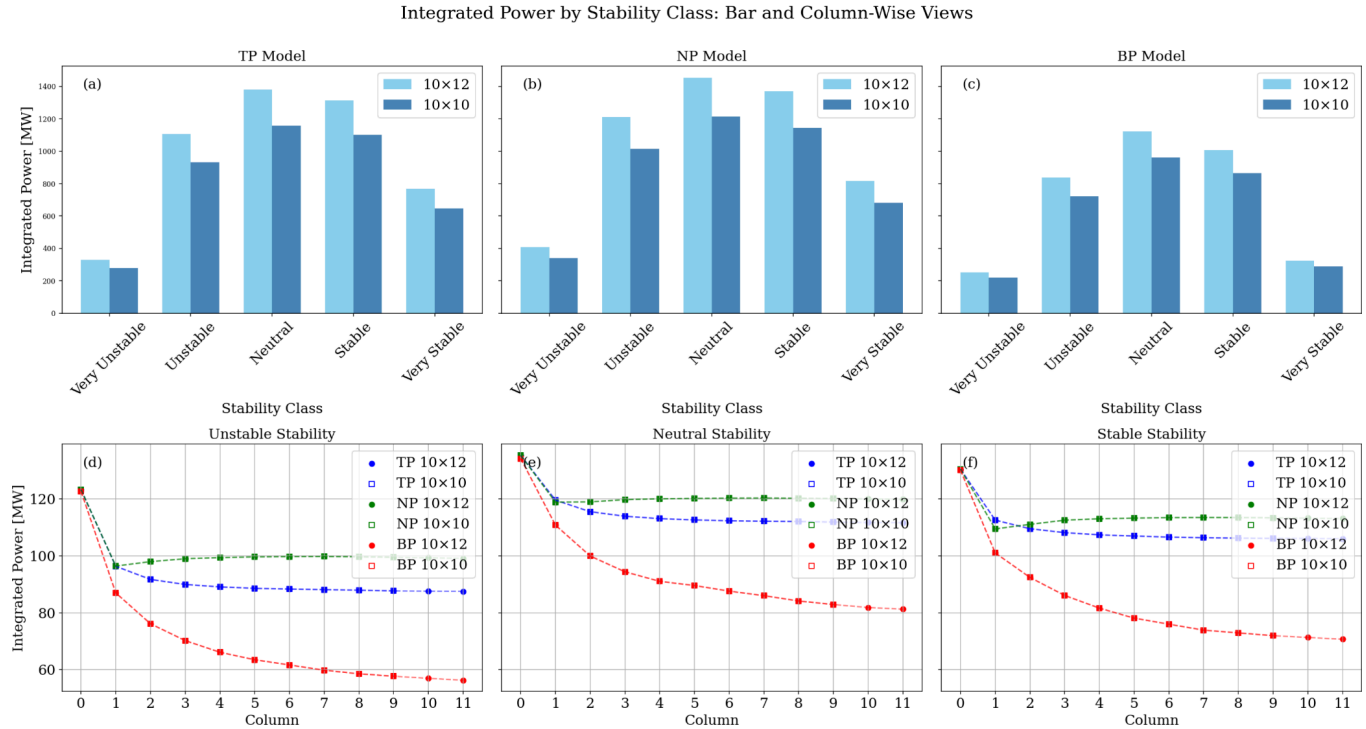


FIGURE 19 | Top row (a–c): Total integrated power output for 10×12 and 10×10 turbine layouts, categorized by atmospheric stability class, for each wake model (TP, NP, BP); and bottom row (d–f): Column-wise integrated power (reversed column order) for the same stability classes (Unstable, Neutral, Stable), highlighting spatial distribution of power output across turbine columns for both layouts. Solid markers represent the 10×12 layout; hollow markers represent the 10×10 layout. All data shown in this figure correspond to a wind direction sector between 267° and 273° , selected to emphasize pronounced wake interactions. The analysis considers both the original 1.8 GW wind farm comprising 120 turbines rated at 15 MW each, and a reduced 1.5 GW layout (10×10 configuration) consisting of 100 turbines.

TABLE 8 | Power reduction and capacity factor (CF) for each wake model and atmospheric stability class.

Stability class	TP model			NP model			BP model		
	Reduction	CF 10 × 12	CF 10 × 10	Reduction	CF 10 × 12	CF 10 × 10	Reduction	CF 10 × 12	CF 10 × 10
Very unstable	15.1%	18.3%	18.6%	16.0%	22.6%	22.8%	12.5%	13.9%	14.6%
Unstable	15.8%	61.4%	62.1%	16.4%	67.4%	67.6%	13.5%	46.5%	48.2%
Neutral	16.2%	76.7%	77.2%	16.5%	80.7%	80.9%	14.5%	62.4%	64.0%
Stable	16.2%	72.9%	73.3%	16.5%	76.1%	76.2%	14.1%	55.9%	57.6%
Very stable	15.7%	42.7%	43.2%	16.4%	45.4%	45.5%	11.1%	18.0%	19.2%

Note: The reduction (%) is computed as the relative decrease in total power from the full 10 × 12 layout to the reduced 10 × 10 layout. Capacity factors are based on a rated power of 15 MW per turbine.

of lateral advection $\mathcal{A}_y$ from a weak sink to a sizable source (+1.43 MW), (iii) a substantial rise in vertical turbulent transport $\mathcal{T}_z$ (+1.58 MW), and (iv) larger mean pressure work $\mathcal{P}$ (+0.78 MW). The geostrophic contribution $\mathcal{G}$ remains a modest source in both cases (slightly larger in CVT2, +0.07 MW), and buoyancy $\mathcal{B}$ is essentially unchanged. On the sink side, the higher production in CVT2 appears as a more negative turbine term $\mathcal{F}$ (−1.77 MW); vertical advection $\mathcal{A}_z$ and dissipation $\mathcal{D}$ are also more negative (−0.87 MW and −0.10 MW, respectively). The residual $\mathcal{R}$ changes sign and magnitude and should be viewed as a closure remainder. Taken together, these changes outline a clear mechanism consistent with prior LES studies of large farms: The CVT2 inflow (rotated and slightly stronger/sheared) reduces wake superposition and enhances lateral supply (↑ $\mathcal{A}_y$), vertical entrainment from aloft (↑ $\mathcal{T}_z$), and pressure-work pathways (↑ $\mathcal{P}$) that replenish momentum within the turbine layer. The result is a less blocky farm-atmosphere coupling, faster wake recovery, and therefore higher farm output with lower wake losses.

5.2 | Farm Downscaling to 1.5-GW Capacity of SNII Phase I

Figure 19 and Table 8 present a detailed analysis of the impact of wind farm size reduction on integrated power production under varying atmospheric stability conditions. The dataset is filtered for a wind direction sector between 267° and 273° over an 11-year period, where wake interactions are among strongest due to the alignment of turbines with the prevailing wind. The comparison is made between the full 10 × 12 layout (120 turbines, ~1.8 GW total capacity) and a reduced 10 × 10 layout (100 turbines, 1.5 GW), the latter aligned with the planned capacity of SNII Phase I. Three wake models are employed and despite having 20 fewer turbines, the reduced 10 × 10 layout delivers nearly comparable total power output across all models and stability regimes. For instance, under neutral conditions using the BP model (Figure 19c), the 10 × 12 layout achieves a capacity factor (CF) of 62.4%, while the 10 × 10 layout slightly improves to 64.0%. Power deficits, shown in Figure 19d–f, are concentrated in the upstream (westernmost) columns due to stronger wake effects under neutral and stable conditions. The 10 × 10 layout eliminates these two columns, leading to a more uniform column-wise power distribution and comparable integrated power over the remaining columns. Notably, the BP model—which does not account for TI—shows a steeper power drop across upstream columns compared to TurboPark (TP) and NP. This contrast highlights the role of TI in mitigating wake losses: Both TP and NP, which incorporate TI effects, produce smoother power profiles across turbine rows under similar conditions.

6 | Conclusions

This study quantified how atmospheric stability modulates wake development, energy/momentum exchange, and power production in a gigawatt-scale offshore wind farm representative of Sørlige Nordsjø II, and benchmarked three engineering wake models (Niayifar-Porté-Agel, TurboPark, BP) against high-fidelity LES (PALM). Two configurations were examined:

a 1.8-GW layout (120×15 MW) and a downsized 1.5 GW layout (100×15 MW; Phase I).

PALM revealed distinct stability-dependent regimes. Under stable conditions, the farm exhibits pronounced speed deficits, upstream blockage, slow wake recovery, and inversion displacement that excites stationary gravity waves with upstream-tilted phase lines, reinforcing blockage. Neutral conditions show efficient entrainment from aloft and relatively rapid recovery with noticeable wake narrowing and flow deflection. Convective conditions enhance vertical mixing, reducing persistent wakes while increasing spatial heterogeneity. Across regimes, the farm induces internal boundary-layer growth, directional veering, and pressure gradients that govern wake overlap and replenishment.

Control-volume kinetic-energy budgets clarify the governing pathways. Streamwise advection is the leading source across regimes, followed by vertical turbulent transport; mean pressure work contributes, in a non-negligible way, when the inversion is displaced. The vertical transport and pressure terms are sensitive to inflow alignment, showing greater enhancement in CVT2 compared to the original experiment (CVT1).

A mechanistic convective sensitivity demonstrated the performance impact of modest inflow changes. Rotating the inflow from 273.3° (CVT1) to 305.4° (CVT2) and slightly increasing wind speed/shear effectively staggered the array relative to the wind, reduced wake superposition, and doubled total farm power from 437.83 to 608.77 MW while cutting average wake loss from 53.28% to 14.90%. Per-turbine kinetic-energy power (sources = sinks) rose from 5.192 to 9.739 MW, driven by stronger streamwise advection, a flip of spanwise advection from sink to source, enhanced vertical turbulent transport, and larger pressure work.

Benchmarking showed best agreement between engineering models and LES under neutral conditions (TurboPark total-power discrepancies <1%), moderate agreement under convective conditions (order 5%–15%, model-dependent), and the largest discrepancies under stable conditions, where neglecting TI-controlled entrainment leads to substantial errors (BP can deviate >50%). TI-aware models (NP, TurboPark) better capture recovery trends across stability classes. Over the 11-year climatology, total wake losses are smallest under neutral conditions and largest under unstable regimes, likely influenced by case frequency and stability classification uncertainties.

Layout/downscaling analysis indicates that reducing from 1.8 (10×12) to 1.5 GW (10×10) trims the most wake-penalized columns (for the southwest sector) and yields comparable total energy with slightly higher capacity factors in several stability classes, offering a low-loss pathway for early-phase deployment.

This work is subject to two practical limitations. First, long-term inflow and stability classification are based on NORA3; magnitudes of wake loss are therefore conditional on that dataset. Because mesoscale products smooth sub-10-minute variability, turbulence intensity may be biased; site calibration (LiDAR/

met-mast) or TI-sensitivity bands are recommended for applications. Second, the computational cost of PALM limits exhaustive coverage across all stability and directional bins; the targeted convective sensitivity was designed to expose causal pathways without prohibitive cost.

In summary, atmospheric stability controls the balance between turbine extraction and atmospheric replenishment. Quantifying the associated energy pathways—advection, turbulent transport, and pressure work—explains when and why analytical wake models succeed or fail, and identifies key drivers (inflow orientation, layout staggering, and TI-aware modeling) to improve early-phase SNII-scale designs with minimal loss of total output.

Author Contributions

The first author was responsible for writing the manuscript, conceptualization, software/processing/plotting, and carrying out the numerical modeling using both high-fidelity and engineering models, project administration, and funding acquisition. The second author providing discussion, software/processing, high-fidelity modeling, reading and commenting on the manuscript.

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During the preparation of this manuscript, the authors used AI to improve language clarity, grammar, and readability. All content was critically reviewed and verified by the authors, who take full responsibility for the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. Supplementary_plots.pdf

Appendix A

Estimation of Monin–Obukhov Stability From ERA5

The Monin–Obukhov length (L) and stability parameter (ζ) are estimated from ERA5 single-level, hourly data following surface-layer similarity theory [42].

A.1 | Input Variables

- Surface pressure p_s [Pa]
- 2-m air temperature T_{2m} [K], 2-m dewpoint temperature $T_{d,2m}$ [K]
- Surface stress components τ_x, τ_y [N m^{-2}]
- Surface sensible heat flux H [W m^{-2}]
- Surface moisture flux E [$\text{kg m}^{-2} \text{s}^{-1}$]
- Constants: $\kappa = 0.4$, $g = 9.81 \text{ m s}^{-2}$, $c_p = 1004 \text{ J kg}^{-1} \text{K}^{-1}$, $R_d = 287 \text{ J kg}^{-1} \text{K}^{-1}$

A.2 | Computation Steps

1. **Virtual temperature:** Compute saturation vapor pressure at dewpoint:

$$e(T_{d,2m}) = 611.2 \exp\left(\frac{17.67 (T_{d,2m} - 273.15)}{T_{d,2m} - 29.65}\right) \text{ [Pa]}, \quad (\text{A1})$$

then specific humidity:

$$q = \frac{0.622 e}{p_s - 0.378 e}, \quad (\text{A2})$$

and virtual temperature:

$$T_v \approx T_{2m} (1 + 0.61 q). \quad (\text{A3})$$

2. Air density:

$$\rho = \frac{p_s}{R_d T_v}. \quad (\text{A4})$$

3. Friction velocity:

$$u_* = \sqrt{\frac{\sqrt{\tau_x^2 + \tau_y^2}}{\rho}}. \quad (\text{A5})$$

4. Virtual heat flux:

$$\overline{w'\theta'_v} = \frac{H}{\rho c_p} + 0.61 T_{2m} E. \quad (\text{A6})$$

5. Obukhov length and stability:

$$\frac{1}{L} = -\frac{\kappa g}{T_v} \frac{\overline{w'\theta'_v}}{u_*^3}, \quad (\text{A7})$$

$$\zeta = \frac{z}{L}, \quad z = 10 \text{ m}. \quad (\text{A8})$$

Interpretation: $\zeta < 0$ indicates unstable conditions, $\zeta > 0$ stable.

Appendix B

Estimation of Damage Equivalent Load

To quantify the fatigue loading experienced by the turbines, the Damage Equivalent Load (DEL) is evaluated for both rotor thrust and torque at the wind farm level. The DEL represents a constant-amplitude load that, over a specified number of cycles, produces the same cumulative fatigue damage as the actual stochastic load time series. This metric provides a compact and physically meaningful way to compare fatigue loads under different operating conditions. The DEL is computed based on the Palmgren–Miner linear damage accumulation rule in combination with rainflow cycle counting [43, 44]. For a load time series of duration T and a reference frequency f_{eq} (here taken as 1 Hz), the DEL is defined as

$$DEL = \left(\frac{\sum_i n_i S_i^m}{N_{eq}} \right)^{1/m} \quad (\text{B9})$$

where

- S_i denotes the load range of the i -th cycle (thrust in kN or torque in kNm) obtained via rainflow counting,
- n_i is the number of cycles corresponding to the load range S_i ,
- m is the Wöhler exponent, here taken as $m = 4$, representative of steel structural components,
- $N_{eq} = f_{eq} \cdot T$ represents the total number of equivalent load cycles, which results in $N_{eq} = 1800$ for the 30-min evaluation period.

As summarized in Table B1, the atmospheric stability regime strongly influences fatigue-load accumulation across the wind farm. The associated spatial distributions of turbine-level DELs are presented in Figure B1. The highest absolute fatigue loads are observed under neutral conditions, with a farm-average thrust DEL of 127.38 kN and a torque DEL of 1086.03 kNm. This is primarily attributed to the high mean wind speeds and significant shear-driven turbulence characteristic of the neutral boundary layer. In contrast, the CVT condition exhibits intermediate fatigue levels (110.87 kN and 1000.95 kNm), where buoyancy-induced mixing promotes rapid wake recovery but also introduces large-scale turbulent fluctuations. The STB case reports the lowest absolute DEL values (36.34 kN and 376.20 kNm); however, the persistence of wakes in the stable regime significantly amplifies the cyclic loading on downstream turbines relative to their isolated counterparts.

TABLE B1 | Farm-average damage equivalent loads (DEL) for rotor thrust and torque, computed over the final 30 min of the simulation ($N_{eq} = 1800$).

Case	Thrust DEL (kN)	Torque DEL (kNm)
CVT	110.87	1000.95
NEU	127.38	1086.03
STB	36.34	376.20

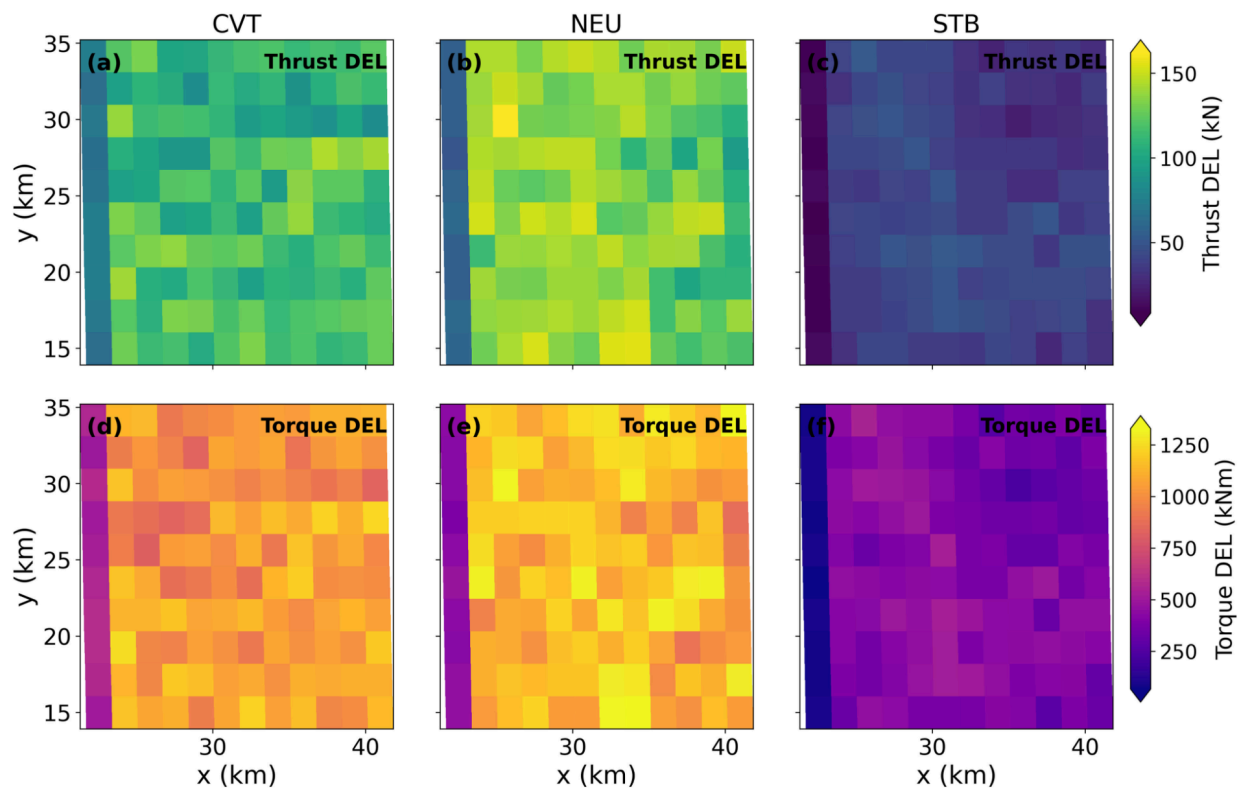


FIGURE B1 | Spatial distribution of turbine-level DELs for rotor thrust (top row) and rotor torque (bottom row) under CVT, NEU, and STB atmospheric conditions. DELs are computed from the final 30 min of each simulation using rainflow cycle counting with a Wöhler exponent of $m = 4$. The distributions illustrate the influence of atmospheric stability on fatigue-load accumulation across the wind farm.