A year-long evaluation of a wind-farm parameterisation in HARMONIE-AROME

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Abstract

The need to mitigate climate change will boost the demand for renewable energy and lead to more wind turbines both onand onshore. In the near future, the effect these wind farms have on the atmosphere can no longer be neglected. In numerical weather prediction models wind-farm parameterisations (WFP) can be used to model the effect of wind farms on the atmosphere. There are different modelling approaches, but the parameterisation developed by Fitch et al. (2012) is most used in previous studies. It models the wind farm as a momentum sink and a source of power production and turbulent kinetic energy. In this paper, we have implemented the Fitch et al. (2012) WFP into HARMONIE-AROME, the numerical weather prediction model that is currently used by at least 11 national weather services in Europe. We used HARMONIE-AROME to make year-long simulations for 2016 with and without the WFP. The results were extensively evaluated using lidar, tower and flight measurements at several locations near wind farms. Including the WFP greatly reduces the model bias for wind speed near offshore wind farms. Wind farms not only affect wind, but also temperature and humidity, especially during stable atmospheric conditions: the enhanced mixing caused by the wind turbines reduces the stratification of temperature and humidity. Including the WFP in HARMONIE-AROME results in a more realistic representation of the atmosphere near wind farms and makes it a more future-proof model for weather forecasting.

A year-long evaluation of a wind-farm parameterisation 1 in HARMONIE-AROME 2

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Key Points:

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• In this study a wind-farm parameterisation is implemented in the numerical weather prediction model HARMONIE-AROME.

• A model evaluation of a full year reveals the wind-farm parameterisation greatly 10 improves wind-speed forecasts close to offshore wind farms. 11

• The presence of wind farms in the model also alters temperature and humidity 12 profiles due to the enhanced turbulent mixing by the turbines. 13

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14 Abstract

The need to mitigate climate change will boost the demand for renewable energy and 15 lead to more wind turbines both on- and onshore. In the near future, the effect these wind 16 farms have on the atmosphere can no longer be neglected. In numerical weather predic-17 tion models wind-farm parameterisations (WFP) can be used to model the effect of wind 18 farms on the atmosphere. There are different modelling approaches, but the parameter-19 isation developed by Fitch et al. (2012) is most used in previous studies. It models the 20 wind farm as a momentum sink and a source of power production and turbulent kinetic 21 energy. In this paper, we have implemented the Fitch et al. (2012) WFP into HARMONIE-22 AROME, the numerical weather prediction model that is currently used by at least 11 23 national weather services in Europe. We used HARMONIE-AROME to make year-long 24 simulations for 2016 with and without the WFP. The results were extensively evaluated 25 using lidar, tower and flight measurements at several locations near wind farms. Includ-26 ing the WFP greatly reduces the model bias for wind speed near offshore wind farms. 27 Wind farms not only affect wind, but also temperature and humidity, especially during 28 stable atmospheric conditions: the enhanced mixing caused by the wind turbines reduces 29 the stratification of temperature and humidity. Including the WFP in HARMONIE-AROME 30 results in a more realistic representation of the atmosphere near wind farms and makes 31 it a more future-proof model for weather forecasting. 32

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Plain Language Summary

Wind power production is steadily increasing. Wind farms are growing both in num-34 ber and size, while weather models evolve to higher resolutions. This means that the ef-35 fect of wind farms can no longer be ignored by weather prediction models. Wind farms 36 essentially decelerate the wind (blockage and wake effects) and increase turbulence, in-37 directly influencing temperature and humidity. In this study, we have included a widely 38 used wind-farm parameterisation in the operational weather prediction model. The model 39 is evaluated using various datasets, e.g. power production data, floating lidar measure-40 ments, and anemometer measurements from a tower. The inclusion of the wind-farm pa-41 rameterisation improves the wind forecasts near wind farms, also improving the estimate 42 in power production. In addition, we are able to model the effects of wind farms on the 43 near-surface temperature and humidity. 44

45 1 Introduction

Offshore wind power production in the European Union (EU) and specifically the 46 North-Sea region is steadily increasing: the Dutch offshore capacity is expected to grow 47 from ± 1 GW in 2019 to ± 11.5 GW in 2030, as part of a total expected increase to ± 70 48 GW in the entire EU (WindEurope, 2017). Wind turbines produce electric energy by 49 extracting kinetic energy from the atmosphere, thereby decelerating (and agitating) the 50 air. This typically results in a downstream decrease in wind speed and increase in tur-51 bulence (e.g. Baidya Roy & Traiteur, 2010; Fitch et al., 2012). As wind farms grow – 52 both in size and number – the impact on weather and climate is expected to become more 53 significant, requiring an adaptation of mesoscale models like HARMONIE-AROME (here-54 after: HARMONIE) to account for the influence of wind farms on the local and regional 55 meteorological conditions. 56

There are several ways in which the effects of wind turbines on the atmosphere can 57 be parameterised in mesoscale models (Fischereit et al., 2021). The implicit – imposing 58 an additional roughness to implicitly model the effect of wind turbines on the atmospheric 59 flow – or explicit, explicitly solving the momentum sink and enhanced turbulence pro-60 duction due to the presence of wind turbines. In the last two decades several explicit pa-61 rameterisations have been developed (e.g. Fitch et al., 2012; Abkar & Porté-Agel, 2015; 62 Volker et al., 2015). The most commonly used and evaluated parameterisation is the Fitch 63 et al. (2012) model implemented in the Weather Research and Forecasting (WRF) model 64 (Skamarock et al., 2019). 65

In this study, we implemented the wind turbine parameterisation from Fitch et al. (2012) in HARMONIE. In the presence of wind turbines, this parameterisation adds an elevated drag term to the atmosphere, which locally decelerates the flow. The kinetic energy that is extracted from the atmosphere, but not converted into electric power, is used as a source term for turbulence kinetic energy (TKE).

HARMONIE with and without the newly-implemented wind-farm parameterisation is evaluated using doppler lidar and tower measurements over the North Sea over
a period of one full year (January up to and including December 2016), instead of evaluating case studies as done in most evaluations of wind-farm parameterisations (e.g. Lee
& Lundquist, 2017; Wu et al., 2022). During the full year, the parameterisation is evaluated for all seasons with varying wind directions and atmospheric stabilities. In 2016,

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measurements were available from two floating lidars in the Borssele wind farm zone (off 77 the Belgian coast), one ground-based lidar in the Westermost Rough wind farm (off the 78 east-coast of the UK), cup-anemometer measurements on the FINO1 tower near the Al-79 pha Ventus wind farm (north of the Netherlands) and aircraft measurements (off the north-80 west German coast). Since all these measurements are in or near existing wind farms, 81 they are ideal for evaluating the newly implemented wind-farm parameterisation. The 82 spatial impact of the wind farms on the wind fields is evaluated using dedicated flight 83 campaigns (Lampert, Bärfuss, et al., 2020). The consequence of the WFP on power pro-84 duction is evaluated using Belgian transmission system operator (TSO) data. Moreover, 85 the year-long experiment allowed us to quantify the impact of the offshore wind farms 86 on the offshore and coastal meteorological conditions. 87

2 HARMONIE-AROME

The wind-farm parameterisation is implemented in HARMONIE-AROME (cycle 89 40h1), a non-hydrostatic model developed by the HIRLAM-C consortium, which is op-90 erationally used in at least 11 countries (Bengtsson et al., 2017). The model uses a semi-91 lagrangian scheme on an Eulerian grid. The turbulence scheme used was HARATU (de 92 Rooy et al., 2021; Lenderink & Holtslag, 2004), which uses a prognostic equation for the 93 turbulent kinetic energy (TKE), and shallow convection following de Rooy et al. (2021). 94 Surface Externalisée (SURFEX) version 7.3 was used as a land surface model (Masson 95 et al., 2013) with the land use classification from ECOCLIMAP II (Faroux et al., 2013). 96 More details about the model physics can be found in Bengtsson et al. (2017) or www.hirlam.org. 97

⁹⁸ **3** Wind farm parameterisation

The wind-farm parameterisation of (Fitch et al., 2012) imposes an elevated momentum sink on the mean flow, where the drag (or thrust) of the individual turbine blades is modelled as a constant (but wind speed dependent) drag force across the area swept by the rotor blades. As the diameter of a wind turbine is about an order of magnitude smaller than the horizontal grid spacing in HARMONIE (currently: 2.5 km), the model accounts for the bulk influence of one or several wind turbines per grid point.

The wind turbine characteristics are defined by the geometry (hub-height z_{hub} and turbine radius r), the cut-in (V_{in}) and cut-out (V_{out}) wind speeds, and by the dimensionless power $(C_{\rm P})$ and thrust $(C_{\rm T})$ coefficients. The latter two describe – as a function of wind speed $V_{\rm hub}$ at hub height – the fraction of kinetic energy that is extracted from the air $(C_{\rm T})$, and the fraction that is converted into electrical energy $(C_{\rm P})$. An example of typical $C_{\rm P}$ and $C_{\rm T}$ curves is provided in Fig. 1.

Given the thrust coefficient $C_{\rm T}$, the thrust force of a turbine (the force opposite to the flow direction and drag force) is defined as:

$$\vec{F}_{\rm thrust} = -\frac{1}{2}\rho C_{\rm T} |\vec{V}| \vec{V} A_T, [\rm N]$$
(1)

where ρ is the air density (kg m⁻³), $\vec{V} = (u, v)$ the horizontal wind vector (m s⁻¹), $|\vec{V}| = \sqrt{u^2 + v^2}$, and A_T is the rotor area (m²). The rate of loss of kinetic energy (KE) then equals:

$$\frac{\partial \mathrm{KE}}{\partial t}\Big|_{\mathrm{drag}} = -\frac{1}{2}\rho C_{\mathrm{T}} |\vec{V}|^3 A_T . [\mathrm{J\,s}^{-1}]$$
⁽²⁾

In practise the rotor of a turbine intersects multiple model levels, and Eq 2 (and all equations in the remainder of this chapter) are solved for each model level k individually, replacing the rotor area A_T with the area intersected by the k-th model level, and the wind speed $|\vec{V}|$, and density ρ with values from the k-th model level, indicated where appropriate by a subscript k. As a result, the momentum sink (and TKE source) is elevated and height dependent.

In general, the total change in KE of a single grid cell with a volume $\Delta_k = (\Delta x \Delta y \Delta z_k)$ m³ equals:

$$\frac{\partial \mathrm{KE}_{\mathbf{k}}}{\partial t}\Big|_{\mathrm{cell}} = \frac{\partial}{\partial t} \left(\frac{1}{2}\rho_k |\vec{V_k}|^2\right) \Delta_k = \rho_k |\vec{V_k}| \frac{\partial |\vec{V_k}|}{\partial t} \Delta_k . [\mathrm{J}\,\mathrm{s}^{-1}] \tag{3}$$

¹²⁷ Combining Eqs 2 and 3, i.e. setting:

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$$\frac{\partial \mathrm{KE}_{\mathbf{k}}}{\partial t}\Big|_{\mathrm{cell}} = \frac{\partial \mathrm{KE}_{\mathbf{k}}}{\partial t}\Big|_{\mathrm{drag}}, [\mathrm{J}\,\mathrm{s}^{-1}] \tag{4}$$

results, after re-arranging, in an expression for the change in velocity with time:

$$\frac{\partial |\vec{V_k}|}{\partial t} = -\frac{1}{2} C_{\rm T} |\vec{V_k}|^2 A_k \Delta_k^{-1}, [\rm{m\,s}^{-2}]$$
(5)

¹³¹ or, in component form:

$$\frac{\partial u_k}{\partial t} = -\frac{1}{2}C_{\mathrm{T}} \ u_k \ |\vec{V_k}| \ A_k \ \Delta_k^{-1}, [\mathrm{m\,s}^{-2}]$$
(6)

$$\frac{\partial v_k}{\partial t} = -\frac{1}{2} C_{\mathrm{T}} v_k |\vec{V_k}| A_k \Delta_k^{-1} [\mathrm{m\,s}^{-2}]$$
(7)

The vertical velocity component is assumed to be unaffected by the wind turbines, and furthermore, drag by the wind turbine tower and nacelle is not included in the parameterisation. The energy that is extracted from the atmosphere, but not converted into electrical energy, is assumed to be converted into turbulence kinetic energy (TKE, per unit mass), i.e. $C_{\text{TKE}} = C_{\text{T}} - C_{\text{P}}$, resulting in:

¹³⁹
$$\frac{\partial \mathrm{TKE}_{\mathbf{k}}}{\partial t} = \frac{1}{2} C_{\mathrm{TKE}} |\vec{V_k}|^3 A_k \Delta_k^{-1} . [\mathrm{m}^2 \,\mathrm{s}^{-2} \,\mathrm{s}^{-1}] \tag{8}$$

Finally, as a diagnostic quantity, the model outputs the electrical power produced by the
wind turbines:

P =
$$\frac{1}{2}\rho C_{\rm P} A_T |\vec{V}_{\rm hub}|^3 [W]$$
 (9)

For a typical offshore wind farm, multiple wind turbines can occupy a single horizontal grid point. Instead of introducing a horizontal wind turbine density – like in (Fitch et al., 2012) – Eqs 6 to 9 are repeated for each individual turbine, allowing different turbine types in a single horizontal grid point. The total tendencies for the horizontal wind components and TKE are adjusted after the turbulence scheme is called and fed back to the model.

- ¹⁴⁹ 4 Experimental setup
- HARMONIE used a 2000×2000 km² domain with 65 vertical levels, 2.5 km horizontal grid spacing, centred around 51.96°N, 4.9°E. The ERA5 reanalysis (Hersbach et al., 2020) is used for the lateral boundary conditions.
- Two simulations were performed: (1) reference simulation without wind turbines, REF, and (2) with the wind-farm parameterisation modelling all offshore wind turbines



Figure 1. Power (C_P) and thrust (C_T) coefficients of the Belgian offshore wind turbines

present in the model domain in January 2016, WFP. The experiments are run from 0101-2016 00 UTC to 01-01-2017 00 UTC. This period was chosen because of the availability of two floating lidars in the Borssele wind farm zone, directly north-east of the (Belgian) Northwind wind farm (Fig. 2). In addition, for this period there are tower measurements from the FINO1 platform, and lidar measurements from the Westermost Rough
wind farm and flights through wind farm wakes in the German Bight (WIPAFF; Lampert, Bärfuss, et al., 2020).

The reference simulation was run for several years before the study period for the 162 Dutch Offshore Wind Atlas (DOWA) project (Wijnant et al., 2019) and therefore had 163 more than six years of spin-up. The WFP run was started 'warm' from the control ex-164 periment and had ten days of additional spin-up time. Both reanalysis simulations used 165 3D-VAR data assimilation (Fischer et al., 2005; Gustafsson et al., 2018) with a three-166 hour cycling time. In addition to conventional observations, Mode-S EHS aircraft mea-167 surements (e.g. de Haan, 2011, 2016) and Scatterometer (ASCAT) (Marseille & Stof-168 felen, 2017) were assimilated. In this study the 3-hour forecast is used as a proxy for the 169 analysis. 170

For the Belgian and Dutch wind farms, the exact (individual) turbine coordinates are available, which could directly be used in the experiments. For the other offshore wind farms in the computational domain (Fig. 2), the available information was limited to the wind farm boundaries and the total number of turbines per wind farm. For these sites, the turbine coordinates were first chosen randomly within the wind farm boundary, and next distributed uniformly using an iterative repulsion method (Witkin & Heckbert, 2005).

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Figure 2. Overview of all $(2.5 \times 2.5 \text{ km})$ grid points with one or more wind turbines (red). Black arrows indicate the locations of measurements used for evaluation. In the left figure the black square indicates the model domain and the grey square the location of the right panel.

This random approach to determine the turbine coordinates can be justified by the fact that within the turbine parameterisation, all turbines are mapped to the nearest 2.5 km \times 2.5 km grid point, making the exact turbine coordinates less important. The wind farm boundaries were obtained from the *The European Marine Observation and Data Network* (EMODnet; Martín Míguez et al., 2019).

The $C_{\rm P}$ and $C_{\rm T}$ curves were obtained from various sources, predominantly from windPRO input database (Acker & Chime, 2011). For a small number of turbines, no $C_{\rm P}$ and $C_{\rm T}$ curves were publicly available, those turbines have been replaced with either reference data from literature, or $C_{\rm P}$ and $C_{\rm T}$ curves from similar turbines. An overview is provided in Appendix A.

187 5 Measurements

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5.1 Borssele Wind Lidars

For the wind resource assessment of the four wind farms in the Borssele wind farm zone (BWFZ), two short-range doppler lidars were deployed near the Belgian offshore wind farms. Fugro executed a Metocean campaign and did measurements for a number

of periods between June 2015 and February 2017. ZephIR 300S lidars were mounted on 192 buoys with a bottom mooring weight at 51.707° N, 3.035° E (Fig. 3, lidar 1) and at 51.646° 193 N, 2.951° E (Fig. 3, lidar 2). Lidar 1 (henceforth BWFZ1) measured for the longest pe-194 riod and there were sixteen measurement periods between June 2015 and February 2017 195 (Fig. 4a). This lidar is located 10 km northeast of the nearest wind turbine. Lidar 2 (hence-196 forth BWFZ2) only measured during five periods and only between February and July 197 2016 (Fig. 4b). This lidar is closer to the Belgian wind farm zones, at 2 km from the near-198 est turbine (Fig. 3). At typical hub heights of about 90 m the uncertainty in floating li-199 dar measurements for wind speeds between 4 and 15 m/s is between 3 and 4.5% (Duncan 200 et al., 2019) 201



Figure 3. Setup of the Borssele wind lidars off the coast of Belgian and the Netherlands. The blue area are the planned wind farm zones, that started to be operational in 2020/2021.

5.2 FINO 1 Tower

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The FINO 1 tower has been providing measurements since 2003 and is located in the North Sea at 54.015 ° N, 6.588 ° E, 50 km north of the Wadden island Borkum (Fig. 2). The water depth at this location is 30 m and the tower reaches a height of 103.7 m above Lowest Astronomical Tide (LAT). The first wind turbines were installed near FINO1 in November 2009 and the Alpha Ventus wind farm became fully operational in 2010. This means that wind measurements for wind directions between 15° to 165° (easterly winds) became disturbed by Alpha Ventus since November 2009. Borkum Riffgrund 1



Figure 4. Availability of the measurements for the two lidars at the Borssele wind farm zone (a) BWFZ1 and (b) BWFZ2, (c) the Westermost Rough lidar (WMR) and (d) FINO 1.

to the south west has been fully operational since 2015, also disturbing the flow in 170° to 300° directions.

Here, we use the cup anomemeters to evaluate the model, since these measure at 212 frequent height intervals (i.e. 34.1, 41.6, 51.6, 61.6, 71.6, 81.6, 91.6, 101.6). The cup anemome-213 ters are manufactured Vector Instruments Windspeed Ltd. type A100LK/PC3/WR with 214 an accuracy of 1 %. The cup anemometers (for measuring wind speed) are on booms on 215 the southeast side of the mast (towards $135-143^{\circ}$) and the wind vanes (for measuring 216 wind direction) on booms on the opposite side of the mast. The wind speed measure-217 ments are corrected for wind mast effects using a measurement correction scheme called 218 the UAM-correction methodWind direction measurements are not corrected. (i.e. West-219 erhellweg et al., 2010, 2012). Wind direction measurements are not corrected. 220

The FINO1 measurements are available for the whole of 2016 and only about 2.5 % of the data are missing (Fig. 4). Due to it's long-term measurements the tower has

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been previously used to evaluate atmospheric models over the North Sea (e.g. MuñozEsparza et al., 2012; Wagner et al., 2019).

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5.3 Westermost Rough Wind Lidar

On top of the Westermost Rough wind farm substation (Fig. 2), Ørsted operates 226 a Leosphere WindCube scanning doppler lidar, providing wind speed measurements be-227 tween 74 m to 324 m height. Westermost Rough wind farm is located off the coast of 228 Yorkshire, UK. Unlike the Borssele lidars and FINO1 tower, this lidar is located in the 229 centre of the wind farm $(53.804^{\circ} \text{ N}, 0.132^{\circ} \text{ N})$, and is therefore always disturbed by the 230 wind turbines. The Westermost Rough (WMR) lidar became operational in mid-January 231 2016, but only has an overall availability of $\sim 14\%$ (1.5 out of 12 months), which limits 232 its usability. 233

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5.4 WIPAFF

As part of the WInd PArk Far Field (WIPAFF) project (Platis et al., 2020), sev-235 eral measurements were taken around wind farms in the German Bight area (Fig. 2). 236 In total 41 flights were carried out, of which 8 were in our current study period (6–10 237 September 2016). The aircraft measurements were carried out using the research aircraft 238 Dornier 128. The aircraft is equiped with sensors measuring temperature, humidity, all 239 wind components, and pressure at 100 Hz. This large dataset of spatial data is very valu-240 able to evaluate mesoscale models with wind-farm parameterisations, and has been used 241 previously to evaluate the Weather Research Forecasting model (WRF) (Platis et al., 242 2021). The measurements are described in detail by Lampert, Bärfuss, et al. (2020) and 243 data are publicly available (Bärfuss et al., 2019). 244

For the purpose of this study we have only used one of the flights to evaluate the 245 spatial representation of the wind farm wakes generated by HARMONIE. This flight took 246 place on September 6 2016, between 12:13 and 15:20 downwind of Amrumbank West wind 247 farm. During this day the average background wind speed was about 7 m s⁻¹ from the 248 south. Therefore the aircraft measurements were taken in a meandering pattern north 249 of the wind farm at hub height (i.e. 90 m). Given the average speed of the plane was 250 54 m s^{-1} and to compare with the model data at a grid spacing of 2.5 km, a 60-second 251 rolling average over the sonic anemometer data is performed. 252

5.5 Power production data

Belgium's high-voltage TSO, Elia, publishes the generated power by their various energy sources, including offshore wind farm power production in 15-minute intervals. Since in 2016 Belgium only had three offshore wind farms (Fig. 2 & 3), we are able to use their power generation data to evaluate the HARMONIE-modelled generated power. The total capacity of these offshore wind farms was 712.2 MW.

259 6 Evaluation

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6.1 Offshore lidar and tower measurements

During the chosen period, all lidars had periods with missing data, as summarised in Fig. 4. For all statistical analyses in this section we use collocated data, i.e. missing data is removed (or masked) in the model dataset as well. In addition, there is no conditional sampling based on (e.g.) wind direction; all available measurements are always included in the statistics.

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6.1.1 Borssele Wind Farm Zone (BWFZ) lidars

As shown in Fig. 3, both lidars were positioned north-east of the Belgian Northwind wind farm. With prevailing winds from the south-west, these lidar measurements are typically disturbed by the Belgian wind farms, making them ideal for assessing the impact of the wind turbines on the wind field, and the ability of the wind farm parametrisation to reproduce the disturbed wind field due to the wake effect of the wind farm.

Figure 5 shows the time averaged vertical wind speed profiles from the reference run (REF), the experiment with the wind-farm parameterisation (WFP), and the Borssele lidars. These are averaged profiles over the entire measurement period for both lidars and represent all different wind directions. However, over the duration of the measurement period of BWFZ1, the wind direction was southwesterly (180–270°) 42% of the time.

For both sites the reference simulation (without wind park parameterisation) overestimates the wind speed, which is most pronounced for lidar location number two, which is closest to the Belgian wind farms at 2 km distance from the nearest turbine. Enabling



Figure 5. Vertical profiles of wind speed, from the reference run (REF) and experiment with wind-farm parameterisation (WFP), compared to the Borssele (a) BWFZ lidar 1, 10 km from the nearest wind farm and (b) BWFZ lidar 2, 2 km from the nearest wind farm. The grey dotted line indicates the mean hub height of the nearest wind farm and the grey shaded areas the area the diameter of the rotor.

the wind-farm parameterisation clearly improves the experiments; for BWFZ2, the mean profile from HARMONIE matches very well with the measurements.

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6.1.2 FINO1 tower

The FINO1 tower is situated directly west of the Alpha Ventus wind farm, and north-284 east of the Borkum Riffgrund wind farm (Fig. 2). Fig. 6a shows the time averaged ver-285 tical wind speed profiles, compared to the corrected FINO1 measurements. In line with 286 the results from the Borssele area, the reference simulation overestimates the wind speed 287 with ~ 0.7 -0.9 m s⁻¹. With the wind-farm parameterisation included, the absolute bias 288 is decreased, but with a slight negative bias at the highest few measurement points, ~ 0.1 -289 0.2 m s^{-1} . This underestimation seems to be partially caused by the mapping of wind 290 turbines to the nearest HARMONIE grid point. In reality the FINO1 tower is west (and 291 with the dominating wind direction: upstream) of the Alpha Ventus wind farm, but in 292 HARMONIE the grid point nearest to FINO1 also houses some of the Alpha Ventus wind 293 turbines, as shown in Fig. 6b. This means that the grid point used for the analysis, di-294 rectly experiences drag from some of the Alpha Ventus turbines, resulting in a reduced 295 wind speed. However, including the wind-farm parameterisation clearly improves the wind 296

²⁹⁷ profile at the tower location due to the many wind farms in the surroundings. This is
²⁹⁸ also the location where the largest impact is expected.

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6.1.3 Westermost Rough lidar

As shown in Fig. 4, the data availability is limited to $\sim 14\%$ of the January to May period, and even less at the three highest measurement heights. Therefore, the analysis here is limited to the lowest 214 m.

Fig. 7 shows the time averaged vertical profiles of the lidar measurements and HAR-303 MONIE experiments. As with the FINO1 and Borssele locations, the reference run over-304 estimates the wind speed. The experiment with wind turbines (WFP) is very close to 305 the averaged lidar observations, especially near hub height. Above the rotor tips the gra-306 dient at which the wind speed increases is underestimated in the model. This results in 307 a bias at 214 m of 0.2 m s⁻¹ for the REF experiment and 0.3 m s⁻¹ for the WFP ex-308 periment. Since the REF experiment also underestimates the wind speed above the ro-309 tor tip, this bias could be caused by an underestimation of the background wind speed 310 or a measured acceleration of the wind above the rotor tip not captured by HARMONIE 311 with the WFP. 312



Figure 6. (a) Vertical profiles of wind speed, from the reference run without wind-farm parameterisation (REF) and experiment with wind-farm parameterisation (WFP), compared to the FINO1 tower. (b) The number of turbines in the HARMONIE grid cells surrounding FINO1



Figure 7. Vertical profiles of wind speed, from the reference run without wind-farm parameterisation (REF) and experiment with wind-farm parameterisation (WFP), compared to the Westermost rough lidar.

6.2 Airbourne measurements

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For the evaluation of HARMONIE with the wind-farm parameterisation the lidar 314 and tower measurements show significant improvements at single locations. However, 315 in order to evaluate the spatial scale of the modelled wakes airbourne measurements are 316 used. The WIPAFF measurement flights are intended to observe the spatial extent of 317 the wind-farm wakes. As mentioned in sect. 5.4, we only use the airbourne measurements 318 carried out during 6 September 2016, with a near-neutral – slightly stable surface layer 319 and an average wind speed of 7 m s⁻¹. In those cases we expect to see a large wake from 320 the wind farm, but not as strong as in very stable conditions (e.g. Zhan et al., 2020). 321 Fig. 8 compares the flight measurements with the HARMONIE simulations following 322 the same model track. For each measurement point the nearest model point in time and 323 space was extracted for both REF and WFP simulations. The model output was inter-324 polated between the nearest two model levels to 90 m, the flying altitude. 325

Close to the wind farm the wind farm wake is captured very well by the WFP (Fig. 8a). Here, at ~4 km distance the velocity deficit is about 2 m s⁻¹ and the width of the wind farm is about 15 km. During this time the background wind speed decreases left to right of the wind farm (negative to positive $x - \overline{x_{turbines}}$), however this is underestimated by the model leading to a bias of 1.0 m s⁻¹ in the WFP run. An 1.5 hours later

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Figure 8. Cross sections through the wind farm wake of Amrumbank West in the German Bight on 6 September 2016, 12:13 – 15:20 UTC. Cross sections are perpendicular to the wind direction at (a) 3.9 km (b) 7.3 km, and (c) 16.8 km distance from the turbines, and (d) a cross section along the wind from the centre of the turbines directly downstream. Crosses indicate 60 s rolling average wind speeds at 30 s intervals from the aircraft measurements and lines indicate the interpolated modelled wind speed along the same flight path (red) reference run and (black) simulation with WFP. The grey are indicate the location of the wind farm.

(~14:30) a cross section was taken at about 7.3 km downwind of the wind farm (Fig. 8b). Here, the HARMONIE WFP run is able to capture the wind speed in the wake of the turbines very well, but now underestimates the wind speed east of the turbines (positive $x - \overline{x_{turbines}}$)) by about 0.7 m s⁻¹. About 10 km downwind of the previous cross section (Fig. 8c), the velocity deficit in the wind-farm wake has been reduced to ~1 m s⁻¹, captured well by in the WFP run. As expected, the REF run is unable to model the velocity deficit caused by the wind farm.

The part of the flight along the wind direction captures the recovery of the wake 338 (Fig. 8d). About 4 km away from the wind farm the wind speed is 5.4 m s⁻¹, at 30 km 339 away the wind speed has only increased by 0.7 m s^{-1} to 6.1 m s^{-1} . Over the same dis-340 tance the model shows a similar reduction in the velocity deficit, 0.8 m s⁻¹. After 30 km 341 the observations show the wake to dissipate quickly, while in HARMONIE there remains 342 a difference between the REF and WFP runs of about $<0.5 \text{ m s}^{-1}$ for at least 70 km down-343 wind of the wind farm. The Fitch et al. (2012) parameterisation is known to produce 344 long wakes (e.g. Shepherd et al., 2020). However, a more systematic evaluation of the 345 size and shape of wakes using Fitch et al. (2012) is needed, with more research aircraft 346 data, scanning doppler lidars (e.g. Rhodes & Lundquist, 2013; Banta et al., 2015), or 347 satellite measurements such as SAR (e.g. Christiansen & Hasager, 2005). 348

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6.3 Power production

When evaluating HARMONIE with the wind-farm parameterisation, power production is a crucial quantity. Power production scales with the velocity cubed (eq. 9), making it sensitive to biases in wind speed. For all of 2016, Elia provides power production data for the Belgian offshore wind farms. This is the total power production of all the offshore wind farms. In 2016 these farms had a total capacity of 712.2 MW (Fig. 3).

Figure 9 shows the comparison between the observed power production and power production obtained from the HARMONIE experiments, both from the reference experiment and experiment with the wind turbine parameterisation (WFP). The bottom panels indicate the absolute and relative differences, averaged over 50 MW bins. The relative bias from the first (0-50 MW) bin should be treated with caution, as conditions where the observed power production equals zero result in an infinitely large relative bias.



Figure 9. Power production calculated from the (a) reference reanalysis (REF) and (b) experiment with wind-farm parameterisation (WFP), compared to the Elia measurements. The solid black line with markers (top row) indicates the mean of the model data calculated over 50 MW bins. The bottom row shows the absolute (c) and relative (d) error of both model experiments.

The power production calculated offline (eq. 9) from the reference experiment clearly 361 overestimates the production, with absolute biases as large as 150 MW, and for low wind 362 speeds (low power production) relative biases as large as 100%. The reference simula-363 tion clearly does not include the power production losses attributed to the velocity deficit 364 created by the wind turbines. Including the wind turbine parameterisation clearly im-365 proves the power production calculated, reducing the absolute bias to a maximum of 50 366 MW at high wind speeds, and the relative bias to $\sim 6\%$. There are a few possible causes 367 for this constant relative bias - e.g. efficiency losses in the turbines or power cables, the 368 use of (manufacturers) turbine specifications which are too optimistic, inaccuracies in 369 the turbine parameterisation, or single turbines that are not operational, or not func-370 tioning optimally. If the aim is to deliver power production forecasts to users, some post 371 processing will be necessary to eliminate these inaccuracies. 372

373

6.4 Impact wind farms on local meteorological conditions

As seen in the previous sections, wind turbines have an impact on the (local) wind conditions. In addition, wind turbines generate TKE, which enhances vertical mixing, potentially influencing other quantities like temperature, humidity, or clouds. Here, we briefly examine the impact of two Dutch offshore wind farms on the local meteorological conditions. In the absence of suitable measurements, the results are limited to comparing the reference simulations with the experiment including wind turbines.

Fig. 10 shows the differences in wind speed (V), potential temperature (θ), and spe-380 cific humidity (q) between the experiments with and without wind turbines for two time 381 periods. During the period March – June the sea surface temperature is colder on av-382 erage compared to the atmospheric temperature and more stable cases are expected. Dur-383 ing September – December the sea surface temperature is generally warmer than the at-384 mosphere above, leading to more unstable cases. For each wind farm, the statistics were 385 averaged over the HARMONIE grid points which have one or more turbines, and aver-386 aged in time. 387

For wind speed, the elevated drag is clearly visible, with a maximum decrease of 1.6 m s⁻¹ near hub height, but a near-surface decrease of 0.3 - 0.0 m s⁻¹. The relatively small wind farm Princes Amalia (120 MW, -0.6 m s⁻¹ during spring and -0.5 m s⁻¹ in autumn) has a smaller impact on the wind speed compared to the larger Gemini (600

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Figure 10. Impact of wind turbines on meteorological variables wind velocity (a,d), potential temperature (b,e), and specific humidity (c,f) over two Dutch offshore wind farms, Gemini to the north of the Dutch coast (black dashed) and Princes Amalia to the west of the Dutch coast (blue solid), where Δ = WFP-REF. The top panels (a – c) are averaged profiles over 1 March – 30 June 2016, the bottom panels (d – f) are averaged profiles over 1 September – 31 December 2016. The horizontal lines indicate the hub height of each wind farm.

³⁹² MW, -1.6 m s⁻¹ during spring and -1.2 m s⁻¹ in Autumn). The modelled velocity deficit ³⁹³ is shown to be stronger in the spring season with relatively more stable cases. Previous ³⁹⁴ research has also shown higher velocity deficits during stable cases compared to unsta-³⁹⁵ ble atmospheric boundary layers (e.g. Dörenkämper et al., 2015).

The enhanced vertical mixing has a weak impact on temperature and specific hu-396 midity. During the period where the atmosphere is on average stably stratified, the en-397 hanced TKE and vertical mixing decreases the stratification, resulting in an increase in 398 temperature and decrease in specific humidity near the surface, and decrease in temper-399 ature and increase in specific humidity at 100-150 m height. At the large wind farm, Gem-400 ini, this average vertical potential temperature variation is between -0.2 and 0.2 K, for 401 the smaller wind farm (Princes Amalia) -0.08 to 0.12 K. The specific humidity during 402 spring, decreases -0.1 for Gemini and -0.07 g kg⁻¹ for Princes Amalia near the surface 403

and increases by 0.04 and 0.02 g kg⁻¹, respectively, above hub height. As a result of the near surface heating and drying, and the cooling and moistening aloft, the relative humidity decreases near the surface, and increases higher up. This could impact the formation of fog or low clouds.

During autumn and early winter the influence of the enhanced vertical mixing by wind turbines is smaller, for potential temperature less than 0.1 K for both wind farms. The well-mixed profiles during unstable conditions are barely influenced by enhanced TKE. However, the near-surface moisture is reduced by the same order of magnitude in the autumn compared to the spring season.

413 7 Conclusion

The Fitch et al. (2012) wind-farm parameterisation was implemented in mesoscale 414 model HARMONIE-AROME, and validated with a variety of observations in the north-415 sea region over a one-year period. The parameterisation reduces momentum and con-416 verts this into turbulent kinetic energy and power production, depending on wind tur-417 bine properties. Two year-long simulations were performed, one including all wind tur-418 bines on the North Sea known up to 2016 and one without any wind turbines. The eval-419 uation with various wind measurements on the North Sea indicates that inclusion of the 420 turbine parameterisation has a positive impact on the modelled wind speeds near (off-421 shore) wind farms. For all locations considered, the absolute bias in wind speed is de-422 creased compared to the simulation without wind farms. Furthermore, the predicted power 423 production – compared to observations from the Belgian TSO – shows a substantial im-424 provement with the turbine parameterisation included. 425

A brief survey of the impact of wind farms on the local meteorological conditions, 426 indicates that in addition to changes in wind speed, other quantities like temperature 427 or humidity are influenced by wind farms as well. These variations in temperature and 428 humidity are more pronounced in periods with more stable conditions, where the enhanced 429 turbulent kinetic energy from the wind turbines increases the mixing of the marine bound-430 ary layer. With the expected increase in number and size of wind turbines in the com-431 ing decades the influence of wind turbines on local to regional meteorology can no longer 432 be neglected. The relatively simple wind-farm parameterisation by Fitch et al. (2012) 433

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- improves modelled wind speed near wind farms and can be used operationally to improve
- 435 weather forecasts and predicted power production.

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443 Data availablity

- ⁴⁴⁴ The HARMONIE-AROME model simulations are available on the KNMI data platform:
- 445 https://dataplatform.knmi.nl/dataset/?tags=Dutch+Offshore+Wind+Atlas

446 Appendix A Wind farm and turbine information

Tables A1 and A2 provide an overview of all the wind farms implemented in the experimental domain, and Table A3 summarises the turbine types and their properties.

449 **References**

- Abkar, M., & Porté-Agel, F. (2015). A new wind-farm parameterization for largescale atmospheric models. Journal of Renewable and Sustainable Energy, 7(1),
 013121.
- Acker, T., & Chime, A. H. (2011). Wind modeling using windpro and wasp software.
 Norther Arizon University, USA, 1560000(8.8), 510.
- Baidya Roy, S., & Traiteur, J. J. (2010). Impacts of wind farms on surface air temperatures. Proceedings of the National Academy of Sciences, 107(42), 17899–
 17904.
- Banta, R. M., Pichugina, Y. L., Brewer, W. A., Lundquist, J. K., Kelley, N. D.,
 Sandberg, S. P., ... Weickmann, A. M. (2015). 3d volumetric analysis of wind
 turbine wake properties in the atmosphere using high-resolution doppler lidar.
 Journal of Atmospheric and Oceanic Technology, 32(5), 904–914.

Name	Latitude (°N)	Longitude (°E)	Turbine type	Ν	Z (m)
London Array 1	51.626	1.496	SWT-3.6-120	175	87
Gemini	54.036	5.963	SWT-4.0-130	150	89
Gode Wind I	54.016	6.983	SWT-6.0-154	55	110
Gode Wind II	54.075	7.007	SWT-6.0-154	42	110
Gwynt y Mor	53.460	-3.599	SWT-3.6-107	160	98
Race Bank	53.276	0.841	SWT-6.0-154	91	110
Greater Gabbard	51.773	1.982	SWT-3.6-107	140	78
Dudgeon	53.265	1.380	SWT-6.0-154	67	110
Veja Mate	54.321	5.860	SWT-6.0-154	67	103
Anholt	56.600	11.210	SWT-3.6-120	111	82
Bard Offshore 1	54.355	5.980	BARD-5.0	80	90
GlobalTech I	54.500	6.358	Areva-5.0	80	90
Rampion Wind Farm	50.660	-0.200	V112-3.45	116	84
West of Duddon Sands	53.984	-3.464	SWT-3.6-120	108	80
Walney 1	53.810	-4.907	SWT-3.6-107	51	84
Walney 2	54.081	-3.605	SWT-3.6-107	51	90
Galloper	51.880	2.040	SWT-6.0-154	56	103
Wikinger Offshore	54.834	14.068	Adwen-5.0	70	75
Nordsee One Offshore	54.444	7.682	Senvion-6.2	54	100
Sheringham Shoal	53.135	1.147	SWT-3.6-107	88	82
Borkum Riffgrund I	53.967	6.562	SWT-4.0-12	78	87
Borkum Riffgrund II	53.967	6.496	V164-8.0	56	105
Amrumbank West	54.520	7.708	SWT-3.6-120	80	90
Thanet	51.430	1.633	V90-3.0	100	70
Nordsee Ost	54.444	7.682	Senvion-6.2	48	97
Butendiek	55.019	7.774	SWT-3.6-120	80	91
Dan Tysk	55.140	7.200	SWT-3.6-120	80	88
Baltica 2	55.070	17.100	SWT-3.6-120	80	78
Meerwind Sued/Ost	54.402	7.707	SWT-3.6-120	80	89
Sandbank	55.190	6.860	SWT-4.0-130	72	95
Lincs	53.191	0.491	SWT-3.6-120	75	100
Burbo Bank Extension	53.483	-3.273	V164-8.0	32	123
Humber Gateway	53.619	0.293	V112-3.0	73	80

Table A1. Overview of wind farms included in the experiments. Latitude and longitude indicate the location in the centre of the wind farm. N are the number of turbines in the wind farm and Z is the hub height.

Name	Latitude (°N) Longitude (°E)	Turbine type	Ν	Z (m)
Westermost Rough	53 805	0.140	SWT 6.0.154	25	100
Horns Boy 2	55 600	0.149 7 589	SWT 2 3 03	01	100 68
Rodsand II	54 558	11 531	SWT 2 3 03	91	60 60
Trianel Borkum II	54.042	6 467	$\Delta rev_{2.5-35}$	40	90
Kontish Flats 1	51.460	1 003	V00_3.0	30	30 70
Kontish Flats 2	51.400	1.035	V112-3 3	15	84
Cunfleet Sands	51.400 51.737	1.073	SWT_3 6_107	18	75
Ormonde	54 088	-3 437	Senvion-5	30	97
Barrow	53 982	-3 283	V90-3.0	30	75
Bhyl Flats	53 380	-3 646	SWT-3 6-107	$\frac{50}{25}$	75
North Hoyle	53.417	-3 448	V80-2.0	30	67
Riffgat	53.692	6.470	SWT-3.6-120	30	90
Horns Rev 1	55.486	7.840	V80-2.0	80	70
Nysted	54.549	11.714	SWT-2.3-82	72	69
EnBW Baltic 1	54.596	12.638	SWT-2.3-93	21	67
EOWDC	57.230	-1.990	V164-8.0	11	120
Hywind 2 Demonstration	57.500	-1.300	SWT-6.0-154	5	98
Årkonabecken Südost	54.780	14.120	SWT-6.0-154	60	102
Alpha Ventus	54.017	6.600	Avera-5.0	12	90
Walney Extension 3	54.087	-3.737	V164-8.0	40	113
Walney Extension 4	54.087	-3.737	SWT-7.0-154	47	111
Luchterduinen	52.403	4.165	V112-3.0	43	81
Prinses Amalia	52.594	4.213	V80-2.0	60	59
Egmond aan Zee	52.594	4.437	V90-3.0	36	70
Belwind I	51.670	2.800	V90-3.0	55	72
Northwind	51.619	2.901	V112-3.0	72	71
Thorntonbank	51.540	2.940	Multiple	54	95
	Table A2.	Table A1 continued			

Name	Ν	P (MW)	D (m)	
Siemens SWT-2.3-82	72	2.3	72	
Siemens SWT-2.3-93	202	2.3	93	
Siemens SWT-3.6-107	563	3.6	107	
Siemens SWT-3.6-120	899	3.6	120	
Siemens SWT-4.0-120	78	4.0	120	
Siemens SWT-4.0-130	222	4.0	130	
Siemens SWT-6.0-154	478	6.0	154	(1)
Siemens SWT-7.0-154	47	7.0	154	(1)
Vestas V80-2.0	170	2.0	80	
Vestas V90-3.0	251	3.0	90	
Vestas V112-3.0	188	3.0	112	
Vestas V112-3.3	15	3.3	112	
Vestas V112-3.45	116	3.45	112	
Vestas V164-8.0	139	8.0	164	(2)
Senvion 5	30	5.0	126	. ,
Senvion 6.2	156	6.2	126	
BARD-5.0	80	5.0	126	(3)
Adwen-5.0	202	5.0	116	(3)
Haliade-6	1	6.0	100	. /
	3908	460×10^{3}		

Table A3. Overview of the wind turbine types included in the experiments. The total installed power equals $\sum N \times P$. Notes: (1) replaced with 6 MW reference turbine from (Bulder et al., 2016), (2) replaced with 8 MW reference turbine from (Bulder et al., 2016), (3) replaced with Senvion 5 turbine.

⁴⁶² Bärfuss, K., Hankers, R., Bitter, M., Feuerle, T., Schulz, H., Rausch, T., ... Lam-

- pert, A. (2019). In-situ airborne measurements of atmospheric and sea surface
 parameters related to offshore wind parks in the german bight. PANGAEA
 https://doi. org/10.1594/PANGAEA, 902845.
- Bengtsson, L., Andrae, U., Aspelien, T., Batrak, Y., Calvo, J., de Rooy, W., ... others (2017). The HARMONIE–AROME model configuration in the ALADIN–
 HIRLAM NWP system. *Monthly Weather Review*, 145(5), 1919–1935.
- Bulder, B., Bot, E., & Marina, A. (2016). Scoping analysis of the potential yield
 of the Hollandse Kust (zuid) wind farm sites and the influence on the existing
 wind farms in the proximity (Tech. Rep. No. ECN-E-16-021 2nd edt.) ECN.
- ⁴⁷² Christiansen, M. B., & Hasager, C. B. (2005). Wake effects of large offshore wind
 ⁴⁷³ farms identified from satellite sar. *Remote Sensing of Environment*, 98(2-3),
 ⁴⁷⁴ 251–268.
- de Haan, S. (2011). High-resolution wind and temperature observations from aircraft tracked by Mode-S air traffic control radar. Journal of Geophysical Research:

477	Atmospheres, 116 (D10).
478	de Haan, S. (2016). Estimates of Mode-S EHS aircraft-derived wind observation
479	errors using triple collocation. Atmospheric Measurement Techniques, $9(8)$,
480	4141 - 4150.
481	de Rooy, W. C., Siebesma, P., Baas, P., Lenderink, G., de Roode, S., de Vries, H.,
482	\ldots van 't Veen, B. (2021). Model development in practice: A comprehensive
483	update to the boundary layer schemes in HARMONIE-AROME. $Geoscientific$
484	Model Development, -(-),
485	Dörenkämper, M., Witha, B., Steinfeld, G., Heinemann, D., & Kühn, M. (2015).
486	The impact of stable atmospheric boundary layers on wind-turbine wakes
487	within offshore wind farms. Journal of Wind Engineering and Industrial Aero-
488	dynamics, 144, 146–153.
489	Duncan, J. B., Wijnant, I. L., & Knoop, S. (2019). DOWA validation against off-
490	shore mast and LiDAR measurements. (Tech. Rep. No. TNO Technical Report
491	2019 R10062). Retrieved from https://www.dutchoffshorewindatlas.nl/
492	publications/reports/2019/05/21/tno-report-dowa-validation-against
493	-offshore-mast-and-lidar-measurements
494	Faroux, S., Kaptué Tchuenté, A., Roujean, JL., Masson, V., Martin, E., & Moigne,
495	P. L. (2013). Ecoclimap-ii/europe: A twofold database of ecosystems and
496	surface parameters at 1 km resolution based on satellite information for use in
497	land surface, meteorological and climate models. Geoscientific Model Develop-
498	$ment, \ 6(2), \ 563-582.$
499	Fischer, C., Montmerle, T., Berre, L., Auger, L., & Ştefănescu, S. E. (2005). An
500	overview of the variational assimilation in the ALADIN/France numerical
501	weather-prediction system. Quarterly Journal of the Royal Meteorological
502	Society, 131(613), 3477-3492.
503	Fischereit, J., Brown, R., Larsén, X. G., Badger, J., & Hawkes, G. (2021). Review of
504	mesoscale wind-farm parametrizations and their applications. Boundary-Layer
505	Meteorology, 1-50.
506	Fitch, A. C., Olson, J. B., Lundquist, J. K., Dudhia, J., Gupta, A. K., Michalakes,
507	J., & Barstad, I. (2012). Local and mesoscale impacts of wind farms as pa-
508	rameterized in a mesoscale NWP model. Monthly Weather Review, $140(9)$,
509	3017–3038.

-26-

510	Gustafsson, N., Janjić, T., Schraff, C., Leuenberger, D., Weissmann, M., Reich, H.,
511	\dots others (2018). Survey of data assimilation methods for convective-scale
512	numerical weather prediction at operational centres. Quarterly Journal of the
513	Royal Meteorological Society, 144 (713), 1218–1256.
514	Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J.,
515	others (2020). The era5 global reanalysis. Quarterly Journal of the Royal
516	$Meteorological\ Society,\ 146 (730),\ 1999-2049.$
517	Lampert, A., Bärfuss, K., Platis, A., Siedersleben, S., Djath, B., Cañadillas, B.,
518	others (2020) . In situ airborne measurements of atmospheric and sea surface
519	parameters related to offshore wind parks in the german bight. Earth System
520	Science Data, 12(2), 935–946.
521	Lampert, A., Bärfuss, K., Platis, A., Siedersleben, S., Djath, B., Cañadillas,
522	B., Emeis, S. (2020). In situ airborne measurements of atmo-
523	spheric and sea surface parameters related to offshore wind parks in the
524	german bight. Earth System Science Data, 12(2), 935–946. Retrieved
525	from https://essd.copernicus.org/articles/12/935/2020/ doi:
526	10.5194/essd-12-935-2020
527	Lee, J. C., & Lundquist, J. K. (2017). Evaluation of the wind farm parameterization
528	in the weather research and forecasting model (version $3.8.1$) with meteoro-
529	logical and turbine power data. $Geoscientific Model Development, 10(11),$
530	4229 - 4244.
531	Lenderink, G., & Holtslag, A. A. (2004). An updated length-scale formulation for
532	turbulent mixing in clear and cloudy boundary layers. Quarterly Journal of the
533	Royal Meteorological Society: A journal of the atmospheric sciences, applied
534	meteorology and physical oceanography, $130(604)$, $3405-3427$.
535	Marseille, GJ., & Stoffelen, A. (2017). Toward scatterometer winds assimilation
536	in the mesoscale harmonie model. <i>IEEE Journal of Selected Topics in Applied</i>
537	Earth Observations and Remote Sensing, $10(5)$, 2383–2393.
538	Martín Míguez, B., Novellino, A., Vinci, M., Claus, S., Calewaert, JB., Vallius, H.,
539	\ldots others (2019). The european marine observation and data network (emod-
540	net): visions and roles of the gateway to marine data in europe. Frontiers in
541	Marine Science, 6, 313.
542	Masson, V., Le Moigne, P., Martin, E., Faroux, S., Alias, A., Alkama, R., oth-

543	ers (2013) . The surface of and ocean surface platform for coupled or
544	offline simulation of earth surface variables and fluxes. Geoscientific Model
545	$Development, \ 6(4), \ 929-960.$
546	Muñoz-Esparza, D., Cañadillas, B., Neumann, T., & Van Beeck, J. (2012). Turbu-
547	lent fluxes, stability and shear in the offshore environment: Mesoscale mod-
548	elling and field observations at fino1. Journal of Renewable and Sustainable
549	Energy, 4(6), 063136.
550	Platis, A., Bange, J., Bärfuss, K., Cañadillas, B., Hundhausen, M., Djath, B.,
551	others (2020). Long-range modifications of the wind field by offshore wind
552	parks-results of the project wipaff. Meteorologische Zeitschrift, 355–376.
553	Platis, A., Hundhausen, M., Mauz, M., Siedersleben, S., Lampert, A., Bärfuss, K.,
554	\dots others (2021). Evaluation of a simple analytical model for offshore wind
555	farm wake recovery by in situ data and weather research and forecasting simu-
556	lations. Wind Energy, 24(3), 212–228.
557	Rhodes, M. E., & Lundquist, J. K. (2013). The effect of wind-turbine wakes on sum-
558	mertime us midwest atmospheric wind profiles as observed with ground-based
559	doppler lidar. Boundary-layer meteorology, $149(1)$, 85–103.
560	Shepherd, T., Barthelmie, R., & Pryor, S. (2020). Sensitivity of wind turbine ar-
561	ray downstream effects to the parameterization used in wrf. $Journal of Applied$
562	Meteorology and Climatology, $59(3)$, $333-361$.
563	Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Liu, Z., Berner, J.,
564	others (2019). A description of the advanced research wrf model version 4.
565	National Center for Atmospheric Research: Boulder, CO, USA, 145.
566	Volker, P., Badger, J., Hahmann, A. N., & Ott, S. (2015). The explicit wake
567	parametrisation v1. 0: a wind farm parametrisation in the mesoscale model
568	wrf. Geoscientific Model Development, $8(11)$, $3715-3731$.
569	Wagner, D., Steinfeld, G., Witha, B., Wurps, H., & Reuder, J. (2019). Low level jets
570	over the southern north sea. Meteorologische Zeitschrift, 389–415.
571	Westerhellweg, A., Canadillas, B., Beeken, A., & Neumann, T. (2010). One year
572	of lidar measurements at fino1-platform: Comparison and verification to met-
573	mast data. In Proceedings of 10th german wind energy conference dewek (pp.
574	1 - 5).
575	Westerhellweg, A., Neumann, T., & Riedel, V. (2012). Fino1 mast correction.

576	DEWI-Magazin, 21.
577	Wijnant, I. L., van Ulft, B., van Stratum, B. J. H., Barkmeijer, J., Onvlee, J., de
578	Valk, S., C. Knoop, Klein Baltink, H. (2019). The dutch offshore wind
579	atlas (DOWA): description of the dataset (Tech. Rep.). Retrieved from
580	https://www.dutchoffshorewindatlas.nl/publications
581	WindEurope. (2017). Wind energy in europe: Scenarios for 2030 (Tech. Rep.).
582	Retrieved from https://windeurope.org/wp-content/uploads/files/
583	about-wind/reports/Wind-energy-in-Europe-Scenarios-for-2030.pdf
584	Witkin, A. P., & Heckbert, P. S. (2005). Using particles to sample and control im-
585	plicit surfaces. In Acm siggraph 2005 courses (p. 260).
586	Wu, C., Luo, K., Wang, Q., & Fan, J. (2022). A refined wind farm parameterization
587	for the weather research and forecasting model. Applied Energy, 306, 118082.
588	Zhan, L., Letizia, S., & Valerio Iungo, G. (2020). Lidar measurements for an on-
589	shore wind farm: Wake variability for different incoming wind speeds and
590	atmospheric stability regimes. Wind Energy, $23(3)$, 501–527.