Review of Mesoscale Wind-Farm Parametrizations and Their Applications

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Abstract

With the ongoing expansion of wind energy onshore and offshore, large-scale wind-farm-flow effects in a temporally- and spatially-heterogeneous atmosphere become increasingly relevant. Mesoscale models equipped with a wind-farm parametrization (WFP) can be used to study these effects. Here, we conduct a systematic literature review on the existing WFPs for mesoscale models, their applications and findings. In total, 10 different explicit WFPs have been identified. They differ in their description of the turbine-induced forces, and turbulence-kinetic-energy production. The WFPs have been validated for different target parameters through measurements and large-eddy simulations. The performance of the WFP depends considerably on the ability of the mesoscale model to simulate the background meteorological conditions correctly as well as on the model set-up. The different WFPs have been applied to both onshore and offshore environments around the world. Here, we summarize their findings regarding (1) the characterizations of wind-farm-flow effects, (2) the environmental impact of wind farms, and (3) the implication for wind-energy planning. Since wind-farm wakes can last for several tens of kilometres downstream depending on stability, surface roughness and terrain, neighbouring wind farms need to be taken into account for regional planning of wind energy. Their environmental impact is mostly confined to areas close to the farm. The review suggests future work should include benchmark-type validation studies with long-term measurements, further developments of mesoscale model physics and WFPs, and more interactions between the mesoscale and microscale community.

Keywords Environmental impact · Mesoscale modelling · Wind-energy planning · Wind-farm-flow effect · Wind-farm wake

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1 Introduction

The annual deployment of both onshore and offshore wind turbines has been growing and is expected to grow in the future (IRENA 2019). Along with this expansion not only is the size of the wind farms increasing (Díaz and Guedes Soares 2020), but also the number of wind farms that are placed in close proximity to each other, that is within a wind-farm cluster, the North Sea being a prominent example. Following Schneemann et al. (2020a), we define wind-farm clusters as an accumulation of wind farms in the direct vicinity with more than a hundred turbines, which can be managed by different operators and may consist of different turbine types and geometries.

To generate electricity, wind turbines extract kinetic energy from the atmosphere. Therefore, they are not passively affected by the incoming flow, but actively affect the flow both upwind (blockage) and downwind (wake). In a wind farm, the effects of individual turbines add up to a global blockage effect and a wind-farm-wake effect. Wind-farm wakes have been observed both from synthetic-aperture radar (SAR) and in situ aircraft measurements to extend several tens of kilometres downstream (Hasager et al. 2006; Siedersleben et al. 2018b; Cañadillas et al. 2020). Hence, with the described increase in density of wind farms, the influence of one wind farm on surrounding wind farms also increases.

Because of the large spatial extent, engineering-type wake models or wake models in high-resolution non-meteorological microscale computational fluid dynamics (CFD) and large-eddy simulation (LES) models (Göçmen et al. 2016; Porté-Agel et al. 2020) are not ideal to study the interactions of those wind farms with the current available computational power. On the one hand, engineering-type wake models are admittedly computationally efficient enough to include neighbouring wind farms, as done for instance in Larsén et al. (2019) and Nygaard and Newcombe (2018), but they assume a constant wind speed and direction over the entire model domain. However, this is not true over such large areas, as the correlation coefficient between wind measurements at two sites decreases with increasing distance in general (Vincent et al. 2013; Mehrens et al. 2016). Thus, wind-farm wakes often meander (e.g., Fig. 4 in Siedersleben et al. 2020) and are highly variable in time and space. Furthermore, engineering-type wake models often lack relevant physical processes, most importantly stability effects, as already pointed out by Emeis (2010). These processes are, however, relevant on wind-farm or wind-farm-cluster scales with a hundred turbines or more. On the other hand, CFD and LES models that capture the variability of wakes are computationally expensive and cannot be applied to large areas of more than 100 km². In addition, wind-farm wakes are influenced by synoptic phenomena such as horizontal wind-speed gradients in coastal areas (Platis et al. 2018; Nygaard et al. 2020) or low-level jets (Miller et al. 2015) that often cannot be captured in engineering-type wake models and CFD models. Finally, wind farms influence not only wind speed but also the turbulence kinetic energy (TKE), temperature, humidity, clouds, and other meteorological or atmospheric parameters (Fitch 2015; Siedersleben et al. 2018a). Thus, they affect mesoscale meteorological conditions—a feedback effect that cannot be captured in CFD models alone.

Mesoscale models equipped with wind-farm parametrizations (WFPs) can represent the complexity of these atmospheric processes. In their review on wind-turbine and wind-farm flows, Porté-Agel et al. (2020) identified mesoscale wind-farm-flow models as important tools that require further improvements and research, as did Veers et al. (2019) in their overview on the current challenges in the science of wind energy.

In line with this requirement, this study aims to review the current status of WFPs suitable for mesoscale models, as well as their role for characterization of wind-farm-flow effects,

environmental impact studies of wind farms, and wind-energy planning. Finally, it aims to point out perspectives for future development and actions in the area of WFPs and mesoscale models. Our review addresses three questions:

1. Which WFPs for mesoscale models exist, how do they differ from each other, and how closely do they agree with measurements?
2. How are the WFPs applied in different areas and what are the findings?
3. What next actions should be taken with regard to mesoscale wind-farm-flow modelling?

To address these questions, a systematic literature-review-based approach, as described in Sect. 2, was used to identify relevant studies. The different parametrizations are reviewed and the results are summarized in Sect. 3. The results from the application of WFPs for the three categories are described, along with results on mesoscale-model sensitivity in Sect. 4. The findings are summarized and the implications for further actions are discussed in Sect. 5.

2 Method

To address the three questions identified in Sect. 1, a systematic literature review was conducted in order to identify relevant studies. The review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standard (Moher et al. 2009). Within the PRISMA standard, publications were identified through a database search and selected or excluded through predefined selection criteria. We conducted an ‘All database’ search in the Web of Science collection with the following two search terms derived based on the guiding questions:

1. TS = ((Regional OR meso*) AND (wake) AND (wind) AND (model OR paramet*ation) AND (farm OR cluster))
2. TS = ((Regional OR meso*) AND ((influence OR effect OR impact)) AND (wind) AND (model OR paramet*ation) AND (farm OR cluster))

Within the search terms, ‘TS’ refers to the ‘Topic’ field, which includes ‘title’, ‘abstract’, ‘author keywords’, and ‘keywords plus’. The search was conducted on 1 May 2020 and in total 665 papers were identified through the two searches (Fig. 1). We then had the possibility to conduct an initial high-level review of the papers and add additional relevant records to the database. Additional records were added based on the cited references in the already identified records identified from the database search, as well as articles based on prior knowledge of the authors. This additional step was necessary to gather a more complete picture on the existing literature by also including publications not indexed in the Web of Science catalogue. In total, 14 additional references were identified (Fig. 1). Relevant added pre-prints were included in the database in their preprint versions, since the 1 May 2020 is used as the cut-off date, after which no more papers are added to the database.

After removing duplicates and records with no full text, 612 records were screened by title and abstract (Fig. 1) to identify eligible studies based on the following selection criteria, which each address different aspects of the guiding research questions:

- Flow scale: addresses mesoscale or regional effects.
- Topic: addresses wind-farm-flow effects.
- Technical: uses or develops a method to parametrize wind-farm-flow effects in mesoscale models.

Fig. 1 PRISMA (Moher et al. 2009) flow diagram of the conducted literature review

Consequently, studies meeting the following descriptions were excluded:

- Flow scale: studies focusing on microscale effects within a wind farm.
- Topic: studies focusing on wake effects of other obstacles or structures or not including any wind-farm-flow effect.
- Technical: studies applying or developing CFD-type wake models or focusing on measurements.

In total, 102 full-text articles were assessed (Fig. 1) by the authors. In order to facilitate an unbiased review of individual studies, the studies within the database were ordered alphabetically based on the first author and assigned to the individual authors of this paper in varying proportions based on the available resources. Studies were summarized in a shared document and discussed in terms of eligibility. Overall, 43 full-text articles have been excluded (Fig. 1), because they do not meet the described selection criteria. Therefore, 59 studies have been included in the current study (Fig. 1). The 59 included studies are summarized in Tables 1 and 2 depending on their parametrization type, respectively. Section 3 presents the results regarding question 1 (Sect. 1) on available parametrizations and their differences, while Sect. 4 presents the results regarding question 2 (Sect. 1) on WFP applications and their findings. To answer question 3 (Sect. 1), prospects for further developments of the parametrizations and applications are discussed in Sect. 5.

Fig. 2 Mesoscale horizontal model grid with a resolution Δx , Δy using a different surface roughness (light brown) to represent the effect of wind turbines (blue) on the mesoscale

3 Overview on Existing Wind-Farm Parametrizations

Two different methods to parametrize wind-farm-flow effects have been identified: (1) an implicit method, which parametrizes the effect as an increase in surface roughness (Sect. 3.1), and (2) an explicit method, which parametrizes the effect as an elevated momentum sink and, in some cases, a source of TKE (Sect. 3.2). After the two approaches are introduced, they are compared in Sect. 3.3.

3.1 Implicit Parametrizations

In implicit parametrizations, the wind-farm-flow effects on the mesoscale flow are parametrized as a change in surface roughness (Fig. 2, brown), similar to the effect of a rougher terrain on the flow. From our literature review we could identify six studies that applied an implicit approach (Table 1).

The equivalent roughness length varies across the reviewed studies between 0.5 and 2.6 m (Table 1). This is due to different ways for deriving the roughness length, due to different targeted farms in terms of turbine density or hub height. In the method of Keith et al. (2004), the height of the lowest model level was also taken into account.

3.2 Explicit Parametrization

While the implicit method can capture the deceleration of the flow around the wind farm, it does not account for the elevated nature of this deceleration and that the surface below the wind turbines can range from water to forestry. To capture this behaviour, explicit WFPs have been developed (Fig. 3) in which the surface roughness is kept unchanged but the combined effect of all wind turbines within a grid cell (Fig. 3a, blue) is effectively represented by a single profile (function of z only for each grid cell) of momentum sink and, for some parametrizations, a TKE source, for the grid cell (orange spot in Fig. 3a).

To include these effects of wind farms in mesoscale models, additional terms are added to the model equations. Mesoscale models are based on the Reynolds-averaged Navier–Stokes (RANS) equations to describe the flow evolution. Using $\bar{\phi}$ to denote the average of some quantity ϕ over the finite time increment Δt and space intervals Δx , Δy , and Δz and ϕ' to indicate deviation of ϕ from that average, i.e. the subgrid-scale perturbation (Pielke 2013), we can write the RANS equations as

Table 1 Reviewed studies applying an implicit parametrization approach

Study	Model	z_0 (m)	Comment
Barrie and Kirk-Davidoff (2010)	CAM	0.86	Derived from Lettau method; Wind-farm roughness length is $z_0 = 3.45$ m but only 25% of grid cell is occupied
Fitch et al. (2013b)	WRF ^a	2.6	Based on LES results. Different expressions for the roughness length of heat, z_t , in farms
Fitch (2015)	CAM ^a	2.6	Following Fitch et al. (2013b)
Frandsen et al. (2009)	KAMM	0.5	Based on Frandsen et al. (2006)
Ivanova and Nadyozhina (1998)	No name	–	Cited together with follow-up article (Ivanova and Nadyozhina 2000) as an example of an implicit method (e.g., Fitch et al. 2012; Porté-Agel et al. 2020), but not enough information is provided in the articles to say exactly how turbine properties are transferred to model equations
Keith et al. (2004)	CAM, AM2 ^a	variable	Parametrized as a drag perturbation increase with respect to a simulation without wind farms ($z_{0,no}$) $\delta C_D = C_D(z_0) - C_D(z_{0,no})$ with δC_D 0.0006–0.016 (0.005 mostly used)

Models are abbreviated as follows: CAM is the Research Community Atmosphere Model, AM2 is the Atmospheric Model, KAMM is the Karlsruhe Atmospheric Mesoscale Model, and WRF is the Weather Research and Forecasting model; z_0 refers to the equivalent roughness length of wind farms used in the study

^aRefers to studies using both implicit and explicit approaches

Fig. 3 Explicit WFPs in terms of **a** horizontal model grid (black solid lines) with resolution Δx , Δy with a grid cell containing several wind turbines (blue stars), which are effectively represented by a single profile (function of z only for each grid cell) of momentum sink, and for some parametrizations a profile of TKE source, for the grid cell (orange) and **b** vertical mesoscale model grid. Figure based on Porté-Agel et al. (2020)

Fig. 4 Historic overview on new explicit parametrization developments

$$\begin{aligned}
 \frac{\partial \bar{u}_i}{\partial t} + \underbrace{\bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j}}_{\text{Advection}} &= \underbrace{-\frac{1}{\rho} \frac{\partial \bar{p}}{\partial x_i}}_{\text{Pressure gradient force}} \\
 &\quad - \underbrace{\frac{\partial \bar{u}'_i \bar{u}'_j}{\partial x_j}}_{\text{Force by turbulent fluxes}} - \underbrace{2\varepsilon_{ijk} \Omega_j \bar{u}_k}_{\text{Coriolis force}} - \underbrace{\delta_{i3} g}_{\text{Gravitational force}} - \underbrace{(\delta_{i1} + \delta_{i2}) \bar{f}_{ti}}_{\text{Turbine force}}. \quad (1)
 \end{aligned}$$

In Eq. 1, u_i denotes the velocity components in the i -direction, where $i = 1, 2, 3$ correspond to the streamwise (x), spanwise (y), and vertical (z) directions, respectively; t denotes time; p denotes pressure; ρ denotes density; ε_{ijk} denotes the Levi-Civita symbol; Ω_j denotes the Earth's rotation vector; δ_{ij} denotes the Kronecker delta; g denotes the acceleration due to gravity; and $\bar{f}_{ti}$ indicates the averaged horizontal forcing due to the action of wind turbines. Since Eq. 1 is written as force per unit mass, $\bar{f}_t$ represents the momentum sink term for a control volume.

An equation for the resolved-scale TKE, with $e = \frac{1}{2} \bar{u}'_i \bar{u}'_i$, can be derived by subtracting the RANS momentum equation from the non-averaged equation and multiplying the resulting equation with u'_i (Pielke 2013; Volker et al. 2015).

$$\begin{aligned}
 \frac{\partial \bar{e}}{\partial t} &= \underbrace{-\bar{u}_j \frac{\partial \bar{e}}{\partial x_j}}_{T(\bar{u}_j)} - \underbrace{\frac{\partial \bar{u}'_j \bar{e}}{\partial x_j}}_{T(u'_j)} - \underbrace{\frac{1}{\rho} \frac{\partial \bar{u}'_j \bar{p}'}{\partial x_j}}_{T(p')} + \underbrace{\bar{u}'_i \bar{u}'_j \frac{\partial \bar{u}_i}{\partial x_j}}_{P(sh)} + \underbrace{\bar{p}_b}_{P(b)} + \underbrace{\bar{p}_t}_{P(t)} - \underbrace{\epsilon}_{\text{Dissipation}}. \quad (2)
 \end{aligned}$$

Here, $P()$ and $T()$ refer to TKE production and transport, respectively, by the process in brackets, where sh , b , and t denote shear, buoyancy, and turbine effects, respectively. Thus, $\bar{p}_t$ refers to volume-averaged turbulence induced by the turbine. All other variables are the same as in Eq. 1.

From the literature review, 10 different explicit parametrizations developed between 2004 and 2018 were identified in total (Fig. 4, bold in Table 2), although two of them, Redfern et al. (2019) and Pan and Archer (2018), are further developments or adjustments of Fitch et al. (2012). All other studies did not develop new parametrizations, but made use of existing ones.

While the WFPs differ in their description of $\bar{f}_{ti}$ and $\bar{p}_t$ in Eqs. (1) and (2), respectively, as presented in detail in Sects. 3.2.1 and 3.2.2, they are all developed on similar assumptions as all have been developed for application in mesoscale models:

Fig. 5 Usage of different WFPs, colour-coded and abbreviated according to Fig. 4, in various models identified from the systematic literature review. Models are abbreviated as follows: COSMO-CLM is the Consortium for Small-scale MOdeling (COSMO) model in CLimate Mode (CLM), METRAS is the MESoscale TRANsport and Stream model, RAMS is the Regional Atmospheric modelling System, WRF is the Weather Research and Forecasting model, AM2 is the Atmospheric Model, and CAM is the Research Community Atmosphere Model

- Turbines are oriented perpendicular to the flow.
- The flow within a model grid box is horizontally homogeneous.
- The effect of the turbine tower is assumed to be much smaller than the effect of the rotor and is ignored.
- The horizontal grid spacing needs to be at least 3–5 rotor diameters (depending on the parametrization).

Although the parametrizations could be included in all mesoscale models, most studies (Fig. 5) made use of the free, open-source Weather Research and Forecasting (WRF) model that already includes a parametrization (Fitch) in their releases. After the Fitch parametrization, the Explicit Wake Parametrization (EWP) by Volker et al. (2015) is the second most applied parametrization. The convenient accessibility of the Fitch parametrization through the WRF model not only increases the number of studies, but also leads to a broader application across different research groups and institutions. All other parametrizations are mostly applied by research groups associated with the developers of the WFP or a limited number of other groups. While this is showing the usage frequency of different parametrizations, it does not necessarily mean that the combination of the WRF model with the Fitch parametrization is the optimum method of parametrizing wind-farm effects.

3.2.1 Parametrization of Turbine-Induced Momentum Sink

The different parametrization approaches for the turbine-induced forces are summarized in Table 3. All WFPs with the exception of the EWP approach (Volker et al. 2015) have the structure of a local thrust force acting at the turbine swept area at a particular level (Fig. 3b). The number of turbines within a grid cell (Fig. 3a) are taken into account as a horizontal

density n_t of wind turbines within that grid cell. While the parametrizations are similar in structure, they nevertheless differ in several aspects: (1) the way $\bar{f}_t$ is derived, (2) the reference wind speed, U , (3) the amount of energy extracted from the flow, and (4) whether they account for subgrid-scale processes.

Following Porté-Agel et al. (2020), two different approaches are identified for defining $\bar{f}_t$: direct and indirect. In the direct approach, the induced force of each turbine is written as $F_t = \frac{1}{2} C_T \rho U^2 A_r$, with U denoting the reference wind speed, A_r denoting the rotor area, and C_T denoting the thrust coefficient. The force is then divided by the volume of a control volume (ΔV) to derive $\bar{f}_t$ in Eq. 1:

$$\bar{f}_t = \frac{1}{2} C_T U^2 A_r / \Delta V. \quad (3)$$

In contrast, in the indirect approach, the turbine is regarded as a sink of kinetic energy. By equating the rate of change of kinetic energy E of the control volume,

$$\left(\frac{\partial E_V}{\partial t} \right)_t = \rho U \left(\frac{\partial U}{\partial t} \right)_t \Delta V,$$

with the extraction rate of kinetic energy by the turbines,

$$\frac{\partial E_t}{\partial t} = \frac{1}{2} C_{KE} \rho U^3,$$

(where C_{KE} is the fraction of the available kinetic energy extracted by the turbine) one arrives at an expression for the momentum tendency,

$$\left(\frac{\partial U}{\partial t} \right)_t = \frac{1}{2} C_{KE} U^2 A_r / \Delta V, \quad (4)$$

which is used for $\bar{f}_t$ in Eq. 1. For instance, Adams and Keith (2013) and Fitch et al. (2012) arrived at the same expression for $\bar{f}_t$, although Fitch et al. (2012) used an indirect approach whereas Adams and Keith (2013) used a direct approach.

In standard actuator-disk models for wind-turbine parametrizations in microscale models, an upstream velocity is required, which is often replaced by a disk-time-averaged velocity (Abkar and Porté-Agel 2015). However, more than one turbine can be placed in one mesoscale grid cell (Fig. 3a) and thus the subgrid-scale wind speed at each turbine is unknown. The reviewed parametrizations apply different velocities to account for that effect (Table 3). Many parametrizations use the horizontal grid-cell velocity at a particular model level or at hub height as the reference velocity (Baidya Roy 2004; Keith et al. 2004; Blahak et al. 2010; Baidya Roy 2011; Fitch et al. 2012; Adams and Keith 2013; Volker et al. 2015). Abkar and Porté-Agel (2015) and Pan and Archer (2018) apply a correction factor to account for an undisturbed upstream velocity based on the layout, whereas Boettcher et al. (2015) use an averaged velocity over the entire wind farm. Redfern et al. (2019) account for veer effects by considering the angle between the wind direction and the turbine axis.

Besides different reference wind speeds, the parametrizations differ also in C_{KE} , i.e., the fraction of kinetic energy extracted from the flow (Eq. 4). They differ with respect to the applied coefficient (C_T or C_P) and to whether the coefficient is constant (Baidya Roy 2004; Keith et al. 2004) or depends on the wind speed (Blahak et al. 2010; Baidya Roy 2011; Fitch et al. 2012; Abkar and Porté-Agel 2015; Boettcher et al. 2015; Volker et al. 2015; Pan and Archer 2018; Redfern et al. 2019) or includes mechanical losses (Blahak et al. 2010). These coefficients are given in Table 3.

Fig. 6 Different definitions of velocity fluctuations within a grid cell. Figure taken from Volker et al. (2015), in accordance with the Creative Commons Attribution (CC BY) license with modified labels

Some WFPs account for subgrid-scale processes. For instance, Abkar and Porté-Agel (2015) and Pan and Archer (2018) try to capture wind-turbine interaction within a grid cell by adjusting the reference wind speed based on the layout. However, neither parametrization takes into account the layout-awareness of wakes in between two grid cells, as each assumes the entire farm to be located in one grid cell. Volker et al. (2015) noted that the vertical wake expansion within a mesoscale grid cell is not negligible and used classical wake theory to derive it.

3.2.2 Parametrization of Turbine-Induced Turbulence Kinetic Energy

There has been an ongoing debate on whether it is necessary to include an explicit source term for turbine-induced TKE in the TKE budget equation [Eq. 2] in mesoscale models. Since individual turbines cannot be resolved in a mesoscale model, the turbine-induced TKE has to interact with the boundary-layer parametrization. Volker et al. (2015) pointed out that, depending on whether the heterogeneous part of the mean flow (e.g., organized motions) is characterized as mean flow kinetic energy or as part of random TKE, one arrives at either very large deviations from the instantaneous velocity (u'') or at very small ones (u'). Therefore, depending on the philosophy used to parametrize a TKE source in a mesoscale grid cell, the direct contribution of individual turbines as a source of TKE is either negligible or relevant (Fig. 6).

Regardless of whether an explicit source term is included in the model equations, turbines are an implicit source of TKE. Through the interaction with the boundary-layer parametrization of the mesoscale model, the shear induced by the momentum sink from the presence of turbines initiates TKE production. Without an explicit TKE source term, TKE builds up gradually downwind of the wind farm due to shear, while with an explicit source TKE production is already increased within the farm (Larsén and Fischereit 2021; Pryor et al. 2020).

Out of the 10 identified parametrizations, three (Keith et al. 2004; Boettcher et al. 2015; Volker et al. 2015) neglect a turbine-induced TKE source term, whereas the other seven (Baidya Roy 2004; Blahak et al. 2010; Baidya Roy 2011; Fitch et al. 2012; Adams and Keith 2013; Abkar and Porté-Agel 2015; Pan and Archer 2018; Redfern et al. 2019) include such a term. The source terms in all parametrizations follow the common form (Pan and Archer 2018)

$$\overline{p}_t = \frac{1}{2} C_e(U) U^3 A_r, \quad (5)$$

with C_e denoting a factor that describes how much TKE is added to the atmosphere due to the presence of the turbines, and all other variables are the same as in Eq. 3. The expression for the source terms differ between the seven parametrizations and are given in Table 4. As for the momentum sink term in Table 3, the expressions differ in the applied reference wind speed [U in Eq. 5], the layout-awareness for the turbines, as well as the value and wind speed-dependence of C_e . For instance, Fitch et al. (2012) use the difference between C_P and C_T as C_e , whereas Baidya Roy (2004, 2011) use a constant value.

As pointed out above, TKE production due to wind-farm-generated shear is handled by the turbulence parametrization of the mesoscale model and an added explicit turbine-induced source term has to be correctly integrated with that turbulence parametrization. In the WRF model, which is the most often applied mesoscale model (Fig. 5), the Fitch parametrization was implemented in connection with the Mellor–Yamada–Nakanishi–Niino boundary-layer parametrization (Nakanishi and Niino 2009) to handle the transport of turbine-induced TKE (Fitch et al. 2012). In earlier versions of the WRF model ($\leq$ version 3.4), TKE advection was activated by default, whereas in later versions this advection had to be activated by the user. In line with observations that turbine-induced TKE is advected by the main flow (Porté-Agel et al. 2020), it was recommended to activate TKE advection for the Fitch and EWP approaches in the WRF model. However, some studies such as Siedersleben et al. (2020) found better agreement with observations when TKE advection was deactivated. One reason for this disagreement is that in WRF versions after version 3.5 and before version 4.2.1 (Fitch 2020) a bug was present, as recently reported by Archer et al. (2020). Due to that bug, turbine-induced TKE was not properly advected even with activated TKE advection, because the integration with the ambient TKE was incorrect (Archer et al. 2020). Archer et al. (2020) claim that the presence of this bug was not evident, since the wrong integration interacted with the high magnitude of TKE that is generated by the Fitch WFP in such a way that relatively realistic TKE profiles at the farm and velocity profiles in the wake were simulated (Archer et al. 2020). They argue that existing studies with the bug need to be revisited to check whether the conclusions drawn by the studies are still valid. A first study by Larsén and Fischereit (2021) indicated that profiles with the bug fix and an adjusted TKE source term are indeed similar to the bug-affected version even for a realistic simulation. However, more studies are needed for proper validation. Therefore, for this review, affected studies have been marked in Table 2 by a star, so readers are aware that the conclusions of these studies could be affected by the bug. In total, 24 out of 43 studies in our database that use the Fitch parametrization are affected. Since the EWP approach does not include an explicit source term (Table 4), simulations with this approach are not affected by the bug.

3.3 Comparison Between Implicit and Explicit Parametrizations

Due to their different parametrization approaches, implicit methods produce the dominant effect of wind turbines near the surface, whereas the explicit method alters the atmosphere directly at the height of the rotor. Since mesoscale models often use Monin–Obukhov similarity theory to parametrize the surface fluxes, a roughness change in the implicit method directly affects these fluxes. In contrast, in the explicit method, fluxes are affected indirectly through resolved and unresolved turbulence.

Three of the reviewed studies (Fig. 1; Keith et al. 2004; Fitch et al. 2013b; Fitch 2015) applied an explicit parametrization alongside the implicit parametrization, making it possible to compare these two different methods directly. While Keith et al. (2004) found that their implicit and explicit methods provide very similar results, Fitch et al. (2013b) found

larger differences between the two methods. In particular, Fitch et al. (2013b) found that the implicit method exaggerates wakes during the day and underestimates them during the night. The implicit method also leads to exaggerated sensible heat fluxes and thus changes in air temperature. Exaggerated influences of wind farms on maximum changes of wind speed and turbulence from the implicit method compared to an explicit method were also found by Fitch (2015) in a global study. In addition, Fitch et al. (2013b) reported that the simulations using an explicit method qualitatively agree more closely with LES results, wind-tunnel measurements, and observations than those using an implicit method.

These findings indicate that the explicit method represents the wind-farm effect in a more physically sound way, leading to more realistic results. In addition, the explicit method has the advantage of accounting for the interaction of turbine wakes with the surface below. Vanderwende and Lundquist (2016) showed that the hub-height wind-speed changes depend on the roughness length of crops around the wind farm. This interaction is also important offshore, where the roughness length depends dynamically on the wave field (e.g., Du et al. 2017). If the roughness length is changed to represent the wind turbines as in the implicit method, this dynamic influence cannot be considered. Therefore, we focus on explicit parametrizations in the remaining analysis.

3.4 Existing Validation of Explicit Wind-Farm Parametrizations

Simulations with WFPs have been validated with different types of measurements, both with in situ (e.g., masts, aircraft, or SCADA (supervisory control and data acquisition) control system data) and with remote-sensing techniques (e.g., lidar, sodar, SAR, or MODIS (Moderate Resolution Imaging Spectroradiometer) satellite images), as well as with very high-resolution LES model results (Fig. 7a). Using these techniques, different parameters have been validated, but most studies focused on wind speed, TKE, and wind power (Fig. 7b).

Often, mast, lidar, and sodar measurements have not been conducted in the direct vicinity of the wind farm. Thus, they are not used to validate the performance of WFPs but are used to evaluate the capability of the mesoscale to model the background meteorological conditions (Lee and Lundquist 2017a; Tomaszewski and Lundquist 2019; Lundquist et al. 2019). As several studies have indicated, it is essential that the background meteorological conditions are well simulated (e.g., Lee and Lundquist 2017a; Siedersleben et al. 2018b, 2020), since otherwise the validity of the WFP cannot be evaluated.

Studies that focused on the evaluation of the WFP itself mostly used the Fitch parametrization followed by the EWP parametrization (Fig. 7). Abkar and Porté-Agel (2015) and Pan and Archer (2018) compared their new WFPs against LES results and the Fitch parametrization. The results of the different validation studies are summarized in Table 2.

It is difficult to draw conclusions on the performance of the WFP from the existing validation studies since the results sometimes contradict each other. For instance, Vanderwende et al. (2016), Abkar and Porté-Agel (2015), and Eriksson et al. (2015) found the TKE to be overestimated by the Fitch parametrization compared to LES results. In contrast, Siedersleben et al. (2020) found a good agreement above an offshore wind farm with flight measurements, if the background meteorology is well simulated. Lee and Lundquist (2017a, b) found good agreement with lidar measurements, although with large uncertainty. This indicates that the validity of the WFPs may also depend on other parameters such as stability or the background environment. In addition, the WRF bug related to the interaction of turbine-induced TKE and TKE advection in the WRF model, as discussed in Sect. 3.2.2, makes it difficult to draw conclusions from the affected studies. Based on this finding, we suggest that benchmark-like

Fig. 7 **a** Applied validation methods and **b** validated parameters in the reviewed studies grouped by WFP and colour-coded and abbreviated according to Fig. 4. In ‘WS Remote sensing’, WS refers to wind speed and includes profiling and scanning lidar, sodar, and radiometer. ‘Others’ include nacelle anemometer, capacity factor, hurricane track, and comparison against other model results; each of those were only used once

validation studies should be conducted in the future to better assess the advantages and disadvantages as well as the validity of individual WFPs. This, and the need for more measurements for verification and validation, are discussed in Sect. 5.

4 Application of Wind-Farm Parametrizations

Following the development of the mesoscale wind-farm parametrizations as described in the previous section, these parametrizations have been applied for a wide range of purposes. In this section, after an overview on applications and model sensitivities (Sect. 4.1), three main application areas have been identified and are discussed in detail: characterization of wind-farm wakes (Sect. 4.2), wind-farm impacts on the environment (Sect. 4.3, and wind-energy planning (Sect. 4.4). Please note that this review focuses on mesoscale model applications using explicit parametrizations, since they have been shown to give more realistic results (Sect. 3.3). For a review on applications of implicit parametrizations, the reader is referred to Abbasi et al. (2016).

4.1 Overview on Applications and Model Sensitivities

Our survey of studies shows that wind-farm parametrizations have been used in different mesoscale and global models (Fig. 5, Table 2). Of those models, the WRF model is the most applied as likely due to its open source status. The mesoscale models with WFPs have been applied both to onshore and offshore environments (Fig. 8a) for different parts of the world (Fig. 8b). However, all reviewed studies were conducted for the Northern Hemisphere and

Fig. 8 Number of studies **a** investigating a specific study area and **b** applied to a specific country or region. Studies are grouped by WFP and colour-coded and abbreviated according to Fig. 4. The colour bar in **b** shows the total number of studies from each region coloured on the map. The pie charts indicate the relative frequency of applied WFPs in each region and the pie chart with blue edge colour in Europe refers to offshore applications

all offshore studies were conducted for northern European seas, almost exclusively for the North Sea. Those two observations reflect the current installed onshore and offshore installed capacities around the world: according to IRENA (2019), about 93% of overall installed wind capacity is located in North America, Europe or Asia and “90% of global installed offshore wind capacity is commissioned and operated in the North Sea and nearby Atlantic Ocean”, i.e. other regional seas surrounding Europe.

Many mesoscale models can be applied in different model configurations: either forced by reanalysis data, often called real mode, or in an ideal mode with simplified profiles for wind, temperature, and humidity that can vary over time and either can be taken from soundings or defined artificially. For early stage developments of the different wind-farm parametrizations, ideal model configurations are often used. Often, relatively simple neutral atmospheres have

Fig. 9 Number of studies applying a WFP in an ideal or real mesoscale model configuration for different years. Please note that for 2020 only studies up to May have been included

been simulated (Fitch et al. 2012; Volker et al. 2015) to be able to compare with LES results or wind-tunnel measurements or for sensitivity experiments. In recent years especially, the number of studies with real model configurations has increased (Fig. 9).

Along with more complex simulations, a trend towards a finer horizontal spatial resolution (Δx , Fig. 10, Table 2) is also visible. Some studies used horizontal resolutions of a few hundred metres to place each turbine of a wind farm in individual cells and account for intra-farm wake effects (e.g., Jiménez et al. 2015; Eriksson et al. 2017). Such resolutions lie within the grey zone or the terra incognita numerical region (Wyngaard 2004; Honnert et al. 2020) between modelling regimes of high-resolution atmospheric modelling (resolution in the order of a few tens of metres) and traditional meteorological modelling (resolution in the order of a few kilometres). Applying mesoscale models in the grey zone means that large coherent overturning structures with a dominant turbulent length scale l start to be partially resolved in simulations having an effective resolution of Δ if $l \approx \Delta$ (Honnert et al. 2020). This violates the fundamental assumptions (e.g., horizontal homogeneity) behind the turbulent parametrizations traditionally used in mesoscale models (Honnert et al. 2020). Hence, the grey zone is not a physical phenomenon, but arises from the assumptions made in the turbulence and shallow convection parametrizations (Honnert et al. 2020). As a consequence, the accuracy and value of the numerical modelling simulations with effective resolutions in that region might be compromised (Honnert et al. 2020). In addition, the assumptions for the derivation of WFPs (Sect. 3.2) are also violated on these resolutions (Fitch 2016). Therefore, it is questionable whether simulation results of mesoscale models with a WFP with such a high resolution can be trusted.

Since the model resolutions applied vary significantly between studies (Fig. 10), this raises the question of which upper limit of resolution is appropriate for applying WFPs. Different studies, conducted both onshore and offshore, found model results to be sensitive to both the horizontal and vertical resolution (Lee and Lundquist 2017b, a; Tomaszewski and Lundquist 2019; Siedersleben et al. 2020; Pryor et al. 2020), indicating that a horizontal resolution of at least 3–5 km is required to obtain reasonable results (Yuan et al. 2017; Tomaszewski and Lundquist 2019; Pryor et al. 2020; Siedersleben et al. 2020). In addition, Pryor et al. (2020) noted that simulated TKE values depend on the grid resolution and higher resolutions are associated with higher TKE values (Sect. 4.2). There is conflicting evidence in the literature as to the dependence of the vertical-resolution (Δz) requirement on atmospheric stability. In idealized neutral conditions, Volker et al. (2015) and Fitch et al. (2012) found only a small sensitivity to Δz (e.g., Volker et al. 2015 who used the neutral condition), while others in real mode (e.g., Lee and Lundquist 2017a; Tomaszewski and Lundquist 2019; Pryor et al. 2020; Siedersleben et al. 2020) found that vertical resolutions in the order of 10–15 m are

Fig. 10 Horizontal (Δx) and vertical (Δz) resolution applied in the reviewed studies in different years (colour- and symbol-coded). Symbols with black edges indicate global climatic studies; panel **b** magnifies the regional studies only (blue area in panel **a**). The grey fading area *roughly* indicates the grey zone for mesoscale models. Note that the grey zone differs depending on the turbulent structures present in a simulation and the parametrizations used. The green areas *roughly* indicate the grid spacing in the horizontal and vertical directions that should not be exceeded for an appropriate representation of wind-farm effects based on the reviewed studies. Please note that the vertical resolutions of the studies are often approximate, since they vary with height and sometimes had to be inferred from the provided information. If no information was given, $\Delta z = 0$

required in order to capture the wake features in stably stratified conditions, as for example the evening transition (Lee and Lundquist 2017b). This emphasizes again the importance of atmospheric stability in wind energy. Overall, the EWP approach seems to be less sensitive to the vertical resolution than the Fitch parametrization (Volker et al. 2015; Pryor et al. 2020), probably due to the missing explicit TKE source term. Although several studies agree on the required horizontal and vertical resolutions, one has to keep in mind that most of those studies are affected by the TKE bug described in Sect. 3.2.2. Therefore, further studies with the bug-fixed WRF model are necessary to confirm these recommendations. Nevertheless, the past studies suggest that model resolution affects the modelled wind-farm effects and thus also the wind-farm impacts on temperature (Tomaszewski and Lundquist 2019, Sect. 4.3.1) and gross capacity factors (Pryor et al. 2020, Sect. 4.4)

Besides the sensitivity of simulation results to resolution, the sensitivity of the parametrizations to the prescribed thrust and power curves (Sect. 3.2) for the individual turbine types were also assessed. In that regard, Cervarich et al. (2013) and Jiménez et al. (2015) found that the coefficients C_T and C_P influence the results, while Siedersleben et al. (2020) found that their influence is smaller than that of the vertical resolution. Siedersleben et al. (2020), Xia et al. (2019) and Vanderwende et al. (2016) found a smaller influence compared to changing the model physics, such as incorporating a TKE source term. Finally, the sensitivity of the model results to the chosen WFP is evaluated, which is discussed in detail below.

The WFPs have been applied to study the impact of wind farms on different parameters. Figure 11 shows the breadth and depth of investigated parameters in the different studies. The impact on the wind speed and TKE were naturally among the most studied parameters and how these parameters are influenced is discussed in Sect. 4.2. The impacts of wind farms on power or capacity factors were also included in a number of investigations and the impacts are discussed in the context of planning of wind energy in Sect. 4.4. Finally, the impact

Fig. 11 Number of studies investigating an impact of wind farms on a certain parameter grouped by WFP and colour-coded and abbreviated according to Fig. 4

on a broad range of other environmental parameters has been investigated. The results on temperature and humidity, clouds and precipitation are summarized in Sect. 4.3.

4.2 Characterization of Wind-Farm-Flow Effects

The individual turbine wakes and how they affect flows and production within single wind farms has been studied for some time and different models have been derived (Porté-Agel et al. 2020). Downwind of the farm, individual wakes mix to a so-called farm wake. The characterization of these farm wakes in terms of spatial and vertical extent is of growing interest. With the number of wind farms increasing, farm-to-farm impacts on power output and power fluctuations become more prevalent. Since measurements are often quite sparse, mesoscale models together with WFPs have been used to characterize these, while in situ measurements have been used for point validations (e.g., Volker et al. 2015; Platis et al. 2018). The characterization is usually done in terms of wind-speed reduction and TKE enhancement.

4.2.1 Impacts on Wind Speed

Figure 12 shows the normalized wind speed at hub height along the main wind direction for different scenarios and two WFPs. In general, an undisturbed flow approaching the wind farm has slightly reduced wind speed ahead of the farm (e.g., Fitch et al. 2012; Volker et al. 2015) due to an induction effect, which is often referred to as the global blockage effect of a wind farm. Within the wind farm, the wind speed is then further reduced by the extraction of kinetic energy from the turbines. Downwind of the farm, the wind speed slowly recovers due to mixing with higher momentum air from outside of the wake. The recovery length can be larger than 60 km as confirmed by in situ aircraft measurements (Cañadillas et al. 2020), lidar measurements (Schneemann et al. 2020a), or SAR images (Hasager et al. 2015). In two-dimensional distributions of wind speed with height or with cross-wind direction, it is apparent that the wind-farm-flow-affected area expands both horizontally and vertically with

Fig. 12 Normalized wind speed at hub height for different scenarios (C1–C4) using the EWP WFP (a) and the Fitch WFP (b). The wind-farm extension is marked by the vertical dotted lines. The scenarios are given in the table, where θ refers to the potential temperature and Fr to the Froude number. Reprinted with permission from Volker (2014)

increasing distance (Fitch et al. 2012; Volker et al. 2015) and speed-ups can be present on the side of the wind farms (Siedersleben et al. 2020).

Each stage of the wind-farm effect on the flow (in front of, within, and behind the wind farm) is influenced by the ambient meteorological conditions, foremost stability. In general, during stable conditions, global blockage effects are stronger (Volker et al. 2015; Schneemann et al. 2020b, Fig. 12) and wake lengths are longer (e.g., Emeis 2010; Fitch et al. 2012; Hasager et al. 2015; Emeis et al. 2016; Lundquist et al. 2019; Cañadillas et al. 2020; Siedersleben et al. 2020; Schneemann et al. 2020a) due to less turbulent mixing. In addition, stable conditions suppress vertical motion and force the flow around the farm rather than extend it vertically. This causes speed-ups at the farm edges and around the farm (Fitch et al. 2012; Nygaard and Hansen 2016; Siedersleben et al. 2020). Another important related parameter is the inversion strength. A stronger capping inversion reduces the velocity deficit within the farm and leads to a different wake recovery (Fig. 12, C3 and C4). Depending on the baroclinicity of the flow, gravity waves can develop and travel horizontally downstream (Smith 2010; Volker 2014).

The wake length and wake structure also depend on the surface conditions. Wakes interact with orography, creating a heterogeneous area of lower wind speed (Prósper et al. 2019). More details on the interplay of individual turbine wakes with orography can be found in Porté-Agel et al. (2020). In flat terrain, the aerodynamic roughness length plays an important role: for a larger roughness length, turbulence intensity is larger in general, which produces a faster recovery rate behind the farm, i.e. shorter wake lengths (Porté-Agel et al. 2020). Offshore, the aerodynamic roughness length and thus turbulence intensity are often smaller than onshore (Emeis et al. 2016), which explains why the wake lengths tend to be longer offshore than onshore (Emeis et al. 2016). However, onshore wake lengths of 50 km have also been simulated (Lundquist et al. 2019).

The different WFPs cause different patterns of wind-speed reduction within the farm and recovery downwind, as shown in Fig. 12 for the EWP and Fitch approaches. The EWP approach shows a more linear reduction within the farm, while the Fitch approach shows a more exponential decrease. In addition, the maximum wind-speed deficit is simulated differently in the EWP and the Fitch parametrization with the EWP parametrization tending

to show smaller wake effects (Volker et al. 2015; Pryor et al. 2018a; Shepherd et al. 2020; Pryor et al. 2020; not visible in Fig. 12). Downwind of the farm, the wind speed recovers in a more linear (EWP) or more exponential (Fitch) way (Fig. 12). The more linear behaviour of the EWP approach can likely be attributed to the combined effect of the subgrid-scale wake expansion (Sect. 3.2.1) and the missing TKE source term (Sect. 3.2.2). The recovery length has been found to be shorter for the EWP parametrization than for the Fitch parametrization over land (Pryor et al. 2018a, 2020; Shepherd et al. 2020), whereas over water Volker et al. (2015) found the opposite in ideal simulations. An analysis of in situ aircraft measurements indicates that wake recoveries are for all stability conditions mostly exponential but can also be approximately linear (Cañadillas et al. 2020).

In the presence of neighbouring wind farms, the wakes of individual wind farms interact with each other (Nygaard and Hansen 2016; Nygaard and Newcombe 2018; Wang et al. 2019b). Due to the upwind wind farm, the downwind wind farm is not approached by a freestream velocity but with an already reduced velocity (Fig. 13), which is, however, more turbulent (Nygaard and Hansen 2016). Because of this reduced velocity, the overall recovery distance increases compared with a single wind farm. By adding and removing an upstream wind farm, Wang et al. (2019b) estimated for an onshore case study in China that the recovery length doubles in the presence of the upwind farm.

One challenge that we identified is that from our review there is no standardized or common definition of a recovery length behind a farm. Studies used for instance the e-folding distance (Fitch et al. 2012), the location of 2% difference between a simulation with and without wind farms (Pryor et al. 2020) or the location where the wind speed has recovered to 95% of the freestream wind speed (Cañadillas et al. 2020). Due to this variety of different definitions, it is difficult to compare wake lengths across studies quantitatively.

4.2.2 Impacts on Turbulence Kinetic Energy

While the wind-farm-flow effect in terms of wind-speed reduction has been extensively studied and validated, the impact on the TKE has received less attention. One reason is that high-frequency measurements, which are required for the derivation of TKE, are costly, storage intensive, and thus are not often available. In addition, the horizontal and vertical distributions of TKE around wind farms is also more complex compared to the velocity deficit. Mast, aircraft, and lidar measurements indicate, respectively, that compared with the ambient TKE, TKE is larger within the farm at hub height (Baidya Roy 2004), above the farm (Siedersleben et al. 2020) as well as downwind within the wake (Lee and Lundquist 2017b), where it is advected with the mean flow (Porté-Agel et al. 2020). Vertically, the largest TKE production occurs at the upper edge of the wake, where mean shear and turbulent fluxes are largest (Porté-Agel et al. 2020).

As with the wind-farm impact on wind speed (Sect. 4.2.1), wind-farm impacts on TKE also depend on atmospheric stability and ambient meteorological conditions. Lee and Lundquist (2017b) investigated the TKE development during the evening transition and found that TKE values within the wake decrease after the evening transition when the atmosphere becomes stable. They also noted that the variations in the vertical velocity component contribute most to the turbulence enhancements above the turbine rotor layer during the evening transition. The role of ambient meteorological conditions was highlighted in Platis et al. (2018) based on aircraft measurements: the TKE development in the wake of an offshore wind farm was superimposed with a TKE evolution due to a large wind-speed gradient from the coast to the open sea.

Fig. 13 Hub-height wind-speed recovery of a one-year-long simulation for 2018 with the Fitch ('FIT') parametrization filtered for stable conditions ($0 < L \leq 500$, with L being the Obukhov length), $250\text{--}270^\circ$ wind direction and wind speeds of $5\text{--}10 \text{ m s}^{-1}$ for the wind farms DanTysk and Sandbank in the North Sea together with SCADA data from DanTysk filtered for the same conditions. Reprinted with permission from Catton (2020) with turbine positions added

The wind-farm impact on TKE is parametrized very differently across the WFPs (Sect. 3.2.2). As a consequence, the simulated horizontal and vertical TKE distributions also differ more strongly between WFPs than the distributions of wind-speed deficits (Sect. 4.2.1). It was found that the Fitch parametrization generally calculates higher TKE values than the EWP parametrization (Volker et al. 2015; Pryor et al. 2020) due to the explicit source term. In their idealized simulations, Abkar and Porté-Agel (2015) found that TKE values simulated by the Blahak approach were consistently smaller than those by the Fitch approach and that those by the Abkar approach were in between irrespective of the wind-farm layout and density.

Besides the different magnitudes, the spatial distribution of TKE also differs between the WFPs. The Fitch approach shows high TKE values within the farm at all levels, while the EWP approach shows a reduction below the rotor due to the extraction of kinetic energy and an increase downwind and above (Volker et al. 2015; Shepherd et al. 2020). Higher TKE values at the upper parts and above the rotor agree better with lidar observations (Lee and Lundquist 2017b) and LES results (Porté-Agel et al. 2020). With greater distance downstream of the farm, the TKE difference between the Fitch and EWP approaches diminishes (Volker et al. 2015; Shepherd et al. 2020).

Simulated TKE values with a WFP also depends on the mesoscale model set-up and the remaining model physics. As already discussed in Sect. 4.1, the horizontal and vertical resolution influences the TKE (Pryor et al. 2020). The interaction of the mesoscale model

Fig. 14 Schematic description of the **a** warming and **b** cooling effects at hub height downwind of offshore wind farms. The dashed and the solid grey lines indicate as the rotor area and the hub height, respectively. The black thick line shows the potential temperature profiles upwind of the wind farms, the impact on the potential temperature profiles of the wind farm is indicated in **a** red and **b** blue. Figure taken from Siedersleben et al. (2018a) in accordance with the Creative Commons License 3.0. (CC BY) with modified labels

physics with the turbulence parametrizations becomes evident through the bug, as discussed in Sect. 3.2.2. Since very few studies investigated the influence of this bug on results, we cannot draw conclusions on the implications for the affected studies (marked by a star in Table 2).

4.3 Environmental Impact of Wind Farms

Due to their influence on the flow and turbulence, wind turbines also affect other atmospheric parameters, with temperature being the most studied.

4.3.1 Impacts on Temperature and Humidity

Observational evidence for an influence of wind turbines on air temperature exists from tower (Baidya Roy and Traiteur 2010; Smith et al. 2013; Foreman et al. 2017) and aircraft measurements at rotor heights (Siedersleben et al. 2018a) as well as for the influence on surface temperature from MODIS satellite measurements (Cervarich et al. 2013; Xia et al. 2017). Applying the WFPs, these observations could be reproduced (Baidya Roy 2011; Xia et al. 2017; Siedersleben et al. 2018a; Xia et al. 2019), although were probably underestimated in magnitude (Cervarich et al. 2013; Xia et al. 2017).

The primary cause for temperature changes is enhanced mixing induced by the turbines: in stable conditions warmer air is mixed downwards (Baidya Roy 2004; Baidya Roy and Traiteur 2010; Fitch et al. 2013a; Shepherd et al. 2020; Miller and Keith 2018; Wang et al. 2019a; Platis et al. 2020), whereas at the upper half of the rotor and above, the air is cooled (Fitch et al. 2013a; Siedersleben et al. 2018a). In the presence of an inversion, its vertical location determines the influence on temperature: in the presence of an inversion at the upper part, or just above the rotor (Fig. 14a), warmer air is mixed downwards resulting in a warming effect at hub height. For lower inversion heights below hub height cooling occurs at hub height, (Fig. 14b, Siedersleben et al. 2018a; Platis et al. 2020).

Near the surface, the magnitude and direction of the kinematic sensible heat fluxes are defined by the gradient between the surface and the atmosphere and the friction velocity, according to commonly applied Monin–Obukhov theory in mesoscale models (Pielke 2013)

$$\overline{w'\theta'} = -K_\theta \frac{\partial \bar{\theta}}{\partial z} = -u_* \theta_*, \quad (6)$$

where w denotes the vertical velocity component, θ denotes the potential temperature, K_θ denotes the exchange coefficient for heat, u_* and θ_* denote scaling variables for momentum and heat, respectively; other variables and the meaning of ϕ' and $\bar{\phi}$ are the same as in Sect. 3.2.

While the magnitude of u_* generally decreases within and downwind of a farm (Boettcher et al. 2015; Porté-Agel et al. 2020), except for rare episodes with accelerated near-surface flow due to downward mixing of faster air (Fitch et al. 2013a), the temperature gradient between the atmosphere and the surface varies. Taking the downward mixing of warmer air into account, Platis et al. (2020) argue that the direction of the wind-farm impact on the fluxes depends on the direction of this gradient between sea-surface temperature and the lower atmosphere, but always results in a net increased sensible heat flux towards the ocean. Boettcher et al. (2015) noted that, due to the reduced value of u_* , the sensible heat flux from the ocean to the atmosphere decreases, which increases the temperature gradient and thus counteracts the effect of reduced u_* . However, they note that this second effect is generally weaker than the effect of the wind-speed reduction by the farm.

All studies agree that the changes in sensible heat flux are in general small and in the order of $1\text{--}10\text{ Wm}^{-2}$ (Fitch et al. 2012; Boettcher et al. 2015; Platis et al. 2020). Correspondingly, near-surface temperature changes (Fitch et al. 2012; Boettcher et al. 2015; Siedersleben et al. 2018a) and surface temperature changes are also small in general (Cervarich et al. 2013; Xia et al. 2017) and in the order of 0.5 K. Since atmospheric stability and the temperature gradient between the surface and atmosphere determine the magnitude and direction of the temperature changes by the turbines, it is evident that general stability effects in onshore and offshore environments during the course of a day, and throughout the year, play a role in observed temperature changes. Onshore stable conditions are present mostly during the night or early morning and thus warming is most notable during these times, while during the day the warming is weakened or cooling occurs both in the air (Baidya Roy and Traiteur 2010; Baidya Roy 2011; Fitch et al. 2013a; Miller and Keith 2018) as well as at the surface (Cervarich et al. 2013; Xia et al. 2017). Offshore, temperature contrasts vary during the course of a year rather than during one day (Emeis et al. 2016) and are modulated by moving depressions or coastal effects when the flow is from the land to the sea (Emeis et al. 2016). Therefore, wind-farm effects are often episodic (Siedersleben et al. 2018a) and strongly depend on the inversion height, which was observed to be as shallow as 30 m offshore in Siedersleben et al. (2018a).

Since the primary cause for the temperature effect of turbines within the wake is enhanced mixing of air masses with a different temperature, studies (Xia et al. 2019; Tomaszewski and Lundquist 2019) have investigated the role of an explicit TKE source term for these changes. They found that an explicit source term is required in the Fitch parametrization to simulate a near-surface warming effect in the farm (Tomaszewski and Lundquist 2019). Without that source term cooling was simulated, which was not evident from MODIS satellite measurements (Xia et al. 2017, 2019). Although all these studies are affected by the bug in the WRF model as described in Sect. 3.2.2, the conclusion is likely be valid even with the bug-fix, since the TKE profile is very similar with the new version and a correction factor (Archer et al. 2020; Larsén and Fischereit 2021). In addition, Shepherd et al. (2020) and Pryor et al. (2018a) noticed that the temperature impact from the Fitch parametrization is generally larger than the impact from the EWP parametrization, which does not include an explicit source term for TKE (Table 4), and that the EWP parametrization tends to show cooling effects more often than the Fitch parametrization.

To derive whether the described warming effect of wind farms is only present episodically, as evident from the observational studies above, or whether it changes the local, regional, or global climate in general, longer periods have to be investigated. Several studies were

conducted with relatively coarse resolution of $\Delta x \approx 30$ km at a country level (U.S.A., Miller and Keith 2018, China, Huang et al. 2019; Sun et al. 2018), continental level (Europe, Vautard et al. 2014) or even globally (Keith et al. 2004; Fitch 2015). The results imply that regional near-surface temperature changes are relatively small, usually smaller than ≈ 0.5 K (Keith et al. 2004; Fitch 2015; Sun et al. 2018; Miller and Keith 2018; Huang et al. 2019), mostly confined to areas close to the wind farm (Keith et al. 2004; Fitch 2015), and statistically significant changes were evident only seasonally, e.g., in winter for Europe Vautard et al. 2014. The effects are highly dependent on the location and size of the wind farm as well as the interaction with the regional weather pattern (Sun et al. 2018; Huang et al. 2019).

While these long-term studies indicate only small effects, one also has to recognize that they all apply models with relatively coarse horizontal and vertical resolutions. Tomaszewski and Lundquist (2019) indicated that a coarser resolution weakens the warming signals, which then span greater areas. Since current computational power does not allow for global 30-year simulations with a sufficiently high resolution to capture wind-farm effects (Sect. 4.1), several studies reduced the target area to country level and used smaller time spans, by simulating, for example, four individual months representative for each season (China, Wang et al. 2019a), by selecting a climatic representative year to simulate (U.S.A., Pryor et al. 2018a, b; Shepherd et al. 2020) or by simulating individual days in a statistical dynamical downscaling method that, when combined, represent 30 years of summer climate (Northern Germany, Boettcher et al. 2015). These high-resolution studies agree with the coarser studies that the impact of wind farms is small (≈ 0.5 K) and varies between seasons and regions (Pryor et al. 2018a, b; Shepherd et al. 2020; Wang et al. 2019a). Statistically significant warming effects were found for Zhangbei, China only for winter (0.2 K, Wang et al. 2019a), whereas Pryor et al. (2018a, b) and Shepherd et al. (2020) noted the largest, and only, significant impacts for Iowa, U.S.A. in summer (up to 0.5 K). In contrast to the cited onshore studies, Boettcher et al. (2015) noted a widespread summertime cooling in northern Germany for a very large offshore wind-farm scenario in the German Bight using their parametrization (Tables 3 and 4) and the mesoscale model METRAS (all other mentioned model results are from the WRF model). For the same area, Vautard et al. (2014) found a slight warming effect. Reasons for this disagreement could include the choice of wind-turbine characteristics and position, or the application of a different wind-farm parametrization that does not include a TKE source term as described above.

In summary, all studies indicate that the wind-farm effect is small (≈ 0.5 K); mostly confined to the wind-farm area; depends on the investigated area, turbine density and wind-farm location; and is strongly dependent on the meteorological situation as well as weather patterns and hence long-term effects depend on the background climate in that area. Taking this into account, the influences of wind farms on near-surface temperature are much smaller compared with changes projected by the Intergovernmental Panel on Climate Change (IPCC) (Collins et al. 2013) and are also primarily caused by a vertical redistribution of heat. In general, WFPs can reproduce the observed temperature changes, although the magnitude is sometimes underestimated.

The influence of wind farms on humidity is less studied than the influence on temperature. In stable situations, potentially with an inversion, a drying of the near-surface atmosphere was noted in several studies, when drier air is mixed down along with warmer air from the wind-turbine-induced turbulence (Baidya Roy 2004; Hasager et al. 2017; Siedersleben et al. 2018a; Tomaszewski and Lundquist 2019). As for the wind-farm effect on temperature, a sufficiently high resolution and an explicit TKE source is required to simulate this effect (Tomaszewski and Lundquist 2019). Baidya Roy (2011) noted that the background meteorological conditions (e.g., stability and total water mixing ratio lapse rates of the atmosphere)

affect the sign of the wind-farm impact on humidity. Averaging near-surface humidity over entire seasons and larger areas in Iowa, Pryor et al. (2018a,b) and Shepherd et al. (2020) found that humidity is slightly increased in the presence of wind farms but with a widespread distribution around zero. Consistent with the discussion on temperature, the EWP approach shows smaller impacts (Pryor et al. 2018a; Shepherd et al. 2020) and has a trend towards moistening of the lower atmosphere (Pryor et al. 2018a), which may be due to the missing TKE source term as indicated by Tomaszewski and Lundquist (2019). Climate-wise, Pryor et al. (2018a,b) and Shepherd et al. (2020) found only significant impacts on humidity for summer for the onshore wind farms in Iowa, U.S.A. The relative increase in near-surface specific humidity amounted to $< 5\%$ and was regionally mostly confined to wind-farm areas.

4.3.2 Impacts on Clouds and Precipitation

Some studies also noted an impact of wind farms on clouds and precipitation. Fitch (2015) found in their global study a slight increase in low clouds above the wind farm due to flow convergence and uplift at the upstream edge and a slight decrease downstream. Boettcher et al. (2015) also noted an effect on cloud development for a large offshore wind-farm scenario in the German Bight that caused a slight intensification of the summer urban heat island for the city of Hamburg (100 km from the coast). Non-conclusive results exist with respect to a wind farm's influence on precipitation: while Fiedler and Bukovsky (2011) found a statistically significant average increase of precipitation of 62 warm seasons in a multi-state area surrounding and to the south-east of the wind farm for a very large wind farm in the central U.S.A., Pryor et al. (2018a) found a small decrease in their year-long simulation in Iowa and also a decrease in seasonal total precipitation.

Changes in precipitation were also found in combination with tropical and extratropical cyclones. The case study of Hurricane Harvey in Pan and Archer (2018) using the WRF model with the Fitch parametrization indicates that offshore wind farms have a strong impact on the distribution of accumulated precipitation over the U.S.A. coastal areas, with an obvious decrease onshore downstream of the wind farms and an increase in offshore areas. Lauridsen and Ancell (2018) noted a statistically significant increase in precipitation for several extratropical case studies in the U.S.A. The impact depended on the wind-farm size and location relative to the extratropical cyclone genesis region and track.

4.3.3 Oceanographic and Ecosystem Impacts

During our literature research (Fig. 1), we also found seven studies that examined the impact on the ocean or lake thermodynamics (Menzel et al. 2007; Alari and Raudsepp 2012; Paskyabi and Fer 2012; Li et al. 2014; Segtnan and Christakos 2015; Afsharian and Taylor 2019; Afsharian et al. 2020) as well as four studies that investigated the marine ecosystem (Moher et al. 2009; Janßen et al. 2015; Floeter et al. 2017; Slavik et al. 2019), and 11 studies investigating land-based wildlife impacts (Loss et al. 2013; Roscioni et al. 2013, 2014; Drake et al. 2015; Bastos et al. 2016; Silva et al. 2017; Skarin and Alam 2017; Newson et al. 2017; Horswill et al. 2017; Heuck et al. 2019; Schaub et al. 2020). While ecosystem studies are beyond the scope of this review, the impacts on marine thermodynamics are physical effects and are therefore briefly reviewed here with the focus on WFPs.

In general, offshore wind farms affect marine thermodynamics in two ways: through the foundation structures, or wind-farm pile, and through a reduced surface wind speed within a confined region in the wake. The foundations can induce internal wakes and vortices through

the interaction with the tidal current (Menzel et al. 2007; Li et al. 2014) and alter the wave field due to wave reflection and diffraction (Alari and Raudsepp 2012). However, none of these aforementioned studies takes the effect of a changed near-surface wind field (Sect. 4.2) into account. This effect has been parametrized using simple wake models by Paskyabi and Fer (2012) and Segtnan and Christakos (2015) to study the effect of changes on the wind-stress curl and wave forcing on the Ekman current and upwelling and downwelling, and by Afsharian and Taylor (2019) and Afsharian et al. (2020) to investigate the impact of wind farms on the thermocline and mixed-layer depth in Lake Erie.

Although these last studies included the effect of wind reductions in the wake, they did not make use of a WFP in a coupled mesoscale model simulation. Due to that, they cannot account for thermal and humidity-related effects of wind farms (Sect. 4.3.1) as well as the altered wave field and thus altered aerodynamic roughness in the wake (Sect. 3.3) and its impact on the atmosphere. This missing coupling could influence the conclusion of the impact of wind farms on marine thermodynamics and is therefore identified as area for future research, as discussed in Sect. 5.

4.4 Planning of Wind Energy

The reduced wind speed and increased turbulence in wind-farm wakes (Sect. 4.2) affects the inflow of a downstream wind farm (Fig. 13), which limits the power production of downstream wind farms. The impact of neighbouring wind farms depends on a lot of factors, such as their distance to each other; the relative frequency of wind directions that are affected by wakes of upstream farms; wake length (to determine whether a neighbouring farm is affected); the frequency of wind-speed range such that the wind turbines exhibit a high sensitivity to changes in wind speed (Volker et al. 2017; Pryor et al. 2018a; Lundquist et al. 2019; Pryor et al. 2020); the spatial extent and density of the individual farms; and their turbine types and layouts (Volker et al. 2017), as well as the background climate. Wind-farm parametrizations along with mesoscale models have been used to study these dependencies. To characterize the impacts of upwind farms on downwind farms, different metrics have been used: the capacity factor, i.e., the ratio between the actual energy output over a period and the maximum possible energy output over the same period (Volker et al. 2017; Pryor et al. 2018a, 2020); the efficiency, i.e., the ratio of the power production with and without wake effects (Volker et al. 2017); the relative power deficit, i.e., the 100% value minus the efficiency (Wang et al. 2019b); the generation loss, i.e. the temporal sum of the difference in capacity factors with and without wakes multiplied by the total capacity (Lundquist et al. 2019); or the annual resource loss, i.e., the average annual wind-speed reduction due to the presence of wakes (Prósper et al. 2019).

In the direct vicinity of a wind farm, average generation losses have been simulated to amount to 5% (U.S.A., distance of several hundred metres Lundquist et al. 2019), average relative power deficits to 6% (China, distance of 2 km Wang et al. 2019b) and the annual resource loss to exceed 6% (Spain, close to the farm, Prósper et al. 2019). With increasing distance these matrices are reduced, but even in heterogeneous terrain Prósper et al. (2019) estimated annual resource losses to amount to 0.5% at about 17 km downstream. All these studies used the WRF model equipped with the Fitch parametrization for their estimation. In comparing the the Fitch and EWP approaches, Pryor et al. (2018a, 2020) and Shepherd et al. (2020) showed that system-wide gross capacity factor are on average 2–6% higher with the EWP approach than with the Fitch approach in Iowa, U.S.A. Although this result is also affected by the bug in the WRF model (Sect. 3.2.2), it is consistent with the described

Fig. 15 Actual power density (APD) relative to reference power density (RPD, no wake) for very large wind farms ($1.1 \times 10^5 \text{ km}^2$) subject to three different wind climates and turbine spacings as simulated with the EWP WFP and the Fitch WFP (here WRF-WF). Figure taken from Volker et al. (2017), in accordance with the Creative Commons Attribution 3.0 (CC BY) license

behaviour for wind-farm wakes of the two parametrizations (Sect. 4.2) and agrees with Volker et al. (2017) for different idealized onshore and offshore scenarios. In addition to this dependence of gross capacity factors on the WFP simulations, Pryor et al. (2020) noted a clear dependency of simulated gross capacity factors for Iowa on the model resolution: with increasing horizontal and vertical resolution, the spatial extent of the area affected by velocity deficits at hub heights in excess of 2% is reduced, which is partly due to the higher wind speeds being simulated in the high-resolution scenarios.

The above studies indicate that the impact of neighbouring wind farms cannot be neglected for estimating global or regional wind-power potential and for planning of wind energy. In this line of thought, the question has been raised whether there is a limit to the extractable power per wind-farm area, i.e. a maximum farm power density (Volker et al. 2017), and whether this limit depends on background conditions (onshore/offshore) as well as farm characteristics. Volker et al. (2017) used idealized WRF simulations with neutral conditions for onshore (Region A in Fig. 15) and two different offshore (Regions B and C in Fig. 15) wind farms with sizes ranging from small (25 km^2) to very large (10^5 km^2) with different turbine spacings (5.25, 7, and 10.5 rotor diameters) to answer this question. They found that offshore in high wind speeds the actual power density exceeds 3 W m^{-2} , while onshore with moderate wind speeds it is limited to about 1 W m^{-2} , which agrees well with WRF simulations for similar large wind farms by Adams and Keith (2013), Miller et al. (2015) and Miller and Keith (2018) for the U.S.A. In addition, they found that onshore regions with moderate wind speeds offer potential locations for very large wind farms, while in offshore regions, clusters of smaller wind farms are generally preferable, and under very high wind speeds, very large offshore wind farms become also efficient. Technical University of Denmark and Max-Planck-Institute (2020) extended the results by Volker et al. (2017) for offshore areas by simulating one climatologically representative year over the German Bight with the EWP parametrization at 2-km resolution, where 20 offshore wind-farm scenarios for 2050 are defined according to capacity density, area used, installed capacity, and number of 12 MW

turbines. The results agree in general with Volker et al. (2017) and in addition the study highlights the influence of the location of the farm, i.e., isolated farms behave differently compared to surrounded farms.

While these results show that, for regional onshore and offshore wind-energy expansion, neighbouring wind farms need to be taken into account across national and state borders in order to make the most out of the available resources, they also indicate that the limits in wind-power production have not yet been reached and the issue of an actual limit in wind-power production remains open for further research.

Wind-farm wakes from neighbouring wind farms cannot only affect the wind resources in the area, but also can also cause imbalances in the power system. Larsén et al. (2019) assessed the impact of wind-farm wakes on power-system imbalance by considering a 2050 offshore wind-farm scenario for Danish waters, which was modelled using the WRF model with the EWP approach. The farms were modelled as a large disk filled with turbines that meet the planned capacity. The results indicate an impact on balancing prices and balancing reserve volumes in response to large-scale wind-farm wakes.

5 Discussion and Conclusion

In the present study, 59 out of 617 potentially relevant publications, identified from a systematic literature-review-based approach, have been reviewed to gain an overview on the state of WFPs in mesoscale models and their applications. The main findings are summarized here and perspectives for future actions are discussed.

5.1 Wind-Farm Parametrizations: Challenges and Opportunities

Different WFPs have been developed with the first ones being implicit parametrizations that represent the wind farms as an area of increased roughness. Several studies show that such parametrizations cannot sufficiently represent wind-farm-flow effects (Sect. 3.3) and therefore further developments have increasingly focused on explicit parametrizations in which wind farms are represented as an elevated momentum sink and possible source of TKE. Ten different explicit parametrizations have been identified, out of which two change some aspects of an existing older parametrization (Sect. 3.2). The ten parametrizations differ in several aspects with respect to their parametrization of the kinetic energy sink (Sect. 3.2.1) and of the TKE source (Sect. 3.2.2). Several attempts to validate the parametrizations with measurements or LES results have been reviewed (Sect. 3.4). From the reviewed literature, three challenges and opportunities for further development were identified:

1. Validation: an increasing effort has been made to validate the wind-farm-flow effects simulated by the different WFPs. However, these studies often focus only on a very short period on the order of hours or days (e.g., Lee and Lundquist 2017b; Siedersleben et al. 2018a; Tomaszewski and Lundquist 2019; Siedersleben et al. 2020). This is not least due to missing long-term observations close to large clusters of onshore and offshore wind farms as well as due to missing access to SCADA data for validation. In addition to these required long-term observations, validation studies should try to assess the several parametrizations alongside each other to identify advantages and disadvantages of the individual parametrizations. Employing common or shared validation and application cases with common resolution and boundary settings will make it easier to compare individual validation studies.

2. Interaction with mesoscale model physics: it has been noted in several studies that the performance of the WFPs depends greatly on the ability of the mesoscale model to simulate the background meteorological conditions (Lee and Lundquist 2017a; Siedersleben et al. 2018b; Platis et al. 2020; Siedersleben et al. 2020). Challenging conditions onshore are related to flow effects in complex terrain. Offshore, storms and coastal effects such as sea breezes and the advection of air masses from the land that cause frequent abnormal profiles (Møller et al. 2020) provide challenges for mesoscale models. Improving a mesoscale model's ability to correctly simulate those situations will also greatly improve the representation of atmospheric interactions with wind farms.

In addition, a WFP has to be implemented in line with the remaining mesoscale model code. As discussed in Sect. 3.2.2, Archer et al. (2020) noted in their recent publication that the explicit TKE source term in the Fitch parametrization was not correctly implemented in older WRF versions. As the Fitch parametrization in the WRF mesoscale model is by far the most applied combination (Fig. 5), 24 out of 43 studies using the Fitch parametrization in our database are affected (marked by a star in Table 2). However, the magnitude of the influence of this bug on the conclusions of these studies and whether they still hold true is not yet known. This is because even the wrong implementation provided a realistic vertical TKE profile at the wind farm and a realistic wind-speed deficit in the wake (Archer et al. 2020; Larsén and Fischereit 2021). In addition, several studies agreed in general with observations (Sect. 3.4, Table 2). Further studies are required to draw final conclusions on the validity of older studies as well as on the new correction factor introduced by Archer et al. (2020) (Table 4).

Finally, several studies found that simulation results are sensitive to the applied vertical and horizontal resolution (Sect. 4.1). Thus, when applying WFPs, the guidelines developed in past studies should be kept in mind in order to avoid erroneous simulation results.

3. Further developments: different opportunities for further developments of the existing parametrizations preferably together with validation datasets can be identified.
 - TKE treatment: while all explicit parametrizations treat wind turbines as a sink of kinetic energy (Sect. 3.2.1), only some also treat them as an explicit source of TKE (Sect. 3.2.2). Several studies indicated that a missing explicit turbine-induced TKE source term results in an underestimation of TKE (Sect. 4.2) and leads to the wrong assessment of the impacts of wind turbines on the near-surface temperature and humidity (Sect. 4.3.1). However, how exactly the explicit source term should be formulated in terms of magnitude and to reflect TKE differences across the wind farm (Sect. 4.2) is still an open question, especially in the light of the wrong implementation of the source term in the WRF source code (Archer et al. 2020). Further developments would unarguably need datasets for validation, which emphasizes the importance of long-term measurements (point 1).
 - Subgrid-scale effects: all explicit parametrizations account for the turbine number density in each mesoscale grid cell to represent the extracted kinetic energy and generated power within one grid cell (Table 3). This assumes non-interacting turbines, and the thrust imparted on the flow is simply the thrust a single turbine would impart multiplied by the number density. First attempts have been made to include layout awareness, i.e. subgrid-scale wake interactions between the turbines within one mesoscale grid cell. However, existing methods are only suitable for very specific layouts (Abkar and Porté-Agel 2015) or require the entire wind farm to fit into one grid cell (Pan and Archer 2018). Other subgrid-scale effects that are included

in some parametrizations are subgrid-scale wake expansion (Volker et al. 2015) or rotor-equivalent wind speed considering veer (Redfern et al. 2019), which was shown to be important for, e.g., ramping events. Future developments should try to combine the efforts into a single parametrization. In addition, wind-farm-yield optimizations such as wake steering, i.e. operating wind turbines under yawed conditions, (Quick et al. 2020) or installing wind turbines of different heights are not yet included in the existing parametrizations. Finally, the WFPs are not yet applicable to vertical axis turbines, although they can potentially exhibit higher energy yields than horizontal axis turbines (Porté-Agel et al. 2020).

- Coupling to microscale models: this review focused solely on mesoscale model parametrizations. However, some subgrid-scale effects could be captured by coupling mesoscale to microscale models, which has been attempted (e.g., Maché et al. 2014; Rasheed et al. 2017; Santoni et al. 2018; Durán et al. 2019; Arthur et al. 2020; Santoni et al. 2020). However, those studies focused mostly on improving the wind modelling for a particular farm and not on farm-to-farm interactions for which much higher computational resources would be necessary. An alternative could be to use low-computational-cost engineering-type wake models (Göçmen et al. 2016; Porté-Agel et al. 2020) to improve the representativeness of microscale effects in mesoscale parametrizations.

5.2 Wind-Farm Parametrizations: Application Perspectives

Three major areas for WFP applications have been identified in this review: characterization of wind-farm-flow effects (Sect. 4.2), environmental impact assessment (Sect. 4.3), and planning of wind energy (Sect. 4.4). The results are summarized below and perspectives for future applications are given.

- The review of wake characteristics indicates that the velocity deficit behind the wind farm depends on the background conditions (stability, surface roughness, orography, etc.) and the interaction with other farms. The different reviewed parametrizations indicate different recovery rates and magnitudes of velocity deficit under different conditions. The influence of wind farms on TKE is less well studied. However, it is likely that TKE will become a more important parameter to study from a mesoscale-modelling perspective, because of its role in determining mixing and wake decay in mesoscale models, and because of research interest at the microscale (modelling, measurement, and wind-tunnel measurements) looking at the evolution of turbulence associated with wakes. Further validation of WFPs is required in that regard (Sect. 5.1). In the same line of thought, stability will also likely become more important as the wind farms and turbines increase in size and power, and therefore a better understanding, and better modelling of stability effects will be of great importance.
- The review on environmental impacts of wind farms indicated that their influence on temperature has been the focus of the existing studies. Several studies showed that wind farms mix warmer air (cooler air) in stable conditions or conditions with inversion heights above hub height (conditions with inversion heights below hub height) downward and can thus alter hub-height temperatures. This mixing changes the temperature gradient between the atmosphere and the surface and together with an often reduced friction velocity within the wake, sensible heat fluxes and thus surface (air) temperatures are altered. However, the changes are usually small (below 0.5 K), mostly episodic during stable conditions, confined to areas close to the wind farms and differ across regions, since they interact

with the local weather pattern and turbine density. Therefore, near-surface-temperature impacts of wind farms are much smaller compared with the projected changes by the Intergovernmental Panel on Climate Change (Collins et al. 2013) and their main cause is primarily a vertical redistribution of heat. The impact on humidity seems to depend on the meteorological background conditions. Existing results on the sign of precipitation change are not conclusive. Implementing WFPs in global unstructured grid models, such as in Imberger et al. (2019), could help to identify remote effects of wind farms, while keeping a high resolution within the wind-farm area and thereby closing the gap between coarse long-term global simulations and high-resolution short-term regional simulations. In addition to atmospheric impacts, studies investigating marine thermodynamics were briefly reviewed. This review indicates that several studies have considered these effects, but wind-farm-wake effects were simulated with rather simple parametrizations for the wind-speed deficits and no coupling between a mesoscale ocean, wave, and atmospheric model equipped with a WFP was attempted. These coupled systems offer a potential for the future research to better account for air–sea interactions in the presence of wind farms with respect to different parameters beyond the wind speed, e.g., temperature and humidity. First attempts in this direction were recently made by Fischereit and Larsén (2021), who used the WRF model coupled to the wave model Simulating Waves Nearshore (SWAN) model with the Wave Boundary Layer model (Du et al. 2017) and the EWP and Fitch WFPs to explore the interaction of wind farms and waves.

- The review on planning of wind energy indicates that mesoscale models equipped with WFPs are useful tools to estimate wind-power resources in the presence of neighbouring wind farms. In line with the different simulated wind-farm-wake deficits in the parametrizations, the capacity factors also vary depending the applied parametrization. Thus for planning, it could be useful to run an ensemble with different WFPs to obtain an uncertainty bound around the expected yield estimate.

Despite these differences and sensitivities, the literature shows that current mesoscale models offer capabilities to capture atmospheric processes at the relevant scales for the prediction of farm-to-farm wake losses, which are not captured by the simple extrapolation of current farm-level engineering-wake-loss models to farm-to-farm scenarios. Whilst it may be possible to retune engineering-wake-loss models to address farm-to-farm scenarios (e.g., Nygaard and Newcombe 2018; Larsén et al. 2019; Nygaard et al. 2020), they would still not capture the physics of atmospheric effects, temporal behaviours and resource inhomogeneities that are increasingly important at the mesoscale. Especially if not only farm-to-farm interactions in the direct vicinity are considered but also those on the range of offshore wind-farm wakes (> 60 km, Sect. 4.2). The assumption of uniform flow and neutral stability becomes invalid (Vincent et al. 2013; Mehrens et al. 2016), since spatial variations of both wind speed and direction become non-negligible and wake meandering is present, as seen in SAR images. With this in mind, there is a need to better link the mesoscale and microscale communities. On the one hand, it would benefit the mesoscale community to have microscale knowledge to improve subgrid-scale intra-farm wake modelling in the WFPs (Sect. 5.1). On the other hand, microscale yield assessments could be improved by knowledge of mesoscale variability, wind-farm wakes, and their feedback on the geostrophic flow.

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Appendix 1: Study Overview

Table 2 summarizes the explicit WFPs identified from the literature review. The following abbreviations are used: *Bal* is balancing, *BL* is boundary-layer height, *CF* is capacity factor, *geo500* is 500-hPa geopotential height, *LH* is latent heat flux, *N* is cloudiness, *P* is power, *PD* is power density, *p* is pressure, *precip* is precipitation, *q* is humidity, *R* is radiation, *RH* is relative humidity, *SH* is sensible heat flux, *T* is temperature, *Ts* is surface temperature, *TI* is turbulence intensity, *e* is turbulence kinetic energy, *WD* is wind direction, *WS* is wind speed, *WSD* is wind-speed deficit. Type of simulations refer to idealized ('i') and real ('r') simulations. 'neut.' refers to neutral stability conditions and 'clim.' to climate representative simulations. Locations are abbreviated using country codes, i.e. U.S.A is United States of America, CN is China, ES is Spain; capital S refers to 'Sea'. RMSE is the root-mean-square error. Validation methods are abbreviated according to Sect. 3.4 and model abbreviations are given in Fig. 5. Note that Δz is often a function of height and refers here to approximate values at hub height (*hh*).

Appendix 2: Differences in Explicit Parametrizations

Tables 3 and 4 summarize the description of the turbine momentum sink term and of the turbine-induced TKE for the different explicit WFPs, respectively, identified from the literature review (bold in Table 2).

Table 2 Reviewed studies applying an explicit WFP

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Abkar and Porté-Agel (2015)	Abkar, Fitch, Blahak	No (i: neut.)			$\underline{e}$, $\underline{WS}$	LES Accurate prediction of turbine-induced forces and e with Abkar WFP; Blahak WFP underestimates turbine-induced e and drag force compared with LES results, Fitch under- or overestimated drag force compared with LES results depending on layout
Adams and Keith (2013)	Adams	WRFv2.2 (r: 30 d)	Onsh. U.S.A.	10 50	PD	
Technical University of Denmark and Max-Planck-Institute (2020)	Volker (EWP)	WRFv3.8.1 (r: clim.)	Offsh. North S	2 17	WS , P , PD	
Blahak et al. (2010)	Blahak	WRFv3.0 (i: stable)	Onsh.	1 16	WS	
Boettcher et al. (2015)	Boettcher	METRAS (r: 40 d)	Offsh. North S	4 20	$\underline{WS}$, N , SH , q , T	SAR, COSMO General agreement with observations from other studies; no details
Cervarich et al. (2013)	Fitch	WRFv? (r: 92 d)	Onsh. U.S.A.	1 60	$\underline{T_s}$	MODIS Qualitatively showing same pattern as observations during day and night. Quantitatively not possible to be compared
Chatterjee et al. (2016)	Fitch	COSMO-CLM (i: neut.)	Onsh.		$\underline{WS}$, $\underline{e}$	LES Accuracies are 12% for WS and 18% for e based on the RMSE
Emeis et al. (2016)	Fitch	WRFv? (r: 1 d)	Offsh. North S	1.6	WS	

Table 2 continued

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Eriksson et al. (2015)	Fitch	WRFv3.5 (i: neut.)	Offsh.	0.333 30	$\underline{WS}$, $\underline{P}$, $\underline{e}$	SCADA, LES LES results show similar wake expansion and e magnitudes as the WRF model. P is overestimated
Eriksson et al. (2017)	Fitch	WRFv3.5 (i: neut.)	Offsh.	0.111	$\underline{WS}$, $\underline{P}$	Mast, LES The WRF model underestimate P ; WS is in the wake is overestimated by 5–7%
Fiedler and Bukovsky (2011)	Adams	WRFv3.0 (r: summer clim.)	Onsh. U.S.A.	30 50	WS , $precip$	
Fitch et al. (2012)	Fitch	WRFv3.3 (i: neut.)	Offsh.	1 15	$\underline{WS}$, $\underline{BL}$, $\underline{e}$, $\underline{P}$	SAR, SCADA General agreement with observations from other studies
Fitch et al. (2013b)	Fitch	WRFv3.3.1 (i/r: diff.)	Onsh. U.S.A.	1 15	WS , T , e , SH	
Fitch et al. (2013a)	Fitch	WRFv3.3.1 (i/r: diff.)	Onsh. U.S.A.	1 15	WS , $\underline{BL}$, $\underline{e}$, SH , T	
Fitch (2015)	Fitch	CAM (r: clim.)		Global (0.9 by 1.25)60	T , SH , $precip$, WS , $\underline{e}$, N , LH	
Hansen et al. (2015)	Volker (EWP)	WRFv? (i: neut.)	Offsh. Baltic S		$\underline{WS}$	SCADA Resolution was not sufficient: entire wind farm in one grid cell
Hasager et al. (2015)	Volker (EWP)	WRFv3.4 (r: 1 d)	Offsh. North S	2 15	$\underline{WS}$	SAR RADARSAT-2 wind-farm wakes compare well with WRF modelling both for direction and extent
Hasager et al. (2017)	Volker (EWP)	WRFv? (r: 1 d)	Offsh. North S	2 20	$\underline{WS}$, $\underline{e}$, T , $\underline{RH}$	SCADA, SAR Similar pattern of farm wakes; comparable magnitude of RH and T profiles; no indication on verification of wake intensity
Huang et al. (2019)	Fitch	WRFv3.4 (r: clim.)	Onsh. CN	30 60	$\underline{e}$, WS , T	

Table 2 continued

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Jiménez et al. (2015)	Fitch	WRFv3.4 (r: clim.)	Offsh. North S	0.333 40	$WS, \underline{P}, WD, TI$	SCADA Model qualitatively reproduces the effect of stability on wakes, but underestimates the P deficit
Keith et al. (2004)	Keith	CAM, AM2 (r: clim.)		Global (2.5 by 2)	T, PD	
Larsén et al. (2019)*	Volker (EWP), Fitch	WRFv3.8.1 (r: clim.)	Offsh. North S	2 17	$WS, \underline{P}, Bal$	SCADA Fitch WFP agrees better than EWP WFP for SandBank and Dantysk in spring and summer
Lauridsen and Ancell (2018)*	Fitch	WRFv3.5.1 (r: clim.)	Onsh. U.S.A.	10	$WS, precip, p, T$	
Lee and Lundquist (2017b)*	Fitch	WRFv3.6.1 (r: 1.25)	Onsh. U.S.A.	0.99 22	$\underline{WS}, e, LH, SH, TI, WD, P, PD$	Surface flux stations, radiometer, profiling lidars, scanning lidar Good agreement between WRF model results and lidar measurements for WSD , although maximum WSD is underestimated by 1 m s^{-1} at lh , e enhancement is underestimated by a factor of two
Lee and Lundquist (2017a)*	Fitch	WRFv3.8.1 (r: 4 d)	Onsh. U.S.A.	1 12	$\underline{WS}, e, P, WD$	surface flux stations, radiometer, profiling lidars, scanning lidar, SCADA SCADA: underestimates P during high WS , low TI and stable conditions; overestimates P during low WS , high TI and unstable conditions; lidar: e measurements follow observations
Lundquist et al. (2019)*	Fitch	WRFv3.8.1 (r: 30 d)	Onsh. U.S.A.	1 12	$\underline{WS}, P, SH, CF$	Sodar, CF WRF overestimates WS , CF agree well

Table 2 continued

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Miller et al. (2015)	Fitch	WRFv3.3.1 (r: 120 d)	Onsh. U.S.A.	12	PD	
Miller and Keith (2018)	Fitch	WRFv3.3.1 (r: clim.)	Onsh. U.S.A.	10 50	WS, P, PD, T	Mast Good correlation with skin-temperature observations
Na et al. (2016)*	Fitch	WRFv3.6 (i: neut.)		0.42 10	WS, e, TI	
Pan et al. (2018)*	Fitch	WRFv3.6 (r: 4 d)	Offsh. U.S.A.	10.667	$WS, p, precip$	Mast. Hurricane track No verification of wake effect, just of background meteorological conditions
Pan and Archer (2018)*	Pan, Fitch	WRFv3.6 (i: neut.)	Offsh.	4 10	WS, e, P	SCADA, LES e agrees excellently with LES results, WS agrees within 10%, P agrees well
Platis et al. (2018)*	Fitch	WRFv3.7.1 (r: 1.5)	Offsh. North S	1.7 40	WS	Aircraft Similar structure and orientation of the wake; the WRF model underestimates WS in general
Prósper et al. (2019)*	Fitch	WRFv3.6 (r: forecast)	Onsh. ES	0.333 25	WS, P, WD	Nacelle anemometer Observed errors have a diurnal cycle and increase with forecast length
Pryor et al. (2018b)*	Fitch	WRFv3.8.1 (r: clim.)	Onsh. U.S.A.	4 25	$WS, q, BL, T,$ $precip, SH,$ LH, PD	

Table 2 continued

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Pryor et al. (2018a)*	Volker (EWP), Fitch	WRFv3.8.1 (r: clim.)	Onsh. U.S.A.	4 25	$T, q, P, WS,$ CF	
Pryor et al. (2020)*	Volker (EWP), Fitch	WRFv3.8.1 (r: 270 d)	Onsh.	2 16	WS, e	
Redfern et al. (2019)*	Fitch, Redfern	WRFv3.8.1 (i: diff.)	Onsh.	1 6	WS, e, PD	
Baidya Roy (2004)	Roy	RAMS (i, soundings: diff.)	Onsh. U.S.A.	2 100	T, q, SH, WS	
Baidya Roy and Traiteur (2010)	Roy	RAMS (i, soundings: diff.)	Onsh. U.S.A.	1 50	$\underline{T}$	2 Masts Near surface warming and cooling dependence on lapse rate reproduced qualitatively
Baidya Roy (2011)	Roy	RAMS (i: diff.)	Onsh. U.S.A.	1 30	$T, q, SH, LH,$ WS	
Shepherd et al. (2020)*	Fitch, Volker (EWP)	WRFv3.8.1 (r: clim.)	Onsh. U.S.A.	4 25	$WS, e, q, T,$ SH, LH	
Siedersleben et al. (2018a)*	Fitch	WRFv3.8.1 (r: 1 d)	Offsh. North S	1.67 35	$WS, \underline{T}$	Aircraft, Mast Model matches the warming and drying effect of the wind farm cluster reasonably well

Table 2 continued

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Siedersleben et al. (2018b)*	Fitch	WRFv3.8.1 (r: 1 d)	Offsh. North S	1.6 35	$\underline{WS}$	Aircraft Upwind WS is underestimated by up to 1.9 m s^{-1}
Siedersleben et al. (2020)*	Fitch	WRFv3.8.1 (r: 3 d)	Offsh. North S	1.67 12	$\underline{WS}, \underline{e}$	Aircraft WFP adds too much e at the upwind side of a wind farm
Sun et al. (2018)	Fitch	WRFv? (r: clim.)	Onsh. CN	30 50	$WS, T, e,$ $geo500$	
Tomaszewski and Lundquist (2019)*	Fitch	WRFv3.8.1 (r: 4 d)	Onsh. U.S.A.	1 12	$\underline{WS}, T, q$	Scanning lidar Background meteorological conditions agree well with scanning lidar
Vanderwende and Lundquist (2016)	Fitch	WRFv3.4.1 (r: 30 d)	Onsh. U.S.A.	1.25 15	WS, e, P	
Vanderwende et al. (2016)	Fitch	WRFv3.4 (i: unstable/stable)	Onsh.	0.3 9	$\underline{WS}, \underline{e}$	LES Underestimates WSD , overestimates e
Vautard et al. (2014)	Fitch	WRFv3.3.1 (r: clim.)	Both Europe	50 50	$T, \underline{WS}, precip,$ LH, SH	Mast Model overestimates WS by 20%
Volker et al. (2015)	Volker (EWP), Fitch	WRFv3.4 (i: neut.)	Offsh. North S	1.12 10	$\underline{WS}, e$	Mast EWP WFP has a bias $< 0.15 \text{ m s}^{-1}$; WRF model results have a bias of 0.5 m s^{-1}
Volker et al. (2017)	Volker (EWP)	WRFv3.4 (i: neut.)	Offsh. North S	1.68 20	WS	
Wang et al. (2019b)*	Fitch	WRFv3.7.1 (r: clim.)	Onsh. CN	0.15 10	$\underline{WS}, PD, \underline{WD}$	Mast WS agrees well, apart from scenario WRF-1000; WD agrees fair with a clockwise deviation

Table 2 continued

Study	WFP	Model (type)	Location	Δx (km) Δz (m)	Parameter	Validation method Validation result
Wang et al. (2019a)*	Fitch	WRFv3.7.1 (r: 30 d)	Onsh. CN	1 10	$\overline{WS}$, T , BL	Mast Fitch WFP simulates accurately the wind around the wind farms
Xia et al. (2017)*	Fitch	WRFv3.6.1 (r: 210 d)	Onsh. U.S.A.	1 20	$\overline{T_s}$	MODIS Moderately good agreement at regional level not at pixel level
Xia et al. (2019)*	Fitch	WRFv3.6.1 (r: 30 d)	Onsh. U.S.A.	1 20	T_s , LH , SH , R , T	
Yuan et al. (2017)*	Fitch	WRFv3.7.1 (r: 8 d)	Onsh. CN	0.2 8	$\overline{WS}$, e , $\overline{WD}$	Mast WS is underestimated by about 30%, direction deviated clockwise by about 10%

Abbreviations are explained in the text. Bold studies indicate studies in which a parametrization was newly developed. Underlined parameters in 'Parameter' have been validated as described in the column on Validation. The WRF version numbers are given; "v?" is used, if the version was not provided in the study.

* marks studies that are affected by the TKE integration bug in the WRF model (Sect. 3.2.2) according to the provided WRF version number. Studies without a WRF version number could not be assessed

Table 3 Overview on the wind-turbine momentum-sink descriptions in the different explicit wind-farm parametrizations (bold in Table 2)

Option Approach	Reference velocity	Turbine momentum sink	Comment
Abkar and Porté-Agel (2015) <i>direct</i>	Wind speed at hub height corrected for undisturbed upstream wind speed for staggered and aligned layout based on LES: $\xi \bar{u}_{r,h}$	$N_f \frac{1}{2} C_T \xi^2 \bar{u}_{r,h} \bar{u}_{i,h} A_{xyz}$ with ξ : correction factor for undisturbed upstream wind speed for staggered and aligned layout $C_T = C_T(\bar{u}_{r,h})$, but $C_T = 0.75$ used in their case study	Accounts for different turbine layouts; never applied in mesoscale model
Adams and Keith (2013) <i>direct</i>	See Fitch et al. (2012)	See Fitch et al. (2012)	Same as Fitch et al. (2012) but derived as direct approach
Baidya Roy (2004, 2011) <i>indirect</i>	Wind speed at hub-height (entire rotor in one layer): $\bar{u}_{r,h}$	$N_f \frac{\left[\frac{1}{2} C_P \bar{u}_{r,h} \bar{u}_{i,h} + \beta \right] A_{xyz}}{z_{xy,z+1} - z_{xy,z}}$ with $C_P = \begin{cases} 0.4 & \text{Baidya Roy (2004)} \\ C_P(\bar{u}_{r,h}) & \text{Baidya Roy (2011)} \end{cases}$ β : constant to remove resolved kinetic energy from that is converted to TKE by the turbines to conserve energy	Entire rotor in one layer

Table 3 continued

Option Approach	Reference velocity	Turbine momentum sink	Comment
Blahak et al. (2010) <i>indirect</i>	Wind speed at height z : $\bar{u}_{rz}$	$N_t(1 + \alpha) \frac{\frac{1}{2} C_a \bar{u}_{rz,xy} \bar{u}_{i,z,xy} A_{xyz}}{z_{xy,z+1} - z_{xy,z}} \text{ with}$ $\alpha = 0.2; \text{ empirical constant proportional}$ $\text{constant relating decrease in total kinetic}$ $\text{energy to increase in TKE}$ $C_a(\bar{u}_{rh}) = C_P(\bar{u}_{rh}) / \eta_{\text{mech}}$ $\text{aerodynamical part of } C_P \text{ that can be used}$ $\text{to harvest kinetic energy } (\approx 0.45 - 0.55)$ $\eta_{\text{mech}}: \text{ mechanical and electrical loss}$ $\text{factor, turbine specific } (\approx 0.85 - 0.95)$	
Boettcher et al. (2015) <i>direct</i>	Averaged three dimensional velocity over entire wind farm (w_f) and all levels containing the rotor ($\bar{u}_{wf}$)	$N_t \frac{\frac{1}{2} C_T \bar{u}_{wf} \bar{u}_{i,z,xy} A_{xyz}}{z_{xy,z+1} - z_{xy,z}} \text{ with}$ $C_T = C_T(\bar{u}_{rh})$	Uses three dimensional velocity
Fitch et al. (2012) and subsequent changes in WRF as documented in Redfern et al. (2019) <i>indirect</i>	Wind speed at height z ($\bar{u}_{rz}$), which is adjusted in later versions in WRF by a normalization factor (f_n) to conserve energy by ensuring that modelled wind and TKE are consistent with total wind energy production (Redfern et al. 2019)	$N_t \frac{\frac{1}{2} C_T \bar{u}_{rz,xy} \bar{u}_{i,z,xy} A_{xyz}}{z_{xy,z+1} - z_{xy,z}} f_n \text{ with}$ $C_T = C_T(\bar{u}_{rh})$ $f_n = \begin{cases} 1 & \text{WRF} < v_{3.6} \\ \frac{\frac{1}{2} (C_P \rho_a \bar{u}_{rh} ^3 A_t)}{\sum_{z=\bar{t}_b} \frac{1}{2} (C_P \rho_a \bar{u}_{rz} ^3 A_{xyz})} & \text{WRF} \geq v_{3.6} \end{cases}$ $\text{with } A_t: \text{ the total turbine swept area}$ $(A_t = (\pi/4) d^2) \rho_a: \text{ air density, constant at}$ $1.23 \text{ kg m}^{-3} C_P = C_P(\bar{u}_{rh}) \bar{t}_b: \text{ turbine}$ $\text{bottom } \bar{t}_t: \text{ turbine top}$	Local thrust force acting on the turbine blade swept area. Forms the basis for other parametrizations (Pan and Archer 2018; Redfern et al. 2019)

Table 3 continued

Option Approach	Reference velocity	Turbine momentum sink	Comment
Keith et al. (2004) <i>direct</i>	Not explicitly stated, but likely the wind speed at height z ($\bar{u}_{rz}$)	$CED \frac{\bar{u}_{rzxy} \bar{u}_{i, zij}}{z_{xy, z+1} - z_{xy, z}}$ with CED : explicit drag coefficient corresponding to 2.8 turbines per km^2 with $h = 100$ m and $d = 100$ m that removes 40% of kinetic energy of the resolved flow; $CED/\Delta z$ depends on the vertical model grid.	Drag coefficient depends on the vertical model grid
Pan and Archer (2018) <i>indirect</i>	Wind speed at height z ($\bar{u}_{rz}$)	$\sum_{n=1}^{N_t} \frac{\frac{1}{2} C_T \bar{u}_{rzxy} \psi \bar{u}_{i, zxy} A_{xyz}}{\Delta x \Delta y (z_{xy, z+1} - z_{xy, z})}$ with $C_T = C_T(\bar{u}_{rh})$ ψ : layout factor, $\psi(BR_n(WD), IBD_n(WD))$ $= \begin{cases} 1 & BR_n(WD) = 0 \\ 0.9615 - 0.154 BR_n & 0 < BR_n(WD) < L_{\infty BR_n} \\ -0.0114 IBD_n & L_{\infty BR_n} \leq BR_n(WD) \leq L_{\infty IBD_n} \\ L_{\infty BR_n} & BR_n(WD) > L_{\infty IBD_n} \end{cases}$ $BR_n(WD)$: fraction of swept area of turbine n blocked by the swept area of any upstream turbine for a given WD $IBD_n(WD)$: weighted average of the reciprocal blockage distances (BD_n) of upstream blocking turbines L_{∞} : infinitely-large blockage distance, = $20d$ used here	Based on Fitch et al. (2012) but accounting for layout and wind direction effects using BR and IBD . Only valid for entire wind farm in one cell

Table 3 continued

Option Approach	Reference velocity	Turbine momentum sink	Comment
Redfern et al. (2019) <i>indirect</i>	Rotor-equivalent wind speed considering veer	Same adjusted equation with normalization factor as in Fitch et al. (2012) but accounting for veer in kinetic energy loss and TKE by multiplying the equation by $\cos \vartheta_{xyz}$ with ϑ : angle between the wind direction and the turbine axis. The rotor-equivalent wind speed is used in the power-production estimation of individual grid cells and defined as $\text{REWS}_d = \sum_{k=1}^N \frac{A_{xyz}}{A_t} \bar{u}_{xyz} \cos \vartheta_{xyz}$	Based on Fitch et al. (2012); shows improvements at least for ramping events and cold pools

Table 3 continued

Option Approach	Reference velocity	Turbine momentum sink	Comment
EWP Volker et al. (2015) direct	Horizontal velocity at hub height ($\bar{u}_{rh}$)	$\begin{aligned}\bar{f}_{1,xyz} &= f_{xyz} \cos(WD_{xyz}) \\ \bar{f}_{2,xyz} &= f_{xyz} \sin(WD_{xyz}) \text{ with} \\ f_{xyz} &= N_t \sqrt{\frac{\pi}{8}} \frac{C_T r_h^2 \bar{u}_{rh,xy} ^2}{\Delta x \Delta y \sigma_e} \text{ with } r_h: \\ &\quad \exp\left[\frac{1}{2} \left(\frac{z_z - h}{\sigma_e}\right)^2\right] \\ \text{rotor radius} &= 0.5d \text{ } z_z: \text{ height of model} \\ \text{level } z \text{ } C_T &= C_T(\bar{u}_{rh}) \\ \sigma_e &= \frac{\bar{u}_{rh}}{3KL} \left[\left(\frac{2K}{\bar{u}_{rh}} L + \sigma_h^2 \right)^{3/2} - \sigma_h^3 \right] \\ \text{Effective length scale for wake expansion} &\text{related to the model grid size with} \\ L &= 0.5\Delta x \text{ } K: \text{ turbulent diffusion} \\ \text{coefficient from mesoscale turbulence} &\text{scheme } \sigma_h = f_r r_h \text{ initial length scale,} \\ \text{related to wake expansion in the near wake} &\text{related to wake expansion in the near wake} \\ f_r: &\text{scaling factor for initial length scale}\end{aligned}$	Grid-cell averaged drag force including sub-grid-scale wake expansion

The equations are given as per component i except for Volker et al. (2015). The following symbols are used: N_t is the number of turbines within a grid cell. $n_t = \frac{N_t}{\Delta x \Delta y}$ is the horizontal density of wind turbines (number of turbines per square meter) with Δx and Δy being the resolution in x and y direction, respectively; d is the rotor diameter. A_{xyz} is the cross-sectional rotor area of wind turbine in one model level bounded by z and $z + 1$ at grid cell x, y . Subscript r denotes the wind speed $\bar{u}_r = \left(\bar{u}_1^2 + \bar{u}_2^2 \right)^{0.5}$; subscript h denotes hub height; other model level are denoted by subscript z ; WD is wind direction

Table 4 Overview on the turbine-induced TKE descriptions in the different explicit wind-farm parametrizations (bold in Table 2)

Option	Term	Expression for $\overline{p}_t =$
Abkar and Porté-Agel (2015)	$\langle \overline{u_i''} \overline{f_i''} \rangle$	$n_t \frac{\frac{1}{2} C_T \xi^2 \overline{u_{r,hxy}} ^3 A_{xyz} (1 - (1 - a)\xi)}{z_{xy,z+1} - z_{xy,z}}$ <p>with $a = 0.5(1 - \sqrt{1 - C_T})$, induction factor of the turbine</p>
Adams and Keith (2013)	See Fitch et al. (2012)	See Fitch et al. (2012)
Baidya Roy (2004, 2011)	$\langle \overline{u_i''} \overline{f_i''} \rangle$	$n_t \frac{\beta \overline{u_{r,hxy}} A_{xyz}}{z_{xy,z+1} - z_{xy,z}}$
Blahak et al. (2010)	$\langle \overline{u_i''} \overline{f_i''} \rangle$	$n_t \alpha \frac{\frac{1}{2} C_d \overline{u_{r,zxy}} ^3 A_{xyz}}{z_{xy,z+1} - z_{xy,z}}$
Boettcher et al. (2015)		Neglected, assumed to arise from shear velocity
Fitch et al. (2012) with correction factor from Archer et al. (2020)	$\langle \overline{u_i''} \overline{f_i''} \rangle$	$n_t \frac{\frac{1}{2} c_f (C_T - C_P) \overline{u_{r,zxy}} ^3 A_{xyz}}{z_{xy,z+1} - z_{xy,z}} \text{ with } c_f: \text{ correction factor}$ $= \begin{cases} 1 & v_{3.5} < \text{WRF} < v_{4.2.1} \\ \text{user-definable, 0.25 default} & \text{WRF} \geq v_{4.2.1} \end{cases}$
Keith et al. (2004)		Neglected
Pan and Archer (2018)	$\langle \overline{u_i''} \overline{f_i''} \rangle$	$\sum_{n=1}^{N_t} \frac{\frac{1}{2} C_T \overline{u_{r,zxy}} ^3 \psi^2 0.5(1 - \sqrt{1 - C_T}) A_{xyz}}{\Delta x_{\text{grid}} \Delta y_{\text{grid}} (z_{xy,z+1} - z_{xy,z})}$
Redfern et al. (2019)	See Fitch et al. (2012)	Accounting for for veer by multiplying the equation in Fitch et al. (2012) by $\cos \vartheta_{xyz}$, with ϑ being the angle between the wind direction and the turbine axis
Volker et al. (2015)	$\langle \overline{u_i'} \overline{f_i'} \rangle$	$\approx -\rho A_r C_T \overline{\frac{r'^2}{\overline{u_{i,h} u_{i,h}}}}, \text{ Neglected}$

C_T and C_P are functions of the hub-height wind speed ($\overline{u_{i,h}}$) as shown in Table 3. Velocities in 'Term' refer to Fig. 6. Variables are the same as those for the respective WFPs in Table 3

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