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Evaluating mesoscale simulations of the coastal flow using lidar measurements

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Key Points:

- Sensitivity study of the WRF model setup to boundary-layer scheme, atmospheric boundary conditions, surface description, sea surface temperatures and horizontal resolution
- First time that a mesoscale model is evaluated with horizontal transects across the coast using lidar measurements.
- Studies the processes that govern the flow in the coastal zone during a 3 month period.

Abstract

The atmospheric flow in the coastal zone is investigated using lidars, mast measurements and model simulations. The Weather, Research and Forecasting (WRF) model is set-up in 12 different configurations using 2 planetary boundary-layer schemes, 3 horizontal grid spacings and varied sources of land use, and initial and lower boundary conditions. All model simulations describe the observed mean wind profile well at different onshore and offshore locations from the surface up to 500 m. The simulated mean horizontal wind speed gradient across the shoreline is close to that observed, although all simulations show wind speeds that are slightly higher than those observed. Inland at the lowest observed height, the model has the largest deviations compared to the observations. Taylor diagrams show that using ERA-interim data as boundary conditions improves the model skill scores. Simulations with the finest horizontal grid show poorer model performance. Modelled and observed spectra were compared and showed that, although having a negative impact on standard performance metrics, simulations with the finest horizontal grid spacing resolved more high-frequency atmospheric motion. The results show that to describe and understand the flow over the coast and the simulations for the WRF model, lidar measurements are of great value.

1 Introduction

There is strong interest in accurate estimation of the wind resource for wind farms that are located in the coastal zone. These areas, defined here as approximately within 10 km of the coastline, have high wind speeds for onshore flow conditions, grid connectivity is relatively easy and requires little additional investment compared to offshore projects. *Barthelmie et al.* [2007] showed that the flow at a distance less than 20 km from the coastline is not in equilibrium with the new surface conditions and to capture the transition, a model is required.

Due to increasing computing power, it has become popular to use the output from mesoscale models to determine the wind resource [*Frank et al.*, 2001; *Dvorak et al.*, 2009; *Tammelin et al.*, 2013]. Mesoscale models are particularly useful for offshore wind resource estimation, due to the absence of complex and unresolved microscale features [*Dvorak et al.*, 2009; *Wijnant et al.*, 2014; *Hahmann et al.*, 2015]. At Fino3 in the North Sea, an inter-comparison of 26 model simulations showed a mean bias of less than 0.25 m s^{-1} at 90 m [*Olsen et al.*, 2017]. Near the coast, mesoscale models have difficulties in correctly simulating the atmospheric flow due to the influence of surface roughness changes [*Floors et al.*, 2013], coastal

44 low-level jets (LLJs) [Hunt *et al.*, 2004] and wave-atmosphere interactions [Lange *et al.*,
45 2004].

46 The Weather Research and Forecasting (WRF) mesoscale model is frequently used to
47 simulate mesoscale flows [Skamarock *et al.*, 2008]. Dörenkämper *et al.* [2015] used WRF
48 model simulations with a horizontal grid spacing of 700 m to show that streaks of lower
49 wind speed resulting from patches of land with higher surface roughness, can extend sev-
50 eral tens of kilometers from the coast during offshore flow. Floors *et al.* [2013] used the
51 WRF model to investigate the impact of vertical resolution and found that it had a negligi-
52 ble impact on the wind profile at one of the locations studied in this paper. Nocturnal LLJs
53 were observed for easterly winds, resulting from cooling of the surface and decoupling of the
54 flow. For westerly winds, the model strongly underestimated the wind speed, which raised
55 the question whether mesoscale models can accurately simulate the flow in the coastal zone.

56 A correct description of all boundary conditions is necessary to simulate the flow in
57 the coastal zone. The impact of changing the model grid spacing, the description of sea sur-
58 face temperature (SST), land cover and atmospheric boundary conditions on the simulated
59 wind speed in the coastal zone for an extended period has not been described extensively
60 in literature. Here we investigate such impacts by using two types of land cover data, two
61 sources of SSTs and two sources of atmospheric (re)analysis data.

62 The large changes in surface roughness and stability and the resulting internal bound-
63 ary layers are often not resolved at grid spacings of ≈ 1 km of the current generation of
64 mesoscale models. Still, Planetary Boundary Layer (PBL) schemes are increasingly being
65 used at very high resolutions, where turbulent motions are partially resolved [Shin and Dud-
66 hia, 2016]. With the increase in computer power, this trend will continue. To understand bet-
67 ter the behaviour of the WRF model and the different PBL schemes at these high resolutions,
68 it is important that the model is evaluated against high-quality measurements.

69 Wind lidars measure the wind accurately and are now widely used for research and
70 industrial applications [Mikkelsen, 2014]. They are usually configured to measure at a num-
71 ber of heights to retrieve the vertical profile of wind speed. Recently, scanning lidars with a
72 steerable scanner head have been developed that are able to point in any direction [Vasiljević
73 *et al.*, 2016].

74 In this study, our goal is to use the scanning lidar measurements to document the sensi-
75 tivity of the WRF model to different setups by investigating vertical profiles, horizontal tran-
76 sects, a combination of all measurements and velocity spectra. The vertical profile of wind
77 speed is determined by the representation of turbulent mixing processes over surfaces with
78 different roughness and stability conditions. The horizontal transects show the model's abil-
79 ity to capture changes in surface roughness resulting from the coastline. All measurements
80 can be combined to compute different error metrics and to identify which setup performs the
81 best. Finally, the impact of the model horizontal resolution is studied using modelled and
82 observed velocity spectra.

83 In Sect. 2 we describe the measurements and the experimental site. Details about the
84 modelling setup and a description of the different sensitivity experiments are given in Sect.
85 3. In Sect. 4.1 we evaluate the simulated vertical profile of mean wind speed at different
86 locations and in Sect. 4.2 we compare the simulated mean horizontal wind speed gradient
87 across the coast with the scanning lidar measurements. In Sect. 4.3, Taylor diagrams are
88 used to provide an overview of the performance of the different model setups. Finally, we
89 study modelled and observed velocity spectra in Sect. 4.4.

90 **2 Measurements**

91 We use measurements from lidars and a mast and the positions of all instruments are
92 given in Fig. 1a and Table 1. The instruments and measurements are described in detail in
93 *Floors et al.* [2016]. The data used in this paper are available for download [*Floors et al.*,
94 2017].

95 The terrain of the experimental area is characterized by grass and crop fields with scat-
96 tered houses and vegetation. The topography around the site is dominated by a steep cliff at
97 the coast, whereas the terrain is undulating inland (see Fig. 1a). To the north of the area, near
98 position 3, the height of the cliff is ≈ 40 m, near position 2 ≈ 25 m and near position 1 it
99 becomes a dike of ≈ 15 m.

100 **2.1 Vertical profiling lidars**

101 The vertically profiling lidars WLS66 and Alizé were operating at position 2. Bura and
102 3E were installed ≈ 1 km and 400 m inland at positions 5 and 4, respectively. Another verti-
103 cal profiling lidar was mounted on a buoy at position 6, ≈ 8 km offshore. Due to high waves

104 during a storm the power generator was damaged and therefore the lidar stopped working on
105 the 7th of December. Due to bad weather and logistical issues, it was not possible to repair
106 the power generator before 11 February. To avoid the influence of breaking waves, the buoy
107 was moved to position 7.

108 The profiling lidars were configured to perform scans in a Velocity Azimuth Display
109 (VAD) mode, i.e the wind vector was reconstructed from four points separated 90° around
110 the zenith. Data higher than 130 m and with a carrier-to-noise ratio (CNR) lower than -22
111 dB were filtered out. A limit of -32 dB is used for Alizé, because it is a long-range lidar with
112 a stronger laser. This can measure up to 2000 m height [*Gryning et al.*, 2016]. These limits
113 were chosen to increase the correlation between the wind speeds obtained from the lidars
114 with those observed at the meteorological mast [*Floors et al.*, 2016].

115 For each of the lidars, the recovery rate is shown in Table 1, which is defined as the
116 percentage of data that fulfilled the filtering criteria divided by the 17281 10-min periods
117 covering the whole campaign that started on 2 November 2015 and lasted until 1 March
118 2016. Note that Alizé and Bura did not start measuring before 9 and 12 of November, respec-
119 tively, which partially explains the lower recovery percentage compared to the mast (position
120 8 in Fig. 1). The lidar buoy recovery rate is much lower than that of the other lidars due to
121 the technical problems and its measurements are split over the two locations.

122 2.2 Scanning lidars

123 The scanning lidars are modified versions of the WindCube 200S from the company
124 Leosphere and have been successfully used in several field campaigns [*Vasiljević et al.*, 2016].
125 They were placed on top of the cliff to have an unobstructed line-of-sight. Different scanning
126 patterns were configured during the experiment, but in this study we only use the measure-
127 ments obtained between 26 November and 17 February [*Floors et al.*, 2016]. Two spatially
128 separated scanning lidars can estimate the horizontal wind speed vector from measurements
129 of the line-of-sight velocity assuming a zero vertical wind speed. The lidars Koshava and
130 Sterenn used this ‘dual setup’ to scan three virtual horizontal lines at 50, 100 and 150 m
131 above mean sea level (amsl) from ≈ 5 km offshore up to ≈ 4 km inland (Fig. 2). The lidar
132 Vara performed a plan position indicator (PPI) scan or sector-scan setup (Fig. 2); it scanned
133 60° of an azimuthal plane up to ≈ 8 km distance. This plane was sampled at three different
134 elevation angles, such that these planes approximately intersected with the height of the three

135 dual setup sampling points ≈ 5 km offshore at 50, 100 and 150 m amsl. Both the dual and
 136 sector-scan setup performed a full scan in ≈ 145 s. The available samples of the wind speed
 137 components were then averaged in periods of 10 min.

138 The availability of the scanning lidars is lower than that of the lidars in VAD mode be-
 139 cause of the long distance to the sampling point. Similarly to the profiling lidars, we require
 140 measurements in all range gates to fulfill a CNR threshold. For the dual setup, the CNR limit
 141 was -26.5 dB, whereas for the lidar in sector-scan mode it was -27 dB. Finally, the mea-
 142 surements from the sector-scan and the dual setup are merged with those from the vertical
 143 profiling lidars and the mast. The lidar beam hit objects in the eastward direction after ≈ 2
 144 km and therefore transects in the range from 5000 m west to 2000 m east of Vara were used.
 145 Sampling points from the dual setup between $x = 445615$ and 446215 m (UTM WGS84,
 146 zone 32V) were removed because uncertainty in reconstruction of the wind speed is too large
 147 when the angle between the line of sights is more than $\approx 160^\circ$. After filtering, 731 10-min
 148 transects remained, i.e a recovery rate of 4.23%.

149 **2.3 Meteorological mast**

150 The Høvsøre meteorological mast is located ≈ 6 km south and ≈ 2 km inland of Vara
 151 (position 8 in Fig.1a). The measurements performed at this mast are thoroughly quality con-
 152 trolled [Peña *et al.*, 2016]. We use the 10-min mean wind speeds obtained with Risø cup
 153 anemometers at the southern side of the mast at 10, 40, 60, 80, 100 and 160 m. Horizontal
 154 velocity spectra were computed from the cup anemometer at 100 m height. The measuring
 155 frequency of the cup anemometer is 10 Hz, but here we are only interested in mesoscale fluc-
 156 tuations and therefore the measurements were down-sampled to 0.1 Hz. The measurements
 157 were linearly interpolated to fill missing data in the 0.1 Hz time series. A fast-Fourier trans-
 158 form was performed on linearly detrended ≈ 14 day periods (2^{11} 10-min periods).

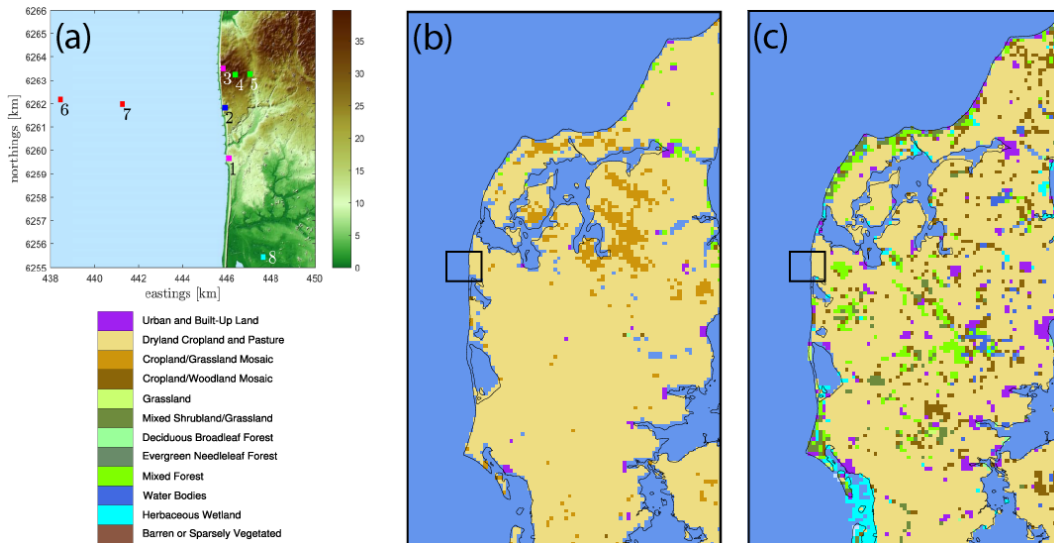
173 **3 Mesoscale modeling**

174 **3.1 Basic setup**

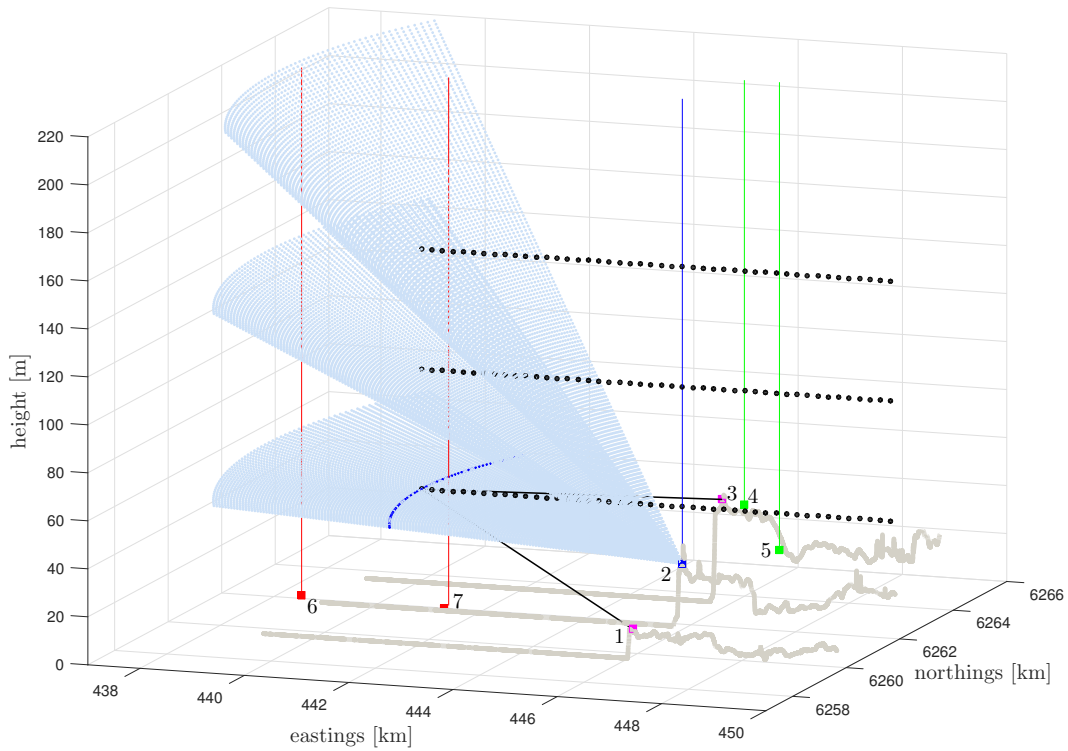
175 We use the WRF model to perform simulations during the measurement period. We
 176 used version 3.6, to which patches and bug fixes were applied [Skamarock *et al.*, 2008; WRF,
 177 2015]. There were 70 vertical model levels, with its highest density near the surface. The
 178 WRF model top was set at 50 hPa. The first model level was at 11 m above the surface and

159 **Table 1.** Positions, names, types, main scanning strategies (usage) and coordinates (UTM WGS84, Zone
 160 32V) of the lidars during the RUNE campaign (see details in the text), including the information of the
 161 Høvsøre meteorological mast. N denotes the number of 10-min mean observations and the recovery percent-
 162 age is given as a percentage of the total number of attainable 10-min intervals. The lidar buoy was used at two
 163 positions. The type is the commercial name given by the lidar manufacturer Leosphere

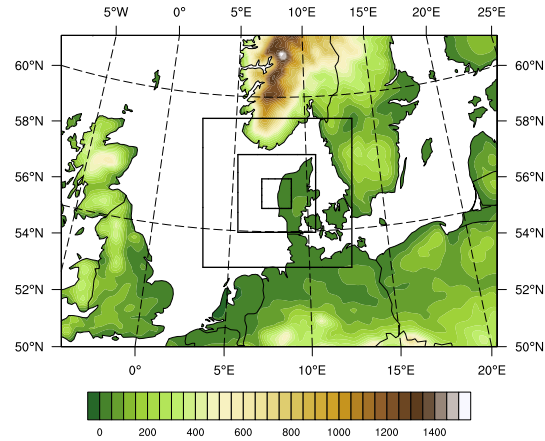
Pos.	Name	Type	Usage	Easting (m)	Northing (m)	Height amsl (m)	N	Recovery [%]
1	Koshava	WLS200S-007	Dual setup	446080.03	6259660.30	12.36	713	4.23
2	Vara	WLS200S-012	Sector scan	445915.64	6261837.49	26.38	713	4.23
2	Alizé	WLS70-001	Vertical Profile	445915.64	6261837.49	26.38	9866	57.09
2	WLS66	WLS7-066	Vertical Profile	445915.64	6261837.49	26.38	9866	57.09
3	Sterenn	WLS200S-006	Dual setup	445823.66	6263507.90	42.97	713	4.23
4	3E	WLS7-007	Vertical Profile	446379.30	6263251.46	43.18	13580	78.58
5	Bura	WLS7-002	Vertical Profile	447040.74	6263273.41	24.93	10910	63.13
6	Lidar Buoy Pos1	WLS7-277	Vertical Profile	438441	6262178	0.00	3859	22.33
7	Lidar Buoy Pos2	WLS7-277	Vertical Profile	440616	6262085	0.00	1375	7.96
8	Høvsøre mast	-	Mast	447642	6255431	0.32	16383	94.80



164 **Figure 1.** (a). Terrain height (in m) and the positions of the instruments denoted with numbered points
 165 (Table 1). The vertically profiling lidars WLS66 and Alizé are collocated with Vara in position 2. Land use
 166 description from the model simulations obtained from the (b) USGS and (c) CORINE data set . The area of
 167 panel (a) is denoted with a black rectangle.



168 **Figure 2.** Overview of the main scanning patterns during the measurement campaign. The light blue points
 169 denote the sector scan from Vara, the black dots denote the collocated range gates from Sterenn and Koshava,
 170 the green lines denote the lidars 3E and Bura, the blue line denotes the lidars WLS66 and Alizé and the red
 171 line denotes the lidar buoy in its second position. The dark blue points from the sector scan denote an arch
 172 from which the wind vector can be reconstructed.



185 **Figure 3.** Surface elevation (m) of the outer model domain with the location of three nested model domains
 186 indicated.

179 there were 8 model levels within the first 100 m. The model domains are shown in Fig. 3 and
 180 cover a large part of northwestern Europe. One-way nested domains were used to obtain a
 181 high horizontal resolution near the experimental site, with a grid-spacing ratio of three be-
 182 tween the parent and child nests. The domain boundaries were chosen such that they were
 183 at approximately the same geographical location for all setups with different horizontal grid
 184 spacings.

187 The simulations were initialized everyday at 0000 UTC and were integrated for 36
 188 hours. The first 12 hours were disregarded as model spin-up period. The instantaneous out-
 189 put of the model was saved every 10 min for the third and fourth nested domains and hourly
 190 for the other domains. The model time step was 65.45 s in the outermost domain and de-
 191 creased with the same factor as the model grid spacing for the nested domains. Spectral
 192 nudging was used above the 25th model level (≈ 600 m) to avoid that the model drifts too
 193 much from the large-scale synoptic conditions. The nudging coefficient was set to 0.0003
 194 s^{-1} for wind, temperature and specific humidity, and it was always set to zero at model levels
 195 lower than the PBL height.

196 The physical parametrizations options included the WRF single-moment 5-class mi-
 197 cro physics scheme, the Kain-Fritsch cumulus parameterization (turned off in domain three
 198 and four), the RRTMG scheme for short and long-wave radiation and the Noah land surface
 199 model.

200 The wind speeds were obtained from the lowest 34 model levels and vertically logarithmically
201 interpolated to the heights of the observations. Horizontally, the grid point closest to
202 the positions where observations were available were extracted.

203 **3.2 Sensitivity studies**

204 The following model sensitivity studies were performed to investigate the impact on
205 the model performance in the experimental area.

206 **3.2.1 PBL scheme**

207 The first-order Yonsei University (YSU) and the 1.5-order Mellor-Yamada Janjic
208 (MYJ) closure schemes were used to represent the PBL [*Noh et al.*, 2003; *Janjić*, 1990]
209 (see Table 2). All sensitivity set-ups introduced further on were performed with both PBL
210 schemes.

211 **3.2.2 Horizontal grid spacing**

212 Three different horizontal grid spacings were used. The first set-up has a spacing of
213 18, 6 and 2 km for the outermost, middle and innermost domain, respectively. The second
214 set-up uses 9, 3 and 1 km in those domains and the finest spacing used four nested domains
215 with a spacing of 13.5, 4.5, 1.5 and 0.5 km. The resolution of the innermost domain is used
216 as a subscript in Table 2. Despite the relatively high resolution, there is still a difference of
217 ≈ 20 m between the observed terrain elevation and that used as input for the simulations
218 with the finest horizontal grid spacing at the position of the cliff. That is partly because the
219 resolution is insufficient in the elevation data itself (see Sect. 3.2.3), but mostly because the
220 WRF model needs input data that is interpolated to the coarser model grid.

221 *Wyngaard* [2004] introduced the concept of modelling in the ‘terra incognita’, i.e.
222 when the scale of the spatial filter of a mesoscale model is similar to the dominant length
223 scale of the flow. For a convective boundary-layer, this characteristic scale is about 1 km
224 and therefore some of our simulations can partially resolve turbulence. However, the PBL
225 schemes in a mesoscale model are developed under the assumption that all turbulent motions
226 are in the subgrid-scale. Because the RUNE experiment took place during winter, stable and
227 neutral conditions prevail and the turbulent eddies are expected to be smaller than in unstable
228 conditions. On the other hand, cold-air advection over a warm North Sea can still result in

231 **Table 2.** Abbreviated name, the atmospheric boundary conditions, PBL scheme, SST source, land-cover
 232 source and the horizontal resolution of the innermost domain of the modelling set-ups used during the RUNE
 233 campaign.

Model	Atmos.	PBL	SST	land	horizontal
Simulation	Bound.	scheme	source	source	grid
	cond.				spacing
					[m]
YSU ₂	FNL	YSU	DMI	CORINE	2000
YSU ₁	FNL	YSU	DMI	CORINE	1000
YSU _{0.5}	FNL	YSU	DMI	CORINE	500
MYJ ₂	FNL	MYJ	DMI	CORINE	2000
MYJ ₁	FNL	MYJ	DMI	CORINE	1000
MYJ _{0.5}	FNL	MYJ	DMI	CORINE	500
YSU _{HRSSST}	FNL	YSU	HR	CORINE	2000
MYJ _{HRSSST}	FNL	MYJ	HR	CORINE	2000
YSU _{USGS}	FNL	YSU	DMI	USGS	2000
MYJ _{USGS}	FNL	MYJ	DMI	USGS	2000
YSU _{ERA}	ERA	YSU	DMI	CORINE	2000
MYJ _{ERA}	ERA	MYJ	DMI	CORINE	2000

229 unstable boundary layers; during 15% of the time of the campaign the modelled PBL height
 230 at position 7 was more than 1000 m.

234 3.2.3 Terrain elevation and land use

235 The description of the land cover is important to correctly assign the surface albedo,
 236 the emissivity and the roughness length to the land around the experimental area. In this
 237 study, the land-use is also vital for correctly positioning the coastline. The standard land-use
 238 description that is often used with the WRF model is based on the 24-category United States
 239 Geological Survey (USGS) data [Anderson *et al.*, 1976]. However, it is a rather outdated data

240 set that represents the land-use conditions in 1992 [Nielsen, 2013]. In the USGS data set the
241 main land use in Denmark is cropland, with very few forests and built-up areas (Fig. 1b).

242 A more recent attempt to describe the land-use in Europe was made as part of the
243 CORINE project. The resulting data set is freely available online [COR, 2006]. The ver-
244 sion used here reflects the land-use situation in 2006 and has a grid spacing of 250 m. The
245 CORINE data are divided in 44 categories, but these were reassigned to the same 24 cate-
246 gories as the USGS data [Pindea *et al.*, 2002]. In the CORINE data set, Denmark has many
247 scattered villages and forests, which is more realistic than the rather homogeneous landscape
248 in the USGS data (see Fig. 1b and 1c).

249 A 25th landuse category is reserved for describing lakes. This can be important in
250 Denmark, because inland water bodies can freeze during winter and can therefore have a wa-
251 ter temperature that is very different from that of the North Sea. The water temperature from
252 a lake in WRF is estimated from the averaged soil temperature in the driving (re)analysis,
253 whereas the SST is determined from a different external data source. Around the experimen-
254 tal site there are several lakes and fjords.

255 Modified SRTM data with a horizontal grid spacing of 90 m was used [Vie, 2015] for
256 describing the terrain elevation in the WRF model.

257 **3.2.4 Sea surface temperature**

258 To investigate the impact of the SST on the simulations, we used two different data
259 sources. The first product is a real-time global (RTG) daily high-resolution (HR) SST anal-
260 ysis from the National Centers of Environmental Prediction (NCEP). The resolution of this
261 product is $1/12^\circ$ [Gemmill, W. and Katz, B. and Li, 2007]. In Table 2 this SST product is ab-
262 breviated as HR.

263 In winter, there can be significant gradients in SST near the coast in Denmark. A prod-
264 uct that resolves well these strong SST gradients near the coast, is the new high-resolution
265 SST data set developed by the Danish Meteorological Institute (DMI). The Level 4 DMI
266 North Sea-Baltic Sea daily analysis has a resolution of 0.02 degrees [Høyer and Karagali,
267 2016]. It has been specifically developed taking into consideration the conditions occurring
268 in the Scandinavian region. These data were provided by GHRSSST, DMI and the MyOcean
269 regional data assembly centre.

270 The mean SST difference between the two data sources during the RUNE experimental
 271 period at positions 6 and 7 was small, but in other places it was significant; at the northern
 272 tip of Jutland, the DMI data set had a mean SST that was $\approx 2^\circ\text{C}$ warmer than the HR data
 273 set. Near the south coast of Denmark there were areas where the DMI data set had a SST that
 274 was $\approx 1^\circ\text{C}$ colder than those from the HR data set.

275 **3.2.5 Driving global analysis**

276 The atmospheric initial and boundary conditions that drive the mesoscale model can
 277 greatly influence the mean wind speed and model skill [Floors *et al.*, 2013]. Therefore, data
 278 from the Final Analysis (FNL) from the NCEP [*National Centers for Environmental Pre-*
 279 *diction, National Weather Service, NOAA, 2015*] and the ERA Interim Reanalysis from the
 280 European Centre for Medium-Range Weather Forecasts [Dee *et al.*, 2011] were used here.

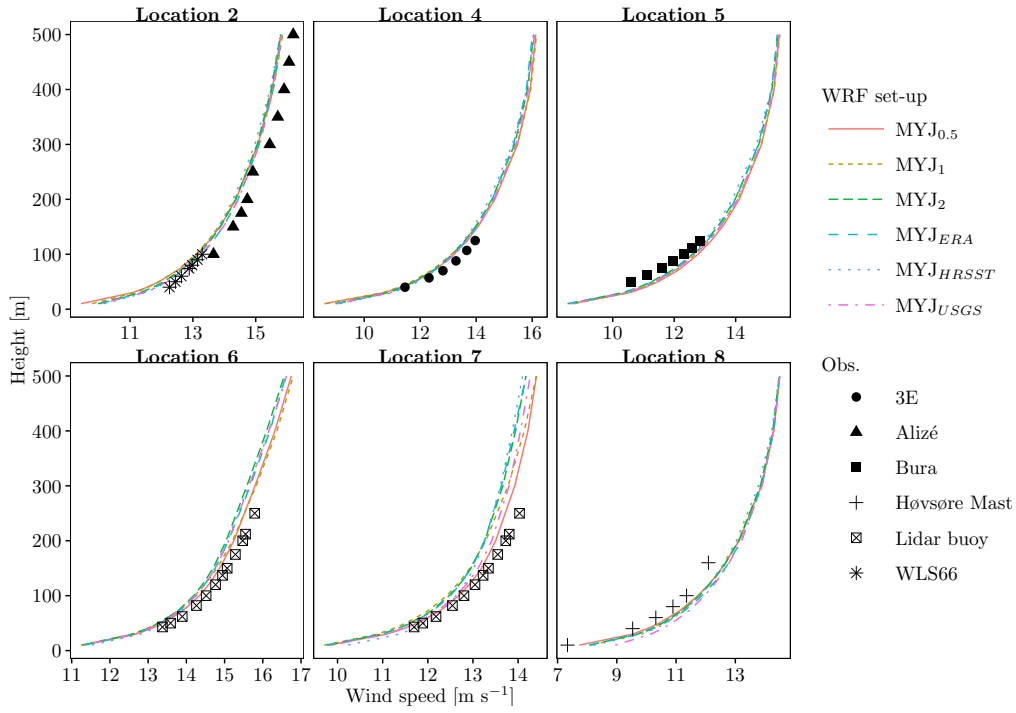
281 Initially all simulations were performed with the FNL data, because these were avail-
 282 able near real-time. All simulations were performed with a delay of ≈ 2 days. The ERA in-
 283 terim data are available with a delay of ≈ 2 months. Because more observations have been
 284 assimilated in this data set compared to FNL, it is more likely to represent most closely the
 285 atmospheric conditions during the campaign. The horizontal grid spacing of the FNL data is
 286 0.25° , whereas it is 0.75° for the ERA interim data.

287 **4 Results**

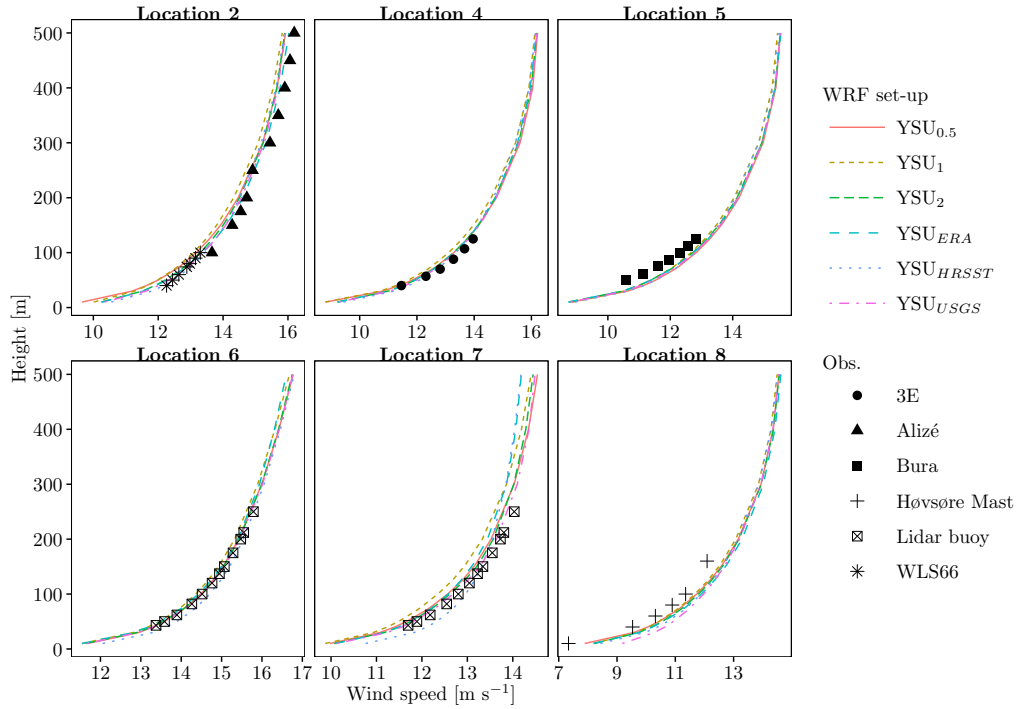
288 **4.1 Vertical profiles**

289 The mean wind speed from the vertically profiling lidars and those simulated by WRF
 290 using the MYJ scheme are shown in Fig. 4. For each panel the observations from the lidar
 291 and the model were merged for each available time stamp, so that they are concurrent. At lo-
 292 cation 2 (at the coast), there are available measurements from both a short and a long-range
 293 lidar. It can be seen that all model simulations underestimate the mean wind speed at all
 294 heights. Near the surface the bias is largest and $\approx -0.7\text{ m s}^{-1}$ using the MYJ_{0.5} simulation.
 295 The mean wind speed near the ground is high due to the lidar position close to sea, where the
 296 wind speed is likely influenced by an orographic speed-up resulting from the cliff.

301 At location 4, i.e. ≈ 1 km inland, the mean wind speed near the ground has decreased
 302 due to the effect of local topography. All model simulations represent the mean wind speed



297 **Figure 4.** The mean simulated and observed wind speed (m s^{-1}) as a function of height (10–500 m) during
 298 the RUNE campaign using the simulations with the MYJ PBL scheme (Table 2) at different locations (Table
 299 1). The number of available 10-min intervals for each panel is shown in Table 1.



300

Figure 5. As in Fig. 4, but with the YSU PBL scheme.

303

at this location quite well, despite an slight underestimation at all heights. At location 5, i.e. ≈ 1.5 km inland, all model simulations slightly overestimate the mean wind speed.

304

305

Offshore, at locations 6 and 7, the mean wind speed is much higher than over land. Larger differences are visible between the different model simulations, partly because of the short observation period. At all heights the simulated mean wind speed is lower than that observed. The MYJ_{0.5} simulation has the highest mean wind speed at 500 m, whereas the MYJ_{HRSST} simulation shows the highest mean wind speed near the surface.

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307

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Location 8 (meteorological mast) is the most inland location and identified from the low mean wind speeds. Here the MYJ_{USGS} simulation has a much higher wind speed near the surface than the other simulations, which is a consequence of the reduced surface roughness in the simulation using the USGS land use (see Fig. 1, panel b). At 500 m above the surface, the differences in mean wind speed between the different simulations are negligible.

311

312

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315

All the simulations that used the YSU PBL scheme are shown in Fig. 4. Generally the results are very similar as when the MYJ scheme is used (Fig. 4), except at the two offshore locations 6 and 7. Here, all simulations with the YSU scheme have a smaller bias than those

316

317

318 using the MYJ scheme. The difference in mean wind speed between the model simulations
 319 and the observations is very small ($\lesssim 0.1 \text{ m s}^{-1}$) at location 6.

320 4.2 Cross sections

321 In this section we evaluate the mean wind speed across the experimental site from 5
 322 km offshore up to 2 km inland. We required that all sampling points fulfilled the quality cri-
 323 teria that are discussed in Sect 2.2. Furthermore, we required availability of the vertically
 324 profiling lidars during the same period, to be able to compare the two data sources. Finally,
 325 we can compare the sector scan that has some sampling points at the same locations as the
 326 the dual setup. An all-sector mean wind speed at all the dual-setup locations using the 731
 327 10-min periods at at 50, 100 and 150 m amsl that remained after filtering are shown in Fig.
 328 6. The model output from all simulations was extracted during the same 10-min intervals.

329 At 50 m amsl and at 5 km offshore, the mean simulated wind speed is slightly higher
 330 than that observed with the dual setup. The sector scan shows a mean wind speed that is
 331 $\approx 0.3 \text{ m s}^{-1}$ higher than that of the dual-setup mainly due to the problems of accurately re-
 332 constructing a wind speed when the wind is perpendicular to the line-of-sight [Floors *et al.*,
 333 2016]. Near the coast this problem is less pronounced due to the shorter arc-length and the
 334 mean wind speed from the dual and sector scan setup agree well.

335 East of the coastline the observed mean wind speed from the dual setup at 50 m amsl
 336 is significantly lower than that simulated. This is likely because the flow in the mesoscale
 337 model needs a few grid points to adjust to the new logarithmic wind profile that results from
 338 the higher surface roughness. Furthermore, the real terrain height is higher than that in the
 339 simulations, which causes the wind speeds obtained from the dual setup to be closer to the
 340 surface. This is because the measurements and simulations could only be compared at a
 341 height relative to sea level and not to the surface (see Sect. 2.2). The effect of horizontal
 342 resolution is visible by the strong decrease in wind speed near the coastline of the simula-
 343 tions with highest horizontal resolution, YSU_{0.5} and MYJ_{0.5}, that can better resolve the fast
 344 deceleration of the flow. Moving towards the land from an offshore position closer to the
 345 coastline, the mean wind speed from the dual-setup decreases more than that from the model
 346 simulations. This is probably due to flow blocking effect of the cliff, which is not represented
 347 in the WRF model simulations.

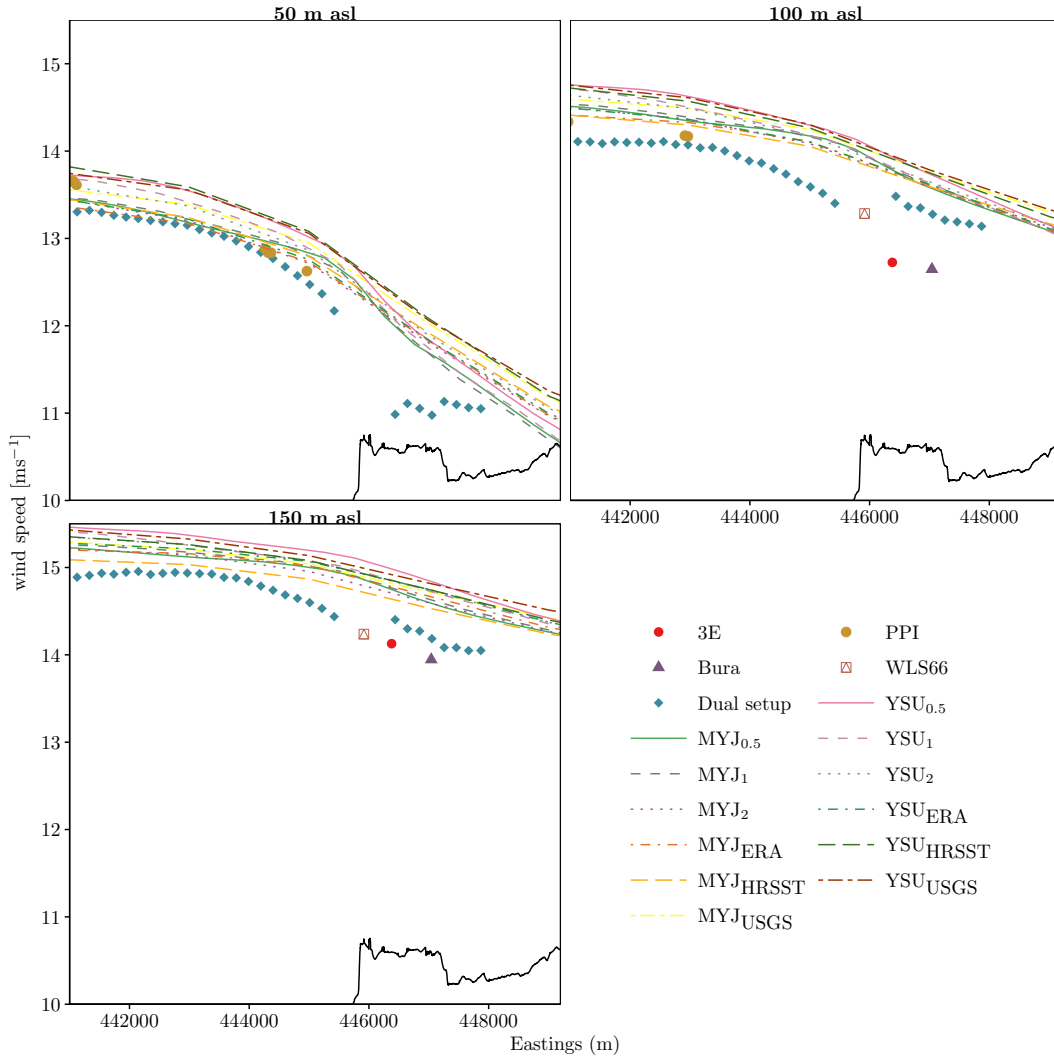
348 At the furthest offshore position reached by the dual setup at 50 m amsl, the YSU_{HRST}
349 simulation shows the highest mean wind speed and the MYJ_{ERA} simulation the lowest. The
350 mean wind speed from all the simulations do differ by less than 0.5 m s^{-1} , so the sensitivity
351 of the mean wind speed gradient to the different model setups is quite low. However, most
352 YSU simulations show a stronger decrease of the mean wind speed eastward of the coastline
353 and higher offshore mean wind speeds compared to the MYJ simulations. A more detailed
354 description of model performance is given in Sect. 4.3.

355 At 100 m amsl, all simulations over-predict the mean wind speed both offshore and
356 onshore. The YSU_{0.5} simulation shows the highest mean wind speed. Although the verti-
357 cally profiling lidars do not measure the wind in the same exact position as the dual setup,
358 the mean wind speed from the vertically profiling lidars also decreases moving from the
359 coastline inland. The mean wind speed from 3E and Bura is lower than that from the dual
360 setup, mainly due to the terrain height at those positions; Bura and 3E measured closer to the
361 ground than WLS66.

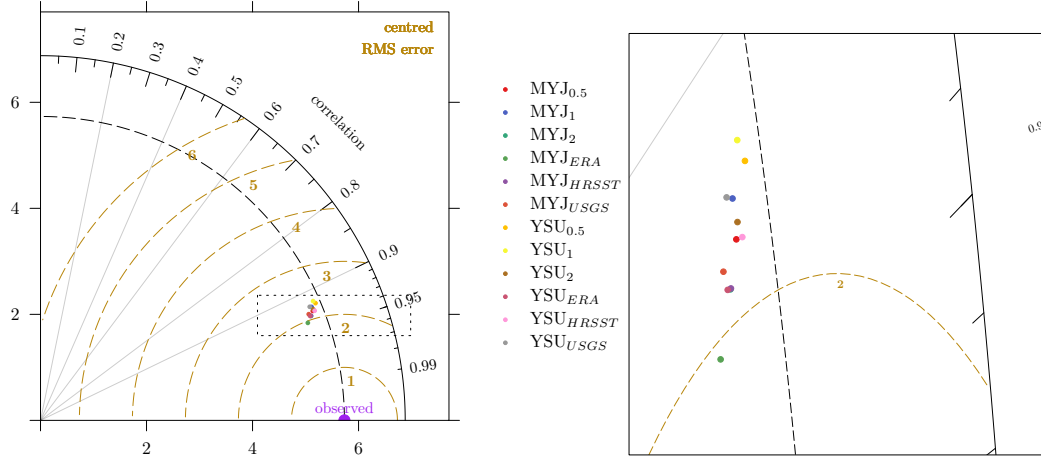
362 At 150 m amsl the east-west gradient in mean wind speed is less pronounced than at
363 50 and 100 m amsl. This is due to the smaller influence of the land at these heights. Still,
364 all model simulations over-predict (by $0.5\text{--}0.8 \text{ m s}^{-1}$) the mean wind speed compared to the
365 dual-setup observations.

366 One could argue that the strict filtering can cause the cross sections to not be represen-
367 tative of the mean wind conditions of the 4 month period. Thus, we also studied the mean
368 wind speed for a shorter scanning distance offshore, such that more transects were available.
369 Including transects that extend to no more than 2 km away from the coast (not shown) in-
370 creased the data recovery percentage to 15%. The over-prediction was slightly smaller for
371 this data set, but qualitatively it did not change the patterns described above.

376 Although the different model simulations show similar wind speeds here, larger dif-
377 ferences in wind speed at 100 m were observed downstream of the coastline on a transect
378 located further north (not shown). This is because of patches of different landuse and rough-
379 ness that were unresolved in some of the 2-km and USGS simulations. This shows that the
380 similar wind speeds of different model set-ups at this transect are partly caused by the homo-
381 geneous terrain that was selected to carry out the measurements.



372 **Figure 6.** The reconstructed mean wind speed obtained from the sector-scan and dual setup and the vertical
 373 profiling lidars between 5000 m offshore and 2000 m inland (points) and the simulations (lines, Table 2) at
 374 three heights asl: 50 m (top left), 100 m (top right) and 150 m (bottom left). The black lines denotes the
 375 terrain height (not to scale).



396 **Figure 7.** Taylor diagrams of the model performance of the simulated wind speed in various setups during
 397 the experiment using all 237493 10-minute intervals from all lidars in VAD mode and the meteorological
 398 mast at all available heights. The area of the plot shown in the right panel is denoted with a dashed line in the
 399 left figure.

382 4.3 Overall model performance

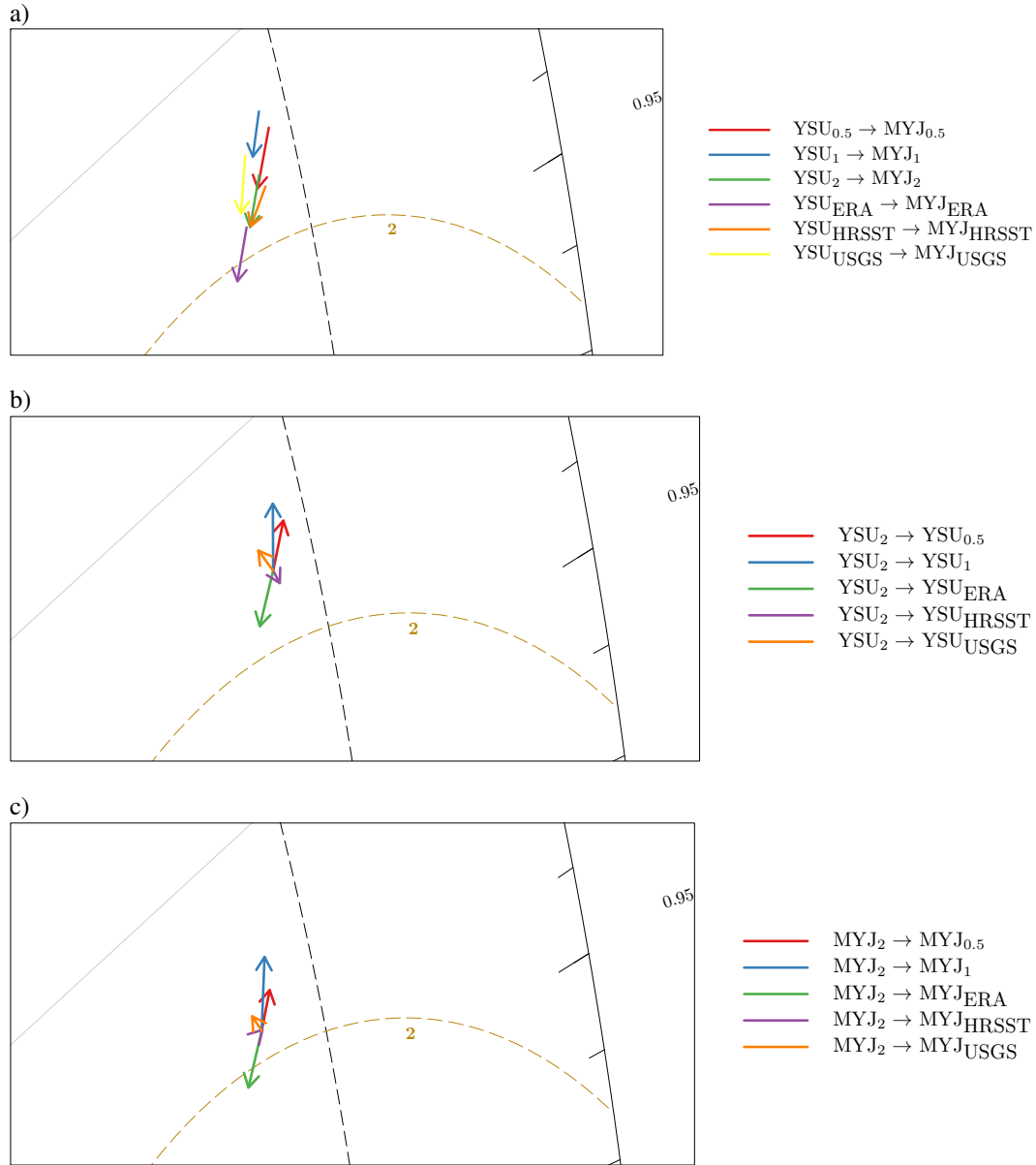
383 We use Taylor diagrams to evaluate the model performance in more detail [*Taylor,*
 384 2001]. The diagrams combine the correlation coefficient (R), centered root-mean-square er-
 385 ror (RMSE) and standard deviation (σ) of observed and modelled variables. The correlation
 386 coefficient, R , is defined as

$$R = \frac{1}{\sigma_x \sigma_y} \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}), \quad (1)$$

387 where N is the number of samples, x_i is the observed variable, y_i is the modelled variable
 388 and the overbar and σ denotes their mean and standard deviation, respectively. The centered
 389 RMSE is defined as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N [(x_i - \bar{x}) - (y_i - \bar{y})]^2}. \quad (2)$$

390 An example of a Taylor diagram is shown in Fig. 7. The distance from the origin de-
 391 notes the standard deviation. For clarity, the standard deviation of the observations is de-
 392 noted with a dashed black line. The correlation coefficient is given by the radial position on
 393 the diagram, with the x -axis denoting a correlation coefficient of 1, i.e. a perfect agreement
 394 between observations and model. Finally, the distance to the point denoting the observations
 395 is proportional to the RMSE.



400 **Figure 8.** Taylor diagrams showing the influence to the wind speed of changing the PBL scheme from
 401 YSU to MYJ (a), the influence of changing the source of SSTs, horizontal resolution, reanalysis data and
 402 land-surface scheme for the MYJ scheme (b) and for the YSU scheme (c) and keeping the rest of the model
 403 configuration constant.

404 The right panel of Fig. 7 shows a zoomed view of the left Taylor diagram, to better dis-
 405 tinguish the different model simulations. The same zoomed area is used for all the other Tay-
 406 lor diagrams in this section, such that we can easily compare the impact of changing a model
 407 setup.

408 Most of the simulations have a RMSE around 2 m s^{-1} and a standard deviation around
 409 5.5 m s^{-1} . However, a more clear overview of the impact of changing an element of the
 410 model configuration can be achieved by drawing an arrow from a ‘control’ simulation to a
 411 simulation with a certain change. If the arrow points downward, it indicates that the corre-
 412 lation coefficient has increased and the centered RMSE has decreased, i.e. a better model
 413 performance.

414 First we investigate the impact of changing the PBL scheme, by drawing an arrow from
 415 those simulations that use the YSU PBL scheme to the ones using the MYJ scheme. Fig.
 416 8a shows that this change leads to a better model performance: all the arrows are pointing
 417 downward, i.e. an increased correlation coefficient and decreased centered RMSE, indicating
 418 that the MYJ scheme performs better than the YSU scheme in this period. However, all ar-
 419 rows are pointing away from the line with the observed wind speed standard deviation, which
 420 means that the standard deviation is lower in the model simulations with the MYJ scheme
 421 than those with the YSU scheme.

422 In Fig. 8b we show the impact of changing the horizontal resolution and the SST, land
 423 and atmospheric boundary conditions using the YSU PBL scheme. Using the ERA-interim
 424 instead of the FNL atmospheric boundary conditions results in an improved model perfor-
 425 mance. This is not a trivial result, because the ERA-interim data has a much lower resolution
 426 but also has more observations assimilated in it.

427 Increasing the horizontal grid spacing from the control 2 km results in a decreased
 428 model performance. Both the YSU₁ and YSU_{0.5} show a lower correlation coefficient and
 429 higher centered RMSE compared to the YSU₂ simulation. The simulations with higher hor-
 430 izontal resolution resolve more atmospheric motions and have a higher variance: this results
 431 in a higher RMSE if the correlation coefficient between the simulated and observed wind
 432 speeds is smaller than one. It is well known that standard metrics are often penalized by in-
 433 creased resolution [Uttal *et al.*, 2002]. This issue is further investigated in Sect. 4.4.

434 To investigate whether the model performance changed only in the surface layer, the
 435 diagrams were split in heights below and above 80 m above ground level. Using USGS data
 436 instead of the CORINE land cover data results in decreased model performance below 80 m
 437 and above 80 m the difference between these simulations was negligible (not shown). Us-
 438 ing the HR compared to the DMI SST product has a very small impact on the model perfor-
 439 mance (Fig. 8c). However, it is possible that larger differences in error metrics are seen in
 440 other regions with larger differences in SST.

441 Fig. 8c shows the same sensitivities as 8b, but using the MYJ scheme. The impact of
 442 changing e.g. atmospheric or surface boundary conditions is very similar compared to that
 443 seen when the YSU scheme is used. This confirms the statistical robustness of the results and
 444 shows that the model responds similarly to changing the boundary conditions when different
 445 PBL schemes are used. The only exception is that the arrow from the MYJ_{0.5} simulation is
 446 shorter, indicating that using a higher resolution with the MYJ scheme does not decrease the
 447 model performance as much as when using the YSU scheme. We do not understand fully the
 448 reason for this, but this issue is further investigated in Sect. 4.4).

449 The error metrics of all simulations are summarized in Table 3. The MYJ_{ERA} has the
 450 lowest RMSE and mean absolute error. The mean bias is not available in the Taylor diagram.
 451 From this metric the MYJ_{ERA} performs well (bias of -0.04 m s^{-1}), but the setup with the
 452 lowest overall bias is the YSU₂ simulation (0.02 m s^{-1}). There is very low mean relative
 453 errors between the simulated and observed mean wind speed, which shows that when mul-
 454 tiple heights and locations are used for a comparison, the mesoscale model predicts the mean
 455 wind speed in this area very well. At individual sites and heights, however, there are still
 456 larger errors mostly due to terrain effects not present in the WRF model (see Fig. 4.1).

460 **4.4 Observed and simulated velocity spectra**

461 The model setups with a higher horizontal resolution resolve a larger range of atmo-
 462 spheric motions. To investigate the impact of increasing the resolution, we compare the spec-
 463 tra of the wind speed from the measurements and the model output from the simulations at
 464 the Høvsøre mast at 100 m. To avoid a noisy appearance in the high frequency part of the
 465 spectrum, the observed spectra were smoothed by computing an average of a maximum of 15
 466 Fourier coefficients in each decade, whereas for the modelled spectra this number was 5. We

457 **Table 3.** Error metrics using 237493 available 10-min measurements from all heights and locations. The
 458 mean absolute error is defined as $\frac{1}{N} \sum_{i=1}^N |y_i - x_i|$, the mean bias as $\overline{y_i} - \overline{x_i}$ and the mean relative error as
 459 $100(\overline{y_i} - \overline{x_i})/\overline{x_i}$. The best performing simulation for each error metric is shown in bold.

Setup	RMSE (m s ⁻¹)	Mean abs. err. (m s ⁻¹)	Mean bias (m s ⁻¹)	<i>R</i> (-)	Mean mod. (m s ⁻¹)	Mean obs. (m s ⁻¹)	Mean rel. err. (%)
MYJ _{0.5}	2.15	1.56	-0.16	0.93	12.11	12.27	-1.31
MYJ ₁	2.23	1.61	-0.16	0.92	12.11	12.27	-1.29
MYJ ₂	2.07	1.50	-0.10	0.93	12.17	12.27	-0.79
MYJ _{ERA}	1.96	1.48	-0.04	0.94	12.23	12.27	-0.31
MYJ _{HRSST}	2.07	1.51	-0.05	0.93	12.22	12.27	-0.39
MYJ _{USGS}	2.11	1.56	0.09	0.93	12.36	12.27	0.73
YSU _{0.5}	2.28	1.65	-0.09	0.92	12.17	12.27	-0.76
YSU ₁	2.33	1.67	-0.16	0.92	12.11	12.27	-1.31
YSU ₂	2.18	1.57	0.02	0.93	12.29	12.27	0.15
YSU _{ERA}	2.07	1.54	0.06	0.93	12.33	12.27	0.47
YSU _{HRSST}	2.14	1.54	0.14	0.93	12.41	12.27	1.14
YSU _{USGS}	2.24	1.64	0.20	0.92	12.47	12.27	1.61

467 also extracted the modelled time series from the second domain of configuration MYJ_{3,0} and
 468 YSU_{3,0} to compare more horizontal grid spacings.

469 *Larsén et al.* [2016] discussed the different frequency (f) ranges of atmospheric spec-
 470 tra: at lower frequencies between $1 \text{ year}^{-1} < f < 1 \text{ day}^{-1}$ the slope of the power spectra,
 471 $S(f)$, versus f in the log-log scale is ≈ -3 , between $1 \text{ day}^{-1} < f < 1 \text{ hour}^{-1}$ it is $\approx -5/3$
 472 and at higher frequencies the uncertainty in slope is rather high and depends on the existence
 473 of a spectral gap that separates mesoscale and turbulent motions.

474 In Fig. 9 (top) the MYJ scheme matches well the observed spectra at frequencies larger
 475 than 1 day^{-1} . Between frequencies of 1 day^{-1} and 1 hour^{-1} , all model simulations gradually
 476 start to under-predict the spectral density. This is caused by the numerical filters that are ap-
 477 plied in a mesoscale model [Skamarock, 2004] to keep a stable model solution. When $f < 1$
 478 hour^{-1} there are distinct differences between the simulation results from different horizon-
 479 tal grid spacings: the MYJ_{0,5} and MYJ_{1,0} simulations have a much higher spectral density
 480 than the other coarser resolutions. The MYJ_{3,0} simulation shows a rather steep decline when
 481 $f < 1 \text{ hour}^{-1}$, showing that it does not resolve these motions with this grid spacing. There-
 482 fore, a 10-minute output frequency with a grid of 3 km spacing is unnecessary.

483 The simulations MYJ_{0,5} and MYJ_{1,0} have a rather different spectral slope when $f < 1$
 484 hour^{-1} compared to the simulations with higher horizontal grid spacing. Skamarock [2004]
 485 argued that such an upward turned tail in the high frequencies indicates a model that has an
 486 non-physical treatment of these atmospheric motions. On the other hand, the observed spec-
 487 tral slope is similar to the modelled one for the simulations MYJ_{1,0} and MYJ_{1,5} and for these
 488 grid spacings it is possible that the model is capable to better represent high-frequency mo-
 489 tions due to the higher resolution.

490 Note that the simulations with a grid spacing of 1 km have a higher spectral energy at
 491 high frequencies than those with 0.5 km spacing. This is likely due to the model configura-
 492 tion in the outer domains; the MYJ_{0,5} has a higher resolution near the site, but the 4th do-
 493 main only covers a small area (see Fig. 3). In domains 2 and 3, MYJ₁ has a higher resolution
 494 than MYJ_{0,5}.

495 The velocity spectra from the simulations using the YSU scheme are shown in Fig.
 496 9 (bottom). In general, simulations with the YSU scheme have higher spectral energy than
 497 those with the MYJ scheme. Particularly the YSU_{0,5} simulation has a higher spectral energy

498 than the observations at high frequencies. This could indicate that these high-resolution sim-
499 ulations do not realistically model high-frequency atmospheric fluctuations.

500 *Honnert et al.* [2011] noted that mesoscale models with ‘terra incognita’ resolutions
501 produce too many resolved fluctuations in a convective boundary layer. *Zhou et al.* [2014]
502 used the Rayleigh-Benard thermal instability theory and a set of idealized simulations to ex-
503 plain the occurrence of this higher variance. Here, the simulations with the finest horizontal
504 grid spacing can be influenced by such modelling issues and this could also possibly explain
505 the higher spectral energy at high frequencies.

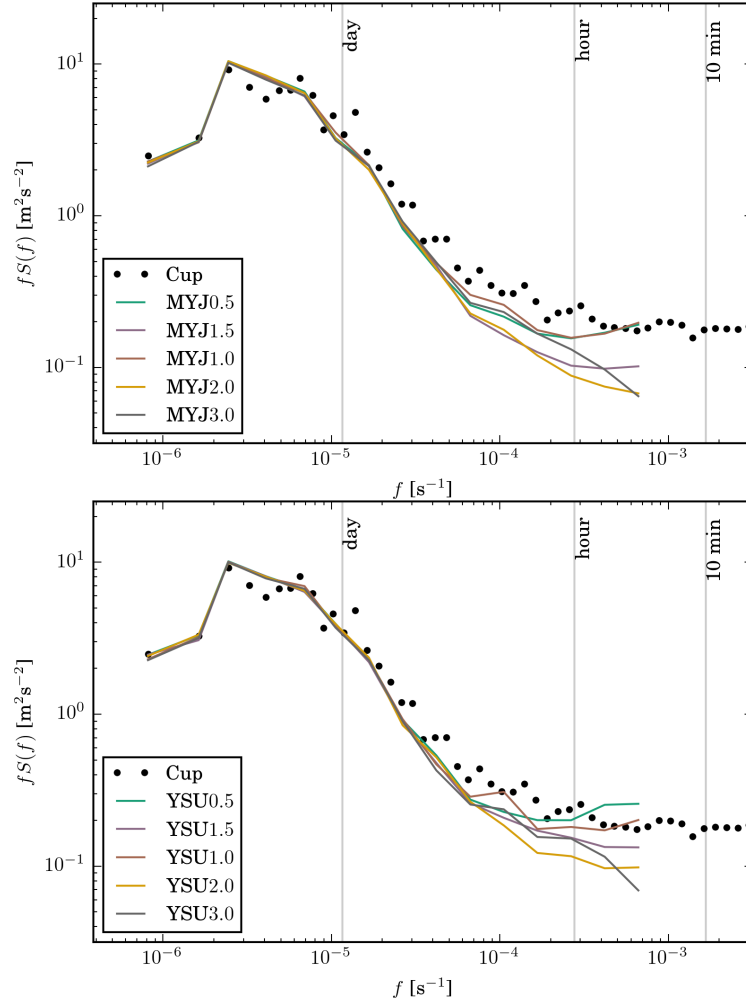
506 Finally, it was found that the velocity spectra were not influenced by the choice of grid
507 point. This was investigated by comparing the modelled spectra ≈ 10 km offshore with those
508 inland near the Høvsøre mast; the velocity spectra at both locations were very similar.

509 The velocity spectra also partially explain the higher RMSE between model and obser-
510 vations of the simulations YSU_{0.5} and MYJ_{0.5}. These simulations also have a higher standard
511 deviation (see Fig. 7) than the simulations with lower resolution. Therefore investigation of
512 velocity spectra of mesoscale model set-ups gives an idea of the model representation of mo-
513 tions in the different scales.

517 **5 Summary and discussion**

518 A number of mesoscale model simulations was performed to test the sensitivity of
519 the simulated wind in the PBL to use different PBL schemes, atmospheric forcing, SST de-
520 scriptions, land use descriptions and horizontal grid spacing for a site along the Danish west
521 coast. The model results were compared with observations from five vertical profiling lidars
522 and scanning lidars at multiple heights and locations.

523 All mesoscale model setups were able to simulate well the mean vertical profile at dif-
524 ferent locations and the decrease of mean wind speed when moving inland was similar as ob-
525 served, despite the relatively coarse resolution of some of the model simulations. The mean
526 wind speed differences among the different setups were very small, although this is partially
527 because of the homogeneous terrain at the experimental site. The YSU scheme had a smaller
528 bias than the MYJ scheme at the offshore positions. This indicates that mesoscale models
529 can estimate the mean vertical wind shear at the hub height of wind turbines well, even in the
530 complex coastal zone.



514 **Figure 9.** Velocity spectra of the model simulations at the Høvsøre mast at 100 m with different horizontal
 515 resolutions using the MYJ (top) and the YSU scheme (bottom) compared to those of the observations from the
 516 cup anemometer.

531 Due to the availability of scanning lidar measurements, we were for the first time able
532 to spatially evaluate the mean horizontal wind speed gradient simulated by the mesoscale
533 model setups. The observed mean wind speed was $\approx 0.5 \text{ m s}^{-1}$ lower than that simulated at
534 the furthest offshore position; however the amount of samples is low. Moving inland from
535 the coast, the mesoscale model did not represent the strong decrease in mean wind speed at
536 50 m well, probably because the microscale features of the terrain are not well resolved, both
537 in the prescribed initial conditions and in the model itself. Increasing the horizontal resolu-
538 tion of the simulations did not result in a better representation of the horizontal gradient of
539 mean wind speed.

540 Despite the small differences in mean wind speed among the different simulations, us-
541 ing Taylor diagrams revealed that there were still differences in other error metrics. Using the
542 MYJ instead of the YSU scheme, caused lower RMSEs and higher correlation coefficients
543 in combination with all model setups. Simulating the flow using ERA interim boundary
544 conditions also led to better model predictions compared to those using FNL data. Using a
545 horizontal grid spacing of 0.5 or 1 instead of 2 km resulted in a higher RMSE and lower cor-
546 relation coefficient, showing that a finer resolution forecast is not always more skillful. Using
547 CORINE instead of USGS land cover description improved the model skill near the surface,
548 but did not have a substantial influence higher up. Using the HR compared to the DMI SSTs
549 only had a minor impact on the model skill.

550 The velocity spectra from the simulations were compared to those obtained from the
551 high frequency cup anemometer data. The observed and modelled spectra agreed well at the
552 low-frequencies ($f \approx 1 \text{ day}^{-1}$), but there were large differences between the simulations
553 with different horizontal grid spacings at high frequencies ($f \approx 1 \text{ hour}^{-1}$). All simulations
554 contained less spectral energy than the observations at frequencies of $\approx 1 \text{ hour}^{-1}$. For the
555 simulations with 0.5 km grid spacing, the tail of the spectra turned upwards at high frequen-
556 cies. This indicates that care should be taken (e.g. by using appropriate parametrization and
557 diffusion constants) when high horizontal resolutions are used in a mesoscale model. Here,
558 the much larger computational costs of using 0.5–1 compared to 2 km grid spacing were not
559 needed to accurately simulate the flow in the coastal zone using the WRF model.

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 567 The data used in this paper are available for download [Floors *et al.*, 2017].

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