Impact of Roughness Length on WRF Simulated Land-Atmosphere Interactions Over a Hyper-Arid Region

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Abstract The aerodynamic roughness length is a crucial parameter that controls surface variables including the horizontal wind, surface temperature, and heat fluxes. Despite its importance, in the Weather Research and Forecasting (WRF) model, this parameter is typically assigned a predefined value, mostly based on the dominant land-use type. In this work, the roughness length is first estimated from eddy-covariance measurements at Al Ain in the United Arab Emirates (UAE), a hyper-arid region, and then ingested into WRF. The estimated roughness length is in the range 1.3–2.2 mm, one order smaller than the default value used in WRF. In line with previous studies, and from WRF model simulations during the warm and cold seasons, it is concluded that, when the roughness length is decreased by an order of magnitude, the horizontal wind speed increases by up to 1 m s⁻¹, the surface temperature rises by up to 2.5°C, and the sensible heat flux decreases by as much as 10 W m⁻². In comparison with in situ station and eddy covariance data, and when forced with the updated roughness length, WRF gives more accurate 2-m air temperature and sensible heat flux predictions. For prevailing wind speeds >6 m s⁻¹, the model underestimates the strength of the near-surface wind, a tendency that can be partially corrected, typically by 1–3 m s⁻¹, when the updated roughness length is considered. For low wind speeds (<4 m s⁻¹), however, WRF generally overestimates the strength of the wind.

1. Introduction

The aerodynamic (or momentum) roughness length ($z_{0m}$) is the height at which the logarithmic extrapolation of the horizontal wind speed in the surface layer assumes the zero value. It is physically related to the geometric roughness of the underlying elements for aerodynamically rough surfaces, being roughly 1/10th of the height of the roughness elements (e.g., Wallace & Hobbs, 2006). A realistic representation of the roughness length is essential for an accurate estimation of the surface transport of momentum, heat, and moisture, based on the Monin-Obukhov (M-O) theory and the similarity relations of Dyer and Hicks (1970) and Businger et al. (1971), an approach widely used in weather and climate models (e.g., Dudhia & Bresch, 2002; Miller et al., 1992). To employ realistic roughness lengths in numerical models is rather challenging, as they are generally a function of the heterogeneity of the land-surface (Reddy & Rao, 2016). The surface roughness of a site is one of the most important parameters, which determines the wind flow. In particular, a rough surface retards the flow compared to a smooth surface, which results in a sharp decrease of the near-surface wind speed and subsequently in changes in the vertical atmospheric profiles and stability (Rao, 1996).

Numerical model simulations are known to be very sensitive to land-surface parameters such as vegetation (e.g., Hong et al., 2009; Rao et al., 2011; Shukla & Mintz, 1982), soil moisture and thermal conductivity (e.g., Massey et al., 2014), and surface roughness length (e.g., Meehl & Washington, 1988; Sud & Smith, 1985). Reijmer et al. (2004) concluded that a change in the roughness length over Antarctica by about three orders of magnitude gives monthly averaged wind speed, air temperature, and sensible heat flux differences of ±2 m s⁻¹, ±10 K, and ±35 W m⁻², respectively. For a vegetated site in the Netherlands, Giorgi (1997) noted...
that the dependence of the surface temperature and sensible heat flux on the roughness length is significant and highly nonlinear. Kim and Hong (2010) found that, using a more sophisticated representation of the roughness length as opposed to the commonly used Charnock formula (Charnock, 1955), the Weather Research and Forecasting (WRF, Skamarock et al., 2008) model biases over the East Asian summer monsoon are reduced. Menut et al. (2013) investigated the sensitivity of mineral dust emission fluxes over northern Africa using satellite-derived roughness length and soil texture estimates. They found that, with the new WRF configuration, the model is able to accurately reproduce the main dust sources and the aerosol optical depth variability in the region. By using an updated zero-displacement plane and aerodynamic roughness length values, roughly three times larger than the default considered in WRF, for a sea breeze event in Tokyo in September 2011, Varquez et al. (2015) reported a much improved simulation of the near-surface horizontal wind speed. Jee et al. (2016) stressed that the use of a realistic roughness length over Seoul leads to an improvement of the friction velocity, wind speed, temperature and relative humidity predictions, and ultimately the model precipitation and Planetary Boundary Layer (PBL) depth forecasts. The papers referred above highlight the important role of the surface roughness length, not just on the prediction of surface and near-surface fields but also on the forecast of the PBL depth.

The present study addresses the estimation of the aerodynamic roughness length over a bare-soil surface using eddy-covariance measurements made available during the UAE Rain Enhancement Program (UAEREP) Project (Nelli et al., 2020). The $z_{om}$ for each type of land surface can be estimated from field measurements made for that particular surface and is known to exhibit temporal variability on both monthly and diurnal time-scales (e.g., D. Zheng et al., 2013). There are estimates of $z_{om}$ for a bare-soil surface only for a few locations outside the UAE, all based on in situ and remote sensing data (e.g., Marticorena et al., 2004; Prigent, 2005; Yang et al., 2008). Marticorena et al. (2004) estimated the surface roughness over North Africa from satellite measurements. An empirical relationship between the observed bidirectional reflectance of the satellite data and roughness estimates from in situ measurements (Greeley et al., 1997) and from the geomorphological maps (Marticorena et al., 1997) was derived. Using this empirical relation, the $z_{om}$ value derived for Western Sahara and Arabian Peninsula regions is nearly 1 mm. A limitation of this method is the high sensitivity of the observations to clouds as well aerosols in the atmospheric column. Prigent (2005) made global estimations of $z_{om}$ for arid and semi-arid regions by using observations from the wind scatterometer onboard European Remote Sensing (ERS) satellite operating at 5.25 GHz. A statistical relationship is derived between the ERS scatterometer backscattering coefficients and quality in situ and geomorphological $z_{om}$ estimates. Based on this parameterized approach, the major deserts in North Africa, Arabia, and Asia have roughness lengths below about 0.2 mm. In addition to satellite-based methods, the surface roughness length can also be computed from in situ-based approaches. For example, K. Yang et al. (2008) estimated $z_{om}$ from observed eddy-covariance measurements during the Heihe River Basin Field Experiment (HEIFE, 1990–1992) in an arid river basin in north-western China. Assuming that the Monin-Obukhov similarity theory holds, the major features of the turbulent heat transfer are first estimated, with the roughness length then computed from the logarithmic wind profile for both neutral and non-neutral conditions. The optimal $z_{om}$ values for the Gobi (absolutely flat) and Desert (sand dunes) flux sites are found to be roughly 0.68 and 2.74 mm, respectively. For different sites in western Germany, Graf et al. (2014) estimated $z_{om}$ from single-level eddy-covariance data using three distinct methods: (i) directly from the logarithmic wind profile; (ii) as (i) but using a regression approach, which accounts for the nonlinearity in $Ψ_{ne}$, the integrated universal momentum function; (iii) flux-variance similarity approach. The authors stressed the need to compare the results of different methods, taking for example the ensemble mean or median of the results, after excluding those that produce outliers, in order to have more robust estimates. Lu et al. (2009) estimated $z_{om}$ indirectly by minimizing the cost function between the friction velocity and that estimated using the logarithmic wind profile around Beijing, China. The surface roughness length is found to be wind-direction dependent, with values in the range 0.001 to 0.01 m. In this work, the aerodynamic roughness length is first estimated using long-term eddy-covariance measurements at one particular site in the UAE, with the new value ingested into the WRF model, which is then run over two months, in the warm and cold seasons. To the authors’ knowledge, this is the first attempt to infer roughness length from in situ observations in the Arabian Peninsula. The determined roughness length was then used in WRF to assess its impact on the surface and near-surface model predictions in such a hyper-arid region.
2. Experimental Setup and Verification Diagnostics

The WRF (Skamarock et al., 2008) model version 3.8.1 dynamical solver, with three-way interactive domains of grid sizes of 12, 4, and 1.333 km shown in Figure 1a, is used to simulate the impact of an updated roughness length for the barren and sparsely vegetated land cover category, the dominant land use type over the UAE as shown in Figure 1b. The outermost domain extends over the Arabian Peninsula, the Arabian Gulf, and Sea of Oman (d01; ~16.4°–31.4°N, 46.3°–61.7°E). The first nested domain covers the entire UAE region (d02; ~20.7°–27.3°N, 50.1°–57.6°E), whereas the innermost grid is centered on Al Ain (d03; ~23.7°–24.9°N, 55.0°–56.3°E).

The model physics options chosen are given in Table 1. A similar setup was used in previous studies over the UAE (e.g., Chaouch et al., 2017; Weston et al., 2018). For all simulations, the Thompson cloud microphysics scheme is used to represent the grid-scale water vapor, cloud, and precipitation processes (Thompson et al., 2008). The subgrid-scale clouds are represented with the Kain-Fritsch scheme (Kain, 2004; Kain & Fritsch, 1990), with subgrid-scale cloud feedbacks to radiation accounted for following Alapaty et al. (2012). The cumulus scheme is switched off in the 4 and 1.333 km grids. The atmospheric radiative heating is calculated using the Rapid Radiative Transfer Model (RRTM) longwave radiation (Mlawer et al., 1997) and RRTMG for Global Circulation Models (RRTMG) shortwave radiation (Iacono et al., 2008) schemes. The exchanges of surface fluxes of momentum, heat, and moisture between land and atmosphere are determined using the Quasi-Normal Scale Elimination (QNSE) Planetary Boundary layer (PBL) and surface layer schemes (Sukoriansky et al., 2005). The land surface model (LSM) employed in the numerical simulations is the Noah LSM (Chen & Dudhia, 2001).

The land cover classes used in this work, Figure 1b, are estimated from the Moderate Resolution Imaging Spectroradiometer (MODIS) measurements at 1 km spatial resolution for the year 2001 (Ran et al., 2010). Following several field campaigns performed as part of the UAEREP project, the soil texture and land use types are adapted to reflect their actual state. The topography employed in the WRF simulations, downloaded from the model's website, is carefully interpolated from a 30″ (or about ~925 m) spatial resolution data set provided by the United States Geological Survey (USGS). The land cover in the Noah LSM is composed of 20 classes, and for each the roughness length is estimated using a predefined minimum and maximum value given in Table 2. The linear interpolation is conducted on a monthly basis, with the minimum $z_0$ corresponding to the minimum in vegetation coverage and vice versa. For the desert land cover type targeted in this work, $z_0$ is always set to 10 mm.

WRF is run for one month in the cold (February 2018) and warm (June 2018) seasons. The model is initialized with Global Forecast System (GFS) data at 0.25° spatial resolution every day at 06 UTC, with the output in the first 6 h forecast of each run regarded as spin-up and discarded. The boundary conditions are updated every six hours, and each simulation is carried over for 72 h with a master time step of 60 s. The model output for each grid is stored hourly with that of the 4 km and 1.333 km grids used for analysis. The WRF predictions are evaluated against (i) 30-minute eddy-covariance measurements at Al Ain’s International Airport (24°16’26.535”N; 55°37’03.2196”E), taken as part of the UAEREP project (Branch & Wulfmeyer, 2019; Nelli et al., 2020), and (ii) hourly station data at 12 sites over the country provided by the UAE’s National Center of Meteorology (NCM), Figure 1c.

The WRF performance is assessed with the bias, Mean Absolute Error (MAE), and Root-Mean-Square Error (RMSE), diagnostics. In addition, the Pearson’s correlation coefficient is used to evaluate the similarity between the temporal evolution of the WRF-simulated wind speed and air temperature and that observed at each station.

3. Estimation of Roughness Length Using Eddy-Covariance Measurements at Al Ain Station

Eddy-covariance measurements from a micrometeorological tower installed in the premises of Al Ain’s International Airport are used to estimate the aerodynamic roughness length, $z_0$ (Nelli et al., 2020). The terrain at the site is nearly homogeneous and obstacle free in the north-west and south-east directions, with major obstacles (namely buildings) located to the south and north-east.
Figure 1. (a) Spatial extent of the 12 km (d01), 4 km (d02), and 1.333 km (d03) domains used in the WRF simulations, (b) dominant land cover category in the 4 km (d02) and 1.333 km (d03) grids, and (c) orography (m) of 4 km (d02) and 1.333 km (d03) grids and location of the 12 weather stations in the latter for which hourly meteorological data is available for evaluation. In (b) and (c), the black rectangle denotes the spatial extent of the innermost nest.

Figure 2. Median (blue) of aerodynamic roughness length (mm) as function of the month of the year. The red curve shows the number of data points used in the calculation of the diagnostics.
Based on the Monin-Obukhov similarity approach, the mean wind speed in the surface layer can be approximated by

\[ U(z) = \frac{u^*}{\kappa} \ln \left( \frac{z}{z_0^m} \right) - \psi_m \left( \frac{z}{L} \right), \]  

(1)

where \( U(z) \) is the near-surface horizontal wind speed (m s\(^{-1}\)), \( u^* \) is the friction velocity (m s\(^{-1}\)), \( L \) is the Monin-Obukhov length, \( \kappa \) is the von Karman constant (=0.4), \( z \) is the measurement height (here 2.3 m), and \( \psi_m \) is the integrated universal momentum function. The horizontal wind speed and \( u^* \) are estimated from ultrasonic anemometer measurements. This instrument is mounted on top of a 2.3 m tower, and its data are archived at a 10 Hz sampling rate.

The surface layer stability is investigated through the Monin-Obukhov stability parameter \( \left( \frac{z}{L} \right) \), where \( L \) is the Monin-Obukhov length, defined as

\[ L = -\frac{u^3}{\kappa g \bar{\theta}_v' \bar{w}'}. \]  

(2)

In Equation 2, \( g \) is the acceleration due to gravity, \( w \) is the vertical velocity, \( \bar{\theta}_v \) is the virtual potential temperature, \( \bar{w}' \) denotes the time-mean, and \( \bar{\theta}' \) the deviation from it. The \( \frac{z}{L} \) values in the range \(-0.01 < \frac{z}{L} < 0.01\) represent the near neutral stability regime, while \( \frac{z}{L} < -0.01 \) and \( \frac{z}{L} > 0.01 \) indicate unstable and stable regimes, respectively (Li et al., 2011). According to Paulson (1970), for the unstable surface layer condition, the universal momentum function \( \psi_m \) is defined as

\[ \psi_m \left( \frac{z}{L} \right) = \ln \left[ 1 + \frac{x^2}{2} \left( \frac{1 + x}{2} \right)^2 \right] - 2 \arctan(x) + \frac{\pi}{2}, \]  

(3)

with \( x = \left[ 1 - \gamma (\frac{z}{L}) \right]^{1/4} \), where \( \gamma \) is a universal constant set to 19.3 (Högström, 1988). For moderately stable conditions (0.01 < \( \frac{z}{L} < 1\)), \( \psi_m \) is defined as

\[ \psi_m \left( \frac{z}{L} \right) = -\beta \left( \frac{z}{L} \right), \]  

(4)

where \( \beta = 6 \) is another universal constant derived from experimental data.
Using Equation 1, the aerodynamic roughness length, $z_{0m}$, can be estimated from the observed surface wind speed, $u_*$, and $L$. Following Graf et al. (2014) the outliers are filtered out by applying two conditions to the data, namely, horizontal wind speed $U > 1.5$ m $s^{-1}$ and $u_*>0.05$ m $s^{-1}$. The measurements collected during the period April–October 2017 and February 2018–January 2019 are used in the present study.

Table 3 shows the monthly mean wind speed $U$, frictional velocity $u_*$, median roughness length $z_{0m}$, and number of data points used in the computation of the three quantities. Following Graf et al. (2014), Janse et al. (2016), and Cullen et al. (2007), the median roughness length is selected instead of the mean value, as it is deemed more representative of the actual $z_{0m}$. All four variables show very little monthly variability, with mean wind speeds in the range 3–4 m $s^{-1}$ and friction velocities mostly between 0.18 and 0.23 m $s^{-1}$, while the roughness length values vary from 1.3 mm in June to 2.2 mm in November and February. These $z_{0m}$ values are within the range of the values cited in the literature for bare-soil surfaces, 0.2–2.74 mm (e.g., Marticorena et al., 2004; Prigent, 2005; Yang et al., 2008). A comparison with Table 2 reveals that the estimated roughness length is roughly one order of magnitude smaller than the default value used in WRF.

In addition to a direct impact on the horizontal wind speed, Equation 1, a change in the surface roughness length will have an effect on the surface exchange coefficients. The exchange coefficient for heat, $C_h$, can be expressed as

$$C_h = \left[ \frac{\kappa^2}{\ln \left( \frac{z}{z_{0m}} \right) - \psi_m \left( \frac{z}{L} \right)} \right] \left[ \ln \left( \frac{z}{z_{0m}} \right) - \psi_h \left( \frac{z}{L} \right) \right],$$

where $\psi_m$ and $\psi_h$ are the integrated similarity functions for momentum and heat, defined in Jiménez et al. (2012). A decrease in $z_{0m}$, with all other parameters being the same, will lead to a lower $C_h$, which will have an impact on sensible heat flux, $H$. In the Noah LSM, the latter is given by

$$H = \rho c_p C_h U (T_{SK} - T_{AIR}),$$

where $\rho$ is the surface air density (kg m$^{-3}$), $c_p$ is the specific heat capacity of the air at constant pressure (J kg$^{-1}$ K$^{-1}$), $T_{SK}$ is the surface temperature (K), and $T_{AIR}$ is the surface air temperature (K), estimated from the air temperature on the lowest model level assuming that the potential temperature is vertically well-mixed just above the surface. A reduced $C_h$ will therefore lead to a reduced $H$. The surface energy budget can be expressed as

$$R_n - G = [SW \downarrow + LW \downarrow - SW \uparrow - LW \uparrow] - G = [SW \downarrow \times (1 - \alpha) + LW \downarrow - \varepsilon \sigma T_{SK}^4] - G = H + LE,$$

where $R_n$ is the net radiation flux, given by the sum of the downward (\downarrow) and upward (\uparrow) long-wave (LW) and short-wave (SW) radiation fluxes, $LE$ is the latent heat flux, $G$ is the ground heat flux, $\alpha$ is the surface albedo, $\varepsilon$ is the surface emissivity, and $\sigma$ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8}$ W m$^{-2}$ K$^{-4}$). In the Noah LSM, the surface temperature, $T_{SK}$, is obtained from Equation 7. If $H$ is reduced, $T_{SK}$ will increase, so as to keep the surface energy budget closed. Hence, a decrease in $z_{0m}$ is expected to lead to an increase in the near-surface horizontal wind speed $U$, Equation 1, a decrease in the sensible heat flux $H$, Equation 6, and an increase in surface temperature $T_{SK}$, Equation 7.

## 4. WRF Sensitivity to Changes in Roughness Length

In this section, the WRF-predicted surface parameters in the simulations with the default and updated roughness lengths are discussed. The focus will be on the horizontal wind speed, surface temperature, and roughness length.
and sensible heat flux, fields that have been shown to be sensitive to the surface roughness length (e.g., Kim & Hong, 2010). Figure 3 shows the WRF predictions, as given by the 4 and 1.333 km grids, for the horizontal wind for the cold (February) and warm (June) season months and for the control configuration (left column) and the difference between the simulations with the updated (2.2 mm for February and 1.3 mm for June) and default (10 mm) roughness lengths (right column). The results are given at roughly the time of minimum (19 UTC or 23 LT; nighttime) and maximum (13 UTC or 17 LT; daytime) diurnal wind speed.
The left panels in Figure 3 show the horizontal wind speed for a typical winter and summer month over the UAE. For both seasons, there is a stark contrast between the land and the adjacent Arabian Gulf: While during daytime the wind is stronger in the former, in association with the sea-breeze circulation reinforced by the background north-westerly winds, at night the highest magnitudes are predicted over the latter, which can be explained by the land breeze circulation (Eager et al., 2008). By and large, the near-surface wind speed is slightly stronger in June when the sea-breeze circulation is more intense and occurs more frequently, even though in both seasons it has a magnitude between roughly 5 and 10 m s⁻¹, in line with published work (e.g.,

Figure 4. As Figure 3 but for surface temperature (°C). The times shown are 03 UTC or 07 LT (a and b) and 10 UTC or 14 LT (c and d) for February 2018 and 01 UTC or 05 LT (e and f) and 09 UTC or 13 LT (g and h) for June 2018, when the skin temperature is minimum and maximum, respectively.
Eager et al., 2008; Naizghi & Ouarda, 2017; Zhu & Atkinson, 2004). It is interesting to note that, on the eastern side of the country right next to the Al Hajar mountains, the horizontal wind speed is much lower during daytime in both months, as seen by the blue shading in (c) and (g). Here, the sea and land-breeze circulations are mostly controlled by the Sea of Oman and not by the Arabian Gulf, and may not be as vigorous, a conclusion also reached by Yagoub (2010). The difference plots look remarkably similar for both seasons, with an expected increase in the strength of the wind, following Equation 1, by roughly 0.5 to 1 m s⁻¹ over the regions where the roughness length is modified (cf. Figure 1b); elsewhere the differences are negligible. This strengthening of the near-surface wind is more significant during daytime when the wind speeds are higher. Reijmer et al. (2004) reported that, when the aerodynamic roughness length was reduced from 3 to 10⁻³ m over Antarctica, the horizontal wind speed changed by ±2 m s⁻¹. Over southern China, Wang et al. (2009) found a decrease of the wind speed of up to 3 m s⁻¹ when the roughness length was increased by roughly two orders of magnitude, due to the urbanization of the region. It is possible then that a change in the roughness length by an order of magnitude in a hyper-arid region, considered in this work, gives a wind speed difference of roughly 0.5 to 1 m s⁻¹.

Figure 4 is as Figure 3 but for the surface/skin temperature. The mean values for the daytime and nighttime temperatures, left column, are in line with those reported in the literature (e.g., Komuscu, 2017). As expected, coastal locations exhibit a smaller amplitude temperature diurnal cycle compared to inland sites, with cooler daytime and warmer nighttime temperatures, due to the moderating influence of the Arabian Gulf (e.g., Zhu & Atkinson, 2004). This is reflected by the negative surface temperature gradient from coastal to inland regions at night and positive during daytime. In winter at night, and as a result of strong radiative cooling, surface temperatures can drop to 12°C, with fog formation being a regular occurrence (e.g., Chaouch et al., 2017; Weston et al., 2018). On the other hand, daytime surface temperatures in some inland regions can exceed 50°C, as a result of the excessive downward short-wave radiation flux arising from a combination of clear skies and dry weather conditions. The sea surface temperature over the Arabian Gulf ranges from 22°C in winter to 32°C in summer. When the roughness length is updated in the model, the nighttime surface temperature stays about the same, with differences generally within ±0.5°C. However, the daytime temperature increases by roughly 1.5–2.5°C. The fact that a change in the surface roughness length has a significant impact on the maximum temperature but a negligible influence on the minimum temperature is consistent with other studies such as June et al. (2018). This is the case because an updated roughness length will affect the surface temperature through changes in the radiative heat fluxes and subsequently in the surface energy budget, Equations 5–7. As the heat fluxes are rather small at night (see Figure 5 in Nelli et al., 2020), the surface temperature is roughly the same in the two simulations. In terms of magnitude, June et al. (2018) reported a roughly 1°C increase in air temperature for a doubling of the roughness length in Indonesia, whereas Reijmer et al. (2004) found an air temperature change of up to ±10°C for a roughness length reduction from 3 to 10⁻³ m over Antarctica. For a vegetated site in the Netherlands, Giorgi (1997) noted a decrease in surface temperature by about 0.4°C when the roughness length was increased from 0.15 to 0.4 m, while an increment of z₀m to 3 m changed the surface temperature by roughly 0.5°C. The magnitude of the surface temperature difference given in Figure 4 is therefore in line with that reported by other authors, larger than that of Giorgi (1997) given the hyper-arid climate of the UAE and consequent lack of vegetation.

The final field shown is the sensible heat flux, $H$, given in Figure 5. The mean values for the daytime and nighttime fluxes, left column, are in line with those reported, for example, in Nelli et al. (2020). At night, the fluxes are close to zero or even negative indicating the presence of an inversion, whereas during daytime they are mostly in the range 150 to 350 W m⁻² in winter and 250 to 450 W m⁻² in the summer. It is interesting to note that over the urban regions (cf. Figure 1b) the sensible heat flux values are rather large during daytime, in excess of 450 W m⁻² in the summer season. These $H$ values are high but not unprecedented: For example, Man Sing et al. (2015) reported that in central business districts of Hong-Kong, the sensible heat flux can exceed 1,000 W m⁻² higher than the surface net radiation flux. As $H$ is rather small at night, the changes in the magnitude of the sensible heat flux when the roughness length is updated will be negligible. During daytime, however, a reduction of the roughness length by roughly an order of magnitude, and in line with Equations 6–7, leads to a decrease in $H$, by roughly 5 to 10 W m⁻². Reijmer et al. (2004) found a change in $H$ of 20–35 W m⁻² when the roughness length was varied by roughly three orders of magnitude over
Giorgi (1997) reported that $H$ increased by about 4 W m$^{-2}$ when $z_0$ was increased from 0.15 to 0.4 m over Cabaux in the Netherlands, but a further increase of the roughness length to 3 m led to a rise in $H$ by roughly 10 W m$^{-2}$. The magnitude of the change in $H$ found here is therefore consistent with that reported in the referred studies. WRF-predicted 2-m air temperature and specific humidity with the default and updated roughness lengths are given in Supporting information S1.

Figure 5. As Figure 3 but for the sensible heat flux (W m$^{-2}$). The times shown are 03 UTC or 07 LT (a and b) and 10 UTC or 14 LT (c and d) for February 2018 and 01 UTC or 05 LT (e and f) and 09 UTC and 13 LT (g and h) for June 2018, when the skin temperature reaches its minimum and maximum values, respectively.
5. Evaluation of WRF Simulations Using Observational Data

In the previous section, the impact of a modification of the roughness length on the near-surface wind speed, surface temperature, and sensible heat flux over the UAE for a winter and summer month was discussed. Here, the performance of the two WRF configurations is assessed against eddy-covariance data at the Al Ain site where the roughness length estimation took place and the 12 NCM stations shown in Figure 1c.

Figures 6 and 7 show the time-series of the three variables at Al Ain for February and June 2018. The left panels show the data for the full month, and the right panels give the WRF biases for the simulations with the control and modified configurations.

For February 2018, the wind speed at Al Ain was generally low, not exceeding 8 m s\(^{-1}\). In line with Nelli et al. (2020), the wind speed diurnal cycle at Al Ain follows a bimodal distribution, with a primary peak in the evening hours, around 18–19 LT, and a secondary peak in the early morning, around 8–9 LT. They result from the interaction of the land/sea-breeze circulation with the topographic-driven winds that arise from the presence of the nearby Al Hajar mountains. The first 11 days were rather cool, with daytime maximum temperatures generally below 25°C and nighttime minimum temperatures at times below 10°C. In the second half of the month, however, it was much warmer, in particular at night, with minimum temperatures above 20°C in the last days. The large (>100 W m\(^{-2}\)) sensible heat fluxes during the day, driven by the strong heating of the land surface by the Sun, contrast with the rather small or even negative values at night, the latter an indication of the presence of an inversion. By and large, WRF over predicts the strength of the near-surface winds typically by 1–3 m s\(^{-1}\), with slightly larger biases when the surface roughness length is updated (maximum differences of ±2 m s\(^{-1}\)), in line with Figure 3. The tendency of the WRF model to overestimate the 10-meter horizontal wind speed in arid regions has been highlighted by other authors such as Gunwani and Mohan (2017), who also reported similar biases. Hari Prasad et al. (2016) in a tropical station in southeast India, Cheng and Steenburgh (2005) and Steeneveld et al. (2008) over the United States, and Borge et al. (2008) over the Iberian Peninsula also reached a similar conclusion. Possible explanations for this systematic discrepancy include (i) a poor representation of its subgrid-scale fluctuations and of the surface drag parameterization in the model; (ii) an inaccurate simulation of the land and/or sea surface temperatures and hence the low-level atmospheric circulation; (iii) uncertainties in the estimation of the roughness length and measured wind speed; and (iv) impact of unresolved topography not accounted for in the WRF runs. In the first 14 days of the month, WRF exhibits a clear tendency to overestimate the nighttime temperature, while in the second half, it is mostly underestimated. These discrepancies are generally within ±2°C, with the simulation with the reduced roughness length giving an improved performance (the bias is generally reduced by up to 2°C), consistent with Figure 4. The larger bias values seen in Figure 6d arise from a tendency of the WRF model to warm up faster in the morning and cool down faster in the evening with respect to observations. This has been reported by Weston et al. (2018) and can be explained by (i) an incorrect representation of the local topography, such as a topographic orientation tilted more towards the Sun in the morning in WRF; (ii) an under prediction of the amount of dust or greenhouse gas concentrations in the atmosphere; and/or (iii) deficiencies in the radiation scheme. Given the referred biases in the temperature diurnal cycle, the sensible heat flux variability will be exaggerated in the two WRF simulations. In particular, if \(H\) is higher than that observed during the daytime, owing to the warmer surface temperatures, and lower at night, indicating a stronger inversion in the model. As for the temperature, when run with the modified configuration, WRF generally gives more accurate sensible heat flux predictions, with a decrease in the bias by up to 50 W m\(^{-2}\).

The model biases highlighted above for the winter month (February 2018) are also mostly present in the summer month (June 2018), as seen by comparing Figure 6 with Figure 7. The magnitude of the wind speed overestimation is slightly larger in the warm season, at times exceeding 8 m s\(^{-1}\). However, the wind speed in June 2018 is also generally higher than that in February, in line with Eager et al. (2008) and Nelli et al. (2020) and Figure 3, due to the stronger land/sea-breeze and downslope-upslope circulations of the nearby Al Hajar mountains. While in February 2018 WRF both overestimated and underestimated the minimum temperature, in June the latter tendency prevails throughout the month, also with respect to the maximum temperatures. This cold bias has been reported by other authors in studies over arid and semi-arid regions (e.g., Valappil et al., 2019; Weston et al., 2018; Zheng et al., 2012) and can at least be partially corrected by modifying the land surface model's configuration (Weston et al., 2018). The diurnal variability of the observed
Figure 6. (a) Observed (black) and WRF-predicted 10-meter horizontal wind speed (m s\(^{-1}\)) for the simulations with the control (red) and modified (blue) configurations for February 2018 at Al Ain location. (c) and (e) are as (a) but for the 2-m air temperature (°C) and sensible heat flux (HFX, positive if upwards from the surface; W m\(^{-2}\)), respectively. (b), (d), and (f) show the correspondent WRF biases.

Figure 7. As Figure 6 but for June 2018.
sensible heat flux is comparable to that in the cold season, except that the higher daytime surface temperatures lead to more positive fluxes during the day, while at night temperature inversions are less frequent compared to the winter month. The tendency of WRF to warm up too fast in the morning and cool down at a higher rate compared to observations is also seen in Figure 7, as are the more skillful predictions of the modified configuration for the air temperature and sensible heat flux.

Figure 8. 2-m air temperature bias (K) with respect to the NCM station data for the control WRF configuration for (a) February 2018 and (c) June 2018. (b) and (d) show the difference between the predictions of the modified and control WRF configurations for the same period. The horizontal axis shows the time in UTC while the vertical axis gives the station number (see Figure 1c for more details).

Table 4
Verification Diagnostics for the 10-m Wind Speed and 2-m Air Temperature at the 12 NCM Weather Stations Given in Figure 1c, for the Control (Modified) WRF Configuration

| Station name (#) | 10-m wind speed (m s$^{-1}$) | 2-m air temperature (°C) |
|------------------|-------------------------------|--------------------------|
|                  | BIAS  | MAE   | RMSE  | $\rho$ | BIAS  | MAE   | RMSE  | $\rho$ |
| Al Shiweb (#1)   |       |       |       |       |       |       |       |       |
| F                | 0.9 (1.3) | 1.6 (1.8) | 2.2 (2.5) | 0.632 (0.613) | 0.1 (0.3) | 1.1 (1.2) | 1.4 (1.6) | 0.975 (0.97) |
| J                | 0.7 (1.3) | 1.7 (2.1) | 2.5 (3.1) | 0.612 (0.556) | −0.6 (−0.5) | 1.3 (1.4) | 1.6 (1.8) | 0.97 (0.964) |
| Al Arad (#2)     |       |       |       |       |       |       |       |       |
| F                | 1.5 (1.8) | 1.8 (2.1) | 2.2 (2.5) | 0.657 (0.639) | 0.1 (0.2) | 1.1 (1.2) | 1.5 (1.6) | 0.975 (0.973) |
| J                | 1.0 (1.5) | 1.6 (2.1) | 2.1 (2.5) | 0.818 (0.786) | −1.3 (−1.1) | 1.6 (1.5) | 2.0 (1.9) | 0.973 (0.973) |
| Al Foah (#3)     |       |       |       |       |       |       |       |       |
| F                | 1.8 (2.0) | 2.1 (2.3) | 2.6 (2.9) | 0.507 (0.497) | 0.1 (0.2) | 1.3 (1.4) | 1.8 (1.8) | 0.96 (0.959) |
| J                | 2.6 (3.0) | 2.8 (3.2) | 3.6 (4.1) | 0.399 (0.375) | −1.4 (−1.2) | 1.8 (1.8) | 2.2 (2.1) | 0.956 (0.953) |
| Al Khazna (#4)   |       |       |       |       |       |       |       |       |
| F                | 2.0 (2.3) | 2.1 (2.4) | 2.6 (3.0) | 0.634 (0.597) | 0.3 (0.4) | 1.2 (1.2) | 1.5 (1.6) | 0.965 (0.963) |
| J                | 2.1 (2.4) | 2.2 (2.5) | 2.8 (3.1) | 0.755 (0.745) | −0.8 (−0.7) | 1.1 (1.1) | 1.5 (1.5) | 0.98 (0.979) |
| Hatta (#5)       |       |       |       |       |       |       |       |       |
| F                | 1.8 (2.1) | 2.1 (2.4) | 2.9 (3.3) | 0.523 (0.493) | −0.4 (−0.3) | 1.5 (1.5) | 1.9 (2.0) | 0.92 (0.915) |
| J                | 2.8 (3.4) | 3.0 (3.6) | 3.7 (4.4) | 0.568 (0.516) | −1.2 (−1.1) | 1.7 (1.7) | 2.0 (2.1) | 0.933 (0.921) |
| Jabal Hafeet (#6)|       |       |       |       |       |       |       |       |
| F                | −0.4 (−0.2) | 2.4 (2.4) | 2.9 (3.0) | 0.505 (0.501) | 0.8 (0.8) | 2.0 (2.0) | 2.4 (2.4) | 0.88 (0.881) |
| J                | −1.0 (−0.7) | 3.2 (3.3) | 3.9 (4.0) | 0.359 (0.338) | 0.9 (0.8) | 2.3 (2.2) | 2.7 (2.6) | 0.783 (0.790) |
| Khatam Al Shaklah (#7)|       |       |       |       |       |       |       |       |
| F                | 1.4 (1.7) | 1.9 (2.1) | 2.3 (2.7) | 0.532 (0.516) | −1.2 (−1.1) | 1.6 (1.5) | 1.9 (1.9) | 0.959 (0.96) |
| J                | 1.4 (2.1) | 2.0 (2.4) | 2.7 (3.3) | 0.669 (0.635) | −1.9 (−1.8) | 2.2 (2.1) | 2.5 (2.4) | 0.954 (0.955) |
| Raknah (#8)      |       |       |       |       |       |       |       |       |
| F                | 1.6 (1.9) | 1.9 (2.1) | 2.3 (2.6) | 0.659 (0.663) | 0.8 (0.9) | 1.6 (1.7) | 2.3 (2.5) | 0.965 (0.962) |
| J                | 1.7 (2.1) | 2.0 (2.3) | 2.4 (2.8) | 0.797 (0.783) | 0.1 (0.2) | 1.7 (1.8) | 2.1 (2.3) | 0.964 (0.961) |
| Rowdah (#9)      |       |       |       |       |       |       |       |       |
| F                | 1.0 (1.3) | 1.5 (1.7) | 1.9 (2.2) | 0.701 (0.697) | −0.3 (−0.2) | 1.0 (1.1) | 1.4 (1.4) | 0.978 (0.976) |
| J                | 1.2 (1.7) | 1.7 (2.0) | 2.3 (2.7) | 0.746 (0.739) | −1.4 (−1.3) | 1.5 (1.4) | 1.9 (1.7) | 0.979 (0.980) |
| Saih Al Salem (#10)|      |       |       |       |       |       |       |       |
| F                | 1.7 (2.1) | 1.9 (2.3) | 2.4 (2.9) | 0.63 (0.611) | 0.8 (1.0) | 1.9 (2.1) | 2.4 (2.5) | 0.969 (0.967) |
| J                | 1.7 (2.1) | 1.9 (2.3) | 2.4 (2.9) | 0.741 (0.705) | −0.9 (−0.7) | 1.3 (1.4) | 1.8 (1.9) | 0.974 (0.969) |
| Swiehan (#11)    |       |       |       |       |       |       |       |       |
| F                | 2.0 (2.4) | 2.2 (2.4) | 2.6 (2.9) | 0.715 (0.72) | −0.8 (−0.6) | 1.4 (1.5) | 1.8 (1.8) | 0.972 (0.971) |
| J                | 2.1 (2.5) | 2.3 (2.6) | 2.9 (3.2) | 0.700 (0.703) | −2.2 (−2.0) | 2.2 (2.1) | 2.6 (2.4) | 0.979 (0.977) |
| Al Ain (#12)     |       |       |       |       |       |       |       |       |
| F                | 0.3 (0.4) | 1.8 (1.8) | 2.3 (2.3) | 0.335 (0.373) | 0.6 (0.6) | 4.0 (3.9) | 4.9 (4.8) | 0.392 (0.602) |
| J                | 0.5 (0.7) | 2.6 (2.6) | 3.3 (3.4) | 0.211 (0.243) | −0.2 (−0.2) | 5.1 (5.0) | 6.0 (5.9) | 0.344 (0.359) |

Note. The letters “F” and “J” denote the February 2018 and June 2018 months, respectively.
In Figures 6 and 7 the WRF predictions are assessed against the observed measurements at Al Ain. However, similar conclusions regarding the model’s performance are drawn for the other sites for which in situ data are available for evaluation. As an example, Figure 8 shows the model air temperature bias for the control simulation and the difference between the predictions of the modified and control WRF runs, for stations 1 to 12, located in the 1.333 km grid, Figure 1c. For February 2018, the most significant bias is an over prediction of both the daytime and nighttime temperatures, while in June 2018 the biases are generally of a smaller magnitude, with a weak cold bias at night at the vast majority of the stations. For both months, the difference between the forecasts of the two WRF simulations generally has the opposite sign to the control WRF run bias, which indicates that the run with the modified configuration gives more skillful predictions. The magnitude of this improvement, however, is smaller than the bias of the control WRF run, not exceeding about 0.6 K. Table 4 shows the bias, RMSE, MAE, and correlation ($\rho$) diagnostics for the two months and simulations and all eight stations. When averaged over all times, the WRF air temperature biases are roughly the same for the two runs, generally within 0.1 K, even though the simulation with the updated roughness length tends to give the smallest values. The same is true for the RMSE and MAE scores, while the correlations, already high in the control simulation mostly in excess of 0.93, do not show much variability. Figure 9 is as Figure 8 but for the 10-m horizontal wind speed. For the control simulation, and for all stations considered, the largest biases occur around 12–14 UTC (16–18 LT), in the local evening time, when the wind speed is typically at the maximum. For stations 3–5, 8, and 11, there is another positive peak of a smaller amplitude in the morning, around the time of the secondary maximum. At other times the wind speed biases are small, except mainly for stations 6 and 12 where the wind strength is under predicted by WRF at night. At these stations, the wind speed is stronger, generally exceeding 5 m s$^{-1}$, with the model predicting weaker winds than those observed. In other words, the model wind speed bias seems to be a function of the strength of the wind, which is further analyzed below. In line with Figures 3, 6, and 7, and mostly in the evening hours, the positive biases are further augmented when the roughness length is reduced, but the negative biases are mitigated. The verification diagnostics given in Table 4 reflect the discussion above: poorer bias, RMSE and MAE scores for the simulation with the reduced roughness length, and comparable correlation coefficients for the two runs, generally in excess of 0.65. The lower scores for the 10-m wind speed compared to the 2-m air temperature can be explained by the higher temporal variability of the latter, more dependent on local-scale conditions and hence harder to accurately simulate.

In order to analyze the dependence of the model’s wind speed bias on the strength of the wind, Figure 10 shows the bias for the 12 NCM stations, for the control and modified WRF configurations and for the two months as a function of the wind speed. As can be seen, WRF has a tendency to overestimate the strength of low winds, in particular for speeds <4 m s$^{-1}$ and underestimate the strength of winds for speeds mostly in excess of 6 m s$^{-1}$. This behavior has been reported by other authors (e.g., Carvalho et al., 2012; Yang et al., 2013) and may be attributed to deficiencies in the PBL scheme. In particular, it is possible that the
model under predicts the turbulent mixing for low winds and over predicts it for high winds. While for low wind speeds the model performance with the two configurations is comparable, with an overestimation of the observed values by around 2 m s\(^{-1}\), for high speeds, in excess of roughly 6 m s\(^{-1}\), the simulation with a reduced roughness length gives more skillful predictions, typically by 1–3 m s\(^{-1}\). In other words, while when all wind speeds are taken into account the two WRF runs give comparable predictions, the improved configuration is more accurate for stronger winds, which are more critical for human and industrial activities (e.g., Stathopoulos, 2009). An analysis of the results of domain 02 (4 km resolution) for the same set of stations revealed generally higher biases of up to 3 m s\(^{-1}\) (not shown), highlighting the added value of having a higher-resolution grid over the target region for the simulation of the strength of the near-surface horizontal wind.

6. Discussion and Conclusions

The roughness length, a crucial parameter for land-atmosphere interactions (e.g., Jee et al., 2016; June et al., 2018; Reijmer et al., 2004), is defined as the height above the surface at which the horizontal wind speed is zero, assuming that its variation in the surface layer follows a logarithmic profile (e.g., Jiménez et al., 2012). Empirically, \(z_0\) is estimated as being about 1/10th of the height of the roughness elements (e.g., Wallace & Hobbs, 2006), but its representation in numerical models is challenging given the land surface heterogeneity within a model grid-box. The common approach is to assign a value or range of values based on the dominant land-use type (e.g., Campbell et al., 2019; Dong et al., 2018), which can be estimated from high temporal frequency observations (e.g., Reddy & Rao, 2016) or remote sensing assets (e.g., Yang et al., 2008).

In this paper, the surface roughness length in a desert site in the UAE is estimated using eddy-covariance measurements and is found to be about one order of magnitude smaller than the default value used in WRF, in the range 1.3–2.2 mm, as opposed to 10 mm. The estimated \(z_{0\text{mod}}\) is, however, within the range of values for barren regions, 0.2–2.74 mm (e.g., Marticorena et al., 2004; Prigent, 2005; Yang et al., 2008). For a month in the winter (February 2018) and summer (June 2018) seasons, the WRF model is run over the UAE with the default and estimated roughness lengths, in a 12 km–4 km–1.333 km configuration, with the hourly predictions of the latter two grids used for analysis. For both months, and in line with expectations and previous studies (e.g., Reijmer et al., 2004; Wang et al., 2009), a reduced roughness length leads to stronger near-surface winds by up to 1 m s\(^{-1}\). As a result of a reduced exchange coefficient for heat, the sensible heat flux is lower by up to 10 W m\(^{-2}\). In order to keep the surface energy budget closed, and given the lower values of \(H\), the surface temperature increases by up to 2.5°C. The sign and magnitude of the
changes in the surface temperature and heat fluxes found here are also in line with those reported by other studies (e.g., Giorgi, 1997; June et al., 2018; Reijmer et al., 2004).

In addition to a direct comparison of the two WRF products, the model predictions are evaluated against weather station data provided by the NCM. At Al Ain, where the roughness length estimation was conducted, WRF is found to over predict the observed 10-m wind speed by roughly 0.5 m s\(^{-1}\), in line with other studies in arid/semi-arid regions (e.g., Gunwani & Mohan, 2017), slightly augmented in the modified configuration (maximum differences up to 1 m s\(^{-1}\)). However, the wind speed bias is dependent on the strength of the wind. In particular, it is found that, while for low wind speeds <4 m s\(^{-1}\) the two WRF configurations give comparable predictions, for speeds mostly in excess of about 6 m s\(^{-1}\), having a more realistic representation of the observed roughness length generates more skillful forecasts, mostly by 1–3 m s\(^{-1}\). A similar dependence of the model wind speed predictions on the strength of the wind has been reported by other authors (e.g., Carvalho et al., 2012; Yang et al., 2013) and may arise from an incorrect representation of the turbulent mixing by the PBL scheme. When compared to the predictions of the 4 km grid, the wind speeds predicted by the 1.333 km grid are generally more accurate, with biases up to 3 m s\(^{-1}\) smaller compared to station data. For air temperature and \(H\), the simulation with the reduced roughness length is more skillful, being able to partially correct the cold bias seen in the warm season, which has been highlighted by D. Zheng et al. (2013).

The biases of these two fields are mostly in the range ±2°C and ±100 W m\(^{-2}\), respectively. The conclusions reached at Al Ain also hold for other stations, in particular for those located in the inland desert where the roughness length was modified.

The analysis conducted here highlighted potential deficiencies in the PBL scheme, in particular with respect to the turbulent mixing and surface drag formulation. A further improvement of the model forecasts can be obtained by optimizing tunable parameters used in the PBL and surface layer schemes, as shown in B. Yang et al. (2017). Alternatively, a new parameterization scheme tailored for arid/semi-arid regions can be developed and subsequently implemented in the model. Some of these improvements will be presented in a subsequent paper.

Data Availability Statement

Data used in the present analysis are available online (https://kudrive.ku.ac.ae/oc-shib/index.php/s/sdUNPlvZlaP2JoC).

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