Assessing the Impact of Changes in Land Surface Conditions on WRF Predictions in Arid Regions

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ABSTRACT: A thorough evaluation of the Weather Research and Forecasting (WRF) Model is conducted over the United Arab Emirates, for the period September 2017–August 2018. Two simulations are performed: one with the default model settings (control run), and another one (experiment) with an improved representation of soil texture and land use land cover (LULC). The model predictions are evaluated against observations at 35 weather stations, radio-sonde profiles at the coastal Abu Dhabi International Airport, and surface fluxes from eddy-covariance measurements at the inland city of Al Ain. It is found that WRF's cold temperature bias, also present in the forcing data and seen almost exclusively at night, is reduced when the surface and soil properties are updated, by as much as 3.5 K. This arises from the expansion of the urban areas, and the replacement of loamy regions with sand, which has a higher thermal inertia. However, the model continues to overestimate the strength of the near-surface wind at all stations and seasons, typically by 0.5–1.5 m s^{−1}. It is concluded that the albedo of barren/sparsely vegetated regions in WRF (0.380) is higher than that inferred from eddy-covariance observations (0.340), which can also explain the referred cold bias. At the Abu Dhabi site, even though soil texture and LULC are not changed, there is a small but positive effect on the predicted vertical profiles of temperature, humidity, and horizontal wind speed, mostly between 950 and 750 hPa, possibly because of differences in vertical mixing.

KEYWORDS: Forecasting; Land surface model; Regional models

1. Introduction

Soil texture and land use land cover (LULC) are two crucial aspects of a surface that determine its characteristics and therefore the in situ meteorological conditions of the site. Soil texture refers to the size distribution of the primary mineral particles in the soil (Dexter 2004). Different soil textures will have different pore sizes (i.e., porosity), and hence the soil texture defines the soil's physical and hydraulic properties (e.g., Cosby et al. 1984; Fernandez-Illescas et al. 2001). As explained in Brown (1998), it is determined by collecting a soil sample and manipulating it by hand, in order to estimate the amount of sand, silt, and clay particles present based on the degree to which their typical properties are expressed. Sand particles are loose (i.e., not aggregated together), and feel gritty to touch; clay, on the other hand, typically forms extremely hard lumps when dry while when wet it is sticky and

plastic. Silt is a granular material with a size between sand and clay, somewhat plastic, feeling smooth and rather silky when wet. Laboratory tests are needed for a quantitative determination of the particle sizes, in particular particles that are too small for sieve analysis. They are based on the fact that particles of a larger size will experience higher fall speeds (Stokes's law), and therefore settle down faster. As detailed in Huluka and Miller (2014), the first step is to add a chemical dispersant, such as sodium metaphosphate (NaO₃P), and mechanically stir the mixture. Two approaches can then be followed: (i) hydrometer method and (ii) pipette method. In the former, the density of the soil suspension is estimated at predefined times using a hydrometer, based on the particle size being measured. In the latter, clay particles are first removed with a pipette at predefined times and sand particles separated with a 53.3- μ m sieve. Afterward, both clay and sand particles are quantified through a gravimetric analysis. On the other hand, the LULC gives information about the land's physical type and how it is currently being used (i.e., urban, cropland, shrubland, desert, etc.), determining surface properties such as albedo, emissivity and roughness length. While the albedo and emissivity are normally estimated using remote sensing assets such as satellites (e.g., Giri 2012; Sun and Schulz 2015; Fritz et al. 2017; Rwanda and Ndambuki 2017), and sometimes through field surveys (e.g., D'Antona et al. 2008), the roughness length is determined from field measurements (Nelli et al. 2020b). The LULC has to be frequently updated as urban areas expand and

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existing arid regions, farmland and forests vary in spatial extent (e.g., [Yagoub and Kolan 2006](#); [Fu and Weng 2016](#)). A correct depiction of the LULC is very important for decision making and research studies on global change (e.g., [Groeneveld et al. 2017](#); [Prestele et al. 2017](#)). Together, the soil texture and LULC essentially determine the surface's physical properties, and hence their representation in numerical models is very important for an accurate simulation of the surface and near-surface fields.

An accurate modeling of land–atmosphere interactions strongly depends on how accurate the surface properties, in particular the predominant soil texture and LULC, are represented in the model. [Göndöcs et al. \(2015\)](#) investigated the sensitivity of the Weather Research and Forecasting (WRF; [Skamarock et al. 2008](#)) Model's response to a more accurate representation of the soil texture and LULC over Hungary, for a heavy precipitation event. They found absolute changes in the latent heat flux up to $\pm 70 \text{ W m}^{-2}$, with spatially averaged differences of $+6.5 \text{ W m}^{-2}$ for the soil texture and -4.3 W m^{-2} for the LULC change. The 2-m temperature differences are in the range from -3 to 0.5 K , with precipitation differences of about $\pm 8 \text{ mm day}^{-1}$, owing to a change in the location of the convective cells. The authors found that, while the simultaneous modification of the soil texture and LULC had compensating effects over some regions, the use of updated surface and soil properties has a nonnegligible impact on surface variables and precipitation predictions. [Ács et al. \(2014\)](#) reported spatially and temporally averaged PBL depth differences of up to 500 m for separate changes in the soil texture and LULC over Hungary. For roughly a month in summer 2013, which comprised both dry and wet weather conditions, [Lin and Cheng \(2016\)](#) analyzed the sensitivity of the WRF predictions to an improved soil texture representation over Taiwan. They concluded that, when set to more realistic values, it leads to a better simulation of soil moisture variations, with an improvement in the magnitude typically by about $0.1\text{--}0.2 \text{ m}^3 \text{ m}^{-3}$. [He et al. \(2016\)](#) reported a statistically significant improvement at the 95% confidence interval of the WRF-simulated 2-m temperature and specific humidity and 10-m horizontal wind speed, for a summer month in eastern China, when updated soil texture and hydraulic parameters are applied in the model. Out of the different hydraulic parameters used in the land surface model (LSM), the wilting point θ_w is found to have the largest influence on the WRF forecasts. [Nguyen et al. \(2016\)](#) tested three observed and one projected LULC data for a regional climate simulation over Central Vietnam. The model was found to give more accurate predictions of the annual precipitation and average temperature when an updated LULC was employed. More recently, [Fonseca et al. \(2019\)](#) investigated the sensitivity of the WRF-predicted surface temperature and relative humidity (RH) for 2-week-long periods at three sites in the Atacama Desert in Chile, to changes in soil parameters that are directly controlled by the soil texture. The authors found a great sensitivity in particular to the soil porosity θ_s , with a less porous soil being more compact and hence having a higher thermal inertia (i.e., reduced amplitude of temperature diurnal cycle), and could not get the model predictions to agree with the in situ observations, probably because of a lack of groundwater table in the LSM, which can

FIG. 1. (a) Spatial extent of the 12- and 4-km domains used in the WRF simulations, and (b) UAE orography (m) from a 30-m digital elevation model ([Hulley et al. 2015](#)), and location of the 35 weather stations for which hourly meteorological data are available for evaluation.

be very shallow in desert regions (e.g., [Huang et al. 2017](#)). The importance of properly defining θ_s , and hence the soil texture, for a correct simulation of the surface temperature has also been highlighted by [Quan et al. \(2016\)](#), for simulations in the Beijing region of China. [Nelli et al. \(2020b\)](#) estimated the roughness length at the Al Ain station in the UAE from eddy-covariance measurements, and found it to be roughly one order of magnitude smaller than that employed in WRF. When the new value, which is a function of the soil texture, was ingested in the model, WRF was found to give more accurate air temperature and sensible heat flux predictions, and it also alleviated the under prediction of wind speeds in excess of 6 m s^{-1} . In summary, published work highlights that a correct representation of the soil texture and LULC is crucial, not just for an accurate simulation of surface/near-surface fields, but also of the thermodynamic profiles in the boundary layer.

The focus of this work is on the United Arab Emirates (UAE), a hyperarid country located in the Middle East, bounded by Saudi Arabia on the western and southwestern side, Oman on the eastern side, and the Arabian Gulf on the northwestern side. As seen in [Fig. 1b](#), the vast majority of the country is flat, but on the eastern side the Al Hajar Mountains rise to more than 3000 m above mean sea level. The mean precipitation rates range from about 40 mm yr^{-1} in the southern desert to 160 mm yr^{-1} in the Al Hajar Mountains ([Ouarda et al. 2014](#)), with a large interannual variability. In fact, at times the standard deviation exceeds the mean annual precipitation

TABLE 1. Physics parameterization schemes used in the WRF simulations.

Parameterization scheme	Option
Cloud microphysics	WRF single-moment 3-class scheme (Hong et al. 2004)
Planetary boundary layer	Quasi-normal scale elimination (Sukoriansky et al. 2005)
Radiation (shortwave)	Rapid Radiative Transfer Model for global circulation models (Iacono et al. 2008)
Radiation (longwave)	Rapid Radiative Transfer Model (Mlawer et al. 1997)
Cumulus	Kain–Fritsch (Kain 2004)
Land surface model (LSM)	Noah LSM (Chen and Dudhia 2001; Tewari et al. 2004)

amounts (Niranjan Kumar and Ouarda 2014). In addition, the country regularly experiences fog and dust events, the former occurring at a higher frequency in particular in the cold season, which cause widespread disruption in road and air traffic (e.g., Bartok et al. 2012; Aldababseh and Temimi 2017). In this paper, WRF is run over the UAE for a 12-month period, both with the default soil texture and LULC and a more realistic representation of them obtained from a dedicated field campaign. The model predictions are assessed with a comprehensive set of observational datasets, ranging from hourly observations at 35 weather stations spread out over the country, to eddy-covariance measurements and radiosonde (vertical) profiles at individual sites. One of the goals of this study, as was the case with some of the works cited above, is to investigate the sensitivity of the model forecasts to a modification of the soil texture and LULC in this hyperarid region. In addition, the performance of the WRF Model over the UAE is assessed with one year simulation for present-day weather conditions, as opposed to previous studies where the focus was just on a few days/individual events (e.g., Chaouch et al. 2017; Weston et al. 2018; Karagulian et al. 2019; Wehbe et al. 2019).

This paper is structured as follows. Section 2 gives details regarding the experimental setup, observational datasets used to evaluate the WRF performance, and the verification diagnostics employed in this study. In section 3 the model predictions are assessed against the surface/near-surface observations, and in section 4 against the vertical radiosonde profiles. The main conclusions of the work are outlined in section 5.

2. Model, datasets, and diagnostics

a. Experimental setup

The WRF Model version 3.7.1 is run in a two-way nested configuration over the UAE (Fig. 1a). The 12-km grid includes the Arabian Gulf and most of the western Arabian Peninsula, with the 4-km grid comprising the UAE and adjacent waters. WRF is forced with the Global Forecast System (GFS; <https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forecast-system-gfs>) forecast data at $0.25^\circ \times 0.25^\circ$ spatial resolution, and is run for the 12-month period September 2017–August 2018, initialized daily at 0600 UTC. Each simulation lasts 72 h, with the first 6 h regarded as model spinup. Chaouch et al. (2017) showed that a minimum spinup time of 5 h is required for this experimental setup, justifying the choice of 6 h. The WRF setup given in Table 1, which is the same as that used in Chaouch et al. (2017) and Weston et al. (2018), is found to give the best performance for this region. This model

configuration has been optimized for the simulation of fog events, which are the main threat to road and aviation traffic in the country. For such applications, Ajjaji et al. (2008) tested six cloud microphysics schemes and found very little difference in the model predictions, with the computationally cheaper WRF single-moment 3-class scheme (WSM3; Hong et al. 2004) employed. Forty-six vertical levels, more closely spaced in the planetary boundary layer (PBL), are considered, the same set of levels employed in Weston et al. (2018). The lowest level is at ~ 30 m above ground level (AGL), and the model top is at 50 hPa (~ 24 km).

In this manuscript, two sets of 12-month simulations are conducted. In the control run, the default soil texture and LULC, as generated by the WRF Preprocessing System (WPS), are employed. In the experiment, a more realistic representation of the two fields is ingested into the model. The improved representation of the soil texture was provided by the UAE's National Center of Meteorology (NCM) and processed using ArcGIS software (<https://www.esri.com/en-us/arcgis/about-arcgis/overview>), whereas the LULC dataset was generated from a dedicated field campaign conducted as part of the UAE Rain Enhancement Program (UAEREP; Al Mazroui and Farrah 2017). The updated soil texture and LULC used in this work are discussed in Aldababseh et al. (2018). In this paper, the authors considered a total of 16 observational datasets. They fall under the categories of climate, water resources, topography, soil capabilities, and soil management. The data are first converted into raster images at a spatial resolution of 105 m, the coarsest resolution of the available spatial layers, before different GIS techniques and a raster reclassification are applied. Afterward, all layers are projected or reprojected using the ArcGIS software. The default and updated soil texture and LULC are given in Fig. 2. Table S1 in the online supplemental material shows the changes in both parameters at the location of the 35 weather stations given in Fig. 1b.

b. Changes in soil texture

Figures 2a and 2b show the default and updated soil textures used in the WRF simulations. As highlighted in Dy and Fung (2016), the soil texture in WRF is taken from the United Nations Food and Agriculture Organization (FAO) global soil data, which has a spatial resolution of ~ 9 km (Sanchez et al. 2009), with a 30-s (or roughly 927 m) dataset employed in the conterminous United States (Miller and White 1998). The updated soil texture is the outcome of a comprehensive field survey conducted by Environment Abu Dhabi as described in

FIG. 2. (a) Default and (b) updated soil texture employed in the WRF simulations. (c),(d) As in (a) and (b), but for the LULC.

Aldababseh et al. (2018). It is at 30-s (~ 927 m) spatial resolution, and is interpolated to the WRF's grids using the nearest neighbor technique. The main difference is the replacement of some of the loam, loamy sand, and clay regions with sand. In other words, the sandy desert areas are expanded in the updated soil texture data. The soil texture determines the soil's physical and hydraulic properties such as porosity and hydraulic conductivity. Table S2 shows the soil parameters for the prevailing soil types in WRF's 4-km domain, as used in the Noah LSM, defined in the file "SOILPARM.TBL." Out of the nine variables given in Table S2, and as highlighted in the appendix, only five are user defined: b parameter, soil porosity θ_s , soil suction ψ_s , saturated soil hydraulic conductivity K_s , and quartz fraction QTZ. The parameters θ_d , θ , θ_w , and D_s are a function of the referred five parameters. As concluded by Fonseca et al. (2019), in arid regions the WRF's surface temperature and relative humidity predictions are particularly sensitive to changes in the soil porosity θ_s , with a less porous soil being more compact and hence having a higher thermal inertia. In other words, when loamy sand, sandy loam, and clay regions are replaced with sand, cooler daytime and warmer nighttime temperatures are expected. In addition to the referred changes in temperature, a decrease in soil porosity also leads to an increase in the surface relative humidity, possibly due to a more efficient transfer of water within the soil (Fonseca et al. 2019). The sensitivity of the model surface predictions to changes in the other tunable parameters listed in Table S2 for desert regions is found to be much smaller. Further information regarding the soil parameters is available

in Fonseca et al. (2019), while a summary of how they impact the model predictions of surface variables is given in the appendix.

c. Changes in LULC

As shown in Figs. 2c and 2d, the changes in LULC include the replacement of a vast area of shrubland over southern parts of the UAE with barren/sparsely vegetated, while in the main cities of Abu Dhabi, Dubai, Sharjah, Ras Al Khaimah and Fujairah, the LULC is set to urban/built-up, in line with its actual state. The default LULC classes are generated from a United States Geological Survey (USGS) dataset, obtained from measurements from the Advanced Very High Resolution Radiometer (AVHRR) satellite (Loveland et al. 2000; Sertel et al. 2009). The new LULC classes, on the other hand, are estimated from Moderate Resolution Imaging Spectroradiometer (MODIS) measurements for the year 2001 (Ran et al. 2010), available with the WRF Model. The spatial distribution of the new LULC data is then manually modified to account for recent changes such as the expansion of the urban areas. The improved LULC is at 3-s (~ 93 m) resolution, and is interpolated to the WRF's grids using the nearest neighbor technique. While the soil texture controls soil-relevant parameters, the LULC impacts the heat and momentum exchanges between the surface and atmosphere. Tables S3 and S4 show the surface properties for the different LULC classes for the prevailing USGS and MODIS LULC categories in WRF's 4-km grid, Figs. 2c and 2d, respectively, taken from the file "VEGPARM.TBL." The minimum and maximum values of leaf area index (LAI; nondimensional

variable that characterizes plant canopies, varying from 0 for bare ground to 10 for dense conifer forests), surface emissivity, albedo and roughness length, correspond to the values for the annual minimum and maximum green vegetation fraction at the site, respectively. The latter are computed from monthly AVHRR data for the period 1986–91, with a spatial resolution of 0.144° or roughly 16 km (Dellwik 2012). The parameters LAI, RS (stomatal resistance), RGL (parameter used in radiation stress function), and HS (parameter used in vapor pressure deficit) are used to compute the canopy resistance as detailed in Jacquemin and Noilhan (1990), with LAI also used to estimate the snow fraction. In addition, SHDFAC (areal fractional coverage of green vegetation) is only considered when the urban model in WRF is activated. Otherwise, as is the case here, the green vegetation fraction used by the model is that read in WPS, estimated from AVHRR data. More information regarding these parameters can be found in (Jacquemin and Noilhan 1990) and Chen and Dudhia (2001). One of the major changes in the LULC is the replacement of some barren/sparsely vegetated regions with urban/built-up. This results in warmer daytime temperatures (note the decrease in surface albedo by roughly 60%), warmer nighttime temperatures (slight decrease in surface emissivity), and weaker near-surface winds (the roughness length increases by a factor of 5000). These differences are consistent with the fact that urban areas are hotter than rural areas due to the effect of anthropogenic heat (e.g., Man Sing et al. 2015). Further details on how the LULC-controlled variables impact the LSM predictions are summarized in the appendix.

d. Observational datasets and verification diagnostics

The WRF predictions are evaluated against three observational datasets:

- Automatic weather station (AWS) and airport station data at 35 sites, shown with stars in Fig. 1b, provided by the National Center of Meteorology (NCM). The following fields are available on an hourly frequency: air temperature, RH, horizontal wind direction and speed, and water vapor mixing ratio. Also available is the daily accumulated precipitation.
- Eddy-covariance measurements at Al Ain International Airport (24.2617°N, 55.6092°E) for the period 1 September–18 October 2017 and 1 February–31 August 2018 (Nelli et al. 2020a). Fields available include surface downward/upward shortwave and longwave radiation fluxes, sensible and latent heat fluxes, and ground heat flux every 30 min.
- Twice daily radiosonde profiles at Abu Dhabi International Airport (24.4331°N, 54.6511°E), downloaded from the National Oceanic and Atmospheric Administration (NOAA) Integrated Global Radiosonde Archive (IGRA; Durre et al. 2006; Durre and Xungang 2008) website.

The model performance is assessed with the bias, correlation ρ , variance similarity η , and normalized error variance α diagnostics. In the equations below, $\bar{X}$ and σ_X denote the mean and standard deviation of X , respectively. The bias, Eq. (1), is defined as the mean difference $\mathbf{D}$ between the model forecasts $\mathbf{F}$ and observations $\mathbf{O}$. The correlation, Eq. (2), is a measure of the phase agreement between the model predictions and the observations, while the variance similarity,

Eq. (3), is an indication of the agreement in terms of amplitude. The last skill score, normalized error variance, Eq. (4), accounts for phase and amplitude errors. Its optimal value is zero, obtained when $\rho = \eta = 1$, with $\alpha < 1$ indicating that the model forecast is more skillful than that of a random forecast, in which case it can be considered as practically useful. More information about these diagnostics can be found in Koh et al. (2012):

$$\text{BIAS} = \bar{\mathbf{D}} = \bar{\mathbf{F}} - \bar{\mathbf{O}}, \quad (1)$$

$$\rho = \frac{1}{\sigma_O \sigma_F} (\mathbf{F} - \bar{\mathbf{F}}) \cdot (\mathbf{O} - \bar{\mathbf{O}}), \quad -1 \leq \rho \leq 1, \quad (2)$$

$$\eta = \frac{\sigma_O \sigma_F}{\frac{1}{2}(\sigma_O^2 + \sigma_F^2)}, \quad 0 \leq \eta \leq 1, \quad (3)$$

$$\alpha = \frac{\sigma_O^2}{(\sigma_O^2 + \sigma_F^2)}, \quad 0 \leq \alpha \leq 2. \quad (4)$$

3. Evaluation of WRF performance: Surface observations

In this section, the WRF performance for the control and experiment simulations is assessed for each season separately: boreal autumn [September–November (SON)], winter [December–February (DJF)], spring [March–May (MAM)], and summer [June–August (JJA)]. In section 3a the evaluation is against weather station data, while in section 3b the WRF predictions at Al Ain are compared with the in situ eddy-covariance measurements.

a. Weather station data

Figure 3 shows the skill scores for WRF's air temperature, relative humidity, and horizontal wind vector bias for the control simulation. The relative difference of the scores between the experiment and control runs are given in Fig. 4. The weather stations, given in Fig. 1b, are classified into three categories: coastal (stations 8, 10, 14, 25, 31, 33, 34), inland low elevation (<200 m; stations 1, 3, 4, 6, 9, 12, 13, 19, 22, 23, 27, 28, 29, 30, 35), and inland high elevation (>200 m; stations 2, 5, 7, 11, 15, 16, 17, 18, 20, 21, 24, 26, 32). An elevation threshold of 200 m was used so as to have roughly the same number of low-elevation (15) and high-elevation (13) stations.

WRF has a cold bias over the UAE, typically of 1–3 K, which is more significant in the warm season and in the inland stations. An inspection of the model predictions at individual stations, also revealed that it is present mostly at night. This can be seen in Fig. 5, which shows the observed and model-predicted air temperature diurnal cycle at three stations for the three seasons: Dubai, a coastal site (station 33); Owtaid, inland low elevation (180 m AGL, station 23); Al Ain, inland high elevation (264 m AGL, station 32). This cold bias has been noted by Chaouch et al. (2017), Weston et al. (2018), and Valappil et al. (2020), and may arise from (i) deficiencies in the LSM, (ii) the representation of surface properties and concentration of atmospheric greenhouse gases and dust, and (iii) the cold bias present in the GFS data used to force the model (e.g., Zheng et al. 2012; Müller and Janjić 2015). The fact that the latter is more pronounced in the summer season

FIG. 3. WRF bias, correlation ρ , variance similarity η , and normalized error variance α for air temperature (bias; K), relative humidity (bias; %) and horizontal wind vector (bias speed; m s^{-1}) for the control simulation. The scores are given for the boreal autumn (SON; red curve), winter (DJF; green curve), spring (MAM; blue curve), and summer (JJA; orange curve) seasons, and for the 35 weather stations organized into three groups: coastal, inland low elevation (<200 m), and inland high elevation (>200 m). The numbers on top of the bias plots indicate the station numbers for which time series of air temperature and/or horizontal wind direction and speed are given in Figs. 5 and 6, respectively.

FIG. 4. As in Fig. 3, but showing the difference in the skill scores between the simulation with the updated soil texture and LULC (EXP) and the control run (CTL). A negative value for the bias (note that the absolute value is taken) and normalized error variance α , and a positive value for the correlation ρ and variance similarity η , denote an improved model performance. Stations for which the soil texture (LULC) changes between the two simulations are highlighted with a “S” (“L”). The numbers on top of the bias plots indicate the station numbers for which time series of air temperature and/or horizontal wind direction and speed are given in Figs. 5 and 6, respectively.

FIG. 5. Diurnal cycle of air temperature (°C) at Owtaid, station 23 in Fig. 1b, Al Ain, station 32, and Dubai, station 33, over (a) SON, (b) DJF, (c) MAM, and (d) JJA. The black curve shows the hourly observed temperature, the red curve is the WRF-predicted temperature for the control simulation, and the blue curve gives the model-predicted temperature for the experiment run. Each dot corresponds to an hourly value, and the horizontal axis is in local solar time (LST = UTC + 4 h).

(Zheng et al. 2012), may explain the larger magnitude of the WRF biases in the warmer months (JJA, followed by SON, MAM, and DJF). Despite this, however, there is a general reduction of the magnitude of the cold bias when a more realistic soil texture and LULC is employed, in particular for coastal and low-elevation inland stations. As seen in Fig. 4, one station stands out, which corresponds to Dubai International Airport (station 33). For this station, a large cold bias in excess of 3 K is mostly corrected when the LULC is updated from barren/sparsely vegetated to urban/built-up, due to the effects of the anthropogenic heat. As seen in Fig. 5, this bias is almost exclusively present at night, with a peak magnitude of about 6 K in the autumn season. When the surface properties are updated, the nighttime bias is significantly reduced to less than 2 K for all seasons and times. Even though the daytime maximum temperature becomes slightly higher than that observed, largely due to the reduced surface albedo and emissivity (by roughly 61% and 2%, respectively, Tables S3 and S4) and their effect on the surface energy budget [Eq. (A5)], overall the impact of the updated LULC on the model performance is largely positive. These changes are consistent with those reported by other authors (e.g., Man Sing et al. 2015). The improvement of the model performance is not just seen in the bias but in all other verification diagnostics considered, even though the scores were already very good in the control simulation, with $\rho > 0.75$, $\eta > 0.9$, and $\alpha < 0.25$. The other coastal station for which the WRF predictions are more accurate in the experiment is Al Qlaa (station 10), for which both the soil texture and LULC are updated. For this site, the model is warmer by up to 2 K in autumn and winter, and colder in excess of 2 K in spring and summer. These biases are mostly halved when the surface properties are updated, with a more than 50% increase in the correlation and decrease in the normalized error variance. In the inland desert, most of the improvement comes from an updated soil texture (loam and loamy sand are replaced by sand), which gives a reduction of the biases by up to 1 K. As for Dubai, this improvement results mostly from a decrease in the nighttime cold bias. One of such stations is Owtaid (station 23), for which the time series for the different seasons are given in Fig. 5. In the Noah LSM, and for a given soil texture, properties such as porosity, soil suction, and quartz fraction are predefined, with the values given in Table S2. As explained in Fonseca et al. (2019), and highlighted in section 2b, out of the different soil parameters, in arid regions the porosity plays the most important role in the surface temperature predictions. A lower porosity means a more compact (i.e., less porous) soil, which should experience lower daytime and higher nighttime temperatures. While the porosity will also impact the soil's hydraulic properties, Eqs. (A2)–(A4), the impact on the thermal properties is more significant, in particular because of the rather low amounts of moisture in the soil in the UAE, generally below $0.1 \text{ m}^3 \text{ m}^{-3}$ (e.g., Schwitalla et al. 2020). As seen in Table S2, the porosity for the loam, loamy sand, and sandy soil types is 0.439, 0.421, and 0.339, respectively. When the loam/loamy sand regions are replaced by sand, the daytime temperatures are only slightly lower, but the nighttime temperatures are higher, consistent with the lower porosity, and explaining the reduced cold bias in the referred

stations. The improvement in the other verification diagnostics is rather small, but they are already very good in the control simulation, with $\rho > 0.9$, $\eta > 0.95$, and $\alpha < 0.1$. At the high-elevation stations, the cold bias is also clearly present, but the impact of updating the soil texture and LULC is rather small: the biases change mostly by less than 0.5 K, with negligible differences in the other skill scores. It is possible that other factors, such as the coarse spatial resolution to properly represent the local topography and deficiencies in the physics schemes in particular in the PBL and LSM, play the dominant role. An inspection of Fig. 4 reveals that the modification in the soil texture accounts for the majority of the improvement in the model performance.

The second column in Figs. 3 and 4 shows the scores for the RH. The RH biases in the control simulation are generally within $\pm 10\%$, mostly positive in the summer when the cold bias is more significant as expected. The largest bias is seen for Dhudna (station 14), located on the east coast, with a magnitude reaching $\sim 24\%$ in the autumn season. This discrepancy is mostly attributed to an incorrect simulation of the near-surface atmospheric circulation. The last column in Fig. 6 shows the horizontal wind direction and speed at the site for the boreal winter and summer seasons. The wind blows from a westerly direction (offshore) from about 2000 to 1000 LT, shifting to a more easterly direction (onshore) from 1100 to 1900 LT. While the strength of the sea breeze is largely captured by WRF, in particular in the cold season, the land breeze is much stronger in the model, with biases of up to 5 m s^{-1} . The increased advection of dry air from the inland desert is therefore consistent with the drier conditions at this station. The impact of changing the soil texture and LULC on the RH predictions is rather small, with differences mostly within $\pm 2.5\%$ for the bias, and ± 0.05 for the remaining scores. The only exceptions are Al Qlaa (station 10) and Dubai (station 33), for which the reduction of the cold bias is more pronounced. It is interesting to note that, even though the air temperature is more strongly corrected at Dubai, by up to $\sim 3 \text{ K}$, the largest improvement in the RH forecasts is seen at Al Qlaa, by up to $\sim 12.5\%$. This can be explained by the changes in the local land-/sea-breeze circulation. The first two columns of Fig. 6 show the horizontal wind direction and speed at these stations for the winter and summer seasons. In line with observational studies (Eager et al. 2008), there is a predominant offshore flow (land breeze) at night, with the wind blowing from a westerly to southwesterly direction at Al Qlaa and a more southerly direction at Dubai, and an onshore flow (sea breeze) during the day, with prevailing northwesterly winds at both sites. The latter is stronger, with the wind speeds peaking at 1500–1600 LT and reaching a maximum of $4\text{--}5 \text{ m s}^{-1}$ in winter and $5\text{--}6 \text{ m s}^{-1}$ in the summer. In both seasons, the sea-breeze strength increases at Al Qlaa and decreases at Dubai when the surface properties are updated, with a shorter sea-breeze duration in the latter in the cold season. As the air over the Gulf is more moist than that over inland regions, in particular in the warmer months when there is increased surface evaporation (Xue and Eltahir 2015), the increased moisture advection at Al Qlaa leads to a local increase in water vapor mixing ratio by up to 2 g kg^{-1} , whereas in Dubai it drops by up to 0.7 g kg^{-1} (not shown). This explains

FIG. 6. Diurnal cycle of horizontal wind (a) direction ($^{\circ}$) and (b) speed (m s^{-1}) at Al Qlaa, station 10 in Fig. 1b, Dubai, station 33, and Dhudna, station 14, for DJF. (c),(d) As in (a) and (b), but for JJA. The conventions are as in Fig. 5.

why the reduction of the RH biases is more pronounced in the former. At the high-elevation stations, the RH biases result from a combination of the air temperature biases, which exceed 3 K at some sites, and the water vapor mixing ratio biases, which can reach almost 5 g kg^{-1} (not shown). The poorer α scores at these locations (still, α is always below 1, indicating that the WRF forecasts can be considered useful) mostly arise from lower correlations, indicating that phase errors prevail over amplitude errors. As for the air temperature, a change in the soil texture and LULC has a negligible effect on all skill scores considered, suggesting that other factors, such as an incorrect representation of the topography and associated local-scale circulations, may explain the less skillful model performance at these stations.

As opposed to the previously discussed variables, WRF exhibits a systematic bias in the simulation of the horizontal wind speed that is largely uncorrected with an improved representation of the soil texture and LULC. In particular, the model has a tendency to overestimate the strength of the wind, typically by $0.5\text{--}1.5 \text{ m s}^{-1}$, with larger discrepancies over the high terrain in excess of 3 m s^{-1} . The largest bias, slightly in excess of 4 m s^{-1} , is noted at Dhudna (station 14), a coastal station on the eastern side of the country. Here, and as seen in the last column of Fig. 6, the strength of the land breeze is largely overestimated by up to 5 m s^{-1} , while the onshore wind speeds are mostly within 1 m s^{-1} of those observed. Given that the station is just downstream of the Al Hajar mountains, it is possible that an incorrect representation of the local topography (and therefore of the land–sea temperature gradient) may explain the stronger nighttime circulation. In addition, the sea-breeze onset and termination times are not fully captured by the model, in particular in the warm season, with generally a late onset and early cessation in WRF. The discrepancies in phase and amplitude explain the poorer ρ ($\sim 0.50\text{--}0.60$), η ($\sim 0.55\text{--}0.65$), and α ($\sim 0.60\text{--}0.65$) scores. The horizontal wind speed biases presented here are comparable to those reported by other authors such as Gunwani and Mohan (2017) over India, Cheng and Steenburgh (2005) over the United States, and Nelli et al. (2020b) and Fonseca et al. (2020) over the UAE. The roughness length at Al Ain was estimated from eddy-covariance measurements (Nelli et al. 2020a), and found to be one order of magnitude smaller than that employed in WRF (Nelli et al. 2020b). Hence, the stronger wind speeds in the model cannot be explained by an incorrect setting of the surface roughness length, as a smaller roughness length would lead to stronger wind speeds (Wallace and Hobbs 2006). It is possible that the stronger winds in the model arise from deficiencies in the PBL scheme or, as suggested by Gunwani and Mohan (2017), a deficient simulation of its subgrid-scale fluctuations and/or a poor parameterization of the surface drag. Mughal et al. (2017) also point out the role of the boundary conditions on the WRF's wind predictions. Having said that, at some stations there is a marginal reduction of the model bias: e.g., at Dubai's airport (station 33), and as seen in Fig. 6, the increase in the roughness length (by a factor of 5000, Tables S3 and S4) when the LULC is switched from barren/sparsely vegetated to urban/built-up, and associated decrease in wind speed, Eq. (A9), leads to a reduction of the bias by $0.25\text{--}0.5 \text{ m s}^{-1}$.

At Al Qlaa (station 10), Fig. 6, there is also a small improvement of the simulation mostly of the strength of the sea-breeze circulation, while at the inland low-elevation ($<200 \text{ m}$) stations, the changes in the skill scores are rather small, with bias differences within $\pm 0.25 \text{ m s}^{-1}$, and ρ , η , and α values within ± 0.05 for the two simulations. As is the case for the other variables considered here, a proper simulation of the wind strength over the high terrain would require a higher spatial resolution in order for the model to properly capture the observed topographic variations (e.g., Gómez-Navarro et al. 2015).

Table 2 shows the verification diagnostics for the daily accumulated precipitation for the full year. The observed and WRF-predicted yearly accumulated precipitation amounts are given in Fig. 7. As can be seen, WRF has a clear tendency to overestimate the observed precipitation, with positive biases in 28 out of the 35 stations (80%), for some exceeding the (rather low) observed total precipitation amounts (not shown). This is in line with other works, which found that WRF is too wet over the UAE (e.g., Wehbe et al. 2019; Fonseca et al. 2020). The impact of the improved soil texture and LULC on the precipitation simulation is small but nonnegligible, in line with Göndöcs et al. (2015), with the model showing reduced biases at 20 of the 35 stations ($\sim 57\%$, at slightly more than half), over all three categories (4 coastal, 7 inland low elevation, and 9 inland high elevation). A further inspection of the data revealed that in 8 of the 20 stations there was a change in the soil texture, in 7 the LULC was updated, while in 8 the surface properties were not modified in the experiment compared to the control simulation (note that at the location of some stations both the soil texture and LULC were updated). The vast majority of the precipitation in the UAE occurs in the cold season, in association with large-scale midlatitude baroclinic systems (Niranjan Kumar and Ouarda 2014; Wehbe et al. 2017, 2018). Hence, its simulation does not depend as much on the representation of the surface properties such as the soil texture and LULC, in line with Göndöcs et al. (2015). The α scores are mostly around 1, indicating a marginally useful model performance. This is largely attributed to lower correlations, generally below 0.5, which can be explained by the intermittent nature of the rainfall and the inherent deficiencies of the WRF Model in capturing it. As for the bias, there is not a clear link between the improvements in the ρ , η , and α scores and the station category, or whether the soil texture and/or the LULC were updated at the site. This further confirms that the improvement in the representation of the referred surface properties has a rather small impact on the model-predicted daily accumulated rainfall.

b. Eddy-covariance measurements at Al Ain

Figure 8 shows the averaged diurnal cycle of the surface downward/upward shortwave/longwave radiation fluxes, net radiative flux, sensible and latent heat fluxes (positive if upward from the surface), and ground heat flux (positive if downward into the soil) at the location of Al Ain International Airport, station 32, for the full period and the two WRF setups. These fluxes are estimated from eddy-covariance measurements, collected as part of the UAEREP campaign, discussed in detail in Nelli et al. (2020a). The model predictions with the

TABLE 2. Verification diagnostics for the daily accumulated precipitation (bias given in mm h^{-1}) at the location of the 35 weather stations highlighted in Fig. 1b. The stations are sorted as coastal, inland low elevation ($<200\text{ m}$), and inland high elevation ($>200\text{ m}$), as in Figs. 3 and 4. Stations for which the soil texture (LULC) changes between the two simulations are highlighted with a “S” (“L”).

		Bias		ρ		η		α	
Station No.		CTRL	EXP	CTRL	EXP	CTRL	EXP	CTRL	EXP
Coastal	8 (S)	0.126	−0.011	−0.006	−0.005	0.912	0.768	1.005	1.004
	10 (L, S)	0.142	0.119	0.037	0.034	0.511	0.522	0.981	0.982
	14	0.671	0.872	0.048	0.051	0.701	0.551	0.966	0.972
	25 (S)	0.036	0.048	0.306	0.475	0.788	0.702	0.759	0.666
	31	0.062	0.028	0.120	0.062	0.389	0.697	0.953	0.956
	33 (L)	0.153	0.223	0.456	0.861	0.350	0.198	0.851	0.829
<200 m	34 (L)	0.026	0.010	0.509	0.598	0.894	0.961	0.545	0.425
	1	0.154	0.169	0.206	0.864	0.247	0.152	0.949	0.989
	3 (S)	0.017	−0.006	0.347	0.383	0.921	0.986	0.681	0.622
	4 (L)	0.0595	0.022	0.067	0.067	0.999	0.973	0.933	0.934
	6 (L)	0.096	0.015	0.481	0.742	0.404	0.999	0.806	0.258
	9 (L)	0.028	0.049	0.125	0.082	0.716	0.522	0.911	0.957
	12	−0.098	−0.098	0.848	0.094	0.470	0.469	0.601	0.956
	13	0.011	0.017	0.299	0.221	0.863	0.684	0.741	0.849
	19 (S)	−0.077	−0.068	0.270	0.033	0.471	0.699	0.873	0.977
	22 (S)	0.022	−0.006	0.058	0.114	0.874	0.917	0.949	0.895
	23 (S)	0.025	0.017	0.092	0.106	0.966	0.999	0.911	0.894
	27	0.146	0.078	0.863	0.524	0.228	0.493	0.803	0.742
	28 (S, L)	0.039	0.070	0.032	0.043	0.525	0.383	0.983	0.984
	29	0.105	0.032	0.273	0.075	0.230	0.488	0.937	0.964
	30	~0	0.002	0.924	0.995	0.803	0.997	0.258	0.008
	35 (L)	−0.050	0.142	0.644	0.731	0.759	0.742	0.512	0.458
>200 m	2	0.064	0.029	0.152	0.058	0.737	0.939	0.888	0.945
	5 (S, L)	−0.076	−0.129	0.443	0.420	0.666	0.393	0.705	0.835
	7 (S, L)	−0.394	−0.390	0.931	0.704	0.288	0.197	0.732	0.861
	11	0.108	0.024	0.880	0.864	0.709	0.957	0.376	0.174
	15 (L)	0.124	0.026	0.201	0.123	0.946	0.991	0.810	0.878
	16	0.078	0.118	0.279	0.281	0.942	0.553	0.737	0.845
	17 (L)	0.102	0.058	0.141	0.162	0.937	0.999	0.868	0.838
	18 (S)	−0.015	−0.043	0.335	0.480	0.784	0.701	0.738	0.663
	20	0.029	−0.020	0.117	0.049	0.994	0.818	0.884	0.960
	21 (S, L)	0.047	0.009	—	—	—	—	—	—
	24	0.007	0.001	0.932	0.909	0.937	0.996	0.126	0.095
	26 (L)	0.024	−0.04	0.491	0.852	0.979	0.658	0.519	0.440
	32	0.092	0.071	0.206	0.284	0.367	0.542	0.924	0.846

two configurations are roughly the same, within $\pm 8\text{ W m}^{-2}$, and the predicted air temperatures are also very similar, as seen in Fig. 5. This is consistent with the fact that the soil texture and the LULC are not modified at the location of this station (Table S1).

The two WRF simulations overestimate the observed downward and upward shortwave radiation flux, more so the latter, suggesting that the surface albedo is higher than in observations. This is confirmed when the albedo is estimated from the data in Fig. 6: it is found to be roughly 0.340 for observations and 0.380 for WRF. The higher albedo is consistent with the colder air temperatures shown in Figs. 3 and 5, and with the reduced upward longwave radiation flux given in Fig. 6d. The overestimation of the downward shortwave radiation flux and the underestimation of the downward longwave radiation flux also suggest reduced cloud cover in WRF. This has been reported by several authors (e.g., R. Kumar et al. 2012; Diaz et al. 2015; Schwitalla et al. 2020; Wehbe et al. 2019; Fonseca et al.

2020; Yousef et al. 2020). It is interesting to note that, despite the reduced cloud cover and subsequent higher surface insolation (note the positive model bias in the net surface radiation flux), the model’s air temperature is generally lower than that observed at nearly all times (Fig. 4). In addition to the higher surface albedo, and as discussed before, the cold bias seen in WRF may be explained by the cold bias present in the GFS data used to drive the model (e.g., Zheng et al. 2012; Müller and Janjić 2015), potential deficiencies in the physics scheme, and/or an incorrect representation of the surface properties and concentration of greenhouse gases and dust. As expected for an arid region, the sensible heat flux is larger than the latent heat flux (i.e., the Bowen ratio exceeds one). They are both overestimated by WRF during the daytime as a result of the excessive surface net radiation flux, driven by the overestimation of the incoming shortwave radiation flux. At night, the (negative) sensible heat flux in the model is lower than that measured at the site, indicating a stronger thermal inversion,

FIG. 7. (a) Observed and WRF prediction for the (b) control and (c) experiment simulations daily accumulated precipitation (mm) for the period September 2017–August 2018.

which is consistent with the colder nighttime temperatures and reduced cloud cover. Nighttime temperature inversions are a regular occurrence in arid/semiarid regions, in particular in the cold season (e.g., [Lazzarini et al. 2014](#)), owing to the clear nights and enhanced surface radiative cooling. The colder nighttime surface temperatures also explains the more negative (i.e., upward, toward the surface) ground heat flux in the model. Regarding the phase (timing) of the diurnal cycle, in WRF the fluxes peak roughly 1–2 h earlier than in observations, and a similar trend is seen in the air temperature data ([Fig. 5](#)). This indicates that, at least at this site, the model warms up faster in the morning and cools down quicker in the evening. Other authors have reported similar findings (e.g., [Weston et al. 2018](#)). Possible explanations include potential deficiencies in the LSM and radiation scheme, an incorrect prediction of the amount of dust and greenhouse gas concentrations in the atmosphere and/or of the local topography.

4. Evaluation of WRF performance: Radiosonde profiles

In the previous sections, the focus was on surface and near-surface model predictions. Here, the WRF vertical profiles at the location of Abu Dhabi International Airport, station 31 in [Fig. 1b](#), are evaluated against radiosonde measurements at the site. [Figure 9](#) shows the temperature, RH, and horizontal wind speed bias as well as the horizontal wind direction from 1013 to 200 hPa, for the individual seasons, and for the two WRF

simulations and GFS data. [Figure 10](#) is as in [Fig. 9](#), but for the normalized error variance. To generate these plots, the WRF and GFS predictions and observations are first interpolated in log-pressure coordinates to a predefined set of pressure levels from 1013 to 200 hPa, at which observational data are typically available for evaluation, before computing the diagnostics. It is important to note that, for the scores to be computed, a minimum of 50 observational data points are required, out of a total of 180 to 184 possible for each individual season, which explains the missing points in the observational data.

As is the case with the surface/near-surface fields, the WRF performance for the individual seasons is generally similar, with comparable biases and α scores. The model underestimates the observed temperature from the surface of up to about 1000–975 hPa, then over predicts it up to roughly 750 hPa, and underestimates it again above that level up to 200 hPa. These temperature biases, however, are rather small, generally within ± 0.5 K, and are generally mostly in the GFS data, in particular above ~ 750 hPa. In fact, and in particular for the spring and summer seasons, the WRF Model is able to partially correct the errors in the GFS forcing data. A similar improvement is seen in the other skill scores including in the normalized error variance, [Fig. 10](#), which is typically smaller by a factor of 2–6 in the WRF simulations compared to the forcing data. In other words, and in the spring and summer months, the model-predicted temperature not only has a

FIG. 8. Average hourly diurnal cycle of the surface (a) downward and (b) upward shortwave radiation flux, (c) downward and (d) upward longwave radiation flux, (e) net radiative flux, (f) sensible heat flux, (g) latent heat flux, and (h) ground heat flux (W m^{-2}) at the location of Al Ain International Airport, station 32, for the period 1 Sep–18 Oct 2017 and 1 Feb–31 Aug 2018. The net radiative flux and the surface heat fluxes are positive if upward from the surface, whereas the ground heat flux is positive if downward into the soil. The black curve shows the observed values, the red curve the WRF predictions for the control experiment (left axis), and the blue curve shows the difference between the forecasts of the experiment and control runs (right axis). The dashed lines in (e)–(h) denote a flux (or difference between fluxes) of 0 W m^{-2} .

magnitude more in line with that observed, its temporal variability is also better simulated by WRF. For all seasons and vertical levels, the model's RH vertical profile resembles that of the GFS data, but with a clear shift to drier conditions, typically by 10%–20%. This tendency is largely positive in particular in the summer season, when it helps to reduce the generally moist profile in the GFS data. The latter is present mostly above 500 hPa, and arises from an overprediction of the observed water vapor mixing ratio (not shown). However, for the other seasons, this dry signal makes the model forecasts less skillful than the forcing data, according to both the bias, in Fig. 9, and α , in Fig. 10, scores. The lower RHs in WRF compared to GFS can be attributed to the slightly warmer temperatures and a drier atmosphere in the model. The latter, which has been reported by other authors such as Shin and Hong (2011) over Kansas in the United States, Boadh et al. (2016) over southern India, and Fountoukis et al. (2018) over Qatar, may also arise from the aforementioned lack of cloud cover (e.g., R. Kumar et al. 2012; Wehbe et al. 2019; Fonseca et al. 2020). The last two panels in Fig. 9 show the bias for the horizontal wind speed and wind direction profiles. Except for the summer season, WRF simulates well both the magnitude

and direction of the horizontal wind vector in the column. The biases are mostly within $\pm 1 \text{ m s}^{-1}$, with the northwesterly winds at lower levels gradually shifting to westerlies above 500 hPa as in the observations, likely due to the presence of the upper-level subtropical jet over the UAE (Niranjan Kumar and Ouarda 2014). The model biases are also of a smaller amplitude compared to those of the forcing data, in particular below 700 hPa. In JJA, however, the WRF biases are of a larger magnitude, reaching 5 m s^{-1} at 200 hPa, even though the shift from the low-level ($>700 \text{ hPa}$) westerly to northwesterly winds, to the upper-level ($<600 \text{ hPa}$) easterly to northeasterly winds in response to the Asian summer monsoon anticyclone, is well captured by the model. For this season, WRF and GFS have a more comparable performance.

At the location of Abu Dhabi's airport, station 31 in Fig. 1b, the soil texture and LULC do not change between the two runs, as seen in Table S1, even though in some of the neighboring grid points the former is switched from clay/sand to loamy sand, while to the northwest, in the city, the LULC is set to urban/built-up, Fig. 2. However, Fig. 9 shows very small but nonnegligible differences between the predicted profiles by the two simulations, in particular below 700 hPa, with the control

simulation giving the best scores below 950 hPa, and the experiment between 950 and 700 hPa. The higher temperatures and wind speeds and lower RHs in the experiment below 950 hPa (the opposite above that level) can be explained by the increased turbulent mixing, as given by the (unresolved) turbulent kinetic energy profiles (Fig. S1). The near-surface atmosphere around Abu Dhabi is typically very moist, due to the rather high surface evaporation from the nearby Arabian Gulf (e.g., Xue and Eltahir 2015), with the moisture advected inland by the prevailing westerly to northwesterly winds, as seen in the wind direction panels. Given this, an enhanced vertical mixing at a given level may lead to drier (and therefore warmer) weather conditions locally and more moist aloft, and vice versa. In addition, the wind is also likely to be stronger, as enhanced turbulence may bring higher momentum air downward (e.g., Yang et al. 2017). Given that the soil texture and LULC are the same at the location of the airport in the two runs, the referred differences in vertical mixing, and hence in the vertical profiles, highlight the nonlocal effect of modified surface and soil properties on the atmospheric flow.

5. Discussion and conclusions

In this paper, WRF is run over the UAE, a hyperarid country, for the 12-month period September 2017–August 2018 with the default and an improved soil texture and LULC dataset. The aim of this work is twofold: (i) evaluate the model performance over the country using a comprehensive set of observational datasets; (ii) investigate the sensitivity of the WRF predictions to an improved representation of the surface and soil properties. The default soil texture and LULC classes are those given by WPS, whereas the updated ones are provided by NCM and obtained from a field campaign conducted as part of the UAREP project. For the soil texture, which controls the soil's physical and hydraulic properties, the main change is the replacement of some of the loamy sand, sandy loam and clay regions with sand, chiefly in the inland desert. The main modification done with respect to the LULC, which mostly impacts the heat and momentum exchanges between the surface and atmosphere, is the expansion of the urban areas in particular around the main cities of Abu Dhabi, Dubai, Sharjah, Ras Al Khaimah, and Fujairah. The observational datasets used for model evaluation comprise hourly weather data at 35 stations spread out over the country, surface radiation and heat fluxes derived from eddy-covariance measurements at Al Ain International Airport, and twice daily radiosonde profiles at Abu Dhabi International Airport.

The main findings of the work are summarized below:

- 1) WRF has a cold air temperature bias over the vast majority of the country, more pronounced in the warmer months and in the inland desert. This bias, which is mostly seen at night, has been highlighted e.g., by Chaouch et al. (2017), Weston et al. (2018), and Valappil et al. (2020), who also ran the model over the country but only for a few days, and mostly in the cold season. It may be explained by deficiencies in the LSM, an incorrect representation of the surface properties and concentrations of greenhouse gases and dust, and is also inherited from the GFS data used to force WRF (e.g., Zheng et al. 2012; Müller and Janjić 2015). The evaluation

of the model-predicted surface fluxes against those observed at Al Ain revealed a higher albedo in WRF compared to that estimated from observations (0.380 for the former and 0.340 for the latter). If this is the case elsewhere in the country, it may also help to explain the referred cold bias.

- 2) WRF systematically overestimates the strength of the near-surface wind at all stations and seasons, typically by 0.5–1.5 m s⁻¹, but in excess of 3 m s⁻¹ over the high terrain. The worst scores are seen at Dhudna, a station on the east coast, just downstream of the Al Hajar mountains. Here, the land breeze is rather strong in the model, with biases of up to 5 m s⁻¹. The onset and cessation times of the land and sea breezes are also not well simulated by WRF, resulting in large phase errors (i.e., lower correlations ρ and hence higher normalized error variances α). This poor model performance has also been reported by other authors (e.g., Cheng and Steenburgh 2005; Shimada et al. 2011; Fonseca et al. 2020; Nelli et al. 2020b). Gunwani and Mohan (2017) suggested that it can be attributed to deficiencies in the simulation of its subgrid-scale fluctuations and in the parameterization of the surface drag, while other sources of error include uncertainties in the measured values, an incorrect depiction of the observed topography, and/or errors in the boundary conditions used to drive the model simulations.
- 3) Employing a more realistic soil texture and LULC data helps in reducing the cold temperature bias, mostly in coastal and inland low-elevation (<200 m AGL) stations, although the impact on the other surface/near-surface fields considered, namely, relative humidity, horizontal wind speed and daily accumulated precipitation, is rather small. When the loamy sand/sandy loam and clay regions are replaced with sand, the soil porosity is reduced, which leads to a higher thermal inertia and hence warmer nighttime and colder daytime temperatures (Fonseca et al. 2019). Overall, in the experiment the model predictions are more skillful, with a typical reduction of the daily mean temperature bias by 1–1.5 K. At the location of Dubai International Airport, and with the replacement of the barren/sparsely vegetated with urban/built-up LULC, a cold bias in excess of 3 K in the daily mean temperature is reduced to just under 0.5 K. The improvement in the WRF performance when the updated soil properties are ingested in the model is also seen in the other verification diagnostics assessed: ρ , variance similarity η , and α . For the high-elevation stations (>200 m AGL), however, the effect of a more realistic soil texture and LULC is very small for all skill scores. This suggests that other factors, such as the representation of the local topography and deficiencies in the physics schemes, may play a larger role. Modifications in the referred surface properties also impact the strength of the land- and sea-breeze circulations mostly at coastal sites, with the associated changes in moisture advection modulating the air temperature and RH biases.
- 4) Despite the cold air temperature bias, a comparison of the surface flux predictions by the model to those estimated from eddy-covariance measurements at Al Ain, revealed

(a)

(b)

FIG. 9. WRF and GFS temperature (K), RH (%), and horizontal wind speed (m s^{-1}) bias, and horizontal wind direction ($^{\circ}$) vertical profiles at the location of Abu Dhabi International Airport for (a) SON, (b) DJF, (c) MAM, and (d) JJA. The red curve gives the WRF scores for the control simulation, the blue curve for the new experiment run, and the green curve for the GFS data. The diagnostics are only plotted if at least 50 observed data points are available. The solid black vertical lines show the optimal scores (i.e., zero bias).

(a)

(b)

FIG. 10. As in Fig. 9, but for the normalized error variance α .

FIG. 10. (Continued)

excessive shortwave radiation flux and too little downward longwave radiation flux at the surface, which suggests a lack of cloud cover when compared with observations. The tendency of WRF to under predict the observed clouds in the UAE has been highlighted by several authors (e.g., R. Kumar et al. 2012; Diaz et al. 2015; Schwitalla et al. 2020; Wehbe et al. 2019; Fonseca et al. 2020; Yousef et al. 2020), and is also consistent with the stronger upward sensible and latent heat fluxes. In addition, the WRF surface fluxes peak 1–2 h earlier than in observations, indicating a tendency to warm up faster in the morning and cool down faster in the evening. This has been highlighted by Weston et al. (2018), and may be explained by deficiencies in the LSM and radiation scheme, an and incorrect representation of the local topography and/or the amount of dust and greenhouse gases in the atmosphere. As the soil texture and LULC are not updated at this station, the difference between the predictions of the control and experiment simulations is rather small as expected.

- 5) The model-predicted vertical profiles of temperature and horizontal wind speed are in close agreement with those derived from radiosonde data, with biases generally within ± 0.5 K and ± 1 m s⁻¹ and α scores smaller than 0.3 and 0.7, respectively. In fact, and in particular for the air temperature and in the spring and summer seasons, WRF is able to partially correct the errors in the GFS data used to drive the model simulations, according to all the skill scores considered in this study. The model-predicted RH profiles generally resemble those of the GFS data, but with a clear dry shift of mostly 10%–20%. While this helps to fix some of the inaccuracies in the forcing data, such as the very moist environment above 500 hPa in the summer season, at times the WRF humidity profile is less skillful than that given by GFS. The drier conditions in WRF have been noted by other authors, such as Shin and Hong (2011), Boadh et al. (2016), and Fountoukis et al. (2018), and are consistent with a lack of clouds, as found to be the case in comparison with eddy-covariance measurements at Al Ain. Despite the fact that the soil texture and LULC are not updated at the location of Abu Dhabi's airport, in the experiment run, there is a small improvement in the vertical profiles of temperature, humidity and horizontal wind speed, mostly between 950 and 750 hPa. This has been attributed to differences in vertical mixing, and highlights the nonlocal impact of an improved representation of the surface and soil properties.

An extension of this work would be to further improve the setup of the model for this region, including conducting a parameter calibration in the LSM. For instance, more accurate estimations of soil properties such as porosity and thermal conductivity (Fonseca et al. 2019), estimated from in situ measurements (e.g., Nelli et al. 2020a,b), can be ingested into the model. In addition, the lower boundary conditions in the model can be improved using both remote sensing data, such as in the National Atmospheric and Space Administration's Land Information System (S. V. Kumar et al. 2012), and hydrologic modeling, such as for WRF-Hydro (coupling between the

atmospheric and hydrological components of the WRF Model; Wehbe et al. 2019) configured as the NOAA National Water Model (e.g., Lahmers et al. 2019). In addition, while in this paper the focus has been on the impact of employing a more realistic spatial representation of the soil texture and LULC, the effect of using more realistic soil and surface-related parameters should also be explored. What is more, it is also important to better represent the topography in the model. The orography used in the WRF simulations is interpolated from a ~ 927 -m spatial resolution dataset, generated by the USGS, which is clearly insufficient to represent the complex terrain in particular in northeastern parts of the UAE. An option would be to ingest the 30-m topography given in Fig. 1b. This, combined with a higher spatial resolution in the model domains, would allow for an improved simulation of the atmospheric conditions in the Al Hajar mountains. It will be left for future work. It would also be interesting to assess the interannual variability of the model performance. In particular, the period targeted in this work, September 2017–August 2018, coincided with a La Niña event. The subsequent year, September 2018–August 2019, featured El Niño conditions. An extension of the model simulations for one more year would therefore allow for an investigation of the impacts of interannual variability in the region. This will also be presented in a subsequent paper.

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APPENDIX

Noah LSM

In the Noah LSM (Chen and Dudhia 2001; Tewari et al. 2004) used in the WRF simulations, four soil layers are considered, with thicknesses of 10, 30, 60, and 100 cm. The soil temperature T_{soil} and soil moisture θ are computed for each layer using the equations below:

$$c_p(\theta) \frac{\partial T_{\text{soil}}}{\partial t} = \frac{\partial}{\partial z} \left[K_t(\theta) \frac{\partial T_{\text{soil}}}{\partial z} \right], \quad (\text{A1})$$

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left(D \frac{\partial \theta}{\partial z} \right) + \frac{\partial K}{\partial z} + F_\theta, \quad (\text{A2})$$

where c_p is the specific heat capacity at constant pressure (J kg⁻¹ K⁻¹), K_t is the soil thermal conductivity (W m⁻¹ K⁻¹), D is the soil hydraulic diffusivity (m² s⁻¹), K is the soil hydraulic conductivity (m s⁻¹), and F_θ represents the sources and sinks of soil water (K s⁻¹; precipitation, evaporation, and runoff).

Equation (A1) is a diffusion equation, which gives the transfer of energy through the soil. As explained in [Dy and Fung \(2016\)](#), $K_t(\theta)$, defined as the rate at which heat is transferred through the soil with an imposed temperature gradient, is obtained from a linear interpolation between the thermal conductivity under dry and saturated conditions. The latter is a function of QTZ, the quartz fraction of the soil, and both thermal conductivities depend strongly on the soil porosity θ_s . These two parameters are a function of the soil texture, as seen in Table S2. The larger QTZ and the smaller θ_s are, the higher K_t will be. A soil with a higher K_t has a higher thermal inertia, meaning that it will warm up less during the day and cool down at a slower rate at night. The specific heat capacity c_p is also computed as a linear interpolation between the values for water, soil, and air.

The first term on the right-hand side of Eq. (A2) represents the diffusive flow component, analogous to the diffusion term in the temperature Eq. (A1), and the second term is the convective flow mechanism forced by gravity. The soil hydraulic diffusivity D and conductivity K are also a function of the soil texture, being computed from the soil parameters given in Table S2:

$$D = D_s \left(\frac{\theta}{\theta_s} \right)^{b+2} = \left[b K_s \left(\frac{\psi_s}{\theta_s} \right) \right] \left(\frac{\theta}{\theta_s} \right)^{b+2}, \quad (\text{A3})$$

$$K = K_s \left(\frac{\theta}{\theta_s} \right)^{b+2}. \quad (\text{A4})$$

Equations (A3) and (A4) show that an increase in the saturated hydraulic diffusivity D_s and conductivity K_s and/or a decrease in the soil porosity θ_s and/or an increase in the b parameter will lead to a higher D and K , and hence to a more efficient transfer of moisture within the soil.

The upper-boundary condition for (A1) is the surface skin temperature T_{SK} . In the Noah LSM, T_{SK} is diagnosed from the surface energy budget given by

$$\begin{aligned} & (\text{SW}\downarrow + \text{LW}\downarrow - \text{SW}\uparrow - \text{LW}\uparrow) \\ & = [\text{SW}\downarrow \times (1 - \alpha) + \text{LW}\downarrow - \varepsilon \sigma T_{SK}^4] = H + \text{LE} + G. \end{aligned} \quad (\text{A5})$$

In Eq. (A5), $\text{SW}\downarrow$, $\text{SW}\uparrow$, $\text{LW}\downarrow$, and $\text{LW}\uparrow$ are the downward and upward shortwave and longwave radiation fluxes, respectively, α is the surface albedo, ε is the surface emissivity, σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$), H is the sensible heat flux, LE is the latent heat flux, and G is the ground heat flux. The albedo α and emissivity ε are directly controlled by the LULC, as seen in Tables S3 and S4. A higher α and ε will lead to a lower T_{SK} : the former means that less of the Sun's shortwave radiation will be absorbed by the surface, therefore making it colder, whereas the latter indicates a higher emission of radiation by the surface. The sensible and latent heat fluxes are given by

$$H = \rho_s c_p C_h (T_{SK} - T_A), \quad (\text{A6})$$

$$\text{LE} = \rho_s C_h (q_G - q_A), \quad (\text{A7})$$

where ρ_s is the density of the surface air (kg m^{-3}), C_h is the surface exchange coefficient for heat and moisture (m s^{-1}), T_A is the surface air temperature (estimated from the air temperature on the lowest model level above the surface, assuming that the potential temperature is vertically well mixed), q_G is the water vapor mixing ratio (kg kg^{-1}) at the surface, and q_A is the water vapor mixing ratio of the air at 2 m. The exchange coefficient C_h is given by

$$C_h = \frac{\kappa^2}{\left[\ln \left(\frac{z}{z_{0m}} \right) - \psi_m \left(\frac{z}{L} \right) \right] \left[\ln \left(\frac{z}{z_{0m}} \right) - \psi_h \left(\frac{z}{L} \right) \right]}, \quad (\text{A8})$$

where ψ_m and ψ_h are the integrated similarity functions for momentum and heat ([Jiménez et al. 2012](#)), L is the Monin–Obukhov length (m), κ is the von Kármán constant (equal to 0.4), z_{0m} is the aerodynamic (or momentum) roughness length (m), and z is the measurement height (m). The parameter z_{0m} is controlled by the LULC, as seen in Tables S3 and S4. A reduction in z_{0m} , with all other parameters being the same, will lead to a lower C_h [Eq. (A8)], and hence a decreased H and LE [Eqs. (A6) and (A7)]. Given the constraint of the closure of the surface energy budget, lower heat fluxes will yield a higher T_{SK} [Eq. (A5)]. A lower z_{0m} will also lead to higher near-surface wind speeds, as the two are related by the equation below, where u_* is the friction velocity (m s^{-1}):

$$U(z) = \frac{u_*}{\kappa} \left[\ln \left(\frac{z}{z_{0m}} \right) - \psi_m(z/L) \right]. \quad (\text{A9})$$

Another important variable directly affected by the parameters given in Tables S2–S4 is the canopy evapotranspiration E_t and consequently LE . As detailed in [Chen and Dudhia \(2001\)](#), in the Noah LSM as coded in WRFV3.7.1 used here, E_t is given by

$$E_t = G_f E_p B_c \left(1 - \sqrt{\frac{W_c}{0.5 \text{ mm}}} \right), \quad (\text{A10})$$

where G_f is the green vegetation fraction, E_p is the potential evaporation, B_c is a function of the canopy resistance, and W_c is the intercepted canopy water content. The canopy water content W_c and the function B_c are expressed as

$$W_c = \frac{\text{CMC}}{5 \times 10^{-4} \text{ m}}, \quad (\text{A11})$$

$$B_c = \frac{1 + \frac{\Delta}{R_r}}{1 + R_c C_h + \frac{\Delta}{R_r}}, \quad (\text{A12})$$

where CMC is the canopy moisture content. The variables used in Eq. (A12) are defined as follows:

$$R_c = \frac{\text{RS}}{\text{LAI} F_1 F_2 F_3 F_4}, \quad (\text{A13})$$

$$R_r = \frac{4\varepsilon\sigma T_{\text{IML}}^4 R_d}{p_s c_p C_h} + 1, \quad (\text{A14})$$

$$\Delta = \left(\frac{2.5 \times 10^6 \text{ J kg}^{-1}}{c_p} \right) \left(\frac{dq_{\text{sat}}}{dT} \right)_{T=T_{\text{IML}}}, \quad (\text{A15})$$

where

$$F_1 = \frac{R_s}{5000 \text{ s m}^{-1} + f}, \quad \text{where } f = 0.55 \left(\frac{\text{SW}_{\downarrow}}{\text{RSL}} \right) \left(\frac{2}{\text{LAI}} \right),$$

$$F_2 = \frac{1}{1 + \text{HS}[q_{\text{sat}}(T_{\text{IML}}) - q_A]},$$

$$F_3 = 1 - 0.0016(298 \text{ K} - T_{\text{IML}})^2,$$

$$F_4 = \sum_{i=1}^{\text{NROOT}} \frac{(\theta_i - \theta_w) d_{zi}}{(\theta_r - \theta_w) d_{z(\text{NROOT})}}.$$

In the equations above, p_s is the surface pressure, R_d is the specific gas constant for dry air ($287 \text{ J kg}^{-1} \text{ K}^{-1}$), T_{IML} is the temperature on the first model level, q_{sat} is the saturation specific humidity, and θ_i and d_{zi} are the soil moisture and depth of the first soil layer, respectively. The parameters RS, RGL, HS, LAI, ε , and NROOT (number of soil layers roots penetrate), defined in Tables S3 and S4, and the soil-related parameters θ_r and θ_w , set in Table S2, directly impact the model-predicted latent heat fluxes. The higher RS, HS, θ_r , and θ_w are, and the lower NROOT and LAI are, the higher R_c will be, which means a lower B_c and E_t and therefore a suppressed LE. For example, when comparing barren/sparsely vegetated regions with urban/built-up ones, the value of RS is lower by a factor of about 5 and LAI is roughly one order of magnitude larger, meaning that E_t , and consequently LE, will be larger for urban areas, in line with expectations (e.g., Man Sing et al. 2015).

Equations (A1)–(A15) show that WRF's surface and soil variables, in particular the surface temperature and heat fluxes and the soil's temperature and moisture, strongly depend on the soil texture and LULC, highlighting the importance of correctly representing these properties in the model.

In addition, and as shown by studies such as that of Göndöcs et al. (2015), the referred surface properties can also impact the model-predicted precipitation. For one thing, a change in the latent heat flux will modify the buoyancy of the near-surface air, and hence the model-generated precipitation. However, when the rainfall is mostly associated with large-scale advection, the effect of having a more realistic soil texture and LULC is much reduced. As also highlighted in the referred paper, the relationship between soil moisture and precipitation has not been clearly established: while some authors argue that a more moist soil will lead to an increase in the convective available potential energy having a smaller impact on the convective inhibition, others reported that the resulting increase in the near-surface water vapor mixing ratio from a more moist soil will lead to cooler surface temperatures and hence to an augmented inhibition. The impact of the surface properties on the precipitation appears to be location dependent.

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