Forecasting global horizontal and direct normal irradiation in the Arabian Peninsula: Sensitivity to the explicit treatment of aerosols

Vineeth Krishnan valappil[1], Luis Martin-Pomares[1], Michael Weston[1]

[1]Dubai Electricity and Water Authority, Dubai, UAE

Abstract

Global horizontal (GHI) and Direct Normal Irradiation (DNI) predicted using an operational three-dimensional atmospheric meteorology-chemistry model and a triple-nesting configuration over the Middle East with a focus on the hot desert climate of UAE is presented. The model runs every day, providing solar radiation components and air quality variables with a temporal step of one hour and a horizon of 72 hours. The model performance was assessed with measurement data of solar radiation from a ground monitoring station in Dubai (UAE) collected over one year, from January to December 2022, of representative and distinct meteorological regimes. We have examined the ability of the model to forecast GHI and DNI values under the RRTM (Rapid Radiative Transfer Model) and different shortwave downward radiation parameterizations. On an annual scale, the GHI and DNI displayed a mean rMBD of 0.51% and 18.7% and rRMSD of 21.6% and 69.7% respectively. The introduction of advanced treatment of aerosols dramatically improves the model performance in predicting GHI and DNI.

Keywords: solar radiation; desert dust; NWP model; Middle East, WRF-Chem, RRTM, aerosol

1. Introduction

The Middle East and North Africa (MENA) region has abundant solar resources and is implementing plans for renewable energy (Nematollahi, Hoghooghi, Rasti, & Sedaghat, 2016, Sgouridis, S. et al, 2016). The demand for electricity keeps rising in large urban environments of MENA, and the need for diversification from conventional energy production is now pushing for methods to reduce carbon emissions towards more sustainable development (Munawwar & Ghedira, 2014). Several solar resource assessment and feasibility studies for concentrated solar power plants (CSP) and photovoltaic plants (PV) have recently been carried out in the Middle East (Charabi & Gastli, 2010; Liqreina & Qoaider, 2014; Mokri, Aal Ali, & Emziane, 2013; Zell et al., 2015). Several research studies over the Middle East have shown that PV systems offer the most reliable and stable solution for primarily hot and humid environments (Pomares, 2017;). Therefore, accurate predictions of Global Titled Irradiance (GTI) derived from solar components of GHI, DNI and Diffuse Horizontal Irradiation (DHI) and local ground albedo in the region are of fundamental importance for efficient grid-connected PV establishments.

Accuracy in determining the expected solar irradiance and electricity production from solar power plants is essential for reducing grid integration costs and for more effective electricity grid management. Unlike wind power, solar radiation predictive capabilities are still nascent. GHI and DNI forecasting are traditionally conducted using various modeling approaches, including statistical models, models based on satellite data and sky cameras, and numerical weather prediction (NWP) models. The forecasting target horizon and spatial and temporal resolution determine the optimum modeling approach. For forecasts over the first minutes up to approximately 1-2 hours ahead of time (nowcasting), time series of solar irradiance can be provided by statistical approaches based on measured solar radiation data and sky cameras at a specific location (Hugo T.C.PedroCarlos F.M.Coimbra & Hugo T.C.Pedro, 2012; Mellit & Pavan, 2010). For forecasts from ~2 hours up to ~5 hours ahead (short-term forecasting), approaches based on the detection of cloud motion derived from satellite remote sensing are used to infer intra-hour solar irradiance with often high spatial and temporal resolution (Chow et al., 2011). The most valuable tool for GHI and DNI forecasting from 6 hours up to several days ahead is a Numerical Weather Prediction (NWP) model.

NWP models inherently include a radiative transfer model that is used to predict GHI and DNI through dynamic modeling of the troposphere. (R. J. Zamora, 2003; Robert J. Zamora et al., 2005) evaluated the hourly GHI predictions of the Fifth-Generation Penn State/NCAR Mesoscale Model (MM5) (Grell, Jimy, & David, 1994) and the National Center for Environmental Prediction (NCEP) Eta Model in certain locations in the USA and

10.18086/swc.2023.11.02 Available at http://proceedings.ises.org

reported model errors on the order of 100 Wm-2 for high aerosol loadings. The ability of MM5 to predict hourly solar irradiance was also studied by (Heinemann, Lorenz, Girodo, & University, 2006), who found a relative root mean square error (rRMSD) of about 50% in Germany. (Perez, Moore, Wilcox, Renne, & Zelenka, 2007) showed an rRMSD of 38% after applying a correction function estimating the hourly-averaged GHI by the National Digital Forecast Database (NDFD) as published by NCEP (Lorenz et al., 2009; Perez et al., 2013). (Mathiesen & Kleissl, 2011) conducted a comprehensive analysis of hourly GHI forecasts from three NWP models (NAM, GFS, and ECMWF) over the continental USA and found biases of up to 150 Wm-2. The capability of the Weather Research and Forecasting (WRF) model to predict hourly averaged solar irradiance in Andalusia, Spain, was examined by (Lara-Fanego, Ruiz-Arias, Pozo-Vázquez, Santos-Alamillos, & Tovar-Pescador, 2012) who found an rRMSD ranging between 10% (for clear-skies) and 50% (for cloudy conditions). (Ruiz-Arias, Dudhia, Santos-Alamillos, & Pozo-Vázquez, 2013), using WRF, validated various shortwave radiation parameterizations in the US and found a superiority of the RRTMG scheme (Rapid Radiative Transfer Model for Global climate models), if reliable aerosol data are provided as input to the model. More recently, (Zempila, Giannaros, Bais, Melas, & Kazantzidis, 2016) focused on the sensitivity of WRF to shortwave irradiance schemes while following a simple approach for investigating the impact of aerosol variations. They found that hourly averaged GHI over Greece is overestimated with all schemes (by 40-70% in terms of relative bias) for all-sky conditions while for clear skies an RMSD ranging between 90 and 110 Wm-2 was found. (Gleeson, Toll, Pagh Nielsen, Rontu, & Mašek, 2016) studied the effect of aerosols on clear sky solar radiation predictions using the Aire Limitee Adaptation dynamique Developpement InterNational – High Resolution Limited Area Model (ALADIN-HIRLAM) numerical weather prediction system for the August 2010 Russian wildfire case while testing three shortwave radiation schemes. They showed a reduction of error in global shortwave irradiance from 15 % at midday to 10% when standard climatological aerosols were used.

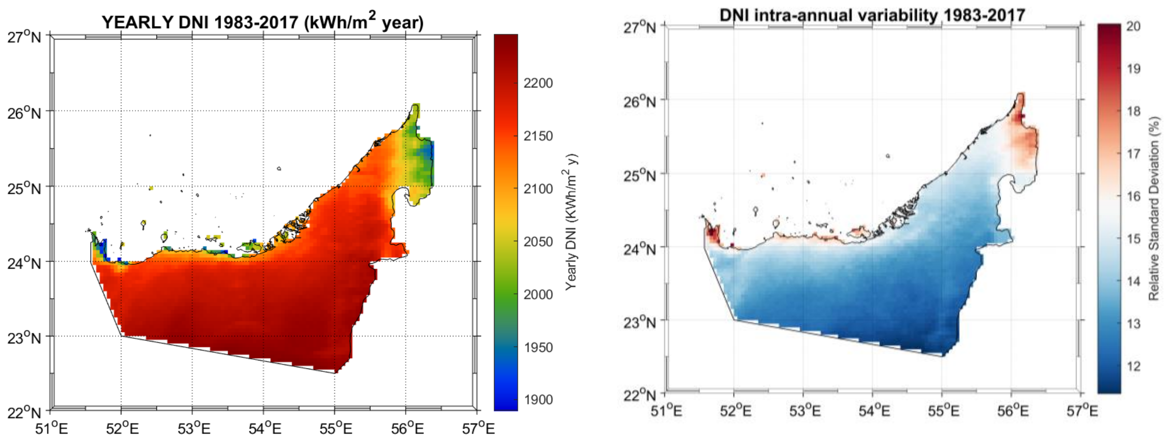

Fig 1: Yearly DNI and intra-annual variability from SARAH2 database. Year period 1983-2017.

One of the advantages of mesoscale NWP models is that they can cover a limited (urban to regional) geographical area and thus can be computationally inexpensive. At the same time, their physics can include additional details compared to global large-scale NWP models. Furthermore, NWP models are well-suited for solar irradiance predictions as they have advanced shortwave solar radiation parameterizations (Ruiz-Arias et al., 2013). However, the fluctuating nature of solar irradiance reaching the surface, caused by highly variable weather and air pollution patterns, is a significant challenge in the cost-effective management, operation, and integration of solar energy into existing electricity supply systems. More specifically, the subgrid-scale variability of clouds and the high temporal and spatial variability of atmospheric aerosol concentrations are the primary sources of uncertainty in predicting GHI and DNI (direct normal irradiance). Complex cloud microphysics (e.g., calculation of total cloud water content) and non-deterministic aerosol patterns are not well represented by NWP models (Heinemann et al., 2006). Traditionally, NWP models either neglect the presence of particles in the atmosphere or (more often) include a simplified aerosol approach (e.g., use of climatological data) while often miscalculating the location and lifetime of clouds resulting in significant biases in solar irradiance forecasting (Lara-Fanego et al., 2012; Thompson et al., 2016; R. J. Zamora, 2003; Robert J. Zamora et al., 2005; Zempila et al., 2016).

In the MENA region, high temperatures during most of the year often result in cloud-free atmospheric conditions due to rapid cloud dissipation. Aerosol concentrations, on the other hand, are high throughout the year due to frequent dust events and other emission sources in urban centers (Kalenderski, Stenchikov, & Zhao, 2013; Rakesh, Singh, & Joshi, 2009; Tsiouri, Kakosimos, & Kumar, 2015). Therefore, consideration of the effect of aerosols in radiation models is crucial to reduce solar irradiance prediction errors in this region. Contrary to ozone, carbon dioxide, and water vapor, aerosols' temporal and spatial variability is larger and more challenging to predict. In this work, we predict GHI and DNI in UAE and the Middle East using a three-dimensional meteorology-chemistry model, including a state-of-the-art prognostic treatment of aerosols.

2. Methodology

The following sections explain the WRF-chem model, the observational datasets, and the model evaluation diagnostics adopted in this study.

2.1. Observational datasets

The solar radiation measurements used in this study were recorded using the Dubai Electricity and Water Authority's (DEWA) high-precision monitoring station in Outdoor Test Facility (OTF) near MBR solar park (Dubai) (Latitude 24.76°N, longitude 55.36°E, altitude 30 meters). DEWA's OTF monitoring station (Fig. 1) is equipped with EKO thermoelectric radiometer, each mounted on an EKO STR-22G sun tracker, which also has a sun sensor kit for improved tracking accuracy. Two EKO MS80 ISO9060:2018 Class A pyranometers are used for measuring GHI and DHI, and one ISO 9060:2018 Class A EKO MS-57 pyrheliometer is used for DNI measurements. A shading ball assembly is also mounted on the tracker for measuring DHI. All data from the station are sampled every second and registered as one-minute averages in Wm-2. Quality checks and routine maintenance are conducted at high frequency (daily or every other day) and involve detailed cleaning of all sensor domes/windows, replacement of the desiccant of sensors when needed, and checking of the sensor shading, sensor tracking, and level/alignment, as well as offline data validation. Additionally, DEWA's air quality monitoring station, located next to the solar radiation station, is equipped with a Thermo-hygrometer (DMA867-875) and an Anemometer (DNA827) and continuously measures (every 1 min) ambient relative humidity, the temperature at 2m, wind velocity and wind direction at 10 meters altitude.

Fig 2: DEWA R&D OTF radiometric station.

2.2. WRF model

The three-dimensional meteorology-chemistry model WRF-Chem version 4.1.1 (Weather Research Forecasting with Chemistry) (Fast et al., 2006; Grell et al., 2005) was employed over the Arabian Peninsula region with an enhanced grid resolution over UAE. The orography of the area and modeling domain is shown in Fig. 3. The topography of the Arabian Peninsula is characterized by flatlands on the eastern side and highlands on the western side. The terrain of UAE is low-lying flat, and barren desert covered with loose sand and gravel. The Al Hajar mountain dominates in the northeastern part, and the rural type of land cover prevails in the western part of the UAE. An urban land cover predominates in the emirates of Abu Dhabi and Dubai, with thick shrublands to the east of Dubai. The WRF-chem model was applied over the Middle Eastern Area using a two-way nested domain (Figure 3). Each domain communicates with its inner/parent domain, and all three run simultaneously. The parent domain is configured to a 50 km × 50 km grid spacing while the intermediate nested domain (focused on the Arabian Desert) to a 10 km × 10 km spacing. The third domain was configured over the region of Dubai (at 2 km × 2 km).

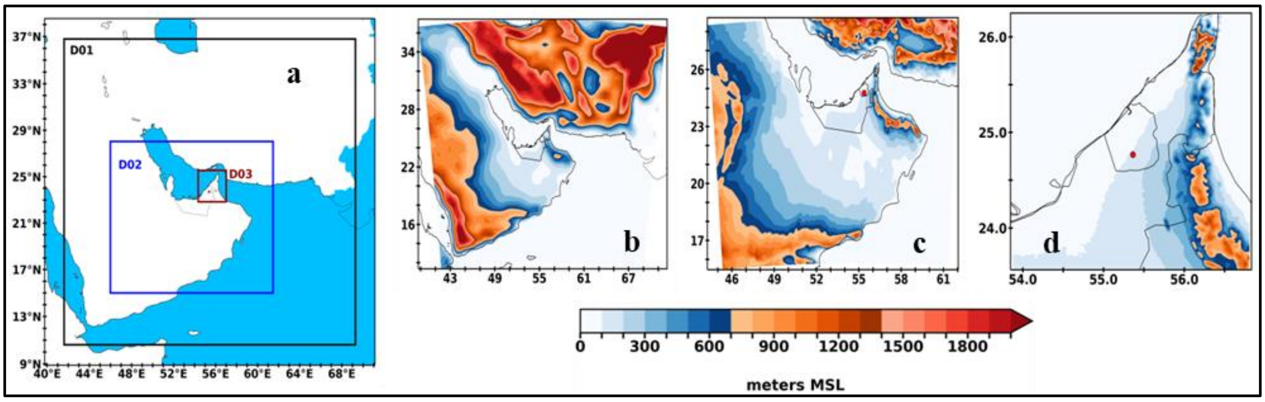

Fig 3: (a) WRF Model domains and orography (m) of (b) D01 (50 km), (c) D02 (10 km), and (d) D03 (2 km) WRF domains.

The physics part of the WRF-Chem stems from the WRF model, a non-hydrostatic meteorological mesoscale model that includes parameterizations of the land surface, planetary boundary layer, and cloud processes. The reference simulations for this work used the Grell 3D cumulus parameterization (Grell & Dévényi, 2002), the Lin microphysics scheme (CHEN & SUN, 2004), the 5-layer thermal diffusion Land Surface Model, the revised MM5 Monin–Obukhov surface layer scheme, the Goddard shortwave radiation scheme, the Rapid Radiative Transfer Model longwave radiation scheme (Mlawer, Taubman, Brown, Iacono, & Clough, 1997) and the Yonsei University boundary layer scheme (Hong, Noh, & Dudhia, 2006). This set of choices has been widely used when applying WRF (e.g. (Lara-Fanego et al., 2012; Ruiz-Arias et al., 2013; Zempila et al., 2016). Information concerning species concentrations propagates into and out of each computational area during model integrations. The WRF-Chem model simulates three essential components: emissions of atmospheric constituents (gases and aerosol particles), transport and the physicochemical transformations of atmospheric species. This grid nesting capability of WRF-Chem allows for a computationally efficient modeling setup capable of spanning large areas in which regional transport of pollutants (e.g., dust) is essential while providing fine resolution in select regions to address small-scale features. The altitude coordinate was discretized into 28 vertical layers in all three computational domains, extending from the surface to approximately 20 km. A Lambert map projection was employed in all the WRF-Chem runs. Dynamic meteorological data were obtained from the Global Forecast System (GFS; ftp://nomads.ncdc.noaa.gov/GFS/) and used to initialize WRF-Chem simulations.

2.3. Model verification

The uncertainty of the numerical predictions was calculated against ground measurements through uncertainty parameters based on data dispersion frequently used in the solar resource community (Espinar et al., 2009; Gueymard, 2014). The dispersion parameters were calculated using relativized versions of the mean bias deviation (MBD), and root mean square deviation (RMSD), as shown in equations (1) and (2), where Yexp and Ymod are the measured and predicted values of the variable, respectively, and N is the total number of points.

$$rMBD = 100 \frac{1}{N} \sum_{i=1}^{N} \frac{(Y_{exp} - Y_{mod})}{\overline{Y_{exp}}} \quad (1)$$

$$rRMSD = 100 \frac{1}{\overline{Y_{exp}}} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(Y_{exp} - Y_{mod}\right)^2} \quad (2)$$

3. Results

This section explains the accuracy of WRF-chem forecasts with ground station measurements. Annual mean GHI and DNI forecast over the study region for day one, day two and day 3 for domain three are shown in Figures 2 and 3, respectively. The annual mean GHI and DNI vary between 200 to 300 Whm−2 and 100 to 400 Whm−2, respectively. The forecasts are also available as time series for single locations accessible through SQL, FTP and web services for operators of solar power plants.

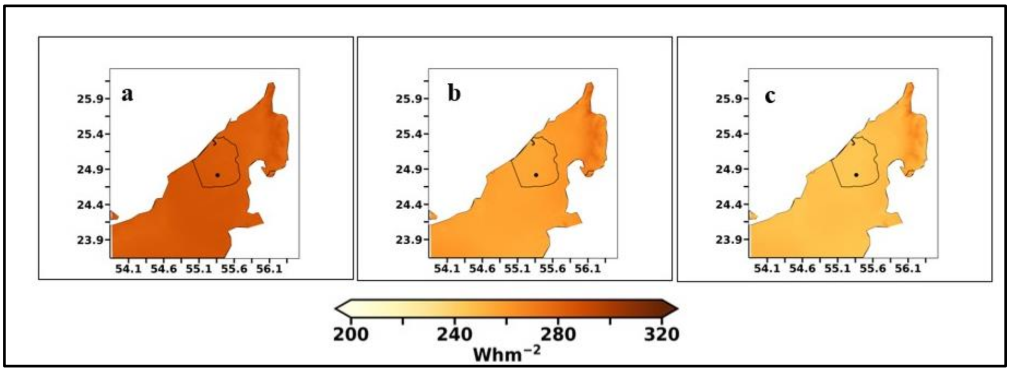

Fig 2: Annual mean GHI (Whm−2) predicted by WRF/Chem (with aerosols) for (a) day1, (b) day 2, (c) day 3 horizon of the forecast over the domain 3.

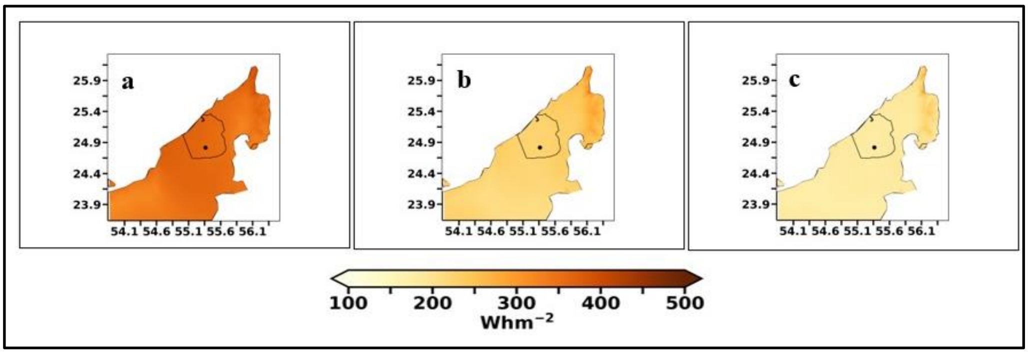

Fig 3: Annual mean DNI (Whm−2) predicted by WRF/Chem (with aerosols) for (a) day1, (b) day 2, (c) day 3 horizon of the forecast over domain 3.

The prediction skill of the WRF-Chem model was quantified using the root mean square deviation (RMSD), the relative RMSD (rRMSD), the mean bias deviation (MBD) and its relative magnitude (rMBD) using the mean value of the measurements for the period analyzed. Table 1 to Table 5 present the validation of the GHI and DNI forecast at the OTF facility. The period of validation for the data from the operational WRF-Chem model and ground radiometric measurements goes from the 1st of January 2022 to the 31st of Dec 2022. The accuracy of GHI and DNI from the WRF-chem model is summarized in Table 1 annually. Overall, the GHI showed a mean bias of 0.60 Wm−2 and mean rMBD of 0.51%, whereas the DNI displayed a mean bias of 69.1 Wm−2 and rMBD of 18.7%. The corresponding RMSD and rRMSD for GHI and DNI are 71.5 Whm−2, 21.6% and

222.2 Whm−2, 69.7%, respectively. The results are further divided into each of the three days of forecast, and the total error for the three days for each season separately is displayed in Table 2 to Table 5.

Tab. 1: WRF/Chem-DEWA Analysis against observations of Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) at the DEWA monitoring station in OTF (Outdoor Test Facility), Dubai, UAE, for JAN – DEC 2022.

	MBD (Whm−2)	**rMBD (%)**	**RMSD (Whm−2)**	**rRMSD (%)**
GHI	-0.60	0.51	71.5	21.6
DNI	69.1	18.7	222.2	69.7

Tab. 2: Prediction skill metrics of WRF/Chem against observations of Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) at the DEWA monitoring station in Dubai for the Winter season (DJF) 2022.

	MBD (Whm−2)		**rMBD (%)**		**RMSD (Whm−2)**		**rRMSD (%)**	
	GHI	**DNI**	**GHI**	**DNI**	**GHI**	**DNI**	**GHI**	**DNI**
0-23 hours	39.6	260.1	9.8	55.7	100.8	332.9	24.3	69.6
24-47 hours	8.3	70.1	1.8	15.1	110.7	292.4	26.4	58.1
48-71 hours	-7.9	-25.3	-2.2	-3.8	24.8	53.7	24.9	53.8
TOTAL (0-71 hours)	13.3	101.6	3.2	22.3	78.7	226.3	25.2	60.5

Tab. 3: Prediction skill metrics of WRF/Chem against observations of Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) at the DEWA monitoring station in Dubai for the Spring season (MAM), 2022.

	MBD (Whm−2)		**rMBD (%)**		**RMSD (Whm−2)**		**rRMSD (%)**	
	GHI	**DNI**	**GHI**	**DNI**	**GHI**	**DNI**	**GHI**	**DNI**
0-23 hours	64.4	341.2	13.1	79.4	90.7	382.7	18.2	88.7
24-47 hours	14.4	75.4	2.1	17.3	91.1	267.2	17.6	59.7
48-71 hours	-18.5	-76.2	-4.3	-15.5	18.3	52.1	18.32	52.1
TOTAL (0-71 hours)	20.1	113.4	3.6	27.1	66.7	234.0	18.06	66.9

Tab. 4: Prediction skill metrics of WRF/Chem against observations of Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) at the DEWA monitoring station in Dubai for Summer (JJA), 2022.

	MBD (Whm−2)		rMBD (%)		RMSD (Whm−2)		rRMSD (%)	
	GHI	DNI	GHI	DNI	GHI	DNI	GHI	DNI
0-23 hours	48.4	263.1	11.6	94.1	113.4	357.5	24.2	128.9
24-47 hours	-51.8	-114.1	-8.1	-25.3	139.1	272.1	27.6	82.3
48-71 hours	-84.6	-170.3	-14.6	-45.4	30.8	78.9	30.7	78.9
TOTAL (0-71 hours)	-29.4	-7.1	-3.7	7.7	94.4	236.1	27.5	96.7

Tab. 5: Prediction skill metrics of WRF/Chem against observations of Global Horizontal Irradiance (GHI) Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) at the DEWA monitoring station in Dubai for Fall (SON), 2022.

	MBD (Whm−2)		rMBD (%)		RMSD (Whm−2)		rRMSD (%)	
	GHI	DNI	GHI	DNI	GHI	DNI	GHI	DNI
0-23 hours	25.9	257.8	5.6	59.8	52.9	288.7	13.2	65.7
24-47 hours	-12.6	35.2	-2.4	11.2	66.4	242.8	15.4	51.8
48-71 hours	-32.8	-87.8	-6.5	-18.1	18.5	44.6	18.5	44.2
TOTAL (0-71 hours)	-6.5	68.4	-1.1	17.6	45.9	192.1	15.7	54.8

In Comparison with observations, the model generally overestimates the GHI for each simulation period, with an RMSD ranging between 18.5 and 139.1Whm−2 and a relative RMSD ranging from 13.2 to 26.4%. Similarly, DNI showed an overestimation of 44.6 and 382.7 Whm−2 and 44.2 and 88.7% for RMSD and relative RMSD, respectively, for different seasons. The winter and Fall seasons displayed better accuracy than the summer or spring seasons. These errors are within the lower end of GHI and DNI errors found in other parts of the world. Interestingly the 48-71 hours (day 3) forecast shows better accuracy than 0-23 hours (day 1) and 24-48 hours (day 2), which could be due to the WRF-chem model's capability to accommodate the aerosol direct and indirect effect.

4. Conclusions

Clouds have, in general, a substantial effect on solar insolation but the mostly cloud-free conditions throughout the year in UAE and its position within the sunbelt favor solar PV adoption as a renewable energy production method. However, high atmospheric aerosol concentrations in this location attenuate solar radiation considerably. This study concentrates on validating operational predictions of global horizontal and direct average irradiation in the Middle East with a particular focus on the UAE using a regional meteorology-chemistry model combined with ground measurements from the continuous operation of a monitoring station in Dubai, UAE.

We have presented the maps to the users and validated the predictions of GHI and DNI. The WRF-Chem model has been running operationally since Jan 2022 providing daily hourly forecasts over UAE and the Arabian Peninsula with a temporal horizon of 72 hours.

Results show that the numerical weather prediction model WRF-Chem systematically over-predicts global horizontal irradiance and Direct Normal Irradiance in Dubai. The WRF chem model overestimates the aerosol direct and indirect effects, leading to increased scattering or absorption of solar radiation reaching the ground. The major source of error can be attributed to inaccuracies in the input emissions utilized for the simulations. In addition, the parameterizations used in the WRF model for aerosols may not be detailed enough to represent the diverse and dynamic nature of aerosol properties and their impact on irradiance. This can lead to inaccuracies in forecasting solar irradiance. This configuration serves as our baseline setup, which will be the foundation for our ongoing refinements and improvements in the model configuration.

Modeling aerosols is especially crucial for fast-changing urban environments like Dubai, which has experienced recent land conversion and rapid urbanization. Over the greater region of the Arabian Peninsula, we already know from a previous publication (Fountoukis, Martín-Pomares, Perez-Astudillo, Bachour, & Gladich, 2018) that the impact of accurate aerosol concentrations on the predicted GHI is considerable (15–20% on average). A previous study (Fountoukis, Martín-Pomares, Perez-Astudillo, Bachour, & Gladich, 2018) also show a prognostic treatment of aerosols in a numerical weather prediction model is essential in regions with high aerosol concentrations. Further improving the anthropogenic emissions inventory, refining model parameterization schemes, and better maintenance of the radiometers are expected to eliminate errors in irradiance forecasts.

5. Acknowledgments

The authors wish to acknowledge the continuous dedication of DEWA R&D infra team on the maintenance and operation of DEWA OTF station.

The authors wish to acknowledge the Photovoltaic Power Systems (PVPS) Programme within the International Energy Agency (IEA) and all the experts who participate in the IEA Task 16 (Solar resource for high penetration and large-scale applications). The development of this work was partly motivated by participation in Task 16 Expert Meetings.

6. References

Charabi, Y., & Gastli, A. (2010). GIS assessment of large CSP plant in Duqum, Oman. Renewable and Sustainable Energy Reviews, 14(2), 835–841. https://doi.org/10.1016/j.rser.2009.08.019

CHEN, S.-H., & SUN, W.-Y. (2004). A One-dimensional Time Dependent Cloud Model. Journal of the Meteorological Society of Japan. Ser. II. https://doi.org/10.2151/jmsj.80.99

Chow, C. W., Urquhart, B., Lave, M., Dominguez, A., Kleissl, J., Shields, J., & Washom, B. (2011). Intra-hour forecasting with a total sky imager at the UC San Diego solar energy testbed. Solar Energy, 85(11), 2881–2893. https://doi.org/http://dx.doi.org/10.1016/j.solener.2011.08.025

Espinar, B., Ramírez, L., Drews, A., Beyer, H. G., Zarzalejo, L. F., Polo, J., & Martín, L. (2009). Analysis of different comparison parameters applied to solar radiation data from satellite and German radiometric stations. Solar Energy, 83(1), 118–125. https://doi.org/doi: DOI: 10.1016/j.solener.2008.07.009

Fast, J. D., Gustafson, W. I., Easter, R. C., Zaveri, R. A., Barnard, J. C., Chapman, E. G., … Peckham, S. E. (2006). Evolution of ozone, particulates, and aerosol direct radiative forcing in the vicinity of Houston using a fully coupled meteorology-chemistry-aerosol model. Journal of Geophysical Research Atmospheres. https://doi.org/10.1029/2005JD006721

Fountoukis, C., Ackermann, L., Ayoub, M. A., Gladich, I., Hoehn, R. D., & Skillern, A. (2016). Impact of atmospheric dust emission schemes on dust production and concentration over the Arabian Peninsula. Modeling Earth Systems and Environment, 2(3), 115. https://doi.org/10.1007/s40808-016-0181-z

Fountoukis, C., Martín-pomares, L., Perez-astudillo, D., Bachour, D., & Gladich, I. (2018). Simulating global horizontal irradiance in the Arabian Peninsula : Sensitivity to explicit treatment of aerosols. Solar Energy, 163(February), 347–355. https://doi.org/10.1016/j.solener.2018.02.001

Fountoukis, C., Martín-Pomares, L., Perez-Astudillo, D., Bachour, D., & Gladich, I. (2018). Simulating global horizontal irradiance in the Arabian Peninsula: Sensitivity to explicit treatment of aerosols. Solar Energy. https://doi.org/10.1016/j.solener.2018.02.001

Gleeson, E., Toll, V., Pagh Nielsen, K., Rontu, L., & Mašek, J. (2016). Effects of aerosols on clear-sky solar radiation in the ALADIN-HIRLAM NWP system. Atmospheric Chemistry and Physics. https://doi.org/10.5194/acp-16-5933-2016

Grell, G. A., & Dévényi, D. (2002). A generalized approach to parameterizing convection combining ensemble and data assimilation techniques. Geophysical Research Letters. https://doi.org/10.1029/2002gl015311

Grell, G. A., Jimy, D., & David, R. S. (1994). A description of the fifth-generation Penn State/NCAR Mesoscale Model (MM5). NCAR Technical Note NCAR/TN-398+STR. https://doi.org/10.5065/D60Z716B

Grell, G. A., Peckham, S. E., Schmitz, R., McKeen, S. A., Frost, G., Skamarock, W. C., & Eder, B. (2005). Fully coupled "online" chemistry within the WRF model. Atmospheric Environment. https://doi.org/10.1016/j.atmosenv.2005.04.027

Gueymard, C. a. (2014). A review of validation methodologies and statistical performance indicators for modeled solar radiation data: Towards a better bankability of solar projects. Renewable and Sustainable Energy Reviews, 39(0), 1024–1034. https://doi.org/10.1016/j.rser.2014.07.117.

Heinemann, D., Lorenz, E., Girodo, M., & University, O. (2006). Forecasting of solar radiation. Oldenburg (Alemania). Retrieved from n:%5CTesis_USB%5CReferencias_Biblio%5CLuis_M%5CRadiacion Prediccion%5Cestado del arte%5CHeinemann-P (Chapter 7, Part II).doc

Hong, S.-Y., Noh, Y., & Dudhia, J. (2006). A New Vertical Diffusion Package with an Explicit Treatment of Entrainment Processes. Monthly Weather Review. https://doi.org/10.1175/mwr3199.1

Hugo T.C.PedroCarlos F.M.Coimbra, & Hugo T.C.Pedro, C. F. M. C. (2012). Assessment of forecasting techniques for solar power production with no exogenous inputs. Solar Energy. https://doi.org/10.1016/J.SOLENER.2012.04.004

Kalenderski, S., Stenchikov, G., & Zhao, C. (2013). Modeling a typical winter-time dust event over the Arabian Peninsula and the Red Sea. Atmospheric Chemistry and Physics. https://doi.org/10.5194/acp-13-1999-2013

Lara-Fanego, V., Ruiz-Arias, J. A., Pozo-Vázquez, D., Santos-Alamillos, F. J., & Tovar-Pescador, J. (2012). Evaluation of the WRF model solar irradiance forecasts in Andalusia (southern Spain). Solar Energy, 86(8), 2200–2217. https://doi.org/10.1016/j.solener.2011.02.014

Liqreina, A., & Qoaider, L. (2014). Dry cooling of concentrating solar power (CSP) plants, an economic competitive option for the desert regions of the MENA region. Solar Energy, 103(0), 417–424.

Lorenz, E., Remund, J., Müller, S. C., Traunmüller, W., Steinmaurer, G., Pozo, D., … Romeo, M. G. (2009). Benchmarking of different approaches to forecast solar irradiance. Proceedings of the 24th European Photovoltaic Solar Energy Conference.

Mathiesen, P., & Kleissl, J. (2011). Evaluation of numerical weather prediction for intra-day solar forecasting in the continental United States. Solar Energy. https://doi.org/10.1016/j.solener.2011.02.013

Mellit, A., & Pavan, A. M. (2010). A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy. Solar Energy. https://doi.org/10.1016/j.solener.2010.02.006

Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., & Clough, S. A. (1997). Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. Journal of Geophysical Research: Atmospheres. https://doi.org/10.1029/97jd00237

Mokri, A., Aal Ali, M., & Emziane, M. (2013). Solar energy in the United Arab Emirates: A review. Renewable and Sustainable Energy Reviews, 28(0), 340–375. https://doi.org/http://dx.doi.org/10.1016/j.rser.2013.07.038

Munawwar, S., & Ghedira, H. (2014). A review of Renewable Energy and Solar Industry Growth in the GCC Region. Energy Procedia, 57, 3191–3202. https://doi.org/10.1016/j.egypro.2015.06.069

Nematollahi, O., Hoghooghi, H., Rasti, M., & Sedaghat, A. (2016). Energy demands and renewable energy resources in the Middle East. Renewable and Sustainable Energy Reviews, 54, 1172–1181. https://doi.org/10.1016/j.rser.2015.10.058

Perez, R., Lorenz, E., Pelland, S., Beauharnois, M., Van Knowe, G., Hemker, K., … Pomares, L. M. (2013). Comparison of numerical weather prediction solar irradiance forecasts in the US, Canada and Europe. Solar Energy. https://doi.org/10.1016/j.solener.2013.05.005

Perez, R., Moore, K., Wilcox, S., Renne, D., & Zelenka, A. (2007). Forecasting solar radiation - Preliminary evaluation of an approach based upon the national forecast database. Solar Energy, 81(6), 809–812. http://www.sciencedirect.com/science/article/B6V50-4MH2KN8-1/1/c8d5d462390cb9b1b469b00411a2fdbb

Pomares, L. M., & Sanfilippo, A. (2017). Analysis of the long-term solar potential for electricity generation in Qatar Analysis of the long-term solar potential for electricity generation in Qatar. Renewable and Sustainable Energy Reviews, 73(June), 1231–1246. https://doi.org/10.1016/j.rser.2017.01.125

Rakesh, V., Singh, R., & Joshi, P. C. (2009). Intercomparison of the performance of MM5/WRF with and without satellite data assimilation in short-range forecast applications over the Indian region. Meteorology and Atmospheric Physics. https://doi.org/10.1007/s00703-009-0038-3

Ruiz-Arias, J. A., Dudhia, J., Santos-Alamillos, F. J., & Pozo-Vázquez, D. (2013). Surface clear-sky shortwave radiative closure intercomparisons in the Weather Research and Forecasting model. Journal of Geophysical Research Atmospheres. https://doi.org/10.1002/jgrd.50778

Sanfilippo, A., Martin-Pomares, L., Mohandes, N., Perez-Astudillo, D., & Bachour, D. (2016). An adaptive multi-modeling approach to solar nowcasting. Solar Energy, 125, 77–85. https://doi.org/10.1016/j.solener.2015.11.041

Thompson, G., Tewari, M., Ikeda, K., Tessendorf, S., Weeks, C., Otkin, J., & Kong, F. (2016). Explicitly-coupled cloud physics and radiation parameterizations and subsequent evaluation in WRF high-resolution convective forecasts. Atmospheric Research. https://doi.org/10.1016/j.atmosres.2015.09.005

Tsiouri, V., Kakosimos, K. E., & Kumar, P. (2015). Concentrations, sources and exposure risks associated with particulate matter in the Middle East Area—a review. Air Quality, Atmosphere and Health. https://doi.org/10.1007/s11869-014-0277-4

Zamora, R. J. (2003). Comparing MM5 radiative fluxes with observations gathered during the 1995 and 1999 Nashville southern oxidants studies. Journal of Geophysical Research. https://doi.org/10.1029/2002jd002122

Zamora, Robert J., Dutton, E. G., Trainer, M., McKeen, S. A., Wilczak, J. M., & Hou, Y.-T. (2005). The Accuracy of Solar Irradiance Calculations Used in Mesoscale Numerical Weather Prediction. Monthly Weather Review. https://doi.org/10.1175/MWR2886.1

Zell, E., Gasim, S., Wilcox, S., Katamoura, S., Stoffel, T., Shibli, H., … Subie, M. Al. (2015). Assessment of solar radiation resources in Saudi Arabia. Solar Energy, 119, 422–438. https://doi.org/10.1016/j.solener.2015.06.031

Zempila, M. M., Giannaros, T. M., Bais, A., Melas, D., & Kazantzidis, A. (2016). Evaluation of WRF shortwave radiation parameterizations in predicting Global Horizontal Irradiance in Greece. Renewable Energy. https://doi.org/10.1016/j.renene.2015.08.057