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Performance evaluation of the Weather Research and Forecasting (WRF) model for assessing wind resource in Greece

Theodore M. Giannaros [a, *, 1], Dimitrios Melas [a], Ioannis Ziomas [b]

[a] Laboratory of Atmospheric Physics, Aristotle University of Thessaloniki, PO Box 149, 54124, Thessaloniki, Greece
[b] Laboratory of Process Analysis and Design, School of Chemical Engineering, National Technical University of Athens, Athens, Greece

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ABSTRACT

This study presents the evaluation of a state-of-the-art numerical weather prediction model, namely the Weather Research and Forecasting (WRF), with respect to the simulation of wind. Numerical simulations were carried out for a 1-year period, focusing on Greece, a study area that constitutes a challenging testbed due to its highly complex terrain. Wind measurements, derived from a network of surface synoptic weather stations, were employed for assessing model performance. The evaluation procedure focused on investigating the ability of the model to reproduce the basic features of the wind field over Greece, as well as on examining its capacity with regards to reproducing the wind resource. Results suggest an overall satisfactory model performance. In particular, the computed model errors were found to be within acceptable ranges, suggesting overestimation of weak and underestimation of strong winds. Seasonal variations of model performance were evident, along with differentiations depending on whether continental or maritime areas were considered. The wind resource of the study area, represented by the Weibull probability density function, was reproduced adequately well in the numerical simulations, while the spatiotemporal variations of the average monthly wind speed were also captured well.

1. Introduction

Rapid depletion of conventional fossil fuels and global environmental problems have been the drivers, throughout the past decade, for the increasing interest in renewable energy resources (RES). Wind energy, in particular, is considered to be one attractive solution for power generation, constituting one of the fastest growing RES sectors in recent years. According to the Global Wind Energy Council (GWEC), the installed global cumulating wind energy capacity has been recording a mean annual growth rate of about 23% during the past decade, reaching approximately 370 GW at the end of 2014 [1]. This ongoing expansion of the wind energy market poses new challenges, primarily related to the identification of areas of high, profitable wind energy potential. Despite the globally growing exploitation of wind energy for power production, the lack of reliable wind data continues to hamper the development of new wind energy projects, especially in developing countries [2].

The assessment of the wind resource of a particular area requires the availability of high-quality wind data. For this, ground-based measurement networks have been traditionally used in the past [e.g. Refs. [2–5]]. However, in situ data are typically scarce and often not available in remote locations. Further, wind measuring campaigns, organized to acquire spatially and temporally detailed data, may lead to irreversible financial losses if results reveal a low wind energy potential for the examined area. Given the constraints of the observational approach, alternative sources for reliable wind data should be employed in order to meet the demand of the wind energy industry for the preliminary assessment of the wind resource of a given area.

In recent years, numerical weather prediction (NWP) models have been gaining increasing attention as an alternative source for wind data [6]. Compared to the observational approach, numerical modeling allows for deriving data at literally any spatial and temporal scale, and at a significantly lower cost. Hence, it is not surprising that the number of wind resource assessment studies based

* Corresponding author.
E-mail address: thgian@noa.gr (T.M. Giannaros).
[1] Now at: National Observatory of Athens, Institute for Environmental Research and Sustainable Development, Vas. Pavlou & I. Metaxa, 15236 Penteli, Athens, Greece.

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on NWP data has recently increased. Jimenez et al. [7] employed the mesoscale MM5 model, coupled with a wind resource assessment software, to study the offshore wind resource of the German North Bight. The same model was used in the study of Lu et al. [8], focusing on the wind resource of a region in East China, while Lazic et al. [9] carried out a performance evaluation of the Eta model, focusing on wind prediction for power generation. More recently, Zhao et al. [10] presented the development of a short-term wind power forecasting system, based on the Weather Research and Forecasting (WRF) model. WRF has been further used for studying the wind resource in Pakistan [11], Denmark [12] and Portugal [13,14].

In Greece, wind energy contributed ~1600 MW in the ~2500 MW of total installed capacity of RES in 2011 [15]. The installed capacity of wind farms is anticipated to further increase in order to meet the target of 20% share of renewable energy in the total final energy production by the end of year 2020 [16]. In this context, the study of the country's wind energy potential has been attracting increasing interest in recent years [e.g. Refs. [17–20]]. The vast majority of the available relevant studies are based on the analysis of measured wind data, whereas the number of studies employing NWP data is currently limited [e.g. Refs. [21,22]].

This study presents the evaluation of a modeling system that was designed to support wind resource assessment applications. The modeling system is based on the WRF model and numerical simulations of the wind climate of Greece were carried out for a full calendar year. The study area constitutes a challenging testbed due to the complex topography that may significantly influence wind flow. In situ data are employed to verify model performance in terms of representing wind conditions and to investigate the capacity of the model with respect to reproducing the observed wind distributions. In this context, the key objective of the current study is to provide a detailed verification of a state-of-the-art NWP model from the point of view of wind simulation and wind resource assessment in a geographical area of particular interest, for which the availability of such studies is rather restricted. On the basis of the reported model evaluation, possible strategies for improving the simulation of the wind field are discussed.

2. Data and methodology

2.1. Study area and observational data

Greece lies in the southeast corner of the European continent, in between 34° and 43° northern latitude, and 19° and 28° eastern longitude. It is a mountainous peninsular mainland covering approximately 132,000 km^2, jutting out at the southern end of the Balkans (Fig. 1a). The topography of Greece is very complex (Fig. 1b), exhibiting features that significantly influence wind flow [e.g. Refs. [23–25]]. Although it has one of the longest coastlines in the world, due to the highly indented coastline and numerous islands, it is also one of the most mountainous countries in Europe.

For the purposes of the present study, wind measurements were retrieved from a network of 10 surface synoptic weather stations, operated by the Hellenic National Meteorological Service (HNMS). The locations of the stations are presented in Fig. 1b, while Table 1 summarizes basic information related to the stations' sites. All stations are located on planar areas and close to the coastline, with the exception of inland station 16648. This particular set of stations was selected based on data availability, covering the period from January 1 through December 31, 2003. Wind data were retrieved at 3 h intervals, referring to a measurement height of 10 m above ground.

2.2. Model setup and numerical simulations

The NWP model used in this study is WRF, version 3.2.1 [26]. Numerical simulations were carried out on a single modeling domain with a horizontal grid resolution of 6 km (mesh size of 250 × 165), focusing on Greece and neighboring countries (Fig. 1a). In the vertical dimension, 33 unevenly spaced full sigma levels were defined, from the surface up to 100 hPa. Shortwave and lognwave radiation were parameterized using the Dudhia [27] and RRTM [28] schemes, respectively. The WRF single-moment 6-class parameterization [29] was employed for representing microphysics, while convection was parameterized with the Kain-Fritsch [30] scheme. Planetary boundary layer processes were parameterized with the Mellor-Yamada-Janjic [31] scheme, coupled to the Eta similarity parameterization [32,33] for surface layer processes. Last, Noah [34] was selected for the representation of land surface processes.

Numerical simulations were initialized using the 6 h temporal resolution and 0.25° × 0.25° spatial resolution operational atmospheric analysis surface and upper-air data, provided by the European Centre for Medium-range Weather Forecasts (ECMWF). Observations, used for carrying out data assimilation, were retrieved from the National Centre for Environmental Predictions (NCEP) ADP Operational Global Synoptic and Upper Air database, at 6 h temporal resolution. Data assimilation was conducted using the advanced three-dimensional variational data assimilation system of WRF, namely WRF-Var, version 3.2.1 [26].

The WRF simulations were carried out for the year 2003. They were initialized at 1200 UTC every 9 days, integrating for a 10-day period. The first 24 h of each simulation were discarded as coinciding with the model's warm-up period. Data assimilation was first performed at the beginning of each 10-day simulation (cold model start) and at 6 h intervals thereafter (cycling model implementation).

At this particular point, one could argue that the use of only 1-year of data restricts the reliability and robustness of the presented results. However, it should be noted that such a period is considered to be the minimum for wind energy assessment studies [e.g. Refs. [6,13]] since it allows for determining diurnal and seasonal variations. Further, it is common to model-based studies to focus on time periods that may be considered to be insufficient for examining in detail the wind resource of an area, especially in terms of the long-term variability. For instance, the performance of the WRF model with respect to the simulation of the wind resource in Gharo, Pakistan, was evaluated for a 1-year period [11]. Carvalho et al. [14] carried out a sensitivity study of the WRF model over Portugal, focusing on a full calendar year, while Giannakopoulou and Nhili [35] implemented the same model over the North Sea for a 1-month period. Using the WAsP and MM5 models, Jimenez et al. [7] examined the offshore wind resource of the German North Bight, focusing on a 1-year period. Last, Zhao et al. [10] utilized a 1-year dataset of WRF simulations in order to train an artificial neural network that they designed for providing day-ahead wind power predictions in China.

2.3. Evaluation methods

To evaluate model performance in terms of providing reliable wind resource simulations, a verification procedure was undertaken for the entire study period. Observed and modeled wind speed data were paired adopting the "nearest neighbor" approach. In this approach, the model grid point nearest to the location of a measurement site was selected for carrying out the verification. Taking also into consideration the operational wind speed limits set for power production from wind turbines [36], the analysis of

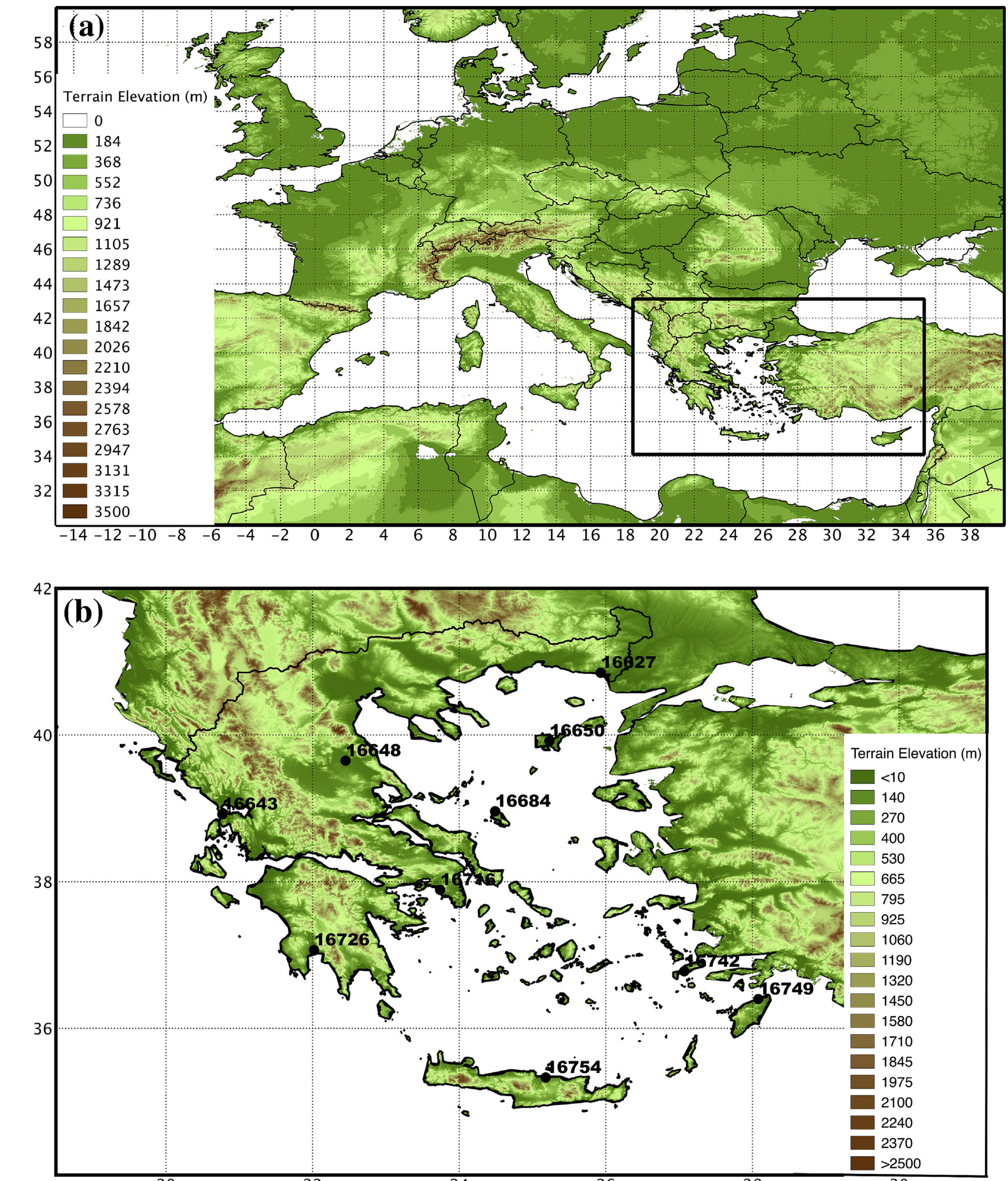

Fig. 1. Topography of (a) Europe with identification of the modeling domain for Greece (black box), and (b) Greece with identification of the surface synoptic weather stations (dots and World Meteorological Organization (WMO) IDs) used for the verification.

model performance was carried out on two datasets. The first dataset, hereafter referred to as “complete” (C), is comprised of all model-observations data pairs. The second dataset, hereafter referred to as “wind resource” (WR), contains the data pairs of the C dataset with measured wind speed greater than 3 m s^{-1} (cut-in speed) and lower than 25 m s^{-1} (cut-off speed).

Table 1
Summary of the characteristics of the 10 surface synoptic weather stations used for the verification. Stations are grouped by geographical location.

WMO ID	Station name	Latitude (°N)	Longitude (°E)	Elevation (m asl[a])
Mainland				
16643	Aktion	38.92	20.77	1.00
16726	Kalamata	37.07	22.02	11.10
16627	Alexandroupoli	40.85	25.93	3.50
16648	Larissa	39.65	22.45	74.00
16716	Athens	37.89	23.74	15.00
Islands				
16650	Lemnos	39.92	25.23	4.60
16684	Skyros	38.96	24.49	17.90
16742	Kos	36.78	27.07	125.00
16749	Rhodes	36.40	28.08	11.50
16754	Heraklio	35.33	25.18	39.00

[a] Above sea level.

Table 2
Model performance metrics for the "complete" (C) and the "wind resource" (WR) datasets, averaged over the entire study period for each measurement site.

Wind speed (m s^{-1})						
Site	BE		RMSE		STDE	
	C	WR	C	WR	C	WR
Mainland						
Aktion	−0.34	−1.37	2.59	2.83	2.57	2.83
Alexandroupoli	−0.15	−1.50	2.39	2.45	2.38	1.94
Athens	−0.32	−1.71	2.16	2.49	2.14	1.81
Kalamata	0.94	−0.39	2.45	2.39	2.26	2.36
Larissa	−0.56	−3.23	2.51	3.87	2.45	2.14
Islands						
Heraklio	0.25	−0.45	2.61	2.39	2.59	2.35
Kos	0.02	−0.51	1.81	1.72	1.81	1.64
Lemnos	0.05	−0.85	2.01	2.04	2.01	1.85
Rhodes	0.49	−0.17	2.88	2.63	2.84	2.62
Skyros	1.65	0.72	3.03	2.58	2.54	2.47

Using the pairs of observed and modeled data in each of the considered datasets (i.e. C and WR), the following statistical measures were computed: (a) bias error (BE), (b) root mean squared error (RMSE), and (c) standard deviation error (STDE). Among these metrics, STDE is considered to be of high importance for the model performance evaluation. This assumption is based on the fact that even if a model exhibits large BE and RMSE values, a low STDE indicates a somewhat constant error in model results, which could be consequently treated as an offset [13]. Conversely, a high STDE value indicates that the model's error is random and, hence, the simulation has a low physical foundation, even if showing low BE and RMSE values.

Besides the computation of the above verification measures, the evaluation procedure also focused on the ability of the modeling system to reproduce the observed wind speed distribution at the measurement sites. For this, the Weibull probability density function (PDF) of wind speed was employed. This particular PDF is widely used in wind resource applications; not only because of being flexible and simple to define, but also due to that it accurately fits experimental data [14]. In this study, the Weibull PDF was determined by the following equation:

$$W_u = \frac{k}{C} \cdot \left(\frac{u}{C}\right)^{k-1} \cdot e^{-\left(\frac{u}{C}\right)^k} \tag{1}$$

where k is the shape parameter, representing the standard deviation of the distribution, and C is the scale parameter, representing the mean state and mean value of the distribution. Both of the above parameters (k, C) were computed with the methodology described in Ref. [5], using the "complete" dataset.

3. Results

3.1. Overall performance

Table 2 presents the model performance metrics that were derived from the C and WR datasets, for each measurement site. On average for the entire wind speed range (C dataset), WRF underestimated wind speed over mainland sites. Conversely, wind speed was overestimated over island sites. However, when the WR dataset is examined, it becomes clear that numerical simulations underestimated wind speed at all measurement sites, excluding the station of Skyros for which a positive BE was computed for both of the two datasets. In addition, it is evident that, overall, WRF performed better over island than over mainland sites. This is highlighted in all computed evaluation measures, for both the C and the WR dataset. Such a differentiation in model performance could be attributed, at least partially, to the simpler topography of the Aegean Sea, compared to that of continental Greece, which could have facilitated the simulation of the wind field.

At this point it is worth noticing that the reported statistical evaluation parameters are in good agreement with previous studies. For instance, Carvalho et al. [13,14] reported BE, RMSE and STDE values of the same magnitude as in this study, examining the performance of WRF in Portugal. Similar verification results were also derived from WRF simulations conducted in Pakistan [11] and USA [37]. Further, results presented in Table 2 agree well with results from studies that employed NWP models other than WRF, such as MM5 [21] and Eta [9].

3.1.1. Mean wind speed

In the frame of the overall model performance evaluation, the spatial distribution of the mean monthly wind speed over the study area was computed using the model data at four reference heights above ground: 10 m, 60 m, 80 m and 100 m. For clarity, results are presented herein only for the average wind speed at 60 m, for one representative month per season.

In January (Fig. 2a), northeastern Greece, west Peloponnesus, Attica and Evvoia are the continental areas that showed the highest mean wind speeds. Conversely, lower values were computed over the plains of continental Greece, not exceeding 4 m s^{-1} on average. Considering maritime areas, the Aegean Sea was clearly found to be much windier than the Ionian Sea, with mean wind speeds ranging from 8 m s^{-1} up to more than 10 m s^{-1} over its northern parts.

Considering spring (Fig. 2b), the mean wind speed over continental Greece was found to vary significantly less than in the winter. Over the plains of central and north Greece, values lower than 3 m s^{-1} were computed, while northeastern Greece and the southern parts of Attica and Evvoia were found to maintain values greater than 5 m s^{-1}. As for the maritime areas, mean wind speeds of similar magnitude were derived for both the Aegean and Ionian Sea.

During summer (Fig. 2c), the spatial distribution of the mean wind speed over continental Greece resembles the one obtained for spring, but with generally decreased values. Most notably however, increased wind speeds were computed for southeastern Aegean Sea. Indeed, northern sector winds, well known as the Etesians, dominate over the Aegean Sea during summer [38]. These winds tend to blow along a northeasterly direction over the north Aegean Sea, turning northerly over the central and south Aegean, before becoming northwesterly near the southwestern coast of Turkey. Etesians have been reported to be associated with sustained near-surface wind speeds that often exceed 15 m s^{-1} [39]. This seems

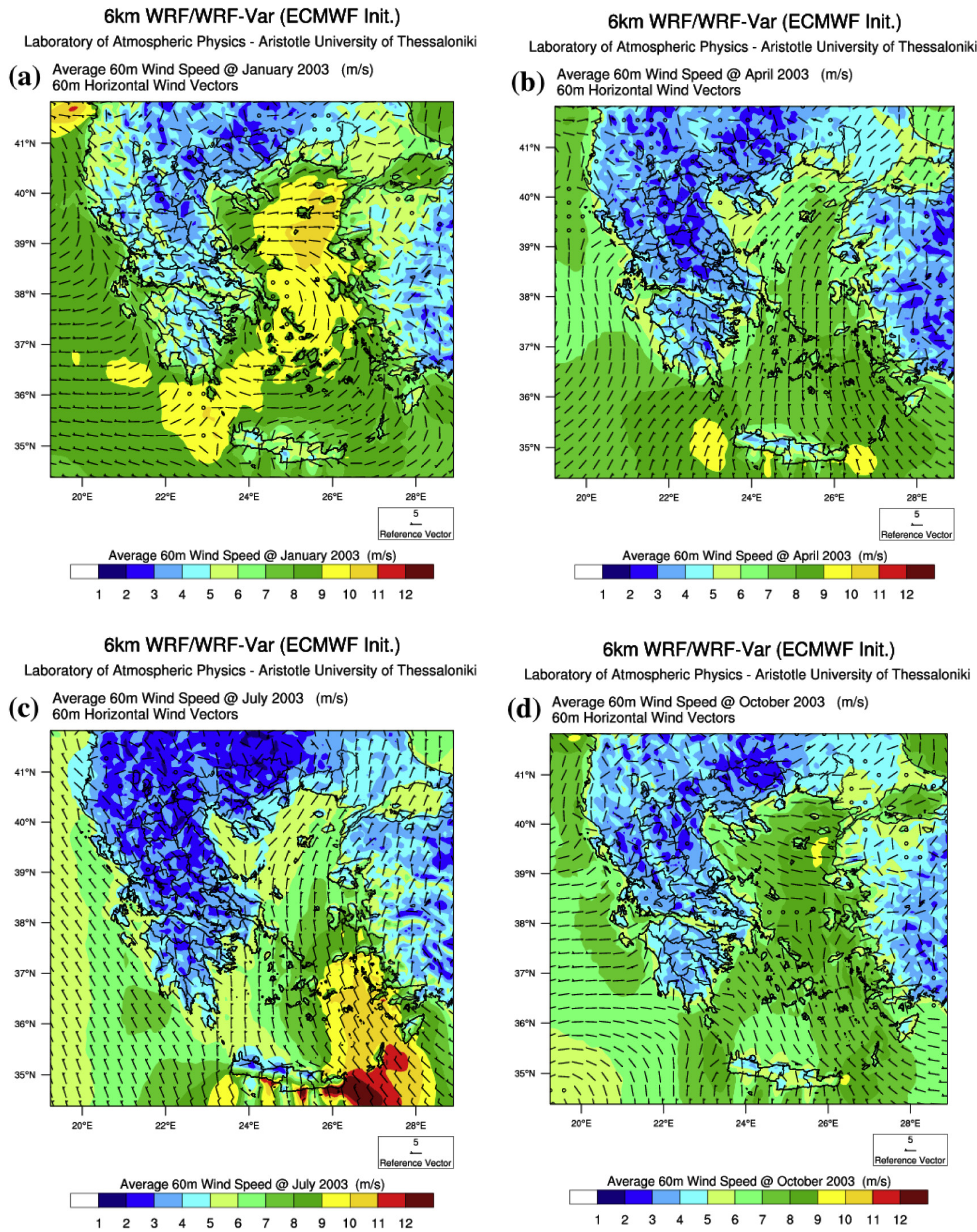

Fig. 2. Monthly average wind speed at 60 m above ground for (a) January, (b) April, (c) July, and (d) October 2003.

to be confirmed in Fig. 2c, where mean wind speeds were computed to locally exceed 11 m s^{-1}.

In October (Fig. 2d), the spatial variability of the mean wind speed was found not to deviate significantly from that of winter, particularly over continental Greece. With regards to maritime areas, differences between the Aegean and the Ionian Sea were generally small, with slightly higher sustained wind speeds over the first.

3.2. Seasonal variations

Focusing on the C dataset, WRF overestimated wind speed over island sites in all seasonal periods (Table 3). Over mainland sites though, winds were overestimated in the cold half of the year (DJF and SON) and underestimated during the MAM and JJA periods. The positive BE values that were derived from the C dataset should be primarily attributed to the overestimation of weak winds in the conducted numerical simulations. Indeed, when data pairs with measured wind speeds less than 3 m s^{-1} are removed (i.e. WR dataset), the resulting model BE values indicate underestimation of wind speed over both mainland and island sites, for all seasons. Overall, irrespectively of which dataset is examined, the data presented in Table 3 suggest that the model performed generally better during the warm half of the year (MAM and JJA) than during the

Table 3
Model performance metrics for the “complete” (C) and the “wind resource” (WR) datasets, averaged over the mainland and island sites, for each of the four seasonal periods (DJF: December-January-February, MAM: March-April-May, JJA: June-July-August, SON: September, October, November).

Wind speed (m s^{-1})						
Season	BE		RMSE		STDE	
	C	WR	C	WR	C	WR
Mainland						
DJF	0.24	−0.99	2.60	2.85	2.59	2.68
MAM	−0.12	−1.88	2.55	2.94	2.55	2.25
JJA	−0.45	−1.95	2.28	2.64	2.44	1.78
SON	0.00	−1.42	2.24	2.58	2.24	2.15
Islands						
DJF	0.91	0.25	2.93	2.65	2.79	2.64
MAM	0.56	−0.34	2.54	2.33	2.47	2.30
JJA	0.16	−0.60	2.27	2.03	2.26	1.94
SON	0.36	−0.39	2.27	2.11	2.24	2.07

winter (DJF) and autumn (SON). One possible explanation for this could be the greater variability of weather patterns occurring in the cold period, compared to the less variable meteorological conditions in spring and summer.

3.3. Model performance dependence on observed wind speed

In order to obtain a more in-depth perspective of model performance, the variation of modeled wind speed error with the measured wind speed and direction data was assessed. For this, observed data were first classified into four bins. Model performance metrics were consequently calculated for each bin. Results are depicted graphically in Fig. 3.

Overall, WRF performed better in the presence of weak (<4 m s^{-1}) and intermediate (4–8 m s^{-1}) winds than when strong (8–12 m s^{-1}) and very strong (≥12 m s^{-1}) winds were observed (Fig. 3a and b). In addition, it is evident that weak winds were overestimated, whereas winds falling in the remaining wind speed bins were underestimated. This is in very good agreement with what has been previously discussed, contrasting the results derived from the C and WR datasets (Sec. 3.1). However, the most striking feature is that the deterioration of model performance with increasing wind speed was exacerbated in the case of mainland sites, resulting to significantly large errors. Indeed, examination of Fig. 3a reveals that the model hardly managed to reproduce very strong winds, showing high BE and RMSE values. On the other hand, the modeled wind speed errors for island sites were significantly lower, also exhibiting a less pronounced variation per wind speed class (Fig. 3b). Last, looking at Fig. 3c and d, one can easily notice that, for all sites, model performance metrics exhibit no particular dependence on the observed wind direction.

The above results seem to confirm what have Carvalho et al. [14] reported in their WRF-based study for Portugal. In particular, there is a very good agreement in that WRF errors do not significantly depend on measured wind direction, while the deterioration of model performance with increasing measured wind speed is also a common finding. However, it must be noted that Carvalho et al. [14] provided better statistical measures, compared to this study, for the strong and very strong wind speed classes. This deviation could be partially attributed to both the higher horizontal resolution used in their numerical simulations (i.e. 5 km) and the generally lower complexity, in terms of topography, of the considered study area (i.e. Portugal).

3.4. Wind resource

The parameters of the measured and simulated Weibull PDFs, derived from the C dataset, for each measurement site, are summarized in Table 4. Overall, the simulated data overestimated both parameters of the PDF, although there were four sites (i.e. Aktion, Athens, Larissa and Heraklio) for which either the shape (k) or the scale parameter (C) was underestimated. The deviations between the observation- and the model-based data were evidently smaller for the C than for the k parameter, suggesting that WRF was able to better reproduce the mean state of the wind distributions

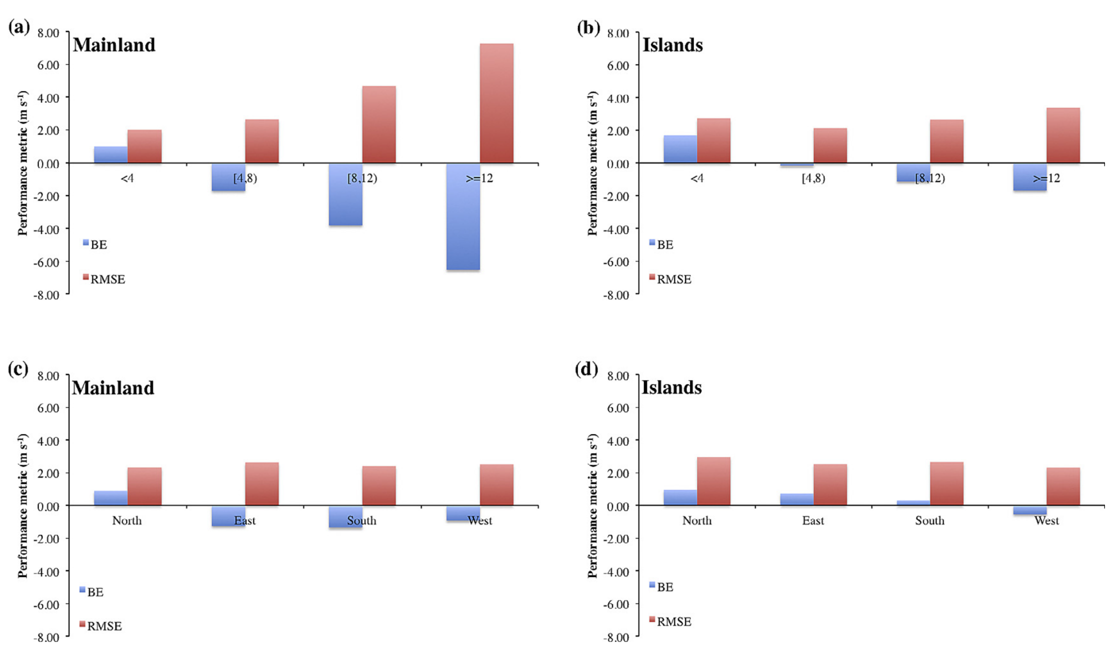

Fig. 3. Modeled wind speed error (BE, RMSE) per observed (a, b) wind speed and (c, d) direction class, averaged for (a, c) continental and (b, d) insular sites. Wind speed classes are defined in m s^{-1}. For wind direction classes North is defined as 315°–45°, East as 45°–135°, South as 135°–225° and West as 225°–315°. Evaluation measures were derived from the “complete” dataset.

Table 4
Comparison between the parameters of the observed and modeled Weibull PDFs. The parameters were derived from the "complete" (C) dataset of each measurement site, considering the entire study period.

Weibull PDF parameters				
Site	k		C	
	Observed	Modeled	Observed	Modeled
Mainland				
Aktion	1.46	1.53	4.29	3.90
Alexandroupoli	1.23	1.89	3.60	3.71
Athens	1.40	1.98	3.55	3.42
Kalamata	1.12	1.60	2.59	3.97
Larissa	0.90	1.37	2.11	1.67
Islands				
Heraklio	1.80	1.71	5.81	6.00
Kos	1.77	2.19	4.85	5.01
Lemnos	1.44	1.85	4.45	4.87
Rhodes	1.72	2.01	5.38	6.31
Skyros	1.31	1.92	5.34	6.68

(represented by C) than their deviations (represented by k). In spite of the reported discrepancies, the model was successful in terms of reproducing the variability of the Weibull PDFs among the examined measurement sites. For instance, observed and modeled data agree in that island sites are characterized by higher and better quality wind potential (i.e. greater values of k and C) than mainland sites.

The capacity of the model in terms of representing wind resource was further examined by focusing on two measurement sites: the mainland site of Aktion and the island site of Rhodes. The decision to select only two sites for extending the analysis has been made to ensure clarity, taking also into account that results are similar for all measurement locations. They only differ according to whether WRF underestimates or overestimates wind speed. Hence, the Aktion site was chosen as representative of the sites in which the model underestimates wind speed and Rhodes as representative of the sites in which wind speed is overestimated (refer to Table 2).

The underestimation of the frequency of strong winds (>8 m s^{-1}) and the overestimation of the frequency of intermediate winds (2–4 m s^{-1}) is evident in all measurement sites where wind speed was underestimated (Fig. 4a). On the other hand, a shifting of the model-based Weibull curve, compared to the observed one, towards the higher wind speeds can be seen in the measurement sites where wind speed was overestimated (Fig. 4b). This shifting highlights the tendency of the WRF model to underestimate the frequency of low and intermediate winds, whereas the frequency of strong winds is overestimated. Similar results were also reported in the recent study of Carvalho et al. [14].

At this juncture of discussion it is worth highlighting the better agreement between the observed and the modeled Weibull PDF for the measurement site of Aktion (Fig. 4a) than for Rhodes (Fig. 4b). It would be expected that the numerical simulation with the lowest errors related to the mean state of the distribution (represented by the C parameter) be the best candidate for representing the actual Weibull PDF. This seems to be confirmed in the present study, since Aktion was found to exhibit a lower error in the scale parameter (Table 4) than did Rhodes and, consequently, a model-based Weibull curve closer to the observed one.

4. Discussion

Although they were not specifically designed for such a purpose, NWP models have been increasingly used in the past years for supporting wind energy applications [6]. Taking into consideration the well-documented limitations of the numerical modeling approach [e.g. Ref. [40]], performance evaluation studies are of particular importance for highlighting the strengths and weaknesses of a model when applied over a particular region. Eventually, this approach allows for defining possible strategies that could be used for improving model performance.

On the basis of the above short discussion, the present study does provide clues regarding the numerical simulation of wind over Greece. One of the key findings was the significant underestimation of high wind speeds, particularly over the mainland. Taking into account the highly complex topography of continental Greece, it could be assumed that one of the main reasons for this underestimation is the adopted horizontal resolution (i.e. 6 km) and the associated smoothing and averaging of orography, which result to the insufficient representation of local effects on wind flow [e.g. Ref. [40]]. The model representation of land use could have also played a role, since it determines the distribution of roughness length values that in turn influence the computation of wind speed [e.g. Ref. [41]]. Therefore, it is reasonable to claim that the simulation of wind could improve by reducing uncertainties in the representation of surface characteristics. This could be achieved by increasing the horizontal grid spacing of the model and/or updating the representation of land use.

The thorough evaluation process also revealed that WRF performs differently, in terms of simulating wind, during the warm and the cold half of the year. Such a model behavior has been also observed in similar past studies, and was partially attributed to the impact of model physics [e.g. Ref. [37]]. To address this kind of uncertainty, it is necessary to carry out comprehensive sensitivity studies focusing on model performance under the employment of different combinations of physics parameterizations. This approach allows for identifying the optimal model configurations regarding the representation of physics and consequently, improving wind

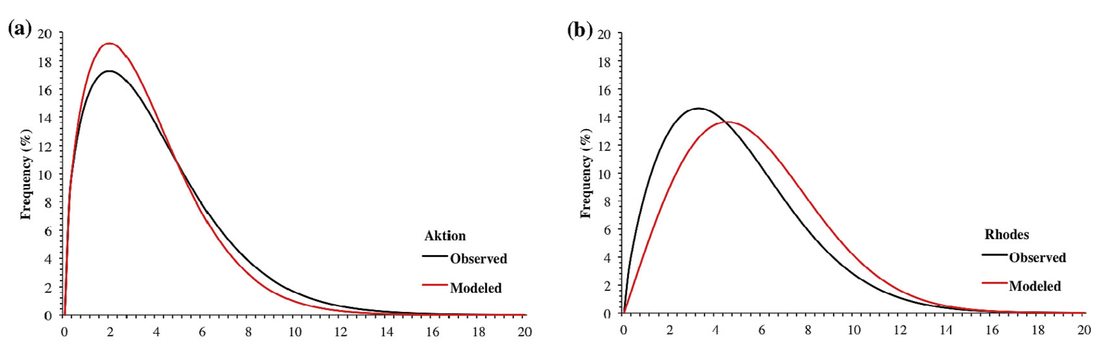

Fig. 4. Weibull PDF curves for the measurement sites in (a) Aktion, and (b) Rhodes.

simulation.

Although data assimilation was employed in this study, there is always the possibility that part of reported biases in the simulated wind field can be due to uncertainties in the initial and lateral boundary conditions used for driving the NWP model [e.g. Ref. [14]]. Hence, alternative data sources for initializing the model, possibly together with the implementation of nudging techniques, could be utilized as a means of improving model performance.

At this juncture of discussion it should be finally noted that for the improvement of wind simulations, particularly over challenging regions such as Greece, statistical approaches may be employed. Kalman filtering is perhaps one of the most well known of such approaches, which has been successfully applied as a post-processing step for improving the accuracy of NWP wind output [e.g. Refs. [40,42]].

5. Conclusions

Numerical simulations with the WRF model were conducted for a full calendar year, focusing on the simulation of the wind field. A challenging study area, Greece, was selected for carrying out the simulations in order to assess the capacity of the model with respect to supporting wind resource assessment applications. For this, ground-based wind measurements were employed for evaluating model performance.

Overall, the conducted analysis revealed a satisfactory model performance. The reported statistical measures were found to lie within acceptable ranges, based on similar past studies [e.g. Refs. [13,37]]. Results showed a clear tendency of the model to overestimate weak winds, whereas strong winds were found to be underestimated. This uncertainty in model simulations was exacerbated over continental Greece, for which significantly large biases were computed for wind speeds exceeding 12 m s^{-1}. As discussed, this could be attributed, at least to a part, to the representation of the complex topography that characterizes continental Greece. This speculation is supported by the lower model errors that were computed for the measurement sites lying in the generally less complicated terrain of maritime Greece.

On a seasonal basis, the model performed better during the warm than during the cold half of the year, for both mainland and island measurement sites. The greater wintertime model errors, particularly when considering wind speeds exceeding 3 m s^{-1} (i.e. WR dataset), possibly indicate uncertainties in the resolved weather patterns. On the contrary, the less variable synoptic-scale forcing that typically dominates in summer may be the reason for the improved model performance.

Concerning wind resource, the examination of Weibull PDFs and associated parameters highlighted a good level of agreement between observations and model results. In particular, it was found that the mean state of the wind distributions (represented by parameter C) was better resolved than the corresponding deviations (represented by parameter k). The higher and better quality wind potential of island sites, compared to continental areas, was also successfully reproduced in the numerical simulations.

Last, the spatiotemporal variability of the mean monthly wind speed over Greece was found to agree well with past studies, such as the recent one of Kotroni et al. [21]. The corresponding analysis showed that northeastern Greece, western Peloponnesus, Attica and Evvoia are the continental regions that exhibit the largest values. Among the maritime areas, the Aegean Sea was found to exhibit higher wind speeds than the Ionian Sea, primarily in winter and summer.

In summary, results of the present study suggest that the WRF model is a NWP tool characterized by adequate capacity with respect to supporting wind resource assessment applications. Exploitation of such a tool is of great importance, particularly for regions like Greece, which are characterized by highly complex terrain and relatively low spatial coverage of wind measurement sites.

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