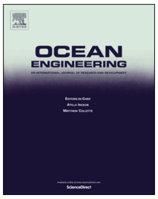
Ocean Engineering 116 (2016) 200–215

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng



The impact of atmospheric data assimilation on wave simulations in the Red Sea

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ARTICLE INFO

Article history:
Received 30 April 2015
Accepted 6 February 2016
Available online 11 March 2016

Keywords:
Red Sea
WRF model
Data assimilation
3DVAR
Wave modeling

ABSTRACT

Although wind and wave modeling is rather successful in the open ocean, modeling enclosed seas, particularly seas with small basins and complex orography, presents challenges. Here, we use data assimilation to improve wind and wave simulations in the Red Sea. We generated two sets of wind fields using a nested, high-resolution Weather Research and Forecasting model implemented with (VARFC) and without (CTL) assimilation of observations. Available conventional and satellite data were assimilated using the consecutive integration method with daily initializations over one year (2009). By evaluating the two wind products against in-situ data from synoptic stations, buoys, scatterometers, and altimeters, we found that seasonal patterns of wind and wave variability were well reproduced in both experiments. Statistical scores for simulated winds computed against QuikSCAT, buoy, and synoptic station observations suggest that data assimilation decreases the root-mean-square error to values between 1 and 2 m s^{-1} and reduces the scatter index by 30% compared to the CTL. Sensitivity clearly increased around mountain gaps, where the channeling effect is better described by VARFC winds. The impact of data assimilation is more pronounced in wave simulations, particularly during extreme winds and in the presence of mountain jets.

1. Introduction

In coastal and open oceans, surface winds and waves are the two major dynamic driving forces responsible for various oceanic phenomena, and they play a vital role in air–sea interactions. By achieving more accurate representations of surface winds as atmospheric forcings in ocean models, we can improve our simulations of oceanic processes (Agarwal et al., 2006; Gan et al., 2005). Traditionally, modelers relied on global model outputs and reanalysis products (e.g., Miller et al., 1994; Bentsen and Drange, 2000; Auad et al., 2001; Rosmond et al., 2002; Brodeau et al., 2010; Dee et al., 2011) to force ocean models because of their wide spatial coverage and long availability in time; however, these forcings are limited by constraints, such as coarse horizontal resolution, significant uncertainties (Shinoda et al., 1999; Yang et al., 1999; Carvalho et al., 2012), and an insufficient amount of data available for assimilation (Putman et al., 2000; Waliser et al., 1999). By downscaling, these limitations can be overcome and mesoscale features can be more accurately described (Giorgi, 2006; Langlais et al., 2009; Wang et al., 2004). In fact, recent developments in numerical modeling and rapid increases in computational resources have enabled modelers to use mesoscale weather models to dynamically downscale global products such that terrain complexities and local physics can be better characterized: reasonably accurate atmospheric fields have been achieved this way (Cardoso et al., 2013; Heikkilä et al., 2010; Jimenez et al., 2013; Soares et al., 2012; Zagar et al., 2006). Although regional atmospheric modeling has proven satisfactory in open oceans (Caires and Sterl, 2005), modeling enclosed seas, particularly those with small basins and steep or complex orography, presents challenges: successful modeling of surface wind is dependent on the closeness of the point of interest in the sea to land (Cavaleri and Bertotti, 2004).

Large-scale (global) models commonly underestimate wind speed in enclosed basins. Instead, a high-resolution configuration with detailed topography would be more effective at resolving mesoscale features, such as mountain–valley contrasts, topographic flow, and gravity waves. Moreover, in coastal areas, higher-resolution models may be able to capture land–sea breezes, drainage winds due to local wind systems, and large land–sea temperature differences. Ralston et al. (2013) and Jiang et al. (2009) followed this approach for the Red Sea, where they downscaled data from the National Center for Environmental Prediction (NCEP) Final Analysis (FNL) with one-degree global fields using

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http://dx.doi.org/10.1016/j.oceaneng.2016.02.020

two nested domains with resolutions of 30 and 10 km. They showed that the downscaled winds in the coarse-resolution domain (30 km) continued to exhibit a strong negative bias while in the high-resolution domain (10 km) winds were more accurately reflected in their wave simulations. Molders (2008) concluded that the Weather Research and Forecasting (WRF) model captures the overall temporal mean variability in wind speed over Alaska with minimal overestimation. However, Wyszogrodzki et al. (2013) analyzed the characteristics of downscaled winds over the contiguous United States between June 2009 and April 2010 and reported that the WRF model overestimates wind speeds, especially over regions with high terrain (negative biases). Other studies suggest that the WRF model has a general tendency to overestimate near-surface wind speeds (at 10 m) and to underestimate daytime surface temperatures over topographically complex regions (Gozzini et al., 2008; Horvath et al., 2012; Roux et al., 2008).

Simply increasing model resolution does not a guarantee that mesoscale features will be more accurately simulated (Anthes, 1983; Mass et al., 2002; Stensrud, et al., 2000; Wehner et al., 2010), mainly because initial and boundary conditions are usually derived from uncertain coarse-grid global outputs and downscaled products are highly sensitive to these values (Mass et al., 2002; Park and Zupanski, 2003). Assimilating the observations that are available in a region of interest can reduce uncertainties in the initial conditions inherited from global outputs, and naturally, the more precise the initial and boundary conditions are the more accurate downscaled wind products are expected to be. Variational data assimilation techniques efficiently combine observations from heterogeneous platforms while satisfying model dynamics and accounting for various uncertainties. These techniques, such as three-dimensional variational (3DVAR) and four-dimensional variational data assimilations, are now extensively used in operational forecasting centers (Kalnay, 2002). Although availability of sufficient observations is essential (Andersson et al., 2006), 3VDAR is an attractive operational approach because it offers relatively low computational costs and reasonable performance (Zhang et al., 2012).

Here, we explore the possibility of simulating accurate high-resolution wind fields for the Red Sea by updating the initial conditions of a mesoscale WRF model using 3DVAR data assimilation. The Red Sea is characterized by highly varying and multifaceted wind fields, suitable to emphasize the difficulty of the situation and the possible approaches. Moreover, its long and narrow shape makes the local conditions very sensitive to even minor changes in the direction of the driving wind fields. In such a narrow basin, small errors in the surface wind direction may induce significant uncertainties in oceanic processes (Ardhuin et al., 2009).

2. The Red Sea

The Red Sea has a meridionally elongated basin that stretches 2250 km between Africa and Asia. It has an average depth of 490 m and a maximum depth of 2300 m. On the coast, high mountain ridges border the Red Sea on either side, no more than 30–40 km inland with peaks of more than 2 km. The study area is shown in Fig. 1. This orography has an important influence on the local dominant wind regimes, characterized by strong seasonal (winter and summer) variability. In summer, NW winds dominate the entire basin, and during winter, typically between October and April, both NW and SE winds are present in the northern and southern parts of the Red Sea, respectively. Each of these winter systems occupies a part of the surface of the Red Sea, with an intermediate zone of calm or weak winds called the convergence zone (Pedgley, 1966), where these two opposing wind systems create complex opposed wave systems in the center of the Red Sea (Langodan et al., 2015). Characteristics of the Red Sea, including circulation, wind and wave conditions, and seasonal changes, have been discussed in the recent literature (e.g., Jiang et al., 2009, Langodan et al., 2014, Ralston et al., 2013, Yao et al., 2014a, 2014b, Zhan et al., 2014). The orography surrounding the basin comprises valleys of different sizes that cut across bordering mountain ridges, controlling local wind regimes; its complexity makes wind and wave modeling very challenging in this region.

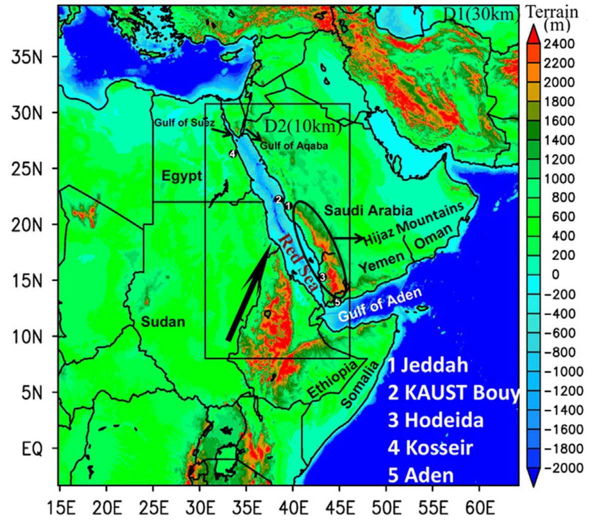

Fig. 1. The two nested domains used in the WRF-ARW model with resolutions of 30 and 10 km for domains D1 and D2, respectively. The black dot shows the position of the instrumented buoy active during the study period.

3. Data and methodology

Advanced Research WRF Version 3.6.1 (ARW, Skamarock et al., 2008) and its WRF Data Assimilation (WRFDA) package were adopted in this study. The resulting wind product was then used for forcing wave model WAVEWATCH III (WW3). Brief descriptions of the models, their configurations, and assimilated observations are given in this section.

3.1. *The WRF model*

A high-resolution WRF modeling domain was implemented following the configuration of Jiang et al. (2009). It includes two, two-way nested domains with respective horizontal resolutions of 30 and 10 km (Fig. 1) each with 35 vertical levels. The outer domain extends from 5°S to 39°N and from 16°E to 64°E, and the inner domain covers the Red Sea basin from 9°N to 30°N and from 31°E to 47°E. For better representation of land–sea contrasts and wind forecasts over coastal regions, coarse-resolution lower boundary sea surface temperature (SST) conditions obtained from FNL data were replaced with time-varying high-resolution SST data from Real-Time Global High-Resolution (RTG-HR) SST values (Gemmill et al., 2007).

Downscaled products for the Red Sea were generated with and without assimilating observations. Simulations were conducted over one year (2009) using a consecutive integration method with daily initialization, similar to Lo et al. (2008) and Jiang et al. (2009). In the first experiment, which we refer to as the Control (CTL) run, the WRF model was initialized from FNL data ($1° \times 1°$) and the boundary conditions were updated every six hours. Simulations were conducted with daily initializations at 1200 UTC