Estimation of significant wave heights using numerical and neural techniques and comparison with buoy and satellite observations

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Abstract

Short term significant wave heights have been evaluated using the numerical WAM model and the results are compared with satellite (Jason-2) and moored buoy measurements. Additionally artificial neural network (ANN) is used to predict significant wave heights over a future time step and such predictions are also compared with corresponding satellite and buoy measurements. The observations from moored buoys monitored by India’s National Institute of Ocean Technology for a period of about four and a half years at three locations in the Arabian Sea and three in Bay of Bengal covering the west as well as east coast of India are involved. The buoy recorded largest waves during the cyclonic condition, and this was confirmed at a location code named: BD11 by the satellite measurements as well as the WAM and ANN based evaluations. The evaluation accuracy reflected in the coefficient of correlation is found to be high in the Arabian Sea than the Bay of Bengal.

Keywords: Significant Wave Height, WAM model, Satellite data, Buoy data, ANN, Real time forecasting.

1. INTRODUCTION

Any engineering activity in the marine environment necessitates knowledge of the significant wave heights. The design of ports, harbors, coastal or offshore structures as well as that of ships or other ocean going vessels depends on the characteristic significant waves. The measurements of wave parameters either in shallow or deep waters over a long period are difficult, especially during bad weather, while observations made from ships which were the main source of wave information in the past decades lack extreme wave data since the ships tended to avoid stormy paths. In this scenario wave observations from fixed platforms and moored buoys have turned out to be the main source of wave information. The moored buoys deployed and monitored by National Institute of Ocean Technology (NIOT) located at Chennai, India have collected the in-situ time series of surface displacements during the study period of 2010 to 2013 at six locations around India’s coastline: three in the eastern Arabian Sea and three in the Bay of Bengal. Periodic calibration exercises are often made to establish the accuracy of the buoy data. The wave sensor Seatex MRU-6 (Motion Reference Unit), incorporates solid-state accelerometers, angular rate sensors and servo flux gate compasses for all three axes. The wave direction measurement is based on rapid samples of heave, pitch and roll, together with the heading, which is then transformed to heave and slopes in a geographic co-ordinate system.
Satellite data are widely used in meteorological and oceanographic applications in then provide crucial information during extreme weather conditions. The availability of surface meteorological data covering large spatial and temporal domain is the main advantage of this data set. However these data sets have less accuracy and low spatial resolution when compared to in-situ measurements. The satellite observations are routinely validated using the NIOT moored buoy data to ensure the quality of the satellite data and also to identify the competence of satellite data in various marine applications. The spatial and temporal variability of the buoy measurement and satellite observations are considered in the validation exercise to minimize the errors. Hwang et al. (1998) compared altimeter wave data with a few buoys in the Gulf of Mexico. Buoy comparisons have been regularly used to assess measurement capabilities of satellite altimeters (e.g., Monaldo, 1988). Significant wave heights estimated from satellite altimeter measurements have been previously compared with buoy data (McMillan, 1981; Dobson et al., 1987 and Monaldo, 1988). Mitsuko Korobkin et al. (2008) did the validation analysis of Jason-1 significant wave heights in the Gulf of Mexico. Significant wave height data from both the Jason-1 and Envisat altimeters have been validated against in-situ buoy data (Durrant et al., 2009). Li and Holt (2009) compared significant wave height, wave speed and wave spectrum derived from the ASAR satellite, buoy and numerical models.

In this study, the WAM model has been used to estimate the waves from wind. The model is widely described in the literature (WAMDI Group, 1998; Komen et al., 1994; Bidlot et al., 2002; Janssen, 2007). After the first implementation of the model in 1988, there have been several improvements. The original version was called WAM-cycle 1 which was updated to WAM-cycle 2, 3 and 4. The changes which were made between the first three versions were with respect to coding while the fourth one incorporated changes in the model physics. The main improvement belonged to the coupling between the sea state and the air flow. While the first three versions used a parameterization for this purpose the fourth version employed a dynamic coupling between wind and sea to deal with the problem (Bender, 1995). In this work the model used for wave simulation is WAM Cycle 4. This is a third generation wave model which solves the wave transport equation explicitly without any assumptions on the shape of the wave spectrum. The 2D spectra are over a matrix (N*M) where N is the number of directional bins (usually 30) and M is the number of frequency bins (usually 25, logarithmically spaced). Thus there are 25 frequency bins and 30 directional bins. From the two-dimensional spectra, several parameters can be computed, e.g. significant wave height, peak wave period. Mazarakis et al (2012) have however reported that the WAM model tends to underestimate wave energy in the region of the Aegean Sea. Wingeart (2001) studied a verification of the WAM model in 2001 and found out that the model, in most cases, underestimated the energy measured by the buoys. Mandal and Prabaharan (2010) reported the wave hindcasting using both WAM and neural models.

To predict a future value of Hs in real time mode a historical sequence of measured significant wave heights is normally considered and a statistical autoregressive method is then employed. When point forecasts at a specified location are needed such time series based models like Auto Regressive (AR), Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA) and soft computing tools are preferred over the numerical models due to their relatively simple modeling techniques and less requirement of computer memory and time. Wave forecasting using artificial neural network (ANN) has been reported by Londhe and Deo (2003) and Jain and Deo (2007).

2. DATA AND METHODOLOGY

The wave parameters are measured by an MRU sensor, which measures absolute roll, pitch, compass and relative heave. These data sets are recorded at a rate of 1 Hz for 17.4 minutes every one hour. It has a measurement range of –20 m to +20 m, a resolution of 1 cm, and an accuracy of 5 cm. The processor on the buoy applies wave analysis software ‘Neptun’, which uses Fast Fourier Transform on the wave record to obtain the power spectrum. Wave parameters are significant wave height, average wave period, mean wave direction etc., derived from the directly derived wave spectrum.
The significant wave height data at locations: AD06, AD07, AD09, BD08, BD11 and BD14 are considered in this study. The Jason-2 altimeter sensed significant wave height is available from September 2009. It has a global coverage at a pixel resolution of 1 deg. (~111 km). The ECMWF (European Centre for Medium-Range Weather Forecasts) wind vectors data are available from January 1970 and have a global coverage at the pixel resolution of 0.25 degree. Such wind vector data are generated in numerical weather prediction models by assimilation of satellite data. Six-hourly values of wind vectors are downloaded from the ECMWF web site (http://data-portal.ecmwf.int/data/d/interim_full_daily/) for the period from January 2010 to July 2013 covering a region from 70°S to 30°N and 19.75°E to 134.75°E at a pixel resolution of 1.25° × 1° and the same is utilised for running the WAM model. The WAM model output is obtained once in an hour. Satellite data is available only as daily averaged data and so the buoy data and WAM model output have been daily averaged for comparison with the downloaded satellite data. Fig. 1 shows the validation carried out at six deep buoy locations.

The ANN related program has been written in MATLAB. The training algorithm selected was common ‘trainlm’. It updates weight and bias values according to the Levenberg-Marquardt optimization method. All input and output values were normalized within the range –1 to 1. All weights and bias values were initialized to a value of 1.0. The transfer function used was ‘logarithmic sigmoid’ uniformly for first hidden and output nodes and ‘purelin’ for the second hidden layer and output layer nodes. In the current work, the output of the network is the predicted value at the required time step. The number of input nodes is 5, hidden nodes are 4 and the output node is 1. After developing the model, it is implemented in the real time wave prediction at AD07 and BD11 location.

3. RESULTS AND DISCUSSION

The ANN has been applied to predict the magnitude of significant wave heights in future from a sequence of preceding observations of certain length. Predictions of the wave heights at intervals of 3 hours have been carried out. Comparisons have been made in between numerical model output, ANN output and satellite and wave buoy measurements. The qualitative assessment has been made with the help of time history plots, while for quantitative one a variety of error measures are used and these are: correlation coefficient (CC), Root Mean Square Error (RMSE), Mean Absolute Error (MAE).
3.1 Comparison of satellite and buoy measurements

It is found that the buoy and satellite observations match well, although the satellite slightly underestimated the buoy data. Among the significant wave height observations the BD08 and BD14 locations exhibit highest correlation of 0.94 and 0.90 followed by 0.86 at BD11 in the Bay of Bengal. The significant wave height was around 2 m in the beginning of the period of study, which reached a maximum value of 3 m on 27th December 2011 due to occurrence of the ‘Thane’ cyclone. The correlation coefficient of the significant wave height was 0.94 (Fig. 2a). The significant wave height from satellite and buoy matched well at location: BD11. The correlation coefficient of significant wave height was 0.86. During the period 15th December 2011 to 1st February 2012 the variation in significant wave height was high due to occurrence of the Thane cyclone (Fig. 2b). The satellite and buoy wave heights at BD14 exhibited a good correlation coefficient of ~0.90 during the period of December 2010 to September 2011 (Fig. 2c). The MAE values seen at locations: BD08, BD11 and BD14 were 0.17, 0.02 and 0.16 respectively. The MAE was very small at the buoy site: BD11 when compared with other buoys.

In the Arabian Sea, significant wave heights during the period of June to July 2013 belonged to the influence of southwest monsoon and both buoy and satellite wave heights ranging from 0–5 m were observed during this period. During the rest of the period the heights ranged from 0–2 m at stations: AD06, AD07 and AD09. The wave intensity of waves was observed to increase as the monsoon season progressed. The time series plot of significant wave height at AD06, AD07 and AD09 showed that there was a very good agreement between the buoy and satellite (Fig. 3) records. The correlation coefficients in between the buoy and satellite data at AD06, AD07 and AD09 were 0.98, 0.98 and 0.82 respectively. The RMSE at AD06, AD07 and AD09 were 0.09, 0.09 and 0.42 respectively. At station: AD09 the correlation coefficient was low and RMSE was high when compared with stations: AD06 and AD07. Incidentally the satellite data had gaps at site: AD09 during the period March to April, 2013 and end of June 2013.

![Figure 2. Satellite data validation with Buoy data at Bay of Bengal OMNI buoy location](image-url)
3.2 Comparison of the WAM output with buoy data

For both buoy and WAM model the maximum significant wave heights were noticed in June 2011. These were 4 m and 3.9 m respectively at the BD08 location. The cyclonic wave activity was underestimated by WAM at the BD08 location. During the cyclone both buoy and WAM model captured the cyclone signal ranging from 3.5 m to 4.5 m at the BD11 location. The model did not capture the wave peaks well at BD14. The model output in general underestimated significant wave heights at the buoy locations. The buoy and model significant wave heights at stations: BD08, BD11 and BD14 exhibited correlation coefficients of 0.94, 0.93 and 0.75 respectively (Fig. 4). Locations: BD08, BD11 and BD14 exhibited MAE values of 0.59 m, 0.66 m and 0.82 m respectively.

Figure 5, shows that the waves were rather small in the beginning of the observation period (November 2012 – May 2013) and they became high at the end of the observation period (June – July 2013) in the Arabian Sea. In the Arabian Sea, maximum significant wave heights observed by the buoy and satellite were 5 m and 3.5 m in June 2013 while minimum were 0.3 m and 0.28 in February 2012 at the AD06 location. The model output was high when compared to the data during 2nd week of May 2013 to July 2013 at location: AD09. During October 2012 to April 2013, buoy and WAM model wave heights ranged from 0.2 m to 2 m. Under the influence of southwest monsoon the average wave height from buoy and model increased steadily reaching a maximum of ~4 m to 5.2 m in June and July 2013 at sites: AD06, AD07 and AD09. The buoy and model significant wave height at AD06, AD07 and AD09 exhibited a good correlation coefficient of 0.96, 0.97, 0.81 and MAE of 0.56, 0.58 and 0.29 respectively.

3.3 Comparison of the WAM model output with satellite data

At the location: BD08 significant wave heights were observed during June 2011 to May 2012. The satellite recorded a maximum wave height of 3.7 m, which was observed on 16th June 2011, while the WAM model estimated the same as 3.8 m, on 20th July 2011. The correlation coefficient between entire model and satellite
Figure 4. WAM model validation with Buoy data at Bay of Bengal OMNI buoy location

Figure 5. WAM model validation with buoy data at Arabian sea OMNI buoy location
data was 0.87. The significant wave height sensed by the satellite matched well with the output of the buoy and WAM model although at BD11 it underestimated the height (Fig. 6). The average values of significant wave heights sensed by the satellite and derived by the WAM model were 1m and 2m, respectively. The wave heights increased to 4.4 m and 3.1 m by December 2011 due to the occurrence of the cyclone. The correlation coefficient at BD11 was 0.80. The same at BD14 was 0.84 (Fig. 6).

The waves exhibit calm conditions (less than 1.0 m) during most of the period. The wave height was less than 2.0 m during October 2012 to May 2013 (Fig. 7). The significant wave height remained between ~2 m and ~3 m for the remaining period and it was occasionally more than 3.0 m for both satellite and WAM model data sets. The time series plot exhibited very good match with the underlying correlation coefficient values of 0.97, 0.96 and 0.82 respectively at AD06, AD07 and AD09 locations. The WAM model slightly underestimated the waves.

3.4 Comparison of ANN predictions with buoy records and satellite data

As mentioned earlier ANN-based predictions were made at the next time step of 3 hours in real time at the various locations under consideration. The significant wave heights observed from November 2012 to July 2013 (2160 data points) were used for testing the network with the buoy measurements. The ANN models developed in this study resulted in the correlation coefficient of 0.99 (Vimala et al., 2012). The mean absolute error was 0.001 m at location AD07. The time series of the forecasted three hourly significant wave heights with the measured three hourly significant wave heights is shown in Fig. 8. Fig. 9 shows the time series of both ANN and buoy wave heights at the BD11 location. An excellent estimation by the network can be seen and this is reflected in the high correlation coefficient and low mean square error and mean absolute error. The coefficient of correlation was 0.98, RMSE and MAE were 0.04 and 0.01 respectively (Table 1). During the observation period, a depression was formed over southeast Bay of Bengal at 9 UTC (Universal Time Coordinated) on 10th May 2013 near latitude 5° N and longitude 92° E. The system further intensified.
into a cyclonic storm by 11th May 2013. The buoy and ANN model have captured the signals of cyclone passage in May 2013.

Figure 11 and Fig. 12 show the comparison of 3 hourly prediction of significant wave height from ANN with satellite data at AD07 and BD11 respectively. AD07 exhibited a correlation coefficient of 0.99, MAE of 0.13 and RMSE of 0.07 whereas BD11 exhibited a correlation coefficient of 0.77, MAE of 0.11 and RMSE of 0.49.

Figure 7. WAM model validation with satellite data at Arabian Sea OMNI buoy location

Figure 8. Comparison between Buoy and ANN significant wave height at AD07 location

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Table 1. Error statistics

| Statistics          | Correlation Coefficient | MAE  | RMSE |
|---------------------|-------------------------|------|------|
| (Nov 2012 – Jul 2013)|                         |      |      |
| AD07                | Buoy with ANN           | 0.99 | 0.004| 0.001|
|                     | SAT with ANN            | 0.98 | 0.13 | 0.07 |
|                     | ANN with WAM            | 0.98 | 0.59 | 0.445|
| BD11                | Buoy with ANN           | 0.98 | 0.01 | 0.04 |
|                     | SAT with ANN            | 0.77 | 0.11 | 0.49 |
|                     | ANN with WAM            | 0.85 | 0.70 | 0.64 |
3.5 Comparison of ANN with WAM model outcome

Figure 12 shows the time series plot of WAM model output and ANN significant wave height values at the AD07 location. The correlation coefficient is 0.98, the mean absolute error is 0.59 and root mean square error is 0.44 (Table 1). Figure 13 shows WAM model output and ANN significant wave heights at location: BD11 and the match can be seen to be good with the underlying correlation coefficient of 0.85.

One limitation of the WAM-4 model noticed was that while it satisfactorily predicted the trend of the high waves, their peaks were underestimated.
4. CONCLUSIONS

The output of WAM model and 3-hourly predictions of ANN as well as the ‘Jason-2’ satellite data matched well with the in-situ observations of the significant wave heights in deep water around the Indian coastline. However, the WAM model underestimated the significant wave heights recorded by both buoys and satellite. The Thane cyclone has also been well captured in the satellite records and WAM model simulations. The performance of the WAM model varied across the east and west coast of India. It was better over the west coast than the east coast of India. In general, the satellite observations provide reliable time series data with large spatial coverage and thus can be used for various marine applications. It was found that ANN’s can act as complimentary prediction models for operational purpose.

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