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DERIVATION OF DESIGN WIND AND WAVE PARAMETERS CONSIDERING CLIMATE CHANGE

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Abstract: *An attempt is made to derive100-year wind speeds and significant wave heights considering the climate change at two deep water locations along the west and east coast of India. Wind and wave measurements made by wave rider buoys for a 7-year period at these locations were used as ground truth. An artificial neural network model was developed for each location to downscale global circulation model data pertaining to wind vectors projected over the next century. Based on the calibrated ANN model and using the input of general circulation model: CGCM3 projections, the wind and wave forecasts were generated for the next century. Thereafter Gumbel and Weibull distributions were fitted to these projected wind speeds and wave heights (that incorporated the effect of climate change) and also to the in-situ historical wind and wave observations made by wave rider buoys (that did not include the effect of climate change). The extreme values of waves and wind were finally extracted from such fits. It was found that the magnitudes of 100-year wind speed and significant wave heights would significantly increase if the effect of global climate change is incorporated in the analysis. Although an exact quantification of the resulting increase is fraught with so many uncertainties the designers should be aware of such possible changes in the design parameters so as to keep appropriate safety margins in their design.*

Keywords: *climate change design waves, design wind, general circulation models, downscaling, artificial neural networks*

INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC 2007) has clearly established that the earth's temperature is rising due to natural as well as human factors. The increase in temperature would mean corresponding rise in air pressure and wind activity and hence that in the wind generated wave activity as well.

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The design of coastal and offshore structures is made on the basis of 100-year wave and wind conditions and it would therefore be of interest to know how these values vary if climate change is taken into account.

Past studies on assessing design wave and wind conditions mostly belonged to the northern Atlantic region. One of the initial studies on assessing effect of climate change on waves is due to WASA (1988) in which a general increase in wave heights at North Atlantic Ocean over a period 1955 to 1994 was recorded. Based on high resolution numerical models Reistad (2001) observed increased storm activities over North Sea and an increase in 100-year significant waves by about 10 percent. Debernard et al. (2002) reported significant increase in magnitudes of wind speed and wave heights over northeast Atlantic, while Wang et al. (2004) noted increase in frequency and size of cyclones and hence that of waves in northeast Atlantic and concluded lowering of return periods typically from 20 to 4 years in case of significant wave heights. An increase of 7 and 18 percent in 99-percentile wind speed and significant wave heights respectively in North Sea was reported by Grabmann and Weiss (2008).

This study presents an attempt to know how 100-year wind speed and significant wave heights would change at two selected offshore locations in India if climate change is taken into account. The locations are code named: DS1 and DS5 and lay along the west and east coast of India off Goa and Machilipatnam respectively in deep offshore as shown in Fig. 1. The measurements of significant wave height and wind speed made by wave rider buoys at these sites by National Institute of Ocean Technology, Chennai, India over the period 1998 – 2005 have been used in this study.

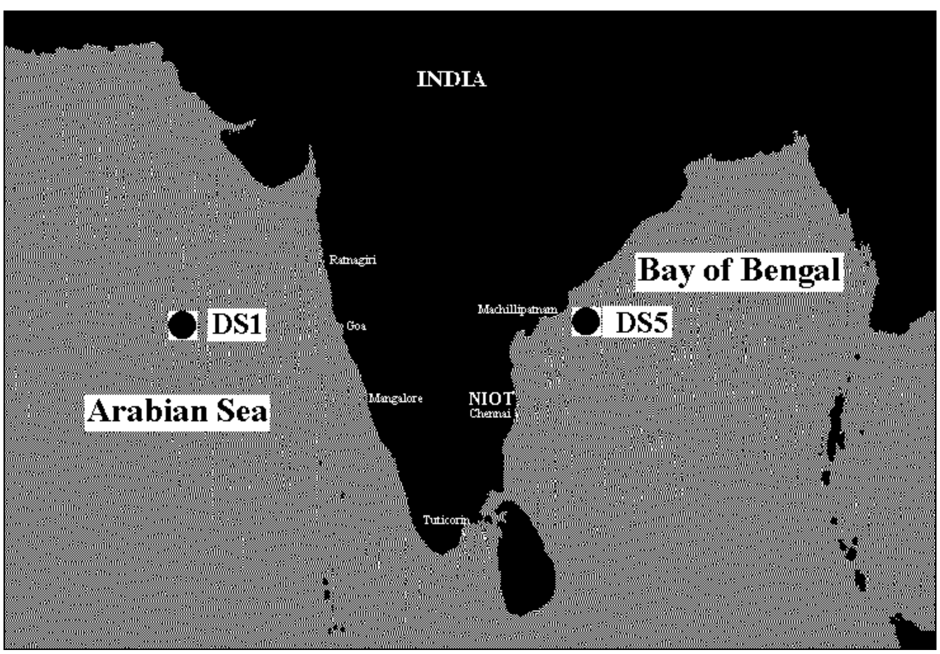

Fig. 1. Indian coastline showing buoy locations: DS1 and DS5

Considering the procedure followed in some of the past works referred to above the approach adopted herein to assess the effect of global climate change at the regional level consisted of following steps: (i) select a general circulation model (GCM) and a specific scenario, (ii) chose a predictor variable such as wind speed components and obtain its future values around the geographical region of interest by running the GCM with respect to the chosen scenario, (iii) collect local data of the predictand variable (say significant wave height and wind speed) (iv) develop a downscaling model by relating predictor and the predictand variables corresponding to the same time instants, (v) downscale the future predictor variables obtained in step (ii) and get future predictand variable values at the local station, (vi) derive design wave and wind parameters on the basis of the projected predictand data and compare the same with those obtained on the basis of past measurements alone.

The details of the resulting analysis are given in the following sections:

THE PROCEDURE FOLLOWED TO GENERATE FUTURE CLIMATE

Projection of climate variables into future can be done using general circulation model (GCM)s. These consist of equations based on principles of conservation of energy, momentum, and ideal gas law. The spatial scale on which GCMs work is coarse and hence downscaling of GCM outputs to small regional scale is necessary. The downscaling using statistical methods involves the two steps of model calibration and application. The former can be based on observed climatological data but if such observations are not available then National Centre for Environmental Prediction / National Centre for Atmospheric Research (NCEP/NCAR) reanalysis data can be used. Reanalysis data are outputs from a high resolution atmospheric model run using data assimilated from surface observation stations, upper air stations and satellite observing platforms and the results obtained using these fields represent those that could be expected from an ideal GCM. In model application the statistical relationship between the reanalysis data and the regional climate variable of interest so developed is used for projecting the regional climate variable to future scenarios corresponding to the GCM outputs. Scenarios provide examples of what might happen in future under particular assumptions. More details of the same can be seen in IPCC (2007).

The present study is based on the statistical downscaling done using artificial neural network (ANN)s. The choice of this method was made considering its success in mapping random input-output vectors in oceanic applications (Jain and Deo, 2006). The downscaling model had the input of daily zonal (east) and meridianal (north) wind speeds. Its output was in the form of daily significant wave heights and wind speeds (separately in two different models) at a specified wave buoy location. The input used in training corresponded to NCEP/NCAR reanalysis data while the one employed in testing and actual application pertained to the third generation coupled Canadian General Circulation model 3 (CGCM3) – A2 scenario. The scenario selected was A2, since it is the worst case scenario in terms of future temperature rise. The data were available at a resolution of 2.5^0. The reanalysis data required for the study were daily zonal and meridional wind speeds for the time period 1998-2005.

For forecasting using the developed statistical downscaling model, daily zonal and meridianal wind speeds for the time period: 2009-2100 were extracted from CGCM3. The spatial resolution of the GCM was 2.8125^0. Apart from the A2 scenario, the GCM data corresponding to 20C3M or IPCC 20th century experiment was also downloaded for the period 1998-2000 to know how well the particular GCM reproduced the present climatic conditions. For this purpose the model performances based on 20C3M data and NCEP reanalysis data were compared. The data sets indicated above were downloaded for an area corresponding to a 4 x 4 grid, which has a total of 16 grid points. Because the resolution of NCEP/NCAR and GCM data were different, interpolation was adopted to match both the resolutions. For such re-gridding the method of bilinear interpolation was adopted similar to Yamaguchi and Noda (2006).

The GCMs do not necessarily perform well in regional climate simulation and large difference or bias between observed and GCM-simulated conditions may exist. The bias in the mean and the variance of GCM atmospheric fields relative to observations or relative to reanalysis data was removed in this study by subtracting the mean and dividing by the standard deviation of the predictor for a predefined baseline period, for both the NCEP and the GCM data. The baseline period selected here is 1961–1990 since it is of sufficient duration to establish a reliable climatology (Wilby et al., 2004)

It was noticed that there was a total of 32 data sets (16 grid points and 2 predictor variables at each point). These data belonged to the period of 1998-2005 for the training set and to 2009-2100 for the testing set. In order to reduce the resulting large dimensionality of data principal component analysis was carried out and those principal components whose contributions were less than 2% to the total variance were not considered and this enabled reducing the dimensionality of the data from 32 to 4.

The artificial neural network used was of usual feed forward back network trained using the Levenberg Marquardt learning scheme. It had two input and one output nodes. The hidden nodes typically 2 were selected by trials. About 80% of available data was used for network training and the remaining for testing. The input parameters included reanalysis data corresponding to daily zonal and meridianal wind (in m/s). The output parameter was daily significant wave height (in m) and wind speed (m/s) separately for two networks. In order to meet the requirement of transfer functions the data were normalized in the range of (-1.0, 1.0). The transfer functions were log sigmoid. Testing criteria used during the testing phase of the network analysis included correlation coefficient, R, mean squared error, MSE, and mean absolute error, MAE.

The trained neural network was further used for forecasting daily significant wave heights and daily wind speeds for a time period of 2009-2100. The daily wind speed data obtained from GCM-CGCM3 corresponding to A2 scenario were used for driving the model. In order to check whether the chosen GCM works well to reproduce the present climatic conditions, the developed ANN model was driven using daily wind speeds obtained from 20C3M experiment. Because the 20C3M data were available up to the year 2000 the developed model was first driven using 20C3M daily wind speed data for the time period 1998-2000 and again, the model was driven using NCEP/NCAR reanalysis data for daily wind speed for the time period 1998-2000. The outputs obtained by using 20C3M and NCEP/NCAR reanalysis were compared with each other with the understanding that the resemblance of these two sets of outputs would confirm that the chosen GCM reproduced the present day conditions well. In this part of the study, the training was done from 1998-1999 and the data corresponding to the year 2000 were used for testing the model.

EVALUATION OF DESIGN WAVES AND WIND

The performance of the developed downscaling model can be seen in an example scatter plot and time history based comparisons of Fig. 2 and 3. These figures pertain to the testing set of significant wave height data at location DS5 along the east coast of India. The resemblance between the target (downscaled) and the realized (measured) significant wave heights can be noticed. The corresponding error criteria were R = 0.81; MAE = 0.50 m and MSE = 0.92 m^2. The high values of R and low magnitudes of MAE and MSE show good performance of the downscaling model. The performance of ANN models at the other locations was similar to this example case.

Fig 4 shows the time series plot showing how the significant wave height (Hs) values predicted using 20C3M and those predicted using NCEP/NCAR reanalysis data varied relatively over the testing time period at station DS5. The predicted Hs values based on NCEP/NCAR reanalysis data and 20C3M data showed a correlation coefficient of 0.89 indicating that the chosen GCM performs well in reproducing the present climate. A similar performance was noted at the other location: DS1 and also for the case of wind speed (U) values.

In the next step the two sets of Hs and U data: one corresponding to in-situ observations by buoys (not incorporating the effect of climate change) and the other set of wave data which was obtained by driving the statistical downscaling model (incorporating the effect of climate change) from years: 2009 to 2100 were separately fitted to Gumbel and Weibull distributions.

The cumulative distribution function, P(X), for any variable X, (like Hs or U) is given by the following expression of the Gumbel distribution:

$$P(X) = \exp - \{\exp - [\alpha (X - u)]\} \quad (1)$$

Where $\alpha = \pi / (6.0\, \sigma^2)^{1/2}$ (2)

$$U = \overline{X} - (0.5772/ \alpha) \quad (3)$$

Where, $\overline{X}$ = mean of all X values and σ^2 = variance of all X values.

The cumulative distribution function for a variable X based on the Weibull distribution in turn is given by:

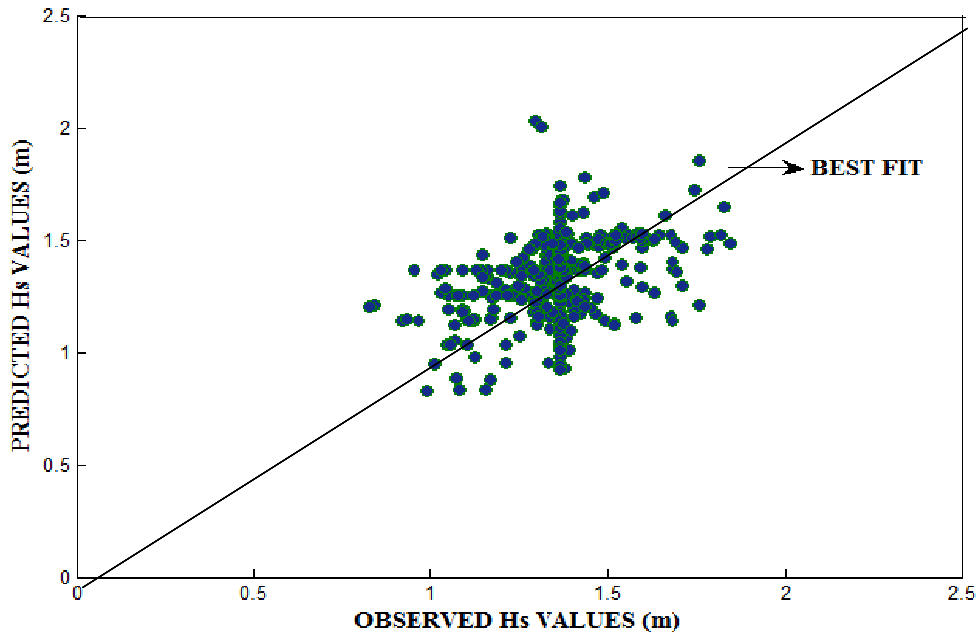

Fig 2. Observed and predicted Hs values at DS5

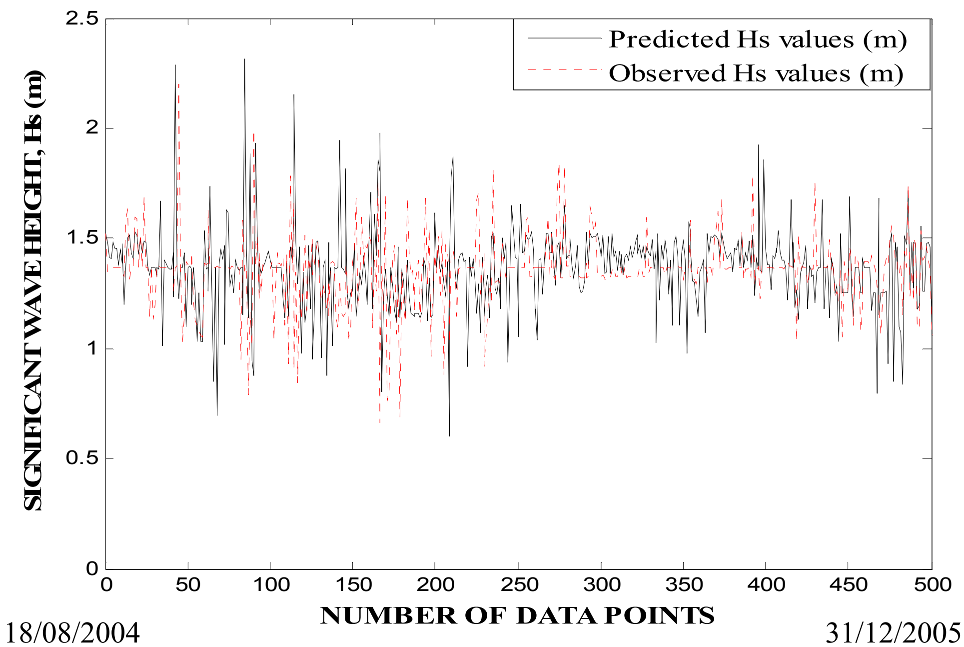

Fig. 3. Observed and predicted Hs at DS5

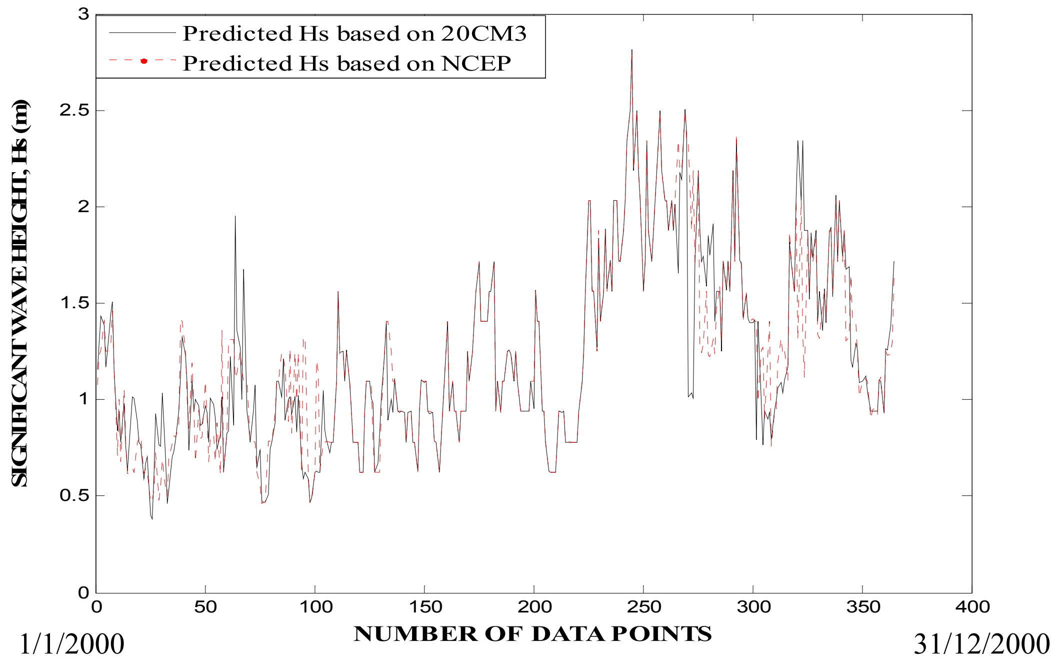

Fig 4. Comparison between 20C3M and NCEP based predictions of Hs at DS5

$$P(X) = 1 - \exp-[(X - A)/B]^{C} \qquad (4)$$

where, A = location parameter, B = scale parameter, and C = shape parameter. These parameters were estimated in this study using the well known statistical method of maximum likelihood.

The P(X) value for a given return period Tr (with single X per day) can be obtained by:

$$P(X) = 1 - (1 / 365T_r) \qquad (5)$$

Using these equations, Hs and U corresponding to Tr = 100 years were derived for both data sets: historical in-situ observations and postulated climate incorporating the climate change. As per the prevailing practice however the design Hs and U are drawn based only on the historical measurements. Tables 1 and 2 show the outcome of this exercise when Gumbel and Weibull distributions were used respectively. At DS1 and based on the Gumbel distribution the difference was 59.37 % in design waves and 45.61 % in design wind while the same at DS5 was 25.14 % in design waves and 44.27 % in design wind. When computations were based on the Weibull distributions these values changed as 51.91 % for Hs and 59.22 % for U at the locationd DS1, and further to 46.66 % for Hs and 73.79 % for U.

Table 1. 100-year values with and without climate change effects based on Gumbel

distribution

Variable	Location	Hs without climate change	Hs with climate change	Percentage difference
Hs (m)	DS1	10.48	16.70	59.37
	DS5	6.35	7.95	25.14
U (m/s)	DS1	17.65	25.71	45.61
	DS5	20.80	30.01	44.27

Table 2. 100-year values with and without climate change effects based on Weibull distribution

Variable	Location	Hs without climate change	Hs with climate change	Percentage difference
Hs (m)	DS1	9.22	14.01	51.91
	DS5	3.67	5.38	46.66
U (m/s)	DS1	17.43	27.77	59.22
	DS5	16.75	29.11	73.79

A clear effect of the climate change in terms of increasing the design wave and wind can be noticed. It is evident from these Tables that at both stations the values with the 100-year return showed considerable increase when climate change was taken into account.

Location DS1 showed higher effect than station DS5 for both Hs and U when Gumbel distribution was considered while no such clear difference was seen when Weibull distribution was concerned. Generally Weibull distribution showed more effect of climate change onHs and U at both the locations. As regards relative effects in Hs and U are concerned no clear picture emerged. It appears that although the effect of climate change in the 100-year wind and wave conditions is certain the exact quantification is subject to a high amount of uncertainties.

In the light of above observations it is argued that from the point of view of safety future designs of offshore installations in these areas should necessarily take into account the effect of climate change and further even the existing design also need to be checked for their adequacy.

This study has many limitations arising out of uncertainties involved at various stages of assessment of climate change effects and it is necessary to address these issues further by adopting alternative methods of design wind and wave height evaluations, different forms of climate models, general circulation models, and scenarios, as well as various types of downloading schemes and by using a much larger database.

CONCLUSIONS

Despite a great deal of uncertainties the effect of climate change in the 100-year design significant wave heights and wind speed over the selected offshore locations in India was clearly noticed in this study.

For the two locations involved the percentage increase in the 100-year significant wave height ranged from 25 % to 59 % while the same was 44 to 74 % in case of the 100-year wind speed.

While exact quantification of the change in design values is difficult due to a high amount of uncertainties at various levels of analysis involved designers should give due consideration to this aspect and revise their safety margins accordingly.

To gain more confidence in the analysis more research into removing the uncertainties in the assessment procedure is necessary.

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