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Comparison of Wind Speeds Derived By Alternative Statistical Downscaling Techniques at the Indian Offshore Sites

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Abstract

The assessment of impact of climate change on offshore industry often calls for region-specific atmospheric and oceanic information over the future. Such information can be derived from the global general circulation models (GCM's). The present GCM's however suffer from the problem of coarse resolutions and systematic error or bias, among other difficulties. To overcome these problems, downscaling or re-gridding from coarse to fine resolution is often practiced . Due to various alternative procedures available for this purpose it becomes difficult to identify the correct scheme to satisfactorily apply for a given problem. At this backdrop, the product of an atmosphere–ocean global climate model is analyzed in this study using three alternative techniques to understand their relative usefulness. These techniques are: (i) bilinear interpolation and quantile-mapping (BIQM) technique, (Li et al. ,2010) (ii) downscaling based on artificial neural network (ANN),(Deepthi et al. 2010) and (iii) downscaling based on Discrete Wavelet Transform-ANN conjunction (DWT-ANN) model.(Nourani et al ,2009)

The monthly wind speeds for the future time slice of 2006-2045 were derived from the Canadian general circulation model (CGGM) resulting from ‘Coupled Model Inter-comparison Project–Phase 5’ (CMIP5) and run for a moderate warming scenario of Representative Concentration Pathway (RCP)-4.5. Such projected wind information was compared with the historical wind over the time slice of 1966-2005 and belonging to the ‘CGCM 20-th century version 3’ (20C3M) models. The study involved the use of National Centre for Environment Protection/National Centre for Environment Research (NCEP/NCER) reanalysis dataset, presumably equivalent to recorded wind and more accurate than the GCM outputs, as the target dataset for removal of bias in the GCM data. Thus the predictor was GCM data while the predictand was NCEP data. The initial conditions responsible for generation of both NCEP/NCAR and GCM data being different, their accuracy at lower temporal intervals may not be high and hence only monthly wind speeds were considered rather than their weekly or daily values.

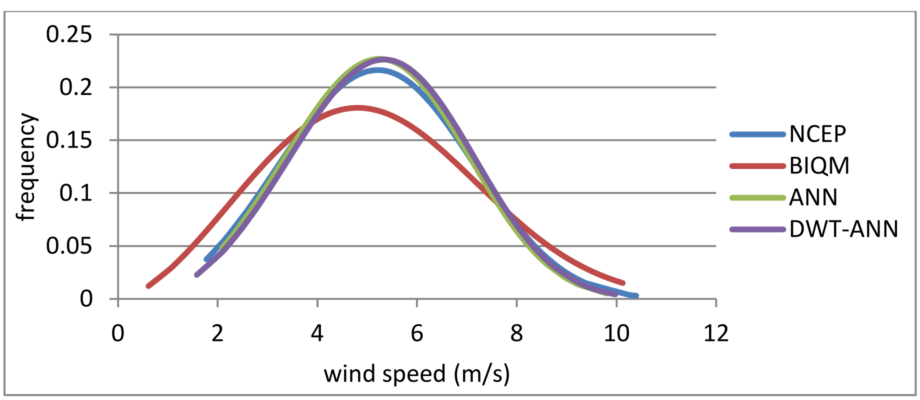
The study belonged to three offshore sites identified for the development of potential offshore wind farms by Government of India and lying along the eastern, southern and western sides of the Indian coastline. The locations are known respectively as: Kanyakumari, Rameshwaram, and Jakhau.

The BIQM method consisted of matching the grid sizes of GCM data with that of NCEP/NCAR data followed by removal of the GCM bias through the quantile mapping. In the ANN technique the standardized input of GCM was mapped with the output of NCEP/NCAR data directly. The DWT-ANN method incorporated removal of bias in the GCM by standardization and eliminating the high frequency noise in it by a wavelet transform; the wind pre-processed in this way constituted the input to the ANN that carried out station-specific downscaling.

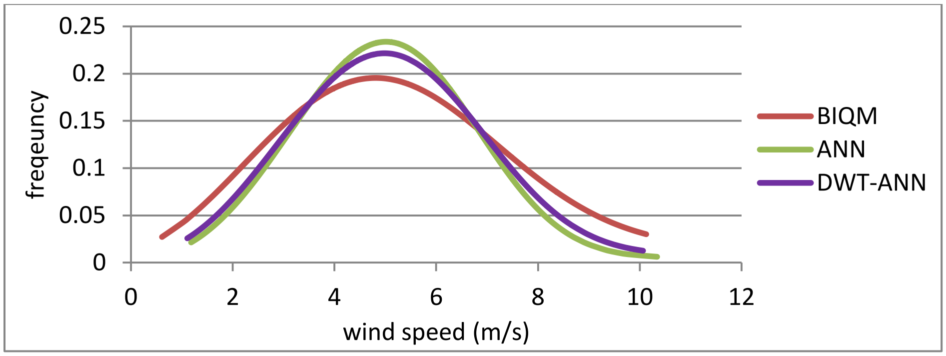
A comparison of the past data generated by the three methods after downscaling the GCM data (or assessment of model performance) was made by comparing their statistics with those of the target (NCEP/NCAR) data. The statistics were the mean, standard deviation, correlation coefficient, R, mean square error, MSE, mean absolute error, MAE. Further, in order to assess the convergence of future data generated by the three downscaling methods to the ensemble average, the Mann Kendall's rank correlation test was employed and this involved testing independence of the generated future data among themselves.

The error statistics of MSE and MAE were found to be the lowest for the DWT-ANN, ranging from 0.96-0.98 m/s and 0.75-0.77m/s respectively for all the locations viewed together. The value of the correlation coefficient between the past GCM data and the reanalysis data was found to be high as 0.8, while the mean and standard deviation of the downscaled GCM data and accurate NCEP data were almost the same.

The downscaled GCM wind over the past and future time slices along with NCEP/NCAR data were fitted to the Weibull probability density function (pdf). (Fig 1). It was observed that the pdf of DWT-ANN product was most close to that of the NCEP/NCAR wind and this was followed by the products of ANN and BIQM. In all the three alternative methods however higher deviations were noticed near the peak frequency than the tails for pdf's of both past and future data.



(a)



(b)

Fig 1 .Model outputs' PDF comparison for past (a) and future (b) at Jakhau Site

A comparison of the extreme values produced by the three techniques was done and this consisted of sorting out the points below 5-th percentile and above 95-th percentile of NCEP/NCAR data, obtaining corresponding points from the outputs of the three techniques, fitting the Empirical distribution function and comparing them. This suggested that ANN and DWT-ANN schemes simulated the extremes better than the BIQM technique.

The lack of statistical dependency across the (future) data projected by the three methods was seen through application of the Kendall's 'Tau-B' rank correlation test.

In summary, the comparison of all the three techniques indicated that the DWT-ANN technique was superior in terms of model performance and well as model convergence when all statistical measures are viewed together. This could be due to its rigorous treatment to the biased and noisy data. On the other hand in the alternative BIQM technique, although the bias was removed by a rigorous quantile matching scheme, the re-gridding (bilinear interpolation) procedure employed later lacked the sophistication of ANN modeling.

Key Words: Climate change, Regridding, ANN, Wavelet transform, Quantile Mapping.

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