Estimating onshore break size from a global wind-wave model using neural networks

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Abstract— Global windwave models such as the NOAA WaveWatch 3 (NWW3) play an important role in monitoring the world's oceans. However, untransformed data at gridpoints in deep water provide a poor estimate of swell characteristics at nearshore locations, which are often of significant scientific, engineeri and public interest. Explicit wave modelling, such as *Simulating Waves Nearshore* (SWAN), is one method for resolving the complex wave transformations affected by bathymetry, winds, and other local factors. However, obtaining accurate bathymetry and determining parameters for such models is often difficult. When target data is available (i.e. from *in situ* buoys or human observers, empirical alternatives such artificial neural networks (ANNs) and linear regression may be considered for inferring nearshore conditions from offshore model output. Using a 6fold crossvalidation scheme, significant wave height (*Hs*) and period was estimated at one onshore, and two nearshore locations. In estimating *Hs* at the shoreline, validation performance of the best ANN was *r=.91*, improving on linear regression (*.82*), SWAN (*.78*), and the NWW3 *Hs* baseline (*.54*)

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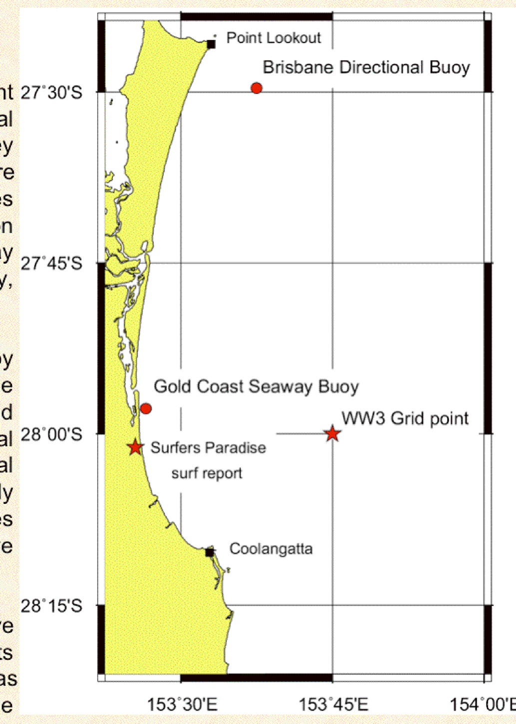
Introduction

Knowledge of swell conditions at specific nearshore locations is often important for research, marine engineering, and policy development. Although global swell models are an effective approximation of open swell conditions, they often become less accurate in the nearshore zone. Variations in nearshore bathymetry, local wind-generated seas and the effects of artificial structures transform deep water swell due to reflection, shoaling, refraction, diffraction and breaking (Londhe,2004). At a particular location, local topography may lead to attenuation or accentuation of long or short period swells, either directly, or by the contribution of local wind conditions.

The propagation of swell in nearshore areas is conventionally studied by running either an actual, or a virtual simulated physical model. Physical scale models require a significant investment of resources for their construction and simulation. For this reason, numerical computer simulation of the local physical environment and local swell conditions is often preferred. However, numerical models themselves require care and expertise in their implementation, typically along with days of processing time, and produce results that are sometimes unsatisfactory, especially in shallow water. These techniques are also sensitive to accuracy of the bathymetric data for the study area.

ANNs may be regarded as a further extension of empirical (i.e. statistical curve fitting to large numbers of observations), as opposed to model-based, attempts to estimate and predict wave behaviour (Deo,2005). The use of ANNs has been reported for numerous applications in the geological and marine sciences, and in particular have been used for forecasting wave climate time series (Makarynskyy, 2005, Deo, 2001, Agrawal, 2002). ANNs have been applied to estimating missing wave buoy data (Balas, 2004), and recently Kalra et. al. (2005) has detailed an ANN-based effort to map offshore wave data to coastal locations. Apart from Kalra et. al.s' (2005) welcome comparison of ANN performance with that of linear regression, most research has not compared ANNs with other forms of swell estimation. As neural networks are unconstrained general-purpose function approximators, with potentially thousands of degrees of freedom, some questions exist regarding the validity of previous work For example, a method of wave forecasting using neural networks was recently reported by Makarynskyy (2004), and subsequently challenged (Medina, 2005) due to issues related to over-fitting, lack of baseline performance comparisons, and an insufficient degree of cross-validation. An empirical approach does not provide the insight into wave propagation processes that is provided by full-scale numerical modelling. However, the advantages include computational efficiency and potentially greater predictive power, without the need for detailed geographic information, or the laborious testing of a range of physical model parameters.

This study aims to estimate significant wave height at the shore, and two nearshore locations using input from the NWW3 l. Non-linear ANNs of varying complexity are compared with: baseline wave heights recorded by the global model, a linear predictor, and with the spectral wave model SWAN. Combined with a k-fold cross-validation experimental set-up, this approach ought to resolve the efficacy of neural networks for the interesting task of bringing global ocean wave model output to nearshore locations. A practical outcome is that NWW3 output may be utilised inexpensively for the emulation or prediction of surf reporter or buoy readings at locations of interest.



The geographical area considered in the study: the nearshore region at the Gold Coast, Australia.

Work in progress: SWAN modelling of areas around Australia

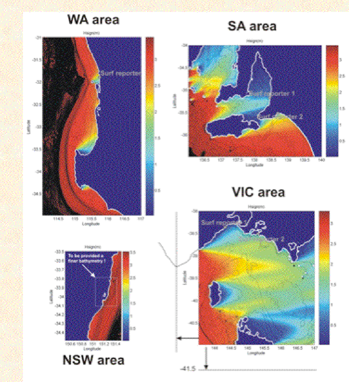
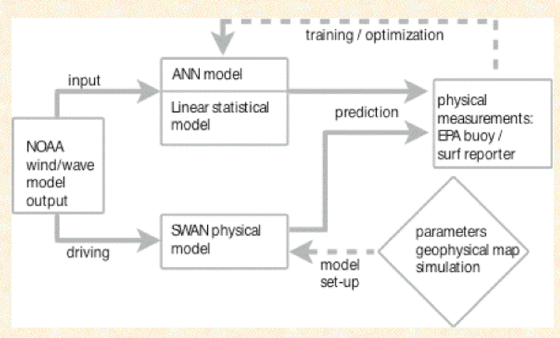


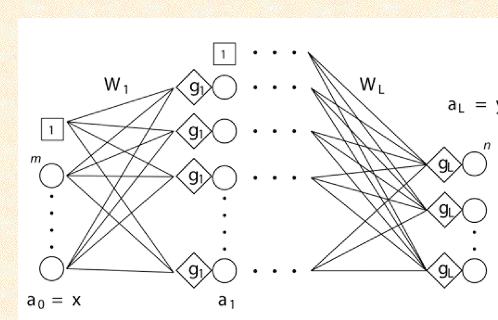
TABLE I
AVERAGE ESTIMATION PERFORMANCE (FOR ANNS, ON 6-FOLD CROSS-VALIDATION SET)

		Surf Reporter		Gold Coast Seaway Buoy				Brisbane Directional Buoy			
	df	H_s		H_s		T_z		H_s		T_z	
ANN linear	13	16.02	*.82*	19.18	*.81*	0.507	*.60*	26.32	*.81*	1.312	*.33*
ANN 3	45	13.15	*.88*	15.72	*.89*	0.509	*.73*	20.63	*.88*	1.112	*.39*
ANN 5	75	11.86	*.91*	15.40	*.88*	0.508	*.72*	20.83	*.88*	1.187	*.41*
ANN 7	105	11.59	*.89*	14.42	*.90*	0.497	*.71*	22.10	*.86*	1.148	*.50*
ANN 9	135	13.26	*.89*	14.35	*.90*	0.487	*.74*	22.87	*.86*	1.148	*.43*
ANN 11	165	12.48	*.89*	15.34	*.88*	0.519	*.70*	21.73	*.87*	1.131	*.43*
SWAN		94.42	*.78*	25.10	*.74*	0.949	*.58*	32.09	*.68*	0.869	*.87*
NWW3 H_s		94.10	*.54*	55.28	*.72*			32.64	*.73*		
		SE (cm)	*r*	SE (cm)	*r*	SE (*C/m*)	*r*	SE (cm)	*r*	SE (*C/m*)	*r*

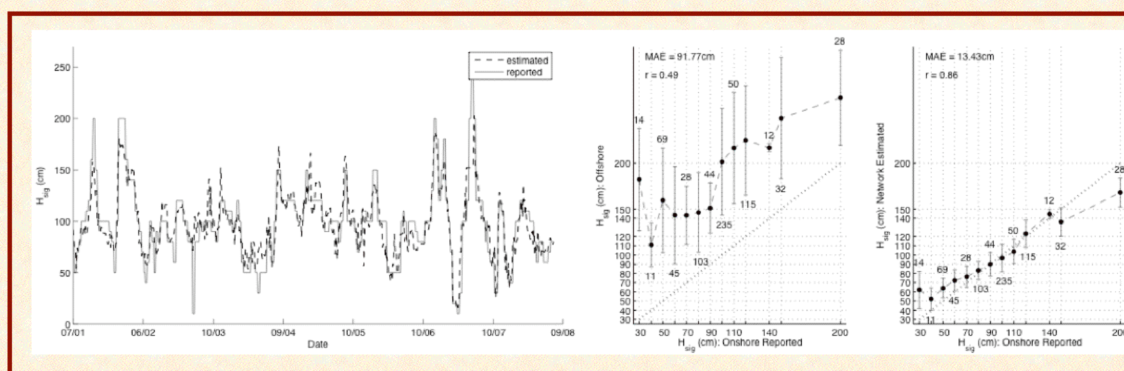
Comparison of estimation performance for estimating surf reporter and buoys from NOAA



Overview of data-flow



Formal structure of an artificial neural network

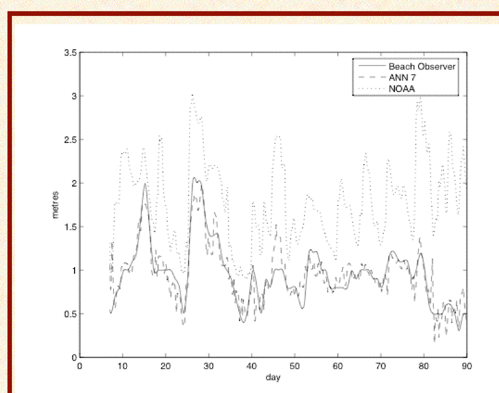


Surf reporter and estimated onshore wave size using ANNs from the offshore model

Results

Empirical estimation using neural networks was performed using transformed and scaled input from NWW3, zero-hour predictions. The target outputs were significant wave heights, as measured by the two wave buoys and the surf reporter. Estimation of the observed wave period, as measured by the two buoys, was also attempted. The available data was partitioned into 6 sections of equal size for the purpose of 6-fold validation. This involved training models using 5 sections, with testing of model performance on the remaining unseen data. For non-linear models (i.e. ANNs with a hidden layer), training was repeated using 10 random initialisation conditions, and the best performing network performance recorded. The process is repeated 6 times, so that each section is used for testing once. Optimisation was halted when performance on the validation set stabilised. Results reported are the average performance over the 6 sections. Networks varied with respect to the number of hidden neurons. All networks had one hidden layer, and used tan-sigmoid and linear transfer functions in the hidden and output layers, respectively. Numerical simulation was carried out using SWAN, and parameters were adjusted several times in order to improve results.

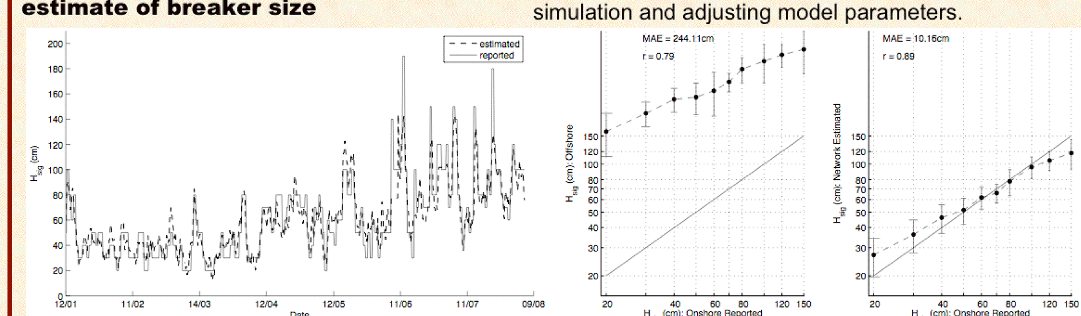
Table \ref{allresults} displays the estimation performance in terms of standard error (SE) and normalised correlation coefficient with the target series. The input to all predictive models was the 13 environmental variables provided by the NWW3 system. The rows compare the performance of ANN architectures with variable numbers of hidden neurons with a linear network (equivalent to linear regression). For wave height, the baseline for evaluating performance is represented by the relationship between the readings from NWW3 and the various target series. As the NWW3 model decomposes swell period into primary, secondary, and wind-driven components, a baseline comparison was not possible for wave period. The figure below displays the best performing ANN for estimation of the surf reporter observations) It should be noted that the ANN output is a concatenation of the six validation sets. Thus the correspondence in the graph is an indication of performance on unseen data.



ANNs transform NOAA into accurate estimate of breaker size

Conclusion

From the table it may be seen that baseline NWW3 has a poor correlation with actual measurements at the buoys and beach, with the relationship being weakest for beach-side surf-reports. ANNs outperformed the linear regression approach for each prediction task, and generally empirical methods were more effective than numerical modelling using SWAN (apart from estimating swell period at the Brisbane Buoy, where they failed to generalise well). This is not surprising, since any theoretical model will be subject to inaccuracies in parameters and survey data. In particular, the current model could have benefited from further calibration, especially in terms of bottom friction. This highlights a significant benefit of empirical prediction, in that good results can be quickly obtained without the need for a long development time of simulation and adjusting model parameters.



Work in progress: Replication over 17 locations Australia-wide. Perth, WA shown above.