Proceedings of Taiwan-EU Symposium on Ocean Observation and Its Applications
November 4-5, 2014, Tainan, Taiwan

Optimization of Real-Time Wave Forecasting with Model Ensemble Results

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Abstract

Accurately forecasting the ocean waves during the typhoon events is extremely important to mitigating and minimising the potential damage to the coastal infrastructure and to protecting the coastal communities. This is particularly relevant to the costs around Taiwan, as annual occurrence of typhoons and their severity are evidently increasing. Due to the complex hydro-meteorological interaction and uncertainties from the modelling systems, ensemble approaches have recently been widely used to provide further insights into the model results for quantifying uncertainties and improving accuracy of the wave forecasting. This paper presents an optimisation on the model-ensemble results for real-time wave forecasting. The proposed approach applies the "locally weighted learning" algorithm to the wave heights predicted by the WAVEWATCH III wave model, which is driven by four different weather models (model-ensembles) to optimize the weightings used in calculating the resulting wave height from four model-ensembles. By doing so, the model behaviour in response to the wind forcing can be captured and reflected by the weightings. The results show that, in comparison with the measurements at selected wave buoy locations, the optimised weightings, obtained from the training process, can significantly improve wave forecasting from the standard mean values, in particular, for the typhoon-induced peak waves. The results also show that the algorithm is easy to implement and practical for real-time wave forecasting.

Keywords: *wave modelling; optimization; ensemble modelling; forecasting; typhoon; WAVE WATCH III; local weighed learning.*

Introduction

Predicting and understanding ocean waves are extremely important for ocean shipping, fisheries, as well as coastal protection and coastal zone management. In particular, the typhoon-induced waves can cause huge damages to properties, infrastructures and human lives. The catastrophic consequences of the typhoon related events have often been seen and reported in Taiwan in recent years. Although it is almost impossible to completely avoid the damages caused by typhoons, more accurately predicting and forecasting the ocean waves becomes ever more important to mitigating and minimizing the impacts from typhoons. However, due to the complex hydro-meteorological interaction and uncertainties from the modelling systems on the forcing conditions and modelling techniques, as well as the uncertainties of other physical parameters, improving the predictions and forecasts can be difficult and challenging. In recent years, the ensemble approaches have been widely used in improving the quantification of the uncertainties from the modelling systems and physical parameters. In wave forecasting, the ensemble approaches can be generally classified into two types: parameter ensemble approach and model ensemble approach. In both types, a particular wave model is used to transform the atmospheric forcing conditions (winds) into wave fields, but the atmospheric forcing conditions can be generated in different ways. The parameter ensemble approach is to use the equally-distributed physical parameters to generate ensembles of forcing conditions using the same weather model. For example, in the work reported by Chen et al. (2010) and Zou et al. (2013), 50 ensemble winds fields were used as the surface forcing for the tide-wave model POLCOMS (Osuna et al., 2004) to produce the ensemble results of waves and storm surge. Then, statistical analysis was carried out to quantifying the uncertainties of the model results in both hydrodynamics and morphodynamics. In contrast, the model ensemble approach uses different weather models to generate surface forcing conditions for the wave model, as each weather model is calibrated to its optimal operational conditions. In the work of Fan et al. (2013 & 2014), the WAVEWATCH III model was used to transform the wind fields obtained from four weather models, namely AVN, JMA, NFS and WRF, developed by different institutions, to model the ocean waves surround Taiwan during three typhoon events. The model results were analysed and mean wave heights and standard deviations were published as the real-time forecasting, together with the observations from a number of wave buoy deployed off the Taiwan coasts. In general, the mean wave heights calculated from four model ensembles agree with the observed wave heights from the wave buoys, but it was clear that during the typhoon events, the peak wave heights were under-represented by the standard mean wave heights. As the peak wave heights during typhoon events often is the most important parameter in decision making, therefore it becomes desirable to improve the methodology used to generate the resulting wave heights from the ensemble wave heights.

In this paper, a “locally weighted learning” algorithm is proposed to optimize the weightings applied to the each ensemble wave height, in order to capture the different model behaviours in response to the wind conditions and thus to improve the wave height forecasting. The study is based on the data (predicted wave heights) presented in Fan et al. (2013 & 2014) for three typhoon events occurred in 2011 and 2012. Whilst the full details can be found in Fan et al. (2013 & 2014), for the sake of clarity, the wave model WAVEWATCH III and the computational domains used are briefly described here.

Modelling System and Computational Domains

WAVEWATCH III is a third generation wave model developed at NOAA/NCEP (Tolman 1997, 1999, 2009) in the spirit of the WAM model (WAMDIG 1988, Komen et al. 1994), which has been widely used to simulate wave field using the wind data from various weather models.

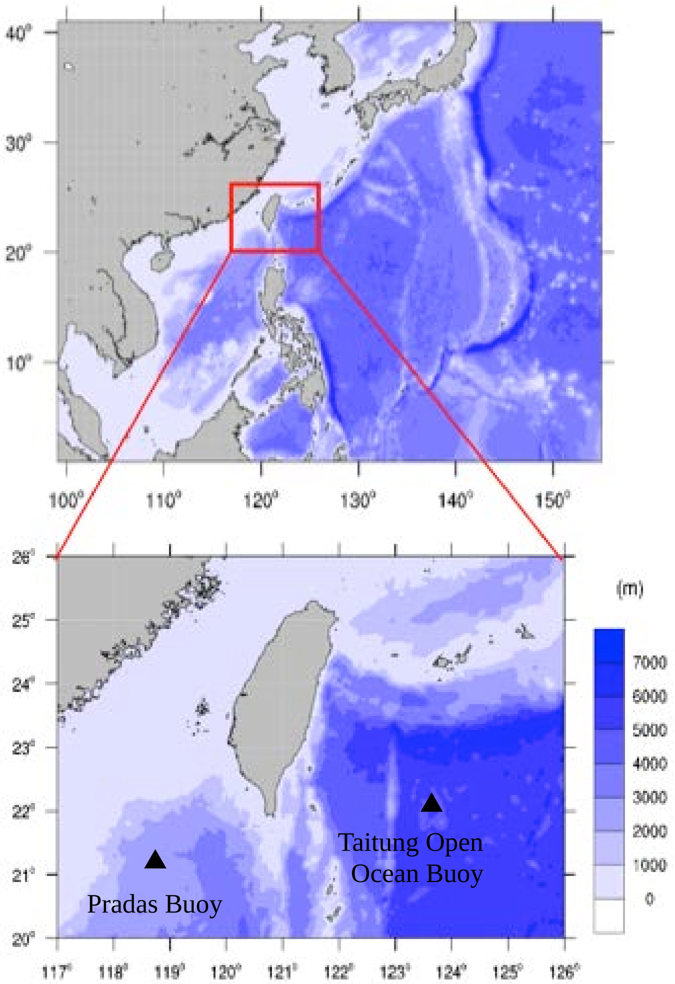


Fig. 1 Computational domains for WAVEWATCH III (▲Buoy locations)

In the work of Fan et al. (2013 & 2014), a nested computational framework, as shown in Fig 1, was used. The coarse grid domain was used to provide the wave boundary condition to fine grid domain. The resolutions of the coarse and fine grids are 0.5º and 0.25º respectively. The modelling system was driven by the wind fields from four weather models, namely, AVN (NCEP Aviation Model), JMA (Japan Meteorological Agency), and NFS (Non-hydrostatic Forecast System). The modelling system was applied to three typhoon events: Typhoon Jelawat occurred in 2012, and Typhoons Nanmadol and Meari in 2011.

The computed mean wave heights using the standard averaging (i.e, equally weighted, ¼) as indicated in Fan et al. (2014) show a general agreement with the measured wave heights. The comparisons at selected locations showed that the forecasted wave heights agree better for the low waves. However, for high waves, in particular those induced by typhoons, the peak wave heights were under-forecasted using the mean ensemble values. Those peak waves, which in fact will have the most significant impacts on the coastal areas and cause the most severe damages, need to be predicted and forecasted more accurately in order to mitigate and minimising the impacts. Close examinations showed that the wave heights generated by different wind fields behaved differently in response to the winds. Using the equal weighted averaging for the mean wave heights may be inappropriate and also incapable in capturing the peak waves. To this end, an optimisation is proposed in this study to find out the optimised weightings to improve the representation of the waves generated from each weather models, especially the peak waves.

Optimization

In this study, optimisation is based on the concept of "locally weighted learning" (Atkeson et al., 1997), which is briefly described here. Assuming that we have a set of wave heights generated by different models (h_i, i=1, N; where N is number of the models), the mean wave height can be calculated with a weighted averaging as:

$$H=\sum_{i=1}^{N} w_i h_i \tag{1}$$

where, H = mean wave height; h_i = wave height from i^{th} model ensemble; and w_i = i^{th} weighting. Where w_i = 1/N, Eq (1) is for the standard averaging. For optimization, weightings, w_i (i=1, N) are determined by the “locally weighted learning” algorithm in an attempt to optimise the weightings for a better representation of the resulting wave height. With a set of measured wave heights at a particular location, a cost function can be established as:

$$J(w)=\frac{1}{2}\sum_{j=1}^{M}\left(H_j-\hat{H}_j\right)^2 \tag{2}$$

where, M = number of the measured wave heights; H = averaged wave heights calculated by Eq. (1), $\hat{H}$ = measured wave heights, and J = cost function. With the Least Mean Squares (LMS) algorithm, the gradient of the J can be estimated as:

$$\frac{\partial J}{\partial w_i}=h_i\sum_{j=1}^{M}\left(H_j-\hat{H}_j\right) \tag{3}$$

and w_i can be estimated with the gradient decent algorithm from Eq. (3). Writing the algorithm in matrix format for the brevity yields the following:

$$\boldsymbol{w}=\left(\boldsymbol{h}^T\boldsymbol{h}\right)^{-1}\boldsymbol{h}^T\hat{\boldsymbol{H}} \tag{4}$$

where, w = matrix of weightings (N); h = matrix of the modelled wave heights ($M \times N$); and $\hat{H}$ = matrix of measured wave heights (N).

In this study, optimisation is carried out by training first, using the results obtained as described previously during Typhoon Jelawat and then the optimised weightings are applied to other two typhoon events: Nanmadol and Meari.

The optimisation is demonstrated at two buoy locations: Taitung Open Ocean and Pratas Data Buoy stations, where the former is located at deep water of more than 6000 m, and the latter is located close to shore as shown in Fig. 1.

Training with Typhoon Jelawat Data

Using Eq. (4) together with the measured wave heights, the weightings at any location can be obtained from a training process. In this study, the measured wave heights at Taitung Open Ocean and Pratas Data Buoy stations during Typhoon Jelawat are used. This includes 128 valid hourly data points out of 144 hourly measurements from 0:00 24th Oct 2012 to 0:00 30th Sept 2012, with the observed peak wave height up to 19 m, as shown in Fig. 2(a). The weightings obtained from the training are list in Table 1. It can been seen that the weightings are different from 1/4, the value commonly used for standard averaging, particularly for AVN and WRF models at Taitung Open Ocean Data Buoy Station, reflecting the fact that AVN predicts wave heights reasonably well and WRF performs poorly at this location, as shown in Fig. 2(a).

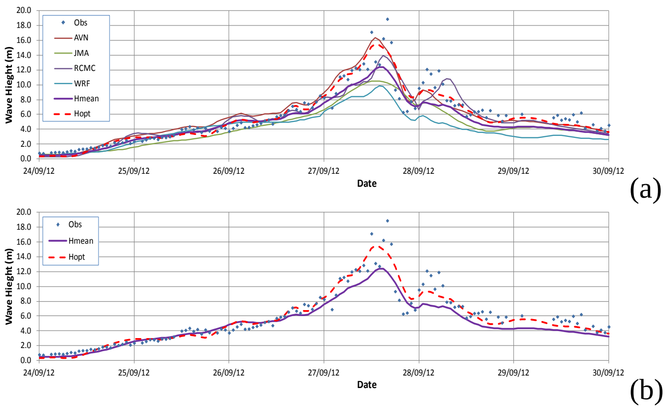


Fig. 2 Time series of the computed and observed wave heights used for training during Typhoon Jelawat at Taitung Ocean Buoy location: (a) with wave heights computed based on wind fields from 4 weather models (AVN, JAM, ECMC and WRF); (b) with mean and optimised weighted wave heights only

Table 1 Weightings from training at Taitung Open Ocean and Pratas Data Buoy Stations

Station	AVN	JMA	RCMC	WRF
Taitung	0.9549	0.2751	0.2667	-0.6453
Pratas	0.3855	0.4937	0.3081	-0.1307

To examine the accuracy of the optimised weightings as listed in Table 1, these weightings are then applied to forecast the wave heights Typhoon Jelawat, which itself was used in training. As shown in Fig. 2(b), it can be clearly seen that with the optimised weightings, the forecasted wave heights (Hopt) are much close to the observed wave heights (Obs), and the peak wave height predictions have been improved significantly, despite the slight under-predictions, as expected.

Fig. 3 shows a scatter plot of the observed wave heights vs the standard mean and optimised weighted average wave heights. It also shows improved averages when using the weightings obtained, particularly for large waves, as indicated by a cycle.

For Pratas Data Buoy Station, the same training process is followed and the optimised weightings are also listed in Table 1. Using these optimised weightings, the wave heights can also be calculated in the same manner.

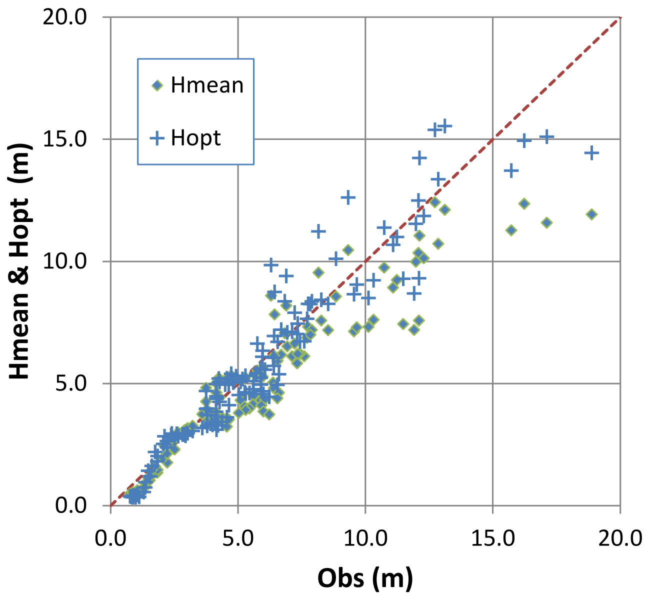


Fig. 3 Scatter plot of mean wave heights (H_{mean}) and optismised weighted average wave heights (H_{opt}) vs obsevered wave heights (Obs) at Taitung Open Ocean Data Buoy Station

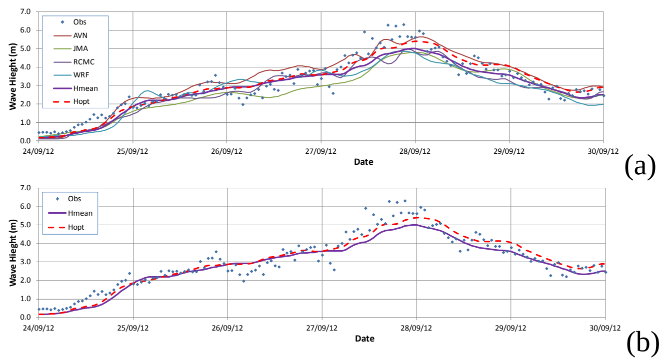


Fig. 4 Time series of computed and observed wave heights used for training during Typhoon Jelawat at Pratas Buoy location: (a) with wave heights computed based on wind fields from 4 weather models (AVN, JAM, ECMC and WRF); (b) with mean and optimised weighted wave heights only

Fig. 4 shows the comparison of model predictions with the standard mean, optimised weighted wave heights and the measurements. At this station, both models AVN and JMA performed equally well, whilst WRF still performed poorly, see Fig 4(a), which are reflected by the weightings. Fig 4(b) shows the improvements of the optimised weighted average wave heights for large waves. The scatter plots (Fig 5) also shows the improved average wave heights.

For other typhoon events: Nanmadol (Aug 26, 2011) and Meari (June 22, 2011), the weighted wave heights with the optimised weightings given in Table 1 are shown in Figs 6 and 8. It is clear that at Pratas, where the wave heights during the typhoons are generally smaller than those at Taitung Open Ocean Data Buoy Station, the optimised weighed averages are better than the standard means.

The large waves for Typhoon Meari have also been well re-produced by the weighted averages, but for Typhoon Nanmadol, the weighted averages are generally slightly higher than the measurements, which nevertheless appears to be acceptable. On average, as shown in Figs 7 and 9, the weighted averages are higher than the measurement, but with a small margin.

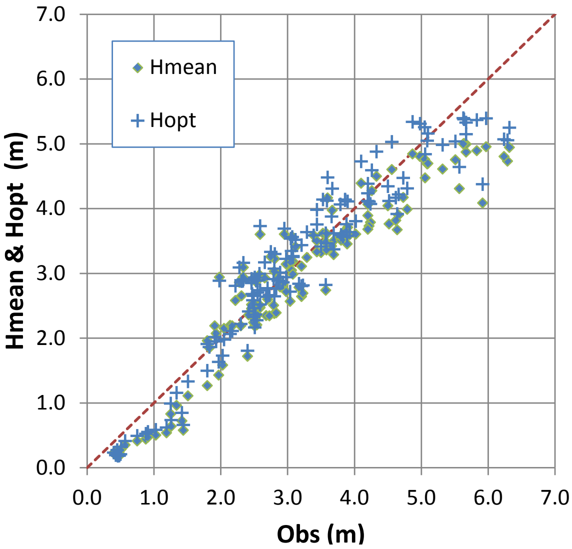
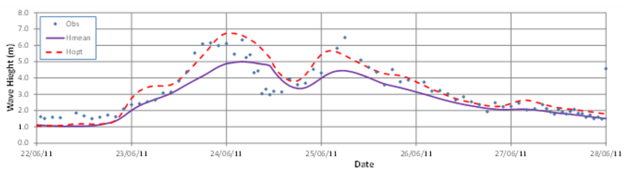
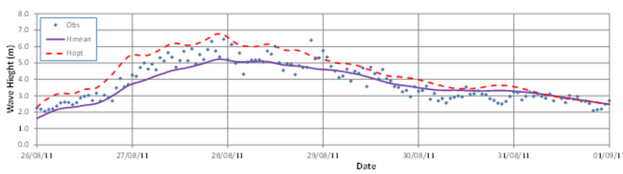


Fig. 5 Scatter plot of mean wave heights (Hmean) and optimised weighted average wave heights (Hopt) vs obsevered wave heights (Obs) at Pratas Station

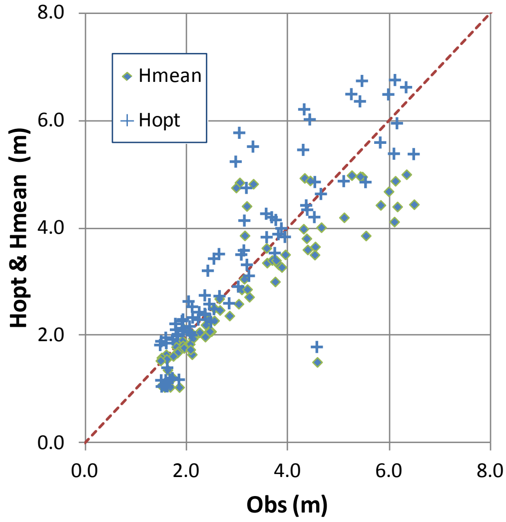


(a)

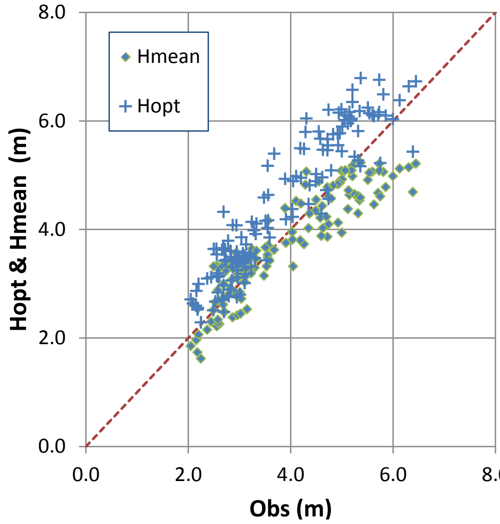


(b)

Fig. 6 Time series of stardard mena and optimised weighted average wave heights at Taitung Ocean Station (a) Typhoon Meari; (b) Typhoon Nanmadol.

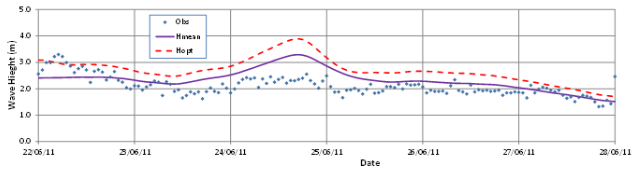


(a)

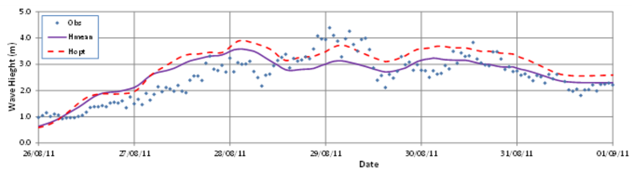


(b)

Fig. 7 Scatter plot of mean wave heights (Hmean) and optimised weighted average wave heights (Hopt) vs obsevered wave heights (Hobs) at Taitung Station for: (a) Typhoon Meari; (b) Typhoon Nanmadol



(a)

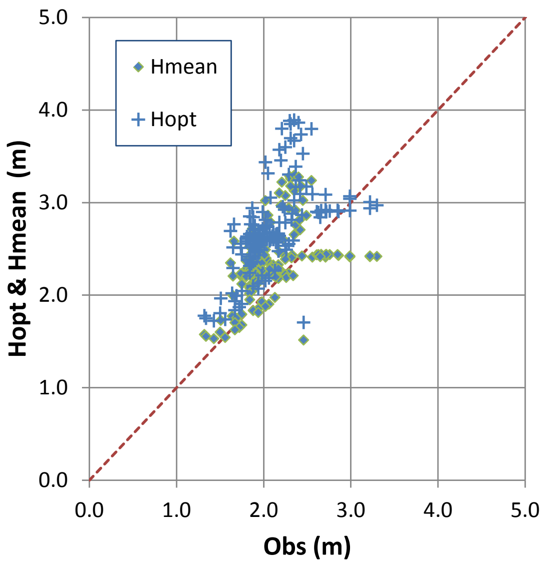


(b)

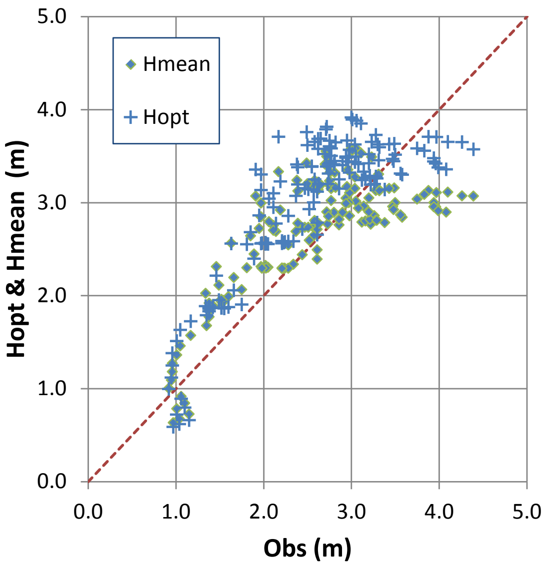
Fig. 8 Time series of stardard mena and optimised weighted average wave heights at Pratas Station (a) Typhoon Meari; (b) Typhoon Nanmadol.

The results clearly show that the "locally weighted learning" algorithm is applicable to optimise the model ensemble results and provide improved wave forecasting in the coastal waters of Taiwan. The algorithm is efficient and easy to implement at particular locations, and the weightings can be updated progressively for real-time wave forecasting.

However, it should be borne in mind that the examples presented in this paper are the results from a short period training, just for around 6 days. It is expected that the results can be further improved if the training is carried out using longer time series of the model results, which will enable to examine fully the variation of weightings with different wave height ranges as an on-going study. In addition, different optimisation algorithms are being explored to deal with the complex hydrodynamic processes.



(a)



(b)

Fig. 9 Scatter plot of mean wave heights (Hmean) and optismised weighted average wave heights (Hopt) vs obsevered wave heights (Hobs) at Pratas Station for: (a) Typhoon Meari; (b) Typhoon Nanmadol

Conclusions

An optimisation has been applied to the model ensemble results obtained from the WAVWWATCH III model forced by the surface winds generated by four weather models. The "locally weighted learning" algorithm was implemented to optimise the weightings for each model results. The optimised weighted averages were calculated and compared with the standard mean wave heights and measurements at Taitung Open Ocean and Pratas Data Buoy stations during three typhoon events (Jelawat, Nanmodol and Meari) in 2012 and 2011. Typhoon Jelawat data at two location (Taitung Open Ocean and Pratas) was using in training. The results show a significant improvement with the optimised weighted averages over the standard means as previously used, particularly for large typhoon-induced waves. It is clear that the proposed optimisation algorithm is well suited the real-time wave forecasting.

Acknowledgements

The authors would like to thank the Central Weather Bureau for providing wind data and the observed wave data. This work was also partly supported by EU-PF7 THESEUS project (Innovative Coastal Technologies for Safer European Coasts in a Changing Climate, Grant No: 244104).

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