Memo

Deltares

To
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Date
27 November 2024

Our reference
11210334-005-ZKS-0005

Number of pages
1 of 6

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Subject
ML model for Eastern Scheldt

1 Summary

This memo is intended for Deltares and Rijkswaterstaat personnel involved in the SWAN North Sea model schematization and operational forecasting systems (RWsOS). It details the training, testing and validation of a Machine Learning (ML) model for SWAN-Kuststrook (KS) in front of the Eastern Scheldt barrier (seaside), as part of the MAD 09 2024 Hydraulica Schematisaties project, within the SWAN North Sea sub-project.

The ML model aims to improve the accuracy of operational wave forecasts at the Oosterschelde 04 (OS4) measurement location by correcting the spectral output of the SWAN-KS model. This improvement will support the ongoing maintenance of the Eastern Scheldt barrier. Unlike previous studies, which did not include OS4, this effort focused on developing a dedicated model specifically for the OS4 location. The key steps involved in this work were to obtain data from: the SWAN-KS model (water level, spectral, and integral wave parameters for OS4), the KNMI Harmonie model (wind direction and wind speed for the Vlakte van de Raan location), and observational data for OS4. Followed by data quality control, training of the ML model, and analysis of the results.

The study demonstrated improved wave spectrum predictions and greater accuracy in integral parameters after applying the ML model corrections, similar to the results of previously trained models (see details in Den Bieman et al., 2023). These findings support integrating this approach into the FEWS operational system for the OS4 location.

2 Machine learning model

This section presents a brief description of the methodology followed during this study. An in-depth explanation can be found in Den Bieman et al. (2023).

In this study, we applied a machine learning model, more specifically a gradient boosting decision tree model (GBDT) called XGBoost, already implemented in Python. A GBDT model make use of multiple decision trees to create a strong predictive model.

The ML model was trained using predictions from the SWAN-KS model, combined with wind input from the HARMONIE model and wave measurement data (see Table 2.1 for details on the various sources and availability). The wave measurement data served as the basis for calculating the target variable, which represents the correction required to match SWAN's output with observed wave measurements. These corrections were calculated for each bin of the frequency spectrum, specifically focusing on energy density, based on the available observational data.

Table 2.1 Overview of input data for the training, validation and testing of the ML model

Variables	Location	Source (RWS Matroos)	Period data availability
Wind speed used in SWAN	Vlakte van de Raan	KNMI HARMONIE model (1)	04/10/2020 – 30/04/2024
Wind direction used in SWAN	Vlakte van de Raan	KNMI HARMONIE model (1)	04/10/2020 – 30/04/2024
Water level used in SWAN	OS4	SWAN-KS (1)	04/10/2020 – 25/11/2022
Spectral wave height predicted by SWAN	OS4	SWAN-KS (1)	04/10/2020 – 13/09/2023
Spectral wave period predicted by SWAN	OS4	SWAN-KS (1)	04/10/2020 – 13/09/2023
Wave direction predicted by SWAN	OS4	SWAN-KS (1)	04/10/2020 – 13/09/2023
Energy density wave spectra	OS4	Observations (2)	01/01/2019 – 01/04/2024

(1) From RWS-Matroos

(2) From Jan-Rolf Hendriks, RWS

For the XGBoost method, the previously optimized model parameters included a maximum tree depth of 25, a minimum of 50 data points per leaf, and a learning rate of 0.05. These parameters were based on the findings of Den Bieman et al. (2023).

The root-mean-squared error (RMSE) is used both as the objective function in the ML model training and to evaluate the performance of the SWAN-KS model and corrected SWAN-KS results (SWAN$_{corr}$).

The total dataset used in the study was randomly split into three subsets: training, validation, and test datasets. The model was trained on the training set, during which the validation dataset is used in the early stopping algorithm. Early stopping helps to determine the number of decision trees to be used in the model. The algorithm stops adding trees when there is no longer an improvement in the model's performance on the validation dataset. Ultimately, once training is complete, the model is evaluated on the unseen test dataset to assess its generalization capabilities. The results of this evaluation are presented in the subsequent section.

The total dataset covers the period from 04/10/2020 to 25/11/2022, a total of 25 months. The timeframe was chosen based on data availability, with water level data being the limiting variable (see Table 2.1). Figure 2.1 presents a visualization of the total dataset for the OS4 location through density scatter plots of wave height, wave period, wave direction, wind speed, and wind direction. These scatter plots illustrate the range of hydrodynamic conditions present in the dataset. In this case, the dataset predominantly includes mild conditions, with wave heights (H_{m0}) of less than 2 meters.

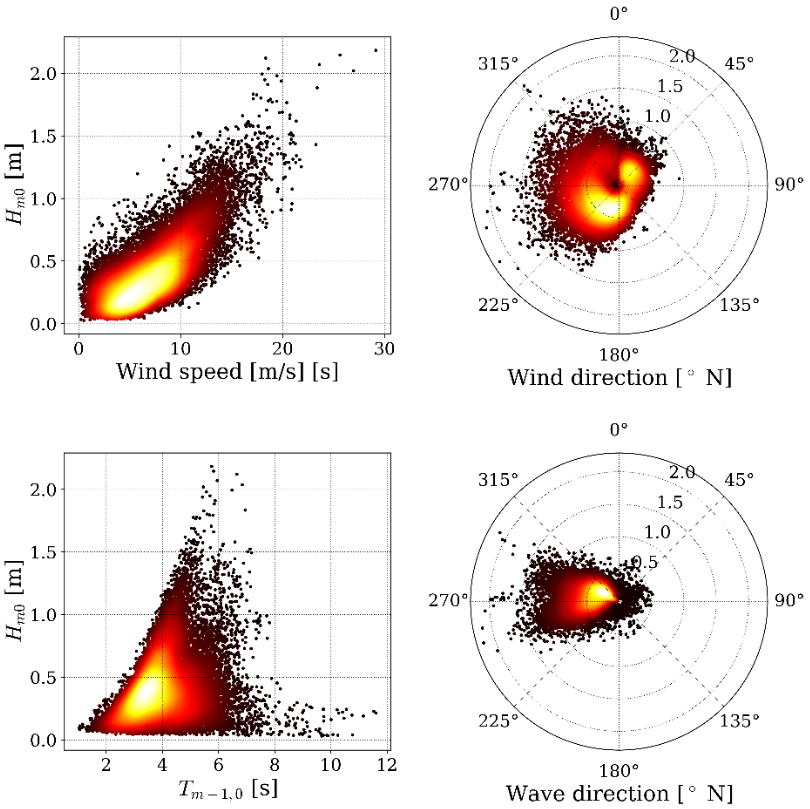

Figure 2.1. SWAN wave data and HARMONIE wind information for the OS4 location used during the ML model training. The upper left panel shows the density scatter of the wave height and the wind speed. The upper right panel shows the density scatter of the wave height and the wind direction. The lower left panel shows the density scatter of the wave height and the spectral wave period. The lower right panel shows the density scatter of the wave height and the wave direction.

3 Results

In this section, we evaluate the performance of the trained ML model on the test dataset. We initially assess how well the model predicts the wave energy density. Subsequently, we evaluate the model's accuracy in predicting spectral wave parameters. To do so, the ML model's predictions are used to correct the initial SWAN spectrum, resulting in a corrected spectrum. This corrected spectrum is then translated into corresponding spectral parameters.

Figure 3.1 displays the root-mean-square error (RMSE) per frequency bin. This figure clearly shows that the RMSE reduction is more pronounced in the middle frequencies, with the most significant improvement occurring between 0.1 and 0.5 Hz.

Additionally, SWAN$_{corr}$'s performance was assessed based on the integral spectral wave parameters, including spectral wave heights (H_{m0} and $H_{m,\mathrm{LF}}$) and spectral wave periods ($T_{m\text{-}1,0}$ and T_{m02}). Figure 3.2 shows a comparison between the spectral parameters predicted by both SWAN and SWAN$_{corr}$ and the observed values from wave measurements for the test dataset. The figure reveals that SWAN$_{corr}$ reduces data scatter, as reflected in the decrease of RMSE across all spectral parameters. For instance, the RMSE reduced from 0.10 m to 0.07 m for H_{m0} and from 0.92 s to 0.40 s for $T_{m\text{-}1,0}$ The most substantial improvement is seen in the spectral periods, where the overprediction by SWAN is corrected by the ML model.

Detailed analysis of the wave spectra and the improvement per frequency bin highlights that the largest effect comes from the redistribution of energy, addressing SWAN's shortcomings, particularly in the upper and lower frequencies (see examples in Figure 3.3). Notably, for this specific dataset, the error in wave heights was already low (RMSE < 0.10 m).

When compared to previously trained models (Den Bieman et al., 2023), similar RMSE reductions were observed. Across the 14 locations, RMSE decreased from 0.21 m to 0.14 m for H_{m0} and from 0.67 s to 0.41 s for $T_{m\text{-}1,0}$. Specifically, in the Western Scheldt region—where the Cadzand and Deurlo locations are somewhere near the OS4 position—RMSE reductions were from 0.15 m to 0.12 m for H_{m0} and from 0.83 s to 0.43 s for $T_{m\text{-}1,0}$. Additionally, the operational SWAN-KS model performed well in estimating spectral wave heights at these Western Scheldt locations, with RMSE remaining below 0.15 m.

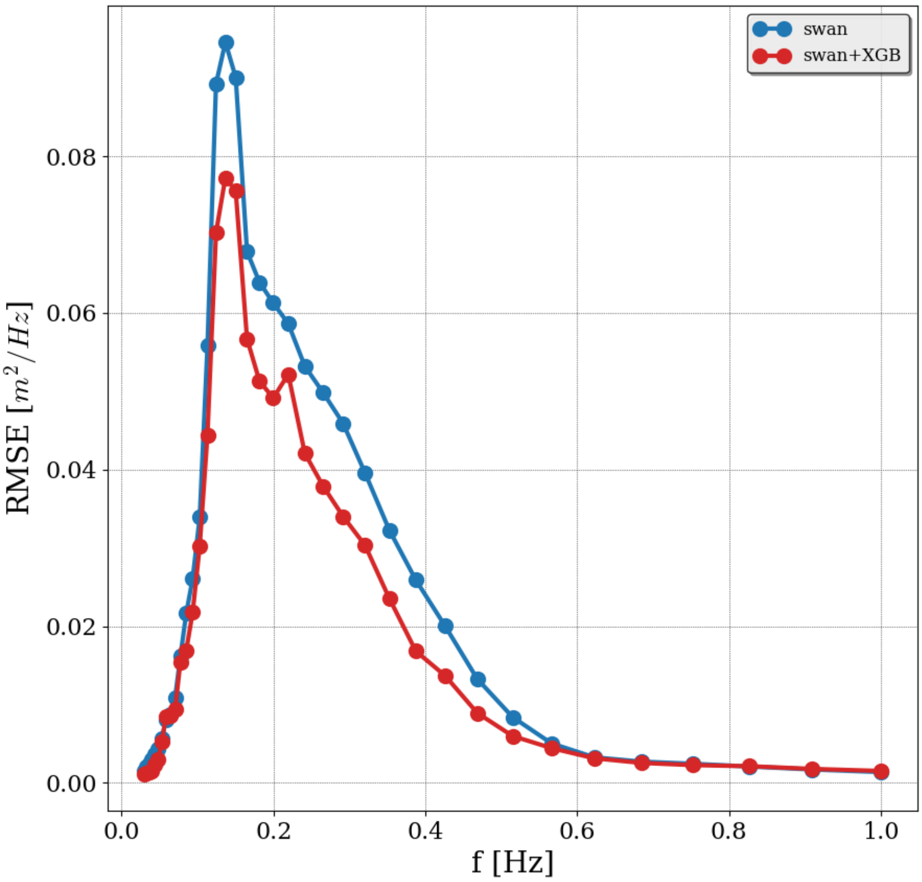

Figure 3.1. Overview of the RMSE per frequency bin for the test dataset. In blue the error associated with the SWAN-KS model and in red the error associated with the SWAN$_{corr}$ *model*

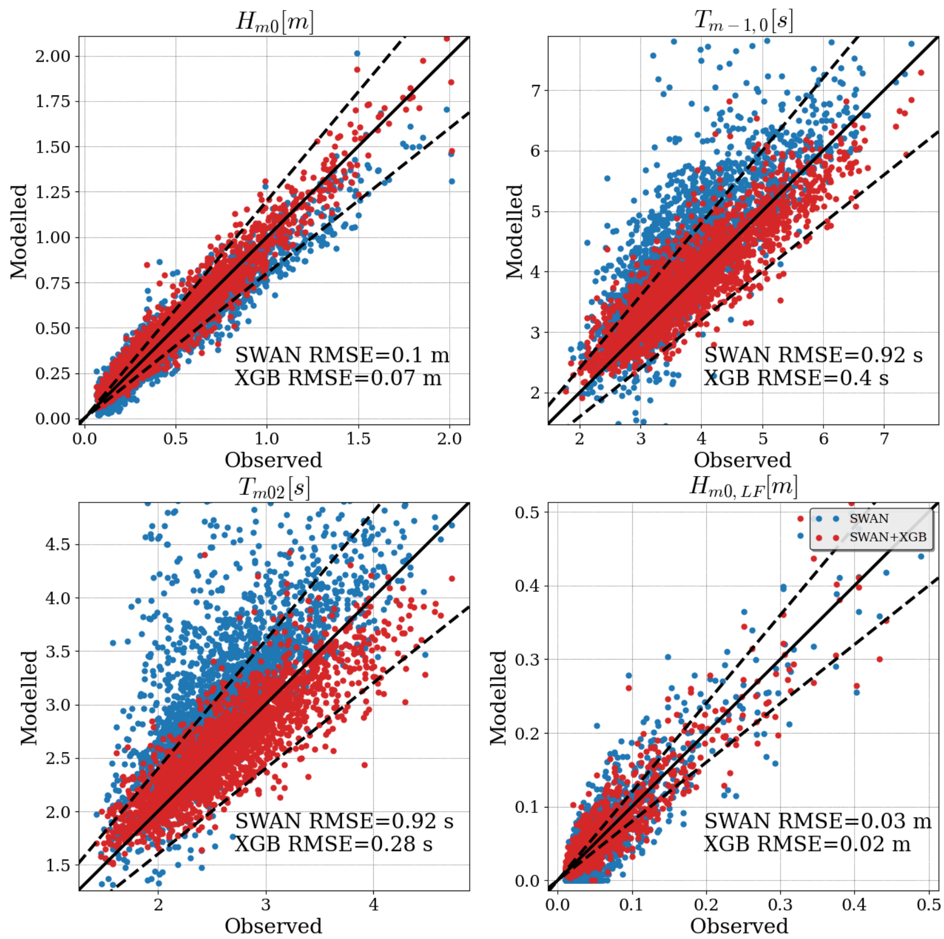

Figure 3.2. Spectral wave parameters and the respective RMSE for the test dataset as predicted by SWAN-KS (blue) and SWAN$_{corr}$ (red)

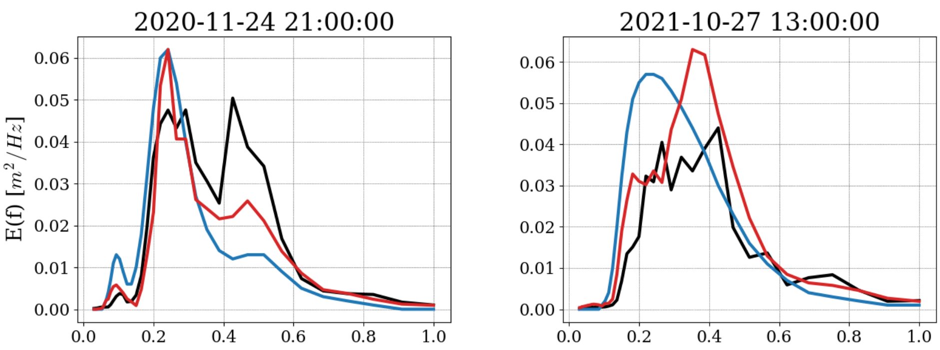

Figure 3.3. Energy density spectra for two moments in time, showing observed (black), SWAN (blue) and SWAN$_{corr}$ (red) predictions. These spectra illustrate the corrections at both lower and higher frequency range.

4 Conclusions and recommendations

The SWAN model, enhanced with XGBoost correction (SWAN$_{corr}$), shows significant improvements over the operational SWAN model. There is a reduction in the RMSE per frequency bin and an improvement in the estimation of the spectral wave parameters, with a 30%, 33%, 57% and 70% decrease in RMSE for H_{m0} and $H_{m,\mathrm{LF}}, T_{m-1,0}$ and $T_{m0,2}$ respectively. These results demonstrate that the SWAN$_{corr}$ model represents a significant improvement over the existing operational wave model, particularly in spectral wave periods, while the operational SWAN-KS model already performed well for spectral wave heights for the OS4 location (RMSE < 0.1 m for H_{m0} and RMSE < 0.03 m for $H_{m,\mathrm{LF}}$).

To implement this model improvement, it is recommended to reintroduce the OS4 location into the SWAN model output. Since September 2023, data from the OS4 location has been unavailable due to updates in the FEWS system. This issue has already been reported to the relevant parties to restore the location's data availability. Once resolved, the implementation of the ML model for the OS4 location can proceed in the same manner as the previous 14 locations trained (Den Bieman et al., 2023).

In this study, we successfully applied the methodology from Den Bieman et al. (2023) to another SWAN-KS model location. The main limitation in extending this approach to additional locations is data availability, highlighting the need for a system to monitor data quality and ensure continuous access to both output data and observational measurements.

5 References

Den Bieman, J. P., de Ridder M. P., Irías Mata M., van Nieuwkoop, J.C.C. 2023. Hybrid modelling to improve operational wave forecasts by combining process-based and machine learning models. Applied Ocean Research 136, 103583. https://doi.org/10.1016/j.apor.2023.103583