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Impacts of physical calibration of a spectral wave model and effects of using different temporal wind inputs

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ABSTRACT: Spectral wave modelling can reduce uncertainties in the estimation of wave energy resource assessment, converter design, extreme value analysis, etc. In spectral models, wave growth is represented with different approaches, resulting in wave resource assessments having large differences especially at high wave values. In this paper a modified version of the North Sea Wave Database is used to quantify the impact of wind temporal fidelity on the wind growth components. The Simulating WAves Nearshore (SWAN) model has been modified, with two different wind inputs used from the European Centre for Medium-Range Weather Forecasts (ECMWF). Results are compared with in-situ measurements an inter-comparison for 20 years (1980-1999). Differences are found on mean and maxima values of wave parameters, with little changes in directionality. However, higher temporal resolution of the wind does not mean always a better hindcast, in fact attention to the calibration of wind-wave growth interactions and whitecaps leads to similar results. Finally, the high fidelity hindcasts are compared, identifying limitations and opportunities for improvements in wave energy assessments.

1 INTRODUCTION

Wave models have emerged as competent tools to assist in covering the metocean gap of information. However, as in any case numerical wave models depend on their configuration, physical tuning, and inputs (i.e. wind, bathymetry, currents, etc.). In 2009 (Cavaleri 2009) discussed the limitations all models have, when it comes to reducing uncertainties in large waves, wave models have a tendency to under-estimate. Since then advancements have been made to the performance of numerical wave models, however the "problem" persists with model under-estimation. Building upon the seminal work of (Komen, Hasselmann, & Hasselmann 1984) that gave way to the WAM-III formulation, that was expanded and modified to WAM-IV and several other configurations ST4, ST6 (Janssen 1988, Rogers et al. 2002, Rogers et al. 2012, Stopa et al. 2016). Improvements in our understanding of wind-wave generation, has allowed several different options to emerge.

Although our understanding and the availability of computational resources keeps on increasing, there is still not clear theory, physical set-up that will create the ``perfect" model. To complicate things further, there are different types of wave models (phase resolving/averaged), and models suitable for different scales (shallow, nearshore, oceanic). Hence, the development of an accurate enough hindcast is determined by several aspects such as the final model usage, modeller's experience, input suitability/quality, regional characteristics, calibration, and validation methods.

Arguably, in all wave models the most influential process is wind generation, and therefore closely connected to wind fields used. Stopa et al (Stopa & Cheung 2014) compared the ERA Interim with NCEP Climate Forecast System Reanalysis (CFSR) to drive a global model (WaveWatchIII), the authors concluded that depending on the Hemisphere wave generation differs and caution is needed when it comes to using a wind dataset. Interim was under-estimating but proved more homogeneous over time, however, for higher values CFSR showed a better agreement. Similar results were reported for higher resolution grids for the cases of Scotland (Lavidas et al. 2017) and the Black Sea (Akpinar et al. 2016, Akpinar and Ponce de León 2016), where the maximum bias performance of CFSR outperformed ERA-interim. However, in both cases the authors did mention the large over-estimations for mean values and larger scatter indices. Which in the case of wave energy assessment may lead to increased over-estimations. Finally, (Stopa 2018) also assessed 10 different wind datasets, the mean performance of generated waves by the model

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wa similar but again larger wave height were differently hindcasted. This study builds upon a calibrated and validated North Sea Wave Database (NSWD) (Lavidas & Polinder 2019, Lavidas 2020a, Lavidas 2020b, Lavidas 2020c, Lavidas 2020d, Lavidas 2020e).

2 WAVE MODEL

For generation of the database a third generation spectral phased averaged model, Simulating WAves Nearshore (SWAN) version 41.20 was used (Delft 2014). For the development of long-term datasets we have to ensure that proper methods are used and most importantly a suitable wave model is utilised (Lavidas & Venugopal 2018, Ingram, Smith, Ferriera, & Smith 2011). The SWAN model is suitable to provide reliable information at the nearshore, as it contains the possibility of modelling complex non-linear interactions that exist near the coastlines. This is highly important, as most first generation wave energy converters (WECs) will be placed near the shoreline, at depths were bathymetry has influence over the metocean conditions.

The model has been set-up with spherical coordinates and a resolution of 0.025°, corresponding to ≈2.25 km longitude (λ) and ≈2 km latitude (ϕ), accounting for the Earth's curvature. Coastline data have been obtained by Amante et al. (Amante & Eakins 2014) and the latest Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG) (Wessel & Smith 1996). Based on the information a bathymetry domain was constructed as input for the model, see Figure 1, the depth is varying "smoothly" without the existence of very sharp depth gradients, due to being on a Continental Shelf. To compare the validated model several locations have been extracted with their coordinates and spatial information given in Figure 3 and Table 1

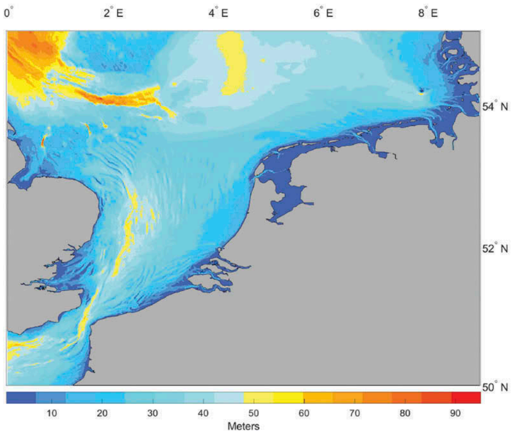

Figure 1. North Sea domain for the study with depth in meters.

Table 1. Locations extracted.

	Longitude	Latitude	Map Number
Brouw	3.61°	51.76°	1
Schouw	3.31°	51.74°	2
Eurdwe	3°	51.94°	3
Eur3	3.27°	51.99°	4
IJ1	4.51°	52.46°	5
IJ2	4.05°	52.55°	6
L91	4.96°	53.61°	7
F161	4.01°	54.11°	8
J61	2.95°	53.81°	9

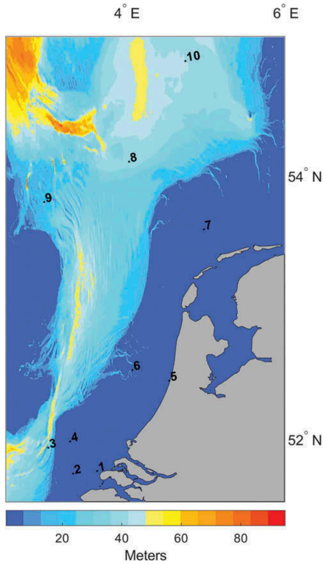

Figure 2. Bathymetry domain depth in meters and locations as numbered in Table 1.

SWAN is a third generation spectral phased-averaged wave model, that accounts multiple physical processes suitable for deep and shallow waters, although arguably it is more efficient for nearshore and Shelf Seas. The wave spectrum is described in time (t) by the action density equation (E), dependent upon angular frequency (σ), direction (θ), frequency (f), energy propagation (c) over latitude (ϕ) and longitude (λ). Sink source terms are used to estimate the wave parameters (see Equation 1), given a specific set of inputs and physical coefficients, with wind input (S_{in}), triads (S_{nl3}), quadruplet (S_{nl4}) interactions, whitecapping ($S_{ds,w}$), bottom friction ($S_{ds,b}$) and ($S_{ds,br}$) depth breaking.

$$S_{tot} = S_{in} + S_{nl3} + S_{nl4} + S_{ds,w} + S_{ds,b} + S_{ds,br} \quad (1)$$

In wave models, generation, propagation and spectrum evolution is dependent on various parameters. Most important source terms are mechanisms of wind S_{in}, and dissipation $S_{ds,w/b/br}$, as they are responsible for wave generation and dissipation. Waves are created by wind surface pressure on the ocean, in wave models this term is modelled by considering a wind drag coefficient (C_D) that contributes to the growth. Wind wave generation is a summation of energy density $E(\lambda, \phi)$ from the S_{tot} (over Spherical coordinates)

3 CALIBRATING FOR WIND

Wind drag coefficients can differ and may enhance or reduce the wave generation capabilities in the model. It is known that wave models tend to under-estimate at lower frequencies (Cavaleri 2009), with accuracy affected by wind components used. SWAN 41.20 introduced an adjusted formulation for wind and whitecapping, similar but not the same to Wavewatch3 (WW3) ST6 (NOAA, Ponce de León, Bettencourt, Van Vledder, Doohan, Higgins, Guedes Soares, & Dias 2017). The wind drag parametrisation requires fine tuning, the sink term of wind input is given in Equation 2

$$S_{in} = A + \beta E(\lambda, \phi) \tag{2}$$

with A linear growth, β is the exponential growth, in order to avoid wave generation at regions below the Pierson-Moskowitz spectrum, β the exponential growth that depends upon estimation of frictional velocity. This in turn affects the momentum flux that is the driver between atmosphere and the ocean surface for wave generation, as the model translates wind at 10 m (U_{10}) to a surface wind, see Equation 3 with an estimation wind drag coefficient (C_D) that depends on U_{10}.

$$U_*^2 = C_D + U_{10}^2 \tag{3}$$

Wind drag estimations have limitations especially for higher wind speeds, where they are known to under-estimate and even limit wave growth, therefore, for every different configuration, the C_D should be adjusted. Kamranzad et al. (Kamranzad and Mori 2019) indicated that even though wind drag parametrisations in models are good at generating waves, they are limited in their performance especially at higher wind values where wave growth is reduced. To alleviate this limitation, a modified formulation was used and since 41.20, a similar approach to that of Rogers et al. (Rogers, Babanin, &Wang 2012) can be activated. All calibration models were tuned using the binned distribution of 36 directions and frequencies, with the latter using a Δf = 0.1. The calibrations were conducted with an Intel Xeon with 36 GB of RAM.

The NSWD used a fully calibrated model with ERA-Interim wind fields, the chosen model was based on the STH123 (ST6) with C_D based on (Hwang 2011), local dissipation (lds): 4.7^{-7} cumulative dissipation (cds): 6.6^{-6}, and scaling 3:35. The scaling option parametrisation aims to correct the mean square slope, Tuning this option has to do with how much energy is allowed to migrate in higher frequencies. With a higher number, lower the amounts that are allowed there, therefore, this can be beneficial to not under-estimate lower frequencies.

This reflected in the detail validation of the model, majority of locations indicate a high agreement for H_{m0} with R within ≈90–94%. For Southern parts of Dutch coastlines (Brouwer, Eur3, Schouw, Eurdwe), R shows a high agreement following the generation trend. Regarding the NSWD bias performance, the database showed an over-estimation by ≈10 cm. Unlike, the trend of mean biases in the NSWD, most maxima values are only slightly under-estimated, usually with a difference of ≈30–80 cm. Scatter Index for all years are with 14–16%, indicating a strong diagonal agreement, and the periods are characterised by mid to high frequency waves, simulated accurately by the model with small under-estimation in magnitude of ≈0.18–0.4 s. For a more in depth look into the validation, please see the (Lavidas & Polinder 2019).

3.1 *Wind inputs*

In the first version of NSWD ERA-Interim winds (Dee et al. 2011) were used, as when the model was constructed a full set of ERA5 winds were not available from 1980s. However, since then ERA5 have been released and closely modified (Hersbach et al. 2019). The ERA5 offer are considered an upgrade from the Interim products, in terms of the wind components, the vertical resolution increased from 60 levels (Interim) to 137 level, with a spatial resolution almost twice as high from 79Km to 39 Km. The wind variables are outputted every 1 hour for ERA5, while Interim was 6-hourly, that implies a better storm representation. The wave boundaries are offered by a newer version of EC-WAM that has three time higher resolution from 1° to 0.36°. Another difference is the data assimilation scheme, for Interim a 4D-Var scheme was used, which at ERA5 was upgraded by using ensemble atmospheric data assimilation leading to reduced biases.

4 RESULTS

Forcing with different winds, even between the same "family" results in different outputs are slightly modified. The results compare individual years from between 1980-1999, with more focus on 1980-1989 and 1990-1999. The reason behind this selection is to asses performance of satellite assimilated and non-assimilated models. Between 1980-1989 the re-analysis is not assimilated with satellite data, whilst for 1990 onward data assimilation exists (Dodet et al. 2020). This in turn allow us to compare the difference in annual and overall terms.

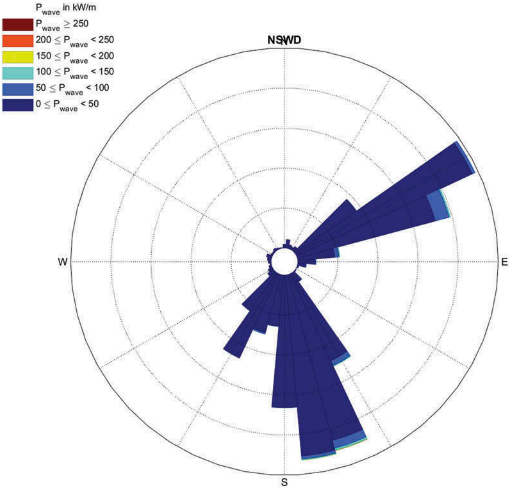

Figure 3. Wave power rose from the ERA-I NSWD 1980-1999.

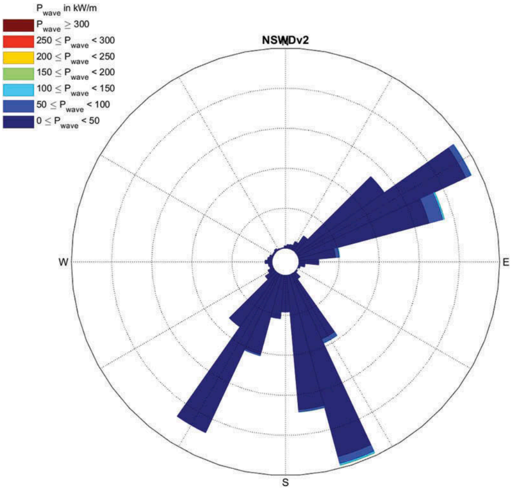

Figure 4. Wave power rose from the ERA5 NSWDv2 1980-1999.

The NSWD driven by ERA-Interim (see Figure 3), shows that most wave power components have a directionality from Easterly and Southern with values $\leq$ 50kW/m. The ERA5 NSWDv2 (see Figure 4) database exhibits similar Easterly and Southern magnitudes, but it also showcases magnitude coming from the South-West. The latter dataset shows there are also less clustered event from the South, with those events having a higher number and smaller intensities in wave power content.

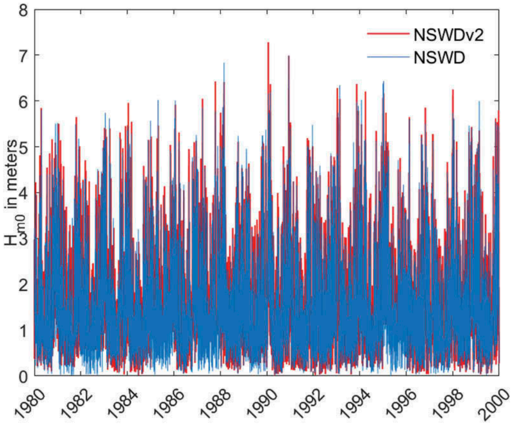

Figure 5. H_{m0} comparison of the dataset 1980-1999, wave generated by the different winds.

Figure 5 shows a direct comparison of the generated combined swell and wind waves, the NSWDv2 showcases higher wave heights at all instances, with particular differences at the highest waves. This can implies that storm conditions, as expected due to temporal and assimilation improvements, to be better captured. However, in the NSWD data the maxima already were only under-estimated slightly, ≈40 cm. Figure 5 shows NSWDv2 is often time more than 0.8-1 meter higher on large wave values. Figure 6 shows only the last year of the on-going hindcast, while the generation trend is similar the difference over large waves are consistent.

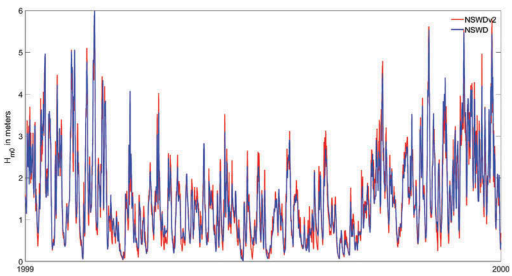

Figure 6. H_{m0} comparison of the dataset 1999, wave generated by the different winds.

Table 2 showcases the differences between NSWD and NSWDv2 in mean values for different variables. Almost universally the NSWDv2 overestimates the means. The difference between the mean values of H_{m0} is $\approx$ 1 cm, see Figure 7. In terms of H_{m0} maxima the differences are higher on average (see Table 3), however, the T_{peak} and T_{m10} are underestimated by the NSWDv2 almost by 1 to 1.5 seconds.

Table 2. Differences of mean values between NSWD and NSWDv2.

	H_{m0}	T_{peak}	T_{m10}	P_{wave}
Brouw	-0.0114	-0.1011	-0.1612	-0.1430
Shoun	-0.0598	-0.1147	-0.1014	-0.4461
Eurdwe	-0.0612	-0.0796	-0.0813	-0.2912
Eur3	-0.0685	-0.1118	-0.1040	-0.4212
IJ1	-0.0651	-0.0055	-0.0446	-0.6040
IJ5	-0.0647	-0.0345	-0.1078	-0.6708
L91	-0.0700	0.0196	-0.1046	-0.2078
F161	-0.1135	0.0899	-0.0850	-1.5565
J61	-0.0729	0.1015	-0.0708	-0.8020

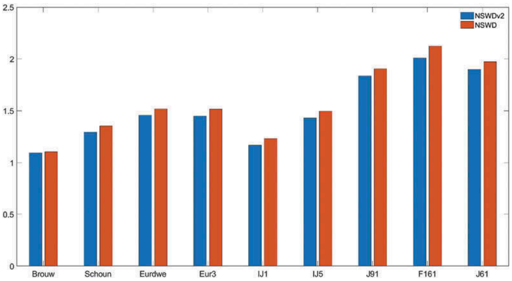

Figure 7. H_{m0} mean values for the datasets.

Table 3. Differences of maxima values between NSWD and NSWDv2.

	H_{m0}	T_{peak}	T_{m10}	P_{wave}
Brouw	-0.1381	0.0000	1.5382	-13.0031
Shoun	-0.2277	0.0000	1.5106	-30.0888
Eurdwe	0.0642	-1.4661	1.0538	-1.6565
Eur3	-0.2916	0.0000	1.2622	-32.3738
IJ1	-0.2819	1.6128	1.1577	-23.7288
IJ5	-0.4577	1.6128	1.2578	-39.6246
J91	0.0997	1.6128	-0.7382	19.1353
F161	0.7264	1.6128	-0.5125	131.2507
J61	0.5467	1.6128	-0.5348	82.9671

5 CONCLUSIONS

Wind inputs have a large impact of wave models, however, physical tuning of wave models allows us to closely match real wave conditions. Furthermore, this can also lead to a "cheaper" computational model, achieving similar accuracies. Forcing winds influence the generation of waves, and result in high waves differences. However, larger waves do not mean a better dataset, while the quality of wind is vital, the physical tuning is and should always be considered of higher importance.

It should be noted that depending on the use foreseen for a wave dataset, different aspects have to given interest. Therefore, while the results of wave hindcasts can be ``optimal" for specific processes and studies, whether these are wave energy, storm surges, Climate Change, etc, they cannot cover all aspects. Although, transferability of hindcasts for other studies is common, the user should be aware of the calibration impacts by a wave model, as if for example one aims to use a hindcast database then the mean bias and scatter index will not be as important as the maximum bias and root-mean-square error.

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