EXPANDING MIKE MS HYBRID WAVE DOWNSCALING: OVERCOMING STATIONARY ASSUMPTIONS FOR CLIMATE STUDIES

Gabriel Vieira de Carvalho[1,2]; Aline Kaji[1]; Pierre Brink Swiegers[3], Johan Henrik Andersson[3], Jacob Tornfeldt Sørensen[3]

This paper introduces the MIKE Metocean Simulator, a novel and efficient hybrid technique for near-shore wave downscaling which advances over existing methodologies by allowing the use of instationary spectral wave propagation within the hybrid dynamical-statistical approach. This modification enables the extension of subdomains beyond the limitations of quasi-stationary wave model propagation assumptions. The MIKE MS's efficacy is validated through a comparative analysis between the stationary and instationary modes, a dynamical instationary simulation, and wave measurements. This study presents advancements in hybrid wave downscaling techniques especially in the context of climate studies where large number of simulations are required for robust assessments.

Keywords: hybrid wave modelling; climate change; Newfoundland and Labrador wave climate

INTRODUCTION

Coastal flooding, driven by high tides, storm surges, and waves, poses a significant threat to coastal regions. It is anticipated that coastal flooding exposure and risk will significantly increase due to sea level rise and socioeconomic growth of coastal areas (Hinkel, et al., 2014; Lincke, et al., 2022). Assessing future coastal flood risk is essential for the planning and implementation of effective mitigation and adaptation strategies. These strategies are crucial for safeguarding the lives and livelihoods of the millions of people living in coastal regions, as well as protecting the economic and environmental value these areas provide. Waves significantly contribute to coastal hazards and accurate projections of the future coastal wave climates are essential to inform and guide coastal flooding mitigation and adaptation efforts.

The assessment of future global and regional wind-wave climate typically relies on results from global spectral wave models forced by 10-meter surface wind speeds from global climate models (GCMs). Several global wave climate projections were developed within the Coordinated Ocean Wave Climate Project (COWCLIP) (Hemer, et al., 2012; Morim, et al., 2020; Meucci, et al., 2024), however, a significant limitation of these models lies in their insufficient spatial resolution to assess the wave climate at a local or regional scale; therefore, requiring downscaling of the offshore wave conditions to nearshore. Furthermore, robust wave climate projections should consider uncertainties in climate modelling by using a multi-model ensemble and considering different socio-economic pathway scenarios (SSPs) (Knutti, et al., 2010; Morim, et al., 2019).

Downscaling offshore wave conditions to nearshore areas can be achieved through process-based models, or so-called dynamic downscaling (e.g., Guo and Sheng, 2017; Casas-Prat and Wang, 2020; Cousineau & Murphy, 2022), statistical methods (e.g. Camus, et al., 2017; Hegermiller, et al., 2017; Lu, et al., 2022) or a combination of both, so-called hybrid downscaling (e.g. Camus, et al., 2011, Camus, et al., 2013; Ricondo, et al., 2023). Dynamically downscaling many GCMs and scenarios can have an immense computational cost, especially when large areas are considered. Addressing this, we expanded on the hybrid wave downscaling framework from Camus, et al. (2013) to develop the MIKE Metocean Simulator (MIKE MS), a cost-effective solution for regional applications. As further explained in subsequent sections, MIKE MS selects discrete events representing offshore wave climate variability, dynamically downscales the subset of events and reconstructs the complete time series at any location within the model domain through statistical interpolation.

The original approach enforced a domain length constraint due to the assumption of quasi-stationary wave propagation modelling — where the domain must be sufficiently small to ensure quicker wave propagation compared to the changes in time in the model forcings. However, to efficiently cover extensive regions, we include the option of using instationary wave simulations with broader model domains to overcome these limitations. Moreover, the MIKE MS framework is designed to handle complex model forcings such as varying waves along the boundaries and spatially varying winds and water levels over the domain at each timestep, which potentially enhances the accuracy of the outputs while also enables the increase in model domain length and represents a scientific innovation, as it has not been attempted in previous hybrid approaches.

In this paper we introduce the MIKE MS framework and present a validation for the system, specifically assessing the use of instationary wave simulations for a relatively large domain.

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[1] DHI Water & Environment Inc

[2] gvdc@dhigroup.com

[3] DHI A/S

MATERIAL AND METHODS

MIKE Metocean Simulator

The MIKE Metocean Simulator (MIKE MS) combines process-based models with statistical techniques to downscale offshore wave climate to coastal areas in a cost-effective way while maintaining satisfactory accuracy. This tool follows the scientific basis and framework developed by Camus, et al. (2013). The MIKE MS basic steps are schematized in Figure 1 and described in the topics below:

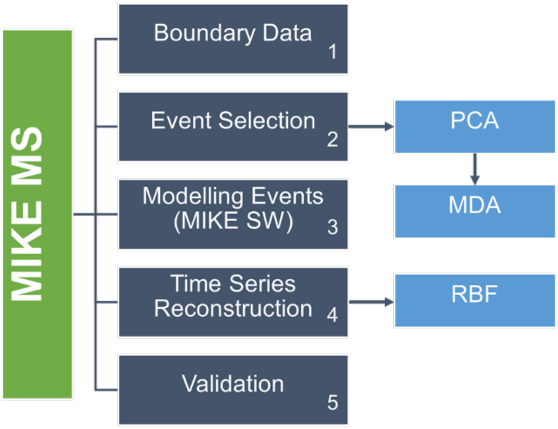

Figure 1: Schematized MIKE MS basic steps.

1. Model Input: Provision of model input data for the whole period of simulation. The model input data can include time series of swell and wind sea wave parameters at multiple points along the model offshore boundaries; space- and time-varying wind components; and space- and time-varying water level fields.
2. Events Selection: Selection of a subset of states from the entirety of model input across all boundaries and over the domain. The event selection involves a two-step process:
   a. Utilizing Principal Component Analysis (PCA) to alleviate the curse of dimensionality's impact on the Maximum Dissimilarity Algorithm (MDA). This method is intended to effectively encapsulate most of the input data variance with an optimal number of principal components (PCs).
   b. Subsequently, the MDA is used to select the most dissimilar states within the PCs space. This selection ensures that the dynamically downscaled events capture a diverse range of variability in model input states.
3. Modeling Events: Dynamical downscaling of the selected subset of events using a state-of-the-art MIKE21 FM Spectral Wave model (DHI, 2024) to calculate wave propagation to nearshore areas.
4. Time Series Reconstruction: Reconstruction of the full time series of wave parameters at each output point using a Radial Basis Function (RBF) interpolator based on the results of the process-based model.
5. Validation: Comparison with wave measurements to assess the system accuracy in representing the observed sea state.

In the following sections, the main steps are described in further detail.

Events Selection

The complete set of forcings and boundaries information for a spectral wave model can represent a substantial dataset. The objective of this step is to select a limited number of states within the model input that best represent the variability of the wave conditions within the model domain. To distinguish and select the events that will be dynamically downscaled, first the dimensionality of the model input needs to be reduced for simplifying the event selection and the final time series reconstruction. The approach used is the Principal Component Analysis (PCA), a statistical technique that aims to create a set of new features in a lower dimensional space while retaining most of the original dataset essential information. Then, the most dissimilar subset of forcing conditions is selected using a maximum-dissimilarity algorithm (MDA).

The main objective of the PCA is to find the minimum number of principal components that explain the maximum variance of the original data. At the end of the PCA, the model input (higher dimensionality) is transformed into principal components (PCs). It is important to check the suitability of the input data and to make all pre-processing prior to applying the PCA. In the present example, the input data was checked for missing values and standardized to ensure each feature has a mean of 0 and standard deviation of 1. The number of PCs used is subject to the user definition and a sensitivity analysis can be conducted to assess the original data variance captured by the PCs. Figure 2 exemplifies the explained variance for each individual PCs, as well as the cumulative explained variance when considering several PCs. It is shown that, for the present experiments, the first three principles components account for 80% of the original input data variance, and a total of 15 PCs are required to represent 95% of the input data variance. In the present experiments, 20 PCs were used, representing 97.5% of the input data variance. The reduction of dimension from 960 to 20 is evident of the large correlation between the variables of the model input.

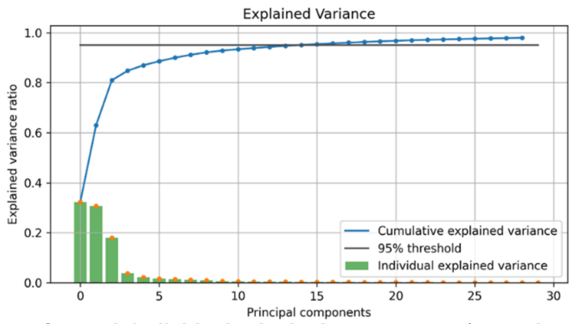

Figure 2: Explained variance for each individual principal components (green bars), the cumulative explained variance (blue line) and the threshold of 95% of the explained variance (black line). It is shown that 95% of the input data variance is explained by the first 15 PCs.

After the dimensionality reduction of the PCA step, the maximum-dissimilarity algorithm (MDA) is applied to select a subset of size M from the N states contained in the model input. The MDA is started by selecting the most energetic state from the model input, and then the rest of the subset sea-states are selected iteratively, calculating the dissimilarity between the remaining data in the model input and the elements of the subset and transferring the most dissimilar to the subset. Figure 3 presents an example of the event selection process result, showing 300 selected states over 2 years of hourly model inputs at the central southern model boundary.

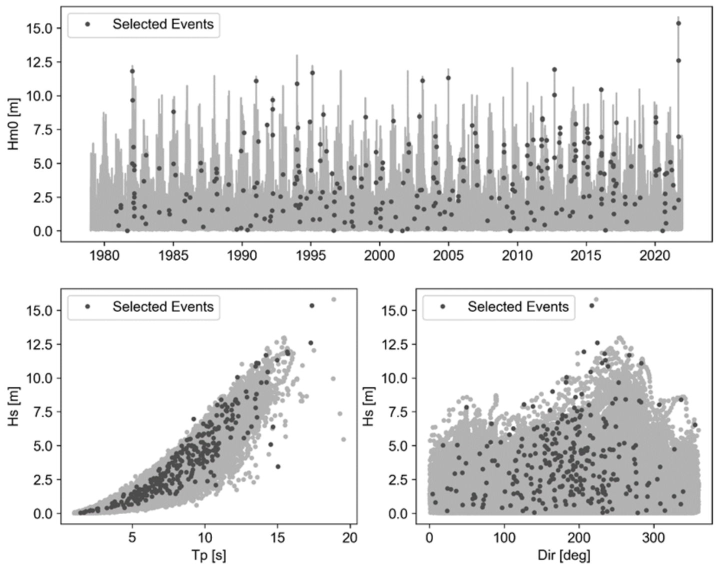

Figure 3: Significant Wave Height time series at boundary (upper panel) and scatter of the Significant Wave Height against Peak Period and Mean Wave Direction (lower panels). Complete set of model wave boundary input at the central southern boundary (light grey) and 300 selected events after completion of the PCA and the MDA steps (dark grey).

Wave Propagation (MIKE SW FM)

The subset of events selected in the previous step are dynamically downscaled using DHI's MIKE21 Spectral Wave (SW) Flexible Mesh (FM) wave propagation model. MIKE21 SW FM is a new generation spectral wind-wave model based on unstructured meshes. The model simulates the growth, decay and transformation of wind-generated waves in offshore and coastal areas, including the main relevant physical processes, such as wave growth by wind action, non-linear wave-wave interaction, dissipation due to white-capping, bottom friction, depth-induced wave breaking, and refraction and shoaling due to depth variations and wave current interaction.
The fully spectral formulation is based on the wave action conservation equation, as described in (Komen, et al., 1994) and (Young I.R., 1999), where the directional-frequency wave action spectrum is the dependent variable. For this study, the selected parameterizations for the source and dissipation terms are based on the Modified WAM Cycle 4 (Günther, et al., 1992). The discretization of the governing equations in geographical and spectral space is performed using cell-centered finite volume method.
MIKE SW FM simulations can be performed using a quasi-stationary or an instationary mode. In the quasi-stationary formulation, which is a similar approach used in Camus, et al. (2013), the time is removed as an independent variable and a steady state solution is calculated for each model input. It is crucial to note that the quasi-stationary approach poses a domain size constraint: the domain must be small enough to ensure that the wave propagation occurs at a faster rate than the change in the forcings along the domain. Disrespecting the stationary assumption can cause a phase shift in the results as well as loss of accuracy in the Hm0 peaks (over or underestimation). In the instationary formulation, the integration in time is based on a fractional step approach. Firstly, a propagation step is performed calculating an approximate solution at the new time level by solving the basic conservation equations without the source functions. Secondly, a source function step is performed calculating the new solution from the estimated solution considering only the effect of the source functions.
The original approach presented by Camus, et al. (2013) runs the dynamical wave model in quasi-stationary mode to be able to consider the subset propagations as independent. In this work we test the hypothesis that dynamical downscaling the selected events using the instationary mode would avoid the domain size constraints due to the stationary assumption. The proposed approach is to set each selected event run with a spin-up time, storing the results only for the last time step (the selected event). Therefore, the time and spatial forcings variability are properly represented in the wave simulation, enforcing higher accuracy to the final stored output for the selected event timestep. During this step it is possible for the user to calibrate the dynamical wave model setup parameters, ideally based on model-data comparisons.
The desired variables to be reconstructed must be defined as outputs of the dynamic wave model, for all desired output locations – as this is one of the inputs for the complete time series reconstruction. The analysis can be focused on one point within the domain – i.e. the location of a wave buoy – or on multiple points. For example, a user can specify a grid of points with defined spatial resolution along the coastal area and use it to reconstruct spatial instantaneous maps and spatial statistics.

Time Series Reconstruction

After the output wave bulk parameters are stored from the simulations of the selected events, the reconstruction of the complete time series is performed by an interpolation technique using a radial basis function (RBF).
The RBF interpolator utilizes the complete set of PCs for all time steps to estimate the target variables (H_{m0}, T_p, x- and y-components of the mean wave direction) for each time step. This is achieved by drawing upon the learned relationship between each target variable values obtained from the dynamically simulated events and their corresponding PCs. The estimated unknown target variable values for each related set of PCs are computed as a weighted sum of the radial basis functions plus a matrix of monomials, which span polynomials of degree 1. The RBF interpolation is mathematically expressed as follows:

$$f(x) = \sum_{i=1}^{N} \alpha_i \, \phi\left(||x - y_i||\right) + P(x)\beta_i$$

where $f(x)$ represents the estimated wave parameters values, ϕ is the chosen radial basis function kernel, and $||x - y_i||$ is the Euclidean distance between the set of PCs (x) linked to the $f(x)$ timestep and the set of PCs (y_i) linked to each dynamically simulated target variable values. The polynomial term $P(x)\ \beta_i$ allows for adjustment based on linear trends or baseline shifts in the time series data. In the present work, the thin plate spline kernel was used:

$$\phi(r) = r^2 \ln(r)$$

where r is the Euclidian distance between data points ($||x - y_i||$).
The optimal coefficients α_i and β_i are determined during the training phase of the interpolation process which involves solving a system of linear equations. The RBF interpolation is trained using the PCs from the dynamically simulated events and their corresponding known target variable values. During this phase, the interpolator determines the coefficients α_i and β_i such that the sum of the weighted radial basis functions plus the polynomial term best approximates the known target variables values obtained in the dynamic simulations. The Mean Wave Direction is reconstructed after the interpolation of the x- and y-components.

MIKE MS BENCHMARK

The experiment design was oriented to objectively evaluate the performance of the MIKE MS algorithm in stationary and instationary modes and assess the accuracy sensitivity to the number of simulated events within the MIKE MS algorithm.
A twin-experiment approach was conducted by setting up three models: a full instationary hindcast for a 2-year period (FULL_HINDCAST), a MIKE MS hindcast in stationary mode (MS_STAT) and a MIKE MS hindcast in instationary mode (MS_INSTAT). Each MIKE MS model comprises a set of runs with an increasing number of events subsets ranging from 40 to 1000 events (Table 1).
Hourly wave measurements from a wave buoy located at the entrance of Placentia Bay (54.685°W/46.980°N, see location in Figure 4) were used to evaluate the model's performance. The assessed wave parameters include H_{m0} and MWD - representative of the full wave spectra. The data covers the full modeled period (01-Jan-2020 to 31-Dec-2021) and were obtained from the Ocean Networks Canada Data Portal.
The complete set of results were compared against the wave bulk parameters reported by the Placentia Bay Mouth wave buoy, enabling the assessment of the MIKE MS algorithm ability to match the FULL_HINDCAST, and to evaluate the systems performance in representing a realistic wave climate.

Table 1: Experiments Design

	Time Range	Output	Number of events
FULL_HINDCAST	2020-2021	Hourly H_{m0} and MWD	-
MS_STAT			40, 60, 80, 100, 120, 140, 160, 180, 200, 300, 500, 1000
MS_INSTAT			

Model Setup

The model domain used for the experiments covers part of the southwest portion of Newfoundland, Canada, encompassing Placentia Bay and Fortune Bay, with a maximum length of 287 Km (3.6°, Figure 4). The FULL_HINDCAST, MS_STAT and MS_INSTAT experiments were set to cover from 01-Jan-2020 to 31-Dec-2021 (2 years).
The bathymetry was obtained from the Canadian Hydrographic Service Non-Navigational Bathymetric Data (NONNA) and interpolated to an unstructured mesh using triangular elements with a horizontal resolution varying from 10 Km to 1.5 Km near the shoreline (Figure 4). The model has three offshore boundaries and a land boundary.
The model was forced with hourly two-dimensional fields of wind speed and direction from the global ECMWF-ERA5 hindcast (Hersbach, et al., 2020) and water level fields from the DTU10 global tide model (Cheng and Anderson, 2011) as well as hourly time series of wave parameters of each spectra partition (sea and swell) at the offshore boundaries. Therefore, for each hour the model forcing state is defined by nine boundary points (three for each lateral boundary) with eight variables each - Swell and Wind-Sea Significant Wave Height (Hm0), Peak Period (Tp), Mean Wave Direction (MWD) and Directional Standard Deviation (DSD) - plus a 2-D wind components field and a 2-D water level field, summing up to 960 individual forcing information each hour, for a total of 17,521 hours (two years). It is worth noting that considering such a high-level of complexity for the wave model inputs was not attempted in previous hybrid wave modelling approaches.
The model provides hourly time series of wave bulk parameters at selected output locations.

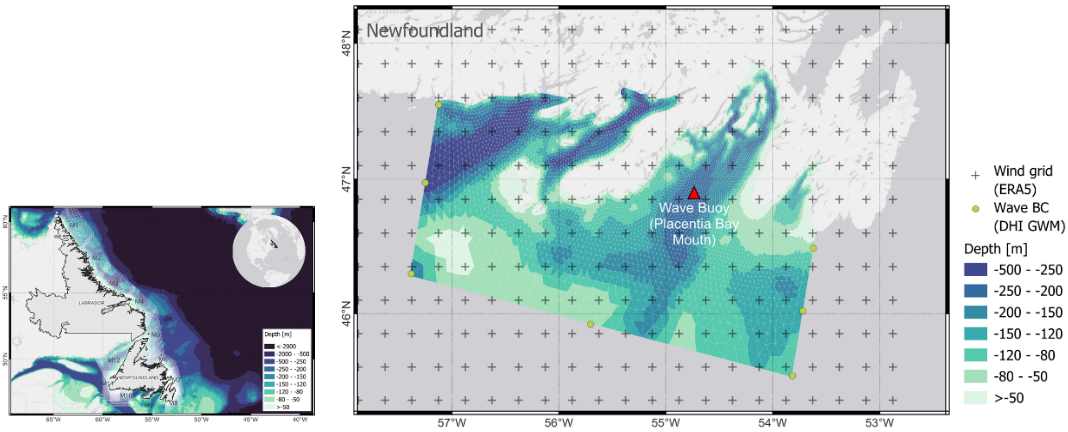

Figure 4: Project Study area (left) and local MIKE MS mesh depicting: the unstructured mesh elements and bathymetry, the wave buoy used to evaluate model results, the wind forcing spatially varying grid, and the boundary points where the wave conditions are imposed into the computational domain.

Error Metrics

The computed comparison metrics are the Root Mean Squared Error (RMSE), the BIAS and the linear correlation coefficient (CORR):

$$BIAS = \frac{1}{n}\sum_{i=1}^{n} x_i - y_i$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$$

$$CORR = \frac{\sum_i((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\sum_i(x_i - \bar{x})^2 \sum_i(y_i - \bar{y})^2}}$$

Where x and y are the modeled and observed values, respectively.

Inter-experiment Assessment and Validation

Figure 5 presents the observed and modeled Hm0 time series for two high energetic events occurred in November 2020. The phase shift and peak overestimation observed in the Hm0 time series for the MS_STAT result indicates that for this model domain length the conditions are no longer stationary. It also shows that the MS_INSTAT successfully corrects this behavior, providing a better fit to the observed Hm0 as well as to the FULL_HINDCAST results. Figure 6 presents the scatter plots comparing observed and modeled Hm0 and MWD for the two MIKE MS experiments with 1000 events and the FULL_HINDCAST, showing very similar accuracy.

It is important to recognize that results of instationary simulations are inherently influenced by antecedent time steps. This interdependence, while seemingly effective in the context of the study area, requires further investigation to ascertain the applicability of the methodology to regions exhibiting greater variability in storm evolution and weather patterns. Presently, it is hypothesized that this challenge may be addressed simply by increasing the number of principal components (PCs) and/or the number of selected events.

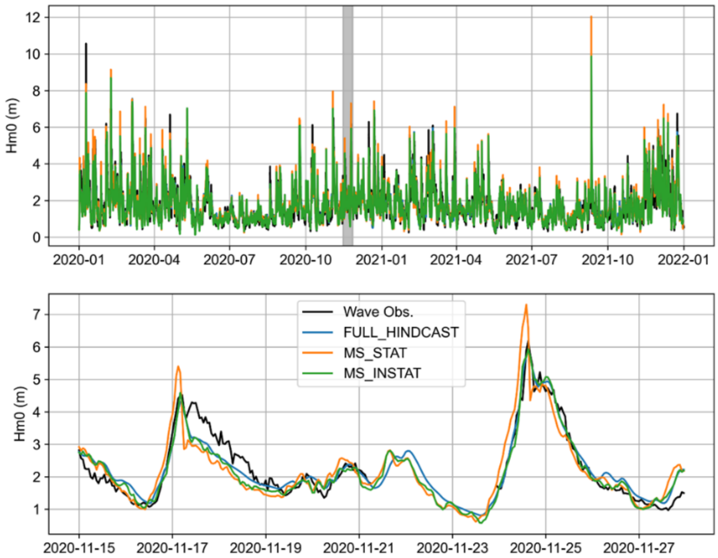

Figure 5: Hm0 time series (observed and modeled) for the entire simulation period (top) and for two consecutive energetic events depicting the phase-shift in the MS_STAT results (bottom).

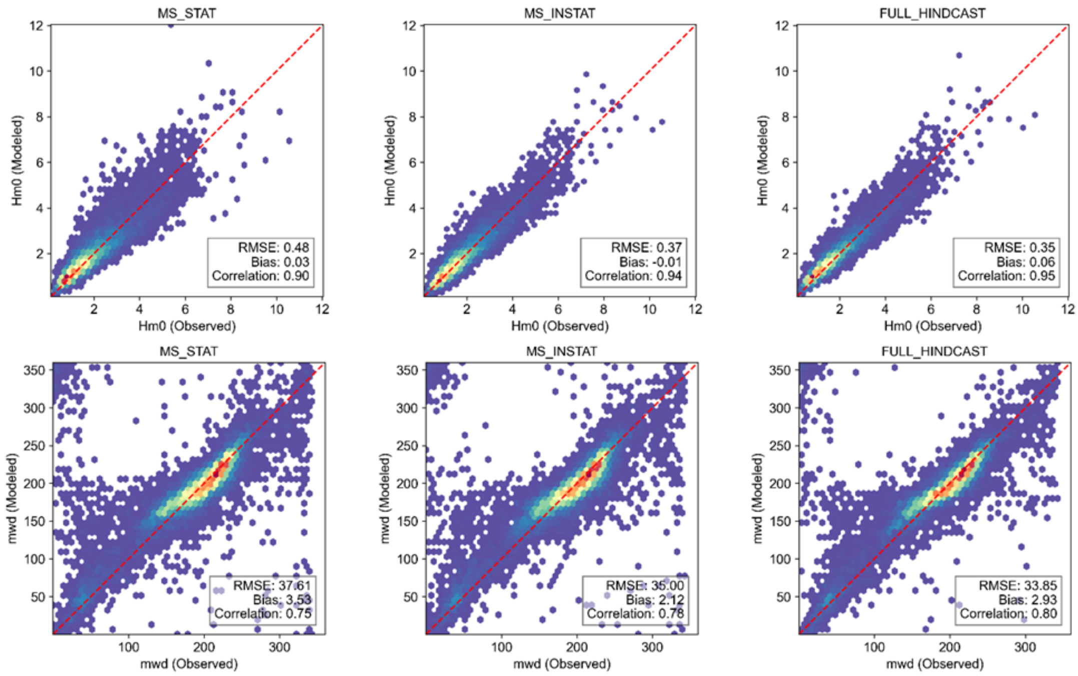

Figure 6: Scatter plots comparing observed and modeled Hm0 and MWD at Placentia Mouth for MS_STAT, MS_INSTAT with 1000 elected events, and FULL_HINDCAST. Each plot includes a 1:1 reference line (red dashed line) and key statistical metrics: RMSE, bias, and correlation coefficient.

For a more comprehensive assessment, Figure 7 present the H_{m0} error metrics between the different experiments and the measurements. For the MS_STAT and MS_INSTAT the plot considers the increasing number of selected events simulated with the wave model. Table 2 and Table 3 present the plotted values for all error metrics and experiments.
A solid line is used to illustrate the RMSE and CORR for the FULL_HINDCAST. This experiment is taken as the best possible solution as errors from this simulation are caused by other factors, such as bathymetric schematization, uncertainties in the forcings, and not by the MIKE MS methodology. Therefore, for the purpose of this assessment, the metrics of the FULL_HINDCAST are considered as target metrics.

For the MS_INSTAT and MS_STAT experiments, it can be noted that the metrics rapidly improves by increasing the number of discrete events up to 200, and then presents an asymptotic behavior. It is also notable that the MS_INSTAT needs less discrete events to reach an accuracy level like the FULL_HINDCAST.

Although relevant for this study objectives, it is important to acknowledge that the performance of the MS_STAT is compromised due to the violation of the stationary assumption for this domain length and this constraint should not hold for smaller domains.

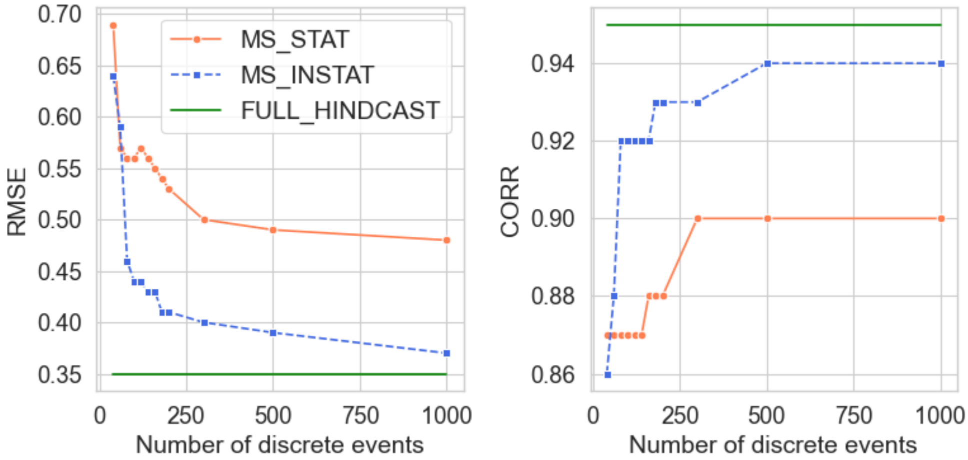

Figure 7: Model-Data Comparison RMSE and CORR between the FULL_HINDCAST, MS_STAT, and MS_INSTAT models against the Placentia Bay Mouth wave buoy for Significant Wave Height (H_{m0}) with increasing number of discrete events simulations.

Table 2: Model-Data comparison metrics (BIAS, RMSE and CORR) between the Placentia Bay Mouth Wave Buoy and the FULL_HINDCAST experiment for Significative Wave Height (H_{m0}) and Peak Period (T_p).

	FULL_HINDCAST		
Parameter	**BIAS**	**RMSE**	**CORR**
H_{m0}	0.06	0.35	0.95

Table 3: Model-Data comparison metrics (BIAS, RMSE and CORR) between the Placentia Bay Mouth Wave Buoy Significative Wave Height (Hm0) and the MS_STAT and MS_INSTAT models with increasing number of discrete events simulations.

	Significant Wave Height (Hs)					
	MS_STAT			**MS_INSTAT**		
n_events	**BIAS**	**RMSE**	**CORR**	**BIAS**	**RMSE**	**CORR**
40	-0.14	0.69	0.87	0.23	0.64	0.86
60	0.05	0.57	0.87	0.20	0.59	0.88
80	0.00	0.56	0.87	0.10	0.46	0.92
100	-0.03	0.56	0.87	0.08	0.44	0.92
120	0.02	0.57	0.87	0.09	0.44	0.92
140	0.03	0.56	0.87	0.08	0.43	0.92
160	0.01	0.55	0.88	0.05	0.43	0.92
180	-0.03	0.54	0.88	0.00	0.41	0.93
200	0.00	0.53	0.88	0.02	0.41	0.93
300	-0.04	0.50	0.90	-0.04	0.40	0.93
500	0.01	0.49	0.90	-0.01	0.39	0.94
1000	0.04	0.48	0.90	-0.01	0.37	0.94

The ability to estimate the directional distribution of H_{m0} is assessed by comparing the wave roses of the MIKE MS experiments against the wave buoy observations (Figure 8). It can be observed that the MIKE MS experiments successfully reconstruct the percentage distribution of the MWD associated with the H_{m0} at site and yield very similar results when compared to the FULL_HINDCAST.

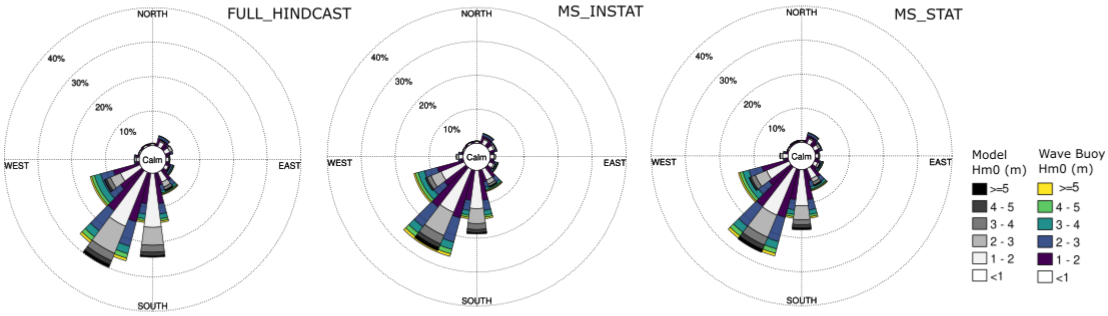

Figure 8: Wave rose (directional histogram) comparisons between the FULL_HINDCAST, MS_STAT, and MS_INSTAT models against the Placentia Bay Mouth wave buoy.

The computational cost gain of this hybrid approach is a function of several factors such as the number of considered discrete events, the number of time series to reconstruct, the range of the reconstructed time series, among others. Nevertheless, it is interesting to note that the number of simulated events needed by the system to provide good results is more related to the representation of the model input variability than to the time span of the time series to be reconstructed and thus, the computational gain increases significantly for long-term projections such as needed in climate studies. For example, the MS_INSTAT using a subset of 300 selected events presented a computational gain of 5 times for a 2-year simulation and a 50 times computational gain for a 40-years simulation while keeping a similar accuracy when compared to wave measurements.

Conclusions

In this study, we presented the MIKE Metocean Simulator (MIKE MS), a novel approach to near-shore wave downscaling that builds upon existing hybrid dynamical-statistical framework and incorporates two main scientific innovations that has not been attempted in previous hybrid approaches. The first is including the option of using instationary wave simulations, overcoming the domain-length constraints when using quasi-stationary wave simulations. The second is the developed approach for selecting cases with varying waves along the boundaries, as well as spatially and temporally varying winds and water levels, providing additional complexity and robustness for the wave downscaling process.

The effectiveness of MIKE MS was evaluated through comparative analyses involving both stationary and instationary modes, alongside a full instationary spectral wave hindcast simulation, and validated using real-world wave measurements.

The proposed modification to the hybrid wave downscaling technique using instationary wave simulations proved to successfully overcome the stationary assumption limitations allowing a broader domain length while keeping a good performance when compared to the best possible solution of running a full instationary spectral wave hindcast simulation. The MIKE MS computational gain increases for long-term projections while maintaining a similar accuracy when compared to running a full instationary hindcast. MIKE MS is approximately 50 times faster than an instationary dynamical simulation over a 40-year hindcast and a higher computational gain is expected for longer hindcasts. This modified approach increases the potential of the hybrid technique especially in the context of climate change studies, where it is of utmost importance to consider the uncertainties in climate modelling by downscaling an ensemble of GCMs and considering different SSPs. Our adoption of a computationally efficient hybrid framework for downscaling nearshore wave conditions proves effective, maintaining accuracy compared to traditional dynamical downscaling. The framework developed during this work can be easily implemented to increase the number of ensemble members in climate wave models downscaling, leading to a more robust assessment of climate change impacts on wave conditions and providing valuable insights for coastal planning and resilience efforts.

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