Uncertainty-associated directional wave spectrum estimation from wave-induced ship responses using Machine Learning methods

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Prologue

- Presentation based on Nielsen *et al*. (2024)
- Thanks to my co-authors (Kazuma Iwase, Raphaël Mounet, Gaute Storhaug)
- Basically, the study is a direct continuation of a previous study, focused entirely on synthetic data

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Research paper

Uncertainty-associated directional wave spectrum estimation from wave-induced ship responses using Machine Learning methods

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ABSTRACT

This paper presents an assessment of three methods used for sea state estimation via the wave buoy analogy, where measured ship responses are processed. The three methods all rely on Machine Learning exclusively but they have different output; Method 1 provides bulk parameters, Method 2 yields a point wave spectrum and the wave direction, while Method 3 gives the directional wave spectrum in non-parametric form. The assessment is made using full-scale data from an in-service container ship in cross-Atlantic service. Training and testing of the methods are made using data from a wave radar, and the three methods perform well. An uncertainty measure, equivalently, a trust level indicator, based on the variation between the post-processed outputs of the methods is proposed, and this facilitates determination of estimates with small errors; without knowing the ground truth.

1. Introduction

The measuring of wave spectra and sea state parameters serves a vast number of engineering and scientific fields; e.g., shipping, offshore wind energy, physical oceanography, wave energy conversion, ocean modelling, weather forecasting and climate research, to mention just a few (Nielsen et al., 2023a). The measured wave spectrum may have a direct use, say, in predicting ship performance and safety levels of a specific ship sailing on a given route, and for producing "weather windows" related to critical lift operations in wind farm installation processes. Or, the measured spectrum may be used indirectly, for instance, to calibrate the outcome of a spectral wave model, and for assessment of mechanisms of surface-water mixing and air–sea fluxes for understanding weather and climate changes.

Among other observation platforms, wave buoys are used to measure waves in the oceans. As an alternative to wave buoys, measured ship responses can be analysed using the analogy between a buoy and a ship. Thus, ships can also act as "wave meters", offering an *estimate* – in real-time – of the sea state exactly at the ship's position, and referring to the technology by the 'wave buoy analogy' (WBA). There is a wide and increasing literature about this technology, with studies for both dynamically positioned and advancing ships, i.e. ships with zero and nonzero forward speeds, respectively, where (Tannuri et al., 2003; Pascoal et al., 2007; Simos et al., 2010; Brodtkorb et al., 2018; Brodtkorb and Nielsen, 2022; Ren et al., 2021; Han et al., 2022; Bisinotto et al., 2024) consider ships without forward speed while (Iseki and Ohtsu, 2000; Iseki and Terada, 2002; Nielsen, 2006, 2008; Nielsen and Stredulinksy, 2012; Montazeri et al., 2016; Chen et al., 2019; Mak and Duz, 2019; Duz et al., 2019; Kawai et al., 2021; Nielsen and Dietz, 2020; Mittendorf et al., 2022; Takami et al., 2022, 2023) consider ships *with* forward speed; emphasising that *all* existing studies are not listed. Accounting for all inherent complexities (e.g., forward speed, detailed hull geometry, size-induced low-pass filtering effect) compared to purpose-built wave buoys, overall, ship-based wave estimation using the WBA is not a competitor but rather a supplement; with real-time spatio-temporal estimates not offered by wave buoys or other observation platforms such as remote sensing and third generation wave models.

Conceptually, the WBA is typically formulated using a model-based framework or using a Machine Learning (ML) framework. The former relies fundamentally on availability of ship (wave-to-response) transfer functions. Machine learning frameworks, on the other hand, avoid the use of transfer functions as wave estimation capabilities instead are learned through training on big datasets of measured (historical) data consisting of ship responses and corresponding sea state information. Each framework has pros and cons, and, ultimately, it could be meaningful to think in directions of a combination through a hybrid

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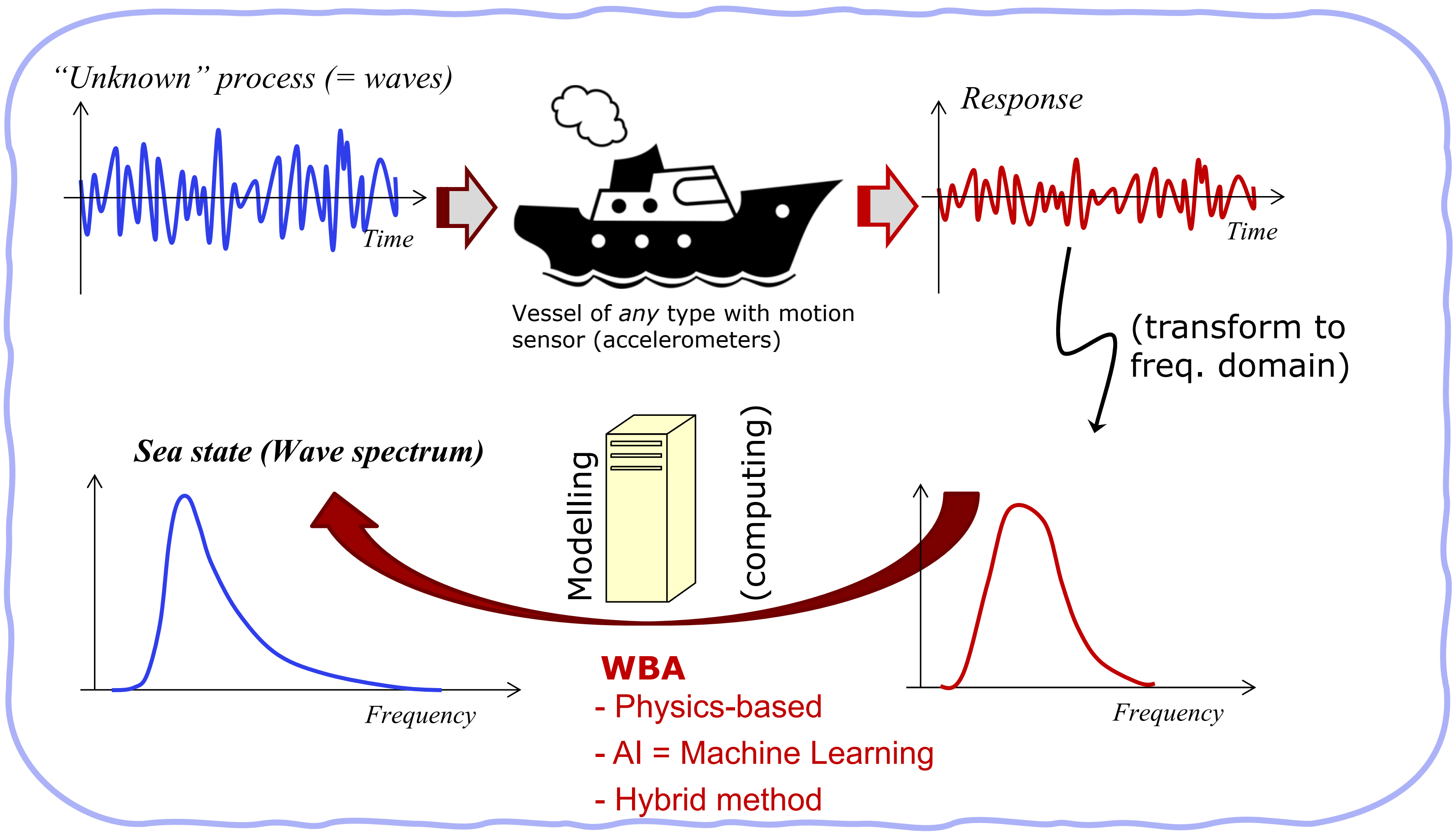
Nielsen *et al.* (2024)
https://doi.org/10.1016/j.apor.2024.104042

Agenda

1. Introduction (aim, objectives, motivation)
2. Methodology
3. Results and discussions
4. Conclusions

Introduction – Schematic illustration (the ship as a wave buoy…)

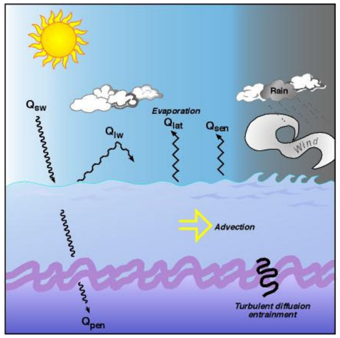
Wave Buoy Analogy (WBA)



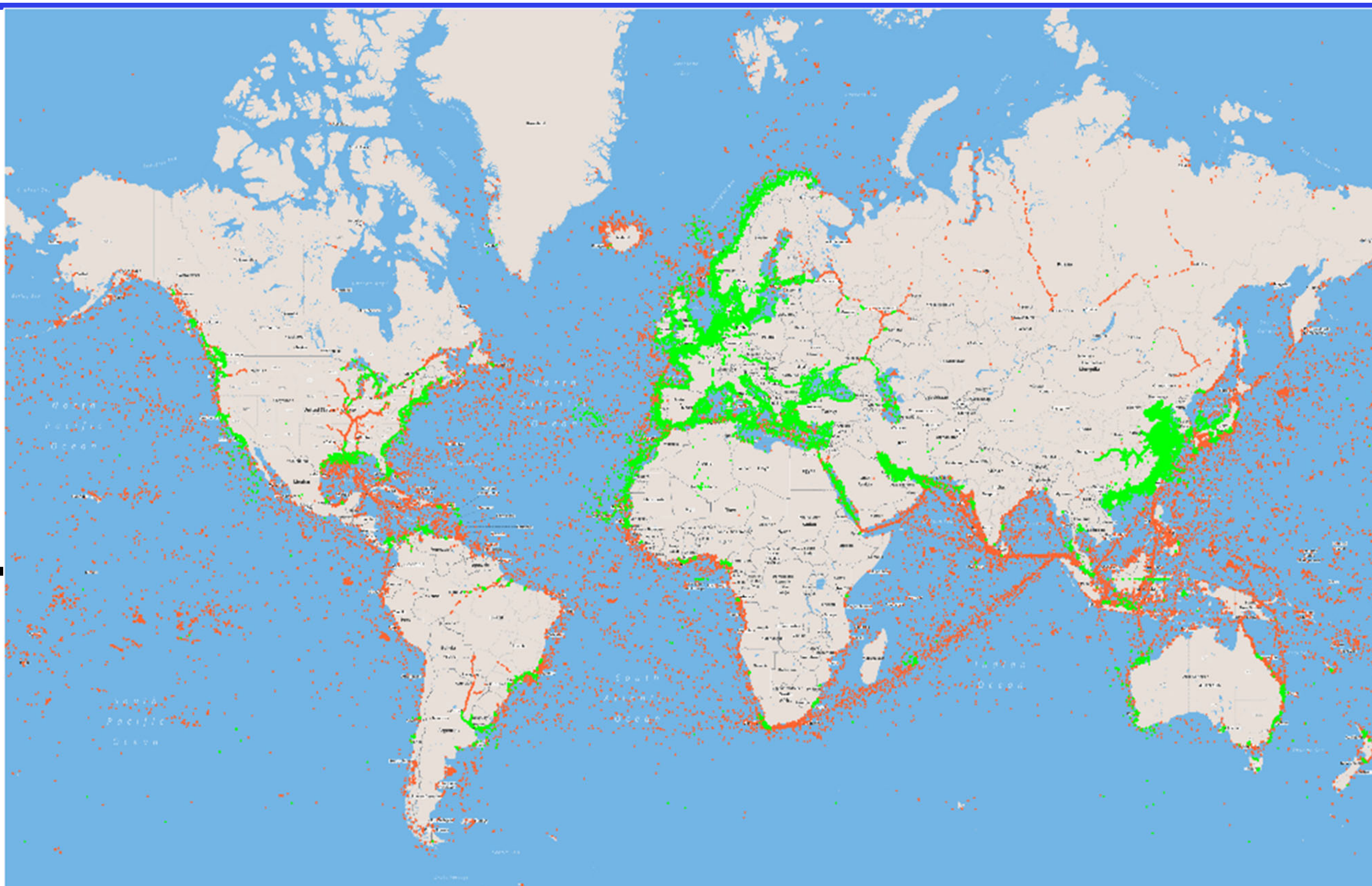
Introduction

- Directional wave spectrum is needed for many applications, e.g.,
  a. Onboard DSS
  b. Ship performance monitoring (safety and fuel consumption analyses)
  c. Updating and calibration of wave databases
  d. Studies related to weather and climate

- Wave estimation using the **ship as a wave buoy is attractive** due to the analogy to the classical wave buoy…



The potential…



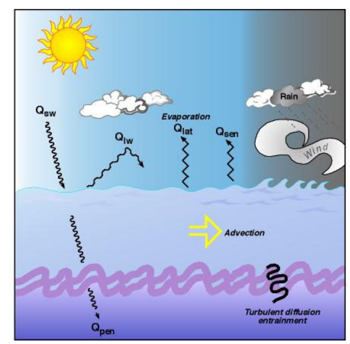
… of ships as sailing wave buoys

Introduction

- Directional wave spectrum is needed for many applications, e.g.,
  a. Onboard DSS
  b. Ship performance monitoring (safety and fuel consumption analyses)
  c. Updating and calibration of wave databases
  d. Studies related to weather and climate

- Wave estimation using the ship as a wave buoy is attractive
  1. ~~Model-based (transfer function dependent) approaches~~
  2. Machine learning (ML) approaches entirely relying on *measured* data

- ML approaches in estimation of the directional spectrum
  – Many unknowns; is dimensionality reduction necessary? (some studies claim/believe)
  – What about forward speed?
  – Can we infer about the associated uncertainty?
  (different frameworks may produce different results)

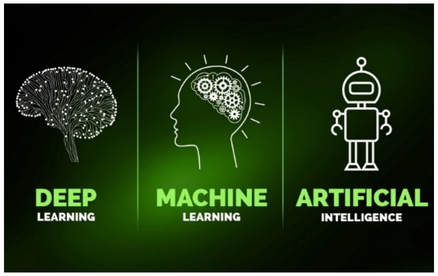


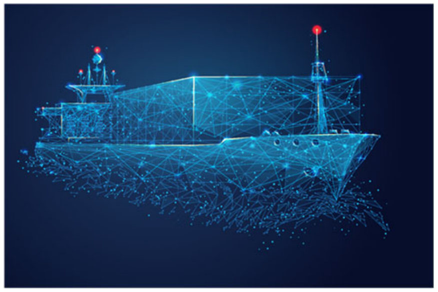
Objectives

1. Make estimation of directional wave spectrum **based exclusively on machine learning** for a ship *with* forward speed

2. Include an uncertainty measure ("level of trust") to estimates of the sea state (wave spectrum)

Motivation for using machine learning





- The use of transfer functions offers introduction of the real physics (hydrodynamics) of the ship; however,
- **the use of transfer functions will typically be associated with a significant amount of uncertainty**;

❖ the **software** / **calculation method** is *always* an approximation of reality, not to mention the use of a linear theory

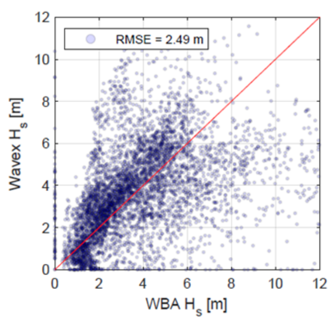
❖ **operational conditions** (speed, draught, damping, GM, etc.) are not always known with a high level of trust, *if* known at all

❖ **All of this is particularly true when practical** (industrial) **applications**, relying on *in-service* data, **are considered**

Motivation for using machine learning, cont'd

- Concrete observations made (Nielsen et al., 2023); although detached from the context
- Nevertheless, for illustrative purposes it serves its meaning…

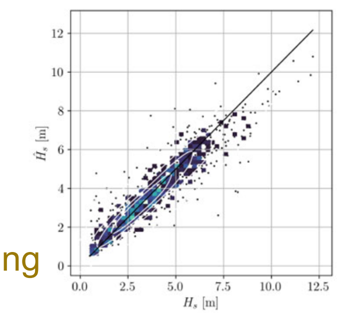
Only wave parameters:

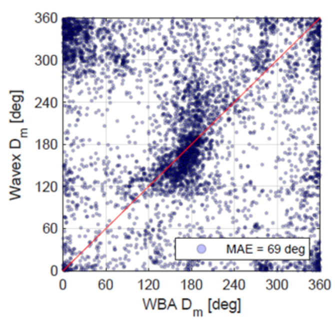


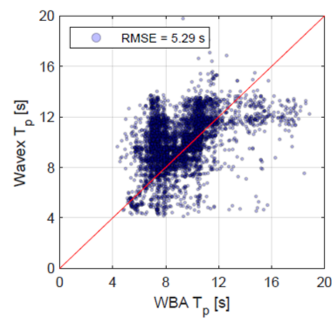
Same dataset… but different frameworks…

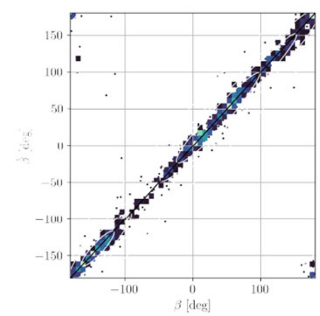
Dependent on Transfer functions

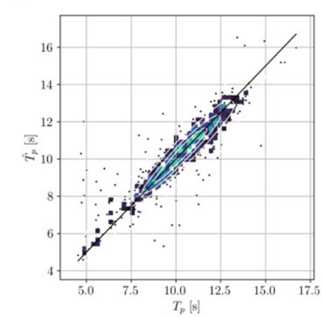
Dependent on Machine learning











Methodology – The “recipe” for what we do

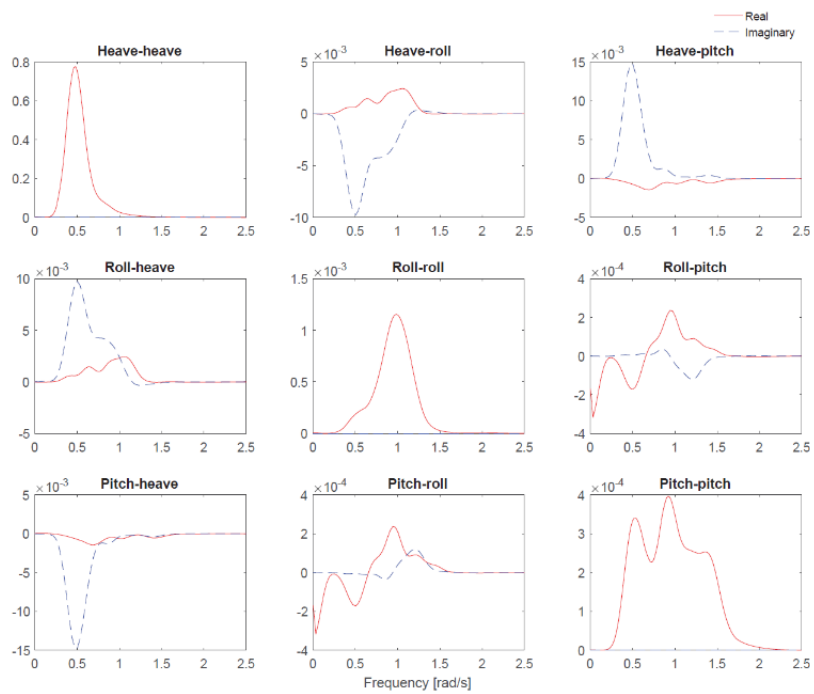
- Three machine learning models are investigated:
  1. Method 1: Outputs integral wave parameters
  2. Method 2: Outputs a point wave spectrum together with mean and peak wave directions
  3. Method 3: Outputs the full directional wave spectrum

- **Input data** is the measured responses (using their corresponding *spectra*), with ship speed as a feature

- **Output data** (target) is the *sea state*; as specified for the given method in study (see above)

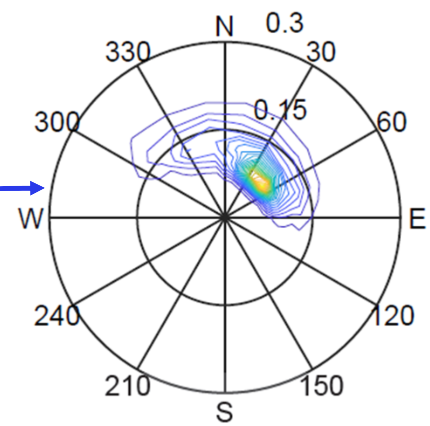
Methodology: Input data vs. Target data

Input



Output

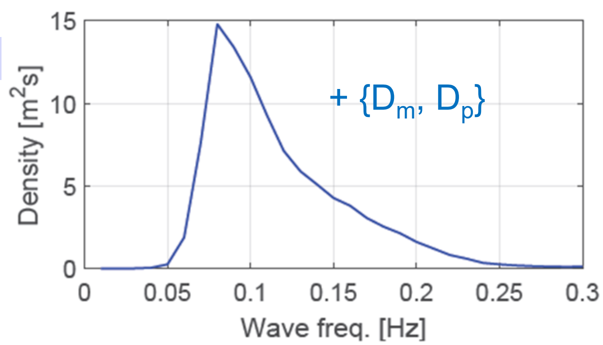
Method 3



Method 2

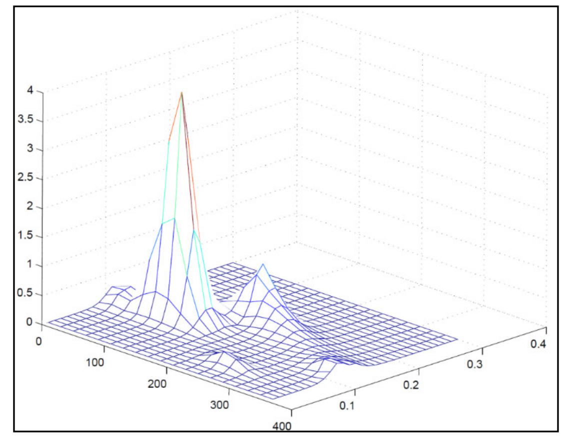
Method 1

$\{H_s, T_z, T_p, D_m, D_p\}$



Methodology: Parameter settings

- **Input** (the same for all three methods)**:**
  - 3 + 6 spectra
  - Discretized at 31 frequencies on the interval 0 – 0.3 Hz
  - In total, 9 x 31 + 1 = 280 input parameters



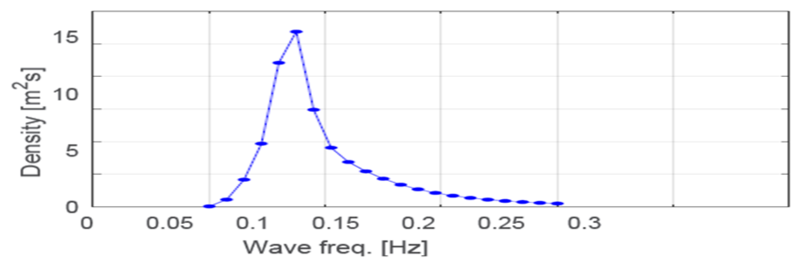
- **Output:**
  - Method 3 has 399 target variables

$$\begin{bmatrix} E_{1,1} & \cdots & E_{1,19} \\ \vdots & \ddots & \vdots \\ E_{21,1} & \cdots & E_{21,19} \end{bmatrix}$$

$$\omega_\iota = 2\pi(0.030 \cdot 1.12^{\iota-1}) \text{ rad/s} , \ \iota = 1:21$$

$$\nu = (0^\circ : 20^\circ : 360^\circ)$$

  - Method 2 has 23 target variables (21 spectral ordinates + D_p and D_m)



  - Method 1 has 5 target variables (H_s, T_z, T_p, D_m, D_p)

Methodology: Machine learning architectures

- Methods 1 and 2: LightGBM (a tree-based learning algorithm)
  - Outputs one parameter, so parallel, independent "streams" are needed
  - Note that a *directional variable* (D_p, D_m) requires two streams as sine and cosine are introduced for handling the ambiguity (0 deg and 360 deg is the same)

- Method 3: Artificial Neural Network
  - Tensorflow (Python)
  - Four layers, activation function is ReLU, with 2,000 nodes in the hidden layers

Wave spectrum characterisation of Methods 1 and 2

- For consistent comparison of the methods, idealized and / or parameterised spreading function are introduced.
  - Bretschneider spectrum (ITTC) and cosine-2*s* function:

$$S_B(\omega) = \frac{A}{\omega^5} \exp\left[-B/\omega^4\right] \ , \text{with}$$

$$A = \frac{H_s^2}{4\pi}\left(\frac{2\pi}{T_z}\right)^4 \ ; \qquad B = \frac{1}{\pi}\left(\frac{2\pi}{T_z}\right)^4$$

$$\varphi(\nu^*) = A(s)\cos^{2s}\left(\frac{\nu^*}{2}\right), \ A(s) = K\frac{2^{2s-1}\Gamma^2(s+1)}{\pi\Gamma(2s+1)}$$

$$E(\omega,\nu) = S(\omega)\varphi(\nu^*) \ ,$$

$$\nu^* = \nu - D_p$$

NB: For Method 2, only the directional spreading function is needed.

Uncertainty in estimate: Trust level indication

- The deviation between the three estimates (Methods 1,2,3) in a given scenario, represented by sample k, is introduced as a quanti-qualitative measure of the uncertainty

- For the directional spectrum, one has

$$\chi(\omega,\nu)(k) = \frac{\left(\frac{1}{N_\lambda - 1} \sum_{\lambda=1}^{N_\lambda} (E_{k,\lambda}(\omega,\nu) - \widetilde{E}_k(\omega,\nu))^2 \right)^{1/2}}{\widetilde{E}_k(\omega,\nu)} \qquad \psi^{E(\omega,\nu)}(k) = \sqrt{\frac{1}{N_\iota N_\nu} \sum_{\iota=1}^{N_\iota} \sum_{\mu=1}^{N_\nu} \chi(\omega_\iota,\nu_\mu)(k)} \ ,$$

$$\widetilde{E}_k(\omega,\nu) = \frac{1}{N_\lambda} \sum_{\lambda=1}^{N_\lambda} E_{k,\lambda}(\omega,\nu)$$

Remarks:

- λ represents the method (1, 2, and 3)
- Mathematically, the uncertainty measure (ψ) is the square root of the mean of the CoV at the discrete spectral point

- **IMPORTANT** observation: The uncertainty measure is computed ***without*** knowledge about the ground truth

Error measures

The hat-notation represents the estimate

- Integral wave parameters:

$$\varepsilon_y(k) = |\hat{y}_k - y_k| / y_k$$

$$y = \{H_s, T_p, T_z\}$$

$$\varepsilon_y(k) = \min\{|\hat{y}_k - y_k|, (360^\circ - |\hat{y}_k - y_k|)\}/180^\circ$$

$$y = \{D_m, D_p\}$$

- Wave spectra:
  - Point spectrum (normalised integrated absolute error)

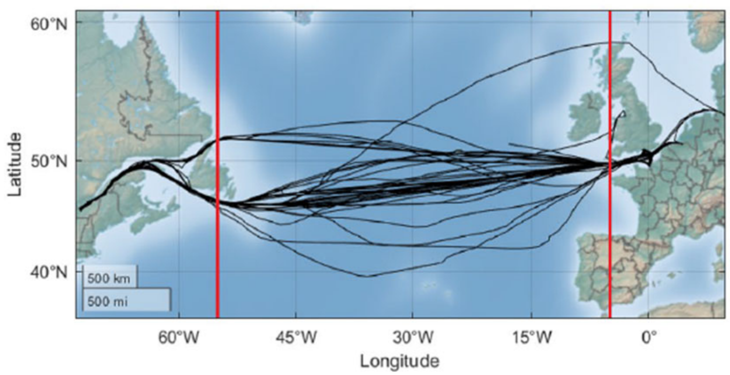
$$\mathrm{NIAE}(k) = \frac{1}{m_{0,k}} \int_0^\infty \left| \hat{F}_k(\omega) - F_k(\omega) \right| d\omega$$

  - Directional spectrum (normalised summed absolute error)

$$\mathrm{NSAE}(k) = \frac{2\pi}{T_p H_{s,k}^2} \sum_\iota \sum_\mu |\hat{E}_k(\omega_\iota, \nu_\mu) - E_k(\omega_\iota, \nu_\mu)|$$

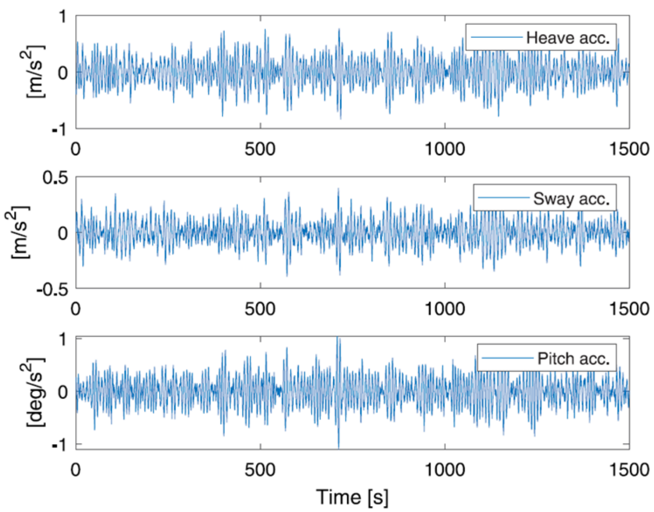
In-service data: Ship, route and sensor installations

L_{pp} = 232 m (length)
B = 32.2 m (breadth)
T = 10.8 m (design draught)
CB = 0.685 (block coefficient)
DWT = 40,900 t (deadweight)



Data recording

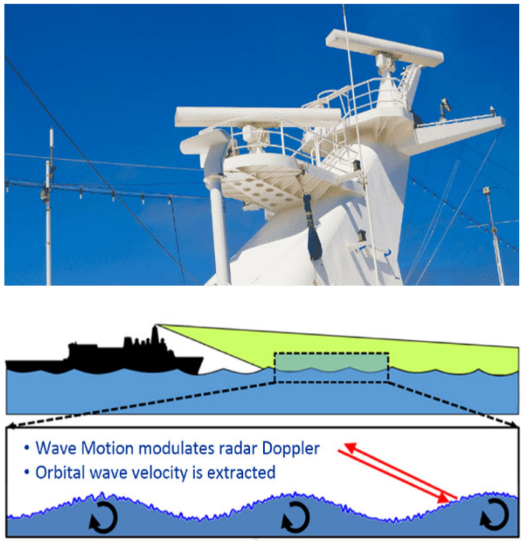
- GPS data (position and speed)
- Wave radar (Wavex by MIROS)
- Motion measurements and strain gauges
- Corresponding transfer functions

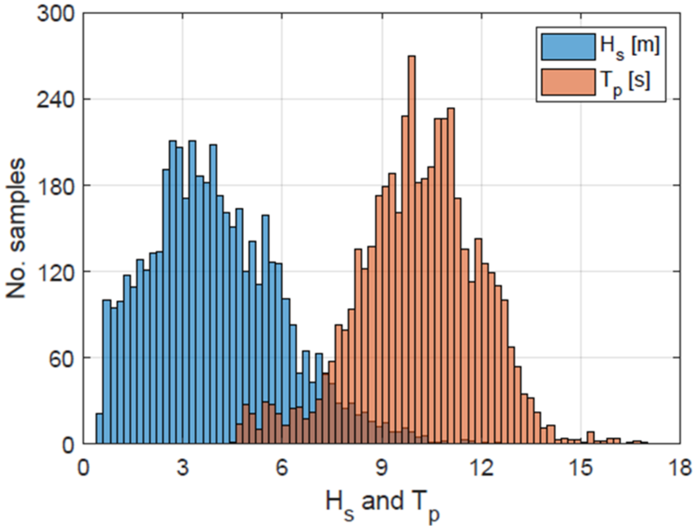


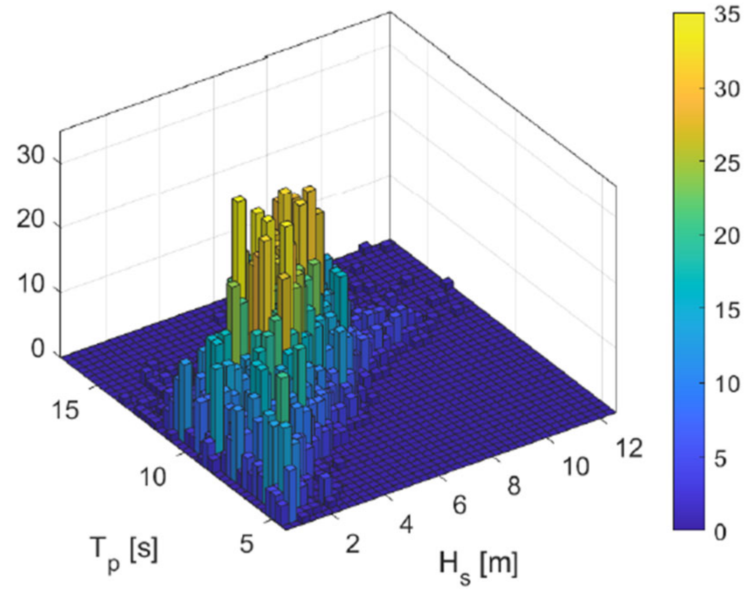
- Time series samples with 25 minutes duration (0.2 s resolution)
- Heave, sway, and pitch accelerations
- About two years of data
- Analysis is made with about 5,000 samples from open-water
- 20% of the data is saved for testing (80% used for training)

In-service data: Sea state estimates by wave radar

- In this study, a wave radar (Wavex by Miros) is the proxy of the ground truth







Results and discussions

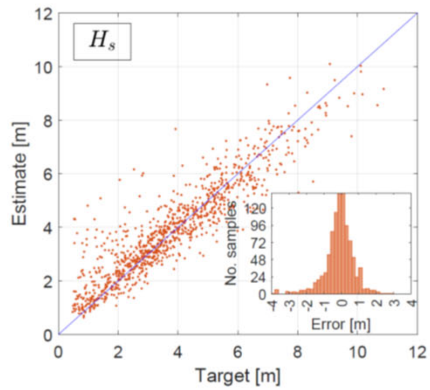
Considerations to the following

1. Comparison of integral wave parameters (Method 1 vs. Method 2 vs. Method 3); which method performs best?

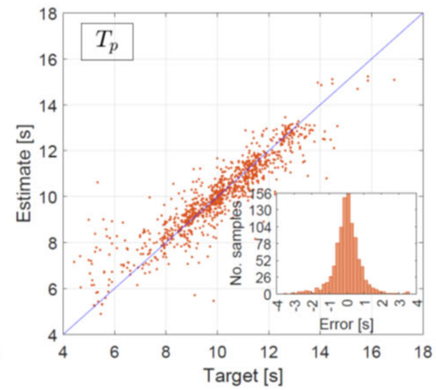
2. Comparison of wave spectra (--- || ---); which method performs best?

3. Associated uncertainty

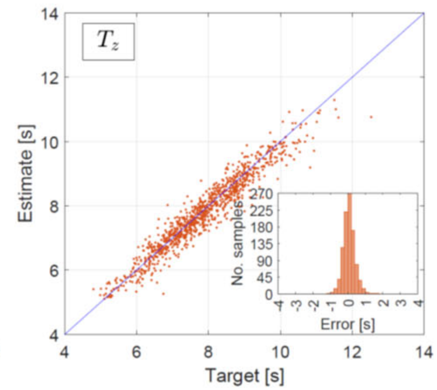
Integral wave parameters – Method 1



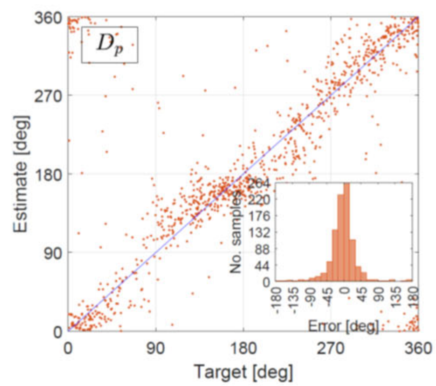
(a) Significant wave height.



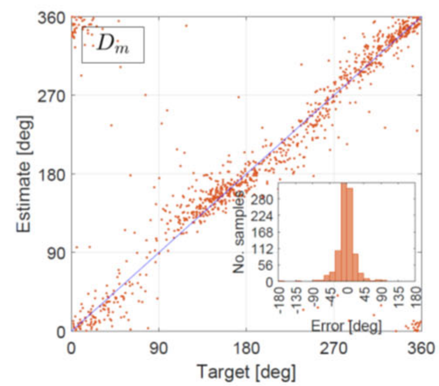
(b) Peak period.



(c) Zero-upcrossing period.

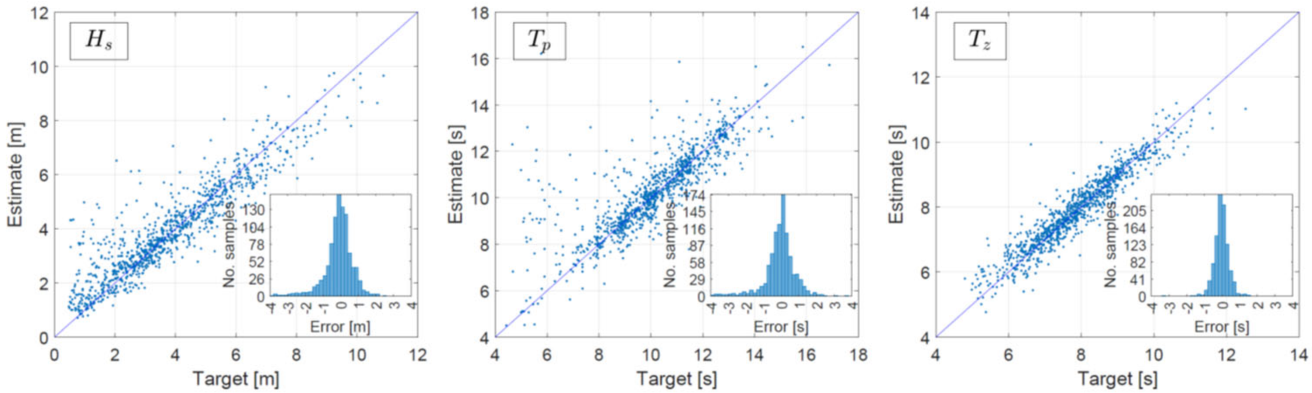


(d) Peak (relative) wave direction.

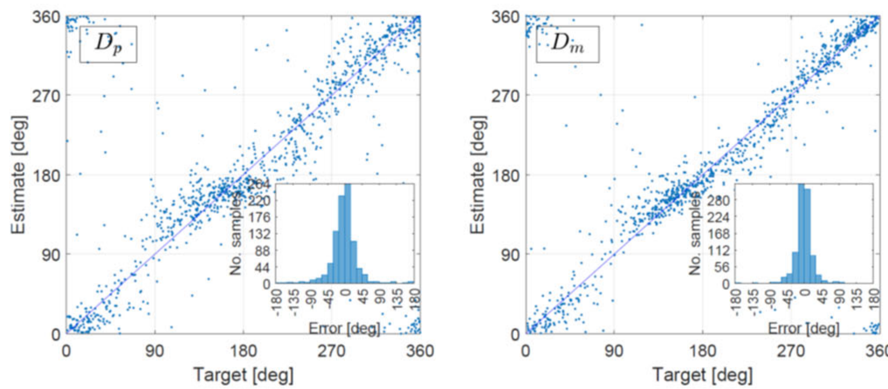


(e) Mean (relative) wave direction.

Integral wave parameters – Method 2

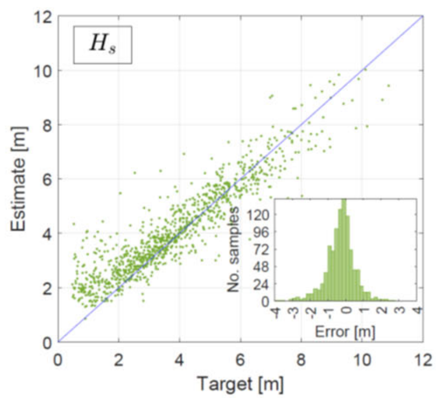


(a) Significant wave height. (b) Peak period. (c) Zero-upcrossing period.

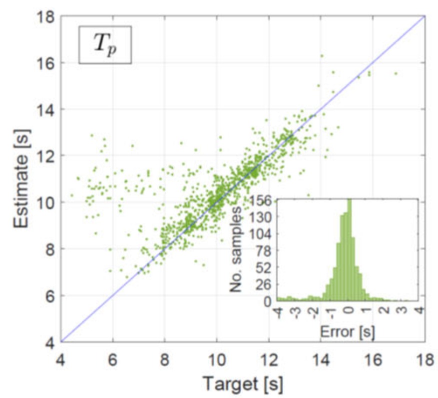


(d) Peak (relative) wave direction. (e) Mean (relative) wave direction.

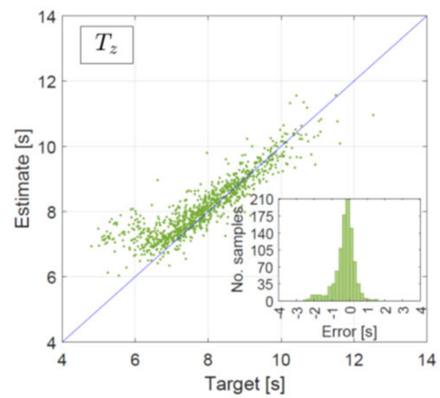
Integral wave parameters – Method 3



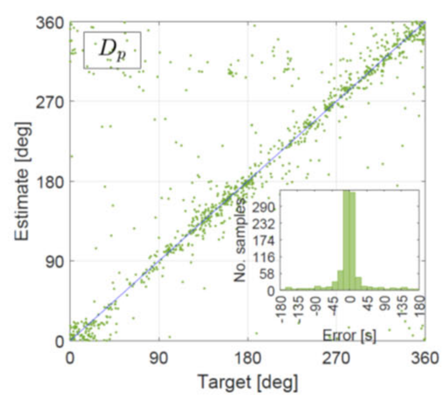
(a) Significant wave height.



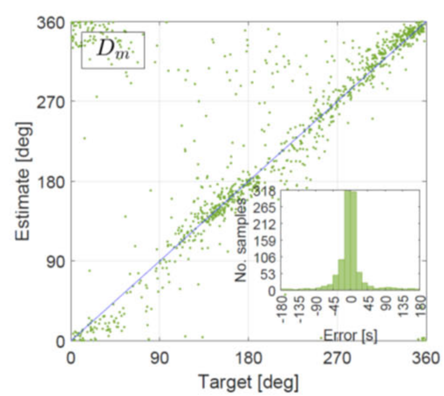
(b) Peak period.



(c) Zero-upcrossing period.



(d) Peak (relative) wave direction.



(e) Mean (relative) wave direction.

Integral wave parameters – Which method is the better?

Parameter		Method 1	Method 2	Method 3
H_s	Mean	0.25	0.26	0.32
	Std	0.55	0.58	0.62
	Q95	0.98	1.06	1.45
	Q75	0.21	0.20	0.25
	Q50	0.11	0.11	0.11
	Q25	0.05	0.05	0.05
T_p	Mean	0.060	0.078	0.101
	Std	0.086	0.156	0.209
	Q95	0.190	0.274	0.540
	Q75	0.070	0.079	0.073
	Q50	0.035	0.038	0.036
	Q25	0.016	0.015	0.017
T_z	Mean	0.033	0.039	0.051
	Std	0.028	0.039	0.080
	Q95	0.088	0.109	0.248
	Q75	0.046	0.054	0.071
	Q50	0.026	0.028	0.036
	Q25	0.013	0.012	0.017

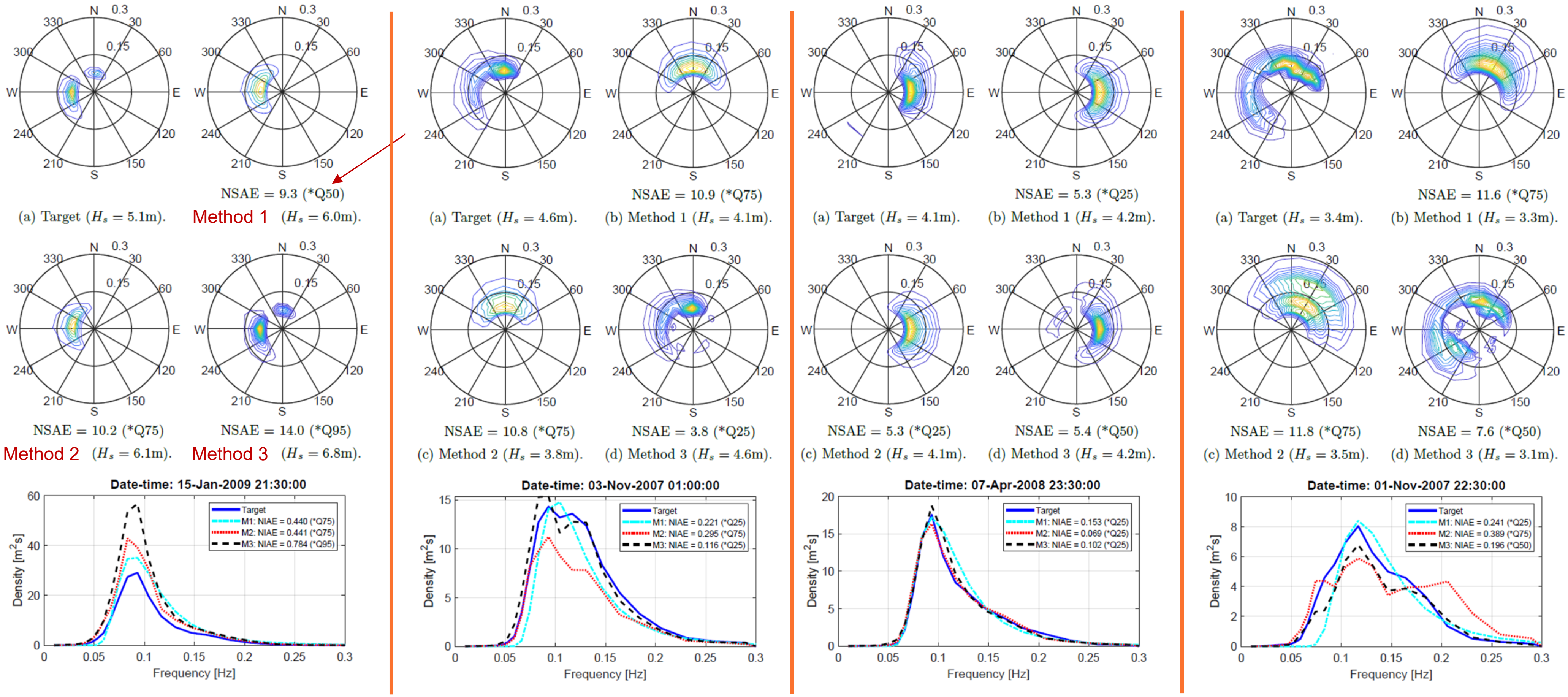
Parameter		Method 1	Method 2	Method 3
D_p	Mean	0.125	0.125	0.124
	Std	0.149	0.149	0.204
	Q95	0.405	0.405	0.655
	Q75	0.150	0.150	0.107
	Q50	0.081	0.081	0.043
	Q25	0.035	0.035	0.016
D_m	Mean	0.086	0.086	0.118
	Std	0.112	0.112	0.178
	Q95	0.265	0.265	0.543
	Q75	0.105	0.105	0.121
	Q50	0.052	0.052	0.050
	Q25	0.024	0.024	0.021

Blue font colour indicates 'best performance'

Answer:

- Not surprisingly, overall, Method 1 performs best

Four arbitrarily selected samples of wave spectra



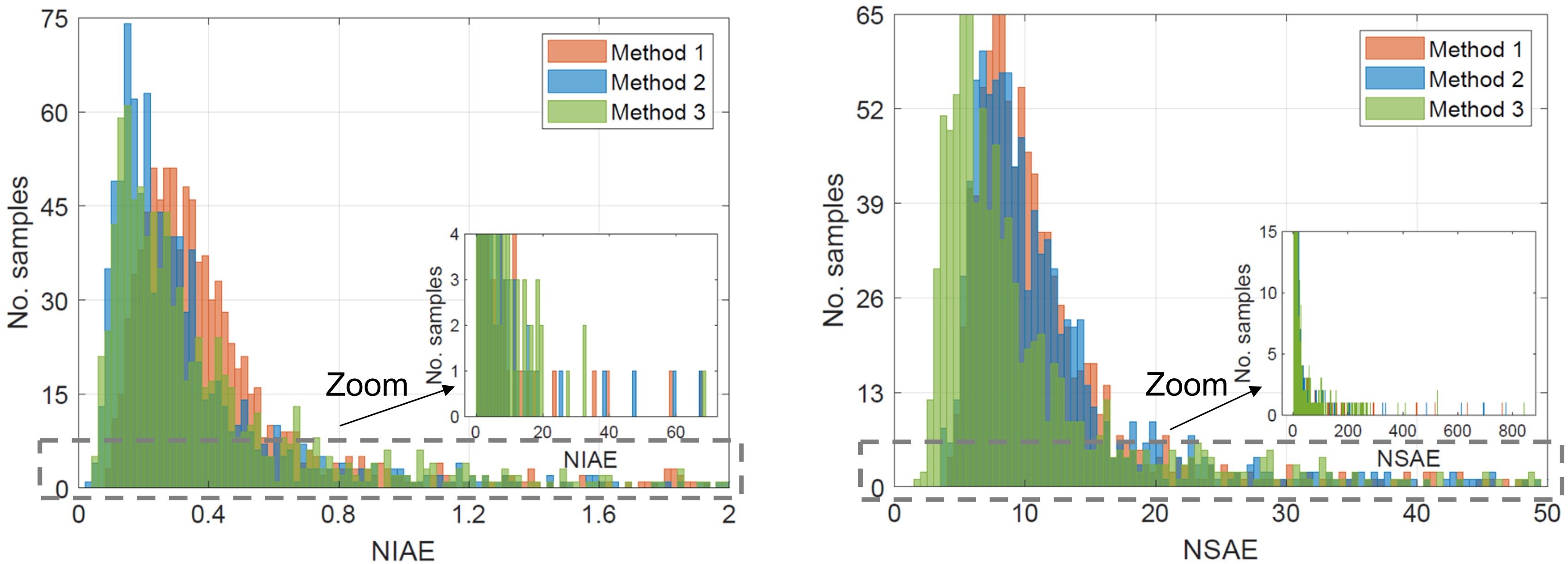
Wave spectra – Which method is the better?

	NIAE			NSAE		
	Method 1	Method 2	Method 3	Method 1	Method 2	Method 3
Mean	0.96	0.97	1.18	16.7	18.2	21.7
Std	3.67	3.92	3.63	42.6	47.6	53.2
Q95	2.90	3.24	5.03	39.1	44.9	90.5
Q75	0.53	0.47	0.64	13.2	13.7	13.7
Q50	0.35	0.27	0.30	9.8	9.7	7.8
Q25	0.25	0.17	0.17	7.6	7.3	5.3

Answer

- Surprisingly(!), overall, Method 1 (still) performs very good, if not best
- But…

Wave spectra – Which method is the better? (cont'd)



Answer:

"… Methods 2 and 3 have better performance for the majority of the data, but this finding is "disturbed" because of a number of samples with very large errors, as noticed from the insets showing the full range of error values." (Nielsen et al., 2024)

Inconsistent ("erroneous") wave spectrum in lower sea states by wave radar

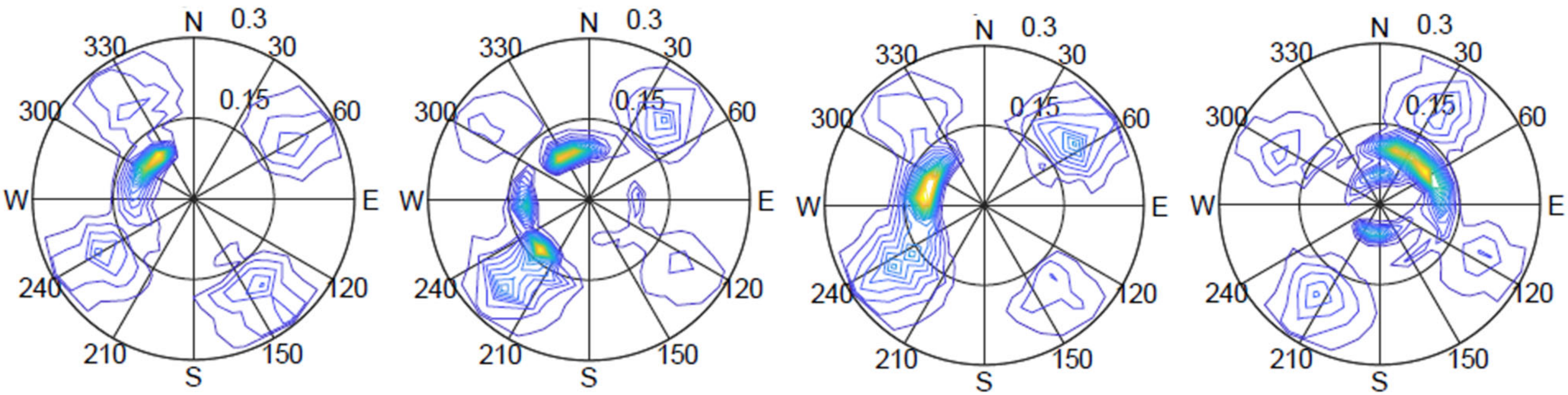
- Observation of peculiar corner partitions…
- Four examples of Wavex estimates of directional wave spectra
  (from time instants separated by several months and different geographical locations)

Message:

The following observations are not reported in Nielsen et al. (2024)

Inconsistent ("erroneous") wave spectrum in lower sea states by wave radar

- Observation of peculiar corner partitions…
- Four examples of Wavex estimates of directional wave spectra
  (from time instants separated by several months and different geographical locations)



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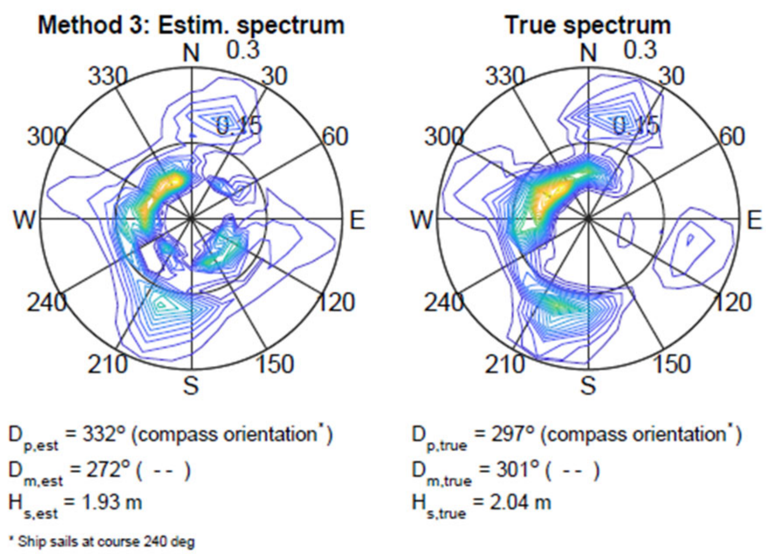
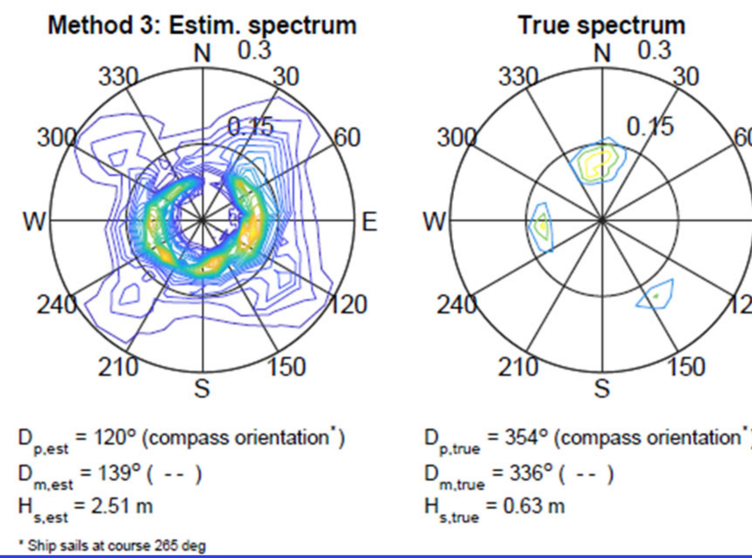
Inconsistent (“erroneous”) wave spectrum in lower sea states by wave radar, cont’d

- Interestingly, the ML framework of Method 3, in fact, has been able to learn these “unphysical” partitions
- That is, in some cases, agreement exists between Method 3 and Wavex but, in other cases, an estimate is produced with the corner partitions, albeit they do not occur in the Wavex spectrum.

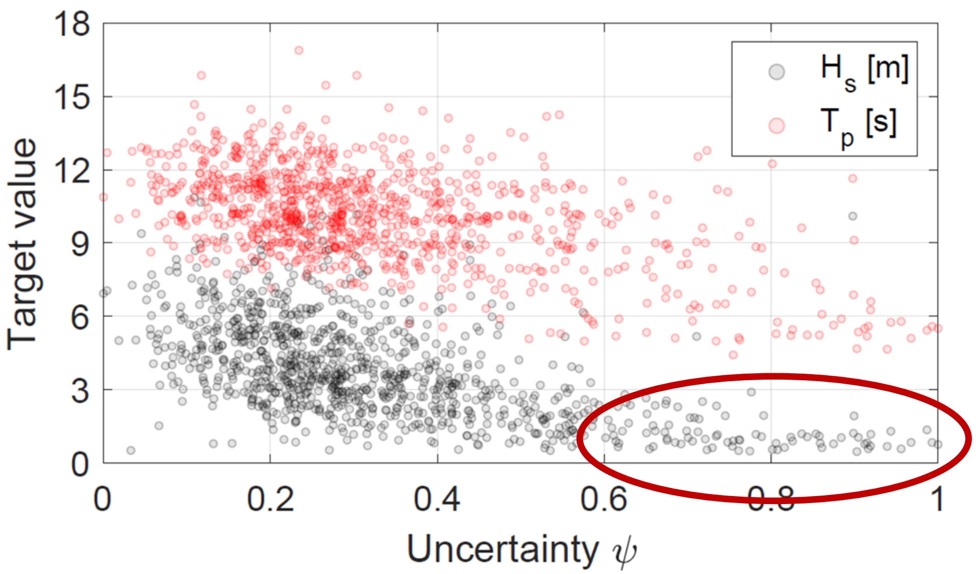




Uncertainty

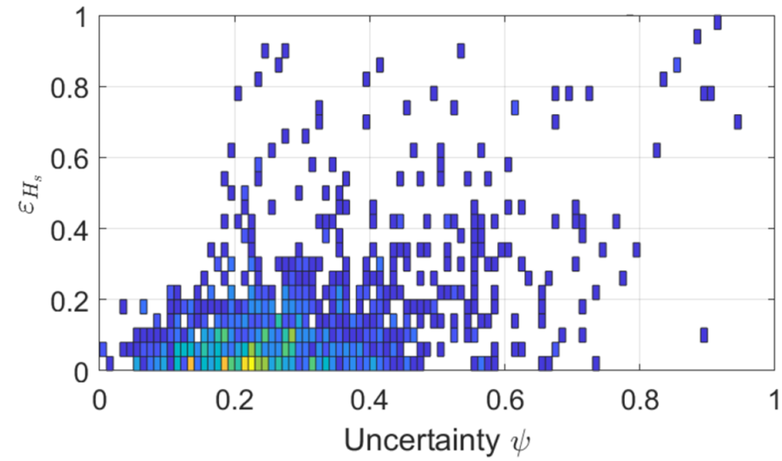
- The peculiar behaviour is also seen in the uncertainty measure when shown together with the *ground true* (target) wave parameters
- All data points (app. 5,000 samples) are shown

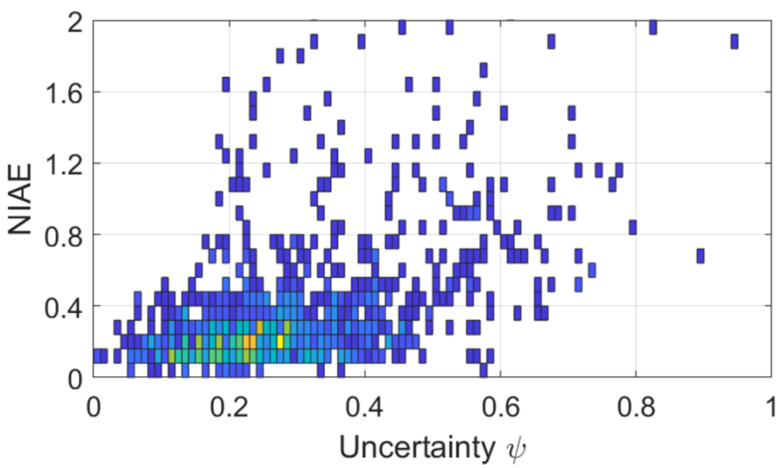
- Large uncertainty appears to occur only for small values of Hs,target and Tp,target

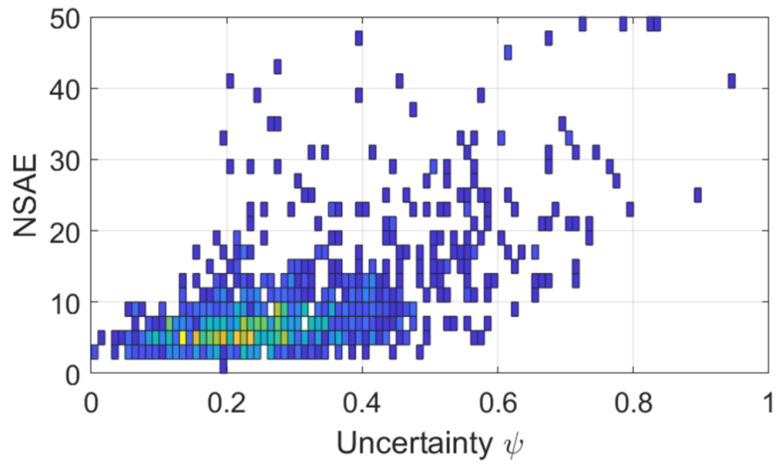


Uncertainty, cont'd

- … and when plotted against the error measures
- **Interesting observation**:
  - *Generally, when the uncertainty measure is small, say, lower than 0.15, errors* are and will *be small*
  - NB: The trust level indicator cannot be used the other way around







Final remarks and conclusions

- Three machine learning methods were investigated; overall they all performed acceptable with reasonable agreement

- An uncertainty measure was proposed based on the deviation between the case-specific results from the three methods
- NB: The proposed idea for uncertainty association is generic

- The uncertainty measure behaved consistently in the sense that little uncertainty was associated only to sea state estimates with a small (normalised) error compared to the "ground truth"
- The **hypothesis is** that it will be known if the estimate is consistent with the ground truth although the ground truth itself is always unknown.

- This study would benefit by being replicated using target wave data obtained from another source (e.g., ERA5)

DTU

Acknowledgements

- Orients Fond, case *SEAFUSION* under the framework agreement ’Orients Fond 2021-2025’
- Danmarks Frie Forskningsfond, grant ID: *10.46540/3164-00087B*
- The *WISE Program for the Development of AI Professionals in the Marine Industry* at Tokyo University of Marine Science and Technology

A/S D/S Orient’s Fond

DANMARKS FRIE FORSKNINGSFOND

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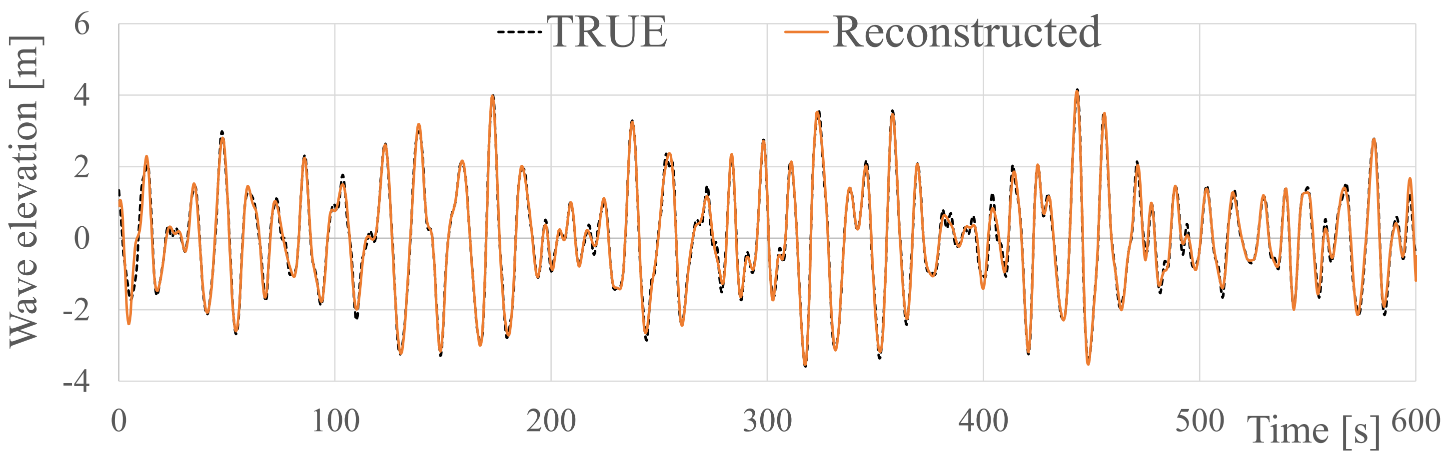
Phase-resolved wave estimation
(reconstruction of encountered wave profile)

NB: The next 8 slides are extra; the content is NOT from the paper (Nielsen et al., 2024).

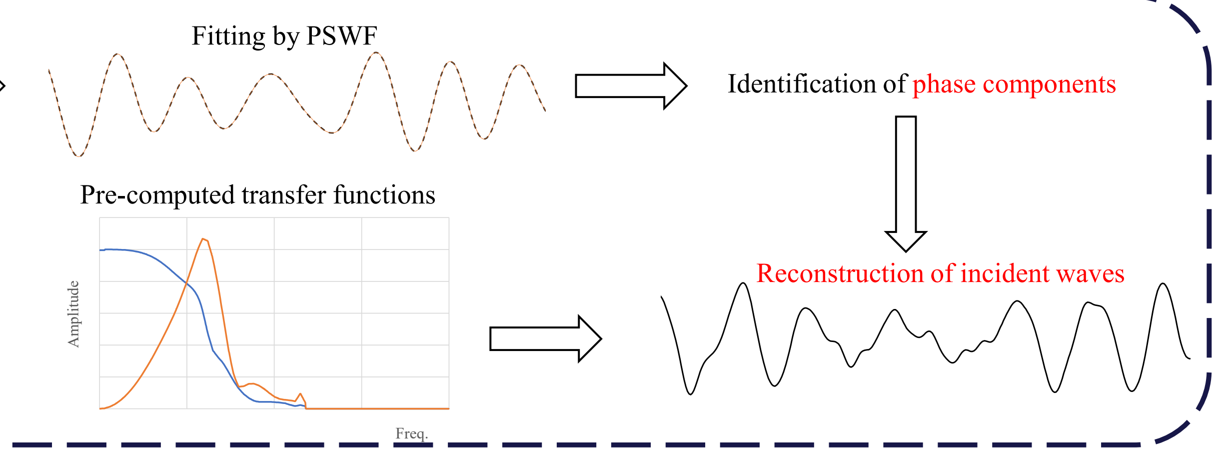
- Analysis of nonlinear processes requires availability of the encountered wave profile (as a time series)
- Applications include, e.g., prediction of large roll angles, fatigue accumulation, estimation of nonlinear roll damping



Methodology: Reconstruction of incident waves

- Response-based reconstruction method for **long-crested waves** proposed by Takami et al.
- **Prolate Spheroidal Wave Functions** (PSWF) is used, by which reconstruction can be made even from *short*-time measurements.

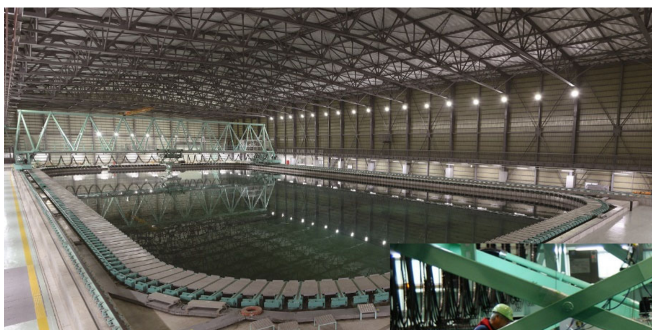
❑ Schematic illustration

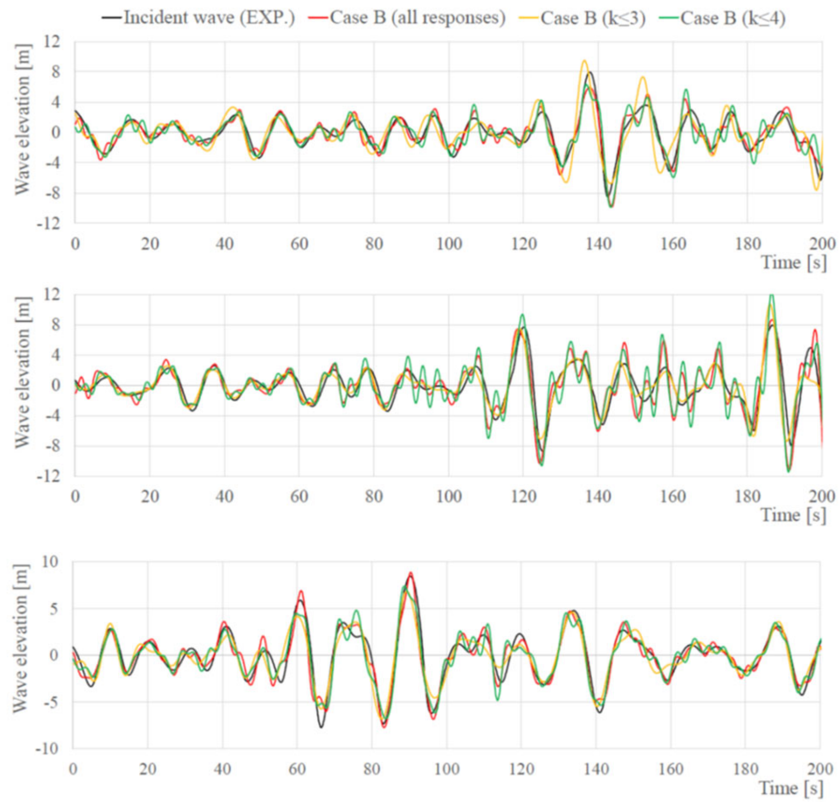


Takami et al. (2022,2023)

Results: Phase-resolved wave estimation

- Experimental data using tests from wave basin at NMRI





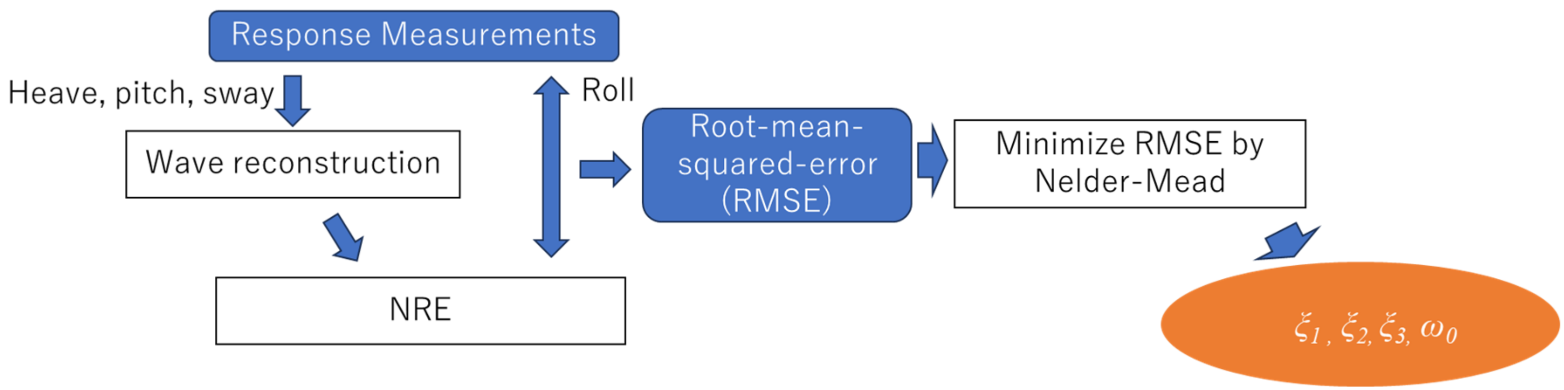
Takami et al. (2022,2023)

Methodology: Roll damping identification

- Linear and nonlinear damping coefficients (ξ_1, ξ_2, ξ_3) and natural frequency (ω_0) are identified by the Nelder-Mead method so that **the nonlinear roll estimator (NRE) reproduce the measured roll motion**.

$$\ddot{\phi}_e(t) = -2\xi_1\omega_0\dot{\phi}_e(t) - \xi_2\left|\dot{\phi}_e(t)\right|\dot{\phi}_e(t) - \xi_3\frac{\dot{\phi}_e(t)^3}{\omega_0} - \frac{gGZ(\phi_e(t))}{r_x^{\,2}} + \frac{M_x(t)}{J_x}$$

- Roll excitation moment M_x is calculated by **reconstructed wave** + pre-computed (3D panel code NMRIW3D-Lite) **response amplitude operator**.

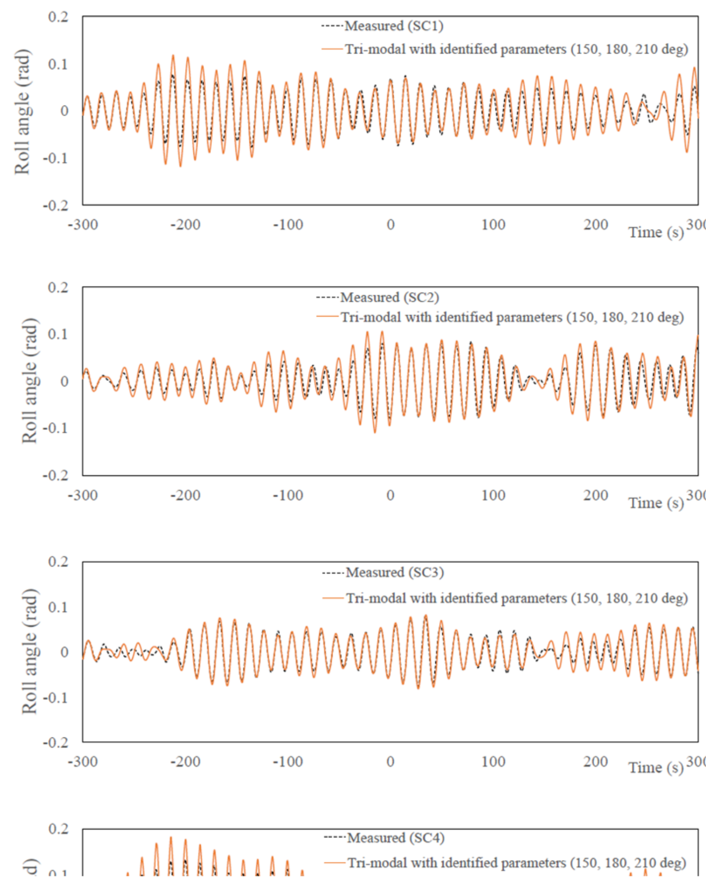


Results: Roll damping identification

- Experimental validation (Takami et al., 2024)
- Five short-crested wave cases (SC1-SC5) were investigated

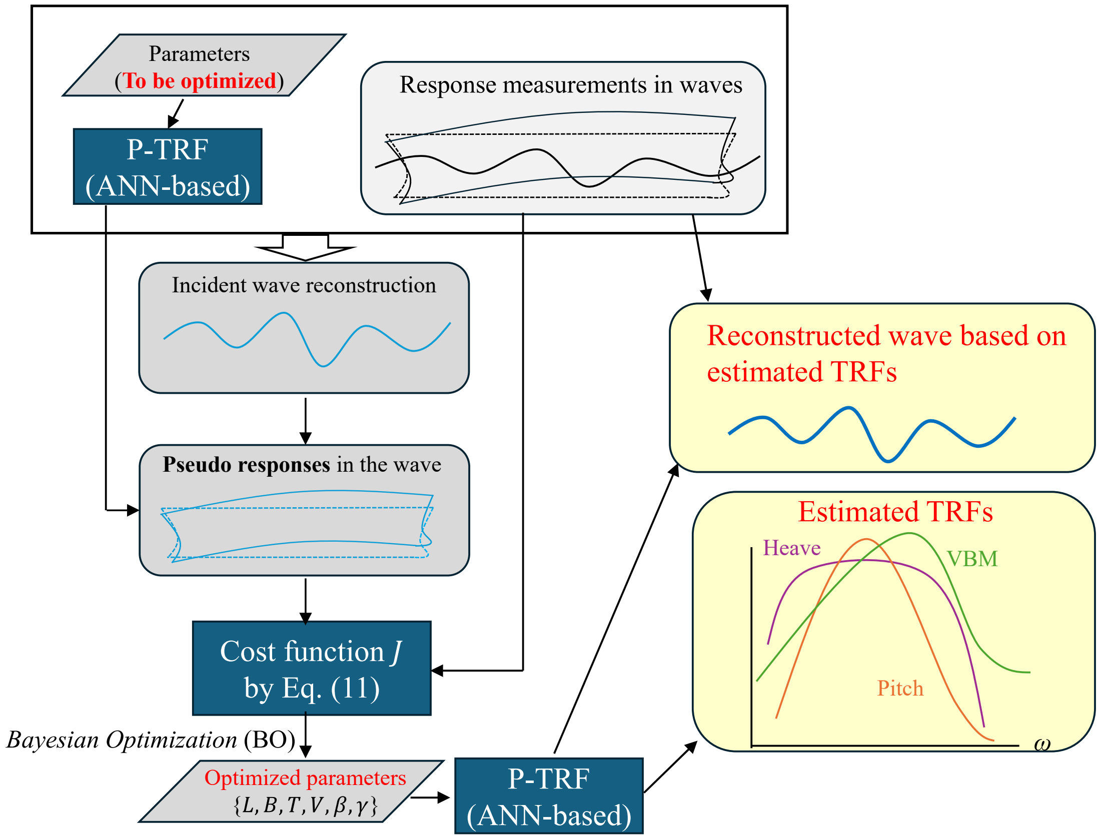
- Comparison against free decay tests (average), only linear and quadratic terms considered:

	ξ_1	ξ_2	ω_0	$RMSE$	$\sigma_{R'}$	ξ_{lin}
SC1	0.018	0.0001	0.447 rad/s	0.540 rad	0.016 rad/s	0.018
SC2	0.028	0.002	0.447 rad/s	0.637 rad	0.016 rad/s	0.028
SC3	0.028	0.0002	0.448 rad/s	0.254 rad	0.014 rad/s	0.028
SC4	0.010	0.243	0.447 rad/s	0.571 rad	0.017 rad/s	0.020
SC5	6.3E-4	0.999	0.442 rad/s	0.756 rad	0.017 rad/s	0.031
Average of SC~SC5	0.017	0.249	0.446 rad/s	-	-	0.025
Free decay (average)	0.008	0.171	0.441 rad/s	-	-	-



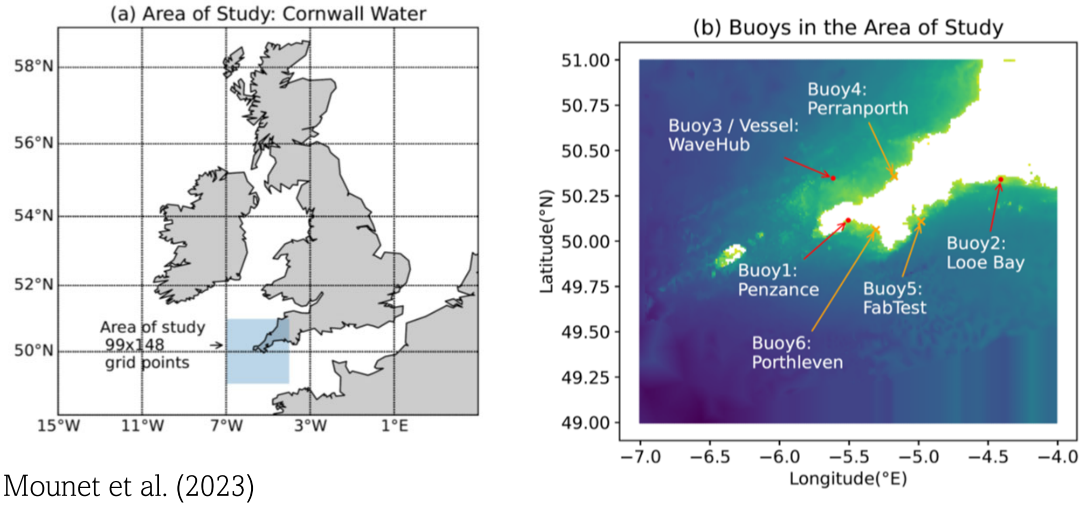
Future studies (1):

Simultaneous estimation of waves and phase-resolved transfer functions



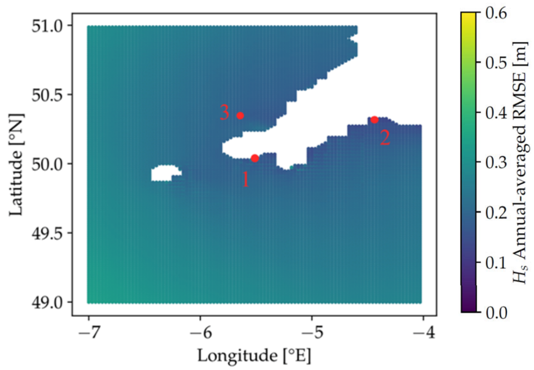
Future studies (2a):
Spatial Wave Data from a Network of Buoys and Ships

- Nowcasting as well as **forecasting of waves on a large-scale geographical domains using multiple observation platforms**, including ships
- Assessment of wave energy resources, operational windows, ship routing, assimilation (weather + waves), …

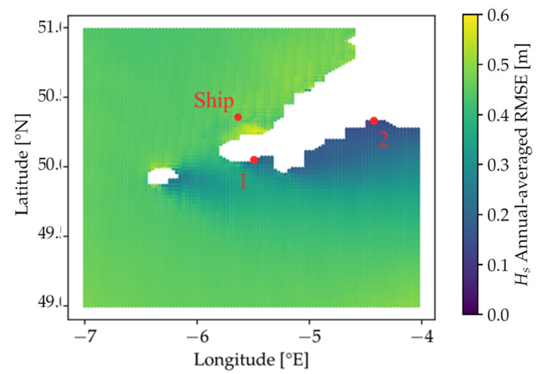


Mounet et al. (2023)

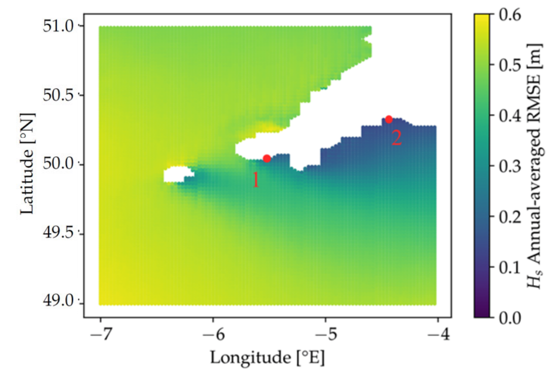
Future studies (2b):
Spatial Wave Data from a Network of Buoys and Ships



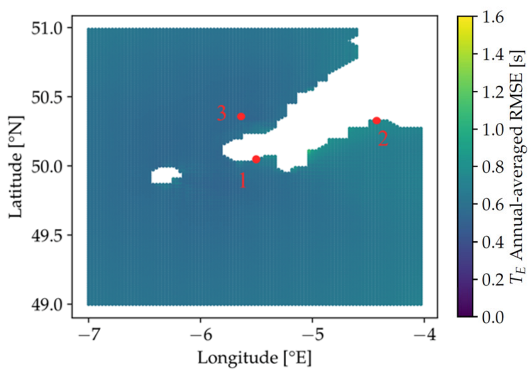
(a) Model 1, H_s-RMSE.



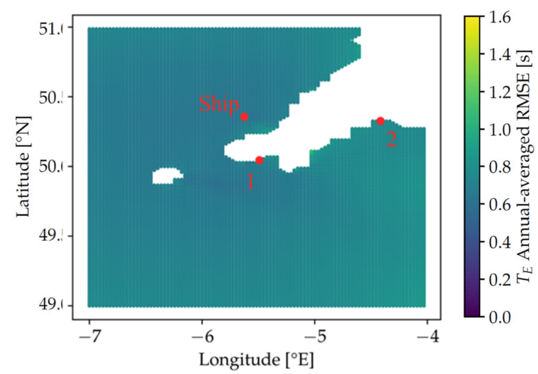
(c) Model 2, H_s-RMSE.



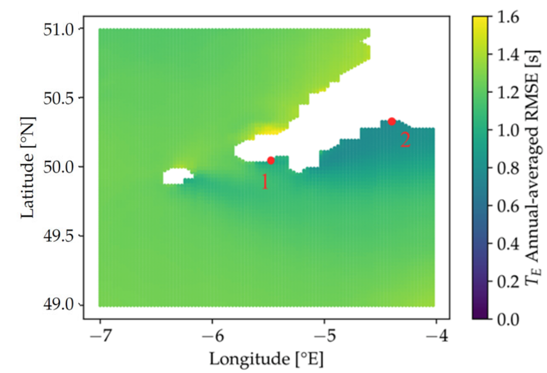
(e) Model 3, H_s-RMSE.



(b) Model 1, T_E-RMSE.



(d) Model 2, T_E-RMSE.



(f) Model 3, T_E-RMSE.

Mounet et al. (2023)

Thank you for your attention

Questions from the floor ?

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