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Nielsen, U. D.; Brodtkorb, A.H. ; Iseki, T.; Jensen, J. J.; Mittendorf, M.; Mounet, R.E.G. ; Sørensen, A. J. ; Takami, T.

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Estimating Waves Through Measured Ship Responses

Ulrik Dam Nielsen
Section for Fluid Mechanics, Coastal and Maritime Engineering,
DTU Construct (Dept. of Civil and Mechanical Engineering)
Technical University of Denmark

Many thanks to all my co-authors

A.H. **Brodtkorb**[2], T. **Iseki**[3], J.J. **Jensen**[1], M. **Mittendorf** [1],

R.E.G. **Mounet**[1,2], A.J. **Sørensen**[2], T. **Takami**[4]

[1]DTU Construct, Technical University of Denmark, Kgs. Lyngby, Denmark

[2]NTNU AMOS, Norwegian University of Science and Technology, Trondheim, Norway

[3]Tokyo University of Marine Science and Technology, Tokyo, Japan

[4]National Maritime Research Institute, Tokyo, Japan

This talk presents…

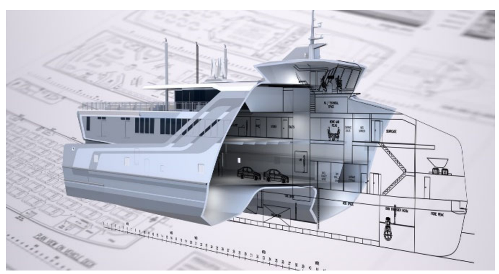
- A brief outline of past an ongoing activities related to the use of ships as sailing wave buoys
  - Emphasis on a hybrid approach ("ML-informed physics-based approach")

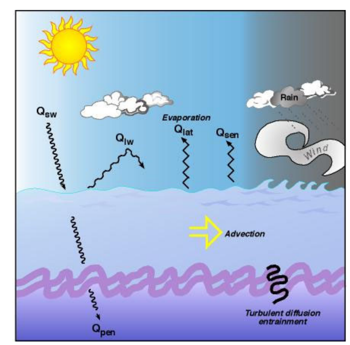
- Just a few glimpses of the associated mathematical theory

- Many slides… so I will try to be swift; but just reach out and we can continue the discussions later

Introduction: Why do we want to *measure* waves?

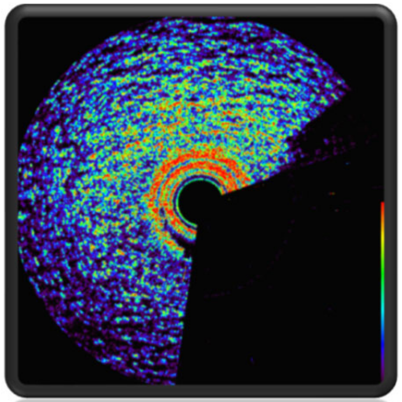
- **Because waves are the fundamental driver of most of the *processes** * **we are concerned about** (as maritime engineers, naval architects, or ocean scientists)
  - * Analysing wave-structure interactions before/during/after operations
  - * Collecting historical data for design and rule specifications
  - * Understanding mechanisms of surface-water mixing and air-sea fluxes

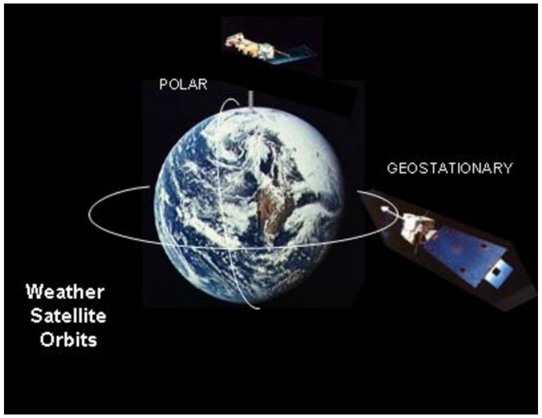




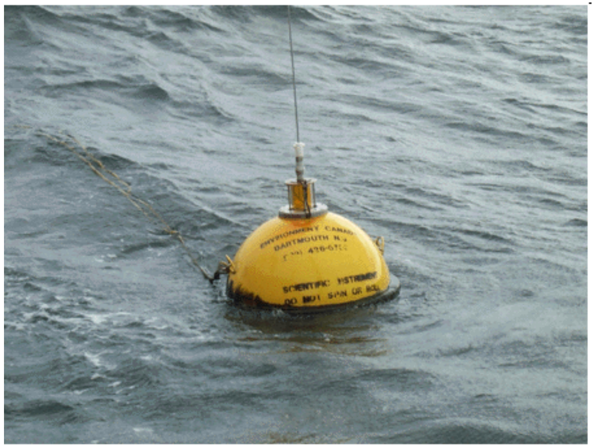
Introduction: How can we *estimate* waves?

- Well-known means for sea state ***estimation***
  - In-situ buoys
  - Remote sensing (aircraft or satellite)
  - Wave radar (X-band marine radar)
  - …
- All with their own pros and cons
- The specific use-case (previous slide) may set different requirements to availability and updating-frequency





Analogy to a wave buoy



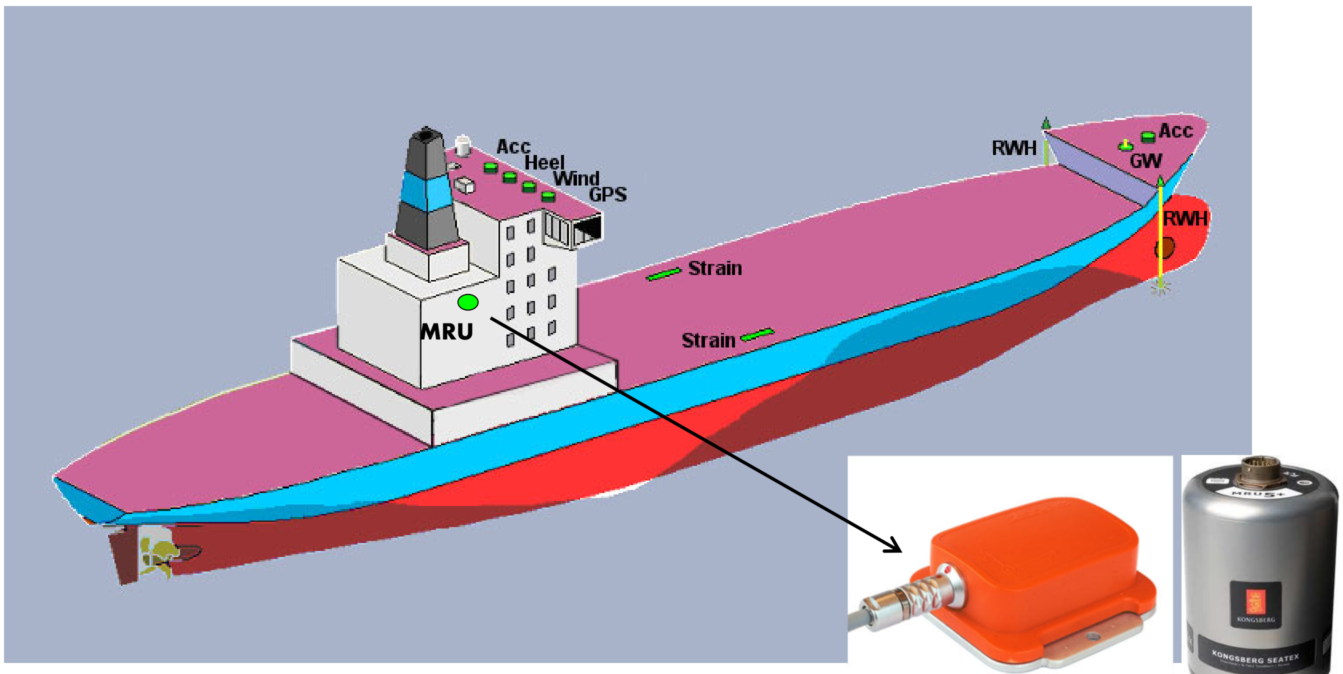
- Measurements of the buoy's motions are processed to give the wave spectrum in real-time and at the buoy's exact position.
- Can we do the same with a ship...?? Yes!

Inherent complexities:

- Geometry
- Size (low-pass filter)
- Forward speed

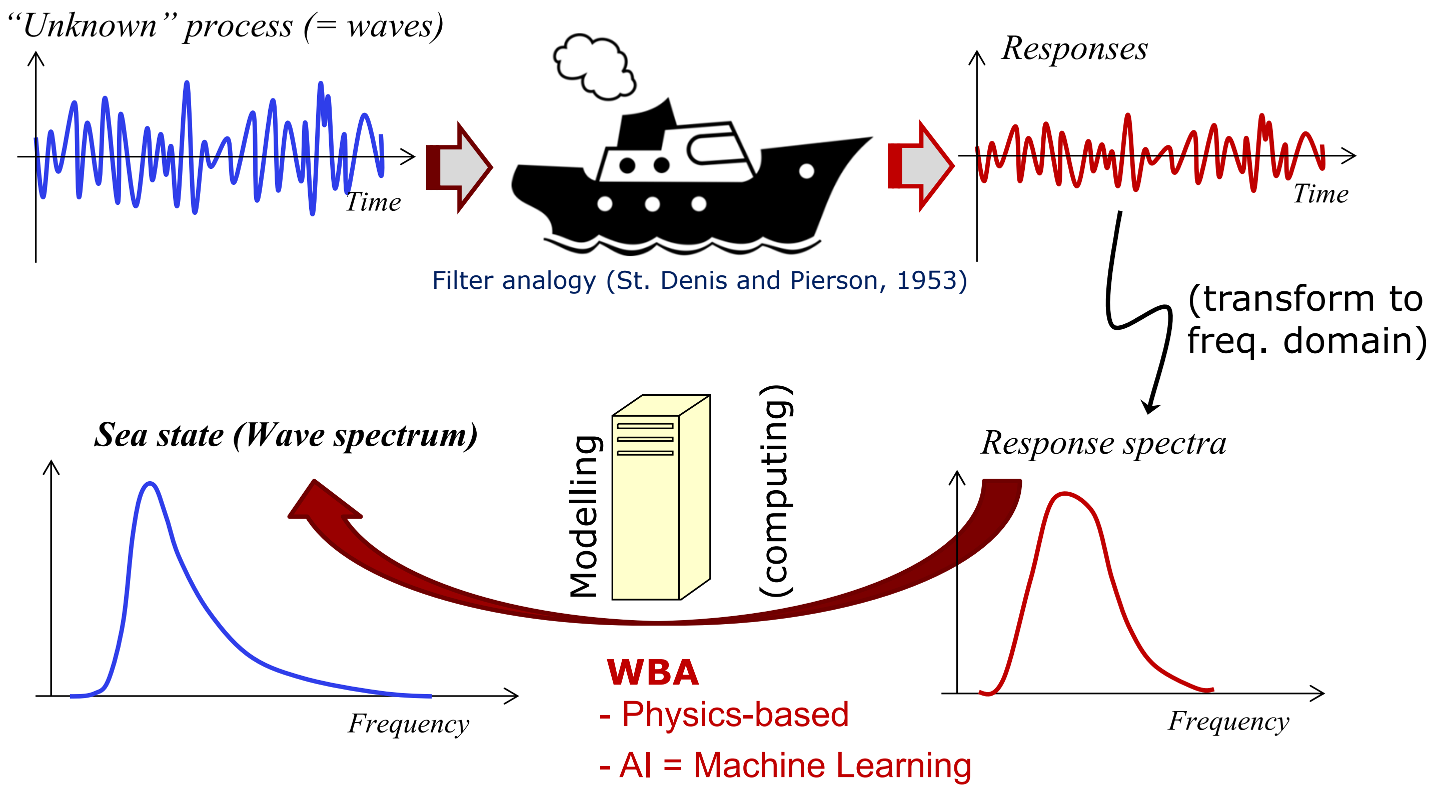
The wave buoy analogy (= *WBA*)

- A ship is like a wave buoy; it responds to the waves… (and has plenty of sensors installed)



MRU: Motion Response Unit

Estimating waves through measured ship responses in a nutshell



Physics-based framework

The governing equation system is based on a comparison of response spectra...

- Motions (e.g. heave,roll,pitch)
- Accelerations
- VBM

$i, j = \{z, \phi, \theta\}$

Measure-ments:

Response spectra $S_{i,j}(\omega_e)$

Physics-based framework

The governing equation system is based on a comparison of response spectra...

- Motions
  (e.g. heave,roll,pitch)
- Accelerations
- VBM

Measure-ments:

Response spectra $S_{i,j}(\omega_e)$

Match?

Error calculation

Theoretical estimate:

Wave spectrum → Complex-valued transfer functions → Response spectra $\tilde{S}_{i,j}(\omega_e)$

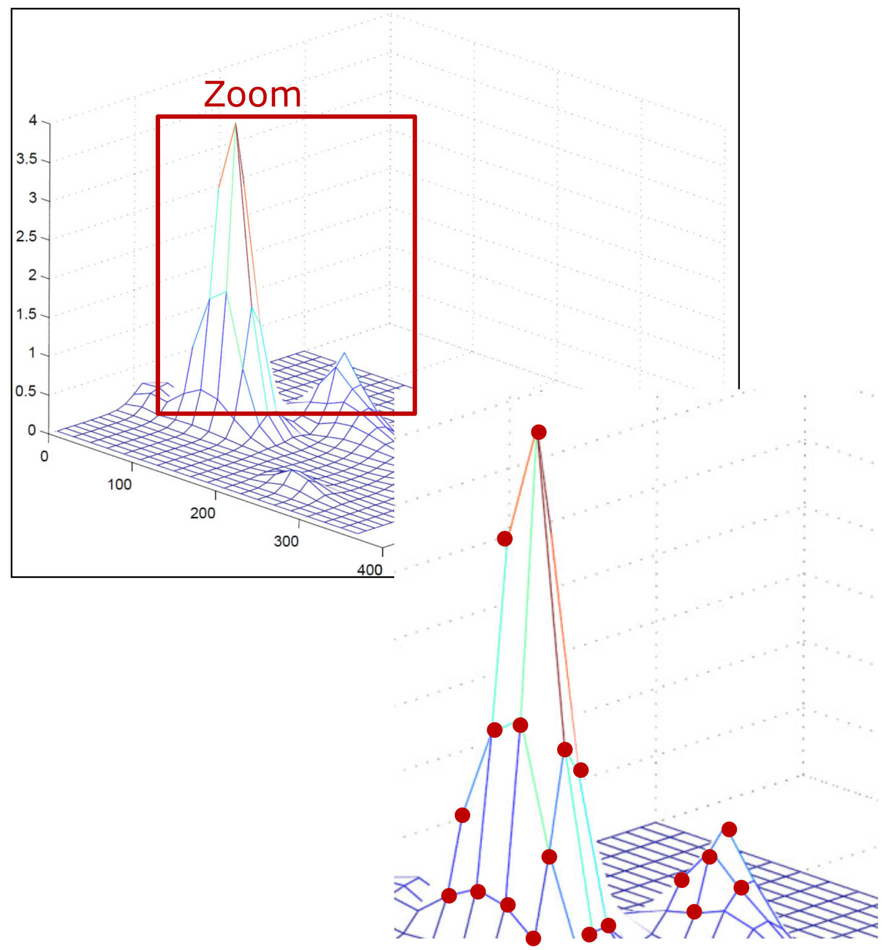
Improve estimate

$$\tilde{S}_{i,j}(\omega_{e,l}) = \int_0^{2\pi} \left\langle \Phi_i(\omega,\beta)\overline{\Phi_j(\omega,\beta)}E(\omega,\mu)\frac{d\omega}{d\omega_e} \right\rangle_{\omega_{e,l}} d\mu$$

Note: Fundamentally, expressions originate from the governing physics (Newton's 2nd law) → ***physics-based*** approach.

Solving the problem

$$\min \sum_{i,j} \sum_{l=1}^{L} \left| S_{i,j}(\omega_{e,l}) - \int_0^{2\pi} \left\langle \Phi_i(\omega,\beta)\overline{\Phi_j(\omega,\beta)} E(\omega,\mu) \frac{d\omega}{d\omega_e} \right\rangle_{\omega_{e,l}} d\mu \right|^2$$



- **Underdetermined equation system solved by a Bayesian (non-parametric) method**
  solving directly for <u>all</u> of the unknown (discrete) spectral ordinates of the spectrum $E(\omega, \mu)$, requiring regularization.

- **Regularization, i.e. smoothing** (minimization of the second order difference) of the spectrum in the two dimensions

- Solution obtained as the **compromise between "goodness of fit" and smoothness**

- A glimpse of the theory…

Solving the problem

$$\min \sum_{i,j} \sum_{l=1}^{L} \left| S_{i,j}(\omega_{e,l}) - \int_0^{2\pi} \left\langle \Phi_i(\omega,\beta)\overline{\Phi_j(\omega,\beta)} E(\omega,\mu) \frac{d\omega}{d\omega_e} \right\rangle_{\omega_{e,l}} d\mu \right|^2$$

- ❑ **Bayesian (non-parametric) method** solving directly for <u>all</u> $K{\cdot}M$ unknowns, requiring regularization.

- ❑ **Parametric method** based on optimisation of *wave parameters* (H_s, T_z, β, ...) in a summation of parameterised wave spectrum formulations (e.g. JONSWAP) and a directional spreading function.

- ❑ **Spectral-residual calculation** solving directly for M unknowns while 'optimising' for the mean heading β used as input for a directional spreading function. (essentially a combination of the other two)

Note: In the general case, forward speed is different from zero →
Consideration of the Doppler shift!

Bayesian method (1)

- Governing equation (matrix notation) established by minimization

$$\chi^2(\mathbf{x}) \equiv \|\mathbf{A}\mathbf{f}(\mathbf{x}) - \mathbf{b}\|^2$$

introducing a non-negativity constraint f(**x**) = exp(**x**).

- Regularization (smoothing) based on minimization of the second order derivative (difference)

$$\varepsilon^2_{1mn} = \sum_{n=1}^{N}\sum_{m=1}^{M}\left(x_{m-1,n} - 2x_{m,n} + x_{m+1,n}\right)^2; \quad (x_{0,n} = x_{M,n},\ x_{M+1,n} = x_{1,n})$$

$$\varepsilon^2_{2mn} = \sum_{m=1}^{M}\sum_{n=2}^{N-1}\left(x_{m,n-1} - 2x_{m,n} + x_{m,n+1}\right)^2$$

$$\varepsilon^2_{1mn} = \mathbf{x}^T\mathbf{H}_1\mathbf{x}$$

$$\varepsilon^2_{2mn} = \mathbf{x}^T\mathbf{H}_2\mathbf{x}$$

Bayesian method (2)

- Principally, the solution is obtained from the minimization of

$$S\left(\mathbf{x}\right) = \left\|\mathbf{Af}\left(\mathbf{x}\right) - \mathbf{b}\right\|^2 + \mathbf{x}^T(u^2\mathbf{H}_1 + v^2\mathbf{H}_2)\mathbf{x}$$

which is equivalent to maximizing the (posterior):

$$p\left(\mathbf{x}|u,v,\sigma^2\right) = c\left(\frac{1}{2\pi\sigma^2}\right)^{\frac{P+KM}{2}} |\det(u^2\mathbf{H}_1 + v^2\mathbf{H}_2)|^{1/2}\exp\left(-\frac{1}{2\sigma^2}S(\mathbf{x})\right)$$

- The solution is controlled by the hyperparameters *u* and *v*; and the *optimum* solution is obtained for minimum of ‘A Bayesian Information Criterion’:

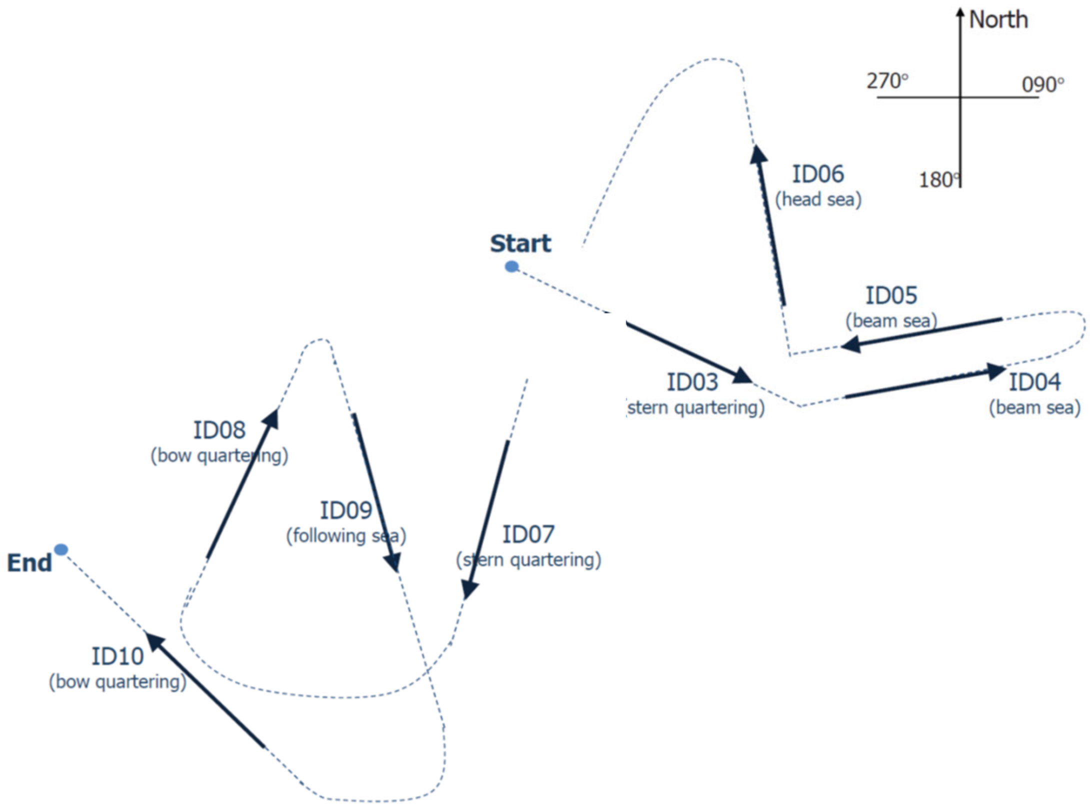
$$\mathrm{ABIC} = -2\ln\int p\left(\mathbf{x}|u,v,\sigma^2\right)d\mathbf{x}$$

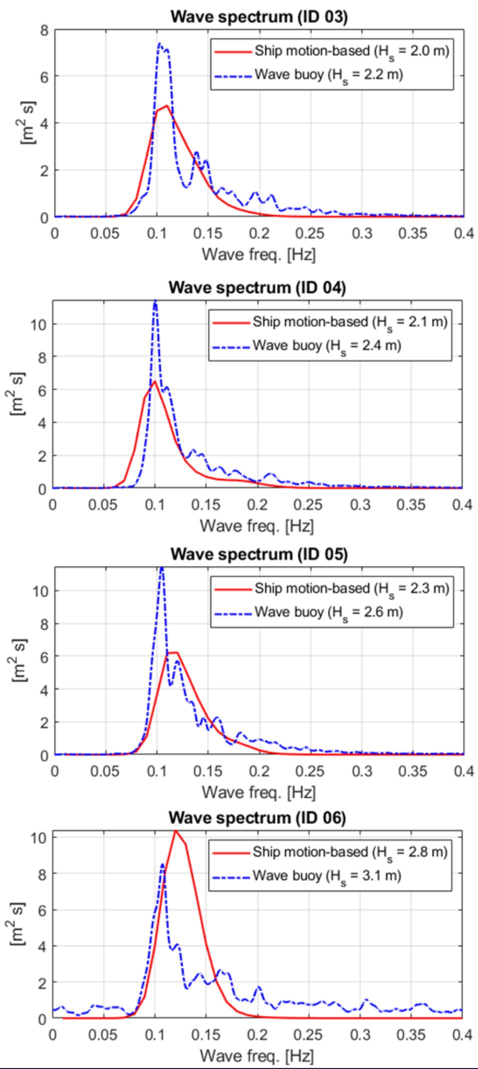
Results (… by the "original", *un*conditioned method)

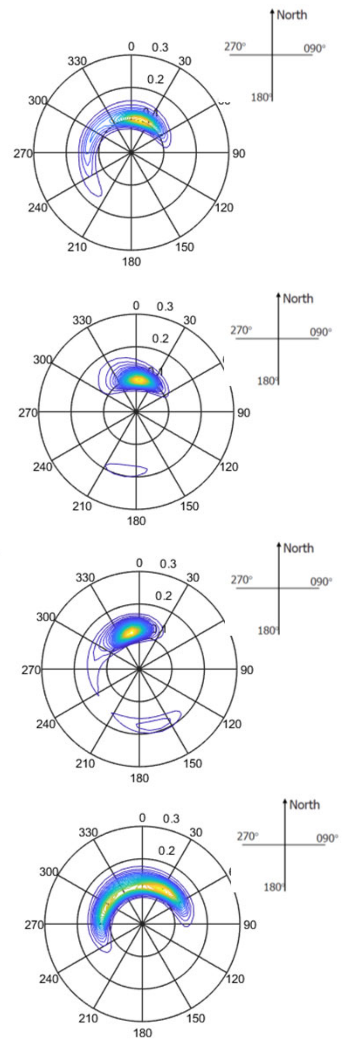
Physics-based framework (Part 1)

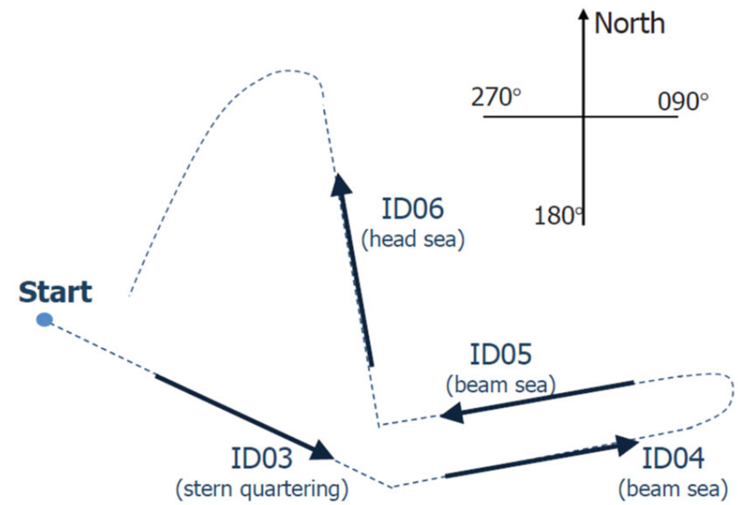
- **Combination of measured data *and* transfer functions**
- Comparison between estimates by a wave buoy and corresponding results using ship motions

Nielsen et al. (2018)







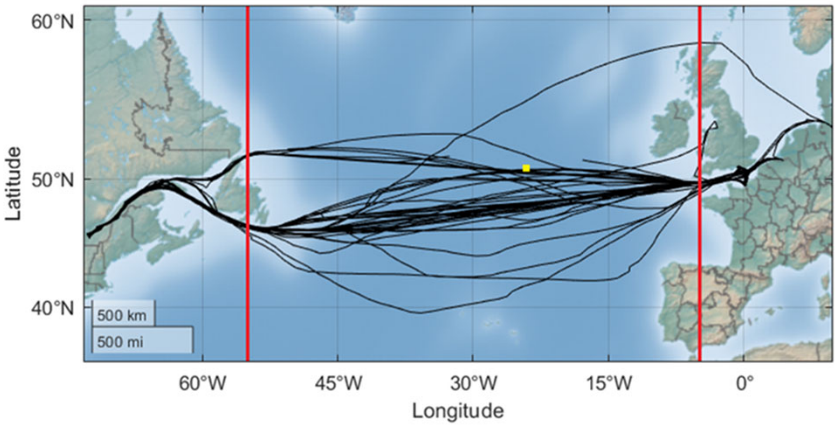


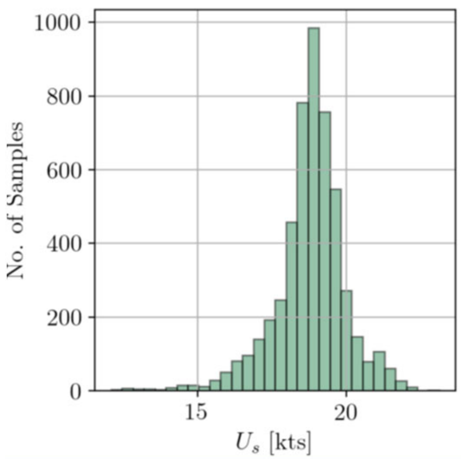
- Similar agreements for the other four cases (ID07 – ID10)… and for the parametric approach even better agreements are obtained (cf. appendix)
- **Main take-away**: Good estimates can be expected under “controlled” conditions where uncertainties in operational parameters are small → RAOs are reliable(!)

Results (... by the "original", *un*conditioned method)

Physics-based framework (Part 2)

- **Combination of measured data *and* transfer functions**
- Comparison with wave radar (Wavex)
- Nearly two years of operational data
- No info about loading condition ($T_{transit}$ = 9.5 m)





Nielsen et al. (2023)

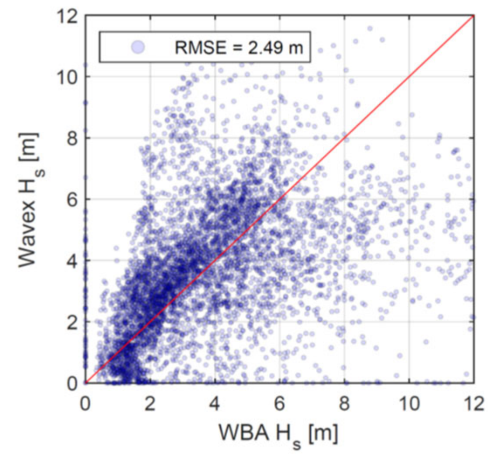
Results (Part 2)

- Physics-based (= 'WBA') vs. Wavex results…
- NB. *All* data is considered.

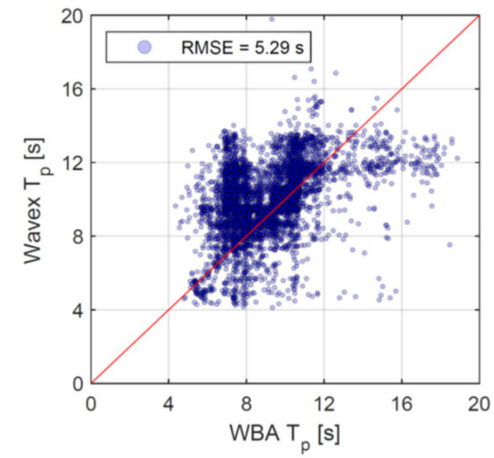
- Can we improve the estimates by the WBA by combining results from ML and physics-based?

- Using a *hybrid framework*…

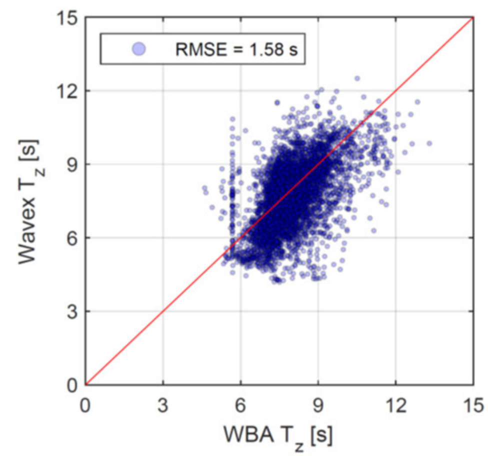
- First, however, what is the motivation for such an approach?

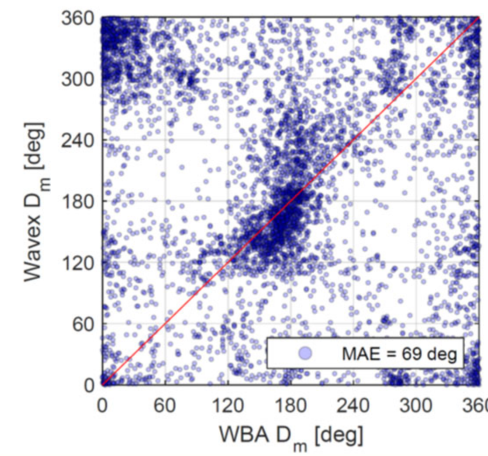


(a) Significant wave height.



(b) Peak period.

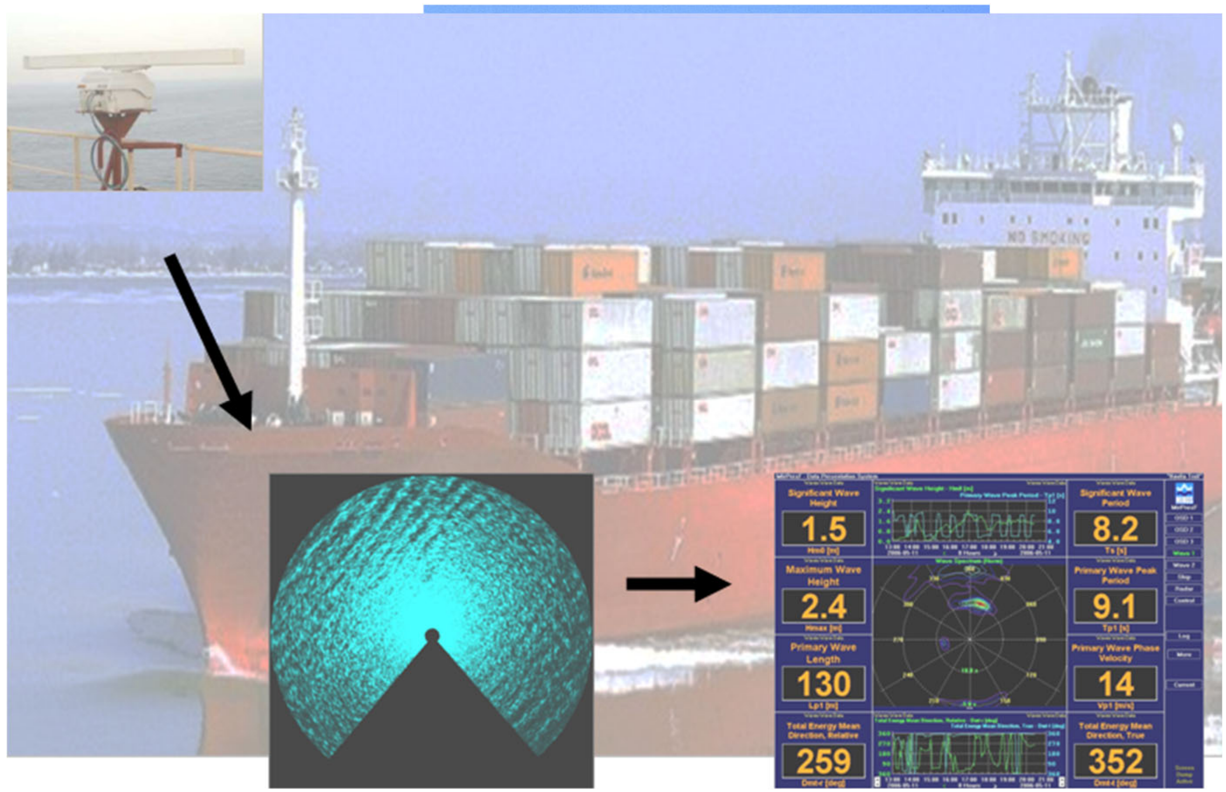




Machine learning-based framework

Machine Learning (ML)

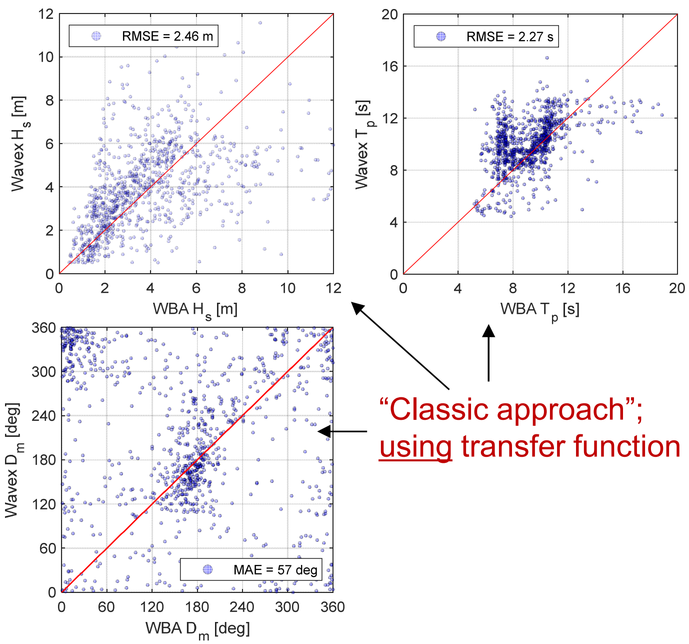
- Training of **convolutional neural networks**; based on the following
  - Two years of ship telemetry data:
    - **MRU** located close to COG
    - Accelerations
    - Strains
    - Speed
  - **Wave data obtained by wave radar** (WaveX from Miros)
  - Targets: H_s, T_p, D_m (or β)



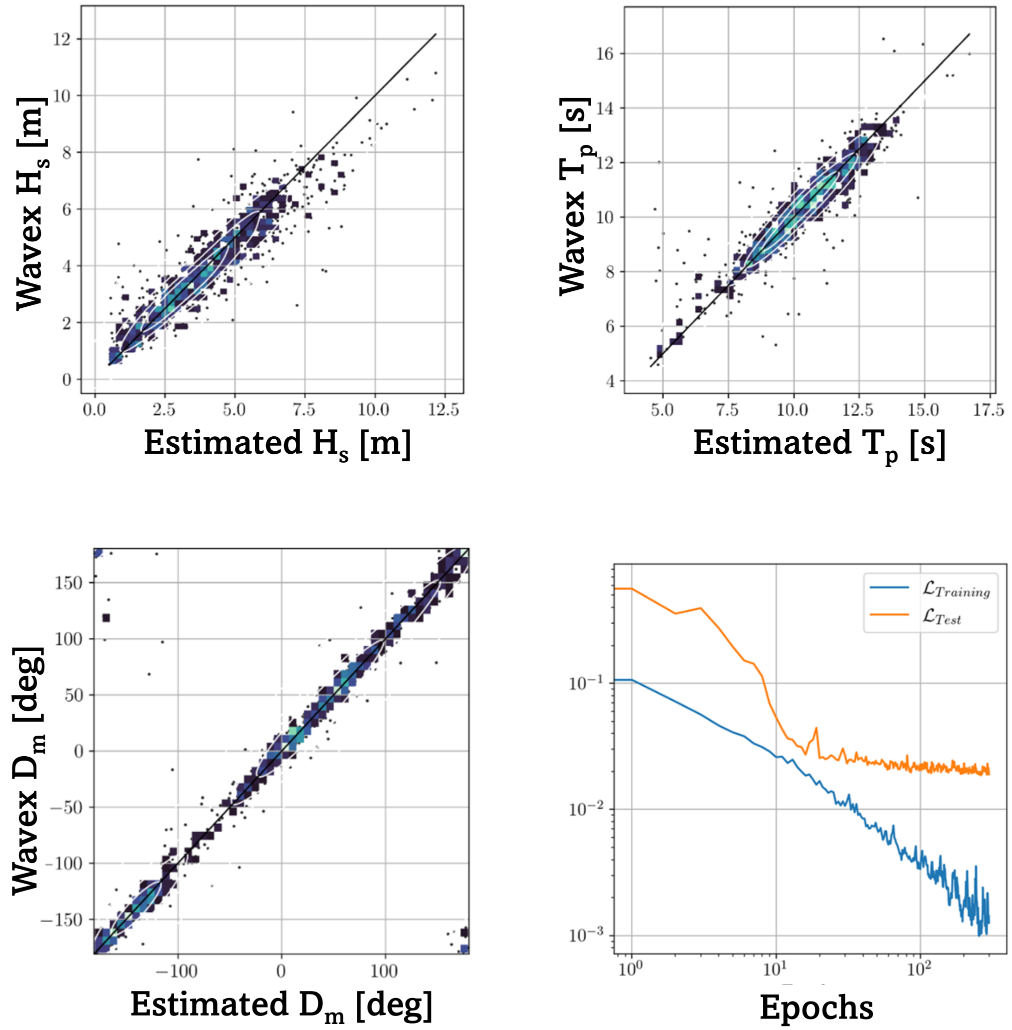
Mittendorf et al. (2022)

Results using ML

- Assessment based on *test* data (20 %); from Mittendorf et al. (2022)
- No use of transfer functions



"Classic approach";
using transfer function



Wave spectrum estimation conditioned on output from machine learning

- **Motivation:**
  1) Physics-based gives the detailed 2D wave spectrum (ML does *not*)
  2) ML provides reliable estimates of wave *parameters* (Physics-based does not *always*; wave direction appears to be the most difficult)

- **Methodology:**
  - Constrain the wave spectrum estimate
  - Formulation of additional equations based on output from the Machine Learning model (Mittendorf et al., 2022); concatenated into the governing equation system:

$$\chi^2(\mathbf{x}) \equiv \|\mathbf{A}\mathbf{f}(\mathbf{x}) - \mathbf{b}\|^2$$

$$\int\int \widetilde{E}(\omega,\mu)\, d\omega d\mu = \frac{1}{16}\widehat{H}_s^2$$

$$\int\int \widetilde{E}(\omega,\mu) \sin\mu \; d\omega d\mu = \widehat{d}$$

$$\int\int \widetilde{E}(\omega,\mu) \cos\mu \; d\omega d\mu = \widehat{c}$$

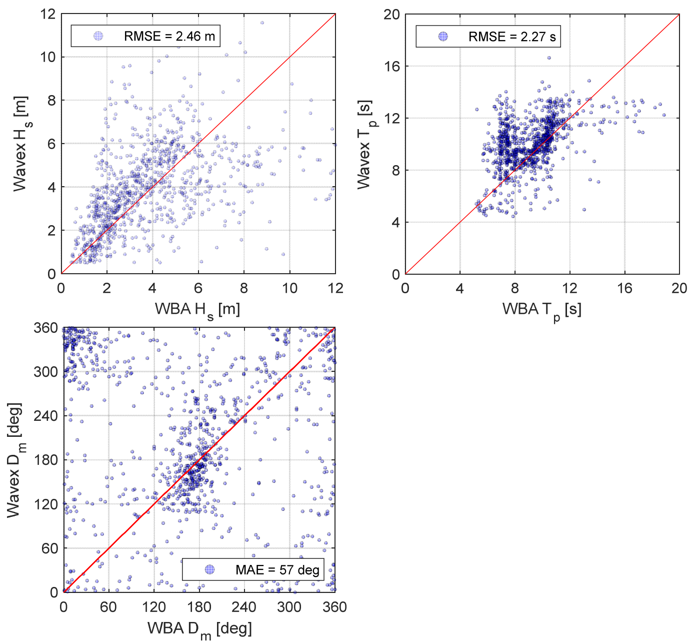
$$D_m = \arctan(d/c)$$

Nielsen et al. (2023)

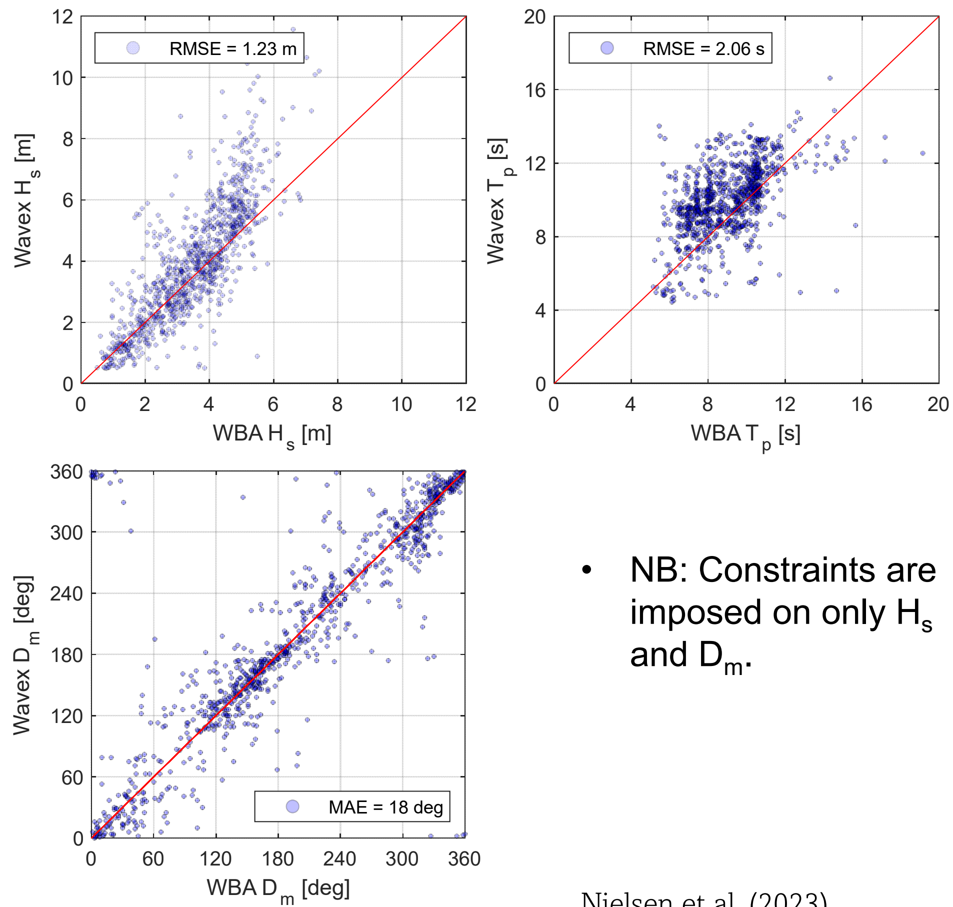
Wave spectrum estim. conditioned on ML

- **Results**

*Un*conditioned estimates



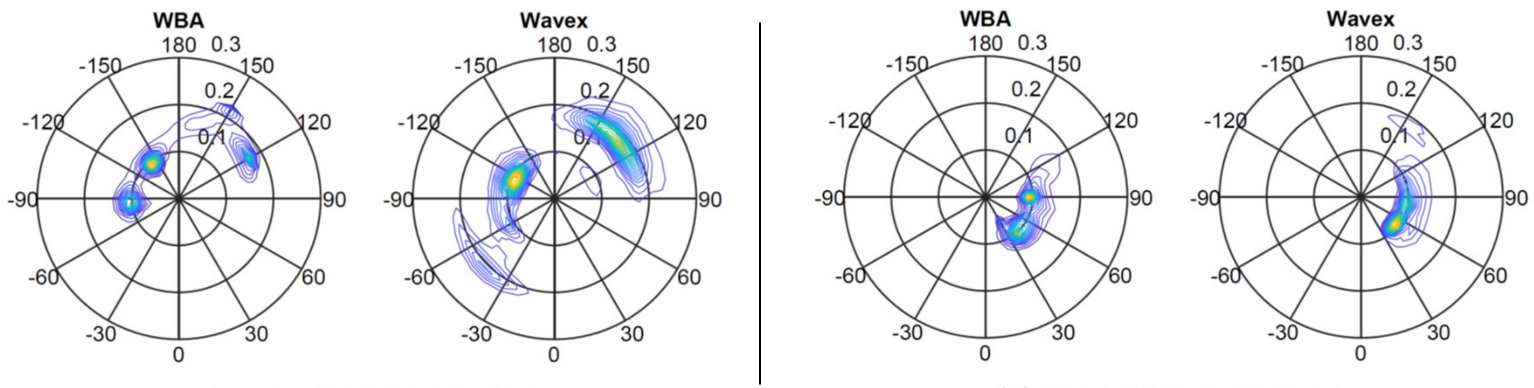
Conditioned estimates



- NB: Constraints are imposed on only H_s and D_m.

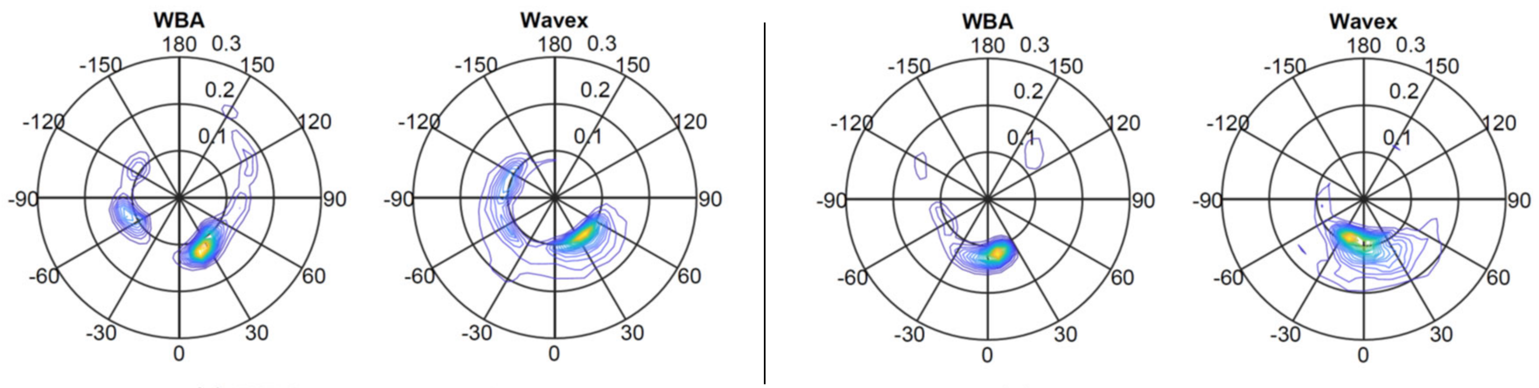
Nielsen et al. (2023)

Directional wave spectra (arbitrary outcomes)



(a) UTC: 24-09-2007 00:00.

(b) UTC: 15-09-2008 02:30.

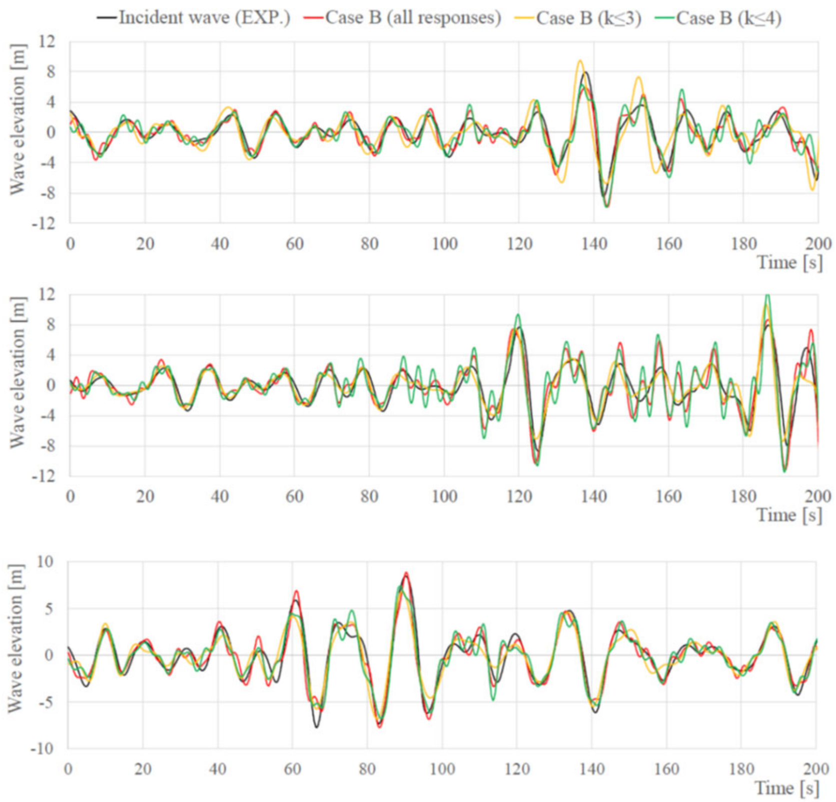


(c) UTC: 30-12-2008 04:30.

(d) UTC: 27-02-2009 13:30.

Future applications (1): Reconstructing the encountered surface elevation

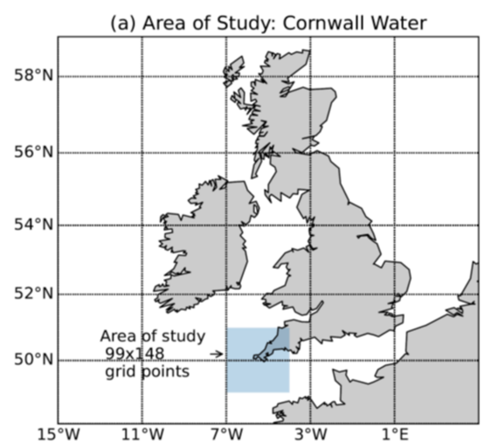
- Investigations made with experimental data (seakeeping model tests)

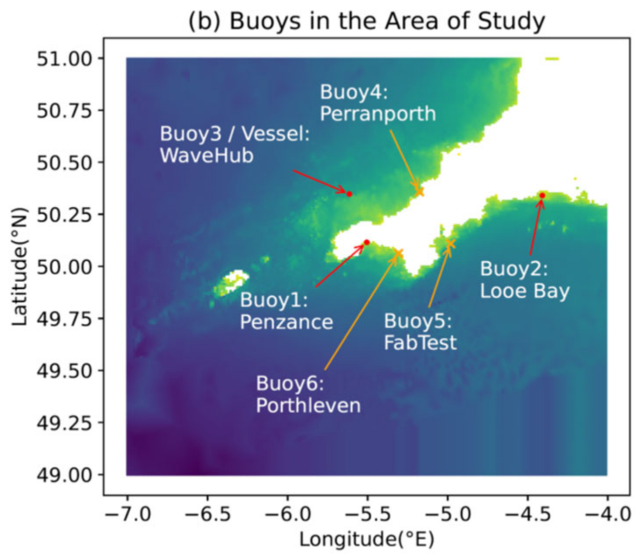


Takami et al. (2022,2023)

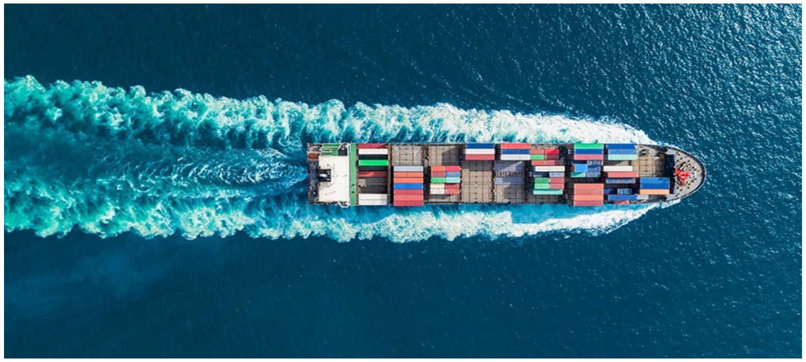
Future applications (2a):
Spatial Wave Data from a Network of Buoys and Ships

- 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), …

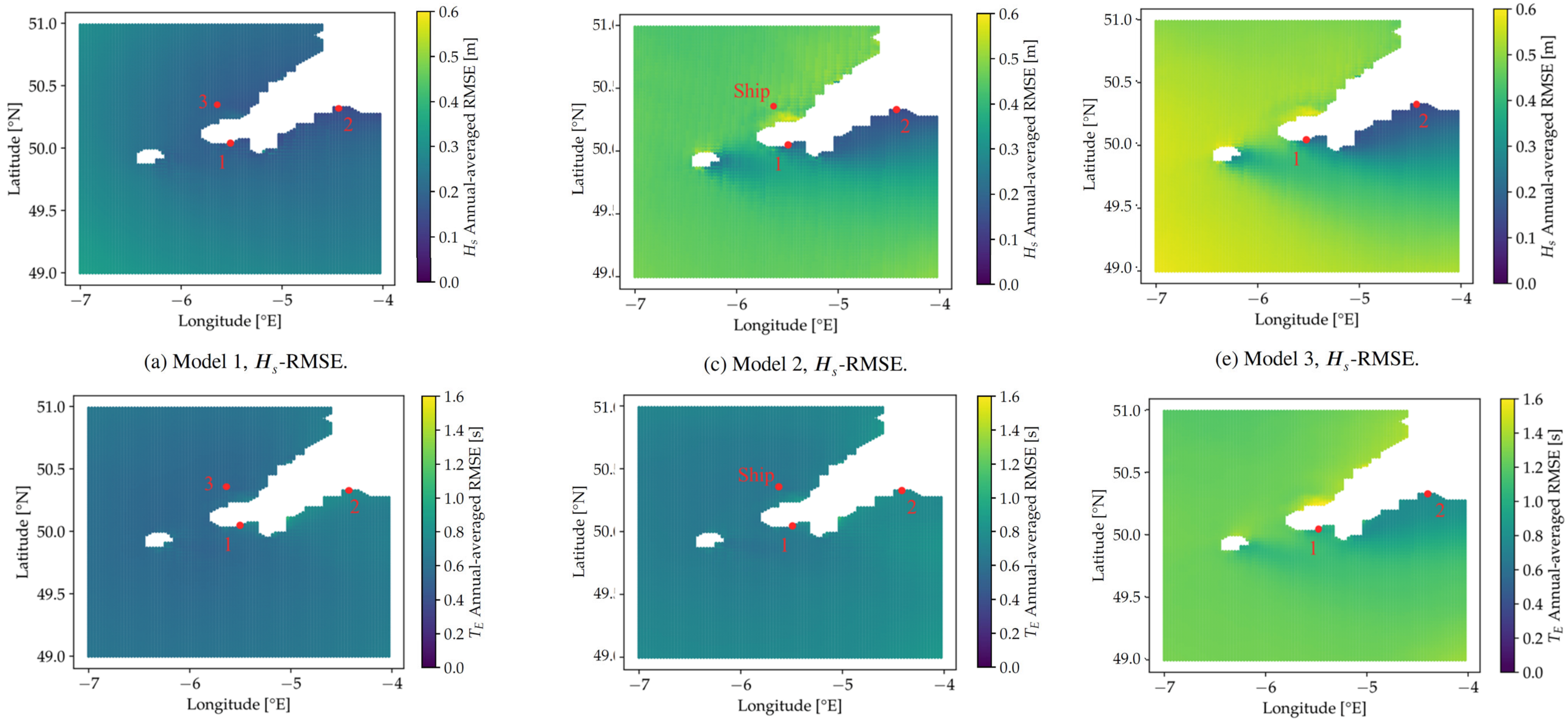




Mounet et al. (2023)



Future applications (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.

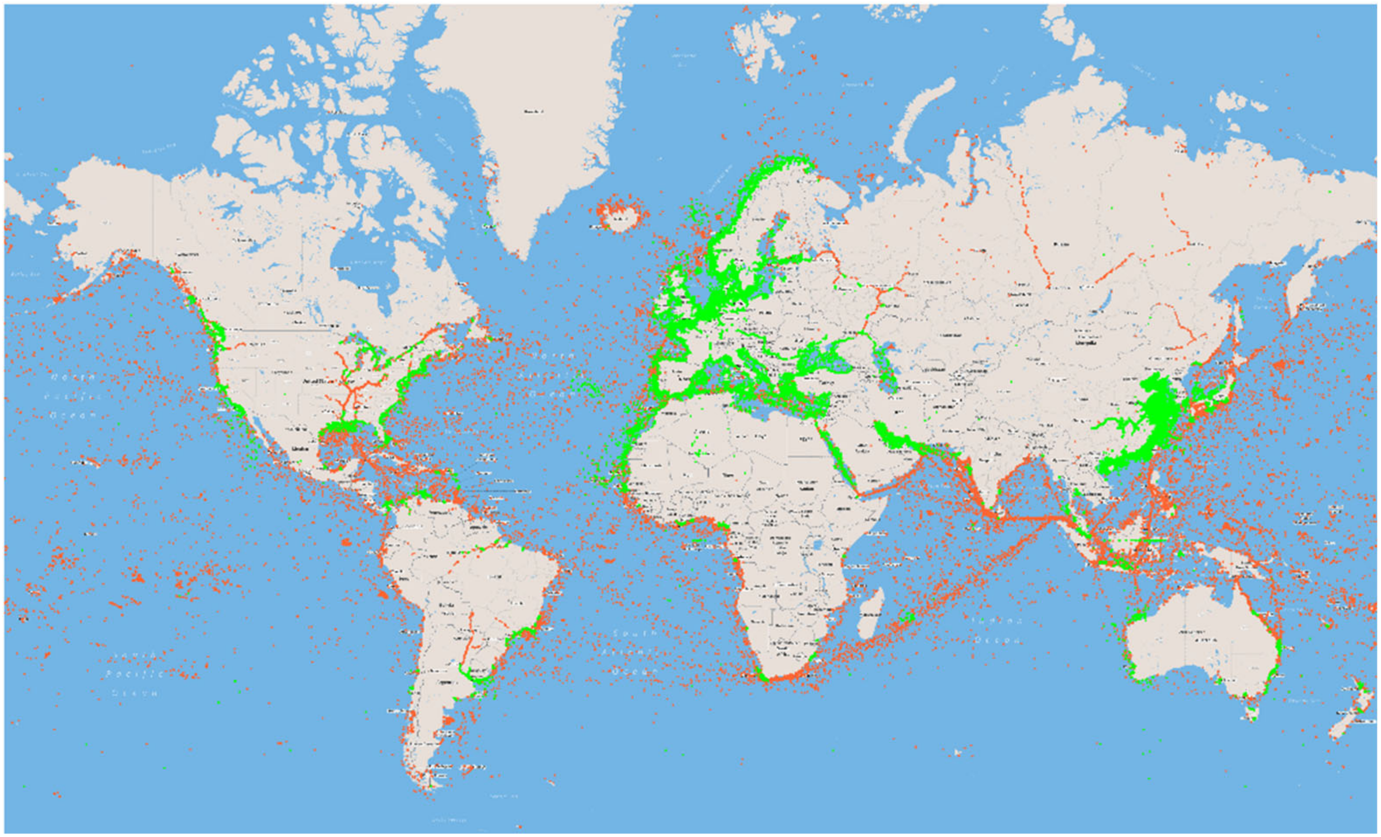
(f) Model 3, T_E-RMSE.

Mounet et al. (2023)

Closing remarks

- DTU has conducted work on the use of ships a sailing wave buoys for the past two decades
- Generally, *the wave buoy analogy* provides reasonable results, with fair agreement compared to other means for wave estimation (remote sensing, wave radar, buoy measurements, spectral wave models); despite “inherent” complexities (hull geometry, relative size, forward speed)
- The use of transfer function requires detailed and exact knowledge about the operational condition (notably loading condition and speed); if not available significant uncertainty can exist
- Machine learning methods - with no need for transfer functions - have shown to yield good results for wave *parameters*; but the (directional) wave spectrum is not available
- A *hybrid approach* (“machine learning-informed physics-based”) is appealing since scarcity of data and other inherent problems related to data can be partly mitigated via use of transfer functions
- The wave buoy analogy appears attractive, considering the large number of ships operating around; future application using multiple ships in a network

The potential…



A **snapshot of vessel positions around the world's ocean** based on data from AIS (green: terrestrial, red: satellites)

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Questions?

Contact
Ulrik Dam Nielsen
udni@dtu.dk