

Towards 3D turbidity by correlating multibeam sonar and in-situ sensor data: the TURBEAMS approach.

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Introduction

Turbidity (or the cloudiness of water) is related to the concentration and type of suspended particles in the water column. These particles may be either of planktonic (both zoo- and phytoplankton) or sedimentological origin (resuspension of surface-bound sediments). Combined they form a cloud of suspended particulate matter (SPM) which affects light penetration in coastal waters.

SPM is regularly monitored in the BPNS using a large suite of instruments. Ocean color satellite imagery is typically used to determine SPM concentrations over vast areas, but is restricted to the surface layer of the water column (Eleveld et al., 2008, Dogliotti et al., 2015). Within the water column, turbidity and SPM have been monitored either in 1D (moorings, ship-based samples, tripods on the seafloor, ...) or in 2D (Acoustic Doppler Current Profiler, ADCP, transects)(Fettweis and Lee, 2017, Van Lancker and Baeye, 2015). SPM variability in coastal environments is highly dynamic and forms complex pattern (Fettweis et al., 2014) that are best captured by comprehensive 3D measurements.

A possible solution lies in multibeam sonars which, next to seafloor bathymetry data, are able to deliver a 3D dataset of backscatter values in the water column (Simmons et al., 2017, Fromant et al., 2021, Simmons et al., 2010, Van Dijk et al., 2024), which can be converted to yield a 3D estimate of SPM concentrations in the water column of the BPNS (Praet et al., 2023). However, the relationship between the acoustic return signal of the MBES and the variable character of SPM is still insufficiently resolved.

To address this issue, Praet et al. (2023) recommended a better monitoring of the varying SPM properties. Images of SPM might prove to be pivotal in this regard, as they provide a direct snapshot of suspended particles and can contain a number of unexplored quantitative parameters. Several types of imaging devices, standard practice in long-term plankton monitoring programs, can yield these images.

In order to address the abovementioned issues and the lack of proficient processing capabilities of water column data in the currently-available software, the TURBEAMS project aims to

1. Develop adequate and purpose-built open-access software able of handling, visualizing and exporting MBES water column backscatter data.
2. Provide 3D SPM and turbidity information using MBES water column backscatter data by correlating the acoustic return signal to a diverse set of in-situ turbidity and SPM measurements.
3. Investigate the potential of images for the characterization of SPM in the BPNS: can we extract quantitative SPM information from these images and can plankton imaging instruments be used for sedimentological studies too?

Methods

Within the TURBEAMS project, an empirical approach is used: Kongsberg Discovery EM2040 300 kHz MBES water column data are gathered and concurrent in-situ optical, visual and acoustic data are obtained using a wide variety of sensors. Other acoustic data consist of Kongsberg Discovery EK80 single beam (SBES) data acquired over a wide range of frequencies (38, 70, 120, 200 and 333 kHz) and Teledyne Workhorse ADCP data (600 kHz). Ping interference of the different acoustic sources is avoided using a ping synchronization system. Optical data include grainsize data obtained with the Sequoia LISST-200X and turbidity data obtained using a Wetlabs ECO NTU OBS sensor. Water samples allow turbidity measurements using Hach turbidimeters (2100Qis and TL2360) and SPM measurements through filtration. Furthermore, 1L water samples were selected at specific stations and timings for subsequent analysis with imaging instruments (ZooScan, FlowCam and Flow cytometer) in the lab. As these imaging sensors cover a different size range, integrating these complementary devices allows us to investigate the suspended particle spectrum from a few micrometers to several centimeters. Data are obtained by performing tidal measurements at three well-studied stations with the BPNS: MOW01, W05 and W08 and by sailing transects between these stations (**Fout! Verwijzingsbron niet gevonden.**).

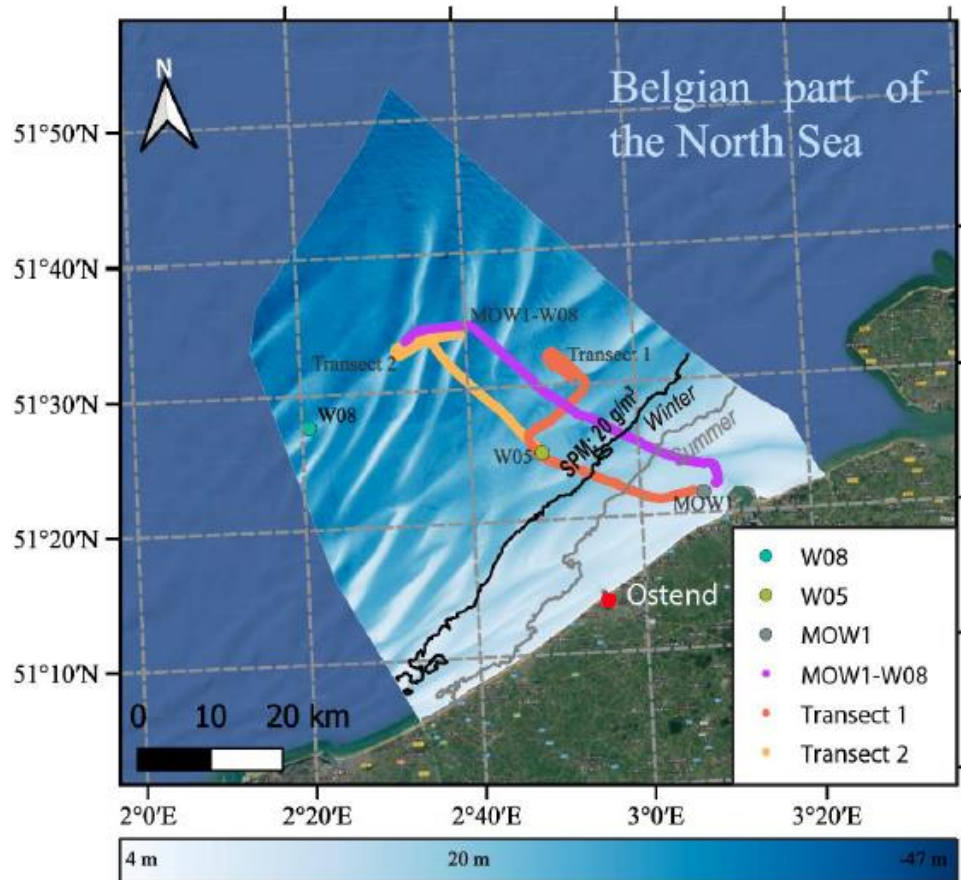


Figure 1: Stations and transects of which data have been gathered during TURBEAMS (Mawet, 2024)

The ZooScan (Hydroptic) is a waterproof scanner that visualizes and analyses zooplankton and other particles larger than $\sim 150 \mu\text{m}$ ESD using scanner technology (Grosjean et al., 2004). The FlowCam VS-4 benchtop model (Yokogawa Fluid Imaging Technologies) automatically visualizes and quantifies particles ($55\text{-}300 \mu\text{m}$) in a moving fluid combining principles of flow cytometry, microscopy and image analysis (Sieracki et al., 1998). The CytoSense (Cytobuoy) flow cytometer (FCM) is based on the principle of imaging flow cytometry (Dubelaar et al., 1999) and outputs optical scattering, fluorescence and imaging data of each particle ($1\text{-}800 \mu\text{m}$) that passes the laser. We have built our own learning dataset for the classification of all unidentifiable non-biological particles, previously incorrectly classified as “detritus”. In this learning dataset, we have morphologically subdivided the “detritus” group for the ZooScan and FlowCam images based on their shape and color (Figure 2). Automatic classification of the images is obtained using the existing and updated learning datasets, after which a series of quantitative parameters (e.g. number of particles, size characteristics and ratio plankton/sediment) were exported from the EcoTaxa and MongoDB databases.

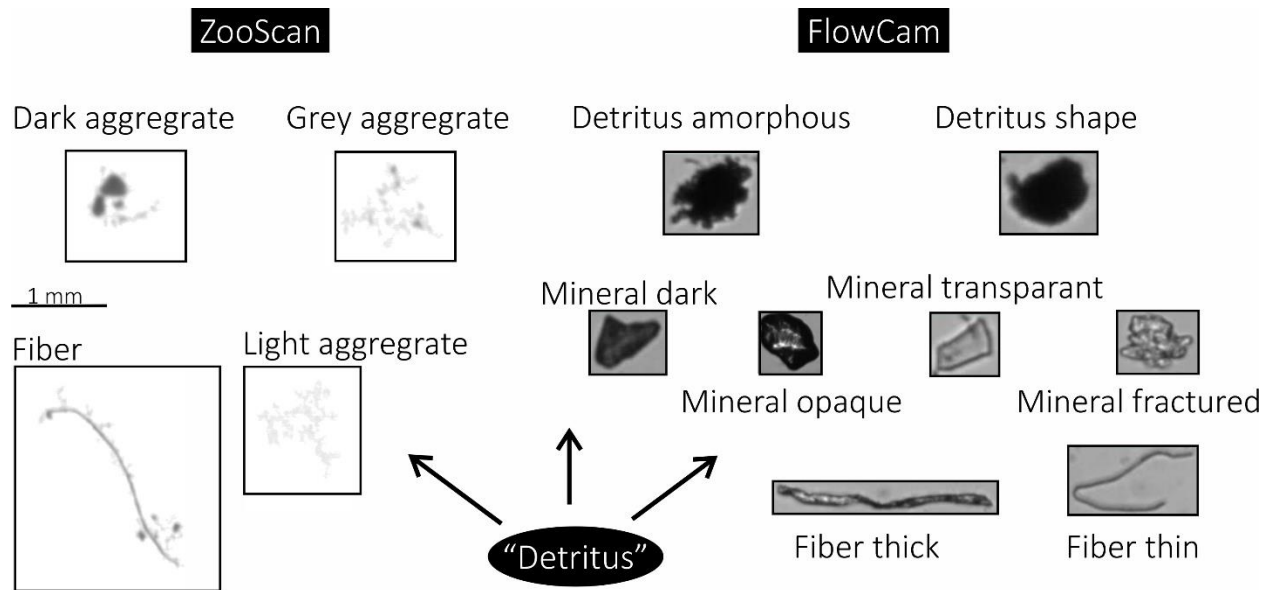


Figure 2: "Detritus" classification of Zooscan and FlowCam images

Several Machine learning (ML) approaches (Robin, 2023, Hermans, 2017) have been tested to derive correlations between acoustic volume backscatter values (MBES, ADCP and EK80 data) and SPM or turbidity measurements obtained from OBS and LISST values. An XG-boost (extreme gradient) model was compared to a multi-linear regression model to evaluate the added value of multi-frequency data. In addition, a probabilistic neural network (PNN; (Robin, 2023)) model was trained to quantify the uncertainty.

Results & discussion

1. MBES processing software

An open-source python-based software, named [PING](#), that allows to efficiently load, visualize and export large datasets of MBES- and SBES water column data has been developed. Within PING, cross-calibration of the MBES water column data with calibrated SBES data from the same frequency allows for correcting sensitivity differences between different beams (Figure 3). The corrected water column images are a powerful tool for detecting spatial SPM variability, sediment plumes or other relevant features present within the water column. Detection is currently performed on individual images, stacks of multiple images and the visualization of relevant 2D profiles of the center beam(s), allowing to quickly visualize a large dataset. Export options within PING are being developed and will contain 3D formats.

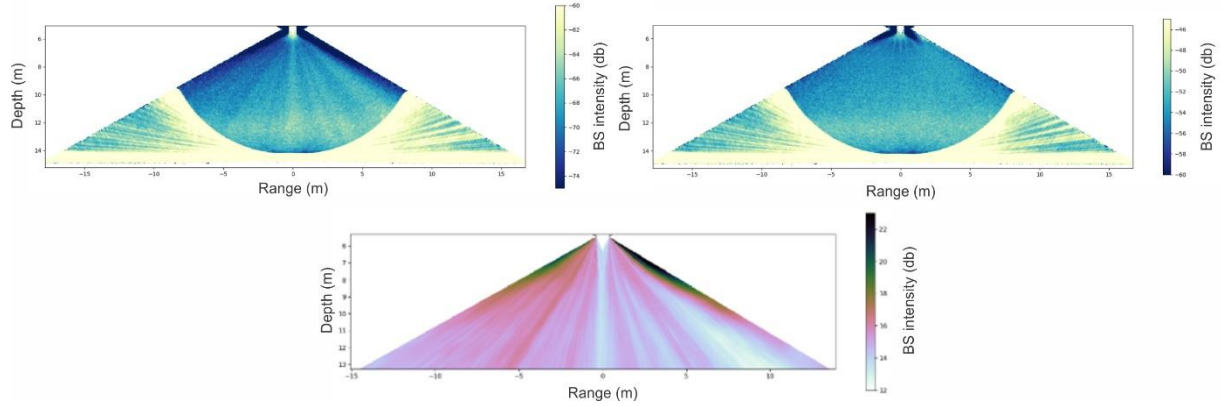


Figure 3: Left: Uncorrected water column image displaying line-like artifacts caused by different beam sensitivities. Middle: Correction beam pattern to be applied on the uncorrected image. Right: Corrected water column image. See Urban et al. (in prep) for more information.

2. Machine learning methods to obtain optimal correlations

Before training our models using ML approaches, the data had to undergo several processing steps, one of which is feature scaling. Machine learning algorithms do not perform well on input attributes with very different scales, as features with larger numerical ranges dominate the learning process. Therefore, standardization of the values has been conducted (Mawet, 2024).

Two important results were obtained based on our initial approaches. First, XG-boost performed better than multilinear regression, especially in the higher and lower turbidity ranges. The reason lies in its capacity to deal with non-linear trends. While the PNN approach also yielded satisfying results including an estimation of uncertainty, XG-boost appears to outperform PNN for all tested datasets (Figure 4). Optimizing hyperparameters is necessary to maximize the performance of both ML algorithms. Second, the use of multi-frequency in XG-boost models improves the prediction of both OBS and LISST data considerably, with r^2 values exceeding 0.95 for all frequencies combined (Figure 5).

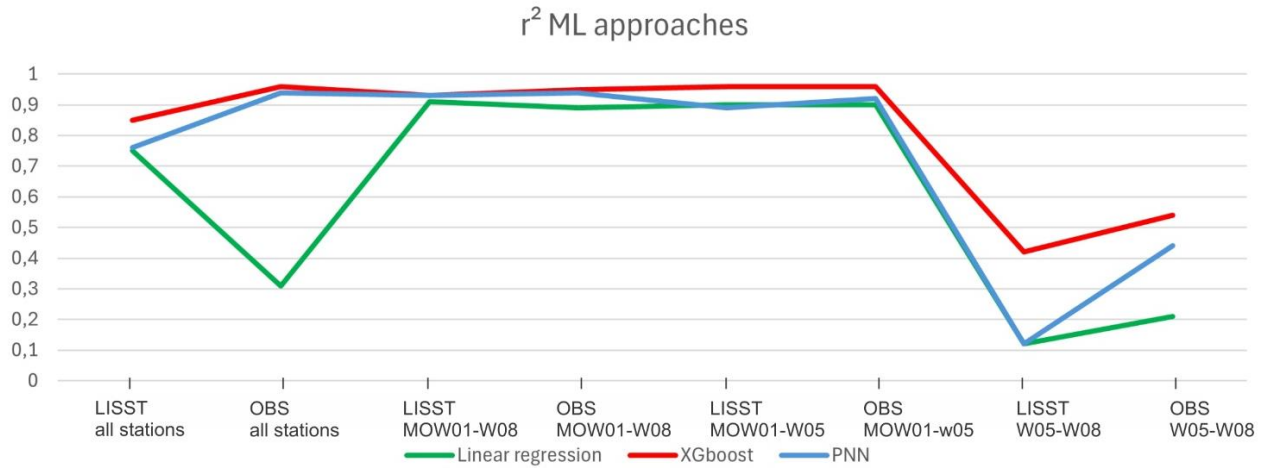


Figure 4: Correlation coefficients (r^2) between multibeam water column data and LISST/OBS data for different scenarios..

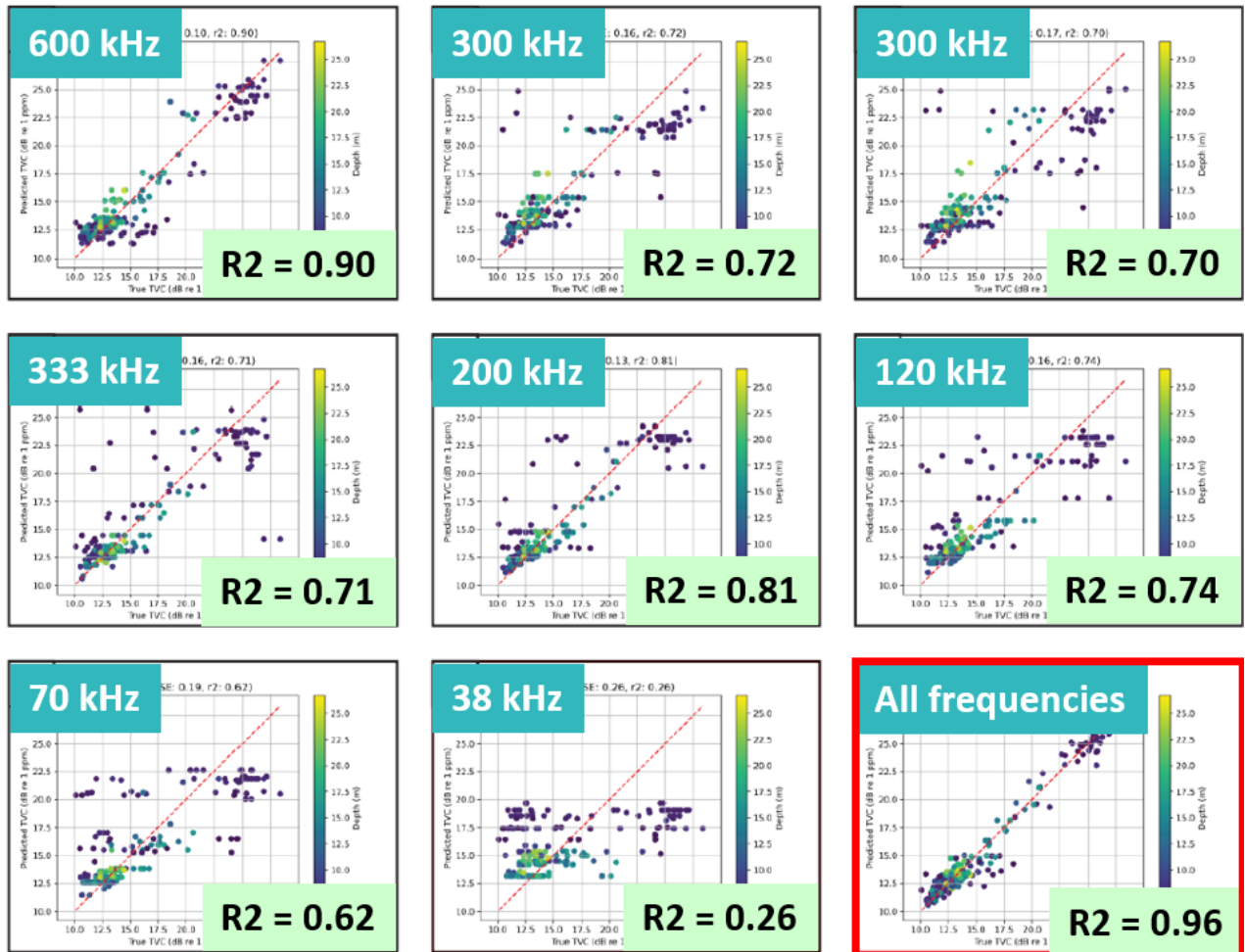


Figure 5: Correlation coefficients (r^2) between measured (LISST) and predicted Total Volume Concentration (TVC). ADCP: 600 kHz; MBES: 300 kHz (transducer 1 & 2); 333, 200, 120, 70 & 38 kHz: SBES data.

3. SPM characteristics using plankton imaging tools

The relative abundances of SPM with biological (zooplankton, phytoplankton, faecal pellets, ...), sedimentological (primary particles, floculli, flocs, fibers, minerals,...) and unknown origin (for size ranges $>150 \mu\text{m}$ and $55\text{-}300 \mu\text{m}$) are shown in Figure 6. It is clear that sedimentological particles vastly outnumber biological particles, both close to shore (MOW01) and offshore (W05 and W08). This implies that the plankton imaging tools have a lot of potential for the identification of SPM.

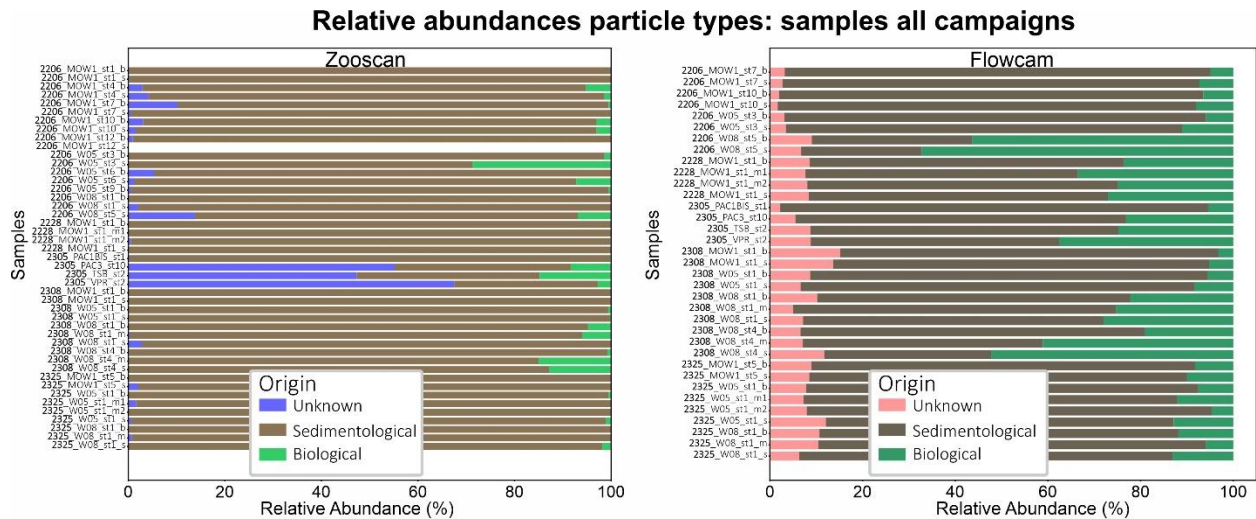


Figure 6: Relative abundances of particle types in the BPNS

Conclusion

TURBEAMS is still an ongoing project in which both the software and the methods are still being developed. PING still needs to implement export options and will see some processing upgrades in the coming year. The machine learning approaches will be further refined by using the calibrated multibeam data that is now available and by testing the generalization of the model between stations and campaigns. Moreover, the data obtained during the project are being used in the framework of sediment plume detection studies, ensuring the usage of both the data and methods in societal-relevant projects. Despite the project being unfinished business, some striking intermediary results pop out

1. Multibeam water column data tend to take a lot of storage space and consequently require a lot of processing power. Software dedicated to these data are needed in order to keep the datasets manageable. PING is an open-access software allowing to load, visualize and export multibeam water column data efficiently. Future improvements will render the software even better suited and invite other expert-users to contribute to its development.
2. Multi-frequency acoustic data are the way forward. Statistics indicate that the usage of multiple frequencies to detect particles in the water column significantly improves the

predictor capabilities. Moreover, since the combination of visual, optical and acoustic methods allow the detection of particles of different sizes and nature, combining methods is key.

3. Devices built for the detection of living plankton are evenly well suited to detect particles with sedimentological origin. Within this project, we visualized and classified for the first time a larger size range of SPM ($\sim 1\mu\text{m}$ - 1 cm), including plankton as well as non-living particles. Refining the classification is the next logical step to improve this method.

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