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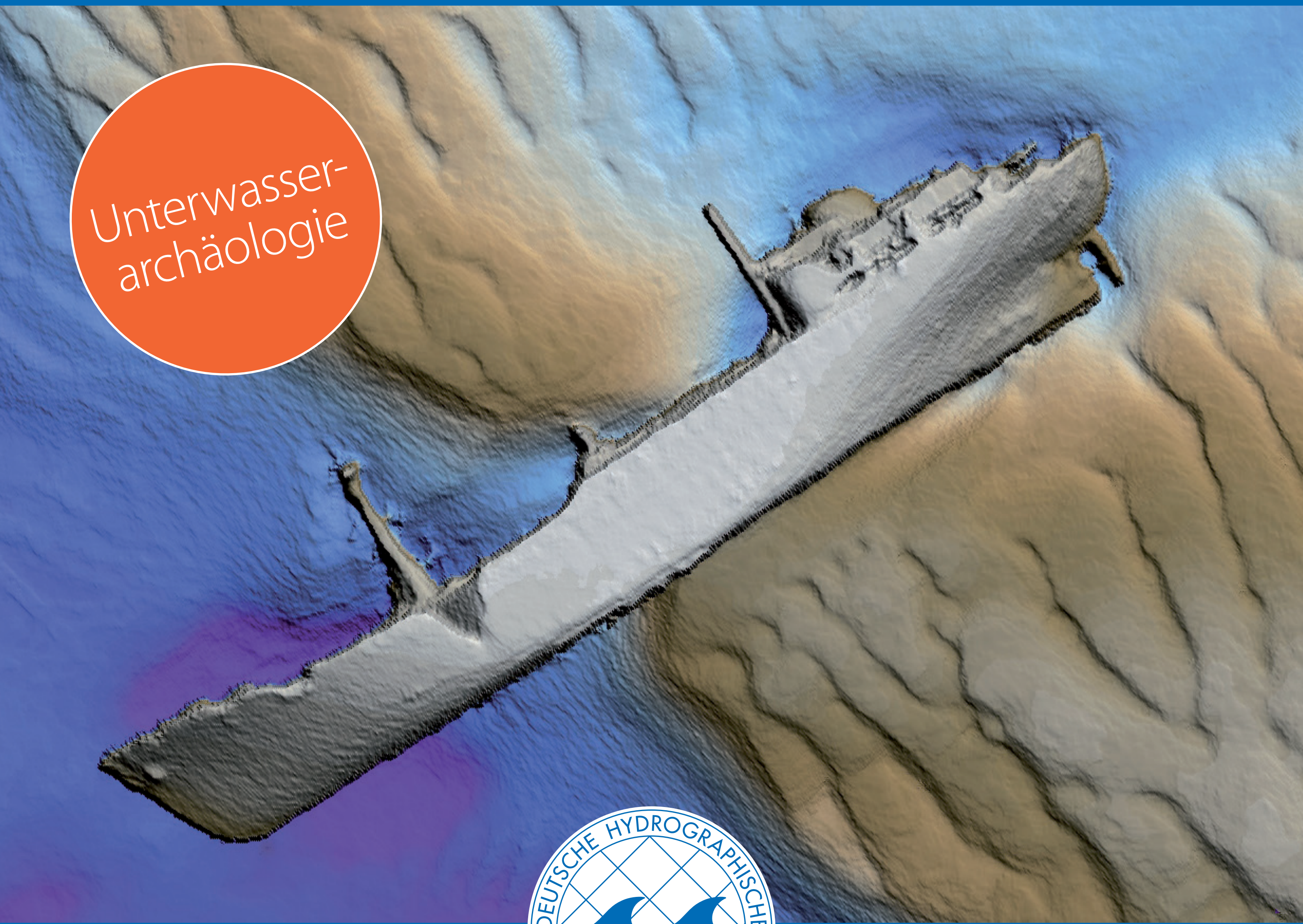

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Analysis of seafloor sediment distribution in the Port of Hamburg using backscatter data from dual-head multibeam systems for the optimisation of a sedimentological model

An article by MUHAMMAD FAIZAN KAYANI

This article presents the analysis and classification of seafloor surface sediments in the Port of Hamburg using normalised backscatter data from dual-head multibeam echo sounder systems to optimise the existing sedimentological model of the Hamburg Port Authority (HPA). Seven locations within the port were selected for detailed backscatter analysis. Ground-truth sediment samples and corresponding median grain size (D50) values were used to develop a machine learning-based sediment classification. A Random Forest regressor was trained on backscatter intensity data and D50 values to predict continuous grain size distributions at the pixel level of backscatter mosaics. Re-substitution and K-fold cross-validation results demonstrate that combining mean backscatter intensities from 200 kHz and 400 kHz significantly improves predictive performance compared to single-frequency inputs. Comparison with the existing HPA sedimentological model shows that the machine learning approach more accurately captures spatial variations in seafloor sediment grain size, particularly in coarse and mixed sediment environments, and provides closer agreement with ground-truth data, whereas the current HPA model tends to oversimplify local sediment dynamics.

multibeam backscatter | sediment classification | machine learning | Port of Hamburg
Fächerecholot-Rückstreuung | Sedimentklassifizierung | maschinelles Lernen | Hafen Hamburg

Dieser Artikel präsentiert die Analyse und Klassifizierung von Sedimenten auf dem Gewässerboden im Hamburger Hafen unter Verwendung normalisierter Rückstreudaten von Dual-Head-Fächerecholotsystemen zur Optimierung des bestehenden sedimentologischen Modells der Hamburg Port Authority (HPA). Sieben Bereiche innerhalb des Hafens wurden für eine detaillierte Rückstreuanalyse ausgewählt. Anhand von Sedimentproben und den entsprechenden mittleren Korngrößenwerten (D50) wurde eine auf maschinellem Lernen basierende Sedimentklassifizierung entwickelt. Ein Random-Forest-Regressor wurde anhand von Rückstreuintensitätsdaten und D50-Werten trainiert, um kontinuierliche Korngrößenverteilungen auf Pixelebene von Rückstreumosaiken vorherzusagen. Die Ergebnisse der Resubstitution und der K-fachen Kreuzvalidierung zeigen, dass die Kombination der mittleren Rückstreuintensitäten von 200 kHz und 400 kHz die Vorhersageleistung im Vergleich zu Einfrequenz-Daten deutlich verbessert. Ein Vergleich mit dem bestehenden sedimentologischen HPA-Modell zeigt, dass der maschinelle Lernansatz räumliche Schwankungen der Korngröße von Bodensedimenten, insbesondere in groben und gemischten Sedimentumgebungen, genauer erfasst und eine bessere Übereinstimmung mit den Bodenproben liefert, während das aktuelle HPA-Modell dazu neigt, die lokale Sedimentdynamik zu stark zu vereinfachen.

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Background

The Port of Hamburg, which is situated on the River Elbe, is a very significant part of the German economy, and it is the destination of hundreds of ships every year. The port area of Hamburg receives large marine traffic, ranging from small ships to large container ships. It is essential to ensure navigation safety. To ensure this, it is essential to understand the sedimentation behaviour of this area.

Sedimentation in the Port of Hamburg shows a clear dependence on river discharge conditions. During periods of low discharge, tidal processes predominate, leading to increased sediment transport from the North Sea towards the port. In contrast, during periods of high discharge, sediment input is primarily controlled by river transport and enhanced upstream erosion within the catchment area (Ohle et al. 2024).

Nowadays, MBES backscatter is widely used to classify seafloor surface sediments better, define marine habitats and support the development of efficient maritime spatial planning. More recent advancements in technology have enabled the acquisition and analysis of backscatter at different sonar operating frequencies (Menandro et al. 2025).

The Hamburg Port Authority (HPA) currently uses the Stratigraphic Morphodynamic Modeling System (SMMS) as its main sedimentological model to describe the spatial distribution of seafloor surface sediments within the port area. This model provides a continuous overview of sediment accumulation over time (Sievers 2021). To test the accuracy of this sedimentology model, advanced backscatter results needed to be compared with this model to improve its accuracy and provide a better classification approach by reducing the need for large sediment sampling campaigns.

Area overview: Port of Hamburg

The Port of Hamburg is located in the tidal-influenced bifurcation zone of the lower River Elbe in northern Germany. The port area is affected by both the river flow and the tidal influence from the North Sea, which together determine the movement, deposition and erosion of sediments (Ohle et al. 2024).

Seven key areas were selected based on their sediment behaviour, hydrodynamic conditions (ebb and flood currents), vessel traffic intensity and the presence of major container terminals. In addition, these areas were chosen because the sedimentological model shows anomalous behaviour in these regions, which requires further investigation within the scope of this research. The selected research areas are: Köhlbrand, Strandhafen, Köhlfleet, Waltershofer Hafen, Vorhafen, Norderelbe 7 and Reiherstieg.

Survey planning and data acquisition

Surveys were planned for all seven mentioned areas. Fig. 1 shows an overview of the boundary polygons of the selected areas over the Port of Hamburg. Surveys for each area were planned to ensure complete coverage and sufficient overlap between the survey lines. The number of track lines varied across areas due to differences in spatial extent.

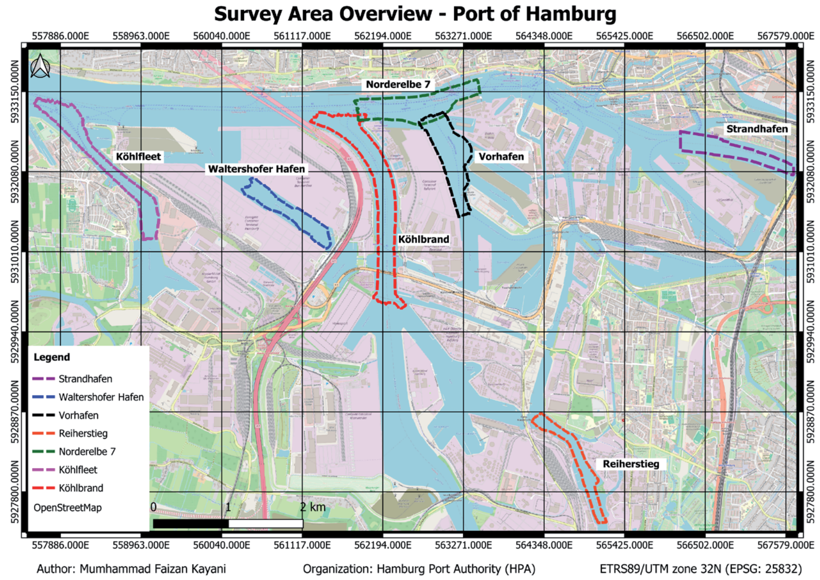

Fig. 1: Survey area overview of all the selected regions in the Port of Hamburg

A total of 14 datasets were acquired using the *Deepenschriewer 1* vessel equipped with a Teledyne Reson SeaBat T20-R dual-head multibeam echo sounder. Frequency-modulated (FM) waveforms were recorded at 200 kHz and 400 kHz, with survey lines designed for 100 % overlap and run in opposite, parallel directions using a 70° swath angle. The automated tracker was enabled throughout to ensure stable and continuous data acquisition. Additionally, one dataset was acquired using multispectral functionality at 200, 300 and 400 kHz. Bathymetric and normalised backscatter data were recorded in S7K format using Teledyne Reson's Sonar UI, while Qinsy served as a navigation display for real-time vessel positioning and tracking.

In this article, the Köhlbrand area is discussed in detail and serves as the primary example to show the entire workflow. The same steps were applied to all the other areas.

Data processing

All the final bathymetric surfaces and backscatter mosaics were generated in Teledyne Geospatial CARIS HIPS and SIPS under ETRS89/UTM Zone 32N (EPSG: 25832) coordinate system. The bathymetric data processing workflow included creating a new vessel file with updated offsets, lever arms and TPU settings and importing the S7K files into CARIS HIPS and SIPS. Navigation and sound velocity profiles were validated and bathymetric data were georeferenced using GNSS and the local geoid (GCG2016). An appropriate grid resolution of 0.5 m was selected based on footprint calculations. Data were cleaned using quality filters, followed by manual swath editing. A CUBE surface was then generated and validated.

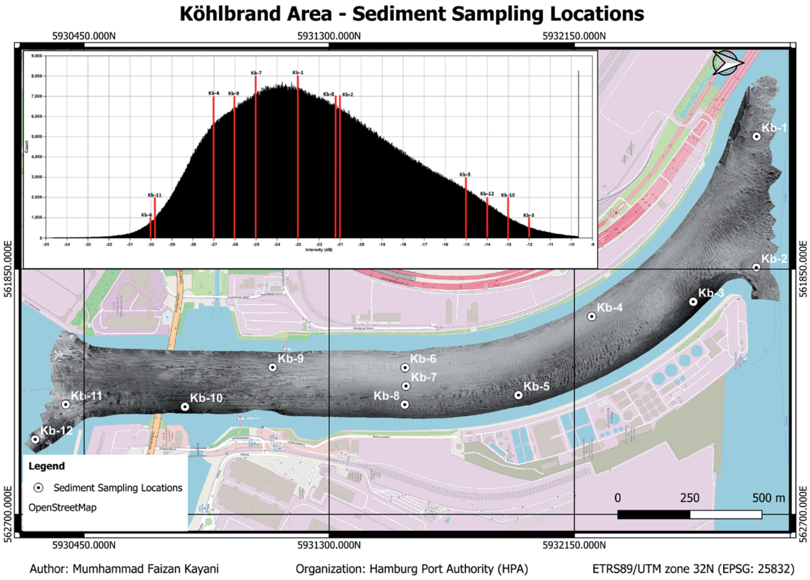

Fig. 2: Köhlbrand area 200-kHz backscatter mosaic and histogram showing the intensity (dB) distribution, with sampling points marked according to their respective dB values and visual contrast

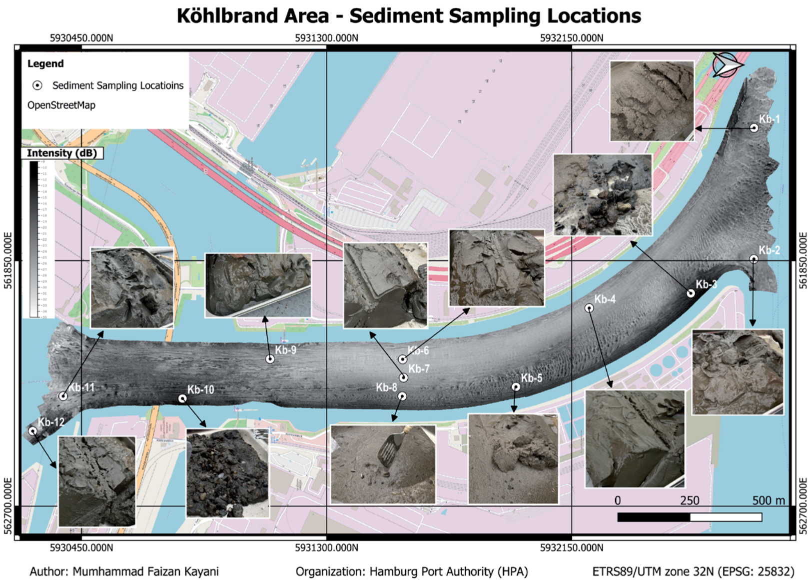

Fig. 3: Sediment sampling locations for Kb-1 to Kb-12 and images of the samples at each location in Köhlbrand

Backscatter mosaics were generated in CARIS HIPS and SIPS using normalised S7K data and the SIPS Backscatter WMA with Area-based AVG engine. A 0.20-m grid resolution was selected for single-frequency mosaics and 1-m resolution for multispectral backscatter to create mosaics of appropriate resolution using compensated 7,058 snippet records, default search radius settings and local absorption corrections. A processed bathymetric surface supported slope and angle-dependent corrections, while beam pattern and AVG corrections were applied to remove transducer artefacts and normalise intensity across incidence angles.

Sediment sampling

A sediment sampling campaign was conducted in which a total of 72 sediment samples were collected using the HPA vessel *Deepenschriewer 3,* equipped with a Van Veen grab sampler. After generating backscatter mosaics in HIPS and SIPS, 74 locations were marked in the selected seven areas. These locations were chosen to represent the full range of sediments, as shown by changes in backscatter intensity in Fig. 2. The selection is guided by histogram analysis of backscatter (dB) values, combined with the visual contrast (light and dark areas) visible on the mosaic. These sampling points were strategically marked to capture sediment variability and ensure diverse sediment coverage.

Köhlbrand area sampling

In the Köhlbrand area, twelve sediment samples were collected at marked locations, as shown in Fig. 2. These twelve locations are named with the abbreviation Kb, which represents the Köhlbrand area. In Fig. 3, sediment samples collected at locations Kb-1 to Kb-12 are shown. The same process was followed for all other areas.

Results and discussion

Bathymetric surface and backscatter mosaic

Final quality control confirmed that all the processed bathymetric surfaces met IHO S-44 Special Order accuracy requirements. Surface statistics are computed in HIPS and SIPS software using depth as an attribute layer with a bin size of 0.01 m. Fig. 4 and Fig. 5 show the maps of processed bathymetric surfaces and backscatter mosaics with their corresponding histograms for 200 and 400 kHz in the Köhlbrand area.

Multispectral backscatter

During this research, the significance of unavailable multispectral backscatter processing functionality for dual-head systems was highlighted, and continuous feedback and test data were provided to the Teledyne CARIS development team. As a result of this collaboration with CARIS, the HIPS and SIPS software, with its latest version 12.1.3, can now process multi-frequency data from dual-head systems. This is an important development for Hamburg port survey operations, particularly with all dual-head systems (T20-R and T50-R).

Multispectral backscatter data were not available for all survey areas due to technical limitations encountered during data processing in CARIS HIPS and SIPS, particularly related to the handling of dual-head systems and multispectral datasets. To address these limitations, the survey design was adapted to include the acquisition of backscatter data at a minimum of two different frequencies, with the research areas surveyed twice. As a re-

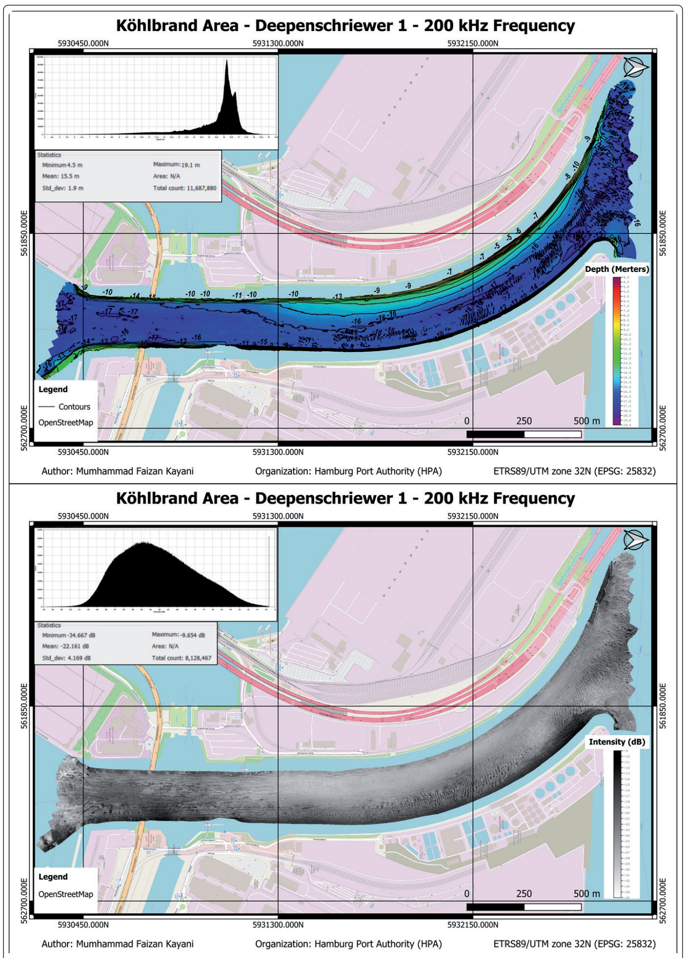

Fig. 4: Processed bathymetric surfaces and backscatter mosaics for the Köhlbrand area *(Deepenschriever 1)* at 200 kHz. The top map shows the 200-kHz bathymetry with its depth histogram, while the bottom map presents the corresponding 200-kHz backscatter mosaic map with intensity histogram

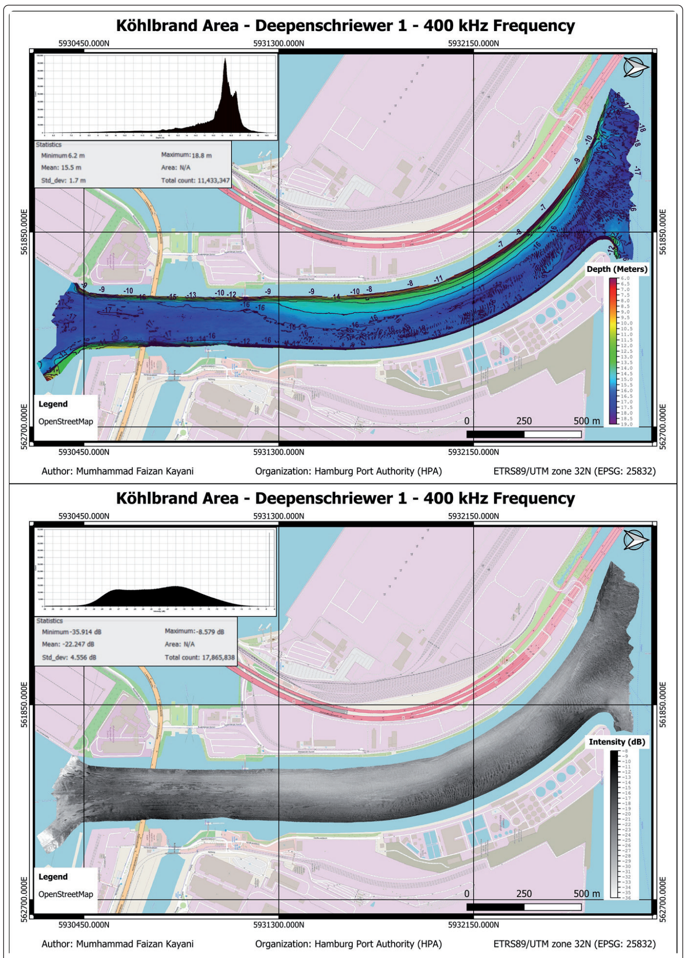

Fig. 5: Processed bathymetric surfaces and backscatter mosaics for the Köhlbrand area *(Deepenschriever 1)* at 400 kHz. The top map shows the 400-kHz bathymetry with its depth histogram, while the bottom map presents the corresponding 400-kHz backscatter mosaic map with intensity histogram

sult, direct multispectral comparisons between frequencies are only possible for a single dataset from the Strandhafen area.

With the new multispectral processing option, it is now possible to get three frequency layers (200 kHz, 300 kHz and 400 kHz) after generating the mosaic. Each frequency layer consists of two slightly different frequencies that come from the two heads of the dual-head multibeam system. The 200-kHz band includes data from 187 kHz and 213 kHz, the 300-kHz band from 287 kHz and 313 kHz, and the 400-kHz band from 387 kHz and 413 kHz. These small differences in frequency make it possible for the software to recognise which head the data comes from and to combine them correctly within each frequency band. A schematic illustration of the multispectral data acquisition concept using a dual-head system is shown in Fig. 6.

A multispectral backscatter mosaic shows frequency-dependent seabed details. At 200 kHz, the mosaic appears smooth, showing broad patterns because lower frequencies penetrate deeper and are less sensitive to small surface variations. The 300-kHz mosaic captures moderate seabed texture changes, while 400 kHz provides the sharpest detail, highlighting fine-scale roughness. In the combined RGB mosaic, 200 kHz is mapped to red, 300 kHz to green and 400 kHz to blue, emphasising differences in sediment response. Blue areas indicate coarser sediments, whereas red or brown areas cor-

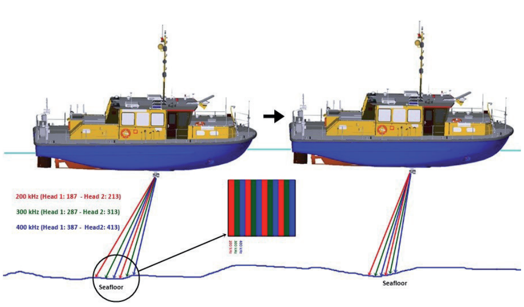

Fig. 6: Schematic illustration of the multispectral data acquisition concept from a dual-head configuration using 200 kHz (187 to 213), 300 kHz (287 to 313) 400 kHz (387 to 413) frequencies with *Deepenschriewer 1* vessel (modified illustration from HPA n.d.)

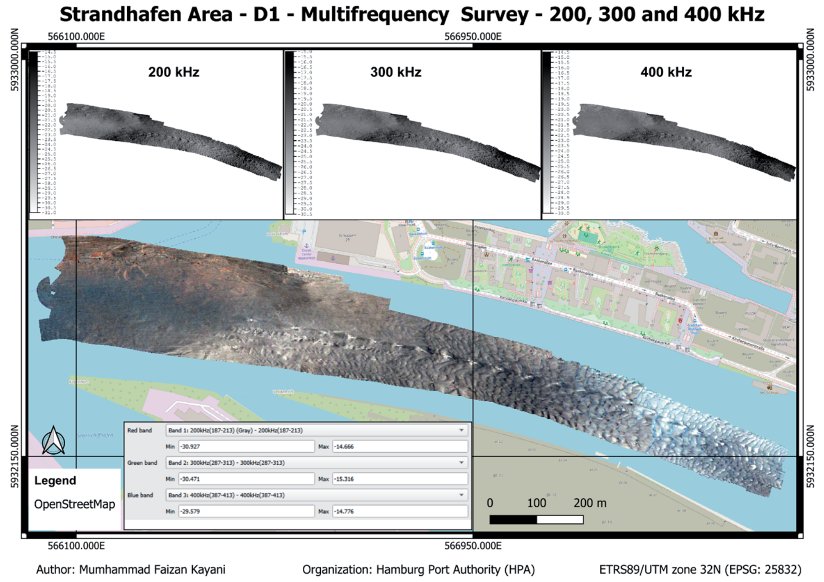

Fig. 7: Multispectral backscatter mosaic with layers 200 kHz, 300 kHz and 400 kHz

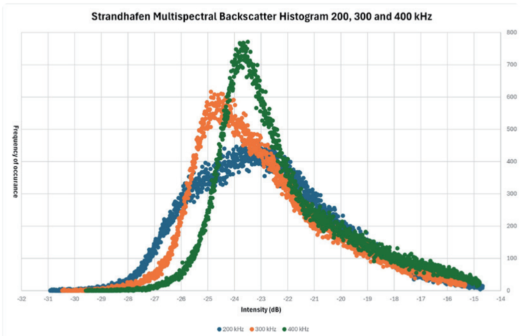

Fig. 8: Histogram comparison of 200-kHz, 300-kHz and 400-kHz backscatter mosaics layers in Strandhafen area (blue: 200 kHz, orange: 300 kHz, green: 400 kHz)

respond to finer-grained sediments. A combined multispectral backscatter mosaic map with layers at 200 kHz, 300 kHz and 400 kHz is shown in Fig. 7, and the histogram comparison is presented in Fig. 8.

Cumulative grain size distribution and mean grain size estimation

After receiving sieve analysis results from the laboratory, grain size data were first checked and corrected to ensure that cumulative percent-finer values increased with particle size. To convert laboratory results into a visual representation on a logarithmic scale and to determine median grain size (D50), the data were processed using forward and inverse splines based on Piecewise Cubic Hermite Interpolation (PCHIP) (Fritsch and Carlson 1980). PCHIP was implemented in Visual Studio using a Python script adapted from SciPy's open-source repository (SciPy Developers 2025), which was further modified.

The spline interpolation provided D50 values for all samples. The applied sieving method was designed for sediments larger than 20 µm, as the smallest sieve size was 20 µm. The resulting D50 values were then classified according to the Udden-Wentworth grain size scale. Fig. 9 shows spline curves for twelve samples from the Köhlbrand, and Table 1 lists their D50 values and corresponding sediment classifications.

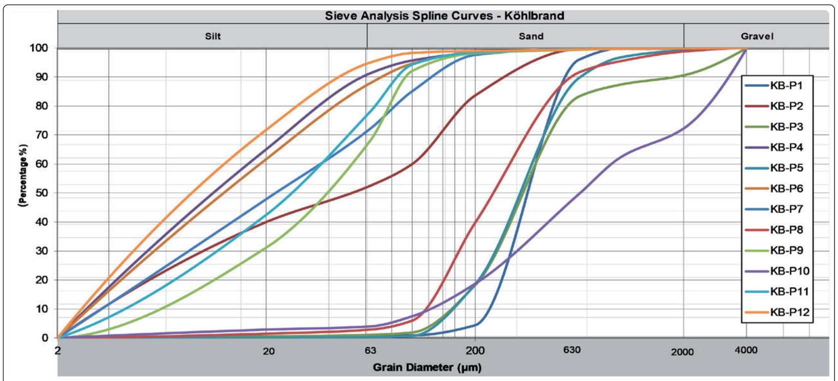

Fig. 9: Köhlbrand area samples cumulative grain size distribution curves (Kb-1 to Kb-12)

Name	D50	Udden-Wentworth Class (D50)
Kb-1	356.5 µm	Medium sand
Kb-2	52.11 µm	Coarse silt
Kb-3	339.14 µm	Medium sand
Kb-4	11.13 µm	Fine silt
Kb-5	329.41 µm	Medium sand
Kb-6	12.5 µm	Fine silt
Kb-7	22.63 µm	Medium silt
Kb-8	244.66 µm	Fine sand
Kb-9	39.47 µm	Coarse silt
Kb-10	636.91 µm	Coarse sand
Kb-11	25.92 µm	Medium silt
Kb-12	8.79 µm	Fine silt

Table 1: Summary of grain size diameters at each location and Udden-Wentworth classification in the Köhlbrand area

Estimation of mean backscatter values per location

To obtain reliable sediment classifications, accurate backscatter intensity (dB) values were extracted at each sampling location. The 200-kHz and 400-kHz backscatter mosaics were imported into QGIS as GeoTIFFs, and sampling points were added as delimited text. Because point coordinates may contain minor positional uncertainty, buffers were created around each location to include multiple pixels when calculating mean dB values using zonal statistics in QGIS.

Given the mosaic resolution of 0.20 m (pixel area = 0.04 m^2), buffer areas were calculated for a radius of 1 m using the circle area formula. This corresponded to approximately 78.5 pixels, respectively. A 1-m buffer was selected because it provides a sufficient number of pixels for stable averaging of intensity values at each sampling point.

Sediment classification using machine learning

A machine learning approach was used to classify sediments by predicting D50 values using a Random Forest regressor, trained on ground-truth and backscatter intensity data. The Random Forest model was implemented in the Python console of QGIS 3.34.1 with a script adapted from the scikit-learn open-source GitHub repository (Scikit-learn Developers 2025a), and it was further modified according to the workflow. The workflow is shown in Fig. 10.

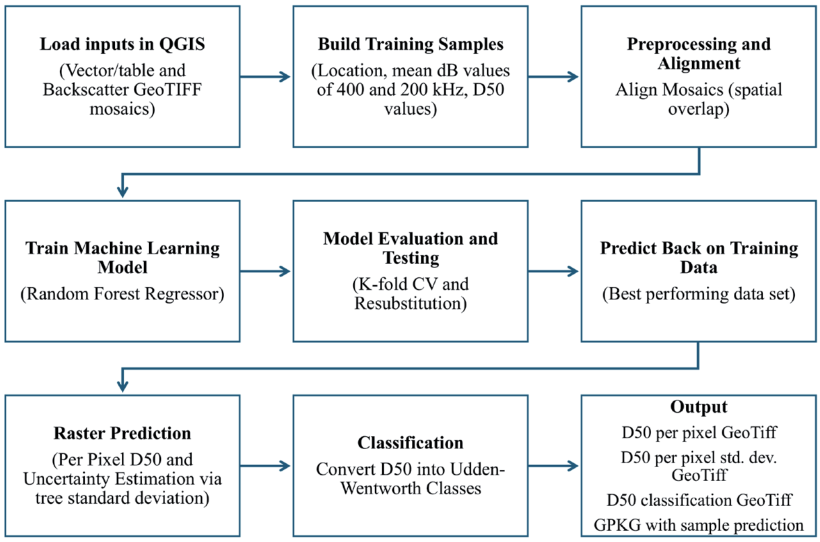

Fig. 10: Workflow of the process used for D50 prediction and classification with a machine learning approach

Stage 1: Preparing input data

The workflow began by preparing two input datasets: the first training dataset contains the mean backscatter intensity values of all valid 72 samples at 200 kHz and 400 kHz, ground-truth sediment labels, D50 values and their geographic coordinates in CSV file format. This is imported in QGIS as a delimited text layer. For the second dataset, 200-kHz and 400-kHz backscatter mosaics were exported as GeoTIFF rasters from CARIS HIPS and SIPS at a specified folder location.

Stage 2: Preprocessing and alignment

The modified Python script is executed in the QGIS Python console using a CSV file and path location to GeoTIFF rasters as input to initiate the training and prediction process. As the two mosaics did not perfectly overlap because they were from different surveys at 200 kHz and 400 kHz at slightly different times. The spatial intersection for both rasters was computed, using only overlapping pixels. The remaining non-overlapping area was not used as input data.

Stage 3: Training Random Forest regressor

During the training stage of machine learning, only samples with available mean_200, mean_400 and D50 values were used. This stage combines the two mean intensities into the feature matrix and the D50 values into the target vector. A Random Forest regressor with 500 trees was trained to learn the relationship between backscatter intensity and ground-truth grain size and make predictions on the training data.

Stage 4: Model evaluation and testing

Model's predictive performance was evaluated using both a re-substitution accuracy test and K-fold cross-validation for three setups: 200 kHz, 400 kHz and a combined 200 to 400 kHz frequency configuration. Both scripts were adapted from scikit-learn's open-source code (Scikit-learn Developers 2025b).

Re-substitution accuracy test

The purpose of testing three datasets was to evaluate the predictive performance on each dataset and use the best input dataset to train the model to achieve the most accurate results. These statistical results showed that, while both single-frequency setups performed reasonably well, the combination of 200 kHz and 400 kHz provided a more accurate and reliable prediction of D50, with a minimum RMSE of 102.69 µm, MAE of 36.29 µm and R^2 value of 0.89.

K-fold cross validation test

This test was run across the same three different setups. The statistical results from the K-fold cross validation test showed that with single-frequency input (200 kHz and 400 kHz), the model performed poorly on unseen data, as shown by high RMSE values and low R^2 values. When both 200-kHz and 400-kHz data were combined, the model performed relatively better by giving an RMSE of 287.08 µm, an MAE of 98.05 µm, and an R^2 of 0.12. Although the improvement was small, the combined values gave a better description of the data than the single-frequency values. This means that using both frequencies together gave better and more useful information than using only one frequency.

Stage 5: Raster prediction and classification

Among the test combinations, the combined setup (200 and 400 kHz) gave the best results in both tests. After this evaluation, the best-performing input setup (combined 200 and 400 kHz) was used to make predictions on the training data and to produce the final raster prediction. The trained model was then applied to the overlapping 200-kHz and 400-kHz mosaics so that each pixel's mean backscatter values could be used to predict its D50 value, and uncertainty was calculated as the standard deviation across all trees in

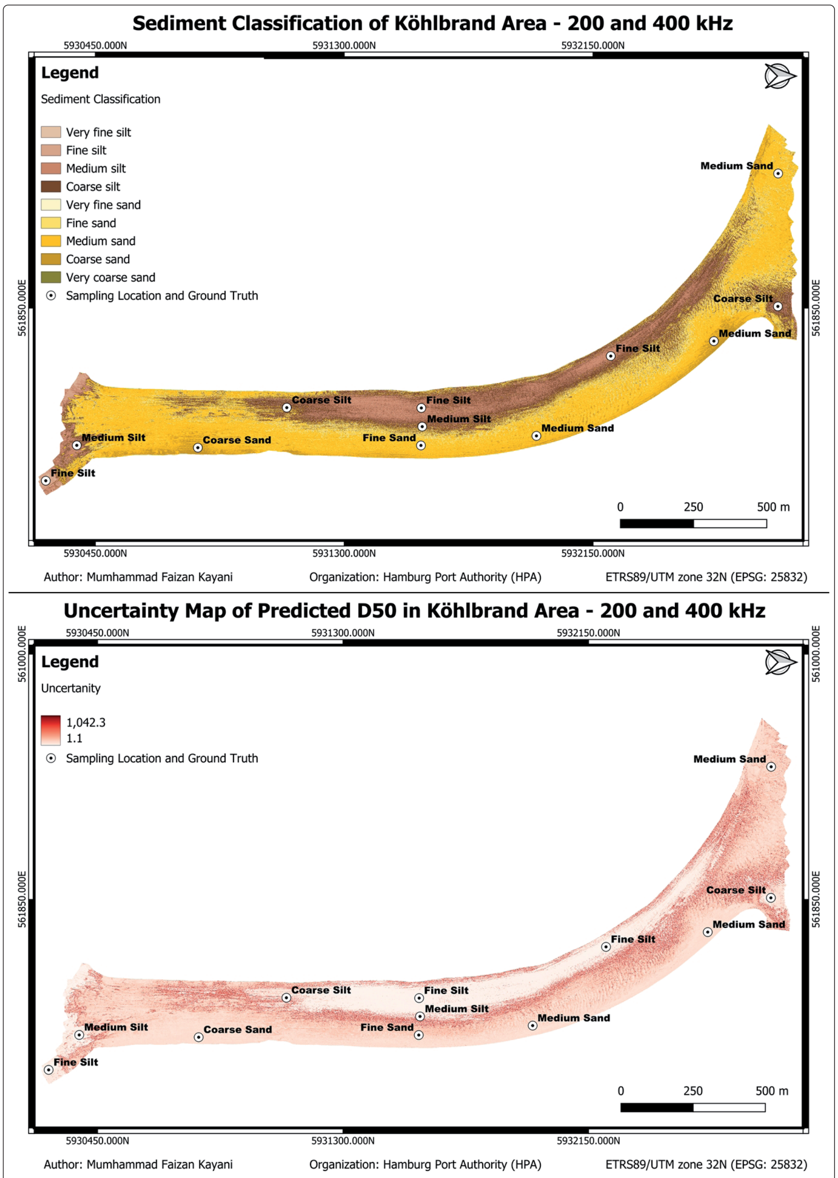

Fig. 11: Sediment classification map of the Köhlbrand area based on D50 values from sampling points. The map displays sediment types according to the Udden-Wentworth scale, with different colours representing each sediment class, based on predicted data from ground truth and intensity values from 200-kHz and 400-kHz frequencies (top). Uncertainty map of model-predicted D50 values in the Köhlbrand area. The map shows the prediction uncertainty, ranging from low (white) to high (red) (bottom)

the forest. The predicted D50 values were then post-processed into sediment classes using fixed Udden-Wentworth thresholds, generating a classification raster with integer class IDs.

Stage 6: Output

The workflow produced three raster outputs: a D50 prediction GeoTIFF, a standard-deviation GeoTIFF representing model uncertainty at each pixel and a D50 classification GeoTIFF as well as a corresponding Geo-package file.

Köhlbrand area sediment classification

In the Köhlbrand classification map, silts are mostly found in the western part of the area, whereas sands are more common in the middle and eastern parts, which matches the D50 classification. Some differences are observed near the boundaries, where the transition is happening between the sediment classes. These small mismatches are likely due to natural changes in the seabed and the limitations of the machine learning model.

The uncertainty map shows that most of the Köhlbrand area was predicted with low uncertainty. The silty region in the middle and the sandy region in the east are more consistent, which means the model worked well in those areas. Higher uncertainty is mainly found at the boundaries between classes, especially where fine silt and medium silt are located. This happens because the values in these areas are close to each other, which makes it harder for the model to separate them with high accuracy. In general, the results agreed with the ground-truth samples, but they also highlighted areas of high uncertainty (red), where the predicted performance is low.

Fig. 11 displays a sediment classification map of the Köhlbrand area with ground truth and a corresponding uncertainty map showing the model's prediction accuracy for the same area.

Comparison of the sedimentological model with machine learning predicted D50

In the Teledyne CARIS BASE EDITOR software, the existing sedimentological model at HPA and predicted D50 surfaces are used to generate a difference surface. The predicted D50 surface (B) is subtracted from the sedimentological model surface (A). This subtraction (A – B) produces a difference surface with both negative and positive values. Areas where A – B = 0 indicate no difference between the two surfaces, A – B > 0 indicates that the sedimentological model predicted a larger grain size than the predicted D50 surface, and A – B < 0 indicates that the predicted D50 surface predicted a larger grain size than the sedimentological model.

In the Köhlbrand area, the mean difference is –175.81 µm, which means that the predicted D50 values are overall larger than those from the sedimentological model. The standard deviation is ±267.88 µm, showing a wide range of differences. The largest difference is –1527.37 µm, where the predicted D50 is much coarser than the sedimentological model. The maximum difference is +187.91 µm, which means that the sedimentological model gave larger D50 values but only in a few areas.

In the Köhlbrand area, most of the eastern and southern parts are shown in blue, indicating that the predicted D50 values are coarser than those from the sedimentological model (A – B < 0). On the other hand, the central part shows more yellow to orange colours, meaning that the sedimentological model gave similar or larger D50 values than those of the predicted model. The difference map between the predicted D50 and the sedimentological model in the Köhlbrand area is shown in Fig. 12.

Per-sample comparison sedimentological model vs. machine learning predicted D50

Köhlbrand area

The parity plot (Fig. 13) of the Köhlbrand shows that most values from the sedimentological model are below the 1 : 1 line. The sedimentological model gives smaller values in sandy sediments than the predicted D50. The difference is most prominent in the medium-to-coarse sand range, where the gap between the two values reached several hundred micrometers. The error metrics also support this, showing a mean absolute error (MAE) of 157.7 µm, a root mean square error (RMSE) of 212.1 µm and a very high mean absolute percentage error (MAPE) of 237.7 %.

The per-sample absolute difference shows these differences. Samples Kb-3, Kb-5 and Kb-10 have large differences, greater than 300 µm. On the other hand, samples Kb-11 and Kb-12 show very small differences, meaning that the sedimentological model gives closer results to the predicted D50 in the fine silt range. This shows that the sedimentological model struggles to represent sandy sediments.

Remaining survey areas

To assess the comparison across different regions of the Port of Hamburg, the predicted D50 values were compared with the ground-truth measurements for six other areas: Strandhafen, Köhlfleet, Waltershofer Hafen, Vorhafen, Norderelbe 7 and Reiherstieg. Table 2 provides an overview of MAE, RMSE and MAPE values.

Sedimentological model and predicted D50 vs. ground truth

Köhlbrand area

In the Köhlbrand area, the predicted D50 values show a similar trend to the ground-truth data and match quite well. Most samples have small differences, with an average error of about 63 µm. There are some noticeable changes at Kb-3 and Kb-10. At Kb-3, the predicted D50 is higher (110 µm) than the ground-truth value, whereas at Kb-10 it is lower by about 130 µm. These differences are primarily observed in areas where the sediments are coarser.

The sedimentological model gives lower D50 values than the ground truth, especially between Kb-1 and Kb-10. The largest differences occur at Kb-3 (370 µm) and Kb-10 (430 µm). This shows that the model underestimates coarse materials and smooths out local changes in the seabed. In finer

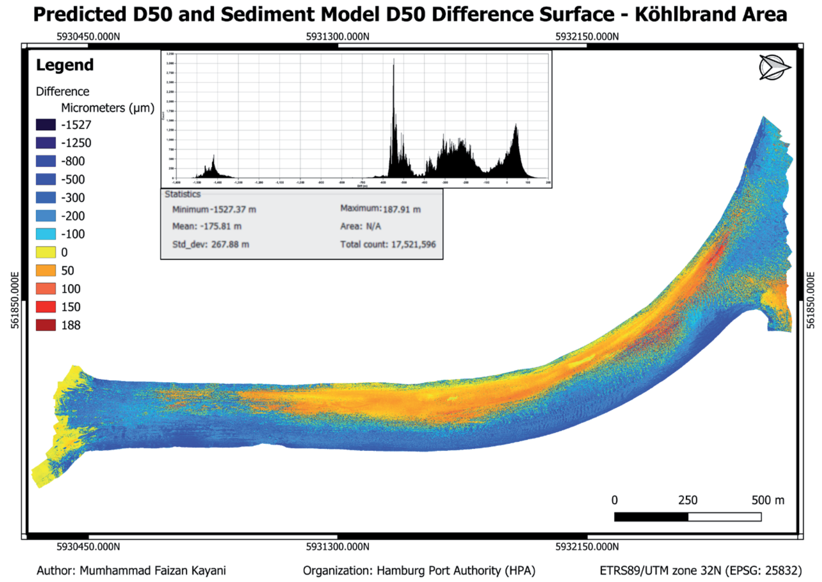

Fig. 12: Predicted D50 and sedimentological model D50 difference surface for the Köhlbrand area. Showing the difference between predicted values and existing sedimentological values, where blue colours represent areas of negative difference and orange to red colours show positive difference

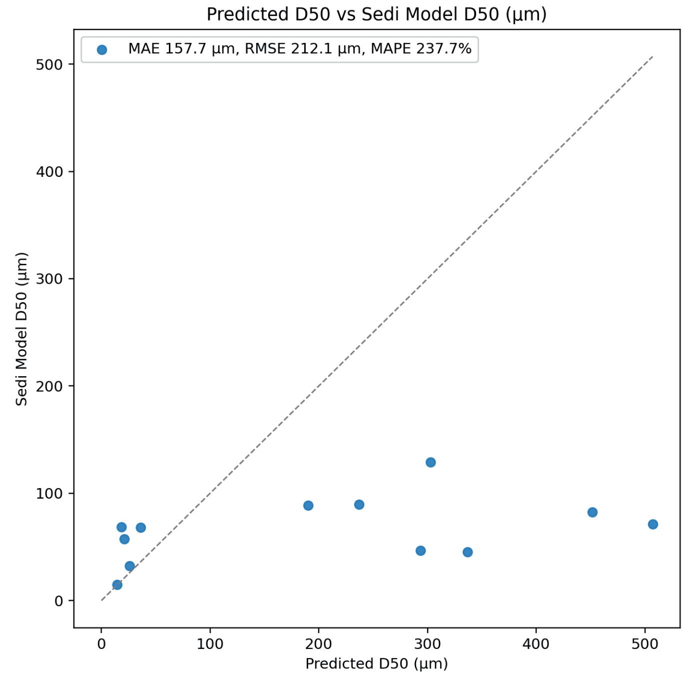

Fig. 13: Parity plot of sedimentological model vs. predicted D50 in Köhlbrand area

Area	MAE	RMSE	MAPE
Strandhafen	211.0 µm	237.1 µm	411.7 %
Köhlfleet	29 µm	70.5 µm	58.8 %
Waltershofer Hafen	136.9 µm	235.6 µm	464.0 %
Vorhafen	67.2 µm	151.3 µm	273.1 %
Norderelbe 7	152.7 µm	219.2 µm	238.8 %
Reiherstieg	81.5 µm	166.0 µm	250.9 %

Table 2: Comparison of predicted D50 and sedimentological model D50 with their error metrics

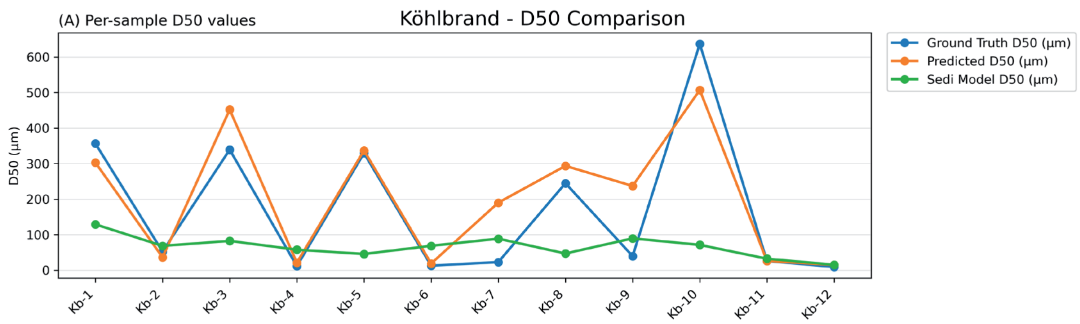

Fig. 14: Per-sample D50 values between the sedimentological model, predicted D50 and ground truth in the Köhlbrand area

areas such as Kb-2, Kb-4, Kb-11 and Kb-12, both models give similar results close to the ground truth. In the Köhlbrand area, the predicted D50 values agree more closely with the ground truth, while the sedimentological model performs better only in fine-sediment areas. Per-sample D50 values and the absolute difference between the sedimentological model, predicted D50 and ground truth are shown in Fig. 14.

Across all other survey areas

Across all the other investigated areas (Strandhafen, Köhlfleet, Waltershofer Hafen, Vorhafen, Norderelbe 7 and Reiherstieg), the predicted D50 values from the machine learning model generally show good agreement with the ground-truth measurements. Discrepancies predominantly occur in areas characterised by heterogeneous or coarser sediments. In contrast, areas dominated by homogenous or fine sediments show only minor differences, often below 20 to 50 µm, indicating stronger model performance under these conditions.

The HPA sedimentological model consistently gives lower D50 values than the ground truth, particularly underestimating coarse and sandy sediments, while performing more accurately in fine-grained environments.

Overall, both approaches demonstrate robust agreement in fine-sediment regions, whereas discrepancies increase with coarser sediment fractions, highlighting the limitations of the HPA sedimentological model in representing coarse-grained seabed conditions.

Conclusion

The results showed that normalised backscatter data from dual-head multibeam systems provide valuable additional information for hydrographic surveys. Based on the findings of this research, the data acquisition and processing workflow has been established as a straightforward procedure, with strong potential for future automation. In particular, the resulting high-resolution backscatter mosaics enable detailed seabed analysis and are well-suited for detecting even small-scale variations and changes in sediment characteristics.

The sediment classification results showed that the machine learning (ML) model performs well when trained and tested on the same data, achieving high accuracy and low error in the re-substitution test. Its generalisation to unseen data was limited, but combining 200 kHz and 400 kHz backscatter data improved performance, achieving the lowest errors (RMSE, MAE) and highest R^2.

In calm, fine-sediment areas such as Vorhafen, Köhlfleet and Reiherstieg, both the ML and HPA sedimentological models produced similar results. However, in coarse or mixed-sediment areas like Köhlbrand, Waltershofer Hafen, Strandhafen and Norderelbe 7, the ML model captured local seabed changes more accurately, whereas the sedimentological model oversimplified conditions. Overall, the ML model better represents coarse sediments and sediment mixtures, providing a more precise prediction of D50 values (mean absolute error 91 µm vs. 110 µm for the sedimentological model).

These results suggest that the HPA sedimentological model could be supported or replaced by a backscatter-driven ML approach, enabling faster, more accurate sediment mapping and better resolution of small-scale seabed changes. Future use of multispectral backscatter data (e.g., 200, 300, 400 kHz) combined with seabed texture information could further improve classification accuracy and enable the model to handle more complex seabed conditions. //

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