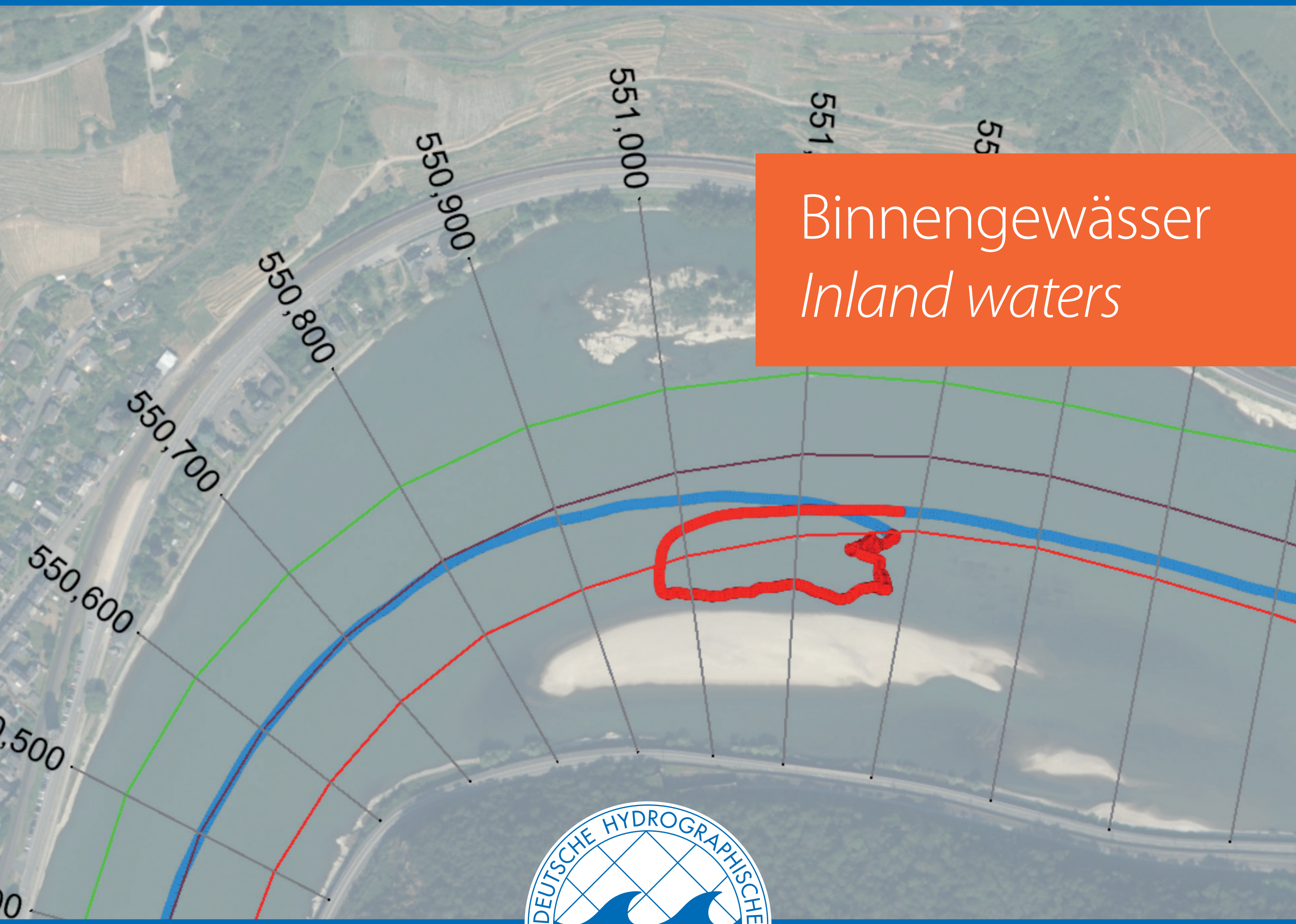
Journal of
Applied Hydrography

HYDROGRAPHISCHE NACHRICHTEN **03/2025** **HN 130**



Binnengewässer
Inland waters

DEUTSCHE HYDROGRAPHISCHE GESELLSCHAFT e.V.
DHyG

DOI: 10.23784/HN130-04

Detection of quartzite blocks in the River Rhine

Development of semi-automatic and automatic approaches for the detection of boulders

An article by MARKUS KRAFT, NILS HOLLMAN, KELLY TORRES, ERIC IDUN, ELLEN HEFFNER, ANNIKA L. WALTER and HARALD STERNBERG

To detect quartzite blocks in the riverbed of the River Rhine near Düsseldorf, a high-resolution multibeam echo sounder (MBES) survey, delivering bathymetry as well as backscatter data, was carried out. The first visual analysis of the retrieved dataset revealed more than 8,600 potential quartzite blocks. To enhance and automate the manual detection process and to obtain additional information about the boulders, two approaches, being a GIS method as well as an AI-approach using a convolutional neural network, are presented.

boulder detection | inland water mapping | autonomous data processing | sonar | MBES backscatter data
Quarzitblockerkennung | Binnengewässerkartierung | autonome Datenverarbeitung | Sonar | Fächerecholot-Rückstreudaten

Im Zuge einer Fächerecholot-Messkampagne zur Detektion von Quarzitblöcken im Niederrheinischen Flussbett bei Düsseldorf wurden sowohl topografische Daten als auch Rückstreudaten in hoher Auflösung erfasst. In einer ersten visuellen Analyse des Datensatzes wurden mehr als 8600 potenzielle Quarzitblöcke erfasst. Um die manuelle Detektion zu verbessern und zu automatisieren und um zusätzliche Informationen über die Blöcke zu generieren, werden zwei Ansätze vorgestellt: eine GIS-Methode und ein KI-Ansatz, der ein neuronales Faltungsnetzwerk verwendet.

Authors
Markus Kraft, Ellen Heffner, Annika L. Walter and Prof. Harald Sternberg work at the HafenCity University Hamburg.
Nils Hollman works at the WSA Rhein in Duisburg.
Kelly Torres and Eric Idun are enrolled students in the Master programme Geodesy and Geoinformatics Specialisation in Hydrography at the HafenCity University Hamburg.

markus.kraft@hcu-hamburg.de

1 Motivation and background

The riverbed of the Cologne Bay commonly consists of quaternary sand and gravel. Despite of that, there is a region north of the city Düsseldorf where the topmost layer not only composes prevalent sand and gravel, but is interspersed with smaller and bigger quartzite blocks. The underlying tertiary silt layer reaches much closer to the surface than usual.

These anomalies date back to approximately 30 million years ago, when the location was part of the former Wadden Sea. Under pressure, the silt and the later vegetation were partially transformed into massive blocks, having a typical dimension of 1 m to 2 m. Since the diameter increases up to 8 m and extends up to 1 m above the riverbed, the blocks form nautical obstacles. Furthermore, the erosion of the riverbed and hydro-morphological processes further expose the quartzite blocks. It is estimated, that there are more than 400 quartzite blocks, which are concentrated in three to four larger areas.

In the past years, several of the blocks, as shown in the Fig. 1, were permanently removed from the riverbed and placed on the left-hand side of the riverbank. Since the Federal Ministry for Digital and Transport instructed the Wasserstraßen- und Schifffahrtsamt Rhein (WSA Rhein) to optimise and improve the shipping channel to increase the depth for shipping purposes (Bundesverkehrswegeplan BVWP 2030, W27 – »Abladeverbesserung und Sohlstabilisierung zwischen Duisburg und

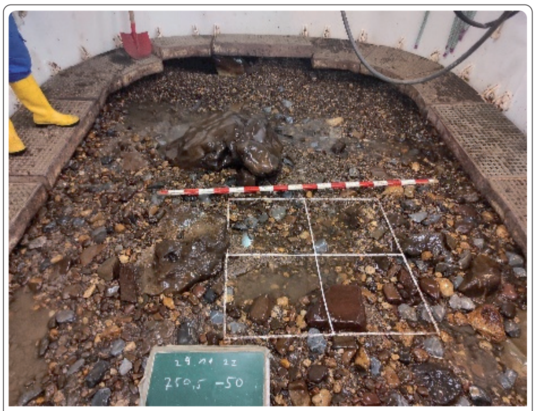


Fig. 1: Riverbed and quartzite blocks taken inside the diving bell of TGS *Carl Straat*

Stürzelberg«), the number and the appearance of the quartzite blocks must be investigated more closely.

The W27 project area is located between Rhine kilometre 722.5 (Düsseldorf) and 769.5 (Krefeld) and split into four legs, prospective construction sites. The Leg TA3 – »Steinerne Bänke« is located in the northern part of Düsseldorf, spanning over a distance of roughly 10 km (Fig. 2). To determine the composition of the riverbed within Leg 3, data from multiple multibeam surveys, spanning over a time period of 20 years, were analysed. Therefore, anomalies in hillshade visuals were manually inspected. This method is not only time-consuming, but also limited to larger blocks that protrude more than 10 cm above the riverbed. Furthermore, it can be difficult to distinguish actual objects from scattered echo sounding measurements. To enable a more thoroughly detection of the quartzite blocks, additional data derived from a side-scan sonar, was investigated. Since this data only revealed larger blocks, the extraction of further information was limited. To validate the existing datasets and to detect smaller blocks as well as flat rocks laying on the riverbed, the usage of backscatter data was considered. Since quartzite has a different backscatter signature in comparison to gravel and sand, the data could be used for a more thoroughly detection of the blocks. In addition, the data could be used for an automated approach which would not only save human effort, but also time. As a consequence, the WSA Rhein instructed the HafenCity University Hamburg (HCU) to survey the test area with a high-resolution multibeam echo sounder, collecting bathymetry as well as backscatter intensity information, and to develop an automated approach for the detection of the boulders.

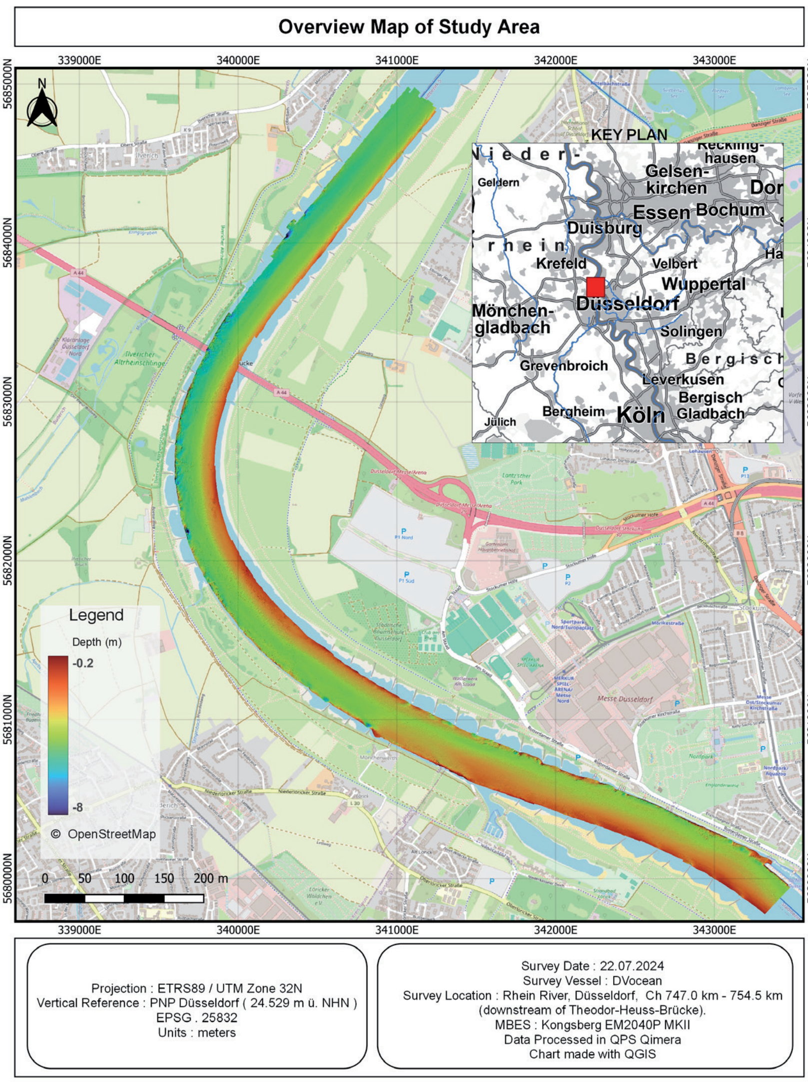


Fig. 2: Overview map of the survey area »Steinerne Bänke« on the River Rhine downstream of Düsseldorf

2 Conducted survey on the River Rhine near Düsseldorf

For the scope of the project, an area between Rhine kilometre 747.0 and 754.5, situated between Theodor-Heuss-Brücke and the Rhine ferry Langst-Kaiserswerth, was surveyed. The area is characterised by a long curve before passing under the highway bridge of A44. Depending on the discharge and the water level height of the River Rhein, the area indicates a water depth up to 8 m. To allow for a sufficient compromise between an adequate water level and not too strong river currents, the survey was conducted between 24th and 31st July 2024 during mean water. Fig. 2 provides an overview map of the survey area, including the measured bathymetry respective to gauge zero of the Düsseldorf Rhine-gauge.

For the data acquisition, the HCU owned survey vessel *DVocean,* which is illustrated in Fig. 3, was used. With a length of about 8 m and a draft of only 0.8 m, *DVocean* is explicitly designed for the operation in shallow waters. For the scope of the project, *DVocean* was trailered to the Rhine. To conduct the survey, a multibeam echo sounder from Kongsberg (EM2040P MKII), a sound veloc-

Fig. 3: HCU owned survey vessel *DVocean* in the harbour Lörick close to Düsseldorf

ity profiler from AML (AML-3 LGR with SV, CT and pressure sensor), an inertial navigation system from iXblue (Hydrins G4) and a Septentrio GNSS positioning system (AsteRx-U3) with two antennas and RTK correction data using SAPOS, was used.

After the equipment of *DVocean* was set up at the harbour Lörick, a patch-test calibration has been performed. The survey area itself was split into 15 survey sections, each having a length of about half a kilometre. The multibeam echo sounder was operated with a frequency of 300 kHz, simultaneously acquiring bathymetric and backscatter data. For quality control, at least one cross-profile within each section, hence every 500 m, was conducted. Sound velocity profiles were taken every 4 hours. To detect the quartzite blocks down to a size of some decimetres and ensure a sufficient point density, a survey speed of 3 knots for survey lines running against the currents, was maintained. Furthermore, lines along the stream direction were surveyed with a 100 % overlap. Therewith a point density of at least 160 points/m^2 (95 % confidence) was achieved and controlled during data acquisition. Due to the strong river current and high traffic volume of inland waterway vessels, manoeuvrability was limited. Additionally, several breakdowns of the inertial navigation system required extra alignments during the survey and delayed the survey routine. The entire survey area with a total length of 7.5 river kilometres was surveyed as close to the river banks as the manoeuvrability allowed.

3 Processing of the acquired data

Overall, more than 230 km of multibeam survey lines were surveyed during the project. To process the derived bathymetric multibeam data, the data was filtered, cleaned and validated using QPS Qimera. Due to the loss of GNSS underneath the highway bridge and the increase of positioning uncertainty, the respective survey lines had to be vertically adjusted. Besides, small outages of the inertial measurement unit were covered by additional survey lines and interpolated. Vibrations of the MBES pole, caused by the strong currents, created small and irreversible ripples within the dataset. However, the cross-check revealed that all datasets met the standards of the special order set by the International Hydrographic Organization (IHO). The total uncertainty results did not exceed 15 cm in horizontal and 5 cm in vertical direction, which was the pre-defined minimum requirement for discovering the quartzite blocks. The backscatter data was used to create an intensity mosaic.

The bathymetry and the backscatter data were used for the manual detection of the quartzite boulders. Fig. 4 exemplarily shows how the manual detection took place in an area around Rhine kilometre 750. Here, numerous boulders were discovered. The corresponding bathymetry for the exact same area is shown next to it. By drawing polygons around the suspicious areas and evaluating the topography, the area size and height of the boulders above the riverbed could be estimated.

4 Preliminary results from manual detection

During the manual processing phase more than 8,000 possible quartzite blocks were identified. Given that different processors made individual decisions, some variation within the detection judgments is expected. The average area of the detected quartzite blocks is 1.90 m^2, with a mean height above the riverbed of 0.28 m. Fig. 5 illustrates the relationship between the mean size and the number of detected quartzite blocks across

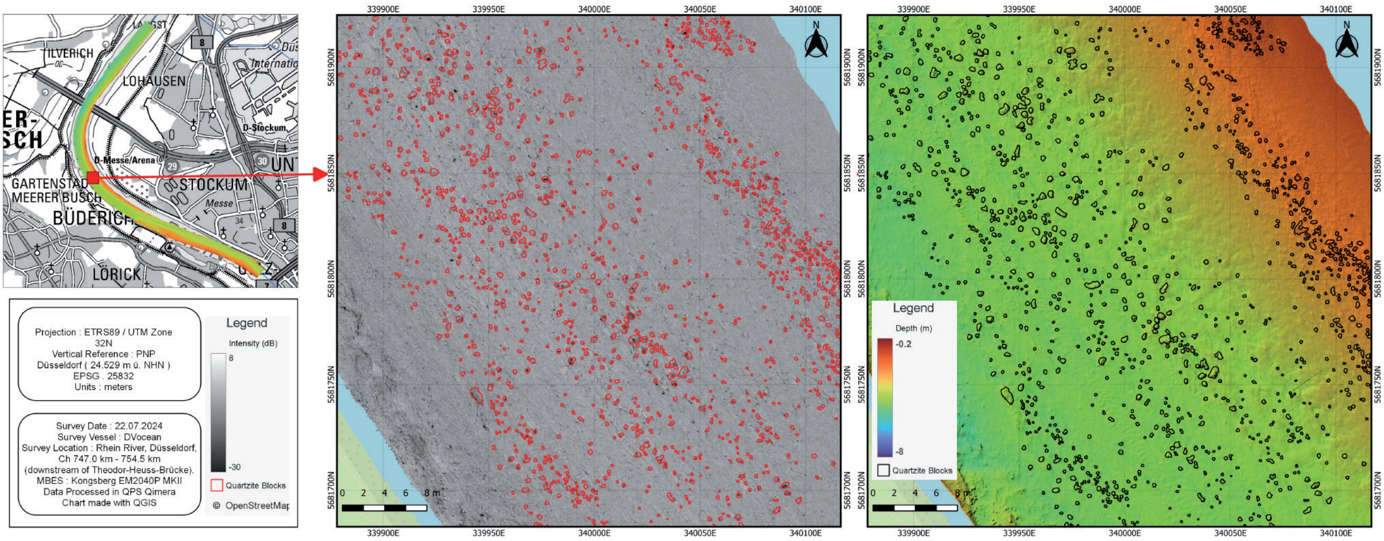


Fig. 4: Detailed zoomed chart at an area of high boulder occurrence showing the intensity (left) and the bathymetry and the polygons from the manual detection (right)

different sections of the survey area, providing insight into their horizontal distribution. While the mean size of the quartzite blocks detected within the first three kilometres of the survey area reaches a few decimetres, the size significantly increases to the metre scale from Rhine kilometre 750.0 onwards. This increase correlates with the beginning of the river bend, likely due to stronger currents on the outer bend, where sediment erodes more quickly exposing the quartzite blocks. Additionally, a significant rise in the number of detected quartzite blocks is observed between Rhine kilometre 750.5 and 751.5, marking the area at the start of the river bend.

5 Conceptualisation of automatic detection approaches

The manual detection process employed in such a project is labour-intensive, requiring considerable working-hours. As the project area expands, the workload substantially increases. To address these limitations, modern approaches integrate advanced techniques that combine multibeam bathymetry and backscatter data for riverbed characterisation. While bathymetry provides information about riverbed topography, backscatter data offers insights to the material composition of the substrate and its texture. The subsequent phase of this project involves the implementation of artificial intelligence to streamline and enhance the detection process. Two separate methods, one semi- and one fully automatic detection approach, will be developed, tested and evaluated.

5.1 Semi-automatic approach with GIS methods

The objective of the semi-automatic detection approach is the classification of boulders by integrating terrain analysis derived from bathymetry with texture analysis from backscatter data.

A key challenge within this approach is to determine which features are most effective to distinguish boulders from other riverbed structures. Not all terrain or texture attributes contribute equally; some may have a stronger influence on classification accuracy than others. To address this, the research involves a thorough analysis of the relationships between the different features.

Image segmentation plays a crucial role in this process by isolating potential boulders from the surrounding sediment based on extracted terrain and texture attributes. Using segmentation techniques, the riverbed is divided into distinct regions where each pixel is classified according to its morphological and textural properties. This step refines the feature extraction process, reducing noise and enhancing the accuracy of boulder detection (Fakiris et al. 2019).

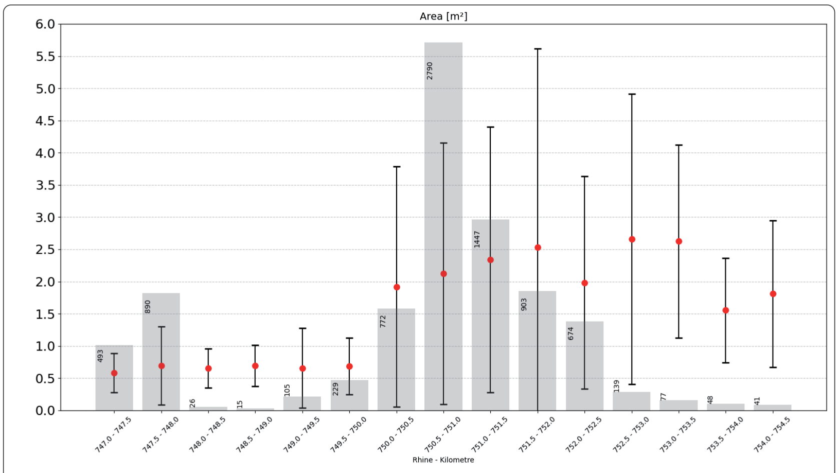


Fig. 5: Mean size of detected quartzite blocks in m^2 depicted by red dots and total number of blocks detected in each survey section

Additionally, statistical methods are applied to examine correlations, and machine learning algorithms are used to develop a classification model. The detected boulders from the segmentation and classification process are compared to a reference dataset created through the manual identification of boulders to ensure its reliability.

To extract the textural characteristics, the Grey Level Co-occurrence Matrix (GLCM) technique is employed. As shown in the Fig. 6, GLCM computes parameters such as homogeneity, dissimilarity, contrast, entropy and mean, which are particularly useful for the detection of regions with abrupt textural changes (Fakiris et al. 2019). Smooth sediment areas typically exhibit high homogeneity, whereas the irregular surfaces of boulders are marked by a higher contrast and dissimilarity values. Additionally, entropy captures the complexity and the randomness of textures, helping to distinguish heterogeneous surfaces from more uniform ones (Janowski et al. 2018).

Parallel, terrain analysis focuses on the quantification of the physical features of the riverbed. Hereby three primary derivatives, being roughness, slope and curvature, are calculated from the bathymetric data. Roughness provides an indication of how much the seafloor elevation varies over short distances, which can indicate the presence of boulders. While the slope or steepness, helps to identify abrupt changes in the underwater landscape, curvature reveals whether the bottom is convex (indicating a rise) or concave (indicating a depression) (Lerodiaconou et al. 2018; Janowski et al. 2021). Together, these metrics provide a comprehensive picture of the terrain, enhancing the overall ability to detect boulders.

The combined analysis of multibeam bathymetry and backscatter data represents a significant advancement in river- and seabed characterisation. The presented semi-automatic method, implemented through Python scripting and GIS soft-

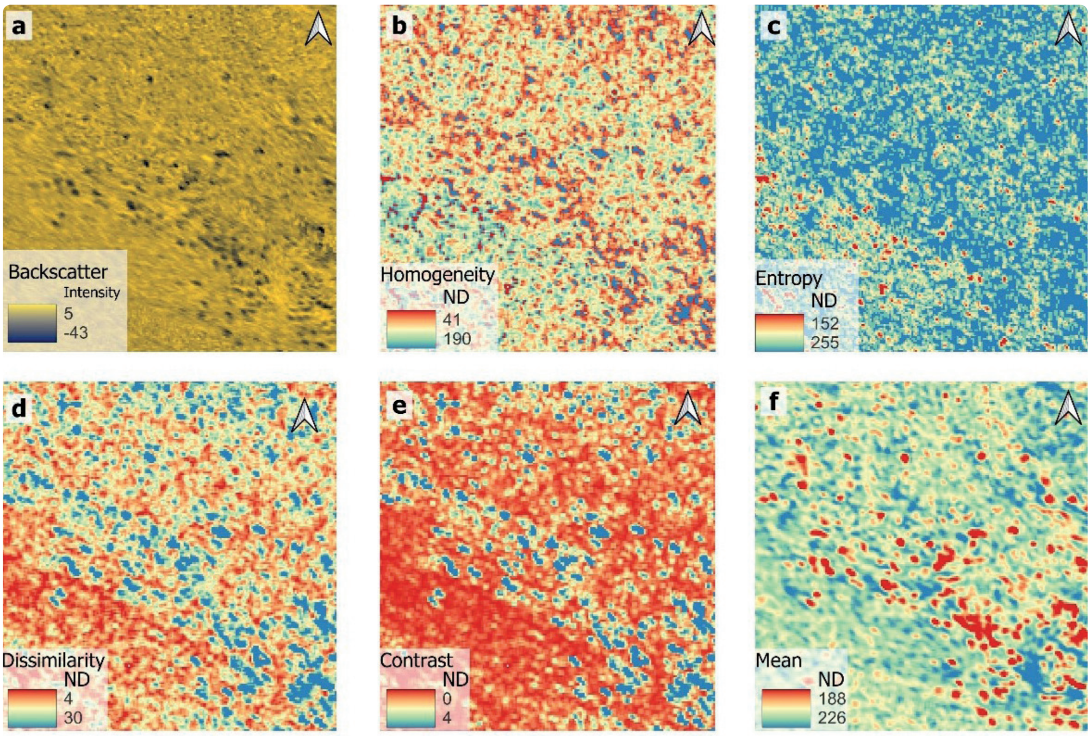


Fig. 6: Backscatter intensity of a subsample in the test area with clearly identifiable quartzite blocks (a) and its corresponding texture analysis using Grey Level Co-occurrence Matrices (GLCM), including homogeneity (b), entropy (c), dissimilarity (d), contrast (e), mean (f)

ware, aims to provide a more efficient and precise approach for detecting boulders.

5.2 Automatic approach with AI methods

The fully automatic detection approach utilises a convolutional neural network (CNN) with a U-Net architecture to improve the detection of quartzite blocks through semantic segmentation, effectively replacing the manual detection method. The selection of the CNN U-Net architecture is based on its proven ability to capture complex pixel-wise patterns and provide detailed shape recognition (Ghosh et al. 2020; Kar et al. 2021). This capability is essential for differentiating objects, particularly in scenarios involving clusters, as opposed to traditional bounding box approaches using for instance the You Only Look Once (YOLO) algorithm.

Previous studies have shown the effectiveness of CNN U-Net architectures in hydrographic surveys. For example, Arosio et al. (2023) and Garone et al. (2023) successfully employed CNNs for the classification of seabed sediments into distinct classes using bathymetric as well as backscatter datasets.

The proposed model will be developed and evaluated using Python, specifically leveraging deep learning libraries such as Keras. For the detection of the quartzite blocks, a binary semantic classification, utilising labelled data from the manual detection process, will be applied. This data will be split into training, validation and test datasets.

The performance of the model will be evaluated by using a range of metrics, including accuracy, precision and recall. Additionally, a confusion matrix analysis will be conducted, with particular emphasis on minimising false negatives, which are critical for the accurate identification of quartzite blocks.

To assess the optimal performance of the model, either the bathymetry dataset, the backscatter dataset or a combination of both will be utilised as input data. Additionally, statistical derivatives, such as slope, roundness and texture features derived from the Grey Level Co-occurrence Matrix (GLCM), will be computed from the datasets. A feature selection analysis will be conducted to eliminate redundancy and enhance the performance of the model.

Since the model will utilise a single setup that incorporates six distinct input datasets, six separate results for comparative analysis will be generated. The considered datasets and combinations are as follows:

- Bathymetry
- Backscatter
- Backscatter + derivatives
- Bathymetry + derivatives
- Bathymetry + Backscatter
- Backscatter + derivatives + Bathymetry + derivatives

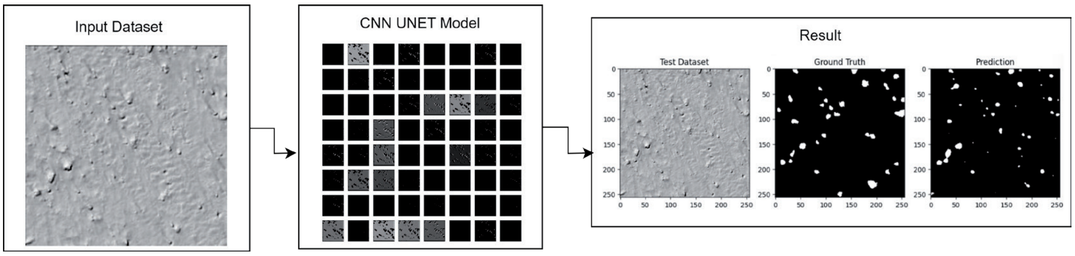


Fig. 7: Workflow for Bathymetry and Backscatter input data using a CNN U-Net model to make reasonable predictions about the presence of quartzite blocks

This methodological approach aims to improve the efficiency and the accuracy of the block detection, facilitating a scalable analysis of the datasets. A schematic diagram, which illustrates the workflow, using the bathymetric dataset as the initial input and demonstrating the predictions of the model, is presented in the Fig. 7.

The predictions generated by the model will be compared to the ground truth data derived from the manual detection. An analysis of the location and the dimensions of the blocks will be conducted to identify areas for improving the model.

6 Conclusion

The study on the detection of quartzite blocks in the River Rhine highlights the challenges and progress in automating the identification of potentially hazardous objects in the riverbed. The high-resolution multibeam echo sounder data, including both bathymetric and backscatter information, has identified over 8,600 potential boulder sites, which were detected through manual inspection. The distribution of blocks correlates to the current change in the river bend, indicated by the high exposure of blocks and bigger size of blocks in this area.

For the second phase of the project two automatic detection methods for the quartzite block detection will be developed. The semi-automatic approach integrates GIS tools and texture analysis derived from backscatter data alongside terrain features from bathymetry. Meanwhile, the fully automated approach uses a convolutional neural network (CNN) with U-Net architecture for a pixel-wise semantic segmentation, aiming to enhance detection accuracy, especially in areas with clustered blocks. Both methods will use the manual detected dataset as their ground-truth data and both approaches will be evaluated with regard to their detection performance. //

Acknowledgments
We want to express our thanks to the students who helped collecting the data during the Rhine project (Tony Sebastian, Eric Idun, Kelly Torres), our captains on board (Hans-Georg Marek, Axel Güter, Cornelius Lohmann) and the students who helped in the manual cleaning and detection procedure (Eric Idun, Kelly Torres, Elmira Omidihezardareh, Julius Nebocat, Johannes Westphal).

References

Arosio, Riccardo; Brandon Hobley; Andrew J. Wheeler et al. (2023): Fully convolutional neural networks applied to large-scale marine morphology mapping. Frontiers in Marine Science, DOI: 10.3389/fmars.2023.1228867

Fakiris, Elias; Philippe Blondel; George Papatheodorou et al. (2019): Multi-Frequency, Multi-Sonar Mapping of Shallow Habitats – Efficacy and Management Implications in the National Marine Park of Zakynthos, Greece. Remote Sensing, DOI: 10.3390/rs11040461

Garone, Rosa Virginia; Tor Inge Birkenes Lønmo; Alexandre C. G. Schimel et al. (2023): Seabed classification of multibeam echosounder data into bedrock/non-bedrock using deep learning. Frontiers in Earth Science, DOI: 10.3389/feart.2023.1285368

Ghosh, Swarnendu; Nibaran Das; Ishita Das; Ujjwal Maulik (2020): Understanding Deep Learning Techniques for Image Segmentation. ACM Computing Surveys, DOI: 10.1145/3329784

Janowski, Łukasz; Jarosław Tęgowski; Jarosław Nowak (2018): Seafloor mapping based on multibeam echosounder bathymetry and backscatter data using Object-Based Image Analysis: a case study from the Rewal site, the Southern Baltic. Oceanological and Hydrobiological Studies, DOI: 10.1515/ohs-2018-0024

Janowski, Łukasz; Radoslaw Wroblewski; Janusz Dworniczak et al. (2021): Offshore benthic habitat mapping based on object-based image analysis and geomorphometric approach. A case study from the Slupsk Bank, Southern Baltic Sea. The Science of the Total Environment, DOI: 10.1016/j.scitotenv.2021.149712

Kar, Mithun Kumar; Malaya Kumar Nath; Dabanga Raj Neog (2021): A Review on Progress in Semantic Image Segmentation and Its Application to Medical Images. SN Computer Science, DOI: 10.1007/s42979-021-00784-5

Lerodiaconou, Daniel; Alexandre C. G. Schimel; David Kennedy et al. (2018): Combining pixel and object based image analysis of ultra-high resolution multibeam bathymetry and backscatter for habitat mapping in shallow marine waters. Marine Geophysical Research, DOI: 10.1007/s11001-017-9338-z