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Segmenting submarine boulders with Random Forest and nnU-Net: from bathymetric rasters to survey-scale size distributions

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Abstract

In the soft-bottom-dominated southern Baltic Sea, geogenic hard substrates are biodiversity hotspots. The lack of open-source, pixel-level segmentation approaches for boulders in MBES data has made it difficult to advance the ecological understanding of boulder fields in the Baltic Sea. This study developed and evaluated two segmentation approaches. A deep learning model (nnU-Net) and a classical machine learning model (APOC-25, based on Random Forest classification) were trained to segment boulders using multibeam echosounder (MBES) bathymetry data at scale. Both models were trained on manually annotated data. Additionally, a pipeline for extracting per-boulder dimension metrics from the resulting segments was developed. The trade-off between annotation effort and segmentation performance was assessed. The nnU-Net model achieved the best overall performance, with a recall of 0.77, a precision of 0.84, and an F_1 score of 0.8. APOC-25, trained on a sparse subset of labelled pixels, reached a recall of 0.73, a precision of 0.51, and an F_1 score of 0.60. Upscaling the input data improved detection performance for both models. Additional analyses of areal coverage bias and detection accuracy were performed, and predictions were compared against side-scan sonar (SSS) annotations at two sites. This study provides open-source tools for systematic boulder mapping, enabling the generation of ecologically relevant baseline data and facilitating habitat mapping, monitoring and restoration.

Keywords: boulder mapping, marine habitat mapping, Baltic Sea, semantic segmentation, deep learning, multibeam echosounder (MBES)

1. Introduction

Geogenic hard substrates are biodiversity hotspots and form an ecological niche in soft-bottom-dominated seabeds [1]. They provide settlement space for sessile organisms, serve as shelter for mobile invertebrates, and provide feeding, spawning, and nursery areas for fish and birds [2]. The size of boulders and cobbles is important for the community composition colonising them as shown by Michaelis et al. [3]. Cobble surfaces are thereby characterised by opportunistic, short-lived species, whereas larger boulders support communities dominated by competitive, long-lived organisms. This pattern reflects a fundamental trade-off between disturbance tolerance and competitive ability since smaller cobbles are naturally more prone to burial by mobile sediments. Boulder fields are dynamic habitats subject to continuous physical reworking through scouring and sediment burial [1]. Naumann et al. [4] showed by automatic per-boulder count that the complexity of boulder fields varies substantially across and within sites. However, per-boulder size distributions and hard-substrate coverage at survey scale have not been systematically characterised in the Baltic Sea, leaving both the structural complexity and spatial extent of reef habitats largely unquantified.

Quantifying this structural complexity is increasingly urgent as the anthropogenic pressures such as nutrient discharge, resource exploitation, coastal engineering, and climate change are growing [2, 5]. In the European Union, reef habitats are protected under the EU Habitats Directive (Annex I, habitat type 1170) and form part of the Natura 2000

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network of protected areas. The Marine Strategy Framework Directive (Directive 2008/56/EC) and the HELCOM Baltic Sea Action Plan (HELCOM, 2021) describe conservation and monitoring obligations requiring Member States to achieve and maintain Good Environmental Status of marine ecosystems. Hence large-area, reproducible mapping of reef habitats is needed for management and conservation [6–9]. Natural boulder reefs are also the target of reef restoration, as boulders in the south-western Baltic Sea were harvested for construction work extensively [10].

Acoustic remote sensing enables non-destructive, large-area characterisation of marine benthic habitats across all water depths [11–13], where optical methods are constrained by water clarity and depth [14]. Commonly used hydroacoustic methods for seafloor mapping are side-scan sonar (SSS) and multibeam echosounder (MBES). Both systems emit acoustic pulses in a fan-shaped swath perpendicular to the vessel track. While SSS provides high-resolution backscatter mosaics, it lacks the topographic information required to delineate individual boulder dimensions. The bathymetry derived from MBES makes it possible to delineate individual boulders as discrete elevation anomalies. Bathymetry from MBES has been used to detect individual benthic structures across diverse habitats, including cold-water coral mounds [15] and individual sponges [16]. In the Baltic Sea, SSS has been widely used for boulder analysis [4, 13, 17, 18]. Manual segmentation of single boulders is time-consuming and not applicable for large survey areas; hence automated segmentation approaches are needed. Recently, Downing et al. [19] demonstrated a semi-automated GIS-AI approach combining bathymetric position index filtering and a Random Forest classifier for boulder detection from 0.5 m resolution MBES data, which achieved an F_1 score of 0.77, comparable to the average of expert manual picks while substantially reducing processing time.

Deep learning architectures such as U-Net were originally developed for biomedical image segmentation [20]. U-Net is a neural network developed for semantic segmentation classifying pixels in categories such as object or background. It uses an encoder to capture the image context and a decoder for object localisation. A subsequent connected-component labelling step can convert the semantic segmentation into an instance segmentation. This is especially useful for boulder mapping, since instance segmentation allows the size of individual boulders to be measured. U-Net architectures have been adapted for remote sensing applications. They have been applied in terrestrial remote sensing, including land cover and forest mapping [21, 22] as well as ocean remote sensing [23]. In marine habitat mapping, they have been used for example for seagrass, coral and intertidal habitat segmentation [24–26]. These applications mainly use optical imagery rather than bathymetric data. Cassol et al. [27] demonstrated that large-scale structures such as dunes can be segmented from MBES bathymetry rasters. Arosio et al. [28] extended this approach to continental-shelf-wide mapping and classification of morphological features on bathymetry. Feldens et al. [29] utilised a U-Net for the segmentation of trawl marks in bathymetric data. Boulders in particular have been successfully mapped using automated methods applied to SSS imagery [3, 4, 17, 18, 30, 31]. Hansen et al. [12] applied a Random Forest classifier to topo-bathymetric LiDAR point clouds to perform point-based classification and detect individual boulders. In point cloud classification, each discrete return is assigned a class label directly in 3D space. However, no equivalent approach for small-scale structures such as boulders has been published for MBES point clouds or bathymetry rasters, where segmentation would enable direct extraction of individual boulder dimensions.

Filling this gap with deep learning is challenging, as annotating MBES boulder datasets is labour-intensive and potentially subjective. Training deep learning models requires large annotated datasets, ideally from multiple annotators. Classical machine learning approaches provide an accessible alternative to deep learning for marine habitat mapping [32]. Training classical machine learning models such as Random Forest classifiers typically works with sparse annotations and on less specialised hardware. Software tools such as Napari [33] and Accelerated Pixel and Object Classification (APOC) [34] allow user-friendly annotation of image data and training of such classifiers. For bathymetric data, it remains unclear how many annotations are required and which approach yields the best segmentation performance for boulder mapping.

In this article we address this gap by (1) developing and providing open-source models for boulder segmentation from bathymetric datasets, (2) evaluating the trade-off between annotation effort and segmentation performance across classical machine learning and advanced deep learning approaches, and (3) presenting a pipeline for extracting per-boulder dimension metrics from segmentation outputs. These tools will enable systematic characterisation of boulder size distributions at survey scale in the Baltic Sea and beyond.

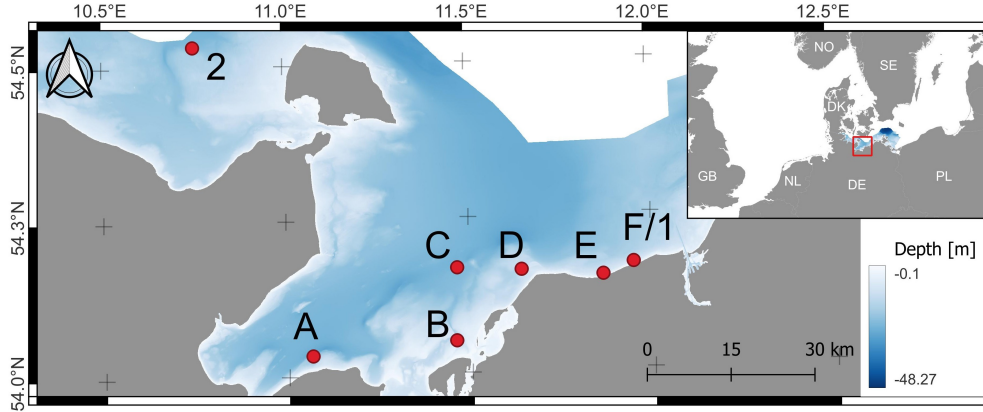


Figure 1: Overview of sites with MBES data. A–F: model development sites (training and held-out test tiles); 1 and 2: independent validation sites. Bathymetry source: provided by the Federal Maritime and Hydrographic Agency (BSH) for scientific use.

2. Materials and Methods

2.1. Study Sites and Dataset Selection

Bathymetric data from the southern Baltic Sea coastal zone were used in this study. The seafloor of this region is characterised by glacial deposits, which form isolated boulder fields where the surrounding till is mostly eroded by wave action and bottom currents [1, 2]. Boulders can be partially or fully covered by unconsolidated Holocene sands, which migrate across the seafloor [35, 36]. Data originated from eight survey sites along the Mecklenburg Bight: six for model development (A–F; training and held-out test tiles) and two for independent validation (1–2) (Figure 1). The sites were selected based on the occurrence of boulders and the availability of high-resolution MBES bathymetry. To improve model robustness and transferability, a heterogeneous dataset was assembled, including data acquired with different MBES systems (R2Sonic 2024, Norbit iwblms) and platforms across multiple survey years, resulting in three spatial resolutions of 0.10, 0.15, and 0.25 m pixel (Table 1). Sound velocity profiles were measured using either a CTD (Site A, B) or a hand-operated sound velocity profiler (Sites C–F, 1–2). Water depths across all sites ranged from 4.4 m to 22.6 m (Table 1). Sites 1 and 2 (Fig. 1), where SSS (Klein 4000, 400 kHz) and MBES data were acquired during the same cruise, were not used for model development. Site 1 is located close to Site F, whereas Site 2 lies away from all development sites. Sites 1 and 2 served two purposes: first, for independent validation of MBES-based boulder identification through comparison with SSS-derived boulder counts (Section 2.6), and second, as representative sites for the analysis of boulder size distributions presented in the Results.

Table 1: Overview of MBES survey sites used for model development (A–F; training and held-out test tiles) and independent validation (1–2).

Site	MBES System	Platform	Year	Resolution (m)	Min Depth (m)	Max Depth (m)
A	R2Sonic	RV EMB	2025	0.25	13.5	22.6
B	Norbit	RV Limanda	2025	0.1	5.9	9.1
C	Norbit	AUV 'SeaCat'	2023	0.1	20.5	21.8
D	Norbit	RV EMB	2024	0.1/0.25	11.3	12.7
E	Norbit	RV Limanda	2025	0.15	6.9	10.5
F	Norbit	RV Limanda	2023	0.1	4.4	9.0
1	Norbit	RV Limanda	2023	0.25	3.2	7.15
2	R2Sonic	RV EMB	2023	0.1	18.2	22.3

RV EMB: Research Vessel *Elisabeth Mann Borgese*, Leibniz Institute for Baltic Sea Research Warnemünde; RV Limanda: Research Vessel *Limanda*, University of Rostock; AUV 'SeaCat': Autonomous Underwater Vehicle, Atlas Electronic GmbH

2.2. Data Preprocessing

Raw bathymetric data from Sites A, C–F were processed in Qimera (Version 7, QPS). The sound velocity profiles were used to correct variations in sound velocity within the water column during processing. Roll, pitch, and heading offsets were corrected by a patch test. Outliers and acoustic artefacts were removed manually. Automated filters were explicitly not applied to avoid smoothing of small-scale topographic features such as boulders. Bathymetric grids were produced using either the Shallow Gridding or the CUBE Shallow algorithm in Qimera, the gridding approach was intentionally varied across sites to increase dataset diversity and improve model generalisation. The spatial resolution was set as high as possible given the data density (Table 1). Remaining gaps in the grid, such as acoustic shadows cast by individual boulders, were filled by interpolation using the GRASS GIS module `r.fill.stats`. For acquisition and processing details of Site B, see Geersen et al. [37]. SSS backscatter processing was carried out in SonarWiz (version 7.12.03, Chesapeake Technology Inc.). Following bottom tracking, geometric and radiometric corrections were applied to remove slant-range and layback distortions and compensate for the range-dependent attenuation of acoustic backscatter intensity. The corrected mosaics were exported as georeferenced GeoTIFFs with a resolution of 0.25 m per pixel.

2.3. Annotation and Training Data Preparation

Boulders were annotated on bathymetry rasters by experts who manually delineated all pixels belonging to individual boulders in QGIS, using the Serval plugin. The dataset of sites A–F comprised 155 tiles, covering a total annotated area of approximately 0.042 km². Tile size varied considerably, with a median of around 100 m² per tile. The dataset contained a total of 3,048 annotated boulder segments. The tiles were split once into 118 training tiles and 37 held-out test tiles, with at least one test tile from each site. No test tile overlaps a training tile. 34 of the 37 test tiles lie between 11 m and 1.1 km from the nearest training tile, and three test tiles at Site D adjoin training tiles from the same annotated area. The held-out test tiles were not used at any stage of model training and served as the basis for all reported performance metrics. Since boulders in the original data can occupy as few as two pixels, the progressive downsampling in the encoder of the deep learning framework risks losing small-scale features before they reach deeper network layers. To increase the pixel representation of small boulders and reduce this information loss, all input rasters and corresponding annotation masks were upsampled by a factor of two and, as a test, by a factor of four prior to training. Bathymetric rasters were upsampled using bilinear interpolation to preserve continuous depth values, while annotation masks were upsampled using nearest-neighbour interpolation to maintain discrete class labels. For the Random Forest classifier, both the original resolution and the upsampled data were tested to determine which yielded the best segmentation performance. Unlike the deep learning approach, which used the full set of annotations, the Random Forest classifier was designed to work with sparse labels. To evaluate how annotation density affects classifier performance, we randomly selected 25%, 50%, and 100% of the annotated boulder segments per tile. For each selected segment, a ring of background pixels surrounding the boulder was included to provide local negative training samples.

2.4. Segmentation Approaches

Two segmentation approaches were selected to evaluate the trade-off between annotation effort, technical requirements, and segmentation performance. As a deep learning approach, we used nnU-Net v2 [38]. As a classical machine learning approach, we employed APOC version 0.12.0 [34], which uses a Random Forest classifier for pixel-based classification.

2.4.1. nnU-Net

nnU-Net is a self-configuring segmentation framework that automatically determines the optimal architecture, preprocessing, and hyperparameters based on the input dataset [38]. It always starts training from scratch. For the given data, nnU-Net selected a 2D PlainConvUNet with an encoder depth of six stages and skip connections. After upscaling, all tiles were resampled to a uniform target spacing of 0.05 m / pixel and depth values were normalised using z-score standardisation computed from the foreground (boulder) class statistics. Training was performed using nnU-Net’s default five-fold cross-validation on the 118 training tiles, in which each fold holds out one fifth of the training tiles for internal validation. Predictions on the held-out test tiles were obtained by averaging the softmax outputs of all five fold models (ensemble). Training was performed over 1,000 epochs using the default nnU-Net configuration.

A single fold took approximately two hours on an NVIDIA GeForce RTX 4070. Segmentation performance was evaluated using the Dice coefficient, intersection over union (IoU), sensitivity, and specificity.

Object-level performance was evaluated using an IoU matching threshold of 0.1, following the convention of nnDetection [39]. This lenient threshold was chosen to prioritise detection over precise boundary delineation, which is particularly appropriate for small, irregular boulders where sub-pixel boundary errors would disproportionately penalise otherwise correct detections. The annotated boulders in the test tiles had a median footprint of 20 pixels on the 2× upscaled grid, corresponding to five original grid cells. At this size, a detection whose outline lies only one upscaled pixel (half the original grid spacing) outside the annotated outline already reaches a median IoU of no more than 0.44. The influence of the threshold was assessed by repeating the evaluation for thresholds from 0.1 to 0.9.

Three nnU-Net configurations were evaluated: 1. 2× upscaled tiles (multi-site, 118 tiles and 2,444 boulder annotations) as baseline; 2. 4× upscaled tiles (multi-site, 120 tiles and 2,909 boulder annotations), to test whether higher pixel representation of small boulders improves detection; and 3. a single-site model trained on site F only, to assess the effect of training-data diversity. All configurations were evaluated on the held-out test tiles (the single-site model on the Site F test tiles only), and the configuration with the highest F_1 is used for the comparison with APOC in the following.

2.4.2. Random Forest Classifier

Boulder detection was performed using APOC, a machine learning toolkit that combines GPU-accelerated image feature extraction with a Random Forest classifier. For each pixel, a feature vector of 13 image statistics was computed from the bathymetric raster using pyclesperanto [40]. These consisted of the original depth value, Gaussian-smoothed images at $\sigma = 2, 3, 4$, and 6 pixels, Difference of Gaussians (DoG) at the same scales, and the Laplacian of Gaussian approximated via a box filter at the same scales. A Random Forest model was then trained using scikit-learn’s Random Forest classifier [41] with 150 trees and a maximum depth of 4. After training, the classifier was applied to full raster tiles using GPU-accelerated inference via OpenCL (pyclesperanto). Boulder pixels were then grouped into individual objects using connected-component labelling, resulting in a raster-based instance label image.

2.5. Boulder Dimension Extraction

Boulder dimensions were extracted from the segmentation predictions. To determine dimensions on the original-resolution bathymetry grids, predictions were downsampled using nearest-neighbour interpolation to the original grid resolution. The footprint area of each boulder was computed as the number of pixels per segment multiplied by the pixel area. The height above the seafloor of each boulder was estimated by determining the seafloor level around the boulder and subtracting it from the boulder top depth. An annular mask of 0.75 m width was applied around each segment, excluding pixels belonging to other detected boulders. The 10th percentile of all valid ring pixel values from that mask was used as the estimator of the seafloor depth around each boulder, as it is robust against single outliers. Boulder top was defined as the shallowest depth pixel value within each boulder segment.

2.6. Validation and Application

To validate that structures identified as boulders in MBES bathymetry are actual boulders, two survey areas were selected where SSS and MBES data were acquired during the same cruise. Since SSS is an established method for boulder detection in the Baltic Sea [13, 17, 31, 42–44], co-occurrence of boulder signatures in both datasets served as an independent confirmation of the segmentation approach. Boulders in the SSS mosaics were identified manually by experts based on characteristic acoustic signatures of high-backscatter returns combined with an acoustic shadow. Boulder counts of SSS annotations and MBES-based segmentation results of APOC and nnU-Net were compared.

2.7. Coverage Bias Calculation

In addition to object-level detection, the total predicted boulder area was compared to the total manually annotated boulder area on the 37 held-out test tiles, to quantify systematic over- or under-estimation at the site level rather than agreement between individual boulders. This aggregate measure is relevant when the management or mapping objective is to quantify total hard-substrate extent, whereas object-level analysis is more relevant when individual boulder counts, sizes, or locations are of interest. For this comparison, predictions were downsampled to the original raster resolution, and areal coverage was expressed as the ratio of predicted to annotated boulder pixels per site, where 100% denotes exact areal agreement.

3. Results

3.1. Effect of training configuration

Upscaling the input bathymetry improved boulder detection for both methods. The APOC classifier trained on 25% (APOC-25) of the annotated boulders (background-to-boulder ratio 9.9:1) reached a mean object-level IoU of 0.389 on 2× upscaled data, compared to 0.198 on the original-resolution data. Recall increased markedly (0.725 vs. 0.334), while precision decreased (0.508 vs. 0.807); the F_1 score rose from 0.472 to 0.598. For nnU-Net, we additionally compared two upscaling factors: the model trained on 2× upscaled tiles outperformed the 4× model across all metrics (4×: F_1 0.766, recall 0.753, precision 0.779; 2×: Table 2). A higher upscaling factor therefore did not yield further gains. All subsequent results are reported for 2× upscaled data.

To assess the effect of training-data diversity, an additional nnU-Net model was trained on tiles from site F only and evaluated on that site’s held-out test tiles. This single-site model reached a lower F_1 score (0.701) than the multi-site model evaluated on the same tiles (0.783).

3.2. Overall detection performance

Table 2 summarises the object-level performance of the final APOC and nnU-Net models. The APOC classifier was trained with 25%, 50%, and 100% of the available boulder annotations. Among the APOC models, F_1 scores ranged from 0.495 to 0.598, with recall and precision both decreasing as annotation density increased. The nnU-Net achieved a recall of 0.767, a precision of 0.843, and an F_1 score of 0.803.

Table 2: Object-level evaluation of all segmentation models on 37 fully annotated held-out test tiles (2× upscaled). Detections are matched one-to-one to ground-truth boulders by intersection over union (IoU); a match with $\text{IoU} \geq 0.1$ counts as a true positive, and all metrics are pooled over tiles. The IoU column is the mean IoU of each ground-truth boulder with its best-matching detection. APOC classifiers ($\sigma = 2, 3, 4, 6$) were trained with varying annotation fractions. The nnU-Net model was trained on 2× upscaled tiles from all areas (118 training tiles, 2,444 annotated segments). bg:boulder = background:boulder ratio.

Model	Annotated boulders	bg:boulder	IoU	Recall	Precision	F_1
APOC-25	25%	9.9:1	0.389	0.725	0.508	0.598
APOC-50	50%	9.9:1	0.384	0.717	0.488	0.580
APOC-Full	100%	~53:1	0.312	0.583	0.431	0.495
nnU-Net	100%	—	0.580	0.767	0.843	0.803

Figure 2 shows the sensitivity of the object-level metrics to the IoU matching threshold. nnU-Net outperformed APOC-25 at every threshold. Under stricter criteria the scores of both models decreased, more strongly for APOC-25 (F_1 0.598 at a threshold of 0.1, 0.382 at 0.5) than for nnU-Net (0.803 and 0.716). For APOC-25, the decrease depended on boulder size. The recall of boulders smaller than 16 pixels was half as high at a threshold of 0.5 as at 0.1 (0.24 vs. 0.48). For nnU-Net, recall decreased by a similar, small amount in all size classes.

3.3. Model comparison across study sites

Figure 3 compares the per-site performance of APOC-25 and nnU-Net. nnU-Net achieved higher precision and F_1 scores than APOC-25 at all six sites. For recall, the difference between the two models was less consistent. The two models performed comparably at sites A and E. nnU-Net achieved higher recall at sites C and D (site D: $R = 0.82$ vs. 0.69), while APOC-25 reached higher recall at sites B and F, marginally at F but substantially at B ($R = 0.91$ vs. 0.66).

3.4. Qualitative assessment of APOC-25 predictions

Figure 4 illustrates the variability in APOC-25 predictions across the six sites. At sites with well-separated boulders on a smooth seabed (sites A and E), the classifier detected nearly all boulders with few false positives ($\text{IoU} = 0.83$ and 0.89). At site B, a rougher seabed was associated with a moderate number of false positives and false negatives ($\text{IoU} = 0.69$, $P = 0.75$, $R = 0.90$). Performance decreased at site C, where boulders were densely clustered ($\text{IoU} = 0.48$, $R = 0.50$); here the classifier missed several smaller boulders while maintaining high precision

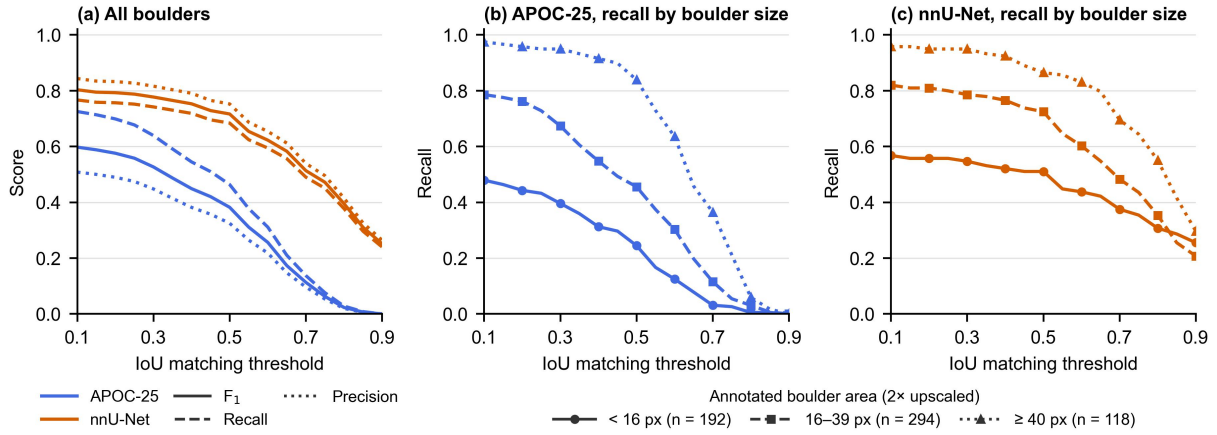


Figure 2: Sensitivity of the object-level evaluation to the IoU matching threshold on the 37 held-out test tiles. (a) Precision, recall and F1 score of APOC-25 (blue) and nnU-Net (orange) over all 604 annotated boulders. (b, c) Recall of APOC-25 and nnU-Net by size class of the annotated boulders, given as footprint in pixels on the 2× upscaled grid (four upscaled pixels correspond to one original grid cell). All other results in this study use a threshold of 0.1.

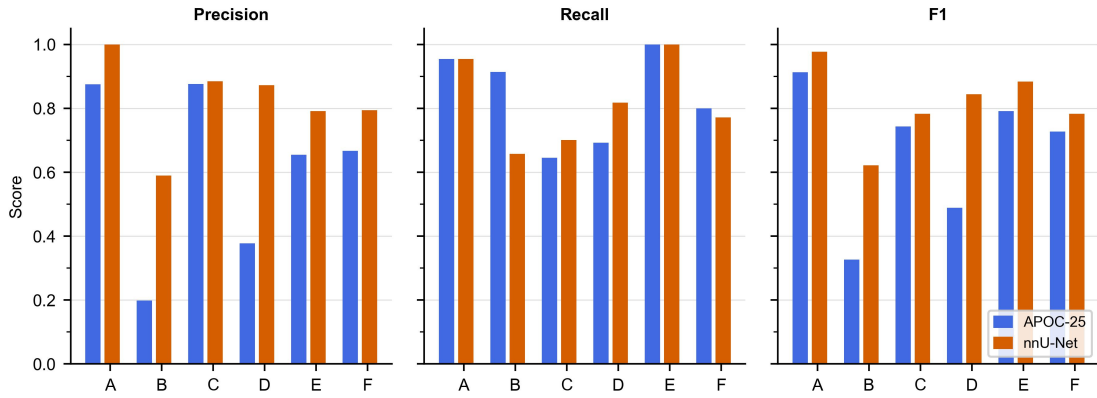


Figure 3: Per-site performance comparison of APOC-25 (blue) and nnU-Net (orange) across the six study sites (A–F). Precision, recall, and F1 score are shown as separate panels. Metrics were computed at the object level on the held-out test tiles of each site.

($P = 0.93$). The lowest precision and IoU occurred at site D. Here, linear artefacts originating from overlapping survey datasets were systematically misclassified as boulders, producing a large number of false positives ($IoU = 0.02$, $P = 0.02$) despite correct detection of the single annotated boulder. Site F shows an intermediate case, with both missed detections and false positives ($IoU = 0.33$, $P = 0.43$, $R = 0.60$).

Figure 5 illustrates that performance can vary within a single site, shown here for site C and the nnU-Net model as an example rather than a site- or model-specific issue. Tile C_{01} had a low IoU of 0.63 and C_{02} a high of 0.80. Precision was high in both cases ($P = 0.84$ and $P = 0.83$). The performance gap was instead driven by recall: C_{01} missed 11 of 38 annotated boulders ($R = 0.71$), whereas C_{02} missed only 1 of 25 ($R = 0.96$).

3.5. Generalisation to independent validation sites and boulder height application

The predictions of the models were compared against manual boulder annotations derived from side-scan sonar (SSS) backscatter mosaics at the two independent validation sites (Sites 1 and 2), which were not included in model development. SSS-based annotation is a well-established reference for boulder mapping and is used here as an indirect ground truth. The side-scan survey covers the majority of the bathymetric survey of Sites 1 and 2. The counts reported in this section refer to the side-scan extent, whereas the counts reported for the per-boulder size analysis (Fig. 6) are

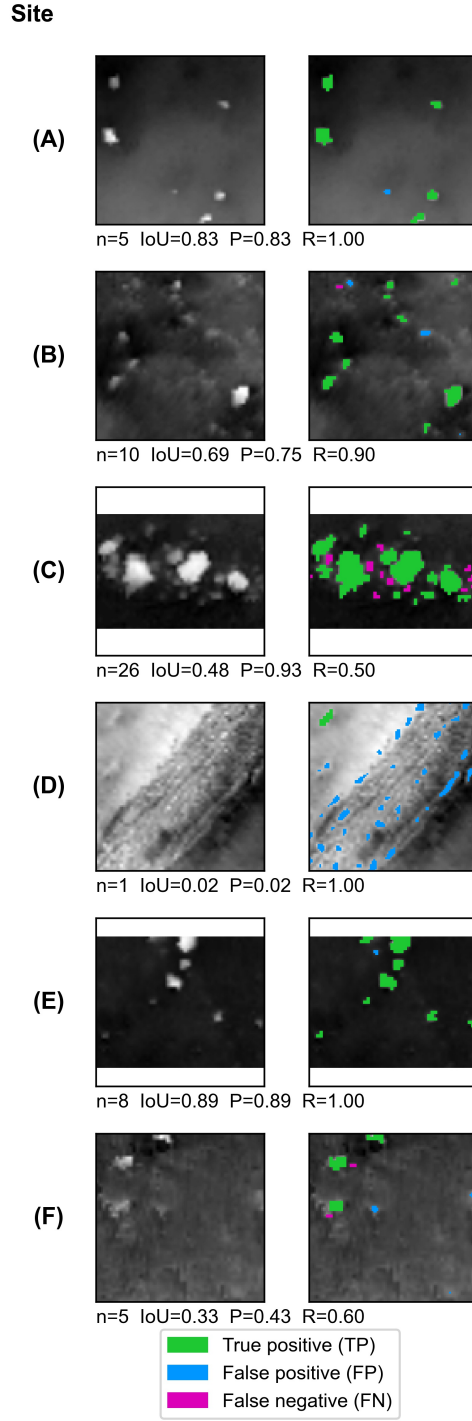


Figure 4: Qualitative segmentation results of the APOC Random Forest classifier (trained on 25% of annotations) across six test sites. Each row shows a 100×100 px crop from one site: bathymetry input (left), and prediction overlay (right). Per-tile metrics are listed below each row: n = number of annotated ground-truth boulders in the crop, IoU = object-level intersection over union ($TP/(TP+FP+FN)$), with objects matched at $IoU \geq 0.1$, P = precision, R = recall. Greyscale is linearly scaled to the local depth range of each tile. Lighter colours are shallower: (A) -21.67 to -22.57 m, (B) -5.89 to -6.37 m, (C) -21.08 to -21.52 m, (D) -11.62 to -12.02 m, (E) -9.72 to -10.54 m, and (F) -7.00 to -7.50 m.

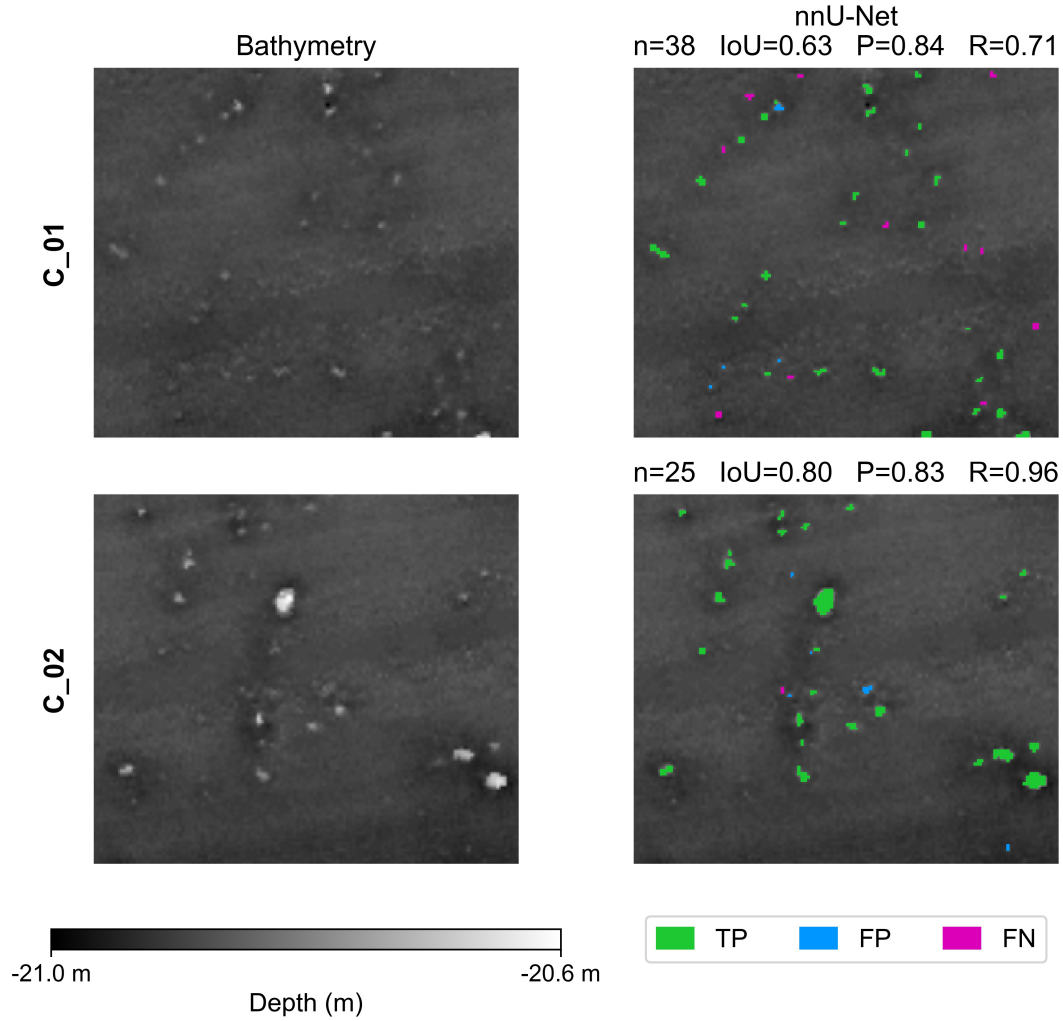
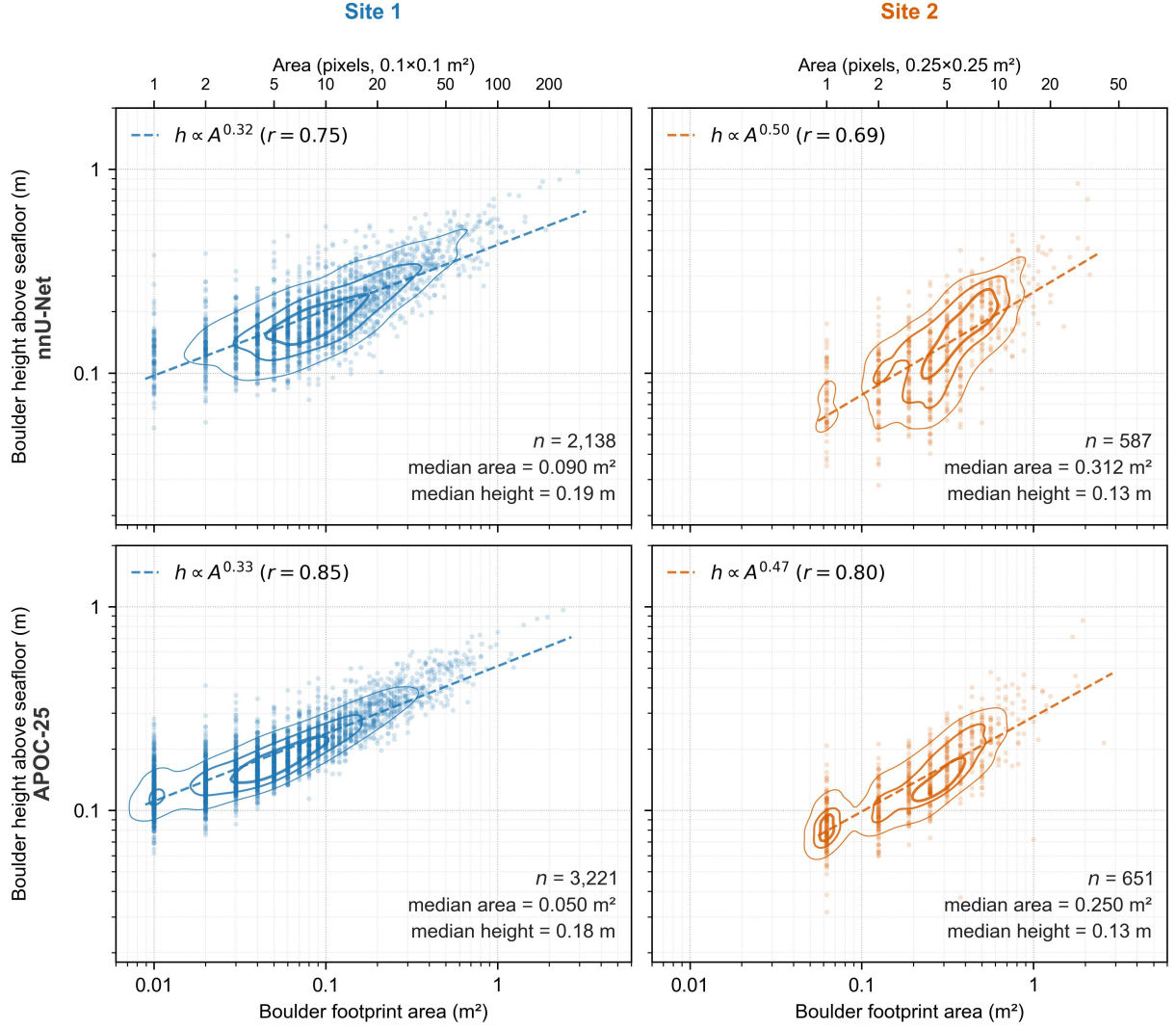


Figure 5: Within-area performance variation at site C for model nnU-Net. Each row shows one tile: bathymetry (left) and prediction overlay (right) with IoU, precision (P), and recall (R) and number of annotated boulders (n).

based on the full bathymetric grid. Figure 7 shows the side-scan sonar backscatter and bathymetry of site 1. While this site was not included in the training data, it is located close to Site F, from which training tiles were taken. Within the annotated region, 1,627 boulders were manually annotated on the backscatter mosaic; the nadir zone and a densely populated area where boulder shadows overlapped could not be reliably annotated and were therefore excluded. APOC-25 detected 2,142 boulders and nnU-Net detected 1,600 boulders within the annotated region. In the dense, unannotated area in the lower portion of the tile, APOC-25 produced a higher number of predictions (864) than nnU-Net (393).

Figure 8 shows side-scan sonar backscatter and bathymetry of Site 2 (not included in the training). 649 boulders were manually annotated on the backscatter mosaic. APOC-25 detected 536 boulders, whereas nnU-Net detected 463 boulders. Both models reproduced the overall spatial distribution of boulders.

Table 3 compares segment counts, the fraction of sub-threshold segments, and key size metrics (median and 90th percentile) between annotations, APOC-25, and nnU-Net predictions on the 37 held-out test tiles (2× upscaled). Annotation overlap indicates sub-threshold predictions that share at least one pixel with an annotated boulder; no annotation overlap indicates isolated false positives. APOC-25 produces 40% of segments below the threshold of 8 pixels, of which 67% have no annotation overlap and thus represent isolated false positives. nnU-Net, in contrast,



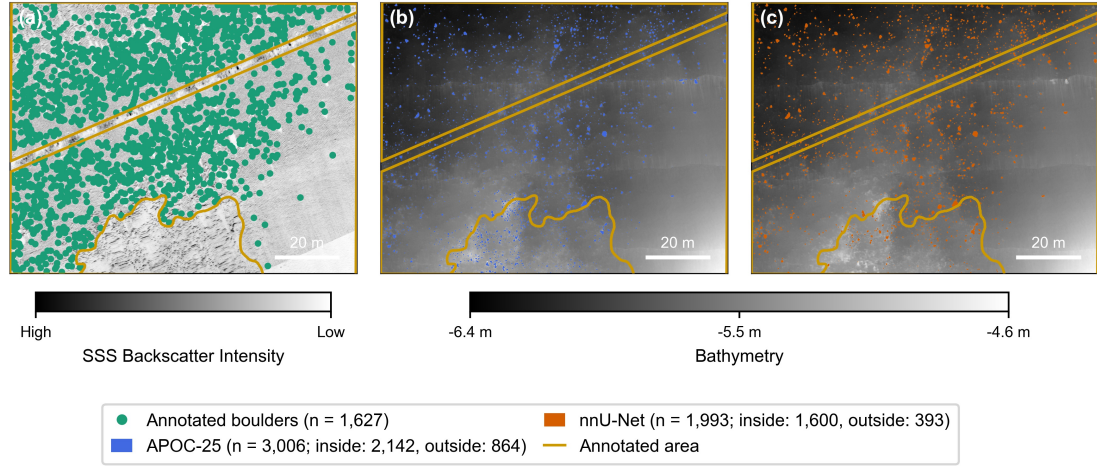


Figure 7: Qualitative comparison of bathymetry-based boulder predictions against manual side-scan sonar (SSS) annotations at site 1. (a) Manual boulder annotations (green, $n = 1,627$) derived from the SSS backscatter mosaic. Used as an indirect ground truth following established practice in boulder mapping. (b) APOC-25 predictions (blue, $n = 3,006$; 2,142 inside and 864 outside the annotated area) and (c) nnU-Net predictions (orange, $n = 1,993$; 1,600 inside and 393 outside the annotated area), both segmented on bathymetry data (shown as background). The annotated area is delineated in yellow. Panels are spatially cropped to the extent of the side-scan sonar survey, which covers the majority of the bathymetric survey area; boulder counts therefore differ slightly from Figure 6.

Table 3: Segment size distribution for annotated boulders and model predictions on the 37 held-out test tiles ($2\times$ upscaled; pixel size 0.05–0.125 m). Sub-threshold segments contain fewer than 8 upscaled pixels (< 2 original pixels), i.e. below the minimum annotation size.

	n (segments)	Sub-threshold (< 8 px)	Sub-threshold composition		Median (px)	p_{90} (px)
			annotation overlap	no annotation overlap		
Annotations	604	6 (1.0 %)	—	—	20	60
APOC-25	852	337 (39.6 %)	113 (33.5 %)	224 (66.5 %)	10	41
nnU-Net	543	80 (14.7 %)	47 (58.8 %)	33 (41.2 %)	16	61

yields only 15% sub-threshold segments, with 41% of those lacking annotation overlap.

Figure 6 shows boulder footprint area against boulder height above seafloor at both independent validation sites. The scaling exponent k , describing the rate at which boulder height scales with footprint area, differed between sites, with $k \approx 0.32$ – 0.33 at Site 1 and $k \approx 0.47$ – 0.50 at Site 2, while Pearson r ranged from 0.69 to 0.85. Within each site, both models showed similar scaling correlation. The median boulder height was similar between models at each site (Site 1: 0.18–0.19 m; Site 2: 0.13 m).

3.6. Areal coverage bias

Table 4 compares the predicted area of APOC-25 and nnU-Net with the total annotated boulder area (coverage bias). The two models showed markedly different behaviour. Compared to the annotated boulder area, APOC-25 ranged from 55% to 207% across the six sites and over-predicted boulder area at five of them, in two cases by roughly a factor of two (sites B and D). The nnU-Net produced more consistent estimates, ranging from 69% to 119%. At site C, both models under-predicted boulder area, most strongly APOC-25 (55% versus 72% for nnU-Net).

4. Discussion

4.1. Model performance

Boulder dimensions and hard-substrate coverage remain unquantified at survey scale. Existing automated approaches largely rely on object-based image analysis (OBIA): Downing et al. [19], for instance, detected boulders

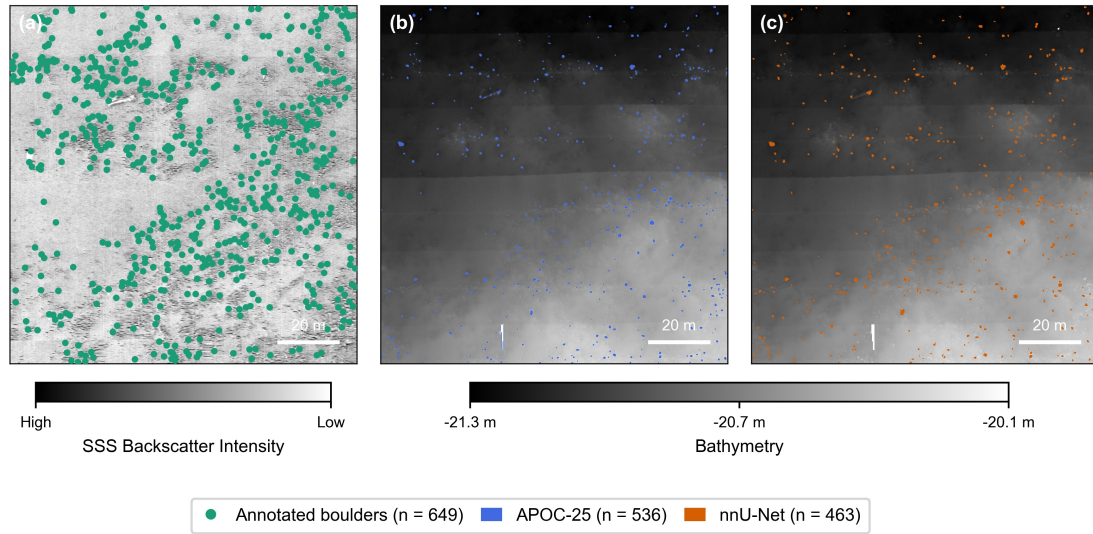


Figure 8: Qualitative comparison of bathymetry-based boulder predictions against manual side-scan sonar (SSS) annotations at site 2. (a) Manual boulder annotations (green, $n = 649$) derived from the SSS backscatter mosaic, used here as an indirect ground truth following established practice in boulder mapping. (b) APOC-25 predictions (blue, $n = 536$) and (c) nnU-Net predictions (orange, $n = 463$), both generated from the bathymetric DEM (shown as background). Panels are spatially cropped to the extent of the side-scan sonar survey, which covers the majority of the bathymetric survey area; boulder counts therefore differ from Figure 6.

Table 4: Areal coverage bias of the APOC-25 and nnU-Net models, evaluated on the 37 held-out test tiles. Coverage is expressed as the ratio of predicted to manually annotated boulder pixels per site, where 100% denotes exact areal agreement.

Site	Annotated Area (m^2)	APOC-25	nnU-Net 2×
A	8.0	118%	94%
B	2.6	203%	69%
C	16.7	55%	72%
D	73.9	207%	74%
E	7.9	124%	99%
F	10.1	105%	119%

with a hybrid GIS-AI approach. While effective for contact detection, this workflow does not preserve boulder morphology, as the final output collapses each detected object into a single point rather than a delineated boundary. More broadly, no open-source, pixel-level segmentation approach for boulders is available for MBES bathymetry rasters. We address this gap by providing open-source models, APOC-25 and nnU-Net, which differ in complexity, training requirements, and performance. nnU-Net achieved the highest scores on all three object-level metrics ($F_1 = 0.803$, Precision = 0.843, Recall = 0.767), outperforming APOC-25 ($F_1 = 0.598$, Precision = 0.508, Recall = 0.725).

The higher precision of nnU-Net may reflect its larger receptive field. Each prediction integrates information from a wider spatial neighbourhood than the local image statistics used by APOC, potentially allowing the model to discount isolated pixel-level responses that lack supporting context. This broader integration may, however, also cause marginal boulders to be discarded, reducing recall. In contrast, the APOC-25 model showed lower precision at small scales, while its higher total boulder count suggested a higher nominal recall that is, however, inflated by spurious detections. This is observed in the scatter plots of boulder footprint area versus height (Fig. 6), which show detections below the manual annotation threshold of 2 pixels. APOC-25 produces substantially more such segments than nnU-Net (Table 3), which is directly reflected in the higher total detection counts at Site 1 ($n=3,221$ vs. $n=2,138$) and in the lower median footprint area (0.050 m^2 vs. 0.090 m^2). As shown in Table 3, 67% of APOC-25 sub-threshold segments in the held-out test tiles lack any overlap with annotated boulders and thus represent isolated false

positives. nnU-Net exhibits a more conservative segmentation behaviour, with fewer sub-threshold segments and a higher proportion of those overlapping with ground-truth annotations (59%), indicating that small nnU-Net detections are more likely to correspond to real but undersized boulders. The accumulation of sub-threshold segments also influences the fitted power-law exponents: the leftward extension of the point cloud in APOC-25 may bias k towards lower values, so that the marginally higher correlation coefficients observed for APOC-25 ($r=0.85$ vs. $r=0.75$ at Site 1) do not necessarily reflect morphometric consistency. The nnU-Net produced more consistent areal coverage estimates across sites, whereas APOC-25 showed large and site-dependent areal bias. Total boulder area should therefore not be read directly from either segmentation method without site-specific validation.

Within the APOC framework, competitive results can be achieved with a fraction of the annotation effort. However, the absolute performance of all APOC variants remains limited. Even the best-performing APOC-25 model produced a precision of only 0.508. This makes APOC unsuitable for applications that require reliable boulder inventories. Where accurate segmentation is needed, nnU-Net is clearly the choice. This is supported by the sensitivity analysis (Fig. 2): at an IoU threshold of 0.5, the F_1 score of nnU-Net remained above 0.7, whereas that of APOC-25 dropped to 0.38. APOC-25 thus locates boulders but delineates them less accurately. The value of APOC lies primarily in its role as a rapid screening tool and as a baseline demonstrating that even minimal annotation effort can capture the majority of boulders (recall = 0.725).

The resolution of the input data is a further decisive factor for boulder detection. The typical resolution of MBES data grids is either 1 m (e.g., grids provided by the Federal Maritime and Hydrographic Agency) or 0.25 m (targeted habitat studies including reef mapping [18, 45, 46]). In shallow waters (< 10 m depth), hydroacoustic surveys can yield grid resolutions of 0.1 m and finer [16, 42]. Upscaling by a factor of two substantially improved detection, but further upscaling to four times the original resolution yielded no additional gains. This reflects the sensitivity of CNNs to small objects, as higher layers downsample the input, reducing their ability to capture fine-scale features [47, 48]. The method is inherently limited by MBES resolution: the smallest detectable boulders are constrained by the grid resolution at which they are captured, and small boulders are also more difficult for the models to learn. Since interpolation adds no new information, the benefit of $2\times$ upscaling lies in increasing the per-boulder pixel footprint, thereby enhancing spatial context for convolutional filters. Further interpolated pixels are redundant, as they do not contain new structural information. Learned super-resolution techniques, such as those applied to backscatter data [30] or used to enhance bathymetric grids via deep learning [49], could potentially recover sub-grid features by learning boulder-specific patterns, offering a promising path for future work.

The extracted boulder footprints and heights were not validated against independent measurements, such as diver or optical surveys, and should therefore be regarded as estimates. Their accuracy is generally not limited by the range resolution of the systems used, which is approximately 1 cm. However, deriving footprints and heights from gridded data introduces uncertainty, especially for boulders at or below the size of the acoustic footprint. With decreasing boulder size relative to the acoustic footprint, heights are increasingly underestimated and boulder footprints increasingly overestimated, until the boulder can no longer be separated from the noise level. The acoustic footprint (across-track $\times$ along-track) varies across the swath and between systems, from approximately 0.09×0.17 m (R2Sonic 2024, 400 kHz) and 0.16×0.33 m (Norbit iWBMS, 400 kHz) at nadir in 10 m water depth to approximately 0.21×0.27 m and 0.38×0.52 m, respectively, at a beam angle of 50° . Variations in beam angle also change the sensitivity to small boulders, which are detected more reliably close to nadir. This can introduce a spatial bias with stripes of higher detection rates parallel to the survey lines.

The reference data used for validation were SSS backscatter mosaics, chosen over alternatives such as video transects, which in the Baltic Sea are limited by turbidity, a narrow field of view, and the difficulty of stitching individual frames into spatially continuous coverage; SSS therefore allowed comparison across a larger contiguous area. This reference, however, validates only boulder counts and not the footprint accuracy of the segmentation. Boulder reefs in the southern Baltic Sea, including Mecklenburg Bight, are related to the substrate type of outcropping glacial till [18, 35]. However, they are structurally diverse [4], and training sites were selected to account for this diversity. At independent validation Site 2, both models under-predicted relative to Site 1, which is located close to training Site F, indicating that generalisation to more distant or different settings is not yet optimal. Seabed morphology and boulder density vary considerably even within a single site, so that the held-out test tiles represent unseen conditions within the development sites. The reported metrics nevertheless describe performance within these sites rather than transferability to new regions. The models should therefore be regarded as regional models. For other regions, sensors or seabed types, retraining with additional local annotations is recommended. With the self-configuring nnU-Net framework

and the published workflow, this required about 2,500 annotated boulders and less than a day of training on a single GPU in the present study. On the two independent validation sites with SSS reference annotations, both models reproduced the overall spatial distribution of boulders. However, APOC-25 over-predicted and nnU-Net under-predicted relative to the manual counts. The APOC-25 over-prediction is driven by its low precision (0.508). This means it finds many false positives, inflating the total count. nnU-Net, in contrast, has a high precision (0.843) that ensures few false detections, but its recall of 0.767 means that roughly one in four boulders is missed, resulting in a net under-count.

4.2. Application

By providing an open, reusable nnU-Net model for boulder segmentation from MBES bathymetry, we enable the reproducible extraction of per-boulder dimensions at survey scale, and thereby the generation of ecologically relevant baseline data for boulder habitats in the Baltic Sea and beyond. It can also facilitate the investigation of questions that were previously unaddressed due to insufficient empirical foundations. One example is regulatory reef assessment. Diverse national and international regulations (e.g., Habitats Directive (92/43/EEC), Nature Restoration Regulation (EU) 2024/1991, Marine Strategy Framework Directive (2008/56/EC), and German Federal Nature Conservation Act (Bundesnaturschutzgesetz, BNatSchG)) obligate Member States to assess and improve the condition of reef habitats (type 1170). Specifically, HELCOM defines a continuous hard-substrate seabed coverage of at least 10% as a reef for the Baltic Sea. Consequently, precise knowledge of coverage degrees is required, which makes automated methods relevant for the workflows of national authorities. Nevertheless, reef classification continues to rely primarily on coarse manual visual estimates of stone abundance or coverage, limiting reproducibility and scalability. The German approach detailed by Heinicke et al. [43] classifies 50×50 m grid cells into 0, 1–5, and >5 stones. However, previous studies [4, 17, 18] indicate that six boulders already represent the lower bound of observed densities, which may reach several hundred per cell. The automated method addresses these limitations by providing reproducible object counts and, additionally, estimates of areal coverage, resulting in a more realistic representation of boulder-field structure.

Beyond regulatory compliance, quantitative knowledge of boulder size on existing reefs is essential for defining condition baselines and facilitating the systematic monitoring of geogenic reef structures, for example, for restoration targets. Boulder size and reef complexity are drivers of the composition of communities colonising hard substrates, with larger boulders providing more stable, less frequently disturbed surfaces than small cobbles [2, 3]. Witte S. et al. [50] argue that increasing the structural complexity of reefs – in a different setting – is important for community composition. Similar effects were reported for the relation between algae composition and boulder size [51]. Our automated extraction of per-boulder footprint and height at survey scale makes it possible to quantify and analyse boulder sizes across large areas. This is valuable for ecological analysis and for applications in fisheries and ecosystem management.

Especially in shallow-water environments, where the seafloor and coastline are continuously exposed to wave and current action, the distribution and cover of stones are subject to considerable spatial and temporal variability. Previous studies have demonstrated that even larger stones can be mobilised under energetic hydrodynamic conditions, highlighting the dynamic nature of these habitats [52–54]. Automated segmentation approaches therefore offer the potential to detect and quantify changes in stone distribution and cover at unprecedented spatial scales and levels of detail. Such information could provide valuable insights into long-term geomorphological processes and environmental changes associated with climate change, including shifts in storm frequency, storm intensity, and erosion dynamics.

The method is not confined to MBES data. In areas which are too shallow for MBES data acquisition, comparable boulder detection has been achieved on topo-bathymetric LiDAR data [12], although LiDAR is depth-limited and constrained by water clarity. Since LiDAR data can be gridded similarly to MBES data, applying our method to these datasets could bridge the gap between shallow waters (inaccessible to survey vessels and mapped by optical methods) and deeper waters (mapped by MBES) to ensure seamless coverage.

5. Conclusion

As no open-source pixel segmentation model was available to segment boulders from MBES bathymetry, boulder dimensions and hard-substrate coverage remained largely unquantified at scale. This study developed and evaluated two machine learning models for automated boulder segmentation and established a workflow for deriving boulder footprint and height. The results demonstrate that automated detection and characterisation of individual boulders

is feasible and reproducible with nnU-Net. The key advance of this work is that individual boulder dimensions can now be quantified consistently across entire survey areas, enabling robust estimates of abundance, coverage, and size distribution. These data support habitat assessment and monitoring requirements under European and national marine conservation frameworks. Beyond the present application, the transfer of our workflow to gridded LiDAR data could bridge optical and hydroacoustic remote sensing for seamless mapping from shallow to deeper waters.

Data availability

Model weights are available at <https://doi.iow.de/10.12754/data-2026-0008> and the training/test bathymetry and annotation data at <https://doi.iow.de/10.12754/data-2026-0007>. Scripts for data pre- and postprocessing, pipeline implementation, and analysis were developed by the authors, with coding assistance from Claude Code (Anthropic). All AI-assisted and author-modified code was reviewed. The full source code is available at <https://github.com/carabini/mbes-boulder-detection>.

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CRediT authorship contribution statement

Aïcha Naumann: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review and editing. Robert Haase: Methodology, Software, Validation, Writing – review and editing. Peter Feldens: Conceptualization, Investigation, Resources, Supervision, Writing – review and editing. Svenja Papenmeier: Conceptualization, Investigation, Resources, Supervision, Writing – review and editing.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used a generative AI assistant in order to support content organization and to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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