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Machine learning as supporting method for UXO mapping and detection

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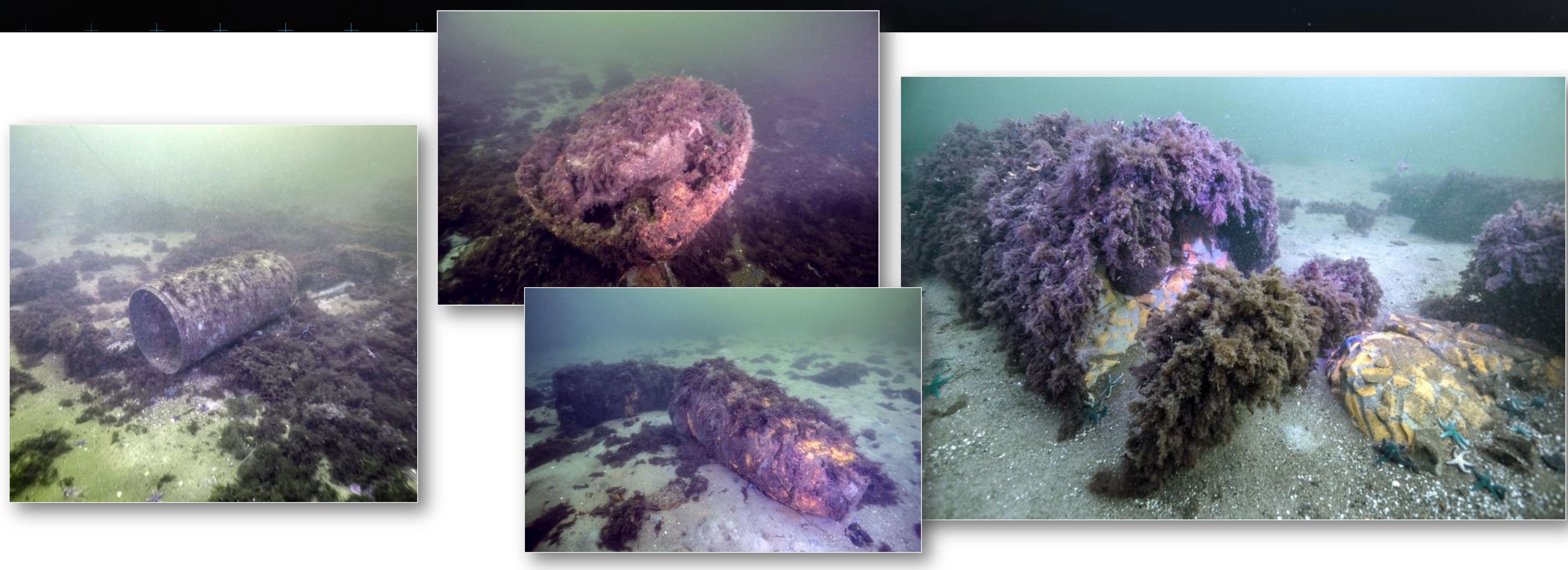
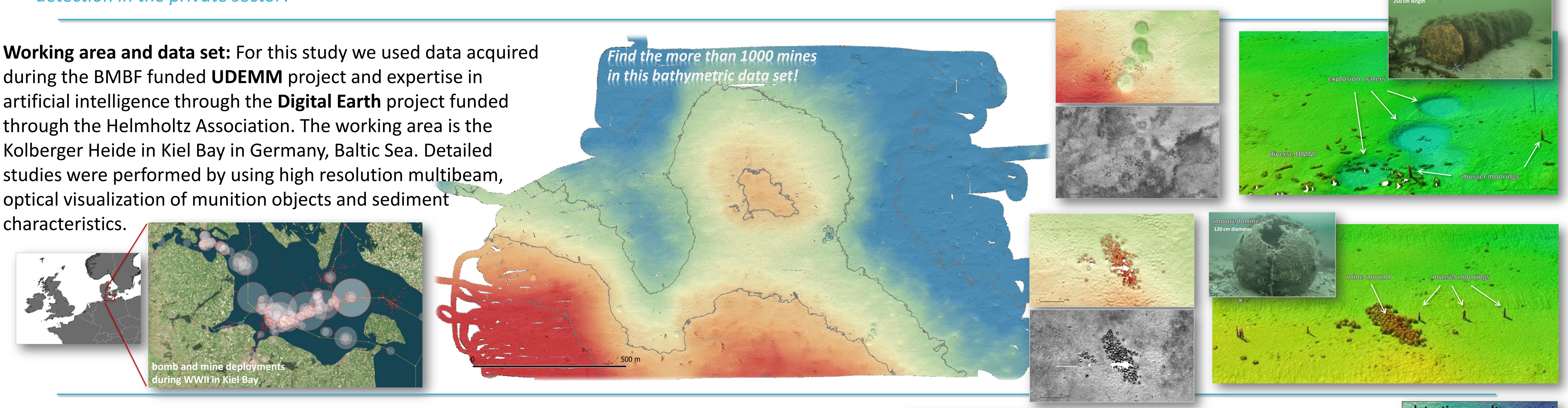
Introduction: Marine munitions, or unexploded ordnances (UXO), were massively disposed of in coastal waters after World War II; they are still being introduced into the marine environment during war activities and military exercises. UXO detection and removal has gained great interest during the ongoing efforts to install offshore wind parks for energy generation as well as cable routing through coastal waters. Additionally, 70 years after World War II munition dumping events, more and more chemical and conventional munition is rusting away increasing the risk of toxic contamination. We addressed the following questions:

- *Can we use data science approaches including ML (supervised and unsupervised), to support munition detection in 'large' spatial data sets?*
- *Should we aim for an all in one ML approach or better iterate to the final result using ML as supportive tool with an expert in the loop?*
- *Should we promote the application of 'approved' ML methods and approaches for a standardized/reproducible munition detection in the private sector?*

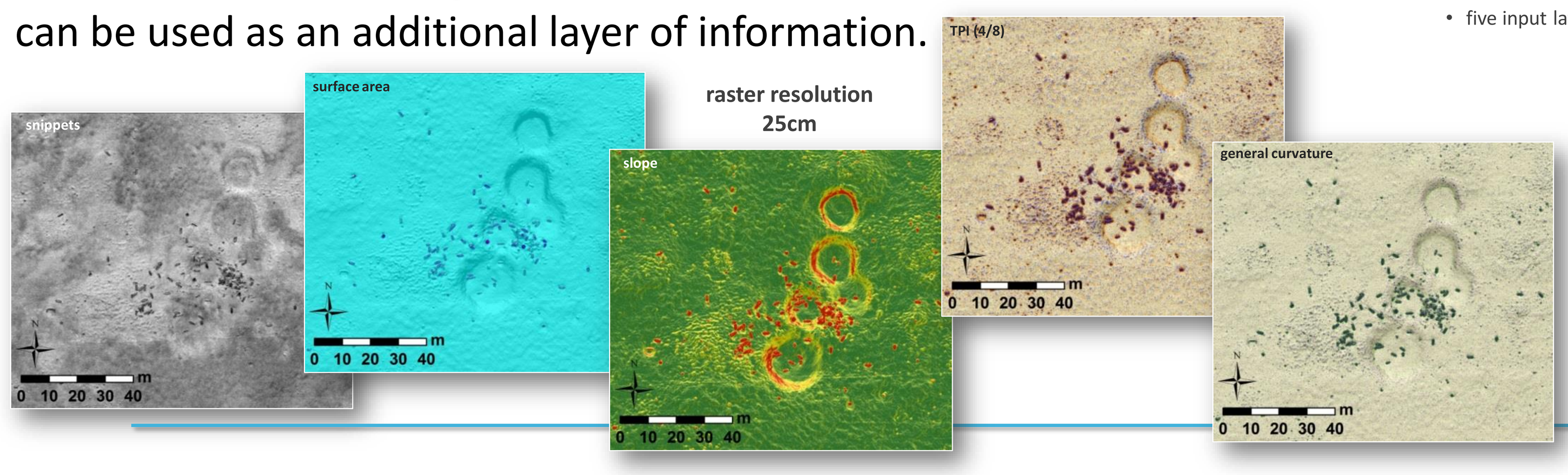


The general detection methodology includes high resolution multibeam mapping, hydroacoustic sub-bottom mapping, electromagnetic surveys with gradiometers as well as visual inspections by divers or remotely operated vehicles (ROVs). Using autonomous unmanned vehicles (AUVs) for autonomous underwater inspections with multibeam, camera and EM systems is the next technological step in acquiring meaningful high resolution data independently of a mother ship. However, it would be beneficial for the use of such technology to be able to better predict potential hot spots of munition targets and distinguish them from other objects such as rocks, small artificial constructions or metallic waste (wires, barrels, etc.).

Working area and data set: For this study we used data acquired during the BMBF funded **UDEMM** project and expertise in artificial intelligence through the **Digital Earth** project funded through the Helmholtz Association. The working area is the Kolberger Heide in Kiel Bay in Germany, Baltic Sea. Detailed studies were performed by using high resolution multibeam, optical visualization of munition objects and sediment characteristics.



First approaches for automated mine detection: Munition objects form morphological features on the seafloor and thus their location can be detected by investigating different bathymetric derivatives in a combined approach. Typical derivatives are slope, curvature, the topographic positioning index (TPI) or the surface area. As multibeams also acquire information about the intensity of the received beam signal, these backscatter value (or snippets) can be used as an additional layer of information.



A Supervised classification - **Classification Dictionary**
- defining value ranges for DMM in normalized MBES derivative and snippet rasters

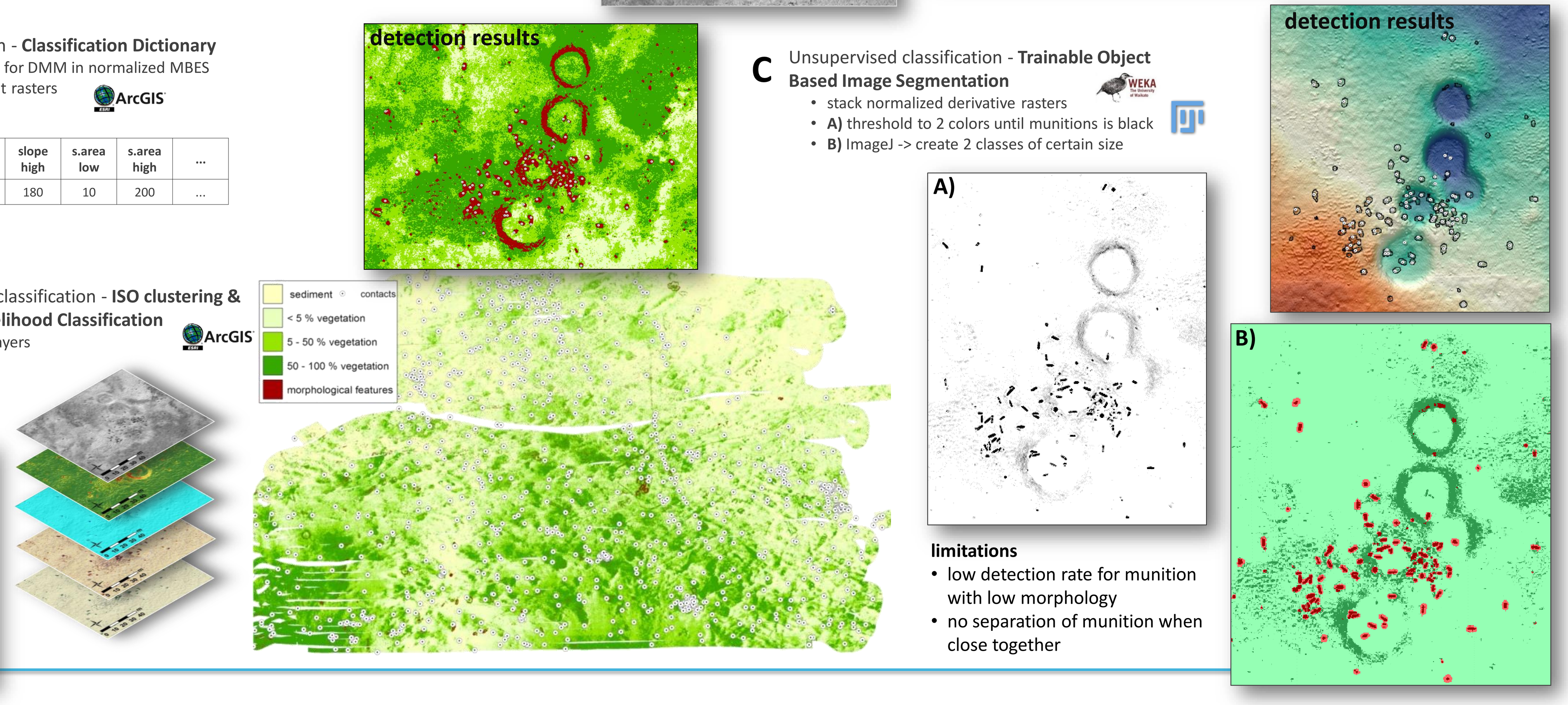
ArcGIS

class	BS low	BS high	slope low	slope high	s.area low	s.area high	...
value	63	140	110	180	10	200	...

B Unsupervised classification - **ISO clustering & Maximum Likelihood Classification**
- five input layers

ArcGIS

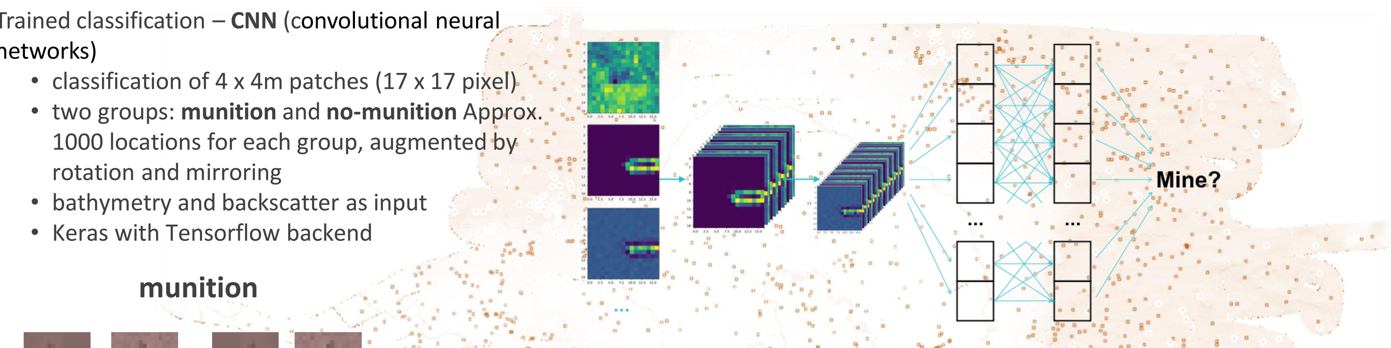
C Unsupervised classification - **Trainable Object Based Image Segmentation**
- stack normalized derivative rasters
- **A)** threshold to 2 colors until munitions is black
- **B)** ImageJ -> create 2 classes of certain size



limitations
- low detection rate for munition with low morphology
- no separation of munition when close together

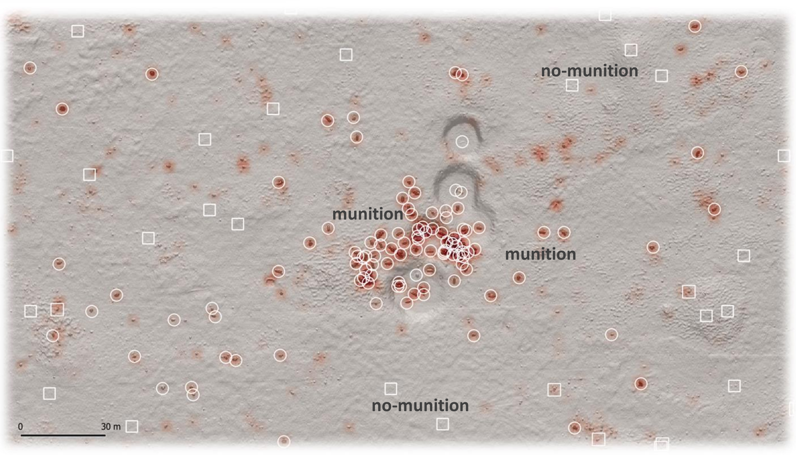
Neural Network approaches: The structure of the data has a high similarity to image data, an area where neural networks are the benchmark. As a first approach we trained convolutional neural networks in a supervised manner to detect seafloor areas contaminated with UXO. We manually annotated known UXO locations as well as known non-UXO locations to generate a training dataset; this was later augmented by rotating and flipping each annotated tile. We achieved a high accuracy using only a subset of the derivatives layers mentioned above as input layers. We also explored the use of further input layers and larger training datasets, and their impact in performance. This is a good example for machine learning enabling us to classify large areas in a short time and with minimal need for manual annotation.

Trained classification – **CNN** (convolutional neural networks)
- classification of 4 x 4m patches (17 x 17 pixel)
- two groups: **munition** and **no-munition** Approx. 1000 locations for each group, augmented by rotation and mirroring
- bathymetry and backscatter as input
- Keras with Tensorflow backend

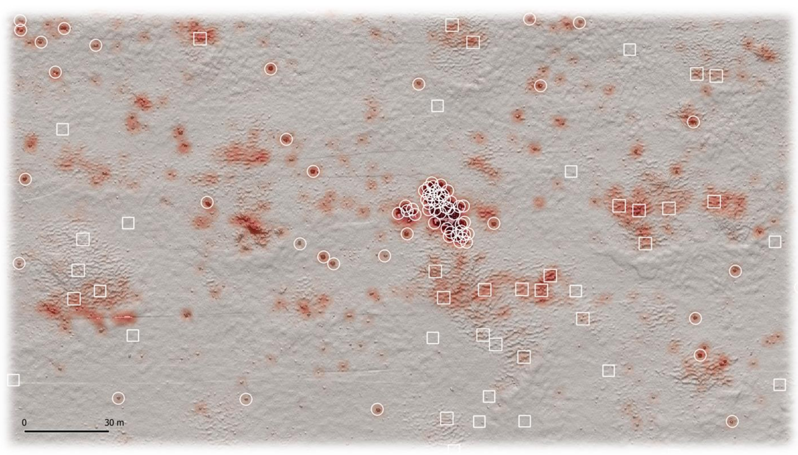


Layer (type)	Output Shape	Param #
conv2d_114 (Conv2D)	(None, 15, 15, 8)	152
conv2d_115 (Conv2D)	(None, 13, 13, 8)	584
conv2d_116 (Conv2D)	(None, 11, 11, 8)	584
flatten_38 (Flatten)	(None, 968)	0
dense_76 (Dense)	(None, 16)	15504
dense_77 (Dense)	(None, 2)	34

Total params: 16,858
Trainable params: 16,858
Non-trainable params: 0



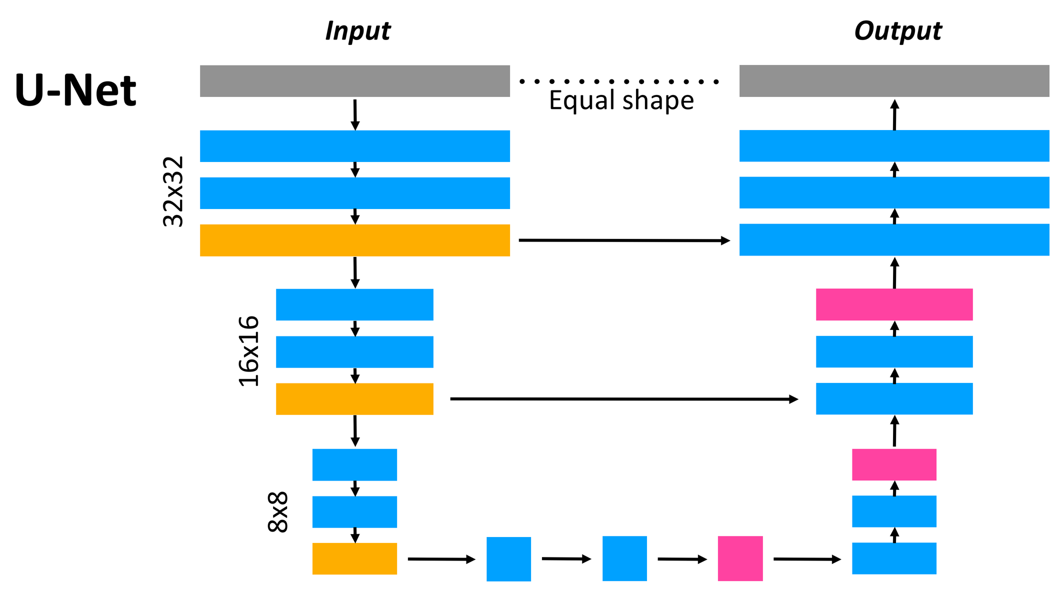
A simple three layer CNN allowed to calculate the probability of a 15x15 cell size tile to contain a munition object (red)



The re-annotating of additional no-munition areas significantly decreased the false-positive identification of certain seafloor substrates and bathymetric attributes.

Next step in automated NN detection: We aim at developing a semantic segmentation algorithm with the following workflow:

- Classify the input data on a pixel basis as UXO or background. It is possible to add other classes.
- The model output is a map of probabilities for each pixel, like a heat map. This should enable the user to spot possible UXO objects.
- Various implementations of semantic segmentation models exist. We use a **U-Net** (Ronneberger et al. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.).



- The approach should create contiguous areas for individual objects, however this is usually not enforced. Counting objects is therefore problematic. The same holds for objects close to each other.
- The term semantic in semantic segmentation refers to the pixels being classified based on the local area. In the model, this is accomplished via convolutions and the reduction in size through aggregation in max-pooling layers(orange). The pink blocks represent the up-convolutions to create higher resolution data.

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