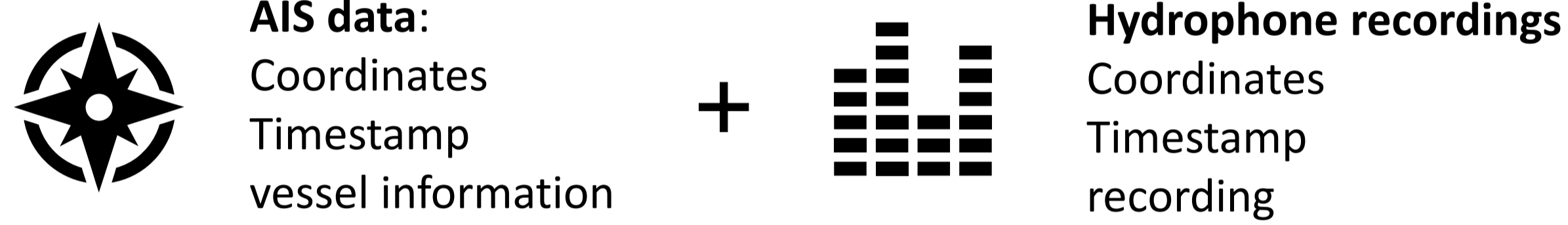
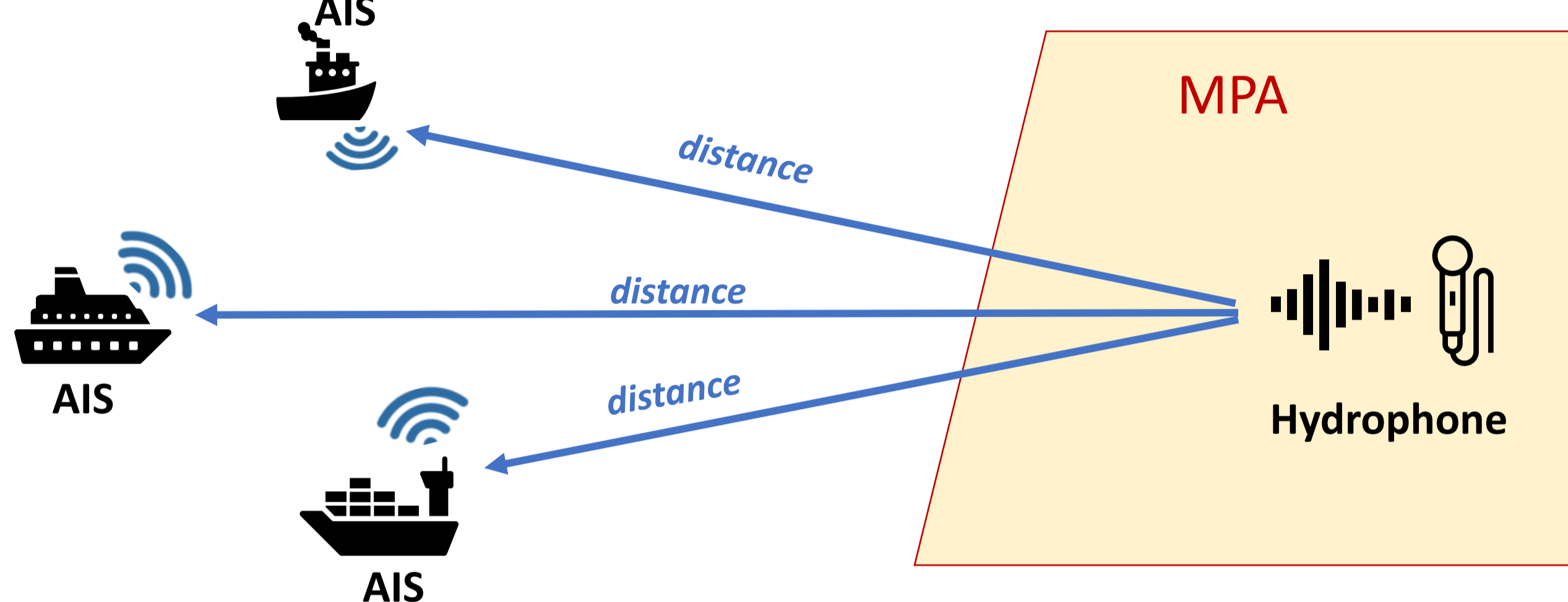


# Classifying vessels using CNNs based on underwater acoustics

Decrop Wout, Parcerisas Clea, Schall Elena, Debusschere Elisabeth, Deneudt Klaas

**1** Implement machine learning techniques for vessel **detection** and **classification** using underwater sound to effectively monitor human activities in areas such Marine Protected Areas (MPAs) or windmill parks.

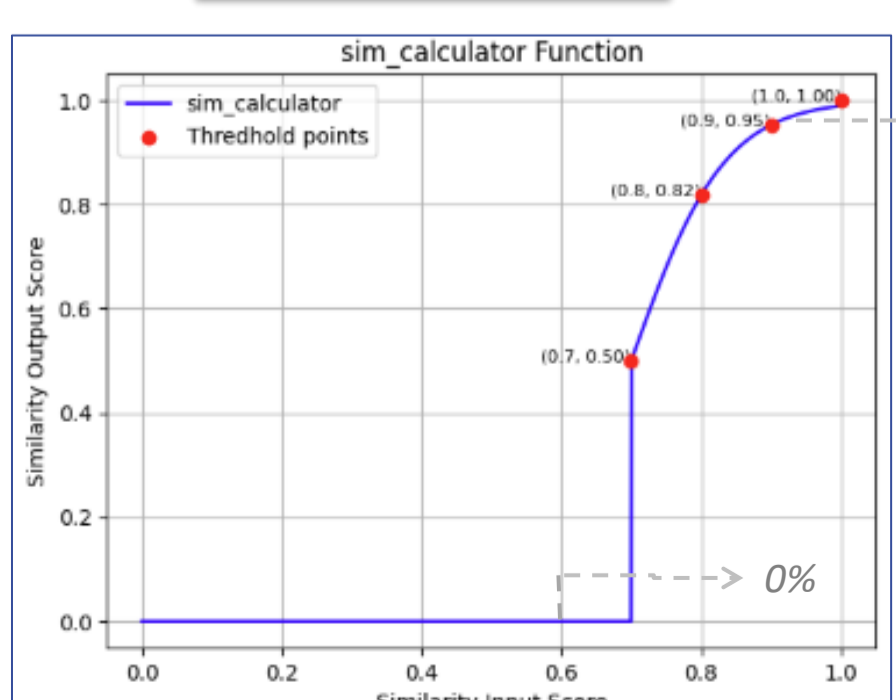
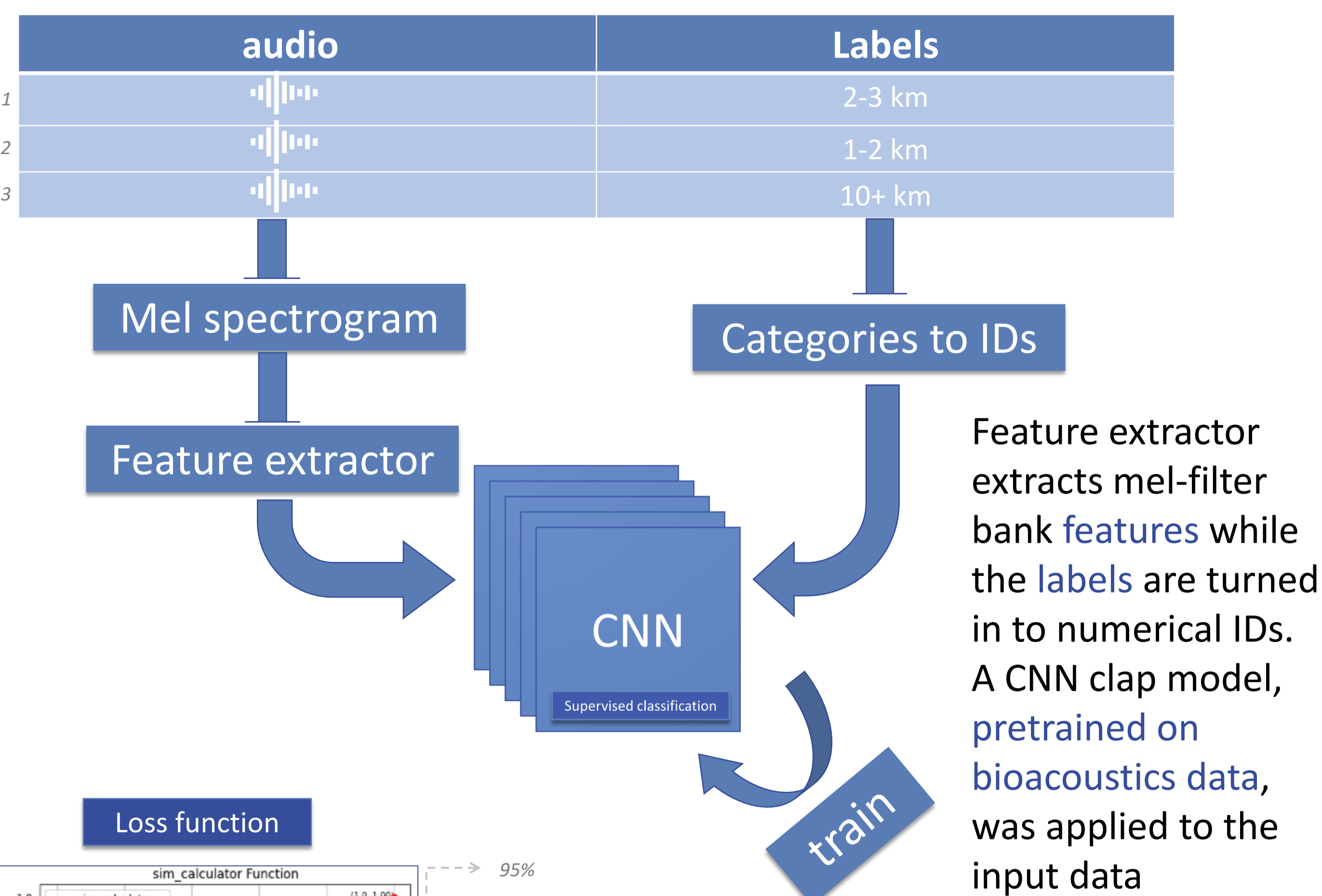
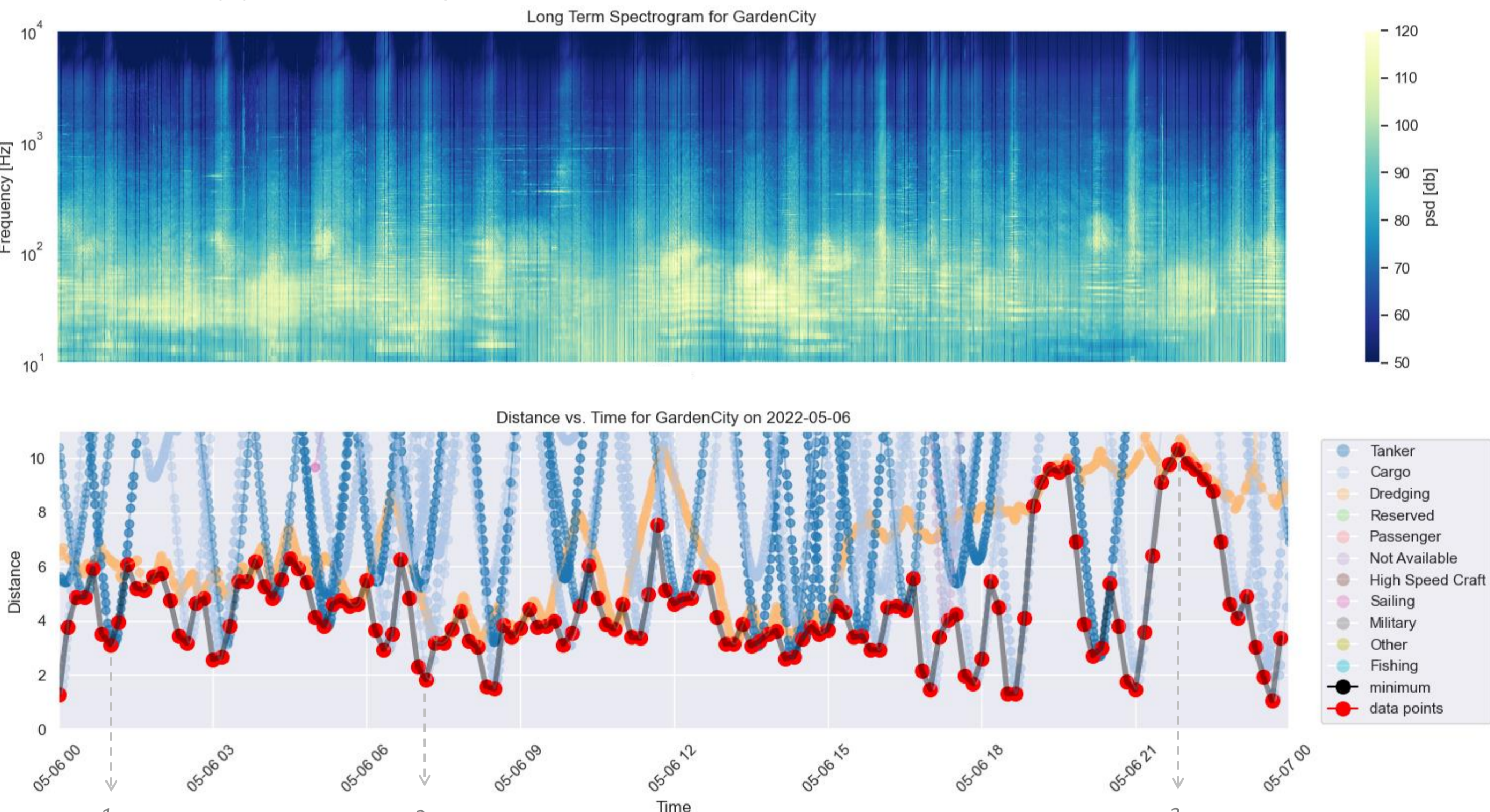
**2** **Creation of the database**  
By combining the coordinates of marine vessels from the VLIZ AIS database with the coordinates of our hydrophone stations at sea, we can calculate the **distance** between the source (vessel) and the receiver (hydrophone station).



This provides a database containing labeled acoustic data suitable for training a Convolutional Neural Network (CNN).

## Training the CNN on labeled data

Ten-second WAV files are sampled every 2 minutes, resulting in a total of approximately 39,000 files.

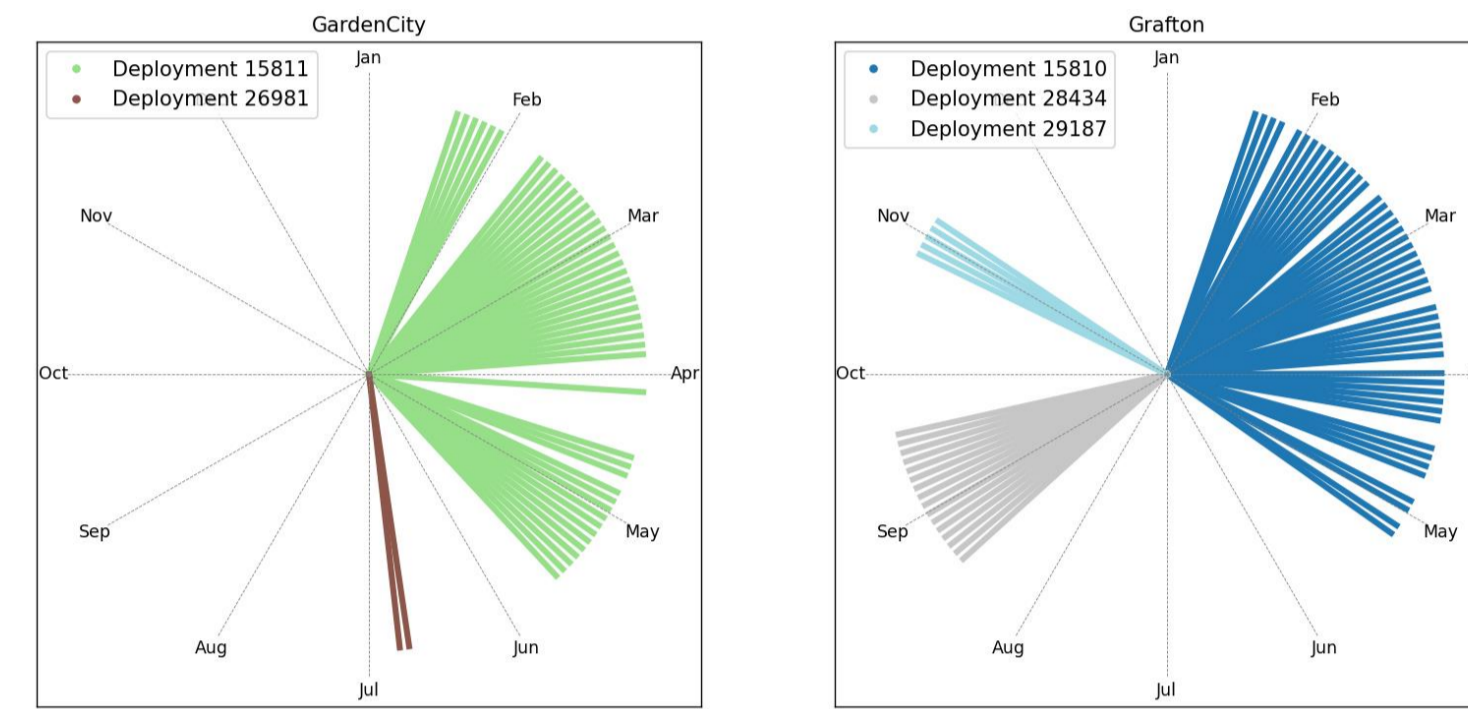
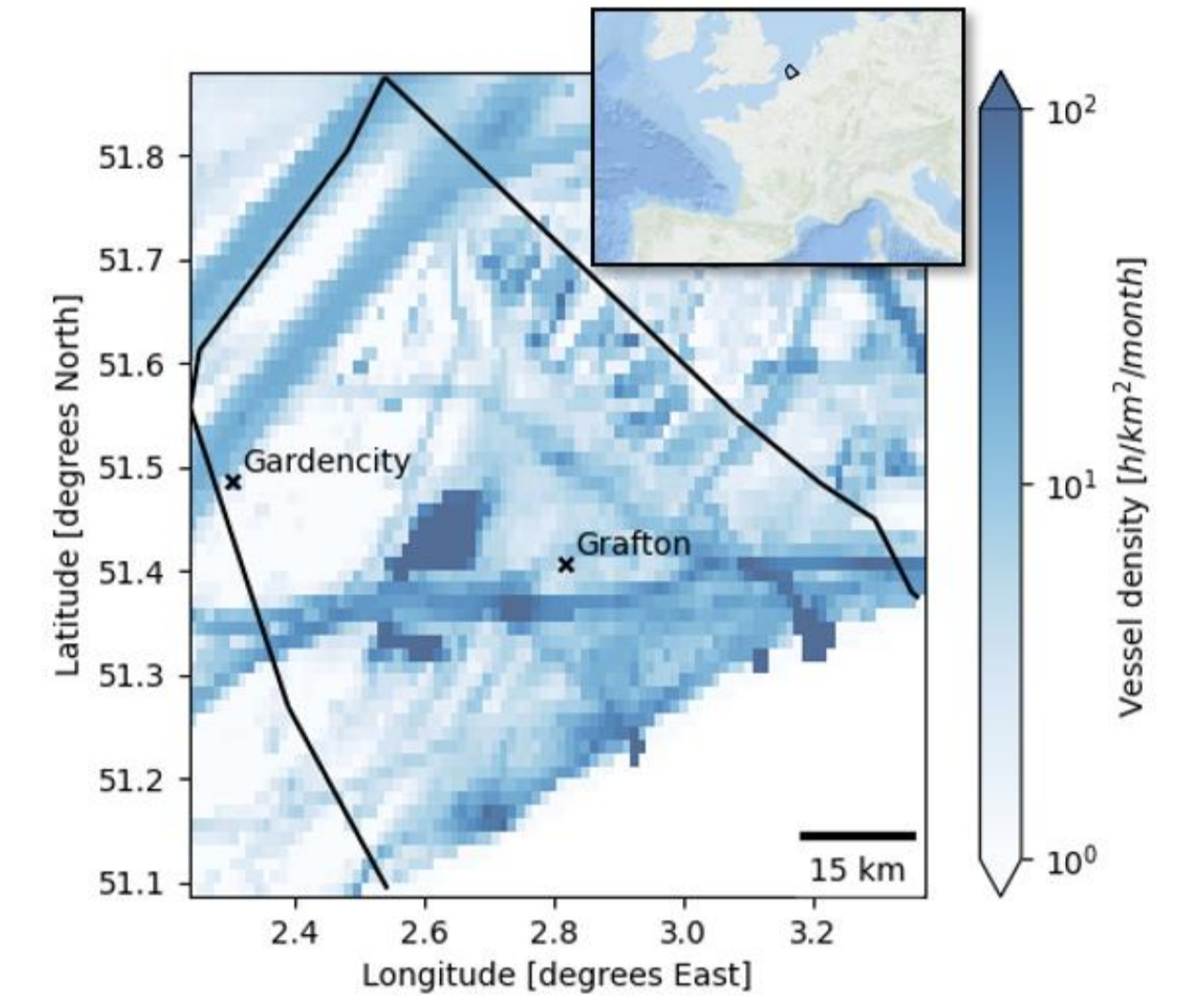


The loss function heavily penalizes errors exceeding 3 km but is more lenient towards deviations within 2 km. For instance, an error of 1 km still achieves 95% correctness, whereas a deviation of 4 km results in 0% correctness.

## 1 Spatio-temporal distribution of hydrophones

### Where?

Hydrophones recording are from two stations in the **Belgium part of the North Sea**. The stations are called **Gardencity** and **Grafton**. The vessel distribution illustrates that both are in the **proximity of high ways**.

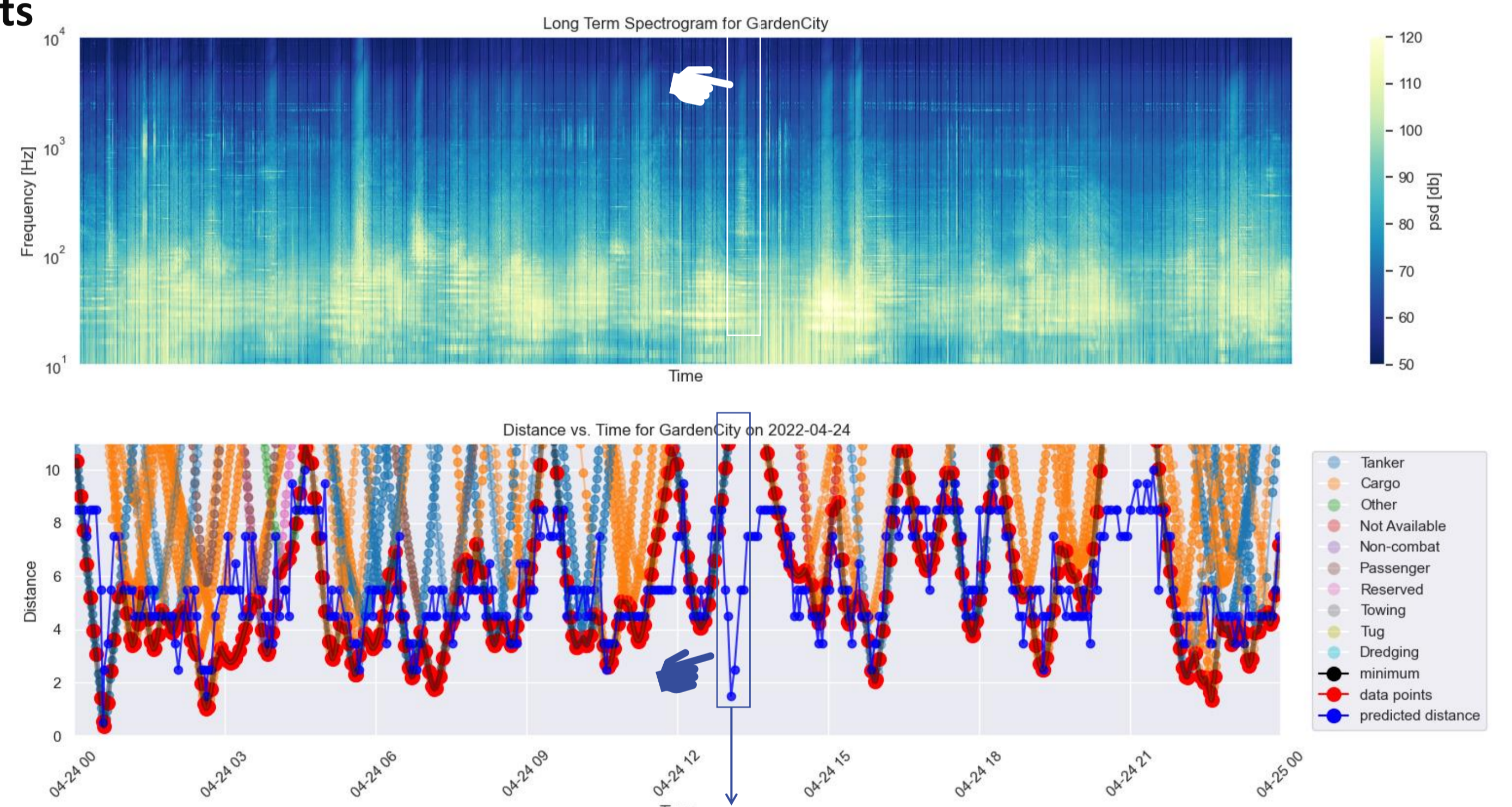


### When?

Hydrophone recordings from **Gardencity** and **Grafton** in 2022. Each station has multiple deployments, shown in different colors, giving a clear picture of underwater sounds.

## 3 Results from ship detection

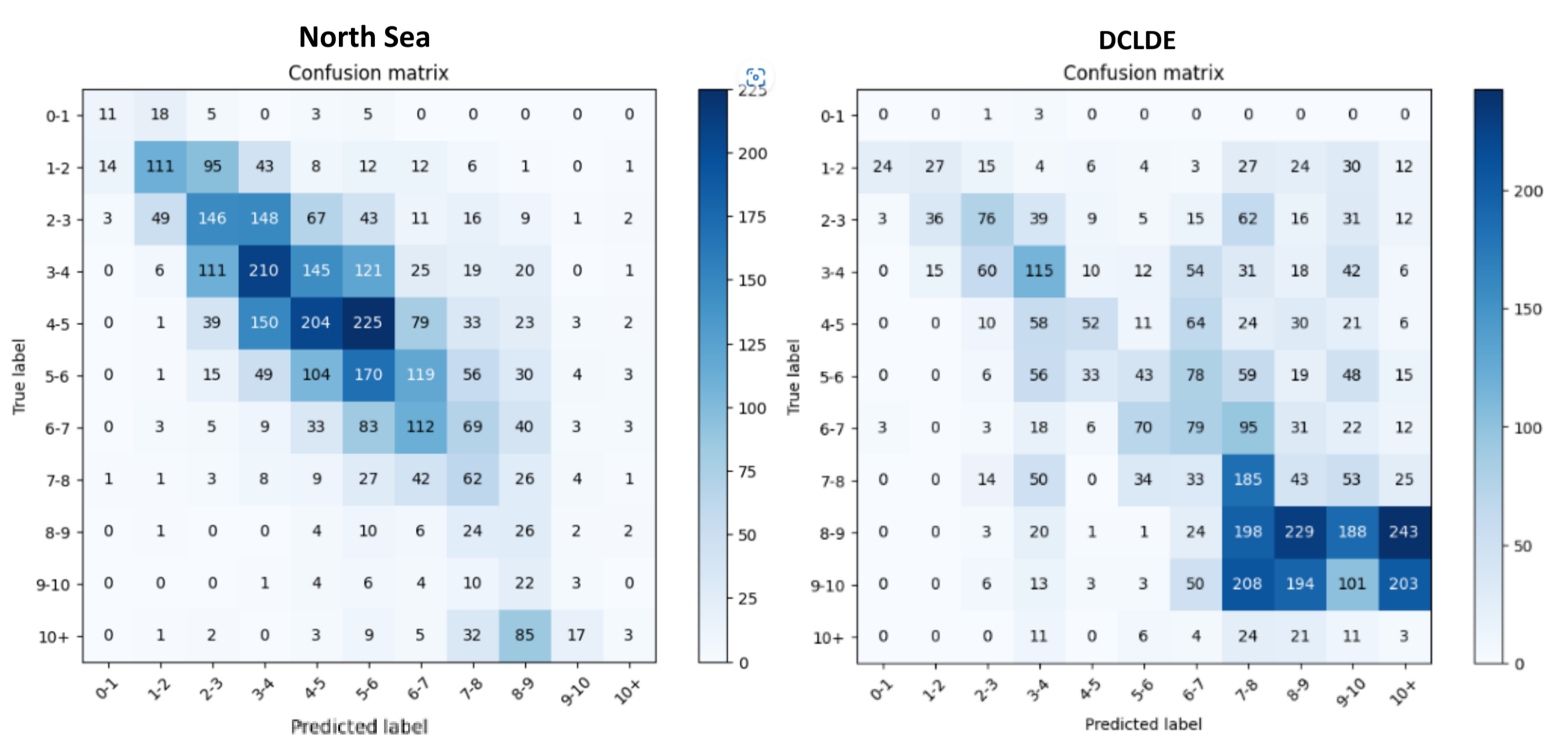
### results



The model effectively identifies **false negatives** and outperforms the original dataset. Some vessels deactivate their AIS, leading to unlabeled vessels on the left side of the confusion matrix.

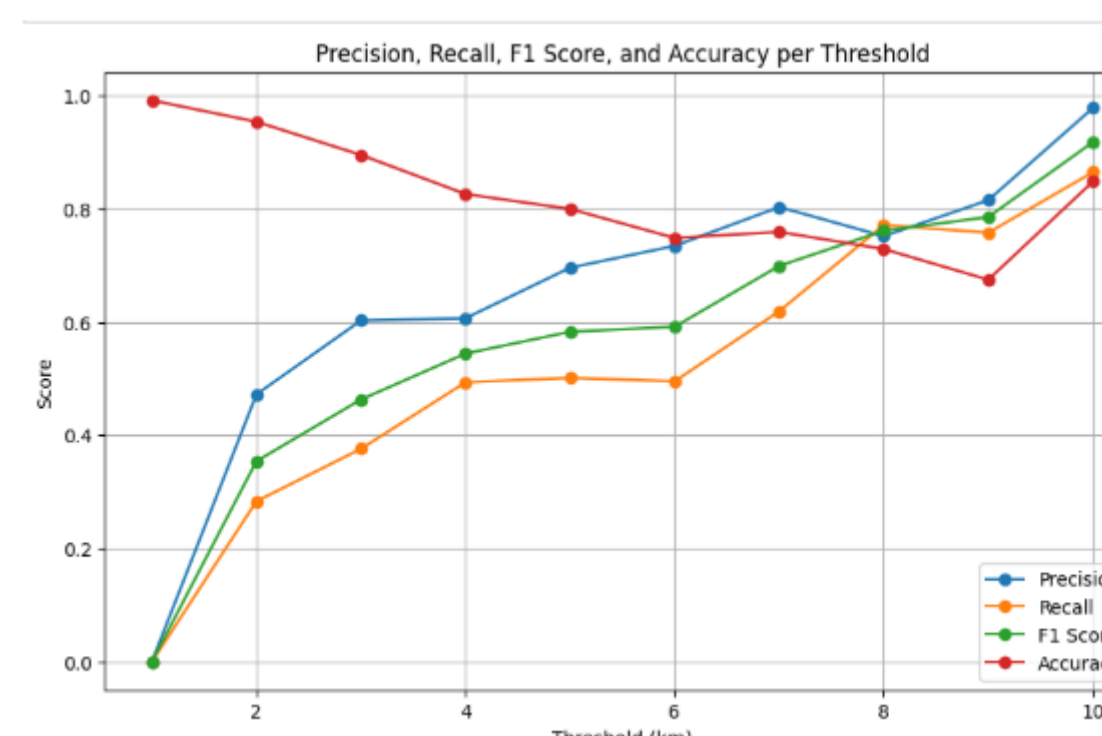
### Re-training on DCLDE dataset

The developed model underwent re-training using 2.8k datapoints extracted from vessel tracks within the DCLDE dataset.



	North Sea	DCLDE
MSE	3.46 km	6.1 km
RMSE	1.86 km	2.47 km

The model **performs effectively** in the **North Sea**; however, when applied to the **DCLDE** dataset, it slightly **overestimates** distances, likely due to differences in **environmental conditions**.



In terms of **detection capability**, the **DCLDE** model demonstrates notable effectiveness in distinguishing the presence or absence of ships, particularly peaking at 10km due to the clearer identification of more distant vessels within the '10+km' category.