

Pilot project on the monitoring of small vessel contribution to continuous underwater noise

Scientific note from DCE – Danish Centre for Environment and Energy

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Data sheet

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Author(s): Mia L. K. Nielsen¹, Cristina Marcolin², Kristian Beedholm² & Jakob Tougaard¹

Institution(s): Aarhus University, ¹Department of Ecoscience and ²Department of Biology

Referee(s): Emily T. Griffiths

Quality assurance, DCE: Camilla Uldal

External comment: The Danish Environmental Protection Agency. [The comments can be found here](#)

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Preface

In September 2024, Aarhus University was contracted by the Danish Environmental Agency to conduct a pilot study to test and evaluate different methods for quantifying the contribution of small boats without AIS to the low-frequency underwater noise. The methods tested were radar, camera, and passive acoustic monitoring, while the implementation of satellite imagery and drone observations is discussed.

Here, we report the methodology for data collection and data processing, we present possible methods for automation of each type of data processing, and we evaluate the methods for implementation into the Danish noise monitoring program.

The agency was given opportunity to comment on an earlier version of the report. The comments from the agency and replies/changes to the final report can be found in the commenting sheet at (see Data Sheet).

Summary

Small recreational vessels, many of which do not carry AIS transmitters, are a major yet under-represented source of underwater noise in Danish coastal waters. This pilot study evaluated three complementary monitoring methods to quantify the presence of non-AIS vessels and assess their potential contribution to underwater noise (D11C2) in the context of the EU Marine Strategy Framework Directive: Passive Acoustic Monitoring (PAM), radar surveillance, and timelapse camera.

For all methods, a substantial proportion of detected vessels were non-AIS vessels, although with clear patterns of variation across time of day, week and season. Across the data, PAM identified 55.6%, radar detected 90.4%, and timelapse cameras 78.2%. For implementing automated detection, the performance varied across methods: radar showed the highest precision and recall (96% / 88%), followed by PAM (86% / 67%) and the timelapse camera system (81% / 69%). The methods differ strongly in spatial coverage, ranging from a few hundred meters for cameras to up to 90 km for radar, and they also vary in detection biases related to sound frequency, vessel size, or visible area (Table 0.1).

Table 0.1. Summary of the proportion of non-AIS boats detected and the precision/recall of each automated method, as well as an over-view of evaluation metrics for PAM, radar and timelapse camera compared to AIS for monitoring small boats without AIS. *Note that for the proportion of non-AIS boats, the data across methods are not fully overlapping (See Section 3).

Feature	AIS	PAM	Radar	Timelapse camera
Proportion of non-AIS boats*	-	55.6%	90.4%	78.2%
Precision/recall	-	86/67	96/88	81/69
Coverage	Very high (national)	Low (local)	High (up to 90 km)	Medium (up to ~1 km)
Detects non-AIS	No	Yes	Yes	Yes
Real-time potential	Yes	Yes (challenging)	Yes	Yes
Vessel type info	Limited	Very limited/untested	Possible but limited	Possible
Bias	Toward commercial vessels and sailboats	Toward closer vessels and more high-frequency vessels	Minimal (towards larger vessels)	Towards vessels with larger visible area
Costs & complexity	Low	Medium	High	Low-Medium

AIS provides excellent spatial coverage at the national scale but fails to capture non-AIS vessels altogether and is biased toward larger commercial ships and sailboats. In contrast, all three tested methods successfully detected non-AIS traffic, though each with its own limitations. PAM is sensitive to nearby and higher-frequency noise sources; radar provides broad coverage but comes with high cost and complexity; and timelapse cameras offer moderate range, but performance depends on visibility and vessel size.

Together, the results demonstrate that small non-AIS vessels constitute a significant proportion of traffic in the study area and are not accounted for in AIS-based soundscape models currently used for assessments under D11C2. Integrating data from one or more of these complementary methods could therefore improve future national monitoring of continuous underwater noise, particularly in coastal areas where small recreational vessels dominate.

1 Acknowledgements

For this project, we want to acknowledge Terma for sharing their radar data and providing software and instructions on how to extract and interpret the data. We want to thank Egå Marina for their assistance in setting up cameras. We want to thank Peter T. Madsen for providing underwater recording equipment and for assisting in the deployment and retrieval of the equipment. For providing the AIS data we acknowledge the Danish Maritime Authority. Finally, we acknowledge that the content of this report forms part of the PhD of Cristina Marcolin, funded by Aage V. Jensen's Naturfond.

2 Background

Underwater noise produced by ship traffic is a major anthropogenic pressure in marine ecosystems. It has been shown to have an impact on a range of species, especially those that rely on sound for communication, navigation and foraging. In Danish waters this includes the harbour porpoise (*Phocoena phocoena*) that frequently encounter vessel noise and show clear negative reactions to noise from individual ships (e.g. Wisniewska et al. 2018).

2.1 Regulatory context for the project

The Danish Environmental Protection Agency is responsible for implementing the EU Marine Strategy Framework Directive (MSFD; https://environment.ec.europa.eu/topics/marine-environment_en) through the national monitoring program (NOVANA), which aims to maintain and achieve good environmental condition across all 11 descriptors of the directive. Descriptor 11 addresses underwater noise and following guidance from the EU Commission (European Commission, Decision 2017/848/EU) assessment of Good Environmental Status is done by means of two criteria, one for impulsive noise (D11C1) and one for continuous low-frequency noise (D11C2). This project focuses on D11C2.

Following further guidance from the Commission (TG-Noise, Borsani et al. 2023) large-scale soundscape models have been developed in recent years to assess large-scale patterns in the indicators for D11C2. These models are the foundation for regional assessments such as HOLAS 3 in the HELCOM area (HELCOM, 2023) and OSPAR's QSR24 (Quality Status Report) for the North Sea (Kinnevig and Tougaard, 2021) and are based on information about shipping density from Automatic Identification System (AIS) data. AIS data provides a range of parameters besides ship position, including vessel type, length and speed. However, AIS transmitters are not mandatory for small vessels and leisure crafts and as these vessels often dominate ship traffic in coastal areas, the models based solely on AIS (in some cases supplemented by VMS data for shipping vessels above 15 m) are known to underestimate noise emissions from ships in coastal habitats (Hermannsen et al. 2019; Nachtsheim et al. 2023). For this reason, regional sea conventions (HELCOM, OSPAR) have highlighted the need to include small recreational vessels in noise assessments (e.g. HELCOM, 2021), but no recommended methods for how to include small boats without AIS in the noise indicators used for assessment of GES are available. The aim of this pilot project is therefore to improve our knowledge on the contribution of underwater noise from small boats without AIS and explore and evaluate methods for quantifying the contribution from small boats, such that this contribution can be integrated into the Danish framework for monitoring and assessment of D11C2.

2.2 Project objectives

This pilot study tested three complementary methods for quantifying presence of small boats without AIS in a coastal area and estimate their contribution to the underwater soundscape. The methods explored were:

1. Passive Acoustic Monitoring (PAM)
2. Radar surveillance
3. Camera surveillance

The outputs from these methods were compared with AIS data to estimate the proportion of non-AIS vessels by season, day of week, and time of day. Building on previous work in inner Danish waters (Hermannsen et al. 2019), data were collected in Aarhus Bay near Egå Marina – a site dominated by small recreational boats and with minimal large-vessel traffic.

2.3 Approach and evaluation

All three methods were treated through the same steps:

- Outline of data collection and data processing steps.
- Evaluation of the ability of each method for quantifying AIS and non-AIS vessels – both manually and automated.
- Recommendations for additional work to further evaluate/develop the method.

Manual validation was performed on a subset of data to assess accuracy of the automated analysis methods explored for processing larger amounts of data for possible integration into the national noise monitoring program.

3 Data collection overview

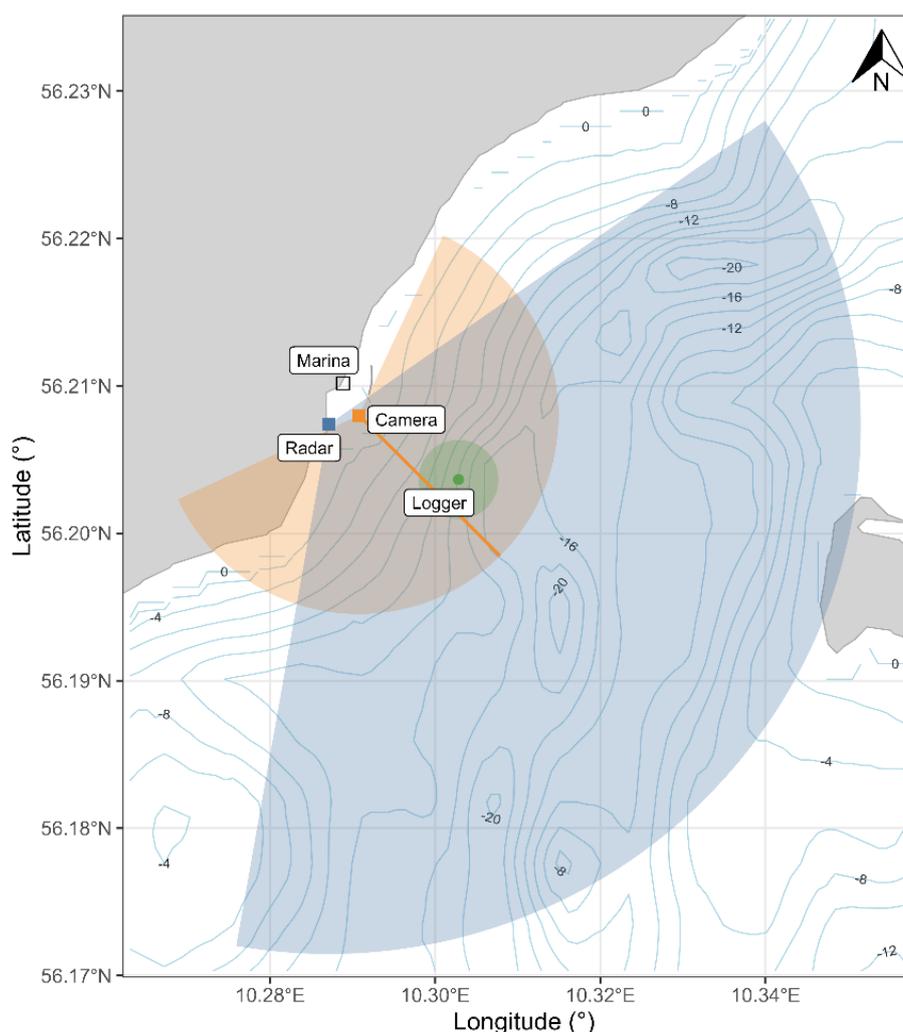
Camera, radar and Passive Acoustic Monitoring (PAM) data were collected with some overlap between June 25, 2025 and October 14, 2025 (Table 3.1). AIS data were extracted for the maximum period to overlap with all data types. Each sensor was positioned to allow for spatial overlap of data collection (Figure 3.1).

Table 3.1. Overview of the position and period where data was collected for the three data types as well as the period where data was extracted for AIS.

Data	Recording start	Recording end	Position (DD)
Radar	2025-06-30	2025-09-12	56.20736, 10.28703
PAM	2025-06-25	2025-09-12	56.20365, 10.30282
Camera	2025-07-31	2025-10-14	56.20800, 10.29076
AIS	2025-06-25	2025-10-14	NA

3.1 Subsets used for data analysis

Figure 3.1. Map of the position of each sensor as well as their spatial coverage. For the camera (orange square), the orange line represents the midline of the horizontal field-of-view, and the shaded orange area is the full horizontal field-of-view. For the radar (blue square) the shaded blue area is the horizontal field-of-view and range of detection. For the acoustic recorder (green point) the shaded green area is the approximate detection range for a boat (500 m).



Within the period of available data, a subset of eight hours was randomly selected and stratified to cover seasonal, time of week and time of day variation, with one hour in each combination (e.g. Peak summer – weekend – daylight; overview of subsets in Table 3.2). This was done for PAM and radar data that were both recording continuously. The mounted timelapse camera recorded at 5-minute intervals during daylight hours only and images were selected to represent seasonal and time-of-week variation for late summer, early fall and late fall, as the camera started recording and ended recording at a later date than both PAM and radar. Due to an unforeseen data gap in the camera data between August 6 and 21, it was not possible to match all periods in Late summer with camera data (Table 3.2). Additionally, the radar data was collected opportunistically, meaning that recordings for this project were procured when the radar was not used for other projects. Due to this, there are gaps in the radar data, and it was therefore not possible to match all periods with PAM data (Table 3.2).

Table 3.2. Overview of the subsets of PAM, radar and camera data. For PAM and radar data the date and time of each 1-hour period is provided. For camera data, the number of images and number of days for each combination of season and time of week is provided as well as a statement of whether there are images overlapping with the 1-hour subset of either PAM or radar.

Season	Time of week	Time of day	PAM (start and end times)	Radar (Start and end times)	Camera (# of images, # of days; Overlap)
Peak summer	Weekday	Daylight	2025-07-01 10:00 to 2025-07-01 11:00	2025-07-01 07:30 to 2025-07-01 08:30	-
			2025-07-01 00:55 to 2025-07-01 01:55	2025-07-01 00:55 to 2025-07-01 01:55	-
		Daylight	2025-07-13 14:00 to 2025-07-13 15:00	2025-07-13 14:00 to 2025-07-13 15:00	-
	Weekend	Night	2025-07-13 01:30 to 2025-07-13 02:30	2025-07-13 01:30 to 2025-07-13 02:30	-
	Late summer	Weekday	Daylight	2025-08-04 07:15 to 2025-08-04 08:15	2025-08-05 07:50 to 2025-08-05 08:50
2025-08-04 01:30 to 2025-08-04 02:30				2025-08-05 22:40 to 2025-08-05 23:40	-
Daylight			2025-08-17 13:10 to 2025-08-17 14:10	2025-08-17 13:10 to 2025-08-17 14:10	300 images across 6 days; No overlap
Weekend		Night	2025-08-17 03:15 to 2025-08-17 04:15	2025-08-17 03:15 to 2025-08-17 04:15	-
					2025-08-04 01:30 to 2025-08-04 02:30
					2025-08-17 13:10 to 2025-08-17 14:10
					2025-08-17 03:15 to 2025-08-17 04:15
Early fall	Weekday	Daylight	-	-	300 images across 22 days
	Weekend	Daylight	-	-	300 images across 8 days
Late fall	Weekday	Daylight	-	-	300 images, 10 days
	Weekend	Daylight	-	-	300 images, 4 days

For consistency between data types, PAM and radar data was divided into 5-min bins within each hour analysed, to provide a snapshot of boat presence for each hour chosen. The choice of 5-min bins per hour comes from the largest time resolution available from the camera data. Due to the different deployment and recording schedules of the data types (Table 3.1), a complete overlap was not possible. The main reason for subset difference for camera versus PAM/radar data is the continuous recording schedule of PAM/radar versus 5-minute interval samples in camera data.

For each hour in the PAM and radar data, three random 5-minute segments were manually processed and used for validation of automated methods. For camera data a subset of 694 images covering seasonal and time of week variation was included for validation of an automated boat detection model.

AIS data for the study area (Figure 3.1). was obtained from the Danish Maritime Authority for the period from June 26, 2025, to October 31, 2025. The AIS data was processed to exclude obviously erroneous coordinates and handle special characters in names, using a custom script in MATLAB (R2025b, Math-Works). For this note, we will generally refer to small recreational vessels as either sailboats or motorboats, depending on their main mode of propulsion. However, within the ship type category for AIS there is no category for motorboats specifically. Thus, boats in the Egå Marina area typically fall into two categories: Sailing or Pleasure. Here, Sailing type refers to ships that are identified by their main mode of propulsion being the sail and Pleasure refers to ships that are best categorised by their main use being recreational. This means that the Pleasure ship category is very broad, including both motorboats and some types of sailboats (e.g. sailing yachts), while sailboats only include sailboats. When sailboat and motorboat is used it is in relation to data obtained for this project, while Sailing and Pleasure ship type is used when referring to AIS data. Both Sailing and Pleasure ship type fall into the recreational vessel category.

3.2 Evaluation of automated detection methods

The metrics and terminology used to evaluate the correspondence between automated detection methods and classification by manual audit follows Roberts & Read, (2015). The classifications of the human observer in the manual audit are assumed to be valid. For a single observation period and a specific category, such as “boat present”, there are two possible classifications of the manual observer, two possible classifications of the automated classifier, and four combinations in total (Table 3.3).

Table 3.3. Terminology for comparing classifications of a human observer (taken to be accurate) and an automated classification algorithm.

		Observer classification	
		Present	Not present
Automated classification	Present	True positive	False Positive
	Not present	False negative	True negative

Thus, to compare performance of human and automated classifiers, the number of True Positives (TP), False Positives (FP), True Negatives (TN) and True Positives (TP) were tallied. The performance of the automated detectors was then characterized as the Positive Predictive Value, PPV and the True Positive Rate, TPR.

$$PPV = \frac{\text{True detections by algorithm}}{\text{All detections by algorithm}} = \frac{TP}{TP + FP}$$

$$TPR = \frac{\text{True detections by algorithm}}{\text{True detections by human}} = \frac{TP}{TP + FN}$$

PPV represents the proportion of positive classifications (detections) by the automated algorithm that match the human observer, and TPR represents the fraction of detections by the automated system also detected by the human observer. Both PPV and TPR has a lower bound of 0% (no vessels detected by the human observer detected by the automated system) and upper bound of 100%. For PPV 100% means that all vessels detected by the automated system were also detected by the human observe, and for TPR 100% means that all detections by the human observer were matched by detections of the automated system. To maintain consistency with the performance evaluations of automated object detection in images, PPV will be referred to as Precision and TPR as Recall. The two metrics are interdependent in the way that one can optimize (increase) one metric, but only at the expense of a reduction of the other metric, completely analogous to the trade-off between type I and type II errors in statistics. Selecting the optimal trade-off between precision and recall can be complicated and discussion of it beyond the scope of this study. Important, however, is that in most cases it is acceptable to use automated systems with less than perfect precision and recall, especially if the magnitude of the errors are known, simply because the uncertainty introduced by these errors are often more than outweighed by the typically significantly higher processing speed of the automated algorithms.

4 Passive Acoustic Monitoring

4.1 Setup of acoustic recording system

One passive acoustic monitoring (or PAM) station was established approx. 1 km outside Egå Marina at a depth of 12 m from June 25th, 2025, to September 12th, 2025. The station was set up following the well-established setup for PAM stations in the noise monitoring program (Tougaard, J., 2019; Figure 4.1). The station consists, bottom to top, of two stone bags for anchoring of the system, an acoustic releaser, a broadband acoustic recording system (SoundTrap ST600HF, Ocean Instruments Inc.), and two floats for stability in the water column and easy retrieval. The distance between the tip of the acoustic releaser and the seafloor was approximately 1 m, making the height of the ST600HF hydrophone about 2 m from the seafloor and 10 m from the surface. The two stone bags weighted approximately 25 kg each. For the release of the system, an Innovasea Ascent AR was used (Innovasea Systems Inc.). Before deployment, the ST600 was synchronized to UTC time.

The ST600HF was set to record continuously from June 25th, 2025, at 00:00 UTC. The sampling rate was set at the maximum, 384 kHz, to collect broadband data that could be used for further analysis. Before deployment, the unit was calibrated with a Pistonphone calibrator at 250 Hz. Clip level was 175.8 dB re. 1 μ Pa. The PAM station was retrieved on September 26th, 2025, three months after the deployment (as per estimated duration time of the ST600HF, based on the settings and sea conditions). The internal clock time was noted down once the ST600HF was retrieved and connected to the computer, to later account for clock drift (assuming linear clock drift from start of the deployment). The available data was then offloaded and decompressed with the proprietary software (SoundTrap Host, Ocean Instruments Inc.).

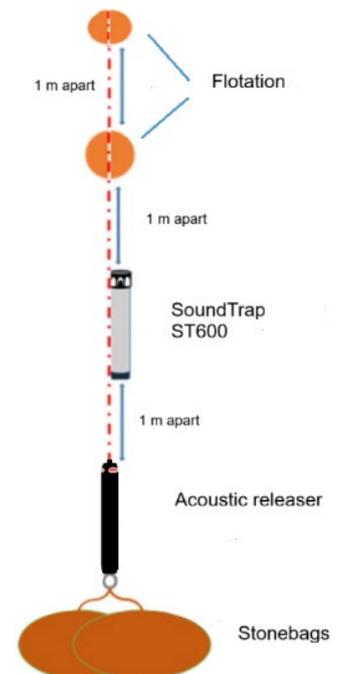


Figure 4.1. Schematic representation of the SoundTrap station setup.

4.2 Detecting presence of boats in acoustic recordings

The ST600 recorded continuously from June 25th, 2025, to September 12th, 2025. For the current scope of the report, the data was downsampled to 96kHz, as each sound file (.wav) produced has a duration of 45 min, to make the subsequent analysis more time efficient. Vessel noise typically has most energy at low frequencies (<1 kHz), although small recreational boats may peak at higher frequencies (>1kHz). Vessel noise is typically recorded at comparatively low sampling rates (Matzner et al., 2010; Santos-Domínguez et al., 2016; Parsons et al., 2021), because of the focus on the low frequency components that propagate far and is the most significant contribution to the regional soundscape. The downsampled audio files have a Nyquist frequency (48 kHz) well above the typical frequencies at which vessel noise peaks. In addition, data was subsampled to obtain randomly selected 1-hour bins per each period (i.e. season/time of week/time of day) chosen to find possible variability across time of year, week and day, as discussed in Section 3. For the PAM data, the subsequent 1-hour bins were then selected and used for analysis (Table 3.2).

To our knowledge, no automated vessel detector for small vessels in PAM data is publicly available nor exists. Here we apply a modified basic detector that was developed to detect boats based on the frequency spectrum. The detection algorithm measures ‘peakiness’ in the frequency spectrum, i.e. deviations from a Gaussian distribution of the spectrum in a limited frequency range that matches the sound of interest. Here we have taken advantage of the fact that the tonal quality of boat noise is qualitatively different from ambient noise stemming from natural phenomena. In the spectral domain of recorded noise, the spectral profile will be mostly sloping gently with frequency and taken over a limited frequency range, the real part of the spectrum is expected to have a Gaussian distribution of sample values. The kurtosis of such a distribution is therefore close to 3. In the presence of rhythmic sound sources such as propeller noise, the excess sound energy manifests itself in discrete frequency bands that are integer multiples of the rotor frequency. The distribution of values over a limited frequency range then becomes heavy right-tailed (high values overrepresented compared to a Gaussian distribution), since the discrete frequency bands are higher than the noise. This heavy tail corresponds to kurtosis values of the spectra larger than 3. Both the frequency band and time bin setting used for the detector was informed by testing different settings on recordings from three different situations; a few boats, no boats and a lot of boats (recordings visualised in Figure 4.2, 4.3 and 4.4).

An appropriate kurtosis threshold is then set to discriminate presence/absence of boat noise in that specific time bin. The threshold was chosen after manually inspecting three of the 1-hour segments, corresponding to different types of recording situations. These three examples are shown below in Figures 4.2, 4.3 and 4.4, depicting what a detection for 1-minute bins look like. Specifically, we show a recording presenting one very clear boat passage (good recording; Figure 4.2), a recording where no actual boat activity is present (silent recording; Figure 4.3), and one where a large number of boats is simultaneously present (noisy recording; Figure 4.4), as good examples of how the detector works in different situations at the current state of development. The figures highlight that the detector can detect presence of boats, especially when only single boats are present at a time, while it will not provide exact detections in periods with high boat density around the recorder. It also shows that, as for any automatic detector, it has detections in time bins where there is no boat noise, i.e. false positives (as it may be seen by the plot showing the silent recording).

When a large number of different boats are present, the kurtosis value is expected to decrease as the combined frequencies and levels will approach a Gaussian distribution. Nevertheless, in that situation there were still periods with high kurtosis and thus detections of the vessels.

Figure 4.2. Example of a single boat pas-sage at the hydrophone. The top panel is a spectrogram visualization of the recording, and the bottom panel is the log10 kurtosis values for the same recording (blue line) with the detection threshold used (dashed line).

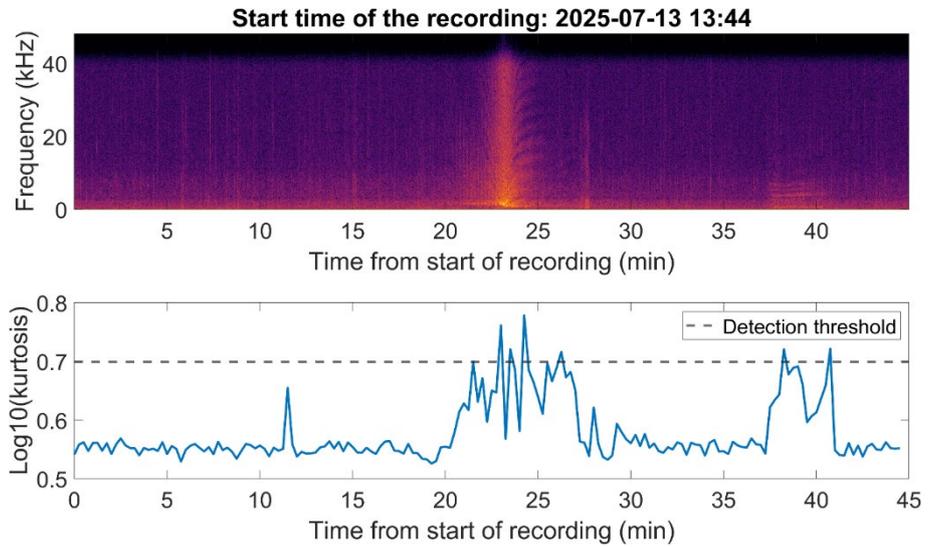


Figure 4.3. Example of a quiet period with no boat passages at the hydrophone. The top panel is a spectrogram visualization of the recording, and the bottom panel is the log10 kurtosis values for the same recording (blue line) with the detection threshold used (dashed line).

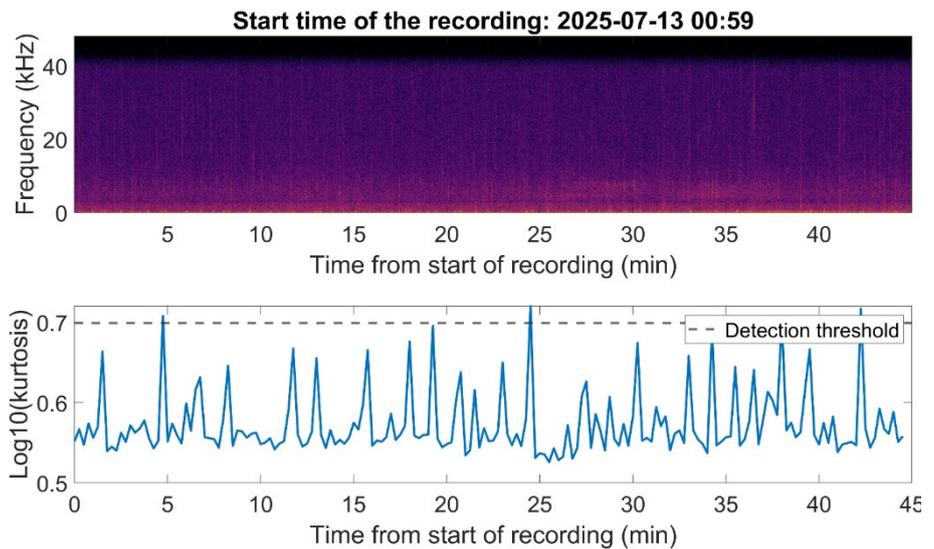
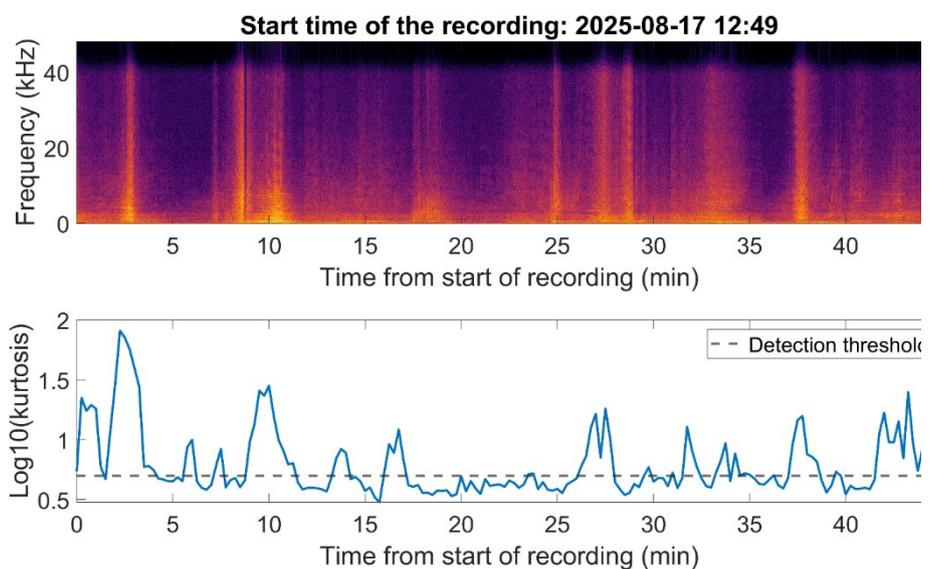


Figure 4.4. Example of a high density of boat passages at the hydro-phone. The top panel is a spectrogram visualization of the recording, and the bottom panel is the log10 kurtosis values for the same recording (blue line) with the detection threshold used (dashed line).



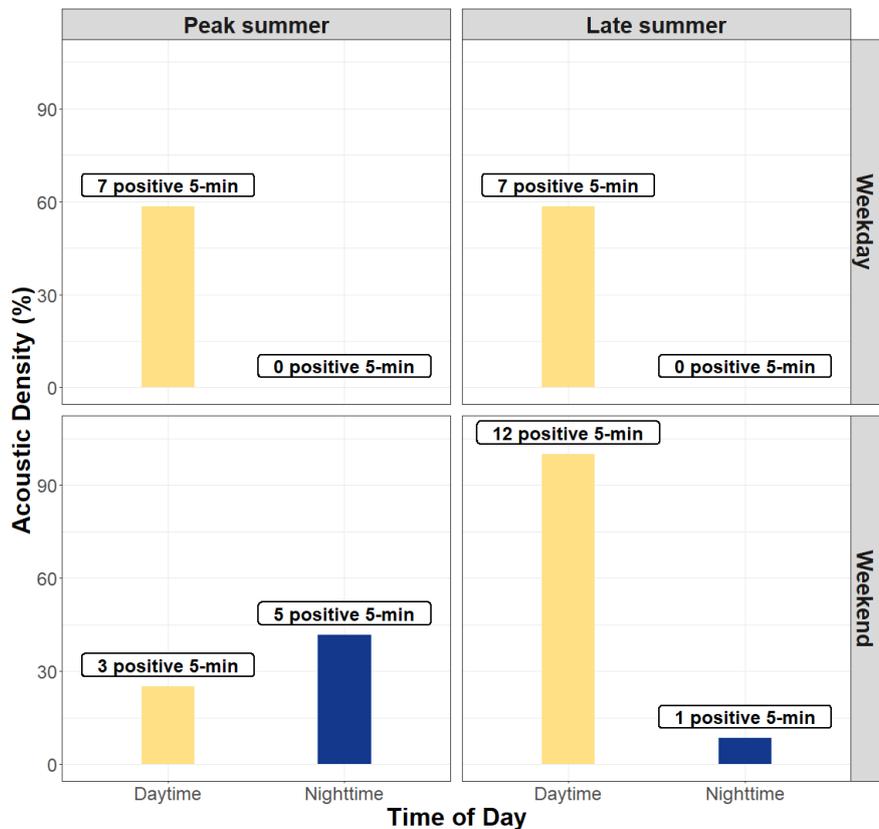
4.2.1 Automatic vessel detection with custom built detector

For the detector to produce presence or absence of boats per each of the 1-min bins, a detection threshold must be set. The detection threshold plays a central role in the results of automatic detections: while choosing a high detection threshold would get rid of false detections (high precision), it would be at the cost of a decrease in true detections (low recall). Our choice for this project was to maximize the true detections while minimizing false detections. For this reason, a detection threshold of $\log_{10}(5) = 0.6990$ was chosen. Particular attention should always be given to the choice of a detection threshold that will be fixed for the entire dataset; thus, we do not recommend considering this threshold universally applicable to recordings of small boat noise in other environments or from other boat types.

The results from the 1-min bin detections were then collapsed into 5-min bins as mentioned in Section 3. From this, we estimated the Acoustic Density of a 1-hour segment: the proportion of positive 5-minute bins out of the total 12 5-min bins in a 1-hour segment. This metric was chosen to be more consistent with the sampling time resolution of camera data available. Also, a higher time-resolution is likely to introduce more false positives.

Results from the automated detection of boats across the eight hours analysed are presented in Figure 4.5. It is clear from this that noise from small recreational boats appears to be mainly present during daytime, while being virtually absent during nighttime, except for the nighttime weekend during the peak summer. To be noted there is also the evident difference in boat noise between a weekday and weekend during the late summer – a difference that is likely to be more evident if more data is included in the analysis.

Figure 4.5. Barplot summarizing the resulting 5-min detections from the automatic detector. The acoustic density (%) is presented against the time-of-day (Day-time vs Nighttime). The stratification across season is shown by column, while time of the week is represented by rows. The labels in each grid represent the absolute number of positive 5-min bins found for each 1-hour segment.



4.2.2 Manually detected positive 5-min bins

To determine the actual performance of the detector, we manually inspected 20% of the analysed recordings for boat presence or absence. The results of this manual inspection are summarized in Table 4.1.

Table 4.1. Overview of the select 1-hour bins across seasons, time-of-week and time-of-day for SoundTrap data, with respective performance numbers per each 1-hour segment.

Season	Time of week	Time of day	Hour Start	Hour End	TP	TN	FP	FN
Peak summer	Weekday	Daylight	2025-07-01 10:00	2025-07-01 11:00	1	1	0	1
Peak summer	Weekday	Night	2025-07-01 00:55	2025-07-01 01:55	0	3	0	0
Peak summer	Weekend	Daylight	2025-07-13 14:00	2025-07-13 15:00	0	2	0	1
Peak summer	Weekend	Night	2025-07-13 01:30	2025-07-13 02:30	0	2	1	0
Late summer	Weekday	Daylight	2025-08-04 07:15	2025-08-04 08:15	2	1	0	0
Late summer	Weekday	Night	2025-08-04 01:30	2025-08-04 02:30	0	3	0	0
Late summer	Weekend	Daylight	2025-08-17 13:10	2025-08-17 14:10	3	0	0	0
Late summer	Weekend	Night	2025-08-17 03:15	2025-08-17 04:15	0	2	0	1

The most important results from Table 4.1 are represented by the number of false positives (FP) and false negatives (FN), that respectively reflects how many positive detections are actual absence of boats and how many negative detections are actual presence of boats. Across all periods, only one of the 5-min bins had a FP detection, while three 5-min bins had FN detections. Overall, this suggests an automated detection function that has a high precision and a fair-to-low recall. This is also evident from the calculated values of Precision and Recall, respectively 86% and 67%, meaning that about 14% of detections are not boats and as many as 33% of boats are missed. The latter may be the result of the aforementioned tendency for the kurtosis value to decrease again with a large number of vessels in the recorded bin.

4.3 Quantifying non-AIS boat traffic in PAM recordings

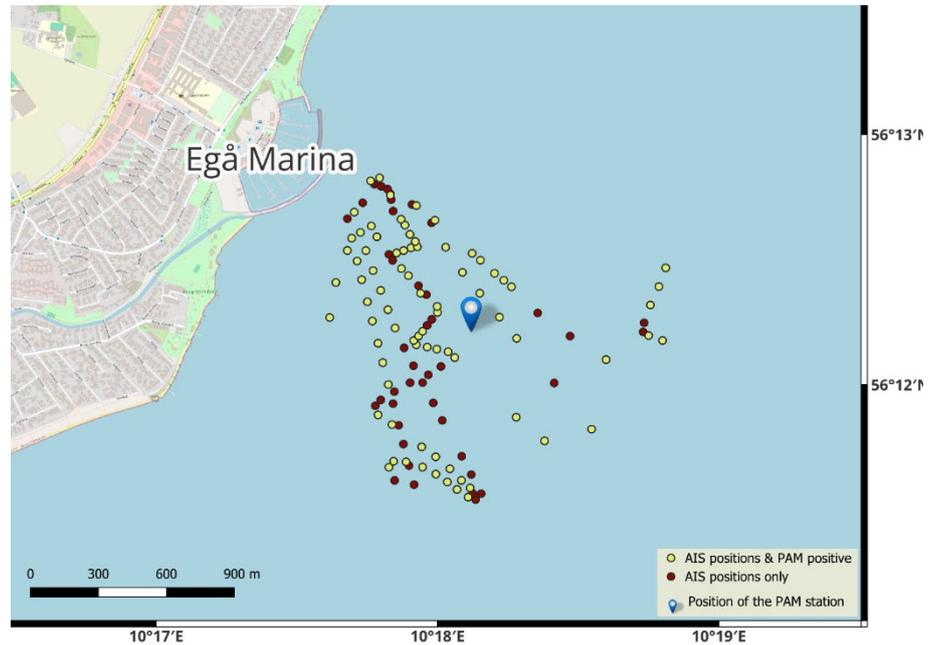
4.3.1 Matching AIS data with PAM boat detections

To use the PAM data to quantify non-AIS boats, we first needed an estimate of the maximum recording distance at which a boat can be detected by the algorithm. This was found by manually investigating radar data for a recording period. From a recording of a boat in the PAM data, we found the time when the boat was at the closest point of approach. This was then used to identify the corresponding track in the radar data. From the position of the boat with timestamps, and the position of the PAM recorder we were able to estimate distance of boat from PAM recorder. From this we found that a loud boat can be detected confidently up to 900 m from the recorder. Different types of engines, different speeds and various environmental parameters can result in a shorter detection range.

The identified detection range was used to filter AIS data, to only include AIS vessels that would be potentially detectable to the acoustic detector. All AIS data of docked vessels (at Egå Marina) were also excluded. The timestamps of the AIS data were then rounded down to the minute and assigned to the respective 5-min bin (created from the 1-hour intervals matching the selection for the PAM data) as one unique entry, to match the detection metric as per the automated detector used for the PAM data. This means that for each 5-minute bin it would either have presence or absence of boats, depending on the AIS data within that time-bin and the selected area. The absolute number

of positive 5-min bins was transformed into a Presence Density (%) that can be compared to the Acoustic Density in subsection 4.4. Figure 4.6 compares the PAM detections against AIS data for 1-min bins in a single hour of data.

Figure 4.6. Map of the area, with position of the PAM station and the positions (from the AIS data) of transmitting boats collected on the 17th of August 2025, between 13:10 and 14:10. Each position corresponds to one row of the AIS data available. The yellow dots represent AIS data that corresponds to a positive 1-min bin in the PAM data. The red dots correspond to AIS data that do not have a corresponding positive detection in the PAM data.



The example shown in Figure 4.6 contains a large number of detections for both PAM data and AIS data, to highlight how the two types of data can inform differently. Importantly, the match between PAM and AIS is purely based on both types of data having “presence” of boats in the same minute. As PAM data does not have information on position this information from AIS data cannot be used to match the two data types. This means that if several boats are detected in a minute, it is not possible from this analysis to find the exact match in the AIS data at present.

After ensuring that only AIS data obtained for the relevant period and area, the dataset of AIS data was composed of 262 observations, of which 68% were sailboats. The results from AIS data as per 5-min bins detections are represented below in Table 4.2. As may be noticed, from AIS data, the boat presence appears to be quite low overall, irrespective of the time of the day, of week or season. The only exception is the 1-hour segment corresponding to late summer, weekend during daylight: here, both AIS detections and PAM detections gave a boat Density of 100%.

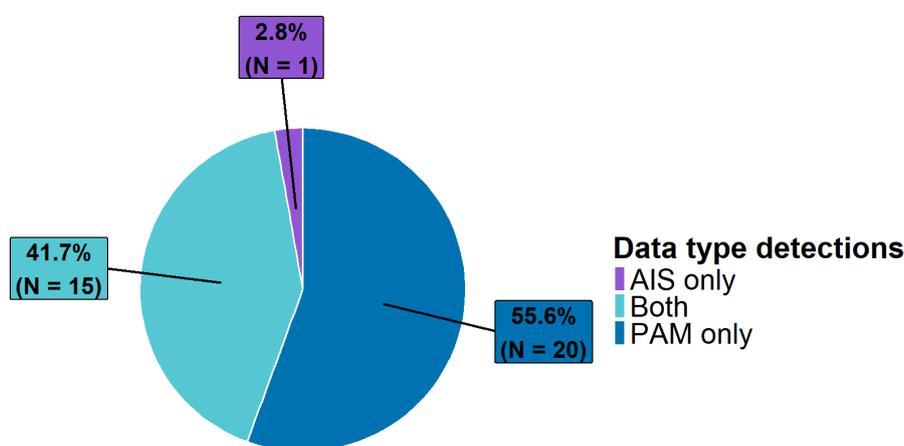
Table 4.2. Overview of the select 1-hour bins across seasons, time-of-week and time-of-day for AIS data, with respective number of positive 5-min bins per each 1-hour segment and the resulting density presence (%). Each hour consists of 12 5-min bins and the Presence Density calculated from the number of positive (boat present) 5-min bins if a 1-hour segment.

Season	Time of week	Time of day	Hour Start	Hour End	N. of positive	Presence
					5-min	Density (%)
Peak_summer	Weekday	Daylight	2025-07-01 10:00	2025-07-01 11:00	2	16.7
Peak_summer	Weekday	Night	2025-07-01 00:55	2025-07-01 01:55	0	0
Peak_summer	Weekend	Daylight	2025-07-13 14:00	2025-07-13 15:00	0	0
Peak_summer	Weekend	Night	2025-07-13 01:30	2025-07-13 02:30	0	0
Late_summer	Weekday	Daylight	2025-08-04 07:15	2025-08-04 08:15	2	16.7
Late_summer	Weekday	Night	2025-08-04 01:30	2025-08-04 02:30	0	0
Late_summer	Weekend	Daylight	2025-08-17 13:10	2025-08-17 14:10	12	100
Late_summer	Weekend	Night	2025-08-17 03:15	2025-08-17 04:15	0	0

4.3.2 Automated acoustic boat detector includes more boats than AIS

Despite these challenges and limitations, the results provide some interesting insights. For example, in the 1-hour segments with daylight, generally more boat presence was detected. Moreover, it is evident that recreational boats are more present during weekends compared to during weekdays. If we then compare these results with AIS detections, AIS clearly underestimates boat presence across the various time periods selected for the analysis. Only a single 1-hour segment (late summer weekend during daylight), matched between AIS and PAM data, with 100% of boat presence. In the other 1-hour segments, the AIS data suggested a very low Presence Density or even an absolute boat absence. This direct comparison of methods is summarized in Figure 4.7. From the pie chart it is possible to appreciate the fact that, of all the detections combined (both AIS and PAM), only 2.8% of them were only detected from the AIS data and not by the PAM data. In addition, more than 50% of the detections were found only in the PAM data by the detector, and the remaining was shared between the two methods.

Figure 4.7. Pie charts of the proportion (in %) of boats presence detected per 5-min bin during the full 8-hour subset: only AIS (lilac) detections compared to the detections from the PAM data only (blue). In light blue, the proportion of detections shared by both AIS and PAM data.



4.4 Evaluation of PAM data to quantify non-AIS boat traffic

For this pilot project, we deployed one PAM station outside Egå Marina, where there is a high concentration of small recreational boats. Applying the newly developed automatic vessel detector enabled us to identify some preliminary results on non-AIS boat presence in the area. It is important to highlight that, currently, there are still limitations to the use of this detector and to the interpretation of these results. First, the data analysed has a small sample size and the data is binary (presence/absence), rather than counts; second, the detector is currently under development, with the scope of this project being as a first validation step. That means that the detector performance, even though the Precision is high (Precision of 86%) it is likely missing a large portion of boats (Recall of 67%). These two metrics are always in a trade-off, meaning that increasing one will result in lowering the other one. For the PAM automated detector in the current report, we have prioritized minimizing false positives at the expense of an increase in false negatives. However, it is clear for the 1-hour segment corresponding to the peak summer weekend during nighttime that noise can generate false positives. In this segment, while boat noise was not present, another source of noise was occurring throughout the recording (Figure 4.3). This noise produced frequency peaks in the spectrum, making its kurtosis high enough to pass the threshold. The source of the noise is unknown, and further investigations would be needed in order to possibly identify the source. For further implementation of this

automated small boat detector, it should be considered further how other types of noise can be clearly separated from boat noise.

4.4.1 Factors influencing the presence of boats and their detectability

It should be noted that the main type of recreational vessel transmitting AIS is sailboats (68% of all AIS entries after filtering). In addition, some of the AIS boats classified as “Pleasure” are sailboats, making it challenging to distinguish between normal motorboats and sailboats. Sailboats, being the main source of AIS data, create a clear discrepancy between recreational boat traffic and actual noise. It is not possible to know from AIS data whether a sailboat has the engine running or not. When the weather allows it, many sailboats have already set sail even before exiting the marina, effectively not contributing to the underwater noise. An important factor to also consider is how the weather plays a role in the presence of small recreational boats. With adverse weather conditions, sailboats are typically the ones found in the area, while motorboats will generally be at sea with better weather conditions, such as low winds and no-to-low cloud cover. Hence, even if a high Presence Density is found from AIS data (whether the information about the type of boat transmitting is correct or not), this may not be reflected on the actual underwater noise (with PAM data that could show a low Acoustic Density); vice versa, a low Presence Density may not match the Acoustic Density due to motorboats generally not transmitting AIS.

These considerations highlight an important flaw of AIS data for small recreational boats, indeed causing an additional problem for a 1-on-1 direct comparison to PAM detections and for further investigation into the contribution of small boats to underwater noise. To create an actual match between the PAM data and the AIS entries, another type of boat detector would need to be implemented, able to confidently associate the noise profile recorded with the AIS transmitting boat. The development of such a detector is well beyond the scope of the report, hence it has not been investigated further.

The results presented in this PAM section clearly show that relying solely on AIS data to monitor presence of small recreational boats can significantly underestimate the noise exposure in this area. Our findings highlight that combining PAM data with AIS provides a more complete picture of small boats activity and noise produced, while further investigation into optimising the detector is needed before it can be integrated into the national noise monitoring program.

5 Radar surveillance

5.1 Radar system and setup of data collection

A SCANTER 5202 radar (X-band, 2-D, pulse compression radar; www.terma.com) positioned at Egå Marina (56.207359 N, 10.287030 E) was used to collect radar surveillance data between June 30, 2025, and September 12, 2025. Data was collected semi-opportunistically, recording continuously except during periods when the radar was in use for other projects. This provided a total of 61 recordings from the radar at Egå Marina spanning 60 different days.

The radar recorded positions of all objects that met the internal criteria for generating a 'unique track id' in the radar software within a range of 5 km between 55-190° relative to North (Figure 5.1). The data from radar recordings can only be viewed in the proprietary software, SCANTER Radar Service Tool (RST). Together with SCANTER Replayer software the recordings could be viewed as in real-time, while extracting additional information about objects and their distance to different points, such as the camera or SoundTrap position. This allowed for manual extraction and verification of object tracks. From RST the data could also be decoded into a .txt format that could be used for further analysis.

Figure 5.1. A screenshot of a recording in the proprietary radar software (RST) with position of the radar (blue point) and detected objects (green points) plotted. Line directions represent bearing and length of line speed over ground. Stationary objects have no lines attached. Many of the stationary objects in this case are permanent markings. Note the positions of the camera (orange point) and the underwater PAM re-corder (pink point). The red dots are detections that have not been assigned a track, as they are likely waves or other transient detections.



Custom scripts were developed in R (version 4.4.1) to parse and extract track information from the decoded files. To examine the variation across season, time-of-week, and time-of-day for detecting boats with the radar, the radar data was subset into eight 1-hour periods to cover the peak and late summer, the week and weekend, and daylight and dark, like the PAM data. A subset of 24 5-minute segments from those eight hours were manually labelled and used for comparison with AIS data, as well as a test set for development of an automated filter for the full eight-hour dataset used here. The reason why only eight hours out of the entire dataset was used here is due to the time constraint of manually verifying the observations.

The manual detections in 5-minute segments were performed within the RST software, while the testing and verification of an automated filter used custom scripts in R.

5.2 Manual detection of vessels in radar recordings

Radar recordings were viewed in the RST software in 24 5-minute segments (Example of the viewer in Figure 5.1). These segments cover all eight combinations of season, time-of-day and time-of-week (Table 3.2). Each segment was viewed in real time but with the option to pause and rewatch to ensure that all detections were recorded. The objects that are assigned to a track by the radar will be assigned a 'unique track id'. This was used to identify the manually detected tracks. The boats that were manually detected this way had a mean speed over ground (SOG) of 2.7 ± 2 knots (mean \pm sd) and an average radar cross section (RCS) of 23.3 ± 26.7 m². Since the area near the coast gives rise to a lot of signal clutter and uncertainty in the radar detections (e.g. near the marina entrance), the area of detection was restricted to distances from the radar between 600 and 3500 meters (Figure 5.1). We also noted that a 'unique track id' would occasionally switch from a moving target to a stationary target if the moving target passed close by a stationary target. We therefore did not keep all track positions based on 'unique track id' but instead kept those for each track that fit the filter thresholds.

Without applying the filtering conditions the radar output will include all detected tracks, including markings, birds, waves and boats. Using radar data without considering this would greatly increase the estimated number of boats. Below are the description of the filter thresholds and an evaluation of the filter accuracy (Section 5.3).

5.3 Applying automatic filter thresholds for radar recordings

First, parameters related to each object detected by the radar were evaluated to find those that would be able to distinguish a boat from noise or permanent markings in the area. From the manual observations we determined that the relevant parameters were:

- **Type:** This represents the type of target, as decided by the built-in algorithms of the radar. A detection will either fall in a category of Target (0), AtoN (1; Aid to Navigate) or echo (2).
- **Quality:** The built-in algorithm will evaluate each detection based on different parameters and assign a quality from 0 to 1. Here, we include only detections with a quality ≥ 0.9 .
- **Radar cross section (RCS), m²:** The radar cross section area is highly dependent on the angle of the signal onto the object, as well as the material that reflects the signal, and can therefore vary substantially across a track of an object. By inspecting the RCS of manually detected boats, it was determined that an RCS greater than 1 will filter out most of the noise.
- **Speed over ground (SOG), knots:** Speed over ground measured in knots is mainly applied to filter out permanent markings that can be identified as having a speed less than 1 knots, while the RCS can be above 1 m², as well as birds that were observed moving at speeds greater than 40 knots with an RCS above 1 m².
- **Number of detections:** Some objects are only detected for less than 20 detections and are therefore likely noise.

After applying the filter, it was then evaluated by comparing the filtered radar detections to the manually verified tracks.

To determine the optimal filter thresholds, we systematically evaluated the trade-off between the Precision and Recall across a range of radar cross-section (RCS) thresholds while keeping vessel speed constrained between 1 and 40 knots, with 1 knot being the optimal threshold for low speeds. Precision was steady across all RCS values, while Recall decreased gradually from RCS = 1 m². Based on this, the final filter conditions were Type = 0, quality >= 0.9, RCS >= 1 m² & SOG >=1 knots and SOG < 40 knots & >20 detections per detected target.

The final filter selection achieves a precision of 0.96 and a recall of 0.88, representing the best comparison for this dataset of removing false positives and retaining true vessel detections. To investigate the filter further we extracted the AIS for the corresponding periods.

The AIS tracks and radar timestamps did not match up perfectly. When this time difference was investigated for known pairs (observed manually) it was found that the lag could be from around 30 seconds to several minutes, with different time lag in different recordings. This lag also becomes clear when looking at the tracks in Figure 5.2, where some AIS tracks were within the period, but their matching radar tracks were not. This temporal difference between radar and AIS tracks likely originates from the difference of the data types, where AIS can have substantial periods (up to 12 minutes) between AIS signals, while the radar has approx. 2 seconds. However, this inconsistency means that we could not match all AIS pairs to radar tracks but looking visually we are confident that the filter did not remove tracks related to boats that use AIS. It is more likely that the filter includes objects that are not producing noise, such as kayaks and stand-up paddleboards.

We compared the number of boats detected by the radar to the number of unique AIS vessels within the spatial and temporal coverage of the radar. Based on this comparison, the radar detected substantially more boats, like small recreational vessels without AIS. The track plot in Figure 5.2 highlights that in periods with low traffic, especially during night, AIS will be able to give a fairly accurate estimate of number of boats. On the other hand, during periods with a lot of traffic, likely from small recreational crafts, AIS will underestimate the boat traffic in coastal areas near marinas.

This is the first step into automatically categorizing objects detected by the radar to use for quantifying non-AIS boats in a coastal area. Further interrogation of the data is needed to test if motorboats or other small boats producing noise can be distinguished from sailboats.

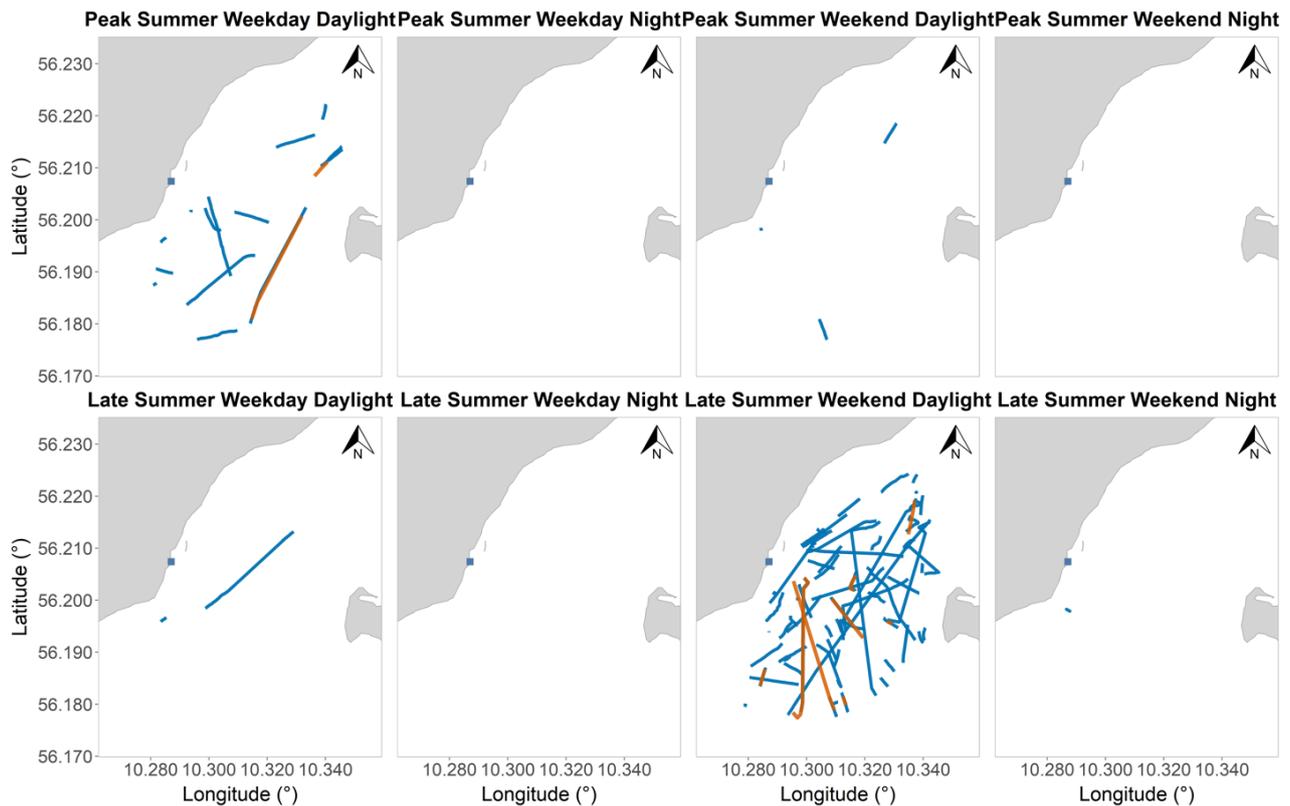


Figure 5.2. Track plots that show all 5-minute manually detected tracks (blue points), as well as the AIS tracks in the same period and area (orange). For all AIS tracks a corresponding radar track was found, although the points do not perfectly match in the plot due to a time delay in radar timestamps compared to AIS timestamps.

5.4 Quantifying non-AIS boats in radar recordings

The validated filter was applied to the full 8-hour subset of radar data. We then summarized the boats present according to the radar detections compared to AIS data for the same period and area.

For the full 8-hour dataset we found a similar pattern to the manually validated subset: the radar can provide a more complete picture of the boat traffic compared to AIS in periods with high density of boats (Figure 5.3). There is a substantial variation in how well AIS represents the actual traffic. For example, during night AIS is likely a good predictor for noise, whereas in peak and late summer it is likely to underestimate the noise. The variation in number of boats in hours with daylight is likely attributable to the weather. For example, in Figure 5.3 there is an evident difference between Peak Summer-Weekend-Daylight and Late Summer-Weekend-Daylight. Both days are Sundays, but while the Late Summer weekend day is sunny with low winds and humidity, the Peak Summer weekend day is cloudy with a humidity of 78% (<https://www.dmi.dk/vejarkiv/>).

At present, the radar is on its own not able to provide information about the type of vessels detected. Overall, we found that ~90% of all boats detected by the radar did not have a corresponding AIS track (Figure 5.4). The vessels with AIS were almost evenly split between Pleasure ($n = 6$) and Sailing ($n = 7$) ship type in the AIS data with a mean length of 10.9 m, where Pleasure ship type can refer to both motorboats and some types of sailboats (e.g. sailing yachts). By going through the AIS tracks and visually comparing them to radar tracks,

it was found that the non-matched AIS was due to a lag in the radar data that resulted in certain radar tracks being filtered from the dataset within the subset time ranges (Table 3.2). Given that the number of unmatched AIS tracks were very low ($n = 2$), it would not change the conclusion.

5.5 Evaluation of radar data to quantify non-AIS boat traffic

For this pilot study, we had access to a fine-scale radar based at Egå Marina. The radar was opportunistically available to record for this project, meaning that there are some gaps in the data. Yet the radar collected data both day and night continuously, meaning that when it was operational it was typically running for 24-hour periods. For this project, the spatial coverage was limited to 5 km from the radar to limit the amount of data for testing the method. Yet these or similar types of radars can detect objects out to ~90 km, with the limitation primarily being clutter from shoreline or human-made structures that would block the signal or create noise. For example, in the Aarhus Bay area, the test radar would not be able to provide data on anything to the East of Helgenæs.

The filter developed had a very good precision, with 96% of detections being true positives, meaning that the filter almost never included a detection that was not a boat. This could indicate a very strict filter, leading to a high number of false negatives and that 12% of boats were missed by the filter. Therefore, the filter is at present excellent at filtering out noise and artefacts but is slightly undercounting the boats in the area. It would require additional work to develop a filter with an improved recall, as well as a filter that can distinguish boats that are emitting noise. Despite the filter missing some true boats, the results clearly show that the AIS data alone is heavily underestimating the presence of boats in periods of high intensity.

Like the PAM analysis, it is evident that AIS is a fair estimation during periods of no-to-low traffic, such as during night. Although the data here does not include winter or spring season, it is likely that especially during the weekday in these periods, AIS will also be a fair estimate of traffic intensity.

From the AIS data, we can see that the vessels are either the ship type Sailboats or Pleasure boats. For the five-minute manual samples, the vessels in with the ship type Pleasure were evaluated and it was found that most of these also had sails. Given this and the result that ~90% of boats were not matched to an AIS signal, a noise model based on AIS in this area will substantially underestimate the noise – particularly during peak periods.

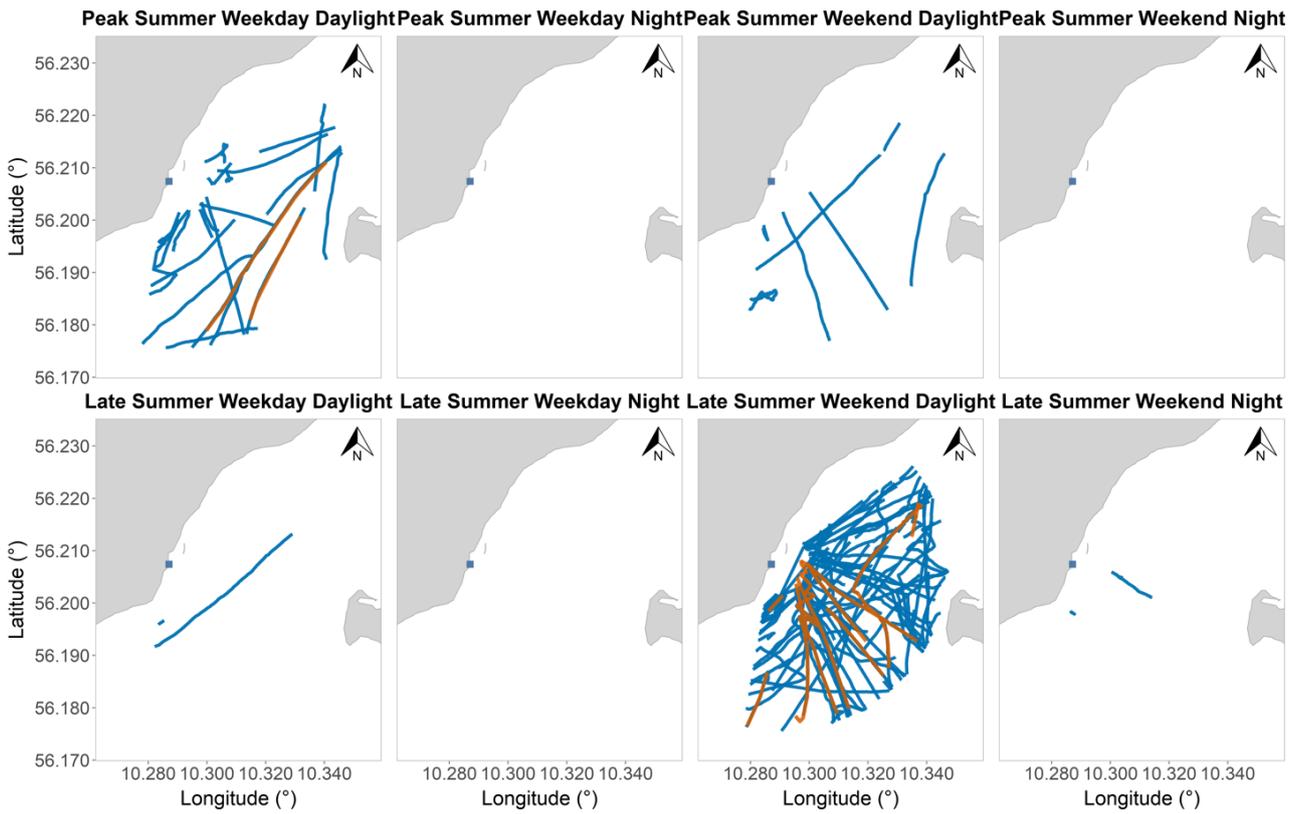
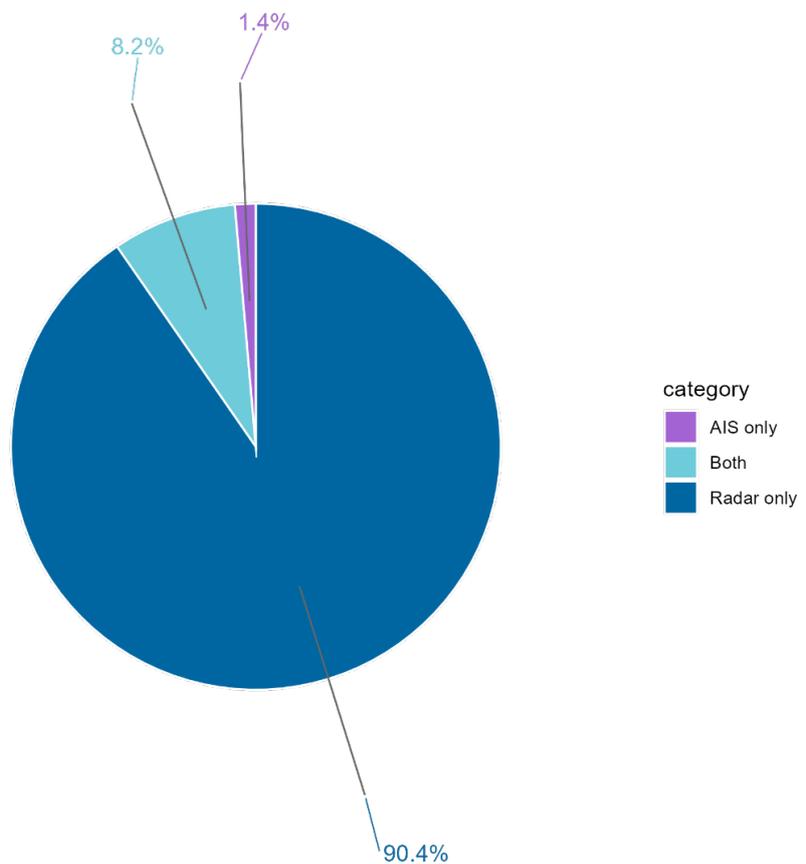


Figure 5.3. Track plot for the eight 1-hour periods for radar (blue tracks) and AIS (orange tracks). For all AIS tracks a corresponding radar track was found, although the points do not perfectly match in the plot due to a time delay in radar timestamps compared to AIS timestamps.

Figure 5.4. Pie chart showing the percent-age of the tracks where only AIS (purple) or radar (blue) was available and where radar and AIS were matched (cyan).



6 Camera surveillance

6.1 Timelapse camera

A tikee 4+ PRO timelapse camera (www.enlaps.io) was mounted at Egå Marina at an altitude of 13 m above sea level (56.20800 N, 10.29080 E) on July 31, 2025. It was preprogrammed to record an image every five minutes from 6am to 6pm. For the duration of sampling, images were extracted to match the change in daylight hours for each day (sunrise to sunset times). This generated a dataset of >13,000 images.

The camera has two built-in lenses (Sony 12 Megapixel, wide angle F2.8, sensor size 1/2.3) and for each image capture there is a left and a right image that is 'stitched' together in the Enlaps software. When combined it gives a field of view of 220° horizontally and 90° vertically in each image with a combined resolution of 7360x2650. The camera field of view spanned from 25° to 245° re North (Figure 3.1).

Like the radar data, a subset of images (n = 694) was manually labelled. These manually labelled images were used to evaluate automatic object detection models as well as to compare against AIS.

6.2 PTZ camera

Additionally, a Pan-Tilt-Zoom (PTZ) camera (Hikvision 4 Megapixel sensor with 32x zoom) was mounted at the site of the radar. Compared to the wide-angle timelapse camera, the opportunity to move and zoom the camera view live can provide information on not only vessel type (e.g. sailboat, motorboat, jetski, etc.), it also has the opportunity to provide data on the size and speed of the vessels if boats pass at a 90° angle (Shipton et al., 2025). Therefore, it was angled to include the area covered by the PAM station within its range. The PTZ used here had integrated object detection and took four pictures when the detection criteria were triggered (an object entering the pre-defined zone of interest; Figure 6.1). In practice this means that the camera was free to move and change position and zoom configuration to stay with an identified target (a boat passing in the field of view when in neutral position). When the target was no longer in the field of view of the camera it would return to the neutral starting position. The initial data was promising, however within the scope of the project we could not get the system running automatically, therefore no results will be presented for this type of camera.

Figure 6.1. An example image from the Hikvision PTZ camera mounted at the radar site at Egå Marina. The image illustrates the zone of interest for detection (large red square) and an automatic detection by the camera (small red square).



6.3 Manual labelling of vessels in timelapse images

A set of 694 images were manually labelled across a period from 2025-7-31 to 2025-9-30 spanning a total of 40 days. The images were randomly selected to cover the variation from time-of-day, time-of-week, season and weather conditions. The camera was the last sensor equipment that was put in place and therefore, the seasonal variation, where the manual validation is available spans August and September. Since the camera was only recording during daylight hours it is not possible to get the variation between daylight and night for this dataset. Additionally, given that the timelapse camera provides snapshots over time in 5-minute intervals, the data for each strata spans a period of several days (Table 6.1).

The images were labelled in the software labelling (Tzotalin 2015), where a bounding box can be drawn around each vessel producing pixel coordinates of the area around the object. All boats were labelled following this protocol: if a mast (or sail) was visible it was labelled as a sailboat and if it did not have a mast (or sail) and was not clearly propelled by oars it was labelled as a motorboat. Note that while motorboats here correspond to the AIS Pleasure ship type, the sailboats could use either Sailing or Pleasure ship type. No human-powered vessels were included (e.g. kayaks and paddleboards). These manually labelled images were both used to compare the camera data to AIS data, in terms of quantifying boats without AIS, as well as to test the potential for applying models to automatically detect vessels in timelapse images. A total of 977 detections were made across all 694 images, where 760 detections were sailboats (78%) and 217 were motorboats (22%). 157 images did not have any boat detections.

The manually detected vessels were combined with the same time in the radar data to estimate a detection range. It was found that most sailboats that have their sail up are visible up to a distance of 1500 m from the camera, while smaller motorboats will only reliably be detected within distances of 1000 m with the camera at an elevation of 13 m. Based on the resolution and elevation of the camera this equals that a small motorboat of 5 meters would amount to 10 pixels at a distance of 1 km but only 5 pixels at a distance of 2 km. This provides a very small area to detect for both a visual observer and the automated detection models, likely to give rise to more uncertainty beyond 1 km. This detection range is mostly limited by the resolution of the camera (7360 x 2650), however, increasing the elevation will make small boats more visible

from waves and at greater elevation the detection range would likely improve as the angle to the boats is increased. Also, with higher elevation it becomes possible to estimate distance to the vessels from the vertical angle to the vessel, quantified on the images as distance below the horizon.

Figure 6.2. Example of a timelapse image with squares drawn to illustrate bounding boxes for a motorboat (yellow) and a sailboat (purple).



Table 6.1. Overview of the periods with manually labelled images.

Season	Time of week	# days	# images
August	Weekday	9	166
August	Weekend	5	159
September	Weekday	15	231
September	Weekend	6	138

6.4 Applying automatic boat detection in timelapse images

We tested the workflow for applying an automated detection model and evaluated it against the manually labelled images. Automated object detection algorithms have been developing fast in recent years, and there are many applications. In recent years, these models have been shown to prove as a useful tool in automatically detecting, and even real-time tracking of small boats (Wilson et al. 2022; Signaroli et al. 2025). For this project we tested 1) the specialized boat detection model trained by Signaroli et al. (2025) to detect small boats and distinguish between sailboat and motorboat, 2) a general pretrained model, YOLOv11m (Jocher & Qiu, 2024; He et al. 2025), and 3) a model fine-tuned on images of boats including the manually labelled images from Egå Marina. All three are based on the machine learning framework YOLO (You Only Look Once) suite of object detectors (Redmon et al, 2016). The models were run in Python 3.10 (Van Rossum et al., 2021) and for the YOLOv11m the Ultralytics YOLO framework was applied (Jocher et al. 2023), which provides an open-source implementation and model-training framework for the YOLO models.

Based on the manual labels, the bounding boxes of boats spanned from 7 to 100 px, meaning that most of the boats would be only a small fraction of the full image (Figure 6.2). To improve detection of small boats, we applied the Slicing Aided Hyper Inference (SAHI) framework (Akyon et al. 2022). This works by ‘slicing’ each image into smaller tiles with an overlap ratio of the tiles in both directions – like a square ‘viewing frame’ that moves across the image evaluating each square and its content separately. The overlap ensures that if a vessel is located near or on a tile boundary it will still be included. Each tile was passed to an object detection model that runs detection on any objects in the current tile. Following the detection on all tiles in an image, the tiles are transformed back to their original image coordinates, which provides bounding boxes for detected vessels. Thus, the final output of the detection is a set of coordinates for bounding boxes in pixel coordinates (xmin, ymin, xmax, ymax), the predicted class of the object (e.g. boat) and the confidence score reflecting the likelihood that the prediction is correct (0-1). The SAHI

settings used were slices of 960x960 pixels with a 0.2 vertical and horizontal overlap, meaning that there is a 20% overlap between tiles. The slicing was applied to all three models.

The fine-tuned model (Model 3) was based on the pretrained YOLOv11m model and was fine-tuned using pre-labelled images, including the manually labelled dataset obtained at Egå Marina. The full training set was made up of 1872 images of boats from the Common Objects in Context (COCO) dataset, 377 images with manually detected boats and 128 negatives (images without boats that are used to train the model on objects to ignore, such as kayaks, paddleboards and rowboats). The model fine-tuning ran for 50 epochs, meaning that the model was trained to recognize boats 50 times, optimizing the boat detection model based on the input it received from pre-labelled images.

Table 6.2. Overview of the evaluation metrics for the pretrained and fine-tuned automatic detection models tested.

Model	Precision	Recall
Boat-detection model (1)	0.04	0.02
Pretrained YOLOv11m model (2)	0.81	0.69
Fine-tuned YOLOv11m model (3)	0.64	0.68

It was found that the best model for this data was the pretrained YOLOv11m model (Model 2), as it had the best score overall for Precision and Recall (Table 6.2). This model detected about 81% of boats correctly, and out of all the boats that were manually detected the model was able to detect about 69% of those. The pretrained YOLOv11m model was therefore used to detect boats in a subset of 1800 images from August to October spanning weekday-weekend.

6.5 Quantifying non-AIS boats in timelapse images

To compare the number of detected boats to the boats with AIS, AIS records were extracted at 30 seconds on either side of each of the image timestamps. This was to ensure that AIS boats with longer recording intervals would be included.

6.5.1 Manually labelled images

For the manually labelled images, where boats were marked as either motorboat or sailboat, we found that in two images there were AIS tracks within 2000 m of the camera within field-of-view, where the observer did not mark a detection. These boats were at 1170 and 1226 m. In two cases, the observer marked only one boat, while there were AIS tracks within 2000 m for two individual boats. These unlabelled boats were at 1371 and 1146 m from the camera. These examples highlight the limitation of the range at the recording altitude and resolution of camera lenses.

In both August and September during weekday and weekend there were comparable differences between the observed number of boats and the boats with AIS, with a slightly lower count for the month of September (Figure 6.3). The observer labelled 79.7% more boats compared to boats present in AIS data (Figure 6.4).

Figure 6.3. Bar chart of the number of boats detected manually (blue) and by AIS (purple) in time-lapse images from August and September during the week and weekend.

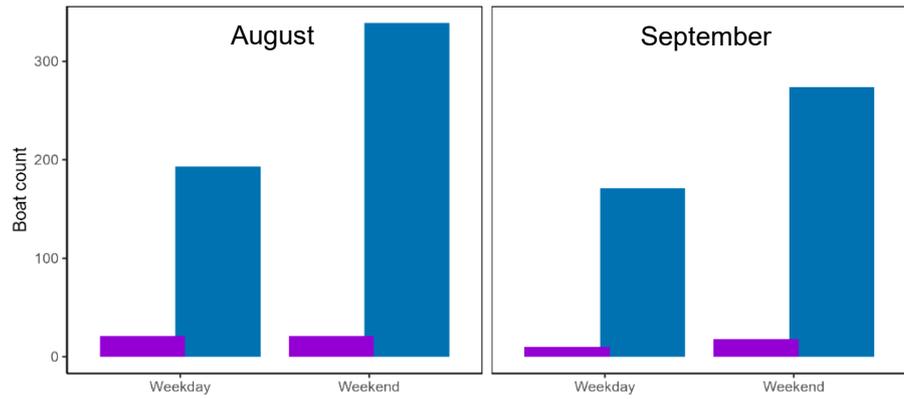
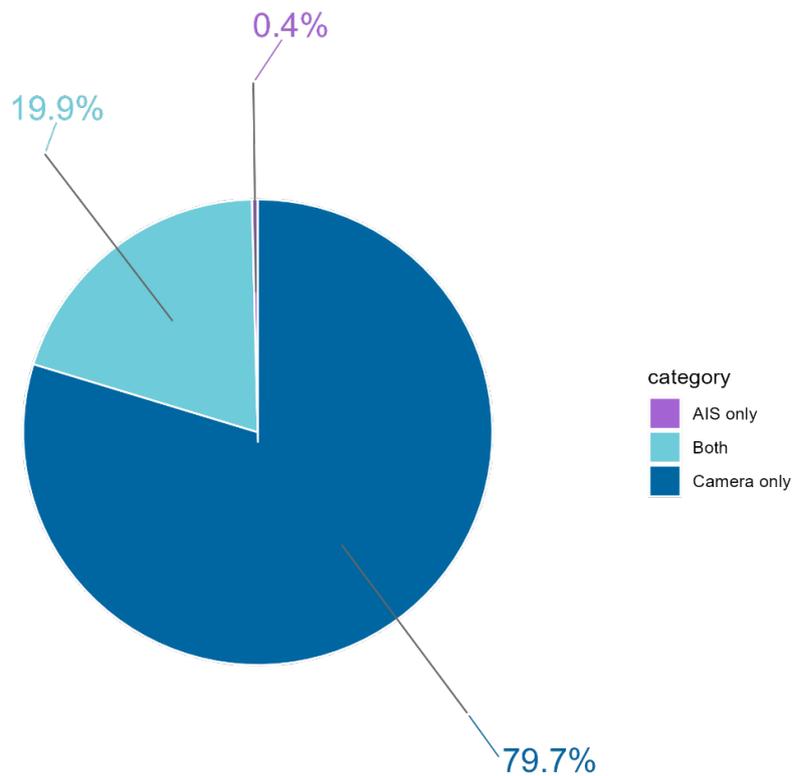


Figure 6.4. Pie chart of the proportion of boats detected manually in timelapse images and the proportion that were included in AIS data for the corresponding period and area.



6.5.2 Object detection model applied to timelapse images

First, we compared the detection by the pretrained YOLOv11m model (Model 2) on the images that also had manual labels to the AIS data to compare it to the results in Section 6.5.1.

Second, the pretrained model was applied to a set of 1800 images with 300 images in each combination of month and time-of-week from August to October. This was to investigate the variation in boat traffic across season and time-of-week.

Comparing the detection from the pretrained YOLOv11m model (Model 2) against AIS data revealed that a similarly high proportion of boats (78.2%) were detected, where corresponding AIS vessels were not detected (Figure 6.5). Although the proportion is lower than what was found for the manually labelled images, this is likely caused by the relatively low Recall of the model.

Figure 6.5. Pie chart of the proportion of boats detected by the pre-trained YOLOv11m model on images with manual labels and the proportion that were included in AIS data for the corresponding periods and the covered area.

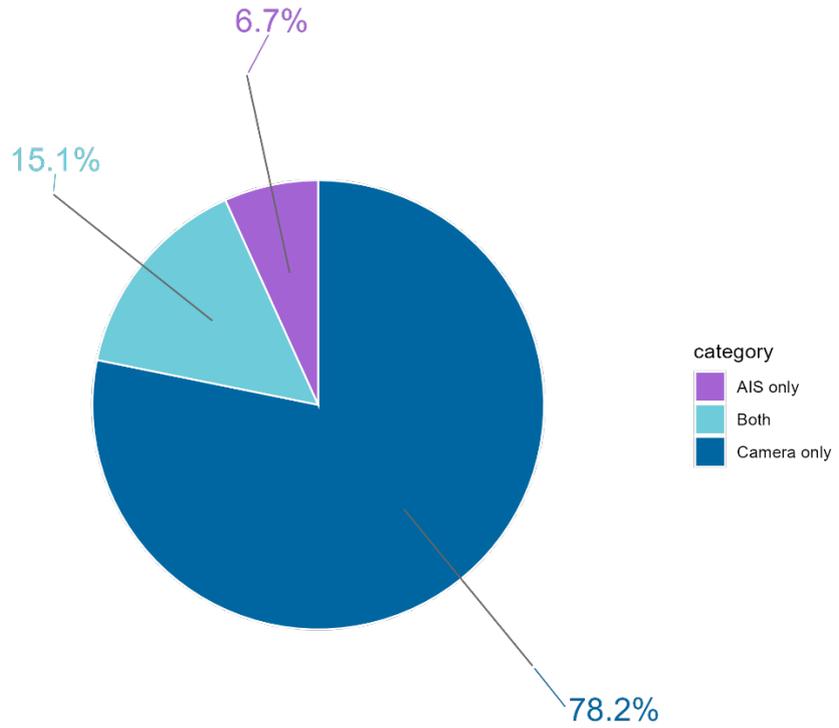
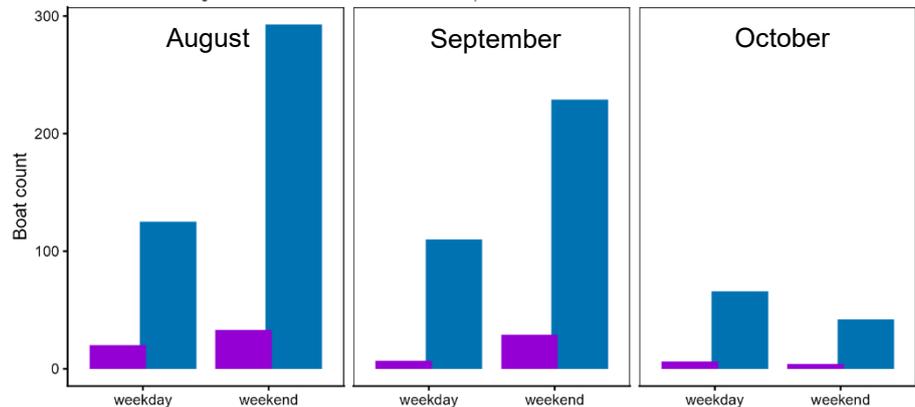


Figure 6.6. Bar chart of the number of boats detected in 1800 time-lapse images from August, September and October by the pretrained YOLOv11m model (blue) and by AIS (purple).



6.6 Evaluation of camera data to quantify non-AIS boats

Camera data offers a complementary approach to AIS-based monitoring, as it allows for visual verification of small boats. In this section we will outline the strengths, limitations, and points for improvement if camera surveillance were added as a means of monitoring the density of non-AIS boats.

The main limiting factor is the resolution of the cameras used. Here, we used a high-resolution wide-angle camera at an altitude of 13 m, which granted a wide field-of-view but only a detection ranges up to 1000-1500 m for most small boats. This could be improved by increasing the installation height of the camera, as this would increase the angle to boats, increasing the visible surface area and thus their detectability. In addition, a higher camera position will allow for accurate distance estimation to the vessels by means of the vertical angle (angle below horizontal) from camera to vessel.

The timelapse camera used here was set up with a power supply and access to the local network. This allowed the camera to operate with shorter frame intervals, down to the minimum for this camera of 30 seconds, which could provide a near-real-time data stream for boat detection in the area. With this setup there is the possibility of developing and implementing automated detection algorithms to identify and localize boats in real time. Similar approaches have been demonstrated by Signaroli et al. (2025), where they trained object detection models to detect both sailboats and motorboats in Marine Protected Areas (MPAs). They applied a setup where a camera sampled an image every 2 seconds at a height of 100 m above sea level and successfully monitored the boats in the area continuously.

The automated detection models applied here require thorough calibration and testing. Here, we investigated both a general detection model (Model 2), a model fine-tuned on images from Egå (Model 3), as well as a highly specialized boat detector model used within an MPA (Model 1; Signaroli et al. 2025). Surprisingly, the boat-detector model performed extremely poorly on our dataset (Table 6.2). This could arise from the model training on images from different perspectives (e.g. drone images, altitude of 100m), higher contrast images or images with only parts of boats included (e.g. the hull or a mast). Visual inspection of the bounding boxes produced from the boat-detector model revealed that this model is likely too sensitive for the timelapse images obtained from Egå, as it would include glare or waves as boat detections. Additionally, it would classify clouds as boats, suggesting that this model has been highly trained on recognizing 'boat-like' patterns without including certain contexts, such as a shore-based perspective found at Egå Marina as it was trained on images from Marine Protected Areas. However, for the domain where this model was developed it performs very well (Signaroli et al. 2025), highlighting that to apply a more specialized model for monitoring small boats within Danish harbours would require a model trained specifically for that purpose. It is unknown how this model would perform if the camera was mounted similarly and monitoring a Danish MPA.

Regardless of the detection method – manual observer or automated detection model – the bias is towards boats with a larger visible profile, such as sailboats. This means that sailboats under sail will appear with a larger surface area, making them easier to observe, as well as present a greater pixel area to detect compared to motorboats with a similar length. This is an important consideration when interpreting the traffic intensity, as certain boat types may be overrepresented.

7 Additional methods examined

7.1 Using satellite imagery to detect non-AIS boats

Satellite remote sensing is a useful means for monitoring vessel activity in coastal water, particularly small recreational boats without AIS. There is an increasing availability of high-resolution optical and radar imagery, which when combined with advanced machine learning algorithms can allow for automated detections – and potentially also classification – of small boats (Zucchetta et al. 2025). The increase in resolution and shift towards using deep-learning methods such as the YOLO framework is moving the field towards fast-speed, accurate vessel detection, even under poor conditions (Fan et al. 2024).

The most widely used satellite systems are the optical sensors, especially for the commercial systems, such as Pleiades, WorldView and PlanetScope – all of which offer a spatial resolution of less than a meter. In addition to the optical sensors, the Synthetic Aperture Radar (SAR) is also becoming more widely used, as this can provide images even when dark and under cloud cover. This method, however, is limited by sensitivity to signal strength from targets and signal clutter near coastal areas.

In a study by Hao & Nabe-Nielsen (2023), high resolution satellite images obtained with optical sensors covering Danish inshore waters were used to quantify the spatial distribution of small boats. They were able to detect boats of lengths less than 20 m with this method and were also able to distinguish between sailboats and motorboats. The images provided from satellite imagery are typically sporadic, for example the Hao & Nabe-Nielsen study used a total of 18 images with a 5x5 m² coverage and a 40-50 cm resolution.

A clear drawback of using satellite imagery is that it is highly opportunistic. For example, Pleiades has no images available for Danish waters since 2020, and to access more fine-scale images and more coverage typically requires a subscription (e.g. WorldView and GeoEye). The ultimate solution for optimal coverage would be to pay for scheduled recordings (still limited by cloud cover), but likely at a prohibitively high cost.

Together, this illustrates the opportunities and limitations of satellite-based small boat monitoring. With high-resolution imagery we can accurately detect and classify vessels, while temporal coverage is restrained by satellite revisit intervals, cloud conditions, and the cost of the commercially obtained data. Most of the images available are single, opportunistic snapshots, which limit the opportunity to obtain data on daily or seasonal changes in a specific area. At present, satellite remote sensing will have to be combined with other monitoring systems to provide continuous monitoring and validation.

- **Strengths:** High-resolution and SAR imagery can detect and classify even small boats; useful for spatial distribution.
- **Limitations:** Temporal coverage constrained by satellite revisit intervals; cloud cover and/or cost; provides opportunistic snapshots.
- **Potential role:** Valuable for large-scale spatial mapping and ecological overlays (e.g. boat density and porpoise habitats), but to improve temporal resolution it requires pairing with other methods; can provide information about boat density in areas unavailable with e.g. camera.

7.2 Using drones to detect non-AIS boats

Although, the present study did not directly test the use of drones to quantify the small boats without AIS, a drone was used for a separate project running at the same time (the Aage V. Jensen project – A Sound Marine Environment; ASME). From this, it was confirmed that drones can collect high-resolution spatial data over relatively short time frames for the small boats, limited mainly by battery life, daylight and operating hours.

Most modern drones can be preprogrammed to fly along pre-defined transect lines. While moving along the transect they capture overlapping images that can be analysed either manually or with automated vessel-detection algorithms. Compared to a fixed camera, such as the timelapse described in section 6, the drone can collect images where the distance to boats is uniform, as it is given by the altitude of flight. This reduces bias arising from difference in perspective and distance to boats, as well as it allows for conditions that support automated analysis (Doukari et al. 2019).

One of the strengths of using drones is that they can be deployed from land and access areas that might not be accessible from a boat or for radar or camera (e.g. areas with cliffs). So far, they have been applied in a variety of studies, either for monitoring presence or used for detection of vessels (Fetterman et al. 2022; Reis-Filho & Giarrizzo 2022). In a study where drones were used to survey fishing activities in coastal waters it was found that drones were able to detect more vessels than either ground-based or boat-based surveys (Reis-Filho & Giarrizzo 2022). Additionally, like the timelapse camera described in section 5 the use of object detection models on drone images shows great promise, with potential for automated and time-efficient monitoring (Provost et al. 2020; Bradley et al. 2019). Thus, this method could be applied for estimating the density of boats without AIS across seasons, time-of-week and time-of-day. Limitations of this system are that flight duration is restricted by battery life, and most flights will range from 15-25 minutes, depending on the model of the drone (extendable by changing to fixed-wing drones). This means that the data will yield transect rather than continuous data as the radar or PAM presented above. Additionally, surveys are limited to having a licensed drone operator as well as by weather conditions, which means no data will be collected in winds >15 knots, rain or during low light. Furthermore, most drone surveys are likely to be limited by the ability of the drone pilot to visually see the drone, as flights beyond visual range involve significantly more training and certificates, and is subject to a very restrictive permission policy from aviation authorities.

- **Strengths:** High-resolution images; flexible deployment; can access areas inaccessible to radar, camera or by boat; supports automated detection models.
- **Limitations:** Short flight duration (15-35 min); weather-dependent; provides transect rather than continuous data.
- **Potential role:** Ideal for targeted surveys and validation of other methods; promising for automated vessel detection and density estimation across season, time-of-week and time-of-day.

8 Comparing PAM, radar and camera

8.1 The problem of small boats in noise monitoring

As described in the introduction, the current monitoring of continuous underwater noise for the MSFD criterion D11C2 is based on AIS (and sometimes VMS) data to inform the soundscape models about ship densities and characteristics and therefore does not include the contribution from vessels without AIS or VMS, most importantly small recreational vessels and fishing boats. This is a known weakness of the current methodology for monitoring, recognised by the EU Commission (Borsani et al. 2023) and the regional seas conventions and development of methods to include the small boats in the monitoring are encouraged (e.g. HELCOM 2021). The results presented in this report contribute to this work by presenting side-by-side comparison of possible methods for quantifying the noise from the small boats. The task of including the small boats into the soundscape models is threefold:

1. Quantification of the small-boat traffic in Danish waters, separated into suitable sub-divisions.
2. Creation of models that can estimate the noise from small boats in individual subdivisions.
3. Modification of current soundscape models to accommodate the input from 1 and 2 above.

Task 1 relates to observing individual vessels on the surface. The larger vessels with AIS and VMS transmitters can be tracked near-continuously and with unique identification, allowing for a detailed modelling of the noise contribution from each individual vessel (see for example de Jong et al. 2021). Such level of detail is not required for the small boats; it would be prohibitively expensive to realize; and would raise serious concerns regarding privacy. Instead, the realistic aim is to obtain sufficient data on small-boat traffic in representative areas of the Danish marine waters to quantify for each subdivision the degree to which current soundscape models underestimate the actual vessel traffic.

In task 2, a robust statistical link is to be established between the small-boat traffic observable on the surface and the underwater noise from the boats. A realistic goal is to create a robust statistical model that can estimate the additional contribution of underwater noise to a sub-region based on the estimates of small-boat traffic obtained from task 1.

Task 3 deals with methods to incorporate the noise contributions modelled from task 2 into the soundscape models currently used in D11C2 assessment. Only a small handful of such models are operational, and none of them operated by Danish institutions. Implementing this last step therefore requires cooperation with the relevant institutions and is most efficiently done through the existing cooperation on joint monitoring and assessment through the regional seas conventions.

8.2 Implementing additional methods to monitor small boats

This note has evaluated three different, complementary methods – PAM, radar and camera – for quantifying the small boats in a coastal area in Danish waters. This area was chosen as there is both a high occurrence of small recreational boats, and a very limited occurrence of large vessels (e.g. container ships, commercial ferries). From all three methods, it is evident that current noise models using AIS data to estimate the underwater noise levels are severely underestimating the actual noise in these areas in periods of high small boat density. PAM provided the lowest difference with >55% of boats only being present in the acoustic data and not in the AIS data. To comply with the requirement of D11C2 the small boats without AIS should be accounted for to provide more accurate estimates of the continuous low-frequency noise in Danish waters. Here, we synthesize the outcome from testing the three methods, comparing their strengths, limitations, and potential roles in a future integrated monitoring framework.

PAM:

- **Strengths:** Directly measurements of underwater noise; detects only vessels that emit noise; continuous data collection; detects non-AIS vessels.
- **Limitations:** Limited spatial coverage; currently binary presence/absence data; false positives from non-boat noise; cannot identify vessel type without additional data.
- **Performance:** High precision (86%) but a low recall (67%); even with a low recall PAM data was able to detect >55% more boats than included in AIS data.

Radar:

- **Strengths:** Continuous data collection; large coverage area (between 30 and 90 km from radar depending on type of radar); detects non-AIS vessels.
- **Limitations:** Require highly specialised equipment; limited vessel type classification; will also include vessels that do not emit noise.
- **Performance:** High precision (>90%) but no classification of vessels; clear demonstration of AIS underestimating small boats during peak periods.

Camera:

- **Strengths:** Visual confirmation of vessel presence and type; good potential for automated classification of different vessel types; low-medium cost; detects non-AIS vessels.
- **Limitations:** Limited coverage to ~1km; bias towards sailboats/boats with large surface area; requires model training on relevant images.
- **Performance:** Good performance of pretrained YOLOv11m model; existing boat detection models performed poorly on data from this study site.

Integrating the different methods would introduce different challenges. An overview of the strengths and limitations of each method is outlined in Table 8.1.

Table 8.1. Summary of the proportion of non-AIS boats detected and the precision/recall of each automated method, as well as an overview of evaluation metrics for PAM, radar and timelapse camera compared to AIS for monitoring small boats without AIS. *Note that for the proportion of non-AIS boats, the data across methods are not fully overlapping (See Section 3)

Feature	AIS	PAM	Radar	Timelapse camera
Proportion of non-AIS boats*	-	55.6%	90.4%	78.2%
Precision/recall	-	86/67	96/88	81/69
Coverage	Very high (national)	Low (local)	High (up to 90 km)	Medium (up to ~1 km)
Detects non-AIS	No	Yes	Yes	Yes
Real-time potential	Yes	Yes (challenging)	Yes	Yes
Vessel type info	Limited	Very limited/untested	Possible but limited	Possible
Bias	Toward commercial vessels and sailboats	Toward closer vessels and more high-frequency vessels	Minimal (towards larger vessels)	Towards vessels with larger visible area
Costs & complexity	Low	Medium	High	Low-Medium

The radar provides unmatched spatial coverage and the potential for real-time tracking. While this is possible, it requires access to the radar systems that are installed near areas of interest with a similar fine-scale resolution (e.g. www.m2marinemonitor.com). For this project, we had access to a stationary test radar, but to broaden the use of radar to quantify small boats without AIS would be possibly by gaining access to data from the network of radars operated by the Ministry of Defence. There are obvious concerns regarding national security connected to the use of this data, but with sufficient cooperation from the radar operators, access to neither the technical facilities, nor the raw data output, is required. It would be fully sufficient to gain access to the output of the automatic classification system of the radars. Even for this data, it is not even necessary to obtain all data. Statistically representative subsamples are fully sufficient, leaving ample room for the military to redact periods with data that may be deemed sensitive.

As supplement to this data, or if access to the surveillance radars cannot be established, is the use of a transportable radar that can be deployed for representative periods on strategic locations on the coast. This would be like the radar used by Petersen et al. (2017), mounted on top of a car trailer containing the electronics and used to provide a density map of small boats in Sejerøbugten.

The ability to visually validate the detections in camera data is a significant benefit, and the camera is the most straightforward to implement. Additionally, this type of data has already been implemented in automated boat detection in different situations and areas (Wilson et al. 2022; Signaroli et al. 2025). However, what we also show here is that the pretrained and existing models are highly specialized for the domain in which they were trained and applying this method to other areas and image-types is not straightforward. Cameras, however, can provide valuable supplementary information to the radar data, because it allows for visual confirmation of classifications that are difficult for the radar. It can also potentially be used as a stand-alone monitoring in areas poorly covered by coastal radars, as the cameras can be mounted on a mast placed in shallow water and powered by solar panels.

AIS alone cannot provide a reliable estimate of vessel activity or noise exposure in Danish waters, particularly during peak recreational periods. In our example we show that in a period with a high intensity of small boats AIS will underestimate the traffic by up to 9 times depending on both the method and the time period investigated. Radar and PAM remain useful for large-scale and acoustic coverage, while timelapse cameras offer a cost-effective solution for near-shore monitoring and vessel-type classification.

PAM is an essential method for quantifying underwater noise but at present there are no methods available to identify vessel types without validation from auxiliary data such as camera or radar. Given this, a hybrid approach combining all four methods (AIS (baseline boat traffic), radar (broad coverage and fine-scale movement), PAM (acoustic measurements of boats), and camera (visual verification and vessel-type classification)) would deliver a very robust monitoring system. However, such a system is not easily implemented and requires further development to logistically be used in a long-term monitoring setup. The central role of PAM recordings in the context of small-boat monitoring, however, is that synoptic PAM recordings and surface monitoring (radar and/or camera) allows for estimating statistical models that can predict the underwater noise from the small-boat density in the area. The goal is not to establish detailed single-source models, allowing prediction of the noise from a single vessel based on its type, size and speed (such as used for the AIS-vessels, see for example MacGillivray and de Jong, 2021). Instead, the models could operate on larger time scales (days or months) and larger geographical areas - the sub-regions referred to in Section 8.1. These sub-regions should be small enough to capture differences between areas with low traffic (e.g. central Kattegat) and high traffic (fjords, belts and straits) and are not required to be aligned with the geographical subdivisions used in D11C2 assessment (habitats and Marine Reporting Units).

Specifically, we propose to further develop the monitoring of continuous underwater noise in Danish marine waters along several lines:

- The current data from all four data sources are used to refine a robust small boat detector on acoustic data, which could easily be implemented into a monitoring framework and be used to create good source model characterisation for individual small-boat types, including relationship to speed.
- Conduction of a larger study to quantify small boat traffic in Danish marine waters on a statistical level. As described above, this would ideally be done in cooperation with the Ministry of Defence, making use of their coastal radars, possibly supplemented by transportable radars and/or cameras.
- Recording of underwater noise by deployment of PAM stations in representative areas together with simultaneous mapping of the surface traffic. Ideally this can be done as part of the large-scale mapping of the surface traffic, for example by rotating a number of PAM stations from area to area, alternatively through dedicated studies. The acoustic recordings need only cover a fraction of the period where surface traffic is monitored by radar and/or video.
- Generalisation of statistical models to make them suitable for generating input to the regional soundscape mapping tools. As mentioned above, this is most efficiently done through cooperation within the Regional Seas Conventions, preferably in the form of one or more joint projects. These could conveniently be connected to the upcoming assessments HOLAS 4 and OSPAR Interim Assessment.

9 Conclusion

We show that AIS alone substantially underestimates the presence of small boats in a near-coastal area, especially small boats that contribute to underwater noise as most small boats with AIS are sailboats. In this scenario, relying on AIS for noise models will not produce reliable prediction for the underwater noise, especially during certain times of the year and day. The three main methods tested here, PAM, radar and camera, each address this challenge differently: PAM measures the noise in the area directly, radar provides large-scale coverage with fine-scale time-resolution, and camera provides visual verification and potential for classification of vessel types. From the additional methods, satellite imagery and drones, flexibility can be added in terms of areas that can be covered but both have temporal constraints.

To provide a correction factor for the noise exposure models, a multi-method approach is required. By combining camera and PAM data, the acoustic boat detector can be validated further, and a measure of the variation in small boat traffic intensity can be derived¹ for select areas. For this to be incorporated into the Danish strategy for noise monitoring, it needs to be evaluated at different sites and not just in a limited area as presented here.

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