

Article

Advanced Technologies for Cetacean Monitoring: A One-Health and Multidisciplinary Approach for Ocean Effective Surveillance

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Simple Summary: The MARCET project (MAC/1.1b/149) aims to monitor the health status of resident cetaceans in Special Areas of Conservation (SACs) of particular interest for whale-watching in Macaronesia. This study, performed in the Canary Islands, Spain, used an autonomous surface vehicle (Waveglider[®]) to detect cetacean species using passive acoustic monitoring (PAM). The automatic detections, via an acoustic acquisition system (Pambuoy), were compared with human detections for the same period. Although automatic detections were lower than human detections, this experiment has allowed the intercomparison of these two techniques, the system's performance, and its improvement by system re-setting. The present work, carried out with a close cooperation between biology, engineering, and oceanography, will integrate with veterinary sciences. The evaluation of ocean ecosystems, cetacean health, and human activities by means of advanced technologies will provide a novel and integrative One Health approach to current and future studies.

Abstract: Within the MARCET European project and community framework, a Waveglider[®] SV2 vehicle was deployed, equipped with a passive acoustic monitoring (PAM) device, in a Special Area of Conservation (SAC) of Gran Canaria (Canary Islands, Spain). The soundscape was continuously recorded from 23 July 2018 until 30 July 2018 and was primarily used for marine mammal sound detection. This study aims to compare these automatically embedded detections from the Waveglider[®] with human expert detections. Furthermore, it provides an assessment of the performance of the automatic detector and discusses the use of this type of technology to monitor wildlife, particularly cetaceans. The MARCET project and this study are only possible due to the multidisciplinary integration of veterinary sciences, ecological, zoological, and biological knowledge and mechanical, communication, and electronics engineering. It represents an excellent example of new technologies, capacities, skills, and cutting-edge knowledge where veterinary science education and training should progressively be involved to contribute to the surveillance and control of ocean health.

Keywords: MARCET; ocean health; Waveglider; PAM; cetacean detections; veterinary science



Citation: Neves, S.; Doh, Y.; Sacchini, S.; Delory, E.; Fernández, A.; Castro-Alonso, A. Advanced Technologies for Cetacean Monitoring: A One-Health and Multidisciplinary Approach for Ocean Effective Surveillance. *J. Mar. Sci. Eng.* **2023**, *11*, 1431. <https://doi.org/10.3390/jmse11071431>

Academic Editor: Giuseppa Buscaino

Received: 1 May 2023

Revised: 10 July 2023

Accepted: 15 July 2023

Published: 17 July 2023



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1. Introduction

As part of the underwater megafauna, marine mammals raise ecologically important and even economic issues through the growing development of whale watching [1,2]. Knowledge of the more than 90 listed cetacean species is still disparate in some areas, and more research on marine mammals is needed for better population management [3–5].

Many species remain on the International Union for Conservation of Nature Red List of Endangered or Vulnerable Species (IUCN 1996). Considering historic and new threats, it is essential to assess the state of populations and define effective conservation measures.

Unmanned Autonomous Vehicles (UAVs) can be defined as self-propelled vehicles designed to operate without a human presence onboard. They are capable of performing various scientific and research tasks in marine environments. These vehicles utilize a combination of sensors, onboard computers, and navigational systems to navigate and execute predefined missions in the ocean. The use of UAVs for marine mammal research has been increasing in the last decade. The main reasons for this increase include being quiet observation platforms, having long survey durations, providing an increase in mission safety (when operating in dangerous or boat-inaccessible areas), ease of replication of missions, and a significant reduction in cost when compared to ship-based missions. Their primary use has been collecting oceanographic data, but in recent years, with the addition of hydroacoustic sensors, they have been increasingly used in marine mammal studies. The main topics of study include their distribution, habitat and abundance determination, and mitigation actions in all stages of the oil and gas industry and renewable energy industry, such as baseline, during operation, and decommission [6]. There are two main types of autonomous marine vehicles: underwater (propeller-driven underwater crafts and underwater buoyancy gliders) and surface gliders (powered surface vehicles, self-powered surface vehicles). The use of a specific vehicle depends on the needs of a project and the characteristics of the embedded or potentially installed sensors [6,7].

UAVs features also allow them to be considered as excellent tools for gathering Essential Ocean Variables (<http://www.goosocean.org/eov>, (accessed on 15 April 2023)), which includes ocean sound [8–10] and marine mammals abundance and distribution [11].

A wide range of autonomous vehicles has been developed and applied to marine sciences. There are two main types of autonomous marine vehicles: underwater (propeller-driven underwater crafts and underwater buoyancy gliders) and surface gliders (powered surface vehicles, self-powered surface vehicles). The use of a specific vehicle depends on the needs of a project and the characteristics of the embedded or potentially installed sensors [6].

Autonomous Surface Vehicles (ASVs) were developed later than underwater versions. As a result, more studies of their application for marine mammal monitoring and research are required. However, according to Verfuss et al. [6], the ASVs are more versatile and suitable for marine mammal monitoring. The reasons are related to their greater capacity to integrate different acoustic acquisition systems when compared to underwater systems and the fact that these vehicles are self-powered. Passive acoustics are becoming an important tool for studying and monitoring animal behaviour, particularly for species that spend most of their time underwater and are difficult to observe directly. The two primary methods for analysing acoustic data are human expert analysis and automatic detection. Studies comparing human expert detection and automatic detections are rare and are very tax-dependent. However, recent studies with birdcall detection by autonomous recorder units and by human observers using broadcast showed that, despite machines and humans having similar hearing abilities, the automatic detectors had a higher detection rate [12–16]. In all the above studies, expert analysis acted as a ground truth. Expert analysts have been used for detecting and classifying events of interest in large acoustic datasets for more than 50 years [17]. This ground truth is obtained visually by scanning through spectrograms and registering the times of individual signals of interest, usually called detections. Despite being time-consuming, this type of manual analysis is flexible and effective, remaining an essential aspect of many recent passive acoustic monitoring studies as a means for obtaining ground truth detections [18–20]. However, manual detections vary as a result of the analysts' experience and sensitivity. True acoustic sources are rarely known, and the ground truth is obtained by a consensus between multiple expert analysts [21].

Automated algorithms are a critical component in the analysis of long-duration acoustic datasets. These algorithms detect and classify sounds, making the analysis process more

efficient and accurate. Without these algorithms, despite their advantages, manual analysis would be extremely time-consuming, especially with long-duration datasets. Expert analysts often fine-tune detectors and classifiers to detect specific species or signals of interest by utilising their knowledge of the typical features of the target signal and the expected range of variability. Metrics are necessary to evaluate the performance characteristics of these algorithms. It is vital to assess their accuracy, precision, and recall in detecting and classifying sounds, allowing for the optimisation and improvement of the algorithms and ultimately leading to more reliable and accurate results [22].

This research is a part of the MARCET project, which is funded by the Interreg MAC program of the European Commission and directly involves Portugal (Azores and Madeira) and Spain (Canary Islands) as member countries and regions, and Senegal and Cabo Verde as third countries. MARCET uses the One Health approach [23,24] to monitor the health status of resident cetaceans in Special Areas of Conservation (SACs), of particular interest for whale-watching in Macaronesian waters, through the participation and synergic cooperation of all relevant disciplines, including biology, veterinary science, engineering, and oceanography.

The present manuscript investigates the feasibility of deploying autonomous surface vehicles as automatized acoustic monitoring equipment. To better understand this subject, we employed a WaveGlider[®]™ in conjunction with an acoustic acquisition system to test an automatic detection algorithm of cetaceans in the Canary Islands and compare it to human-based detections. This effort represents a successful model of applying the One Health approach [23,24] in a multidisciplinary framework and helps to improve monitoring capacities in the areas of interest by providing additional information on cetacean species and their distribution and strengthening ocean health monitoring skills.

2. Materials and Methods

2.1. Field Study Area

The Canary Islands, located off the northwest coast of Africa, is a hot spot for cetaceans due to their unique geographic and oceanographic conditions, where approximately a third of the world cetacean biodiversity [25,26] can be found. The archipelago is situated in the subtropical convergence zone, where the northern and southern trade winds meet [27]. This convergence zone creates a meeting point for warm and cold-water masses, leading to high levels of productivity and biodiversity in the ocean surrounding the islands [28]. The archipelago is also subject to intense upwelling, which occurs when cold, nutrient-rich water from the ocean's depths rises to the surface [27]. This upwelling is due to the trade winds pushing the surface water away from the islands, allowing deeper water to rise to the surface. The increased nutrients in the water support a diverse food web, attracting cetaceans to the area. There is also a strong influence of tidal currents, which bring food to the surface and create areas of high productivity. Cetaceans can feed on these resources, making the area an ideal habitat for them [28].

Additionally, the Canary Islands are located near deep water channels, which allow cetaceans to move freely and safely in the area. These channels also provide opportunities for breeding and nursing, making the Canary Islands a vital breeding ground for cetaceans [28–30].

2.2. Data Collection

Data collection was conducted between the 23 and 27 July 2018, resulting in a 227 km acoustic survey performed by the autonomous surface vehicle Waveglider[®]™ SV2 (Figure 1).

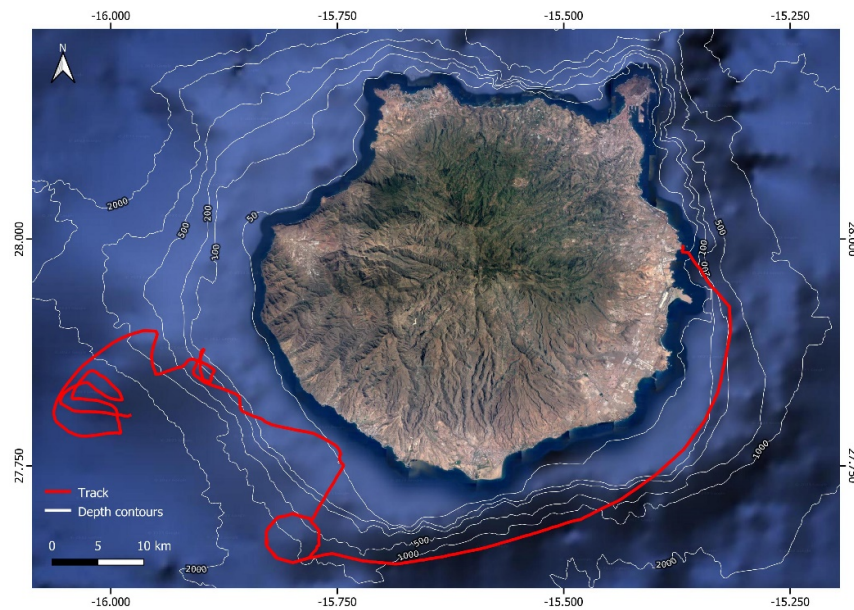


Figure 1. Map with the track of the ASV used in the survey. Source: <http://obsplatforms.plocan.eu/vehicle/USV/35/> (accessed on 15 April 2023).

The autonomous surface vehicle (Waveglider[®]™ SV2) was equipped with a Pambuoy recording system. It was comprised of a Reson/Teledyne TC4014-5 hydrophone Teledyne Marine, Aberdeen, UK, (-161.9 dB re $1\mu\text{Pa}/\text{V}$ ($+/-3$ dB), 15 Hz–480 kHz) and a SAIL Decimus[®] digital acquisition and processing system (sampling rate of 50 kHz in 16 bits, with 26 dB gain, with continuous recording) housed in a tow-fish attached to the sub-surface glider by a 15-m cable assembly with floats and weights fitted to its length (Figure 2), mitigating the transmission of vehicle structural vibration and movement to the transducers. The recording system remained at approximately 5 m depth throughout the navigation with this configuration.



Figure 2. The recording system used with the Waveglider[®]™ Sv2 (Pambuoy system).

The processing system used PAMGuard (v1.14) [31] with default click and whistle detectors. The PAMGuard Automatic Detector Assessment (PADA) data was transmitted via Iridium Satellite and displayed in near real-time at the PLOCAN platforms observatory webpage. (<http://obsplatforms.plocan.eu/vehicle/USV/35/>, (accessed on 15 April 2023)). The acoustic data was stored in the Decimus system as “x3” compressed files, while

the acoustic detections were stored as PAMGuard binary files specific to PAMGuard (PAMGuard data file—*.pgdf)

2.3. Data Analysis

All binary files were loaded with Matlab[®], and two types of outputs were identified: clicks and whistles. Additionally, the “x3” files were decompressed, and a human specialist analysed the resultant *.wav files to determine the type and number of vocalisations encountered during the wave glider mission.

To determine the efficiency of the PAMGuard Automatic Detector Assessment (PADA), a Human Expert Detection Assessment (HEDA) was performed. This human expert analysed and classified the natural sounds between 23 July 2018 at 11 h 2 min and 27 July at 7h 54 min (a total of 93 h). The HEDA functions as the ground truth. For this, the operator listened to the audio files in combination with the visualisation of the recording’s spectrogram and reported each detected event. The acoustic events were classified according to the type of sound (“whistle” or “click”). A *t*-test was performed to statistically assess the difference between whistle and click detection for PADA and HEDA. Generally, clicks are more associated with cetacean navigation and foraging behaviours, while whistles are associated with cetacean communication, group cohesion, and individual identification [32–34].

Therefore, from the raw signals, the detection aims to notify the appearance and disappearance of a desired acoustic event. It is characterised in reception by a variety of energy of the signal measured around a reference value. An audio signal segment is a portion of the audio signal regarded by PAMGuard as a sufficiently interesting acoustic event to be analysed by its predictive algorithms. Then, algorithms determine if the segment is a cetacean’s sound (positive detection) or not (negative detection).

The concepts illustrated in Table 1 were defined to evaluate the detector’s performance.

Table 1. Matrix explaining the concepts of positive and negative detections, false positives and false negatives.

Detection Outcome	Actual Condition
Positive Detection	Signal Present
False Positive	No Signal Present
Negative Detection	No Signal Present
False Negative	Signal Present

Positive detection refers to the correct identification of a signal or event. A false positive occurs when a signal is detected, but no actual signal is present. Negative detection refers to correctly identifying the absence of a signal or event. A false negative occurs when a signal is present but is not detected.

For each positive click detection, we tested if its corresponding date was included between DC1 (Date Click) and DC2. DC1 was noted at the beginning of all clicks minus 0.5 s. DC2 was the end of all clicks noted, plus 0.5 s. If a positive detection of a click was included between DC1 and DC2, a supplementary « True positive detection » was counted. If a positive click detection was not included between DC1 and DC2, a supplementary « False positive detection » was counted. The same method was used for whistles and cetacean sound processing.

To evaluate the automatic detector performance three descriptors were calculated: Accuracy, Recall, and F-Score [35]. Accuracy is equal to $A1/B1$, where $A1$ is the number of accurate positive detections, and $B1$ is the number of positive detections. Recall is equal to $A1/B2$, where $B2$ is the number of audio signal segments which are authentic cetacean sounds. F-Score is a harmonic mean of accuracy and recall. F-score indicates in one single value if the detector is operational or not. [36]. F-Score equals $2 \times (\text{Accuracy} \times \text{Recall}) / (\text{Accuracy} + \text{Recall})$.

3. Results and Discussion

To the best of our knowledge, the performance of PAMGuard detectors has yet to be evaluated using autonomous surface vehicles. Consequently, this study represents one of the first applications of this technology for cetacean monitoring.

The Wave Glider acoustic survey resulted in 93 h of recordings of the soundscape of the South-east and South-west coasts of Gran Canaria. The associated binary files resulting from the PADA yielded a total of 92,629 positive click detections, while the expert analysis (HEDA) yielded 599 acoustic events as true clicks (Figure 3).

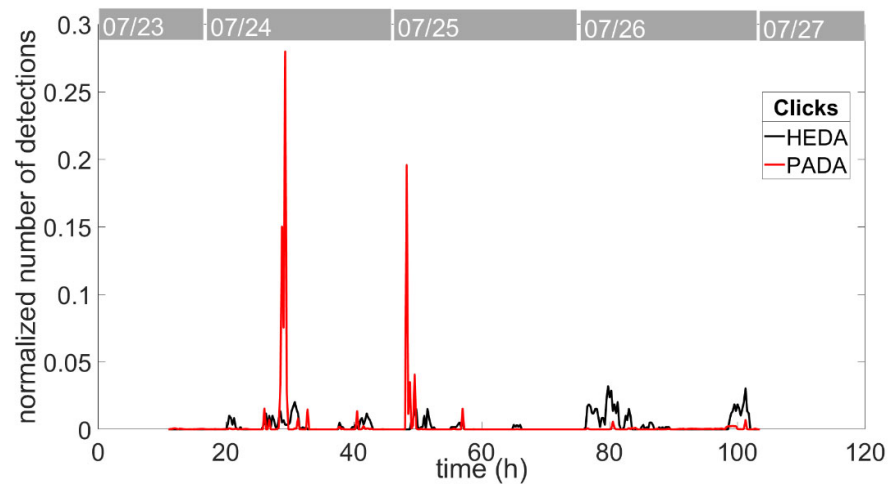


Figure 3. Comparison of the normalized number of PADA click detections in red and the normalized number of HEDA click detections in black throughout the time of the survey (in hours).

For the whistle detection, PADA yielded a total of 16,603 positive whistle detections while HEDA yielded 3854 acoustic events as true whistles (Figure 4).

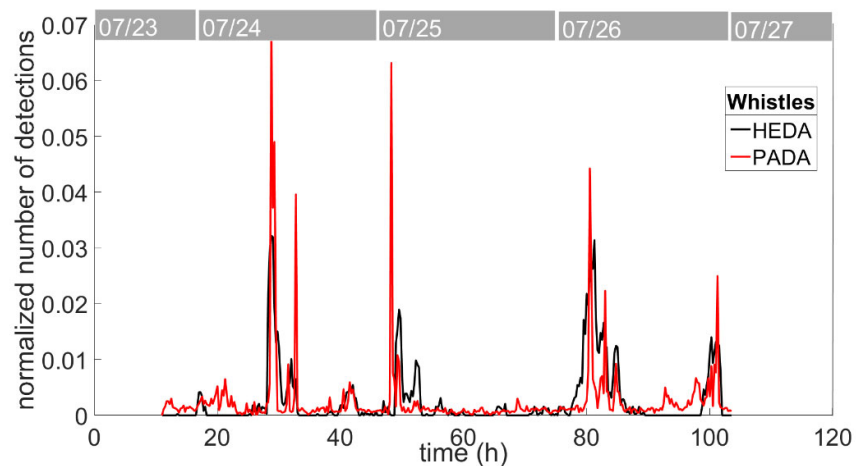


Figure 4. Comparison of the normalized number of PADA whistle detections in red and the normalized number of HEDA whistle detections in black throughout the time of the survey (in hours).

The results of the *t*-test indicate that there is a statistically significant difference between the PADA and HEDA number of clicks ($t = 15.66$, $df = 1$, $p < 0.001$) and in the number of whistles ($t = 15.66$, $df = 1$, $p < 0.001$). Consequently, the difference between the two values is unlikely to be due to chance or random variation but rather is likely to result from an actual difference between the compared groups. Specifically, the PADA analysis had a much higher number of clicks and whistles when compared to the HEDA group.

The performance descriptors are detailed in the Table 2 below:

Table 2. Results for all the descriptors calculated to evaluate the performance of the PAMGuard automatic detectors used for clicks and whistles: Accuracy, recall and F-score.

Descriptor	Cetaceans Click (%)	Cetaceans Whistles (%)
Accuracy	33	13
Recall	22	19
F-Score	26	16

The evaluation of the automatic detector yielded an accuracy of 33% for the cetacean clicks and 13% for the cetacean whistles. This result means that only these percentages represent correctly positive detections of clicks and whistles, respectively.

The recall, measuring the detector's ability to identify authentic cetacean sounds, was found to be 22% for clicks and 19% for whistles, indicating that only these percentages of the actual cetacean clicks and the actual cetacean whistles were successfully detected.

The F-Score, which combines accuracy and recall, was calculated to be 26% and 16% for clicks and whistles, respectively, reflecting the overall operational performance of the sensor in detecting true positive instances.

Therefore, based on these values, we can conclude that the automatic detector tends to underestimate cetacean sounds while potentially overestimating non-cetacean sounds as cetacean sounds. This result indicates a need and a possibility for improvements to enhance the detector's ability to accurately detect authentic cetacean sounds while minimizing false positive detections. The major ascertainment concerns the sensitivity of the whistle detector used, as the number of detections was rarely equal to 0. These data highlight a problem with this detector's definition or configuration.

Despite the critical difficulty of drawing broader uncertainty metrics in this short-period deployment, the results could probably be improved with the capability to adjust the detection parameters and integrate new versions of the algorithm. In addition, despite the low detection rates, our experiment has allowed us to assess the variation of cetacean sound productions in time and space. Acoustic activity can also be directly linked to the density of cetacean presence, even if this requires a preliminary characterisation of the detection probability function and the distance between individuals and the vehicle [37,38]. This last aspect can be challenging with a single hydrophone. Attenuation models and cetacean source level priors can help establish a distance source-receiver estimator.

Accuracy, Recall, and F-score obtained in this study were relatively low when compared with similar studies using a human observer (ground truth) and automatic detectors from PAMGuard [39]. Graphical analysis provides temporal elements on both detectors. Clicks are often well detected with PAMGuard, with a tendency to be overestimated when there are no cetacean clicks and to be underestimated when the received level is low. This result could be explained because the automatic detector cannot discriminate if the clicks are coming from marine mammal activity or not, and the settings will have to be adjusted.

PAMGuard has been used extensively and successfully in the detection of marine mammals in the mitigation and renewable energies contexts, such as beaked whales (through automatic detection of their clicks) [40], seals and porpoises [41], and whales [42,43]. Studies on the performance of PAMGuard have shown that for whistles, the recall can reach up to 79.6% [39]. However, when pooling the analysis of several species, as in the case of our study, the recall dropped to 58.5% (12 species included). Furthermore, PAMGuard accuracy was evaluated in detecting dolphin whistles and revealed a low accuracy (66.4%) when compared with other types of detectors based on artificial intelligence [44]. However, for clicks, an accuracy of 80.5% was described when analysing Risso's (*Grampus griseus*) and Pacific White-sided (*Lagenorhynchus obliquidens*) dolphins' clicks [45].

When evaluating a comparison between human experts and automatic detection for four baleen whales in the U.S., it was revealed that the automatic detectors installed in an autonomous underwater vehicle, SLOCUN (using different software than the present study), had a medium Accuracy, Recall, and F-Score higher than 99, 48 and 64% in the

15-min period detections [46]. This shows that it is possible to achieve a high performance of acoustic detectors using autonomous vehicles. Nowadays, automatic detectors can also use neural networks to learn and improve their detection algorithms [47,48]. Furthermore, recent studies support adopting artificial intelligence technology to improve the automatic environmental monitoring of marine ecosystems [44].

Since we used a closed system for the near real-time analysis in our study, it was not possible for the automatic detector to be modified, adjusted, or optimized. As a result, this might be responsible for the lower metrics values we found. Another aspect to consider is that, in our study, PAMGuard detectors were used in an autonomous surface vehicle with a towed array, which are different conditions from the ones used in the studies described previously.

The above studies [39–44,46–48], including our present study, highlight promising perspectives for cetacean population monitoring and reasonable price/energy cost acoustic transects [6,49]. However, precautions must be taken when trying to estimate population densities with a surface autonomous vehicle [38,50,51] as the usual assumption, that the animal's speed is slow compared with the vessel's speed, is violated. As such, this can introduce overestimation bias [52].

Although each specialist has worked primarily on their fields of expertise, the MARCET project and the mission of this study have required an enormous coordination effort and exchange of experience between veterinary sciences, ecological, zoological, and biological knowledge and mechanical and communication engineering, in particular, regarding the configuration, application and results assessments in the use of cutting-edge marine and maritime technologies to monitor ocean sound. In our understanding these facts represent an excellent example of the application of the One Health approach [23,53] to contribute to monitoring cetaceans populations and ocean health.

4. Conclusions

Marine mammals are considered excellent bioindicators of ocean health. They are known as umbrella species, being at the top of the food net and, therefore, sentinels of the oceanic ecosystems. Considering past overexploitation of these species and current global threats, it is essential to continue assessing cetaceans' health status and define effective conservation measures.

Autonomous Surface Vehicles are more versatile and suitable for marine mammal monitoring than AUVs due to their greater payload capacity and ability to access additional renewable energy sources such as solar and wind energy. Our study has shown a positive and effective use of the Waveglider[®] SV2 to perform the passive acoustic monitoring of different cetacean species on the Canary Islands Atlantic seawaters.

Acoustic detections have become essential for studying and monitoring animal behaviour, particularly for species that are difficult to observe directly. Despite the substantial lack of precision metrics in our medium-term deployment of the Waveglider[®] SV2 for soundscape monitoring, this result could be easily mitigated or enhanced by gaining access to an open and adjustable detector vehicle system; therefore, it could be reset. The parameter settings for the open-source PAMGuard detectors can be investigated, modified for score improvement, and adapted for multiple conditions.

The MARCET project and the mission described in this study represent a successful model of the application of the One Health approach, only possible due to the multidisciplinary integration of key disciplines not used to work together. Essentially, this study covers the configuration, deployment, piloting and assess the results of marine advanced and cutting-edge technologies applied to the evaluation of the ocean environment health status, the detections and evaluation of the cetaceans population and, with these data, contribute to developing more sustainable, eco-friendly and respectful human exploitation of our marine resources.

Author Contributions: Conceptualisation: S.N. and A.C.-A.; Methodology: S.N., E.D. and A.C.-A.; Data curation and Analysis: Y.D. and S.N.; Writing—original draft preparation: S.N. and A.C.-A.; Veterinary Services evaluation and writing—review and editing: S.S. and A.F.; Passive Acoustic Monitoring evaluation and writing—review and editing: E.D. and Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by MARCET (MAC/1.1B/149) and MARCET II (MAC/4.6c/392) projects, approved in the first and second calls of the 2014–2020 Interreg MAC Program, cofounded by ERDF-EU Funds.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this research article is available for public access. The PADA data utilized in this study can be viewed at <http://obsplatforms.plocan.eu/vehicle/USV/35/> (accessed on 15 July 2023). In addition, all raw files used in this research can be requested at access@plocan.eu. To comply with the data sharing policy of MDPI, all data used in this research is open access and available to the public. The data includes raw data, processed data, and metadata used in this research. The data is available without restrictions on its use, sharing, or reuse, and it can be accessed through the links provided above. The data has been provided with the understanding that it will be used for research and educational purposes only. The data should be appropriately cited in any publications or presentations that make use of it, in accordance with standard academic practice.

Conflicts of Interest: The authors declare no conflict of interest.

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