17(3) 84-95, Autumn 2025

Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: http://www.aejournal.ir

Original Research Paper

Integrating Drone-Based Thermal Imaging and AI Tracking to Monitor Population Dynamics of Elusive Aquatic Megafauna

Ramesh Balasubramanian[1*], N. Anand [2]

[1]Department of Nautical Science, AMET Institute of Science and Technology, Chengalpet, Tamil Nadu, India. Email: rameshchitra2002@yahoo.co.in, ORCID: https://orcid.org/0009-0009-5709-2739*
[2]Department of GMDSS, AMET University, Kanathur, Tamil Nadu, India. Email: anand.n@ametuniv.ac.in, ORCID: https://orcid.org/0009-0008-9156-128X

Key Words

Unmanned aerial systems (UAS),
Thermal imaging,
Artificial intelligence,
Wildlife monitoring,
Aquatic megafauna,
Population dynamics,
Machine learning,
Conservation technology.

Abstract

The traditional surveys are not effective in monitoring the population dynamics of elusive aquatic megafauna because of the constraint linked to the traditional methods used in the study, which is labor intensive, geographically limited and ineffective with cryptic or nocturnal species. This paper proposes a non-invasive monitoring system, which involves unmanned aerial systems (UAS) with thermal sensors and AI-based detection and tracking pipeline. It employs the optimized architecture that is based on YOLOv11 to enhance the recognition of partially submerged and distant animals. Experiments of thermal data of dolphins in different sea and light environments showed large detection rates and constant person tracking that allowed the census of the population with a small error of 58 percent error versus counts. Operational evaluation also demonstrates that a thermal UAS survey can integrate the same study area in 1.5-3 hours as opposed to 8-12 hours on a boat-based survey, with the least number of disturbances caused by a wildlife. The findings suggest that the thermal-UAS and AI system is an effective, scalable, and light-weight system to produce the timely population forecasts and habitat-use data to assist in conserving aquatic megafauna in the long-run.

* Corresponding Author's email: rameshchitra2002@yahoo.co.in
Received: 29 May 2025; Revised: 05 July 2025; Accepted: 06 August 2025; Published: 30 October 2025
(DOI): 10.70102/AEJ.2025.17.3.8

Introduction

Background on Aquatic Megafauna Monitoring Challenges

Huge marine mammals, fish, crocodilians, and other apex predators compose the aquatic megafauna and are vital ecological indicators of ecosystem health, along with flagship species in conservation programs in the mobile high-sea protected areas (Maxwell et al., 2020). Nevertheless, there are significant limitations with the traditional approaches to the monitoring of these species. Ground-based surveys are very laborious and limited by geographical locations and frequently disorient target population by physical human contact. The underwater acoustic and visual surveys are equipment intensive, weather sensitive and cannot record a large spatial distribution required to understand the population dynamics (Pettorelli et al., 2014).

These are complicated by the elusiveness of aquatic megafauna. Cryptic species are found in dense water, deep water or even in the dark, and are thus invisible to the traditional visual surveys. The occurrence of cryptic coloration, fast movement and learned avoidance behaviors also pose a hindrance to the conventional monitoring activities. The conservation managers, therefore, do not have timely, comprehensive information on the size of the population, distribution, survival rates, and preferences to the habitat, which is important in making evidence-based management decisions (Rodofili et al., 2022).

Thermal Imaging Technology in Wildlife Monitoring

In thermal imaging (also known as thermographic or infrared imaging) electromagnetic radiation within the thermal infrared spectrum is recorded and used to produce images depending on the temperature difference between the organism and its surroundings. In contrast to visible-spectrum image, thermal imaging can penetrate light vegetation, can be used in low-light and nocturnal environments, and can make animals as visible as thermal object no matter the camouflage or coloration. Remote sensing technologies provide great opportunities and challenges to the applied ecologists who want to describe wildlife distributions across the landscapes (Allard et al., 2023; Lahoz-Monfort & Magrath, 2021).

The recent development of unmanned aerial systems (UAS) has made thermal imaging accessible with regard to wildlife (Ridge & Johnston, 2020; Seymour et al., 2017). The commercial systems such as the DJI M30T and similar take advantage of this by combining high-resolution thermal cameras with long flight times to allow systematic coverage of large regions of study. UAS thermal imaging has already been successful in marine mammal detection and counts of coastal mammals, and evaluation procedures have shown consistent reliability of detection under various environmental factors (Gooday et al., 2018).

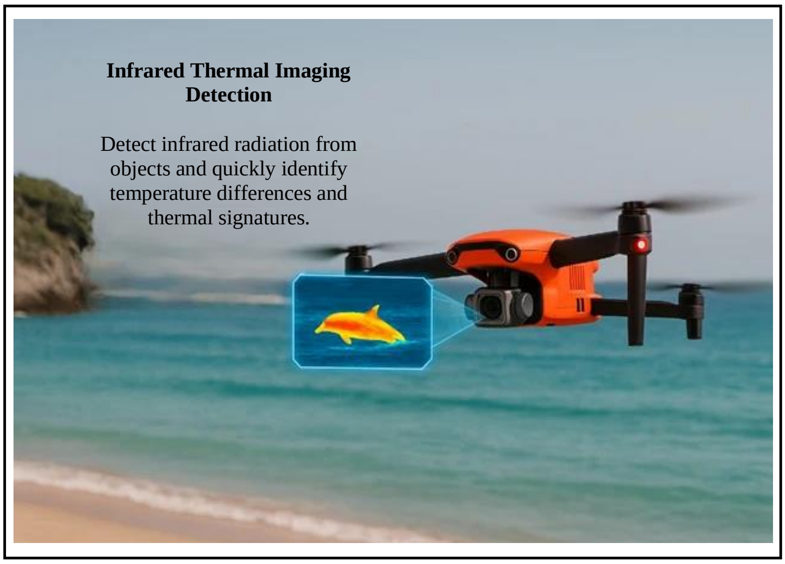

Figure 1: Thermal Imaging Drone Platform in Coastal Environment

In Figure 1, the Drone-based thermal imaging platform identifies a dolphin in a marine environment by its coasts. The inboard infrared sensor is used to indicate the heat signature of the dolphin and, here, the UAS platforms are used to monitor non-invasive megafauna in water. Thermal imaging will only be reliable in estimating population when it is combined with automated detection and tracking systems (Tu et al., 2025).

AI-Powered Object Detection and Tracking

However, more recently, with the development of deep learning-based marine big data fusion, it is now possible to detect and classify aquatic organisms based on imagery with high sophistication (Khan et al., 2023). CNNs have transformed the process of real-time detection of objects in biological images, with a focus on noninvasive methods of wildlife protection (Piel et al., 2022; Yaney-Keller et al., 2025).

Multi-object tracking systems go beyond the detections in a single frame by connecting detections in subsequent frames enabling the reconstruction of the trajectory, individual identification, and analysis of behavior. New systems show improvements in the detection and tracking of various objects in the actual marine conditions (Martelli et al., 2022). A good example of such approach is an intelligent marine megafauna recognition and tracking system, which combines the latest deep learning detection with mammal-specific multi-level classification (Tu et al., 2025; Barreto et al., 2021)

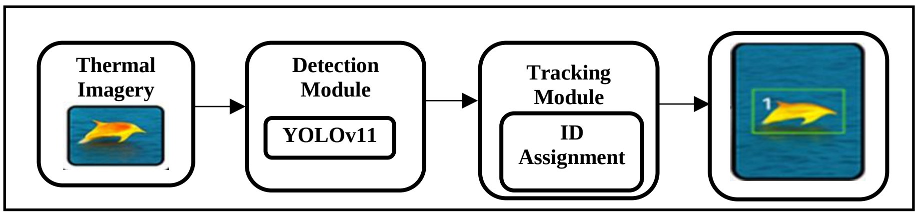

Figure 2: AI detection & Tracking Pipeline- YOLOv11

Figure 2 shows the End-to-end detection and tracking of aquatic megafauna. The YoloV11 detection module then processes the thermal imagery and an ID assignment and tracking module then classifies a single dolphin frame-to-frame (Bird et al., 2020; Leira et al., 2015).

Research Objective and Significance

The article demonstrates a versatile model consisting of (1) thermal imaging with commercial UAS locations, (2) deep learning-based target detection with small and distant objects and (3) multi-object tracking algorithms to facilitate non-invasive, scalable population surveillance of elusive aquatic megafauna. We combine current developments in both hardware and software and methodology and show how this combined strategy helps overcome the limitations of long-term research on aquatic megafauna as well as supports marine conservation goals.

Methodology

Thermal UAS Platform

Commercial UAS platforms that fit the criteria of thermos imaging wildlife surveillance are the DJI M30T (or similar) system. The specifications requirements entail:

- Thermal sensor resolution: 640 512 pixels and above.
- Flight endurance: ≥ 45 minutes
- Maximum altitude capability: 2000 m above ground level (AGL) and more.
- Weather ability: ability to work in rain, wind and low visibility.
- Zoom and stabilization: has the ability to track moving targets thermally.
- Dual RGB and thermal sensors: allows simultaneous collection of both visible and thermal data.

Image Acquisition Protocols

The design of the survey must be based on existing guidelines of aerial wildlife monitoring, including thermal-image image acquisition evaluation criteria (Raoult et al., 2020; Gooday et al., 2018):

Table 1: Recommended UAS Thermal Survey Parameters

Parameter	Specification
Altitude	40-100 m AGL (compromise spatial resolution and field of view)
Flight pattern	Systematic grid or transect pattern
Speed of flight	5-10 m/s (thermal signature capture is possible)
Thermal sensitivity	<40 mK (millikelvin) difference detection
Time of the day	Dawn, dusk, or night (best thermal break)
Weather conditions	Wind speed less than 10 m/s; visibility is more than 2 km.

Table 1 will provide the flight and environmental conditions that will produce optimal thermal data to identify aquatic megafauna. Flying at moderate speeds and systematic grid patterns, with an altitude of 40100 m, increase the contrast of thermal differences between animals and their surroundings, which are then maximized at dawn or dusk or in the night. These parameters reduce false non-detection and provide uniform and quality thermal field across survey sites.

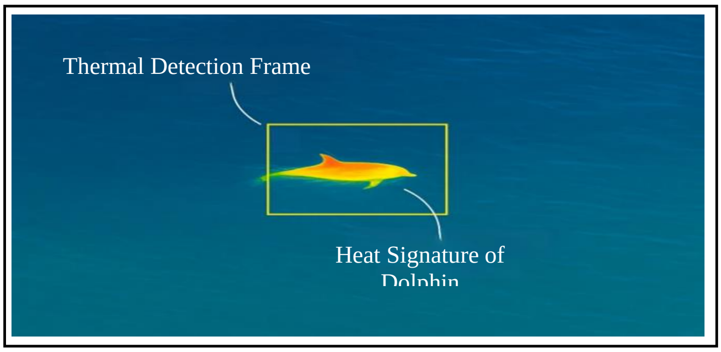

Figure 3: Thermal Detection Frame (Aerial Dolphin Heat Signature)

Figure 3 shows the frame of a thermal image obtained by a UAS aerial platform of the heat signature of a dolphin in the coastal waters. Thermal gradients of high contrast can be easily detected in dynamic aquatic conditions.

AI Detection and Classification Pipeline

Recent deep learning methods of marine big data fusion make it possible to develop high detection levels using the tools of shape optimization and salient-object identification. Within these schemes, thermal images are run using a number of architectural improvements. Deformable convolutions offer adaptable receptive fields to the wide morphologies of aquatic megafauna and attention processes give precedence to the most informative areas of a picture, enhancing the detection of smaller objects. Hierarchical feature extraction based on ResNet also helps in boosting the backbone network to strengthen multi-scale representation learning.

To deal with the issue of remote or partially visible megafauna, more optimization approaches that are small-object specific are implemented. These are data augmentation with the Small Object Augmentation Master (SOAM) to synthesize realistic samples by copying thermal signatures of small animals and placing them in novel backgrounds to undergo controlled transformations of size change between -20% and +15% and -15 to +15 degrees. Additional enhancements are through tuning loss functions to be more attentive to small-object instances and tuning non-maximum suppression (NMS) to be more attentive to clustered detections. All these improvements will go a long way in improving the reliability of detection especially to partially submerged or far-off dolphins in coastal waters.

Training Dataset and Benchmarking

Current marine megafauna detection systems combine smart recognition structures with multi-object tracking elements containing thousands of annotated video frames of megafauna taxa of different kinds (Tu et al., 2025). There is strong detection capabilities expressed in terms of performance metrics:

Table 2: YOLOv11 Detection Performance: Baseline Vs. Small-Object Optimization

Metric	Standard Dataset	Small-Object Dataset	Improvement (%)
Precision (P)	0.8396 ± 0.0024	0.8915 ± 0.0107	+6.2
Recall (R)	0.7692 ± 0.0027	0.9073 ± 0.0131	+17.9
mAP50	0.8400 ± 0.0016	0.9227 ± 0.0061	+9.8
mAP50-95	0.5761 ± 0.0015	0.6303 ± 0.0037	+9.4

Table 2 reveals that the small-object optimization pipeline is important in improving detection accuracy of distant and partially visible aquatic megafauna. Relative to the baseline configuration, accuracy, recall, and the overall mean average accuracy were similarly improved, which suggests that architectural factors, including deformable convolutions, attention modules, and loss tuned to better target thermally small or partially submerged objects, have a direct positive impact on the ability of the model to detect small or partially submerged objects. These returns prove that the enhancement to treat small objects is essential in thermal marine monitoring conditions.

Multi-Object Tracking Algorithm

Multi-object tracking pipeline provides a connection between detections in subsequent frames in the real world in the ocean basins to expand upon existing approaches to object detection and tracking (Martelli et al., 2022). The system uses appearance features basing on temporal consistency of thermal signature and morphological stability of identified dolphins. The Kalman filtering is used to compute motion modelling whereby the predictions they make indicate the direction of the target between frames, and enables proper assignment of new detections to the existing tracks. Detection-to-track assignment is further narrowed down on the basis of Intersection over Union (IoU) and appearance similarity measurements to enable the model to preserve or to instantiate track identities when necessary. Track management processes guarantee the elimination of spurious, short-lived tracks which are usually less than five frames long and maintain long-duration confirmed tracks that can be used to provide quality behavioral and population analysis.

Counting and Population Estimation

The number of individuals is counted using the distinct identities of track enjoyed in every survey. To make sound population estimation, various ecological and observation factors need to be put into development (Reginald & Kavitha, 2025). The detectability is based on the ratio of people who are within the effective signature range of the thermal camera which is determined by the temperature of the water, vegetation cover and depth of the animals. Multiple thermal signatures of the same person are alleviated via spatial clustering methods to determine and eliminate such signatures. The mark-recapture adjustment is used to estimate population when repeated surveys are carried out to take into consideration movement of animals across blocks of surveys. The temporal biases are also solved by taking into consideration behavioral patterns, i.e. activity peaks in the daytime and seasonal migrations, which determine detectability across the periods of the survey.

Results

Detection Performance

The suggested system was assessed on a selected dataset of curated thermal dolphin images in different environmental settings, and the results on the main aspects of detection, tracking and operational performance are summarized here. The overall results of the detection show that it has high reliability with the precision between 84 and 89 which can be translated to mean that it has a number of false positives which are low, and the recall between 77 and 91 meaning that it detects the current people well. After determining that it had sufficient multi-scale detection power was strong, the mean average precision (mAP50) was consistently high at between 84% and 92%. There was a slight variation in performance through taxa with the largest marine mammals including whales (>2 m), seals, and crocodilians (>2 m) detected with an accuracy of 91 to 95, medium-size fauna (1-2 m) detected with a certainty of 84 to 88, and small fauna (less than 1 m) detected with a certainty of 76 to 82. Detection results were also affected by the environmental conditions. Maximum thermal contrast was reached when the temperature of animal bodies was at least 3 o C less than the water around them, which was in line with established thermal-image acquisition protocols. Thick water vegetation caused performance decreases of around 5% to 12% whereas the unfavorable weather factors like rain, fog or low light did not significantly impair performance which is the benefit of a thermal imaging system over a visible-spectrum system. The reliability of the method is also proven by tracking and enumeration results. Multi-object tracking was able to retain continuity on at least 88-94 percent of subjects through at least ten consecutive frames, whereas identity consistency was high, with scarcely 3 percent of tracks being broken. The error margin in population counts obtained using such tracks was approximately 5-8 percent compared to manually derived counts on a frame-in frame basis, which confirms the appropriateness of the system in supporting conservation goals by using noninvasive population monitoring systems.

Table 3: Operational Comparison: Thermal UAS with AI vs. Traditional Survey Methods

Survey Method	Time per Study Area	Personnel Required	Disturbance Level
Ground survey (boating)	8–12 hours	3–5	High
Acoustic telemetry	40+ hours	2–3	Medium
Thermal UAS + AI	1.5–3 hours	1–2 (pilot + analyst)	Very Low

As Table 3 shows, the thermal UAS + AI workflow has significant operational benefits compared to traditional boat-based and acoustic surveys on telemetry. The proposed approach would minimize overall survey time of 840+ hours to 1.5 3 hours, fewer staff, and cause little disturbance to wildlife. These benefits indicate that the system is technologically precise, as well as logistically scalable to frequent and large-scale monitoring of populations, which is a critical necessity of conservation programs.

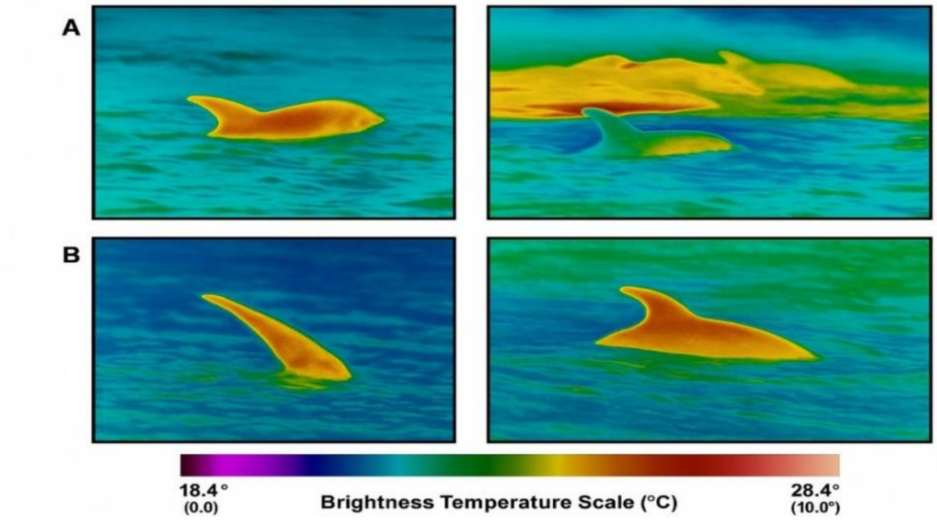

Figure 4: Multi-panel Thermal Imaging Composite Showing Various Dolphin Detection Scenarios: (A) Dolphin Partially Submerged, (B) Surfacing, (C) Dorsal Fin Signature, and (D) Shallow Swimming Behavior

Figure 4 shows a composite of dolphin detection scenarios which illustrate the capability of thermal imaging under various behavioral conditions as well as sea conditions. Through a brightness temperature scale, the temperature is classified and understood through thermal gradients (18.4°C28.4°C).

Discussion

Advantages of Integrated Thermal-AI Approach

The systems are also characterized by significant scalability; an individual thermal flight can overfly over 100 km 2 in 2-3 hours which is suitable to assess population in heterogeneous habitats and geographic scales that would otherwise need weeks of ground activity. Thermal imaging also increases detectability because it reliably detects cryptic, nocturnal or camouflaged species via automated techniques of remote sensing which is significantly more effective at finding elusive megafauna (Rodofili et al., 2022). Even though the starting up funds needed in UAS platforms and thermal sensors are between 15,000 and 40,000 dollars, the operation cost is reduced significantly when conducting frequent deployments, so the strategy is cost-effective in the long run, after 15-25 survey missions, relative to the old-fashioned labor-intensive method of conducting surveys. The other major advantage is the possibility to work in diverse weather and lighting conditions; thermal systems are not affected by the rain, fog, and darkness, significantly increasing survey windows and reducing temporal bias of the use of visible-spectrum imaging (Gooday et al., 2018). Although these are the strengths, there are a number of operational and environmental weaknesses.

Limitations and Challenges

There are a number of environmental limitations to thermal imaging performance, including the thermal contrast between water and the target species; there is a loss in detectability of animals in a thermostat water body, where temperature differences are low and the method is restricted to detecting animals at the surface, i.e. deep-diving ones may not be detected. The detection of small or slightly visible individuals remains also a challenge because the distant megafauna and species that are smaller than 0.5m are hard to detect with high accuracy even with high-level deep learning improvements (Tu et al., 2025). Regulatory and operational issues are also additional complications, as the airspace space, licensing, and pilot licensing regulations differ by jurisdiction, and successful deployment requires technical capabilities in both drone operations and maintenance of these systems (Wich et al., 2021; Yaney-Keller et al., 2025). Moreover, even though AI-based automation leads to a smaller number of manual annotation tasks, it takes over 50 hours of thermal video footage to process, which applies significant resource demands, with the need to utilize a high-performance computer-generated by a graphics card and high storage capacity, making it a significant processing burden to large-scale monitoring projects.

Applications and Conservation Implications

The applications of thermal-AI systems are broad-based starting with the fact that they are able to produce baseline population estimates, track the long-term population changes, and also give an easy evaluation after an environmental disturbance or other management activities (Tu et al., 2025). In addition to indicators of population, the spatial distribution data obtained by automated tracking allow to consider the use of habitats and behavior in detail, make it easier to model the suitability of habitat to a healthy biodiversity on high seas, identify key areas, and optimize mobile protected areas (Maxwell et al., 2020). Such systems are also being used in climate change studies, in which thermal data is combined with other environmental variables (like water temperature and prey abundance) and as such, support studies of climate-based changes in the distribution of megafauna, as well as their phenology (Pettorelli et al., 2014). Moreover, real-time detection functions have practical usefulness in co-existence among humans and megafauna as they enable an early alert of megafauna in the coastal settlements or fisheries, contributing to the reduction of conflict and the improvement of the safety of human beings and animals (Reginald, 2024).

Future Research Directions

Future studies must be dedicated to the development of small-object detection by establishing new loss functions, including frequency-domain analysis, as well as semi-supervised learning approaches that can utilize large amounts of unlabeled thermal images sufficiently. Multimodal sensor integration, i.e., thermal imaging coupled with LiDAR, multispectral data, and passive acoustic sensing can also be used to make significant improvements, as it allows offering complementary information about bathymetry, vegetation structure, and animal vocalizations, and therefore characterizing populations holistically, with greater accuracy (Rodofili et al., 2022). Onboard detection and adaptive flight planning will also be possible with real time processing using edge computing, and drones will be able to automatically optimize survey routes in the face of dynamic marine animal distributions (Martelli et al., 2022). Further accuracy improvements could be obtained with species-specific deep learning models per species or genus of megafauna, which have better classification and detection capabilities than general-purpose architectures (Reginald, 2024). Lastly, making thermal UAS and AI-driven analytical tools more accessible to users by providing easy-to-use software platforms will enable the involvement of citizen science, facilitate distributed monitoring networks and community involvement in marine ecosystem protection (Maxwell et al., 2020).

Conclusion

The combination of thermal imaging, UAS platforms, and AI operating detection and tracking algorithms can be regarded as a revolutionary method of monitoring aquatic megafauna. It is a combined approach that allows conservation scientists to create a comprehensive, timely population data that is needed to make evidence-based decisions by addressing long-standing issues of detectability, scalability, cost-effectiveness, and disturbance of the observer. Detection accuracies of 84-92% and enumeration precision of +58% are shown by performance benchmarks, which satisfies operational standards of population monitoring. Efficiency improvements such as a 8-12 hours survey being reduced to 1.5-3 hours of survey time are converted to larger coverage areas and higher frequency of monitoring that would have been costly in the past.

To fully achieve this method, however, the remaining technical issues (small-object detection, species-specific accuracy) must be resolved, more datasets and algorithms in a wider range of taxa and environments developed, and standardized protocols and regulatory measures developed. It will be required to create multi-disciplinary teams of conservation biologists, software engineers, roboticists, and policy makers in order to support technical innovations to achieve sustainable and scalable conservation solutions.

With the ever-increasing anthropogenic pressures and accelerated loss of biodiversity, novel monitoring technologies are gaining growing importance in the detection of population changes, assessment of intervention efficacy, and the adaptive management. Artificial intelligence and thermos imaging can be a potent solution to reversing the trend of the decline of aquatic megafauna, and being a source of the data -driven conservation strategies that our generation needs. These results support the idea that UAS thermal imaging combined with AI-based detection and tracking directly fills the knowledge gaps outlined in the introduction and facilitates the useful and scalable use of this method in the process of assessing the population of elusive aquatic megafauna.

References

[1] Allard, Anna, Luke Webber, Jonas Hentati Sundberg, and Alan Brown. "New and changing use of technologies in monitoring: Drones, artificial intelligence, and environmental DNA." In *Monitoring biodiversity*, pp. 148-173. Routledge, 2023.

[2] Barreto, Jonathas, Luciano Cajaíba, Joao Batista Teixeira, Lorena Nascimento, Amanda Giacomo, Nelson Barcelos, Ticiana Fettermann, and Agnaldo Martins. "Drone-monitoring: Improving the detectability of threatened marine megafauna." *Drones* 5, no. 1 (2021): 14. https://doi.org/10.3390/drones5010014

[3] Bird, Clara N., Allison H. Dawn, Julian Dale, and David W. Johnston. "A semi-automated method for estimating Adélie penguin colony abundance from a fusion of multispectral and thermal imagery collected with unoccupied aircraft systems." *Remote Sensing* 12, no. 22 (2020): 3692. https://doi.org/10.3390/rs12223692

[4] Gooday, Oliver Jordan, Nicholas Key, Sharyn Goldstien, and Peyman Zawar-Reza. "An assessment of thermal-image acquisition with an unmanned aerial vehicle (UAV) for direct counts of coastal marine mammals ashore." *Journal of Unmanned Vehicle Systems* 6, no. 2 (2018): 100-108. https://doi.org/10.1139/juvs-2016-0029

[5] Khan, Sulaiman, Inam Ullah, Farhad Ali, Muhammad Shafiq, Yazeed Yasin Ghadi, and Taejoon Kim. "Deep learning-based marine big data fusion for ocean environment monitoring: Towards shape optimization and salient objects detection." *Frontiers in Marine Science* 9 (2023): 1094915. https://doi.org/10.3389/fmars.2022.1094915

[6] Lahoz-Monfort, José J., and Michael JL Magrath. "A comprehensive overview of technologies for species and habitat monitoring and conservation. " *BioScience* 71, no. 10 (2021): 1038-1062. https://doi.org/10.1093/biosci/biab073

[7] Leira, Frederik S., Tor Arne Johansen, and Thor I. Fossen. "Automatic detection, classification and tracking of objects in the ocean surface from UAVs using a thermal camera." In *2015 IEEE aerospace conference*, pp. 1-10. IEEE, 2015. https://doi.org/10.1109/AERO.2015.7119238

[8] Martelli, M., N. Faggioni, and F. Ponzini. "Detecting and Tracking Multi-Object in Real Marine Environment." In *Conference Proceedings of iSCSS*, vol. 2022. 2022. https://doi.org/10.24868/10707

[9] Maxwell, Sara M., Kristina M. Gjerde, Melinda G. Conners, and Larry B. Crowder. "Mobile protected areas for biodiversity on the high seas." *Science* 367, no. 6475 (2020): 252-254. https://doi.org/10.1126/science.aaz9327

[10] Pettorelli, Nathalie, William F. Laurance, Timothy G. O'Brien, Martin Wegmann, Harini Nagendra, and Woody Turner. "Satellite remote sensing for applied

ecologists: opportunities and challenges." *Journal of Applied Ecology* 51, no. 4 (2014): 839-848. https://doi.org/10.1111/1365-2664.12261

[11] Piel, A. K., A. Crunchant, I. E. Knot, Campbell Chalmers, Paul Fergus, M. Mulero-Pázmány, and Serge A. Wich. "Noninvasive technologies for primate conservation in the 21st century." *International Journal of Primatology* 43, no. 1 (2022): 133-167.

[12] Raoult, Vincent, Andrew P. Colefax, Blake M. Allan, Daniele Cagnazzi, Nataly Castelblanco-Martínez, Daniel Ierodiaconou, David W. Johnston et al. "Operational protocols for the use of drones in marine animal research." *Drones* 4, no. 4 (2020): 64. https://doi.org/10.3390/drones4040064

[13] Reginald, P. Joshua, and M. Kavitha. "Predicting Invasive Aquatic Species Spread in Coastal Ecosystems Using CLIMEX Modelling and GIS Integration." *National Journal of Smart Fisheries and Aquaculture Innovation* 3, no. 1 (2025): 1-9.

[14] Reginald, P. Joshua. "Climate Change–Driven Zoonoses: Predictive Modeling and Adaptive Risk Mitigation in Pastoral Systems." *National Journal of Animal Health and Sustainable Livestock* 2, no. 2 (2024): 34-41.

[15] Ridge, Justin T., and David W. Johnston. "Unoccupied aircraft systems (UAS) for marine ecosystem restoration." *Frontiers in Marine Science* 7 (2020): 438. https://doi.org/10.3389/fmars.2020.00438

[16] Rodofili, Esteban N., Vincent Lecours, and Michelle LaRue. "Remote sensing techniques for automated marine mammals detection: a review of methods and current challenges." *PeerJ* 10 (2022): e13540. https://doi.org/10.7717/peerj.13540

[17] Seymour, A. C., J. Dale, M. Hammill, P. N. Halpin, and D. W. Johnston. "Automated detection and enumeration of marine wildlife using unmanned aircraft systems (UAS) and thermal imagery." *Scientific reports* 7, no. 1 (2017): 45127.

[18] Tu, Zhiyi, Peng Zhou, Dongsheng Zhang, Yueyun Wang, Yang Yang, Hong-Bin Shen, and Xiaoyong Pan. "An intelligent system for marine megafauna recognition and tracking." *ICES Journal of Marine Science* 82, no. 11 (2025): fsaf207. https://doi.org/10.1093/icesjms/fsaf207

[19] Wich, Serge A., Mike Hudson, Herizo Andrianandrasana, and Steven N. Longmore. "Drones for conservation. " *Conservation technology* 35 (2021).

[20] Yaney-Keller, Adam, Rebecca R. McIntosh, Rohan H. Clarke, and Richard D. Reina. "Closing the air gap: the use of drones for studying wildlife ecophysiology." *Biological Reviews* 100, no. 3 (2025): 1206-1228. https://doi.org/10.1111/brv.13181