SPACEWHALE: Using AI to detect whales from space

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Abstract: This study presents a novel application of Artificial Intelligence (AI) to detect whales in satellite imagery, offering an unprecedented approach to assessing whale distribution and population trends in remote areas. Traditional methods for monitoring whale populations are often limited by accessibility, cost, and the challenges of covering vast ocean areas. By employing advanced AI models for object detection, our service SPACEWHALE uses a semi-automated process for identification of whales in high-resolution satellite images (e.g. WorldView 2), and very-high resolution (e.g. WorldView 3 and Pléiades Neo), enabling large-scale, consistent monitoring of whale populations. Human reviewers verify the AI-detected whales to species. Use of AI significantly improves the efficiency of image analysis compared to an only-human process. We provide an overview of SPACEWHALE projects that have been conducted successfully in multiple locations globally, including remote sub-Antarctic islands. In doing so, we demonstrate how the approach contributes to knowledge gaps around the occurrence and distribution of whales in little/unstudied regions or can complement baseline surveys to support Environmental Impact Assessments for marine development and conservation initiatives. Looking forward, AI-driven satellite monitoring could provide essential data for adaptive management strategies. The integration of AI with satellite imagery opens transformative opportunities in marine conservation, advancing efforts to protect vulnerable species in a rapidly changing environment.

Keywords: AI, satellite imagery, whale monitoring, baseline studies, impact assessment, adaptive management, conservation, remote areas, high seas

1. INTRODUCTION

Effective monitoring of marine megafauna is crucial for understanding ecosystem health, informing conservation strategies, and mitigating human impacts on vulnerable species. Whales have historically suffered dramatic population declines due to commercial whaling, which drove many species to the brink of extinction (Clapham *et al.*, 1999). Following implementation of the moratorium on commercial whaling, many populations have begun to recover; however, they are now facing a new and growing array of pressures such as bycatch in fisheries, pollution, and disturbance or collision with vessels (Avila *et al.*, 2018). Climate change is also altering oceanographic conditions, potentially shifting prey availability (Campana *et al.*, 2020) and migration routes. Meanwhile, global commitments to combat climate change, such as national and international targets for renewable energy expansion, are driving rapid development in offshore environments. Large-scale wind farms, increasing maritime traffic, and expanding industrial activities introduce heightened risks of habitat displacement, vessel strikes, noise and chemical pollution, and other disturbances. Without effective monitoring, impacts of these activities on whales may go undetected, delaying or undermining conservation and mitigation efforts.

Traditional survey methods, such as ship and aerial surveys, as well as Passive Acoustic Monitoring (PAM), can be costly, time-intensive, and tend to cover relatively small areas close to shore, and pose safety risks to surveyors. For example, vessel surveys can stay at sea for 1-2 months (depending on size of ship and hardiness of crew); however, they travel at ca. 10 kts while surveying, so coverage of a large area requires considerable time, consequently, most of the high seas are un-surveyed (Kaschner *et al.*, 2012). An aerial survey, on the other hand, is conducted faster at ca. 100-120 kts; however, it is typically restricted to coastal areas due to logistical constraints. Combined vessel and aerial surveys and use of multiple platforms can cover large areas reasonably quickly (Gilles *et al.*, 2023); however, the planning and funding of these is complex, particularly when survey areas overlap multiple national jurisdictions. Such large-scale surveys tend to happen on decadal scales as opposed to annual or seasonal, limiting their ability to detect population-level trends. PAM is another method in which devices are deployed and left to record for months at a time; however, these only detect animals that vocalise within their detection range, so acoustic monitoring is difficult to convert into counts of individuals for most species, and still require a vessel and crew to maintain the devices periodically for continuous data recording. Therefore, remote and high-seas regions, as well as rural coastal areas without supporting infrastructure, remain vastly under-monitored.

Recent advances in Very High-Resolution (VHR; ~30 cm resolution) satellite imagery have shown that large whales can be detected (Fretwell *et al.*, 2014, 2023; Cubaynes *et al.*, 2019; Corrêa *et al.*, 2022; Hodul *et al.*, 2023). These satellites take a “snapshot” of the area of interest and have the capability to capture very large and remote areas almost instantaneously. Researchers can afterwards detect whales with a minimum of about 9 m in length, as this size allows sufficient features to be represented in VHR satellite imagery for reliable identification. Smaller species can be detected if they occur in groups or have specific features such as the white body of beluga whales (Sherbo *et al.*, 2024). In certain cases, when an animal possesses a particularly large and distinct feature, it is even possible to identify individuals from space (Hodul *et al.*, 2023). Whales have also been detected in WorldView-2 imagery having a resolution of ~46 cm per pixel (Höschle *et al.*, 2022). Upcoming higher-resolution satellites (~10-15 cm resolution) are expected to enhance the ability to detect smaller species such as dolphins, porpoise and seals.

Analysis of satellite imagery is time consuming and tedious, so animals might be overlooked. Consequently, it offers an ideal opportunity to use Artificial Intelligence (AI) to accelerate and improve the accuracy of detections. Workflows have been developed to achieve this and several AI methods, e.g. Faster R-CNN and YOLOv5, have been tested (Borowicz *et al.*, 2019; Green *et al.*, 2023).

Here, we focus on the SPACEWHALE technique which has been established to provide a suite of services from satellite image acquisition, AI-based object detection, to human verification (Borowicz *et al.*, 2019; Höschle *et al.*, 2021, 2022). This paper explores how SPACEWHALE supports impact assessments, enhances adaptive management strategies, and contributes to conservation in data-deficient areas.

2. METHODS

2.1. Satellite Image Acquisition

Satellite imagery is collected using commercially available VHR satellites, such as WorldView-3 and WorldView-Legion (Maxar Technologies), and Pléiades Neo (Airbus). These satellites provide sub-meter resolution imagery (~30 cm per pixel), which is sufficient to detect individual whales at or near the sea surface (Borowicz *et al.*, 2019; Höschle *et al.*, 2021, 2022). The panchromatic band (black-and-white, ~0.3 m) and multispectral bands (visible, including coastal blue, which penetrates deeper into water and near-infrared, ~1.2 m) enhance visibility, particularly for detecting submerged whales in clear conditions. Through SPACEWHALE, satellite tasking can be scheduled in advance for targeted surveys, and environmental conditions such as cloud coverage and sea state are checked for every satellite pass.

2.2. AI-Based Whale Detection

Once acquired, satellite images undergo pre-processing to enhance clarity and reduce noise. The applied enhancements consist of contrast enhancement and advanced denoising techniques. Following these image processing procedures, the refined imagery is subsequently forwarded to the AI pipeline for further analysis. The SPACEWHALE system then applies a Faster Region-Based Convolutional Neural Network (Faster R-CNN) trained on down-sampled digital aerial video images of minke whales and other species, as well as drone footage from various species and locations and satellite imagery from previous acquisitions. The AI model scans the images, detecting objects that match known whale features such as body shape, size, and contrast against the surrounding water. The algorithm produces bounding boxes around detected objects, assigning a confidence score to each detection (Figure 1).

2.3. Human Verification and Species Identification

Since AI detection focuses on increasing the true positive rate as high as possible, false positives may be also detected; therefore, all candidate whale detections are reviewed by a team of experienced human analysts to confirm the detection and identify the species. Experienced reviewers classify detections into three confidence categories: definite, likely, and possible whales. They assess features such as whale morphology, surfacing behaviour, and spatial positioning relative to known whale habitats. In cases where species identification is ambiguous, detections may be categorized as "unclassified whales".

Validated whale detections are then georeferenced and compiled into spatial distribution maps, which can be integrated with Geographic Information Systems (GIS) for further analysis.

3. RESULTS

The SPACEWHALE methodology (Figure 1) has demonstrated high accuracy and precision in detecting whales from satellite imagery, although performance varies depending on image resolution, environmental conditions, and species characteristics (e.g. colour, size, behaviour). Studies evaluating its effectiveness have shown that AI-assisted detection can significantly enhance the efficiency of whale monitoring. Additionally, AI has potential to detect more animals in the imagery than can be seen by human observers. For example, the SPACEWHALE faster R-CNN object detection method was applied to imagery previously analysed by hand in the Pelagos Sanctuary and 13 additional whales were identified which were missed by the manual review process.

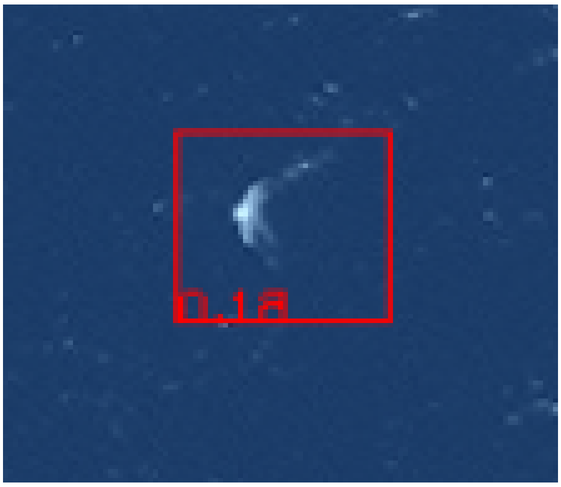

Figure 1: Example WorldView-3 satellite image of a fin whale (Balaenoptera physalus) lunge feeding with open jaw © 2020 Maxar Technologies.

Borowicz *et al.* (2019) assessed the accuracy of Convolutional Neural Networks (CNNs) trained on digital aerial images from minke whales and applied them to WorldView-3 satellite imagery. Their best-performing model, ResNet-152, achieved 100% precision, meaning no whales present in the imagery were missed, and 94% recall, indicating a low rate of false positives. These results demonstrated the feasibility of AI-assisted whale detection, though distinguishing whales from visually similar ocean features, such as waves and whitecaps, remained a challenge.

Höschle *et al.* (2021) further evaluated the effectiveness of VHR satellite imagery and AI models in detecting large whale species. This study found that automation significantly reduced the manual workload of analysing satellite images (from 3 hr 20 min to 1 hr for 100 km^2) while maintaining high detection accuracy. Verification of AI-detected whale-like objects as well as species-level identification highlighted the necessity of a semi-automated approach in which AI improves detection efficiency, but final classification relies on expert review.

In Höschle *et al.* (2022), satellite-based whale detections were compared with boat-based surveys in Port Ross, New Zealand, to verify the methodology. The satellite-based method (using coarser 46-cm resolution imagery from WorldView-2) observed similar numbers of juvenile and adult southern right whales; however, fewer calves were detected. This demonstrated that the SPACEWHALE methodology can provide complementary data in explored regions and provide baseline data in unexplored regions.

Several factors influence the precision and accuracy of the SPACEWHALE methodology. Image resolution plays a crucial role, with VHR images (~0.30 m) improving detection accuracy, particularly for smaller whales and calves, while high resolutions (~0.50 m) increase the likelihood of misclassifications. Environmental conditions, such as cloud cover, whitecaps, and rough seas, can obscure whale features and reduce detection accuracy. Additionally, larger whale species, such as blue whales, tend to be detected with higher confidence than smaller, more cryptic species. AI model training datasets are also a critical factor, as training data for some species or behaviours is currently limited.

4. DISCUSSION

As has been demonstrated, SPACEWHALE offers a unique tool for monitoring whales across vast areas. Despite its many advantages, satellite-based whale monitoring is not without its challenges. One of the primary limitations is with satellite tasking constraints, as VHR satellites are commercial assets, and acquiring new imagery requires scheduling dedicated overpasses. This process is subject to availability conflicts, and weather conditions, meaning that researchers may face delays or be unable to obtain data during key biological periods, such as calving or migration seasons. Additionally, the cost of acquiring (very) high-resolution satellite imagery remains a significant barrier. While satellite monitoring can be more cost-effective than repeated aerial or vessel-based surveys over large areas, individual image acquisitions can be expensive, especially for researchers or conservation organisations with limited funding. The cost scales with the size of the survey area, frequency of data collection, and resolution required, making long-term monitoring efforts financially challenging.

Another key disadvantage is the limited availability of pre-existing high-seas data within online repositories, which restricts access to historical satellite imagery. Most archived satellite data are concentrated over terrestrial, coastal and economically significant regions, as these are the areas where commercial tasking has traditionally been focused. In contrast, large areas of the high seas—where many whale populations migrate and feed—have received far less attention resulting in sparce coverage and limited accessibility in imagery archives. This means that researchers seeking to monitor whales in international waters may have to rely exclusively on new, costly image acquisitions, limiting the feasibility of broad-scale, long-term studies in these remote areas. Additionally, persistent cloud cover and rough sea states can reduce detection success in some areas. Addressing these limitations will require continued investment in satellite technologies, improvements in AI detection models, and increased collaboration between governments, commercial satellite providers, and conservation organisations to enhance data accessibility and affordability for marine monitoring.

Despite these challenges, satellite monitoring still offers huge opportunities for monitoring and management of whales, particularly as additional satellites come into operation, the resolution of imagery increases, and costs might decrease in future. One of the most significant benefits is its ability to fill critical knowledge gaps in remote and high seas regions, where traditional survey methods are either impractical, prohibitively expensive, or come at high health and safety risk. Many whale populations inhabit vast, isolated areas, such as the sub-Antarctic islands, the Southern Ocean, and the deep offshore waters of the Pacific and Atlantic, where systematic monitoring has historically been sparse (Kaschner *et al.*, 2012). The use of VHR satellite imagery could allow researchers to detect whales in these under-surveyed regions, providing valuable data on population size, distribution, and seasonal movements. This is particularly important for species whose ranges extend beyond national jurisdictions, as conservation efforts in international waters often lack comprehensive baseline data.

By establishing baseline population distributions in areas where no prior data exist, SPACEWHALE offers a powerful tool for conservation planning. Governments, researchers, and conservation organisations can use these data to assess whether certain areas serve as critical habitats, such as breeding, calving, or feeding grounds, and prioritise them for future protection. In regions without the physical infrastructure to support vessel or aerial surveys, such as the high seas, polar regions, and developing coastal nations, satellite-based AI monitoring provides a cost-effective alternative. This approach can help inform global efforts, such as those led by the International Whaling Commission (IWC), the Convention on Migratory Species (CMS), and the Important Marine Mammal Areas (IMMA) initiative, to enhance conservation in previously unmonitored waters. This could also support the COP15 30x30 initiative of protecting 30% of the world’s land and marine environments by 2030.

As human activities expand into offshore environments, particularly for renewable energy projects, deep-sea mining, and increased shipping operations, robust Environmental Impact Assessments (EIAs) are essential to mitigate potential effects on whale populations. SPACEWHALE provides a non-invasive, large-scale monitoring approach with 100% surface coverage that can generate baseline whale population data before marine development projects commence, ensuring that critical habitats and migration corridors are properly accounted for in planning processes. By systematically detecting whales over time, satellite-based monitoring can identify key aggregation areas, helping developers and regulators to design projects that minimise disruption to marine megafauna.

Beyond baseline assessments, SPACEWHALE also enables long-term monitoring of whale populations before, during, and after industrial activities, allowing for the evaluation of mitigation measures. By comparing pre- and post-impact population trends, researchers can assess the effectiveness of management strategies, such as seasonal restrictions on construction, noise mitigation technologies, or designated exclusion zones. Additionally, satellite-based AI detection can identify large-scale distribution shifts resulting from anthropogenic disturbances, such as offshore wind farms, oil and gas exploration, increased maritime traffic, and rising underwater noise pollution. Detecting these shifts early can help decision-makers adapt mitigation strategies more reactively, as opposed to waiting ten years for the next survey, minimising cumulative impacts on vulnerable whale populations.

With an improved ability to detect wide-scale population changes and distribution shifts, SPACEWHALE enhances data-driven decision-making for dynamic conservation efforts. For example, if satellite monitoring detects an increase in whale presence in an area of high shipping activity, authorities could implement temporary speed restrictions or adjust shipping lanes to reduce the risk of vessel strikes. Similarly, if whales are observed using a new habitat previously unrecognised as important, Marine Protected Area (MPA) boundaries could be adjusted to provide better conservation coverage. These types of responsive, data-driven management actions are becoming increasingly important as whale populations recover from historical exploitation while facing new threats from a rapidly changing marine environment.

Incorporating AI-assisted satellite monitoring into adaptive management frameworks could also improve global efforts to monitor and mitigate climate change impacts on whales. As ocean temperatures rise and prey distributions shift, whale migration routes may change, requiring flexible and proactive conservation measures. SPACEWHALE has the potential to transform how we record and protect marine megafauna, ensuring that conservation actions remain effective, timely, and scalable in a rapidly evolving world.

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