Megafauna from Space: Using Very High Resolution (VHR) Satellite Imagery to Detect Whales and Sharks

Lianna Gendall, Jocelyn C. Nelson, Rebecca Martone, Lara Slapcoff, Aisha Uduman, Paul Grant, Romney McPhie

Species at Risk Program
Fisheries and Oceans Canada
200-401 Burrard Street
Vancouver, BC
Canada
V6C 3S4

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MEGAFAUNA FROM SPACE: USING VERY HIGH RESOLUTION (VHR) SATELLITE IMAGERY TO DETECT WHALES AND SHARKS

By

Lianna Gendall[1], Jocelyn C. Nelson[2], Rebecca Martone[3], Lara Slapcoff[4], Aisha Uduman[4], Paul Grant[5], Romney McPhie[4]

Species at Risk Program
Fisheries and Oceans Canada
200-401 Burrard St
Vancouver, BC
V6C 3S4

[1] Spectral Remote Sensing Laboratory, Department of Geography, University of Victoria, 3800 Finnerty Road, Victoria, BC, Canada V8P 5C2

[2] Fisheries and Oceans Canada, Science Branch, Pacific Region, Pacific Biological Station, 3190 Hammond Bay Road, Nanaimo, BC, Canada V9T 6N7

[3] Ocean Decade Regional Collaborative Center for the Northeast Pacific Ocean, Tula Foundation, P.O. Box 25039, Campbell River, BC, Canada V9W 0B7

[4] Fisheries and Oceans Canada, Species at Risk Program, Marine Team, 200-401 Burrard St, Vancouver, BC, Canada V6C 3S4

[5] Fisheries and Oceans Canada, Science Branch, Pacific Region, Institute of Ocean Sciences, 9860 West Saanich Road, Sidney, BC, Canada V8L 4B2

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Emerging technologies for detecting and monitoring large-bodied animals – or ‘megafauna’ – are becoming increasingly important for assessing presence, abundance, density, distribution, and health status, and for mitigating threats to at-risk species. Recent work globally has shown that marine megafauna, such as baleen whales, can be successfully detected using very high resolution (VHR) satellite imagery, allowing for scientific studies, monitoring, and forecasting in remote and inaccessible areas. In Canada, the Canadian Space Agency in collaboration with Fisheries and Oceans Canada and Transport Canada recently launched a smartWhales initiative funding numerous research and development projects leveraging satellite detection data to protect the North Atlantic right whale (*Eubalaena glacialis*). In the Northeast Pacific, numerous megafauna species, such as the blue whale (*Balaenoptera musculus*), the fin whale (*Balaenoptera physalus)*, and the basking shark (*Cetorhinus maximus*), are listed under Canada’s *Species at Risk Act* as either endangered or threatened. The application of VHR satellite imagery in the Pacific region is recommended to supplement traditional surveys using boat, land, and/or aerial platforms, to support a greater understanding of species at risk and their habitats and to work towards their survival and recovery. Automated detection using machine learning and VHR, in particular, has the potential to increase the capability and efficiency with which megafauna are detected and monitored, and forecasting using these technologies can be used towards threat mitigation and marine planning.

Résumé

Gendall, L, Nelson, J.C., Martone, R., Slapcoff , L., Uduman, A., Grant, P., and McPhie, R. 2022. Megafauna from space: Using very high resolution (VHR) satellite imagery to detect whales and sharks. Can. Manuscr. Rep. Fish. Aquat. Sci. 3248: x + 50 p.

Les technologies émergentes de détection et de surveillance des animaux de grande taille - ou « mégafaune » - deviennent de plus en plus importantes pour évaluer la présence, l'abondance, la densité, la distribution et l'état de santé, et pour atténuer les menaces pesant sur les espèces en péril. Des travaux récents à l'échelle mondiale ont montré que la mégafaune marine, telle que les baleines à fanons, peut être détectée avec succès à l'aide d'images satellite à très haute résolution (VHR), permettant des études scientifiques, la surveillance et la prévision dans des zones éloignées et inaccessibles. Au Canada, l'Agence spatiale canadienne, en collaboration avec Pêches et Océans Canada et Transports Canada, a récemment lancé l'initiative SmartWhales finançant de nombreux projets de recherche et développement qui profitent de données de détection par satellite pour protéger la baleine noire de l'Atlantique Nord (*Eubalaena glacialis*). Dans le Pacifique Nord-Est, de nombreuses espèces de mégafaune, telles que le rorqual bleu (*Balaenoptera musculus*), le rorqual commun (*Balaenoptera physalus*) et le requin pèlerin (*Cetorhinus maximus*), sont répertoriées en vertu de la Loi sur les espèces en péril du Canada comme étant en voie de disparition ou menacées. L'application de l'imagerie satellitaire VHR dans la région du Pacifique est recommandée pour compléter les relevés traditionnels à l'aide de bateaux, de plates-formes terrestres et/ou aériennes, afin de favoriser une meilleure compréhension des espèces en péril et de leurs habitats et d'oeuvrer à leur survie et à leur rétablissement. La détection automatisée utilisant l'apprentissage automatique et le VHR, en particulier, a le potentiel d'augmenter la capacité et l'efficacité avec lesquelles la mégafaune est détectée et surveillée, et les prévisions utilisant ces technologies peuvent être utilisées pour l'atténuation des menaces et la planification marine.

Glossary

Active satellites: Satellites that use their own energy source to emit radiation towards a specific target of interest which is then reflected back to the sensor in order to monitor said target of interest.

Algorithm: A sequence of calculations that follows a process/set of rules in order to solve a specific problem.

Attitude control device: A device located on a satellite which controls the satellite's orientation in space.

Automated detection (system): A system that ingests satellite imagery and automatically classifies, counts, and/or identifies targets of interest within the image without human supervision.

Availability bias: The amount of time a species spends at the surface versus at depth.

Citizen science: A process where the general public participates in scientific research to increase data collection and knowledge creation on specific topics of interest.

Convolutional Neural Network (CNN): A complex machine learning computer vision algorithm that use image features like colour, shape, and texture to infer the contents of an image.

Crowdsourcing: A process in which a large number of people (paid or unpaid) collect and/or process data.

Data augmentation: A process where additional images for training machine-learning algorithms are created by altering the pre-existing images within the original training dataset by rotating, cropping, inverting, changing the scale and/or brightness level of the images.

Directional correlated random walk: A random walk is a process for determining the probable location of a target of interest using a sequence of discrete, fixed-length steps in random directions. Specifically, in a directional correlated random walk the direction in which a step is taken is correlated with the last direction of movement and is commonly used to model animal movements.

Forecasting (system): A system that can predict the movement of a target of interest once an observation of that target has been made in space and time by using previous information like the target's historic distribution, and/or habitat characteristics.

Local Ecological Knowledge: Knowledge gained through personal observation and interactions with local ecosystems that can be passed down through generations but is not directly tied to Indigenous ways of knowing.

Machine learning: Is the use and development of computer systems that are able to learn and adapt without human instructions by using algorithms/statistical models to analyze and draw inferences from data.

Megafauna: Large-bodied animals.

Multispectral satellite imagery: Multispectral imagery captures light in specific ranges of the electromagnetic spectrum, also known as bands (e.g., red, green, blue, near-infrared), which can be viewed together to make a true colour image similar to what would be seen with the human eye.

Noise-reducing filters: Algorithms that reduce noise (speckling) in imagery in order to see targets of interest clearer.

Orthorectified: A process where geometric distortions are removed from imagery so that the locations of objects within the imagery match the spatial accuracy and precision of a reference map and elevation models.

Panchromatic band: A band collected by a satellite that captures a wide range of the electromagnetic spectrum (across the visible and near-infrared range) and creates a greyscale image of the relative brightness of objects within an image.

Pansharpening: The panchromatic band is combined with the multispectral bands to enhance the resolution of the colour image to that of the resolution of the panchromatic band.

Passive remote sensing: Uses the sunlight reflected off the Earth's surface to create an image.

Real-time detection (system): A system that ingests satellite imagery as close to its acquisition time as possible and feeds the imagery into an automated detection system which lets users know if a target of interest has been detected within the imagery almost instantaneously.

Remote sensing: The process of monitoring an area and/or object without making physical contact with the object (see passive vs active remote sensing for more information).

Resolution (Spatial): The linear measurement of the side of a single pixel that makes up an image; the smaller the number the higher the resolution and the more detail that can be seen within the image.

Revisit time: The time elapsed between the collection of images of the same point on the Earth's surface by a satellite.

Semi-automated detection (system): A system that ingests imagery and flags any that have possible occurrences of targets of interest in order to minimize the time associated with visually classifying all the imagery manually.

Spectral: Colour, specifically referring to the brightness of a certain object at different wavelengths of the electromagnetic spectrum.

Spectral signature: The shape of the curve when the brightness of a certain object is plotted across the different wavelengths of the electromagnetic spectrum.

Supervised (classification): Is a human-guided type of data classification where the human picks the classes and assigns samples to each class in order to train the classifier.

Swath width: The width of an image that a satellite captures perpendicular to its path of movement.

Tasking: When users pay to have a satellite actively collect imagery over a specific area within a specific time window.

Traditional Ecological Knowledge: Knowledge gained through personal observation, cultural practices, and interactions with local ecosystems that is passed down through multiple generations associated with Indigenous ways of knowing.

Unsupervised (classification): Is a type of data classification where the software decides what classes are present within the data and places them into those classes.

Very high-resolution satellite imagery: Imagery collected by a satellite with a spatial resolution lower than 1 m.

Acronyms

AOI – Areas of interest

BCCSN – BC Cetacean Sightings Network

CC – Central Coast

CHS – Canadian Hydrographic Service

CNN – Convolutional Neural Network

CSA – Canadian Space Agency

DFO – Department of Fisheries and Oceans, Canada

FSR – Fluvial Systems Research Inc.

GSTS – Global Space Technology Solutions Inc.

IP – Inner Passage

IPCA - Indigenous Protected and Conserved Areas

M – resolution of the multispectral bands

NIR – Near infrared

NMCA – National Marine Conservation Area

NMSO – National Masters Standing Offer

NWVI – Northwest Vancouver Island

NWVIO – Northwest Vancouver Island Offshore

P – spatial resolution of the panchromatic band

SAR – Synthetic Aperture Radar

SARA – Species at Risk Act

SARP – Species at Risk Program

SS – Southern Salish Sea

SSN – (DFO) Shark Sightings Network

SWAMM – The Space Whales and Arctic Marine Mammals (Program)

SWVI – Southwest Vancouver Island

SWVIO – Southwest Vancouver Island Offshore

TC – Transport Canada

VHR - Very high resolution (satellite)

Introduction

Following the International Commission on Whaling's establishment in 1949, some whale populations are recovering (Punt and Donovan, 2007). For other species and populations, their statuses cannot be effectively evaluated due to data deficiencies (Punt and Donovan, 2007). Surveys are crucial for assessing marine megafauna presence, abundance, density, distribution, and health, among other characteristics. Surveys are particularly important for data deficient species and species at risk, where information on abundance and distribution is used for assessment and ongoing recovery efforts. Traditionally, marine megafauna are monitored using boats, planes, ground stations, hydrophones, live-capture and tagging surveys (Höschle *et al.*, 2021). These traditional surveys are logistically complicated and very expensive in cases where species inhabit remote areas, have large ranges, and/or are seasonally migratory (Kaschner *et al.*, 2012; Höschle *et al.*, 2021).

With the emergence of new remote sensing technologies, innovative methods have been developed to monitor megafauna using satellite imagery (Höschle *et al.*, 2021). Over the past decade, improvements in technology have enabled satellites to capture imagery at a sub-metre spatial resolution (pixel size); this imagery is known as very high resolution (VHR) satellite imagery (Abileah, 2002). Medium- to large-sized cetaceans, including southern right whales (*Eubalaena australis*; Abileah, 2002; Fretwell *et al.*, 2014; Cubaynes *et al.*, 2019; Corrêa *et al.*, 2020), North Pacific humpback whales (*Megaptera novaeangliae;* Cubaynes *et al.*, 2019), and fin whales (*Balaenoptera physalus;* Cubaynes *et al.*, 2019; Guirado *et al.*, 2019), have been detected using VHR imagery, highlighting the potential use of this technology to monitor marine megafauna in remote and inaccessible locations and at a large scale (Fretwell *et al.*, 2014; Cubaynes *et al.*, 2019; Bamford *et al.*, 2020; Clarke *et al.*, 2021; Höschle *et al.*, 2021; Charry *et al.*, 2021; see Appendix A).

Abileah (2002) was the first to propose using VHR satellite imagery to detect whales; however, the resolution of imagery was not yet high enough to detect whales with complete certainty. After a 2014 change in legislation in the United States allowed commercial satellite imagery companies to start producing imagery at very high resolutions (i.e., less than 50 cm; MAXAR Technologies, 2014), more focus was put on developing robust methods to detect marine megafauna. Fretwell *et al.*, (2014) successfully identified southern right whales in VHR satellite imagery in 2014, and after the launch of the world's highest resolution satellite to date in 2014 – Worldview 3 with a spatial resolution of 31 cm – many studies successfully identify whales using satellite imagery (Borowicz *et al.*, 2019; Cubaynes *et al.*, 2019, 2020; Fretwell *et al.*, 2019; Guirado *et al.*, 2019; Bamford *et al.*, 2020; Corrêa *et al.*, 2020; Charry *et al.*, 2021; Clarke *et al.*, 2021; Höschle *et al.*, 2021).

Per unit area, and as the technology develops further, VHR satellites have the potential to provide cheaper and safer means of studying marine megafauna in remote places compared to traditional surveys. Some studies have even proposed and successfully used this technology to monitor whale stranding events (Fretwell *et al.*, 2019; Clarke *et al.*, 2021). While VHR satellite detection and monitoring cannot fully replace traditional survey methods, when used in tandem with traditional methods, they can allow researchers and governments to deepen their understanding of species – including species at risk – and increase the ability to monitor across large areas. For implementation at a large scale, some automated detection methods have been developed using machine learning algorithms (Borowicz *et al.*, 2019; Guirado *et al.*, 2019). These algorithms increase the capability and efficiency of megafauna detection from satellite imagery (Borowicz *et al.*, 2019; Guirado *et al.*, 2019) and are the first step in developing real-time detection and forecasting models that can be used for threat mitigation and marine planning.

In Canada, a smartWhales initiative was launched in 2021, funding numerous research and development projects that use VHR satellite detection to monitor and protect the North Atlantic right whale (*Eubalaena glacialis*; Hodul, pers. comm., 2022; Pisano, pers. comm., 2022; Tsui, pers. comm., 2022). In addition, a Space Whales and Arctic Marine Mammals (SWAMM) program was also established in 2021, which uses VHR satellite imagery to detect and estimate the densities of beluga whales (*Delphinapterus leucas*), narwhals (*Monodon monoceros*), and potentially walruses (*Odobenus rosmarus*) in the Canadian Arctic (Watt, pers. comm., 2022).

On the Canadian Pacific Coast, there are several whale and shark species that are listed under Canada's *Species at Risk Act* (SARA), including the fin whale, North Pacific humpback whale, blue whale (*Balaenoptera musculus*), sei whale (*Balaenoptera borealis)*, North Pacific right whale (*Eubalaena japonica*), basking shark (*Cetorhinus maximus*), and multiple ecotypes of killer whale (*Orcinus orca*). While traditional survey methods have been successful in increasing our understanding of all megafauna species on the Pacific Coast of Canada, VHR satellite detection – especially an automated detection system and/or forecasting system – could aid in answering aspects of megafauna population biology and advance recovery efforts. Additionally, there are numerous large-scale initiatives such as spill response planning, and monitoring and management of marine protected areas, such as National Marine Conservation Areas (NMCAs), on the Canadian Pacific Coast that could benefit from the compilation of a VHR satellite imagery database and advances in satellite detection methodologies.

Given the growing interest in using VHR satellite imagery and advanced analysis methods to detect and monitor marine megafauna, this report: 1) reviews the use of VHR satellite imagery to detect marine megafauna, globally and nationally; and 2) explores the potential uses of this technology on the Canadian Pacific Coast. Specifically, the first part of the report outlines: the development of VHR satellite imagery technology; the emergence of using VHR satellite imagery to detect megafauna; and the general opportunities and challenges associated with this approach. Ongoing research in Canada and globally is highlighted. The second part highlights the availability of VHR satellite imagery and some considerations and applications, with a focus on the Pacific Coast. To demonstrate the type and quality of VHR imagery availability for the Pacific Coast, a case study for basking shark areas of interest is included.

Current State of Science

2.1 The emergence of VHR satellite imagery technology

Since the first satellite, Sputnik 1, was launched by the Soviet Union on October 4, 1957, the development of satellite technology has radically changed the way researchers gather data at large scales (Lanius, Logsdon and Smith, 2013). The first image of Earth's surface was taken by the U.S.'s Explorer 6 satellite in August 1959 (Cabby, 2014) and the Landsat series, first launched in 1972, revolutionized the understanding of the Earth's environment with its freely available global coverage of medium resolution (60 to 30 m spatial resolution) satellite imagery (Williams, Goward and Arvidson, 2006). Into the late 1980s, the French SPOT satellite series further increased the availability of medium resolution satellite imagery with the launch of SPOT 1, 2 and 3, which offered 20 m multispectral satellite imagery accompanied with its higher resolution 10 m panchromatic band (Courtois and Traizet, 1986). Multispectral imagery captures light in specific ranges of the electromagnetic spectrum, also known as bands (e.g., red, green, blue, near-infrared), which can be viewed together to make a true colour image similar to what would be seen with the human eye (Coffey, 2012). The panchromatic band captures a much wider range of the electromagnetic spectrum and creates a greyscale image (Amro *et al.*, 2011). Because this band is collected at a higher resolution (e.g. for SPOT 2, the panchromatic band is 10 m and the multispectral band is 20 m), it is used to see finer details within imagery and can be combined with the multispectral bands, known as pansharpening, to enhance the resolution of the colour imagery (Amro *et al.*, 2011).

Changes in U.S. legislation in the mid to late 1990s allowing higher resolution imagery (up to 1 m) incentivized American companies to start producing higher resolution satellite imagery than foreign providers (Abileah, 2002). Among a myriad of launch failures and satellite malfunctions, the company Space Imaging successfully launched IKONOS 2 in 1999, which serviced the globe with the production of 1 m panchromatic and 4 m multispectral imagery (Abileah, 2002). Following the IKONOS 2 launch, a number of sub-metre resolution (or very high resolution, VHR) commercial satellites became available in the 21st century, such as Quickbird 2, Worldview 1, Worldview 2, and Geoeye 1. A list of VHR satellites of 60 cm or better resolution is provided in **Table 1**. The Worldview 3 satellite launched in 2014 provides the highest possible resolution with its roughly 30 cm panchromatic band, along with Airbus' newly launched Pleaides Neo satellite constellation. However, Worldview 3 imagery can now be sharpened to 15 cm resolution with MAXAR's new enhancing artificial intelligence 'HD Technology'. Worldview 4, launched in 2016, was supposed to also provide this VHR imagery; however, Worldview 4 suffered from an attitude control device failure in 2019 (MAXAR, January 07 2019), and thus only 3 years of archived imagery are available from Worldview 4.

Table 1: Summary of VHR satellites with spatial resolutions of 60 cm or better. In the second column, P represents the spatial resolution of the panchromatic band and M represents the resolution of the multispectral band. Swath width represents that of an image taken at Nadir (straight down).

Satellite	*Resolution (m)*	*Launch Date*	*Revisit Time*	*Swath Width*	*Providers*
Worldview 3	0.31 P (0.15 HD*) 1.24 M	August 2014	<1 day	13.1 km	MDA or Apollo
Pleaides Neo Constellation (Four satellites)	0.30 P 1.2 M	April & August 2021	<1 day	14 km	Airbus or Apollo
Worldview 4	0.31 P 1.24 M	January 2016-January 2019*	<1 day	13.1 km	MDA or Apollo
Geoeye 1	0.40 P 1.65 M	September 2008	3 days	15.2 km	MDA or Apollo
Worldview 2	0.40 P 1.85 P	October 2009	1.1 days	16.4 km	MDA or Apollo
Kompsat 3A	0.40 P (from 0.55 P) 1.6 M (from 2.2 M)	March 2015	< 1 day	12 km	Apollo
SkySat Constellation (21 microsats)	0.50 P (older 0.72-0.90 P) 0.81 M (older 1.00 M)	November 2013	<1 day	8 km	Planet or Apollo
Superview 1	0.50 P 2.00 M	December 2016	1 day	12 km	Apollo
Pleaides 1A/1B	0.50 P (from 0.70 P) 2.0 M (from 2.8 M)	December 2011	<1 day	20 km	Airbus or Apollo
Worldview 1	0.50 P	September 2007	1.7 days	17.6 km	MDA or Apollo
Quickbird 2	0.60 P 2.4 M	October 2001-December 2015*	2.4 days	16.8 km	MDA or Apollo

*HD refers to MAXAR's new proprietary artificial intelligence sharpening software 'HD Technology'
*Worldview 4 was unable to continue collecting imagery past January 2019 due to an attitude control device failure
*Quickbird 2 was taken out of operation in December 2015 due to orbit decay after 13 years of imagery collection

Satellites can either collect continuous images of the Earth's surface, like the Landsat series, or they can collect imagery in areas and at times when consumers pay for it; the latter is known as 'tasking'. Most commercial VHR satellites are task-based, including all VHR satellites of 60 cm or better resolution listed in **Table 1**. Tasking imagery can be quite costly (e.g., between 45USD/km^2 to 62.50USD/ km^2 with a minimum purchase area of 100 km^2 as of March 2021); however, consumers can access the archives of previously tasked imagery at lower costs (e.g., between 14USD/ km^2 to 24USD/ km^2 with a minimum purchase area of 25 km^2 as of March 2021) (see **Section 2.5** below for more information on the cost of archived versus tasked imagery). Earth observation satellites like the ones listed in **Table 1** use the sunlight reflected off the Earth's surface to create an image, known as 'passive remote sensing'. Active satellites use their own energy source to emit radiation which is reflected back to monitor specific areas of interest (Natural Resources Canada, 2022). Although no work has been published on using active satellites such as Synthetic Aperture Radar (SAR) to monitor wildlife, methods are currently being developed (Hodul, pers. comm., 2022).

With the investment and development of satellite technology on the rise, higher quality imagery at lower costs and higher coverage are becoming available (Höschle *et al.*, 2021). Two more satellites of the Pleaides Neo constellation will be launched in late 2022 (Airbus, October 28, 2021, Airbus, March 8, 2022) and MAXAR plans on launching the first of its six new Legion satellites in 2022 to add to its current Worldview and Geoeye satellites in orbit, which will allow MAXAR to provide imagery at a resolution of 31 cm to 50 cm for most locations on the Earth's surface (primarily low to mid-latitudes) up to 15 times in a single day (MAXAR, 2022).

2.2 The development of using VHR satellite imagery to detect megafauna

Satellite imagery of varying resolutions provides the opportunity to non-invasively survey large-bodied animals (or 'megafauna') over large areas. Schwaller *et al.*, (1984) were the first to establish that aggregates of Adelie penguins (*Pygoscelis adeliae*) could be monitored on Ross Island in the Antarctic using Landsat imagery. Following this study, satellites have been used to detect several wildlife species from space, including the African elephant (*Loxodonta africana*; Yang *et al.*, 2014), Weddell seals (*Leptonychotes weddellii*; LaRue *et al.*, 2011), southern elephant seals (*Mirounga leonine*, (McMahon *et al.*, 2014) polar bears (*Ursus maritmus;* Stapleton *et al.*, 2014), walruses (Boltunov *et al.*, 2012), masked boobies (*Sula dactylatra;* Hughes *et al.*, 2011), domestic cattle (*Bos taurus;* Begall *et al.*, 2008), and numerous species of penguin (Barber-Meyer, Kooyman and Ponganis, 2007; Fretwell *et al.*, 2012; Naveen *et al.*, 2012; Lynch and LaRue, 2014, 2014; LaRue, Stapleton and Anderson, 2017). A global review by LaRue *et al.*, (2017) emphasizes that wildlife found in open landscapes, with large body sizes, strong habitat associations, and high colour contrast with their environment make ideal candidates for VHR satellite imagery detection. Marine megafauna are good candidates for monitoring from space because they are large-bodied, inhabit open spaces, and are often found in specific areas for feeding/breeding activities.

Abileah (2001) first proposed using VHR satellite imagery as a possible means of detecting marine mammals in the early 2000s. Abileah (2002) tested the ability to detect whales in satellite imagery using the IKONOS 2 satellite imagery at a 1 m panchromatic band resolution. Whale-like objects were detected in imagery of the Hawaiian Islands Humpback Whale National Marine Sanctuary in Maui, and a killer whale was passably identified in an enclosure at the SeaWorld Marine Park in San Diego, California (Abileah, 2002). Although whale-like objects were detected in both images, the 1 m resolution of the IKONOS 2 satellite was unable to capture enough detail to confidently identify these objects as whales.

Following advancements in satellite imaging technology, Fretwell *et al.*, (2014) used Digital Globe's (now MAXAR's) Worldview 2 satellite imagery at a 50 cm panchromatic resolution to successfully manually identify and count southern right whales in part of the world's largest breeding aggregation in the Golfo Nuevo, Peninsula Valdes, Argentina. This study was made possible because of the Golfo Nuevo's calm seas and the southern right whale's propensity to gather in large groups at predictable times of the year for breeding. Along with manual counting, Fretwell *et al.,* (2014) tested a number of supervised (human-guided) and unsupervised (calculated by software) classification methods to identify whales. Although manual classification resulted in the best overall results, the authors found that a simple threshold classification method was able to find 84.6% of the total whales within the imagery, hinting at the possibility of automation in the future.

Cubaynes *et al.,* (2019) were the first to use Worldview 3 (31 cm panchromatic resolution) imagery to detect baleen whales: fin whales in the Ligurian Sea, humpback whales in Hawaii, southern right whales in the Peninsula Valdes, and grey whales (*Eschrichtius robustus*) in Laguna San Ignacio. The authors were able to differentiate species because they focused on areas where only one type of whale occurred, or where multiple morphologically distinct whales occurred. They only looked at regions where whales aggregate in high numbers, and used imagery taken in optimal conditions with no clouds and calm seas. They present a manual method for counting whales with different levels of confidence, which has since been adapted by other researchers (Bamford *et al.*, 2020; Corrêa *et al.*, 2020; Charry *et al.*, 2021). Cubaynes *et al.,* (2019) highlight that species can be hard to differentiate when multiple morphologically similar species occur in the same region, such as on the Pacific Coast of Canada.

Cubaynes *et al.,* (2020) attempted to categorize the spectral (colour) differences between species to help with species' differentiation at the satellite level by measuring the *in situ* spectral signature of previously frozen skin samples of eight different whale species: the bowhead whale (*Balaena mysticetus*), minke whale (*Balaenoptera acutorostrata*), Bryde's whale (*Balaenoptera edenii*), sperm whale (*Physeter macrocephalus*), sei whale, humpback whale, fin whale, and North Atlantic right whale. A few fresh samples of bowhead whale skin from the Inupiat subsistence harvest were also analyzed. The authors found no discernable difference between species. However, they also found that frozen whale skin darkens over time, most likely confounding their results. In comparison, Abileah (2002) did find differences between the spectral signatures of live blue, grey, and humpback whales in aerial imagery suggesting that there may be spectral differences between species; however, more work is needed to identify those differences.

Due to the high contrast between beluga whales and their surroundings, Charry *et al.,* (2021) was the first study to successfully detect medium-size cetaceans (3-5 m) using VHR satellite imagery. Not only were the authors able to detect beluga whales in Cumberland Sound, but they were also able to detect narwhals in Tremblay Sound in the Canadian Arctic. This suggests that other species of medium-sized cetaceans or marine megafauna, such as killer whales or basking sharks on the Pacific Coast, may be able to be detected given comparable size and contrast characteristics.

Several studies have compared whale detection using traditional survey methods (boat-based and aerial) versus VHR satellite imagery. Bamford *et al.,* (2020) compared whale density estimates from ship-based surveys to those determined using VHR satellite imagery in the Gerlache Strait of the Western Antarctic Peninsula. The authors found that the satellite imagery was able to detect densities in the same order of magnitude as that of ship-based surveys. However, a direct comparison could not be made because the satellite imagery was collected a week to ten days prior to the ship-based surveys. Corrêa *et al*., (2021) compared the ability of very high (70 cm), high (5 m, 3 m), and medium (10 m, 30 m) resolution satellites[1] to detect southern right whales in a breeding ground on the south-central coast of Santa Catarina, Brazil and drew comparisons with aerial survey data. They were not able to identify any whales in the 10 m and 30 m resolution imagery because of the coarse resolution. In the high and VHR categories, they found no significant difference between the number of whales found in the satellite imagery compared to the aerial imagery. Canadian researchers have also been able to capture satellite imagery at the same time as an aerial survey; results are currently being prepared for publication (Hodul, pers. comm., 2022). While more work is needed to draw direct comparisons between traditional and satellite methods of data collection, results to date suggest that satellite imagery is a promising new method for identifying marine megafauna.

Automated Detection Systems

Many of the studies cited above highlight the need for the development of automated or semi-automated detection systems because manual inspection of satellite imagery is prohibitively time-consuming at large scales (Cubaynes *et al.*, 2019, 2020; Bamford *et al.*, 2020; Corrêa *et al.*, 2020; Charry *et al.*, 2021; Höschle *et al.*, 2021, Cubaynes and Fretwell 2022). Two papers currently exist that focus on automated detection efforts with respect to marine megafauna detection from VHR; both Guirado *et al.*, (2019) and Borowicz *et al.*, (2019) present automated detection methods for identifying whales in VHR satellite imagery using a machine learning algorithm known as a Convolutional Neural Network (CNN). CNNs are a network architecture for a kind of machine learning called deep learning. CNN algorithms learn directly from images, taking in large volumes of data to be processed and transformed to create an output, or image classification. Specifically, computer vision algorithms like CNNs use image features like edges, colour, texture, and (complex) shapes to extract features that summarise the contents of an image into a feature map. This feature extraction reduces the image dimension to a hidden set of network layers that learns to detect and classify different features in an image as model output.

These algorithms have been used to automate the object detection analysis of camera-trap data, aerial imagery, and time-lapse photography (Weinstein, 2018). CNNs are a specific kind of machine learning algorithm that learns distinctive features of different objects from training images and then applies this learning to make predictions about similar objects in new images (LeCun, Bengio and Hinton, 2015). Compiling datasets of training imagery is time consuming (Cubaynes and Fretwell 2022); however, smaller training datasets can be supplemented using data

[1] The satellites Corrêa *et al*., (2021) compared were Pleiades 1A (very high, 0.70 m resolution), RapidEye (high, 5 m resolution[1]), Planet Scope (high, 3 m resolution), Sentinel 2 (medium, 10 m resolution), and Landsat 8 (medium, 30 m resolution).

augmentation[2], and researchers can start with pre-trained algorithms that have some already built-in knowledge[3] (or feature extraction preprocessing) to minimize training time and computational resources (Ren *et al.*, 2015; Guirado *et al.*, 2019).

Borowicz *et al.*, (2019) used a CNN to develop a semi-automated detection system that identifies possible whales within satellite imagery. Their model can detect imagery containing whale-like objects; however, manual inspection is still needed to remove false positives. In contrast, Guirado *et al.*, (2019) developed a fully automated two-step approach using open access data and software. This approach first identifies imagery where whales are present and then locates/counts the number of whales within each image. The authors specifically trained their algorithm with open-source images of whales and tested their model on Google Earth imagery in ten marine mammal hotspots around the globe. They were able to identify whales in seven out of the ten hotspots, with some areas not being fully assessed due to the poor quality of imagery. These first machine-learning algorithms show promise for the development of automated detection systems, real-time detection, and forecasting systems in the future, allowing regional- to global-scale assessments of marine megafauna.

A recent paper by Cubaynes and Fretwell (2022) presents a training and testing dataset of 633 annotated whale 'objects', created by surveying 6,300 km^2 of satellite imagery captured by WorldView-3, WorldView-2, GeoEye-1 and Quickbird-2 VHR satellites, for various regions across the globe. Four species are covered: southern right whale, humpback whale, fin whale, and grey whale. The authors note 'the larger a training dataset is, the more accurate and transferable to other satellite images [an automated detection] algorithm will be'. To this end, their 'Whales from Space dataset' is publicly available on the Natural Environmental Research Council (NERC) UK Polar Data Centre repository, with the aim of initiating the creation of a central database that can be built upon by researchers.

2.3 Ongoing research in Canada

Two large-scale initiatives related to detection of marine megafauna using VHR satellite imagery exist in Canada to date: (1) the Space Whales and Arctic Marine Mammals (SWAMM) program, established in 2021 and led by Fisheries and Oceans Canada (DFO) in collaboration with MDA Ltd., Whale Seeker Inc., and MAXAR; and (2) the smartWhales initiative, initiated in 2021 and led by CSA in collaboration with DFO and Transport Canada (TC).

The SWAMM program is funded through a SARA Nature Legacy grant (2021–2023) and focuses on using VHR satellite imagery of the Canadian Arctic to detect and estimate population size/density of belugas, narwhals and possibly walruses. Preliminary findings of this work are

[2] Data augmentation refers to creating additional images for training by altering the images within the original training dataset by rotating, cropping, inverting, changing the scale and/or brightness level of the images. Most machine-learning software allow users to easily increase the number of training images through data augmentation.

[3] Starting with an algorithm that has already been trained to identify other targets of interest, such as boats, is known to enhance performance when training the algorithm to identify new targets of interest, including whales.

described by Charry *et al.*, (2021), who were able to manually count beluga and narwhals in VHR satellite imagery of Tremblay Sound and Cumberland Sound in the Canadian Arctic. Larger areas of the Canadian Artic have also been imaged, and in collaboration with MDA – a company that specializes in satellite imagery and geospatial services – SWAMM program researchers have used a crowdsourcing method to count the whales through the MDA Geohive platform (Watt, pers. comm., 2022). This crowdsourcing approach enables them to quickly process large areas and enabled them to make initial density estimates of both narwhals and belugas within 11 different estuaries (Watt, pers. comm., 2022). In addition to the crowdsourcing approach, SWAMM program researchers and collaborators are currently: (1) supporting the development of an automated detection algorithm; (2) attempting to assess the depth at which whales can be seen in satellite imagery using artificial whale cut-outs set at different depths (see **Figure S1, Appendix A.2**); (3) attempting to collect concurrent imagery with an aerial survey to make a direct comparison between the two methods; and (4) attempting to collect imagery in beluga overwintering grounds. Regarding the latter, they have attempted to collect aerial imagery in January and February of 2022 but are limited as a result of the low light conditions (Watt, pers. comm., 2022).

The goal of smartWhales (2021-2023) is to advance solutions using satellite data to help detect, monitor, and protect the endangered North Atlantic right whale (NARW). Five companies and their collaborators were funded with a $5.3 million grant (see **Table S1, Appendix A.2**; Government of Canada, 2022). Out of these five consortiums, three are focused on the detection and monitoring of NARWs using VHR satellite imagery (stream 1), and two are focused on the prediction and modelling of NARW habitat (stream 2). In stream 1, the three consortiums are led by Hatfield Consultants Ltd., Global Spatial Technology Solutions Inc. (GSTS), and Fluvial Systems Research Inc. (FSR) and in stream 2, the two consortiums are led by Arctus Inc., and William Sales Partnership (WSP) Canada Inc.

- In stream 1, each consortium is developing an automated detection algorithm using machine-learning tools. The overarching goal for stream 1 is to develop a software that can 'ingest' satellite imagery, detect NARWs in close to real-time, and then alert relevant stakeholders in order to prevent anthropogenic harm to whales, such as ship strikes and entanglements. As of February 2022, all stream 1 consortiums are in the early stages of algorithm development, as the program is in the start of the second year of a three-year timeline (2021 –2023). In addition to developing an automated detection algorithm, the consortium led by FSR was also able to collect imagery during an aerial survey of NARWs and a comparison is currently being prepared for publication (Hodul, pers. comm., 2022). For more details on each consortium's project in stream 1, see the personal communications section of the annotated bibliography in **Appendix A.1**.
- Stream 2 consortiums, which are also operating on a three-year timeline (2021–2023), are focused on developing oceanographic products that model and predict NARW habitat. The consortium led by Arctus Inc. plans on doing this by using satellites that monitor and models

that predict the ocean's colour to track NARW primary food source of zooplankton, specifically *Calanus* sp. in the Gulf of Maine and the Gulf of St. Lawrence (Belanger, pers. comm., 2022).

2.4 Ongoing research globally

On the global scale, the following initiatives are underway. This is not an exhaustive description, but a snapshot of some of the large-scale initiatives and work underway in other countries and regions that have shaped the field of megafauna detection using VHR satellites to date:

- The British Antarctic Survey, who are responsible for publications from Fretwell *et al.*, (2014, 2019); Cubaynes *et al.*, (2019, 2020); Bamford *et al.*, (2020); and Clarke *et al.*, (2021), are continuing their work within the Wildlife from Space Program which focuses not only on whales (southern right, humpback, grey, fin, and sei whales) but on walruses, penguins, seals and albatrosses as well (British Antarctic Survey, 2022). In Canada, the British Antarctic Survey are current collaborators on the smartWhales initiative with the consortium led by GSTS (see **Table S1, Appendix A.2**).
- In Germany, Bioconsult SH in collaboration with ocean ecologists at Stony Brook University in New York and HiDef Aerial Surveying Ltd. in the United Kingdom, run the SPACEWHALES program funded by the European Space Agency. The initial stage of the program is responsible for publications from Borowicz *et al.*, (2019), and Höschle *et al.*, (2021), and in the second phase they are currently working on applying the algorithm developed by Borowicz *et al.*, (2019) on specific species and areas of interest.

While the use of VHR satellite imagery to date, worldwide, has largely focused on whales in the marine environment (with the exception of penguin work in the Antarctic), recent studies have speculated that VHR imagery might be used to detect and monitor other large marine species. As stated in Williamson *et al.*, (2019), "certain elasmobranch species may be suitable for monitoring using satellite imagery…. Certain species such as … basking sharks… have both the requisite colour contrasts with the landscape and sufficient size to be successfully identified using VHR satellite imagery". With improvements in the technology (e.g., higher resolution satellites, resolution enhancing artificial intelligence, advancements in automated detection), the number of species in the marine environment that can be detected and monitored using VHR satellites will no doubt continue to grow. For example, many species of sea turtle are listed as threatened by the International Union for Conservation of Nature (IUCN; Casale & Ceriani, 2019) and in Canada, the loggerhead (*Caretta caretta*) and the leatherback (*Dermochelys coriacea*) sea turtles are listed as endangered species under SARA (James, 2001; COSEWIC, 2010). A preliminary study by Casale & Ceriani (2019) showed that satellite imagery could be used to identify beach tracks of nesting loggerhead, leatherback and green (*Chelonia mydas*) turtles in Florida, showing that the applications of VHR satellite imagery will continue to grow.

2.5 Challenges and opportunities associated with satellite detection of marine megafauna

Traditional field-based methods for surveying marine megafauna are complex. It is widely recognized that these methods are expensive, require trained personnel, and have limited coverage in space and time, especially in remote regions (Kaschner *et al.*, 2012; Fretwell, Staniland and Forcada, 2014; Guirado *et al.*, 2019; Höschle *et al.*, 2021). VHR satellites now cover the globe daily, can image very large areas at any given time of the year, and can access remote locations. Because of this, VHR satellites offer a non-invasive, increasingly effective, and increasingly cost-effective way to understand marine megafauna. In combination with traditional survey methods, VHR satellite imagery has the potential to fill major data gaps across large remote areas of the coast and ocean and could help inform proper conservation and management strategies for poorly known species, and species at risk. Although the number of potential opportunities and applications for this work is high, several challenges do exist. With growing advancements in satellite imagery technology, solutions to many of these challenges are likely in the future.

Cost

While VHR satellite imagery can offer a cheaper alternative to traditional (e.g., boat- or aerial-based) surveys, given that most VHR satellites are currently commercially owned, imagery can still be cost prohibitive at a large scale, especially for organizations that lack funding, such as non-government organizations, academics, First Nations and/or developing nations. For example, 100 km^2 (minimum purchase area) of tasked or recent (within 90 days of acquisition) Worldview 3 imagery costs approximately $3250.00 USD. However, VHR satellite imagery companies are starting to offer discounted rates to academics - promoting collaborations between governments, academics, and industry - and costs of VHR imagery is and will continue to slowly decrease through time as more imagery and satellites become available. Notably, over the past decade multiple companies such as Airbus and Kompsat have dropped their prices and the Northern Sky Research Satellite Capacity Pricing Index Report found that in 2019 prices declined by ~18% and in 2020 prices continued to decline by ~13% (Northern Sky Research, March 11, 2019; Northern Sky Research, March 20, 2020). Additionally, in contrast to tasking imagery, which can be quite expensive, VHR satellite imagery is available in archives at lower costs. For example, after 90 days of the acquisition date the price of 100 km^2 of Worldview 3 imagery drops from $3250.00 USD to $2250.00 USD. A limitation of using only archived imagery is that, while archives supply a vast number of VHR satellite images, they are limited to areas that were previously tasked by past consumers. Thus images of, for example, the open ocean or relatively unpopulated areas are sometimes limited and patchy in coverage. Most imagery has been and is tasked for land-based applications, which means optimal environmental conditions for the detection of marine megafauna, such as a calm sea state, may be uncommon in archives.

Environmental Conditions

Many marine environmental conditions can negatively impact the detectability of megafauna in satellite imagery, as they can in traditional survey methods. Conditions such as clouds, haze, sun glint, waves, swell, water turbidity, and algae blooms all have the potential to negatively impact the detection of marine megafauna in satellite imagery, not only by limiting the visibility of whales within imagery but by also impacting whale behaviour, habitat usage, and movement patterns. Sea state, in particular, is known to impact the detectability of whales from boats and aerial surveys (Bamford *et al.*, 2020; Höschle *et al.*, 2021). In satellite imagery, poor sea state causes swell and waves that make whales hard to differentiate from background noise, e.g., Bamford *et al.*, (2020) detected 40 percent fewer whales in poorer sea conditions. Abileah *et al.*, (2002) suggest editing imagery with noise reducing filters - originally developed to improve the detectability of submarines and underwater mines in satellite imagery - to rectify this issue. However, how environmental factors (or covariates) influence whale behaviour and movement, and lead to differences in detection, remains poorly understood.

In addition to typical noise reducing filters, some algorithms are able to remove sun glint from imagery and primarily use the near-Infrared (NIR) band (Doxani *et al.*, 2013), meaning that the signal of a whale in the red, green, and blue bands is most likely preserved. Unfortunately, clouds and haze cannot be removed from imagery; however, with the development of active satellites, such as Synthetic Aperture Radar (SAR) satellites, images can be taken through clouds and haze. Hoschle *et al.*, (2021) do highlight that radar sensor technology needs to improve to be able to detect marine megafauna, but people are actively working on developing these methods (Hodul, pers. comm., 2022).

Different constituents in ocean water, such as suspended sediment, dissolved organic matter, and algae blooms, can all impact the depths at which a target of interest (such as a whale) can be detected, and methods still need to be developed to account for these variables (Cavanaugh *et al.*, 2021). Overall, to minimize errors associated with poor environmental conditions, imagery should be collected during optimal conditions until researchers are able to quantify the impacts of each factor and account for them during estimations of densities/abundances.

Time Requirements

Manual analysis of imagery is time consuming, albeit the time commitment is comparable to the analysis of imagery from traditional survey methods such as aerial surveys. Cubaynes *et al.*, (2019) found that it took approximately 3 hours and 20 mins to visually interpret 100 km^2, whereas Corrêa *et al.*, (2020) found it took approximately 12 hours and 40 mins to interpret 100 km^2 of satellite imagery. Moreover, in terms of effort required, visual passes of imagery by multiple different observers are necessary to minimize observer bias (Bamford *et al.*, 2020; Corrêa *et al.*, 2020; Charry *et al.*, 2021). Researchers are implementing crowdsourcing initiatives (Watt, pers. Com.., 2022) and are developing preliminary automated detection algorithms (Borowicz *et al.* 2019, Guirado *et al.*, 2019), increasing the efficiency with which imagery is analyzed (see **Section** *Methodological Considerations* below for details). Machine learning is a rapidly evolving field and innovative approaches are progressively outperforming previous ones.

Size Detection Limits

The spatial resolution of satellite imagery will dictate the smallest feature that can be observed within a given image. Abileah (2001) established that IKONOS 2 (1 m panchromatic resolution) had too coarse of a spatial resolution to confidently identify whales and initially, it was thought that only great whale species (of sizes larger than 10 m) could be detected using imagery with a spatial resolution of 50 cm (Fretwell, Staniland and Forcada, 2014). Charry *et al.*, (2021) were able to identify medium-sized cetaceans (i.e., 3-5 m) using 31 cm resolution imagery. Through the SWAMM program, it was discovered that when comparing Worldview 2 (50 cm resolution) and Worldview 3 (31 cm panchromatic resolution) imagery, belugas have such a high contrast with their environment that they also could be identified within the 50 cm Worldview 2 imagery, but narwhals could not (Watt, pers. comm., 2022).

Species Differentiation

Whales are easily distinguishable by their spectral features from other large objects found in imagery like boats and airplanes (Cubaynes *et al.*, 2019) but so far, no studies exist that use satellite imagery to detect and identify whales from areas where multiple morphologically similar species occur. Cubaynes *et al.*, (2019) were able to point out some distinct characteristics between similar species such as callosities on the heads of southern right whales and long pectoral fins on humpback whales; however, their study focused on areas where only a single species occurs at any given time. Cubaynes *et al.*, (2019) argue that differentiating morphologically similar species, such as Bryde's whales and fin whales, where they co-occur is likely difficult using satellite imagery at the current resolution available. Some work shows that there are spectral (colour) differences between morphologically similar species such as blue, grey and humpback whales in aerial imagery (Abileah, 2002), but Cubaynes *et al.*, (2020) were unable to capture the spectral difference between frozen skin samples of seven species (as described earlier). Automated detection algorithms have not yet been built to differentiate species where multiple similar species co-occur[4]. More work is needed to understand whether it is possible to detect similar species with 31 cm panchromatic resolution, and if so, how to discriminate between species in satellite imagery, both using manual and automated methods. Building a library of live whale spectra would be one early step toward addressing this challenge.

Availability Bias

Bamford *et al.*, (2020) were the first to present the difficulty of accounting for availability bias when using satellite imagery. In traditional survey methods, the availability bias - or the amount of time a species spends at the surface versus at depth - is accounted for. To adjust surface estimates, data from dive loggers or from satellite telemetry are used to calculate the amount of time that individuals from certain species spend underwater, and these data are then combined with the depth at which an individual can be detected using traditional methods (boat- or aerial-based; Borchers *et al.*, 2013; Westdal *et al.*, 2013). How to accurately account for availability bias in

[4] Ongoing work in Canada through the smartWhales program will need to overcome the challenge of species differentiation in the near future, given the focus on detecting NARW in waters where multiple species of great whales occur.

satellite imagery has not yet been determined, i.e., the depth at which an individual can be detected at has not yet been determined. VHR satellite image resolution decreases with depth, with detection depth likely dependent on a complex function of water turbidity and surface roughness, and with the far-blue or violet part of the spectrum penetrating deeper into the water column than other colour bands (Fretwell et al. 2014).

Data on availability bias for aerial surveys can be adapted and approximated for satellite-based methods (see Bamford *et al.*, 2020), but more work is needed to be able to accurately calculate density/abundance estimates using satellite imagery. Charry *et al.*, (2021) proposed using whale-like cut-outs made of spectrally similar materials set at different depths to determine the detection limit for satellite imagery in the Canadian Arctic (see **Figure S1, Appendix A.2**). While this has not yet been successfully carried out due to logistical difficulties associated with cut-out deployment, SWAMM researchers are planning to deploy cut-outs in the summer of 2022 (Watt, pers. comm., 2022).

Environmental Impacts

No direct comparisons exist between the negative environmental impacts of traditional survey methods versus satellite-based methods. For example, it is difficult to quantify the amount of carbon released from the creation/launch/upkeep of satellites compared to the daily operations of boats or airplanes. However, it should be noted that there are some inherent risks associated with the number of satellites launched into space. Specifically, the number of objects in orbit around the Earth is increasing (approximately 27,000 as of May 2021; Garcia, 2021); and collisions are becoming more common, exacerbating the issue of space debris (Witze, 2018). A total of 95% of objects orbiting Earth are partial or whole inactive satellites (Witze, 2018) and every time one of these objects re-enters and burns up in the Earth's atmosphere it releases aluminum and free radicals which may be altering Earth's albedo or causing small holes in the Earth's ozone layer (Boley and Byers, 2021). In recognition of this issue, regulations and solutions for the space debris problem are being developed (Witze, 2018; Boley and Byers, 2021).

Opportunities on the Canadian Pacific Coast

3.1 Satellite imagery availability

Three major commercial satellite imagery providers exist in Canada: MDA, Planet, and Airbus and one secondary supplier exists: Apollo Mapping. MDA is the main supplier of MAXAR imagery (previously known as Digital Globe) and has access to Worldview, Geoeye, and Quickbird satellites (see **Table 1**, above, for more details). The Government of Canada has an ongoing National Masters Standing Offer (NMSO)[5,6] with MDA Prices of imagery (for tasking

[5] When contacting these companies for quotes, it is important to reference these NMSO agreements. The NMSO for MDA is under the agreement number E60SQ-120001/003/SS.

[6] It should also be noted that even though standing offers do exist for the government, most companies offer discounts to academic institutions as well.

and archived imagery) vary based on year of acquisition, resolution, number of bands included and product type. Information on the different product types can be found in the DigitalGlobe Core Imagery Product Guide. The MAXAR imagery archive can be explored online via their Discover platform. Platforms like this allow users to search through large databases of archived imagery to see what is available for their specific area of interest. The platform allows users to select a location on the Earth's surface by drawing a rectangle or polygon or uploading a shapefile and browsing through imagery with a number of filters such as cloud cover percentage, acquisition angle, sun elevation, satellite type, resolution, and acquisition date. The MAXAR archive imagery provides the most coverage of the Pacific Coast of Canada from a single satellite imagery producer.

Planet[7] provides VHR satellite imagery through their SkySat Constellation of 21 satellites launched between November 2013 and August 2020. SkySat offers 50 cm resolution imagery and averages 5-7 revisits per day. Planet has two different methods for browsing their archived imagery database: a web-based platform or an integrated API system that works with ArcGIS, QGIS, or Google Earth Engine. These platforms can be accessed online after signing up for a Planet account. Planet's archive of SkySat imagery has little to no imagery available for the Pacific Coast of Canada. As of 2022, tasking imagery for specific areas of interest would be the only option if solely using SkySat imagery to assess marine megafauna on the Pacific Coast. Planet was unable to supply any pricing for publication.

Airbus[8] is responsible for the Pleiades satellites which includes Pleiades 1A, 1B, and the Neo constellation. Pleiades 1A and 1B have captured 50 cm resolution imagery since 2011. Pleiades Neo supplies the highest resolution imagery from Airbus at a 30 cm resolution, similarly to MAXAR's Worldview 3 and 4. Only two out of the four satellites of the Pleiades Neo constellation are currently in orbit, with the two others planned for launch in 2022. Like SkySat, there is a limited amount of archived Neo imagery available for the Pacific Coast of Canada. However, Neo is available for tasking at a daily revisit rate. No pricing was available for publication.

Lastly, Apollo Mapping is an American company that is a secondary distributor of satellite imagery. It redistributes imagery from 19 different companies including Planet, MAXAR, and Airbus. Because it is a secondary distributor, it has access to the largest satellite imagery database of the companies listed above. No official standing offer exists between the Government of Canada and Apollo Mapping. However, it offers some VHR satellite imagery from Kompsat 3 and SuperView 1, which are not included in the NMSOs for MDA, Planet, or Airbus. Apollo Mapping's platform, Image Hunter, allows an individual to search through all the archived satellite imagery from different providers instead of searching each company's fleet separately and thus is a great way to understand what VHR imagery exists for any given region before reaching out to specific suppliers.

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[7] The NMSO for Planet is under the agreement number E60SQ-120001/005/SS.

[8] Airbus has two NMSOs under the agreement numbers: E60SQ-120001/006/SS and E60SQ-120001/001/SS.

Within the federal government, the Canadian Hydrographic Service (CHS) has already purchased satellite imagery for the majority of the Pacific Coast of Canada. This imagery is made up of Worldview 2, 3 and 4, Geoeye, Quickbird and aerial images. The database is organized in the British Columbia Geographic System 1:20,000 scale grid system. All the images come already pansharpened and orthorectified. These are high quality products for mapping but lack some additional information like associated metadata and the NIR band. This information is useful for things like masking-out land with the NIR band, correcting for atmospheric impacts, or obtaining the true spectral signatures of marine megafauna with the satellite measured reflectance. Most imagery lists the acquisition date and time in the file name; however, some are missing this information. Even though these images lack some information, they can still be used with the type of automated detection algorithms that are being developed in Atlantic Canada, given that these algorithms are being trained using aerial imagery that is similarly formatted (Hodul, pers. comm., 2022). Although these images have already been purchased by the federal government, gaining access may be challenging based on who is accessing the imagery and why. For internal access, a 'DFO Internal End User Restriction Form' is needed. However, for academics or outside collaborators a 'Direct User License Agreement' (DULA) needs to be approved by the CHS.

CASE STUDY:
Available imagery for the endangered basking shark in Canadian Pacific waters

The basking shark is one species of non-cetacean marine megafauna for which there is a strong conservation-based rationale for developing new technology to monitor abundance and distribution. The Pacific population of the basking shark is listed as Endangered under SARA and has been since 2010. Numerous recovery measures are identified in the Action Plan for this species that relate directly to identifying and reporting on basking sharks and their habitat within Canadian Pacific waters (Fisheries and Ocean Canada, 2020). Investigating the potential use of emerging technologies and identifying potential collaborations that may support understanding of basking sharks in Canadian Pacific waters are also included as recovery measures within the Action Plan. While the use of VHR satellite has not been tested for shark species specifically, as mentioned above, Williamson *et al.*, (2019) described basking shark as a suitable elasmobranch species for detection using VHR satellite imagery due to their large body size (up to approximately 40 ft (12 m) in length), colour contrast with their surrounding environment and their open ocean habitat (**Figure 1**).

Figure 1: Aerial image of basking sharks from Crowe *et al.*, (2018). Aerial imagery can be downgraded and used to train automated detection algorithms for the detection of basking sharks in the future.

To illustrate the viability of a VHR satellite-based 'pilot project' focused on the basking shark, the availability of archived VHR satellite imagery for areas of interest on the Pacific Coast of Canada was explored. Specifically, seven areas of interest (AOI) were identified by the SARP based on known historical areas of concentrated abundance (McFarlane *et al*., 2009) and areas with more recent sightings (**Figure 2**) Using Apollo Mapping's Image Hunter platform, a search was conducted for all available VHR satellite imagery (< 60 cm resolution) with a cloud cover of less than 15%, between the months of May to September (2009-2021), when basking sharks are known to occur on the Pacific Coast of Canada. All imagery listed in **Table 1** (above) was included in the search with the exception of the SkySat series due to a current (February 2022) software bug within the Image Hunter platform. An additional search for any available SkySat imagery on Planet's web-based platform was conducted, but no imagery was returned. CHS also provided a list of all imagery available from the CHS database described in **Section 3.1.** The amount of available satellite imagery for each area is summarized in **Table 2**.

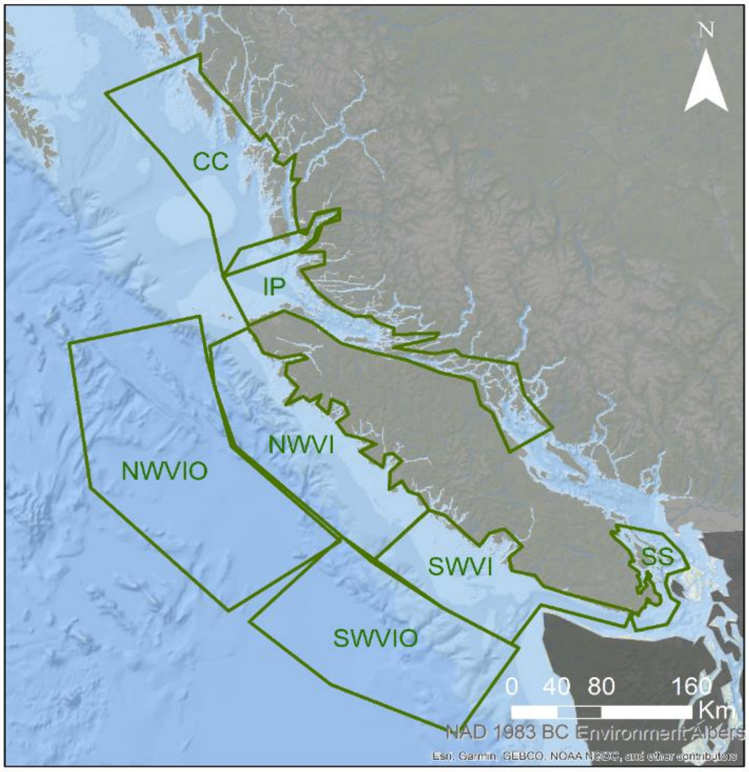

Figure 2: Basking shark areas of interest. CC: Central Coast, IP: Inner Passage, NWVI: Northwest Vancouver Island, NWVIO: Northwest Vancouver Island Offshore, SWVI: Southwest Vancouver Island, SWVIO: Southwest Vancouver Island Offshore, SS: Southern Salish Sea

Table 2: Basking shark AOI satellite imagery availability. Satellite imagery with a resolution of ~30 cm comes from Worldview 3 (WV3), Worldview 4 and Pleaides Neo; ~40 cm resolution comes from Geoeye, Worldview 2 and Kompsat 3; 50 cm comes from Pleaides 1A, 1B, Worldview 1 and SuperView-1; and 60 cm resolution comes from Quickbird 2. The Canadian Hydrographic Service (CHS) imagery is not included in the grand total column.

AREAS OF INTEREST	TOTAL	~30 CM	~40 CM	50 CM	60 CM	CHS
INNER PASSAGE	792	68	285	398	41	244 (69 WV3)
SOUTHERN SALISH SEA	526	45	228	223	30	99 (7 WV3)
SOUTHWEST VANCOUVER ISLAND	543	77	170	272	23	91 (50 WV3)
SWVI OFFSHORE	27	0	8	18	1	0
NORTHWEST VANCOUVER ISLAND	363	31	115	196	21	102 (22 WV3)
NWVI OFFSHORE	5	0	0	5	0	0
CENTRAL COAST	285	23	100	146	16	186 (62 WV3)
GRAND TOTAL	2541					722

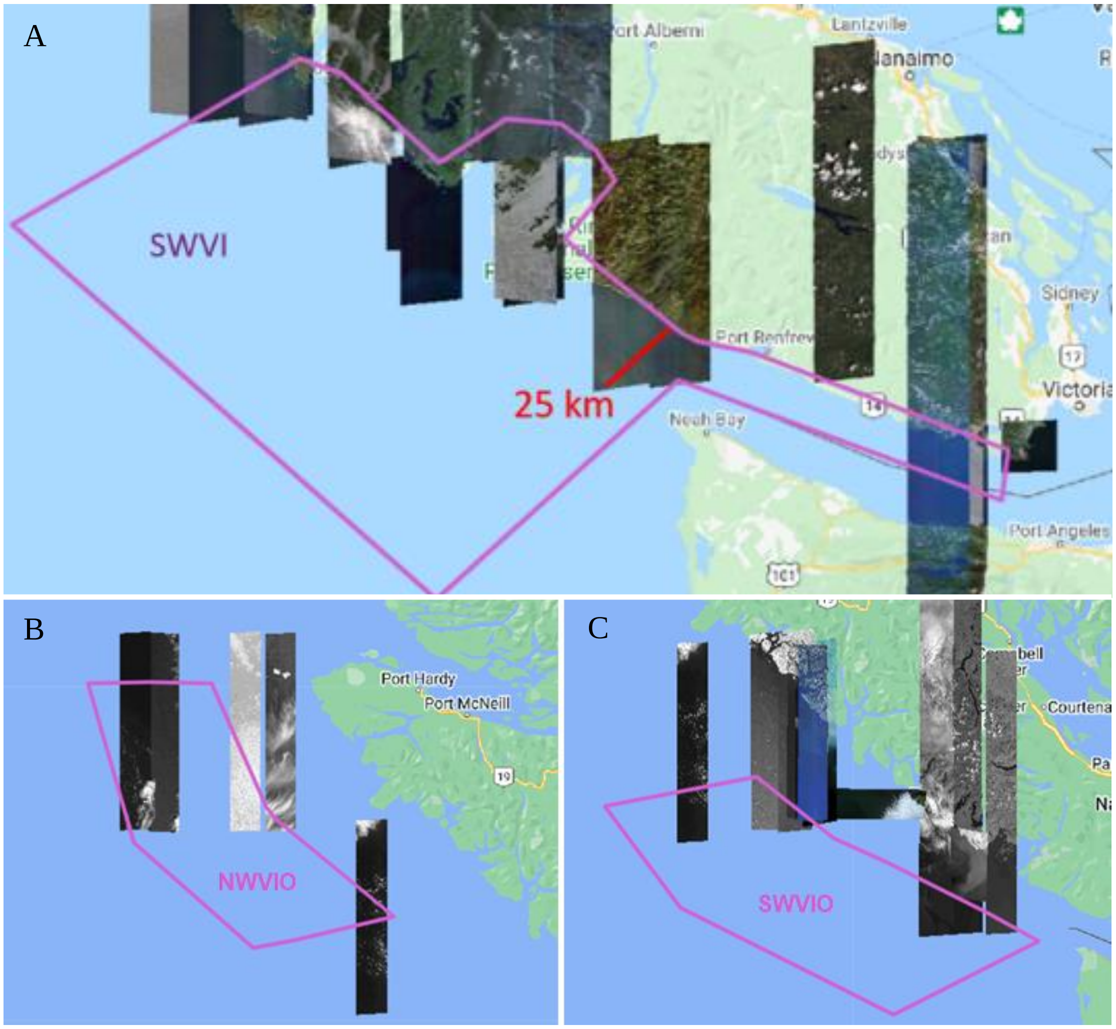

Figure 3: Clips of imagery from Apollo Mapping's Image Hunter showing: A) a subset of imagery from the Southwest Vancouver Island (SWVI) area; B) the total amount of available imagery for the Northwest Vancouver Island offshore (NWVIO) area; and C) the total amount of available imagery for the Southwest Vancouver Island offshore (SWVIO) area.

Based on the search described above, a large number of VHR satellite images are available for basking Shark AOIs on the Pacific Coast of Canada. The largest amount of satellite imagery is available for the inner passage (IP) area followed by the Southwest Vancouver Island (SWVI) area and the Southern Salish Sea (SS) area. As expected, areas of high population density such as the SS and the IP have more imagery available than remote and unpopulated areas such as the Central Coast (CC). Markedly, the SS region covers approximately six times less area than the Northwest Vancouver Island (NWVI) area but has 1.4 times more archived satellite imagery available. Predictably, both the offshore areas, the Northwest Vancouver Island Offshore (NWVIO) area and the Southwest Vancouver Island Offshore (SWVIO) area have the lowest amount of satellite imagery available. Most archived imagery ends within 25 km of the coastline (**Figure 3A**), showing how limited open ocean imagery is to date. Similarly, the CHS imagery ends within 19 km of the shore. A total of five images were found in the NWVIO area, and 27 for the SWVIO area (**Figure 3B & C**); no CHS imagery exists for the offshore areas.

A consideration when compiling a database of VHR satellite imagery for monitoring basking sharks – or any other marine megafauna species – is that not all archived imagery was collected in optimal conditions. Within the imagery listed in **Table 2**, some had obvious white caps, fog, glint, or haze (as illustrated in **Figure 4**), which impede the detection of basking sharks. A preliminary inspection can be done through any browser platform to eliminate imagery acquired in poor conditions. However, because of the large amount of imagery found during the search described above, none were eliminated in this preliminary analysis. Platforms present images in a degraded resolution, which, in some instances, can make it difficult to gauge environmental conditions (e.g., sea state). In such cases, imagery providers can be consulted and can sometimes offer temporary licences to view the imagery at a better resolution through the browser platforms before purchasing.

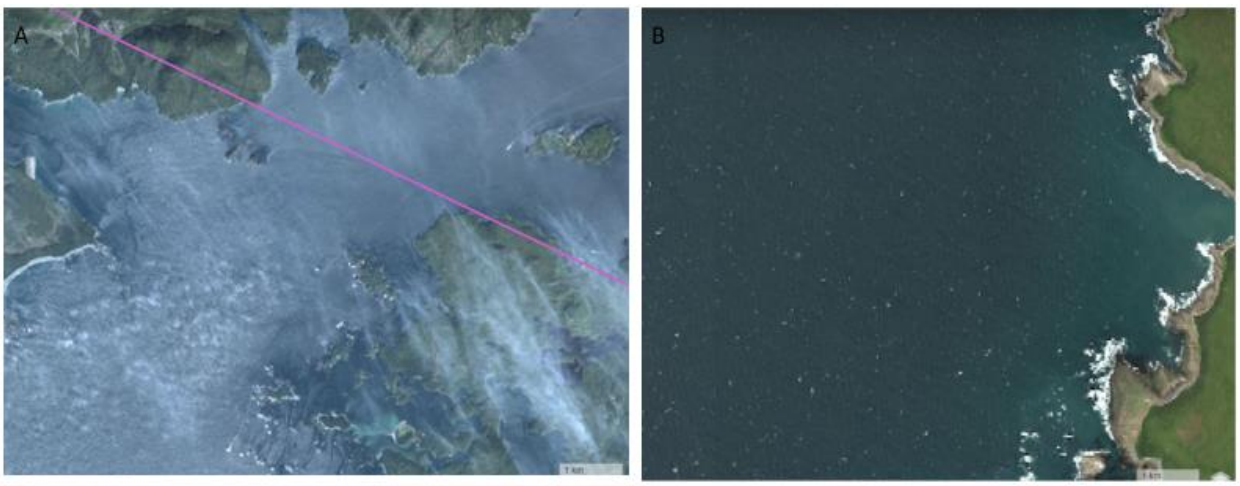

Figure 4: Clips of imagery from Apollo Mapping's Image Hunter showing: A) a Quickbird image that has a combination of fog, glint, haze and low-lying clouds; and B) a Worldview 2 image showing rough sea conditions including white caps and shore waves.

In terms of analyses, the manual detection methods described by Cubaynes *et al.*, (2019) would be overly time-consuming if applied to the 3263 images summarized in **Table 2**. In contrast, using a crowdsourcing method like that developed by the SWAMM program or adapting an automated detection algorithm like those being developed on the East Coast of Canada (see **Section 2.3**) would be suitable for this amount of data. With respect to using the East Coast algorithm(s), a dataset of annotated images of basking sharks and other possible co-occurring species on the Pacific Coast, as well as other possible confounding objects such as kelp forest canopy, would need to be compiled for algorithm training. This imagery could be sourced from anywhere in the world where these species exist, and not necessarily from the Canadian Pacific Coast. (Pisano, pers. comm., 2022, Baduini, 1995; Sims *et al.*, 2000; Crowe *et al.*, 2018). At the scale of the current areas of interest (~11,500 km^2) purchasing all available VHR satellite imagery is likely cost prohibitive (see **Section 2.5** regarding imagery costs). However, an initial proof of concept project could focus on: 1) one or two areas of interest; 2) using the highest resolution imagery available; and/or, 3) solely using imagery from the CHS database.

Species differentiation and availability bias are other important things to consider for a 'pilot project' on basking shark. For availability bias, a correction factor has not yet been created for the Pacific population of basking shark (Fisheries and Ocean Canada, 2016) and thus, a satellite pilot project would solely focus on increasing the number of basking shark observations across the coast. Determining population characteristics, such as abundance and density, are not possible until availability bias is addressed for the Pacific population. However, availability bias data (e.g., Westgate *et al*., 2014) could be used from other parts of the world with the assumption that the foraging behaviour is equivalent between oceans. For species differentiation, the majority of the imagery summarized in **Table 2** comes from satellites of either 40 cm or 50 cm resolution, and although some research has successfully used this resolution to detect whales (Fretwell *et al*., 2012), species differentiation where multiple species co-occur may be difficult or impossible. Work by Cubaynes *et al*., (2019) and Charry *et al.,* (2021) suggest using the highest possible resolution imagery when needing to differentiate between species or to detect medium-sized marine megafauna such as basking sharks. To explore this challenge on the Pacific Coast, aerial imagery of basking sharks and different marine megafauna found in Pacific waters could be downgraded to match the different resolutions of available satellite imagery (30 cm to 60 cm) and compared to see if humans and/or algorithm(s) could detect the difference between target species. Additionally, collecting spectra from archived aerial imagery or live animals would help determine if the spectral differences between species would allow them to be differentiated in satellite imagery from colour alone.

For future work on basking sharks, actively tasking imagery at this scale is likely cost prohibitive, given the high costs associated with tasking (relative to using archived imagery). However, if certain subareas within the areas of interest are highlighted as basking shark 'hotspots', e.g., through work with archived imagery, combined with ongoing sightings reports and improved habitat modelling, the possibility of tasking for smaller areas could be explored. Another possible direction for tasking satellite imagery could be to develop a 'tip and cue system' with one or more satellite imagery companies to task imagery in real time when basking shark sightings are reported to the DFO Shark Sighting Network (SSN) or the global Shark Pulse network. Overall, even though there are challenges associated with developing a satellite imagery monitoring program for basking sharks, an initial project would be viable with the amount of VHR satellite imagery available for the Pacific Coast of Canada and could yield information in support of future projects.

3.2 Considerations and Additional Applications on the Pacific Coast

In addition to the basking shark, several cetacean species in the waters of the Northeast Pacific Ocean could benefit from the adoption of a satellite imagery monitoring program, including large cetacean species listed as at risk under SARA as well as a few species not currently listed under

SARA, such as the sperm whale and minke whale. There are also many medium- to small-sized cetaceans that may or may not be detectable in VHR satellite imagery that occur in the Northeast Pacific such as four beaked whale species, eight dolphin species and two porpoise species (Ford and Nichol, 2014). While traditional survey methods have increased our understanding of megafauna on the Pacific Coast of Canada, many questions remain on population abundance, density, distribution, and habitat usage, especially in remote areas. VHR satellite imagery could aid in answering these questions and help managers implement species planning and policy to advance recovery efforts. **Section 3.1** (above) demonstrated the types of imagery available for the Pacific Coast and possible limitations associated with the types of imagery available. In this section, more challenges associated with using VHR satellite imagery to monitor marine megafauna are explored specifically for the Pacific Coast, and the possible applications of a VHR satellite imagery monitoring program are briefly presented. Lastly, the broader benefits of compiling a VHR satellite imagery dataset and monitoring program for the Pacific Coast are described.

Environmental Considerations

Knowing how environmental factors occur across space and time on the Pacific Coast is important in understanding how well VHR satellite imagery will work for detecting marine megafauna in certain areas. Challenges associated with satellite imagery acquisition and interpretation increase in severity moving from south to north along the coast of North America (Cavanaugh *et al.*, 2021). The Pacific Coast of Canada is characterized by higher amplitude tides, more complex topography, steeper bathymetry, more turbidity, complex currents, and lower sun angles than further south (Cavanaugh *et al.*, 2021). Additionally, along the Pacific Coast of Canada, northern portions of the coast experience more cloudy days making the availability of satellite imagery more limited (Cavanaugh *et al.*, 2021). Sea state is also a major consideration when trying to detect marine megafauna from space along the Pacific Coast. Monitoring in sheltered regions of the coast such as the Strait of Georgia, the Inner Passage or within the many fjords will be easier compared to monitoring in open ocean areas where identification of megafauna will be limited by large waves and swell (Thomson, 1981). Multiple datasets exist that look at wave height and wind such as the MSC50 wind and wave hindcast model (DFO, 2022), the British Columbia daily regional wave height forecasts, and the Windy global wave, swell and wind forecast model; these can be referred to when choosing imagery to buy from archives or when tasking satellite imagery. In terms of time of year, the spring and summer months have less cloud cover and calmer seas, resulting in improved imagery during a time when many species migrate back to the Pacific Coast. Targeting species in the winter months will be more challenging because of the difficult environmental conditions, as well as the lower availability and coverage of good quality archived satellite imagery.

Species Considerations

Additional factors limiting the ability to detect marine megafauna on the Pacific Coast using VHR satellites are species' distributions, behaviours, and morphologies. The marine megafauna species found on the Pacific Coast often occur in low densities spread across large areas. In contrast, most of the work done to date on using VHR satellite imagery to detect megafauna has focused on areas with large and consistent aggregations of the target species (e.g., breeding aggregations; Höschle *et al.*, 2021). On the Pacific Coast of Canada, there are currently no known, specific regions or areas where megafauna species congregate in high densities. Past research carried out using traditional methods does highlight areas where species are most likely to be found; this information, such as the locations of sightings, of feeding grounds or species distribution models, can be integrated into satellite monitoring programs (e.g., Mizroch *et al.*, 2009; Dalla Rosa *et al.*, 2012; Ashe *et al.*, 2013). Additionally, spatial density models (Watson *et al.*, 2020, Fisheries and Oceans Canada, 2021) or areas where there is high risk associated with vessel strikes (Nichol *et al.*, 2017) can be used to inform satellite imagery acquisition (either of archived imagery or new, tasked imagery), to inform threat mitigation. In other words, survey and modelling work can be used to target satellite efforts, but large-scale satellite monitoring across the entire Pacific Coast is still cost prohibitive.

Similar species such as grey, fin, sei, minke and humpback whales also co-occur on the Pacific Coast of Canada, making species identification difficult in satellite imagery. Some morphological characteristics like the general size or shape of species, or specific characteristics like the callosities on the heads of North Pacific right whales or the long pectoral fins on the humpback whale, can be used to differentiate species; however, these traits may not visible depending on the position or behaviour of the whale in the water, i.e., when spyhopping or breaching (Cubaynes *et al.*, 2019; Guirado *et al.*, 2019). For morphologically similar species that reside in similar areas, research on characteristics or behaviours like 'distance from shore' or 'feeding strategy' can be included in monitoring programs to help differentiate species (Duffus, 1996; Gavrilchuk and Doniol-Valcroze, 2021), but it is important to note that species will not be able to be differentiated with one hundred percent accuracy at the current resolutions offered (Cubaynes *et al.*, 2019; Höschle *et al.*, 2021).

Methodological Considerations

With the above considerations in mind, the most efficient and effective way to monitor species in the Northeast Pacific using VHR satellite imagery is by developing automated (or semi-automated) detection algorithms, potentially in combination with crowdsourcing. Crowdsourcing is a method that has been used to sift through substantial amounts of images by leveraging large numbers of decentralized volunteers to generate data (Hollings *et al.*, 2018; Su, Sui and Zhang, 2020). For any crowdsourcing, time, effort, and/or compensation are needed to mobilize public users and to assess the quality of the data before use (Su, Sui and Zhang, 2020), and significant expertise is needed to differentiate large whales species within satellite imagery (as described above). However, crowdsourcing does hold some promise for binary detection (e.g., whale versus non-whale object), especially if combined with automated or semi-automated detection methods to minimize the amount of imagery inspected by users (Hollings *et al.*, 2018). Additionally, crowdsourcing can be used to train detection algorithms (automated or semi-automated) with annotated images. Even fully automated detection algorithms are still reliant on large databases of annotated images for reliable automation, particularly so if the goal is species-level detection and classification. Multiple crowdsourcing platforms exist, including MAXAR's Geohive, Zooniverse, Geo Wiki, or Amazon Mechanical Turk. In the field of marine megafauna detection, crowdsourcing has already been used to identify and classify manatee, humpback whale, and dolphin vocalizations through the Cetalingua Project, and in Canada, the SWAMM program has used crowdsourcing to locate and count beluga and narwhal whales in VHR satellite imagery of estuaries in the Arctic using the MDA Geohive platform (Watt, pers. comm., 2022).

Multiple different approaches can be used when developing automated or semi-automated detection algorithms for marine megafauna. The first semi-automated detection approach, is to develop a basic algorithm that flags images with possible megafauna sightings for manual inspection, removing a large percentage of the imagery and thus reducing time associated with manual detection (Borowics *et al.,* 2019). This approach can be combined with crowdsourcing or a simple manual detection method (Cubaynes *et al.*, 2019) to collect data from the remaining imagery. Another option is to develop an algorithm which selects images with possible megafauna sightings and then identifies the location of each possible sighting within each image (Guirado *et al.*, 2019). No algorithm (globally)[9] has been trained to differentiate species yet; thus, until such an algorithm becomes available, manual inspection of each possible megafauna observation would still be needed to differentiate species on the Pacific Coast which again requires time and personnel with expert knowledge. Efforts on the Pacific Coast could be focused on developing a fully automated detection algorithm that is able to differentiate species, but this requires more effort than the already established methods described above. One promising approach might be building on the algorithm work by the smartWhales initiative. Although the smartWhales algorithms are being developed for a singular species (NARW), they are the first algorithms aiming to identify a specific species in waters where multiple (similar) species occur (Hodul, pers. comm., 2022, Pisano, pers. comm., 2022, Tsui, pers. comm., 2022). Once these algorithms can differentiate NARW from co-occurring species, they could be trained to recognize and differentiate Pacific Coast species.

For the development of any of these algorithms, as well as for their transferability to other regions, training datasets are needed (Cubaynes and Fretwell 2022) and need to include target species in different positions/behaviours and non-target objects that could be confused with megafauna such as boats, waves, and shallow rocks. To overcome this challenge, two methods exist to lower the amount of training data needed: (1) data augmentation; and, (2) adapting pre-trained algorithms from related image detection and classification tasks (Borowicz *et al.*, 2019; Guirado *et al.*, 2019). On the Pacific Coast most surveys are boat-based, meaning the availability of aerial imagery for training algorithms is low (Spaven, pers. comm., 2022). However, algorithms can be trained with imagery from other parts of the world and imagery is available through open archives (Guirado *et*

[9] Ongoing work in Canada through the smartWhales program will need to overcome this challenge of species differentiation in the near future, given the focus on detecting NARW.

al., 2019, Cubaynes and Fretwell 2022). Training images for some of the Pacific species that co-occur on the Atlantic coast could also be procured through data sharing agreements like those used in the smartWhales initiative, and training datasets are routinely increased in size through data augmentation to improve performance of machine learning models (Ren *et al.*, 2015; Borowicz *et al.*, 2019; Guirado *et al.*, 2019). Numerous data scientists on the Pacific Coast have knowledge and expertise on developing machine learning algorithms, and a few have already developed (or are developing) algorithms to detect whale vocalization and track species using hydrophone data (e.g. Dewey *et al.*, 2015; Poupard *et al.*, 2019; Hendricks *et al.*, 2019; Joy *et al.*, 2021). This knowledge and expertise could be used to build, modify, and/or train an algorithm for the detection of marine megafauna from satellite imagery on the Pacific Coast, or even to develop an algorithm that ingests multiple types of data (e.g., acoustic, visual, aerial, satellite; see **Section** ***Looking Ahead*** below).

Additional Potential Applications

Beyond species' population monitoring for the purposes of assessment or recovery, there are numerous large-scale initiatives on the Pacific Coast of Canada that could benefit from the procurement of VHR satellite imagery and the advancement of automated detection algorithms for megafauna (and/or other targets of interest, such as boats). For spill response planning, for example, the Pacific Coast of Canada offers a unique challenge, with more than 25,000 km of coastline, much of it in extremely remote locations. For this reason, it is crucial that spill response planners within government and beyond have access to the best available satellite data during planning, preparedness, and response. Real-time, automated detection of megafauna, as well as forecasting (see **Section** *Looking Ahead* below), could be used to inform adaptive response plan development and actual responses in the event of a spill. Additionally, the Northern Shelf Bioregion (NSB) Marine Protected Area Network (MPAn), once designated, the Parks Canada Agency National Marine Conservation Areas (NMCAs), and Indigenous Protected and Conserved Areas (IPCAs), among other marine spatial planning initiatives, face similar challenges with respect to large-scale monitoring and enforcement that could be aided by using VHR satellite imagery-based projects and programs. VHR satellite imagery can be used to map and monitor ecologically important habitats such as salt marshes, eelgrass beds, and kelp forests, and can be used to monitor and regulate human-made disturbances and/or developments such as log booms, archeological sites, fish farms, oyster farms, kelp farms, harbours, and float houses. Monitoring frameworks for spatial management initiatives that consider all the applications of VHR satellite imagery together will be more beneficial than ones that consider one-off applications. Since cost remains high with respect to purchasing VHR satellite imagery at a large scale, fostering partnerships (e.g., government-to-government) and collaborations with multiple stakeholders can lead to cost-sharing and fund-leveraging for VHR satellite imagery-based projects/programs. In addition to local partnerships and collaborations, with the initiation of the UN Decade of Ocean Science for Sustainable Development (2021-2030), global support can be leveraged for the advancement of a marine megafauna detection system using VHR satellite imagery, and knowledge can be shared through endorsed programs like the MegaMove Action.

Looking Ahead

Obtaining population-based estimates for megafauna species on the Pacific Coast of Canada remains difficult using a single-survey approach, or even from a combination of field-based survey methods. Researchers currently rely on data from a variety of sources such as directed boat- and ship-based surveys, opportunistic surveys, the BC Cetacean Sighting Network (BCCSN), the DFO SSN and BC Coast-Wide Hydrophone Network (Ford and Nichol, 2014; Dewey *et al.*, 2015; Joy *et al.*, 2021), among other sources. A VHR satellite imagery monitoring program would increase the amount of data collected on the Pacific Coast, especially in remote regions, allowing researchers and managers to make more informed decisions on species management and conservation.

Looking ahead, there is great potential for developments in space-based data and advanced analysis methods (such as real-time and forecasting) to lead to combined or integrated systems that generate a greater understanding of species and result in real-time threat mitigation. The BCCSN has already implemented an alert system where real-time observations of cetaceans and sea turtles submitted by members of the public are used to alert ships to reduce the risk of disturbance and/or collisions (BC Cetacean Sighting Network, 2022). In the future, a real-time 'tip and cue' system could be developed where sightings from the BCCSN and/or the DFO SSN are used to initiate the collection of satellite imagery in a certain area(s) where species of interest are observed; this would limit costs associated with covering (or tasking) large areas with VHR satellite imagery (**Figure 5A**). Alternately, a more costly type of real-time alert system could be developed, consisting of VHR satellites continually collecting imagery over a specific area (e.g., of high threat/risk) in combination with an automated detection algorithm to alert boats when a species of interest is detected in an area (**Figure 5B**). Lastly, a system to aim for might be one in which all the above elements, plus forecasting (predicting animal movements following sightings) using other types of data, like environmental, historic, local and/or traditional ecological knowledge, and satellite imagery of ocean conditions and/or food sources such as plankton, are combined in a cyclical way to increase detection and threat-mitigation for marine megafauna. This system might consist of, for example: citizen science reporting of sightings; continual (or cued) VHR satellite imagery collection and analysis via automated detection; and other types of continual (or cued) data collection (such as acoustic data from hydrophones). This species-specific detection data could be integrated with environmental data and historical data (e.g., megafauna density, local and/or traditional ecological knowledge) in a stochastic movement model to predict animal movements that inform real-time and future trajectories and locations of vulnerable whales (**Figure 5C**). Work to develop such a system for southern resident killer whales (SRKW) is already underway by researchers at Simon Fraser University to reduce the risks of vessel strikes and noise disturbances (Randon *et al.*, 2022). Specifically, this forecasting system uses a stochastic movement forecast model that specifically considers bathymetry, biophysical oceanographic variables, Chinook salmon data, and historic densities of SRKW to predict the location of a SRKW up to 2.5 hours after a given sighting from hydrophone or the BCCSN. While this forecast system (or model) is currently focused on sightings and acoustic data, it can intake (or ingest) any type of positional data. VHR satellite imagery could be used to augment the coverage of this particular system once it starts to provide real-time whale detections in the Salish Sea and adjacent waters (Joy, pers. comm., 2022).

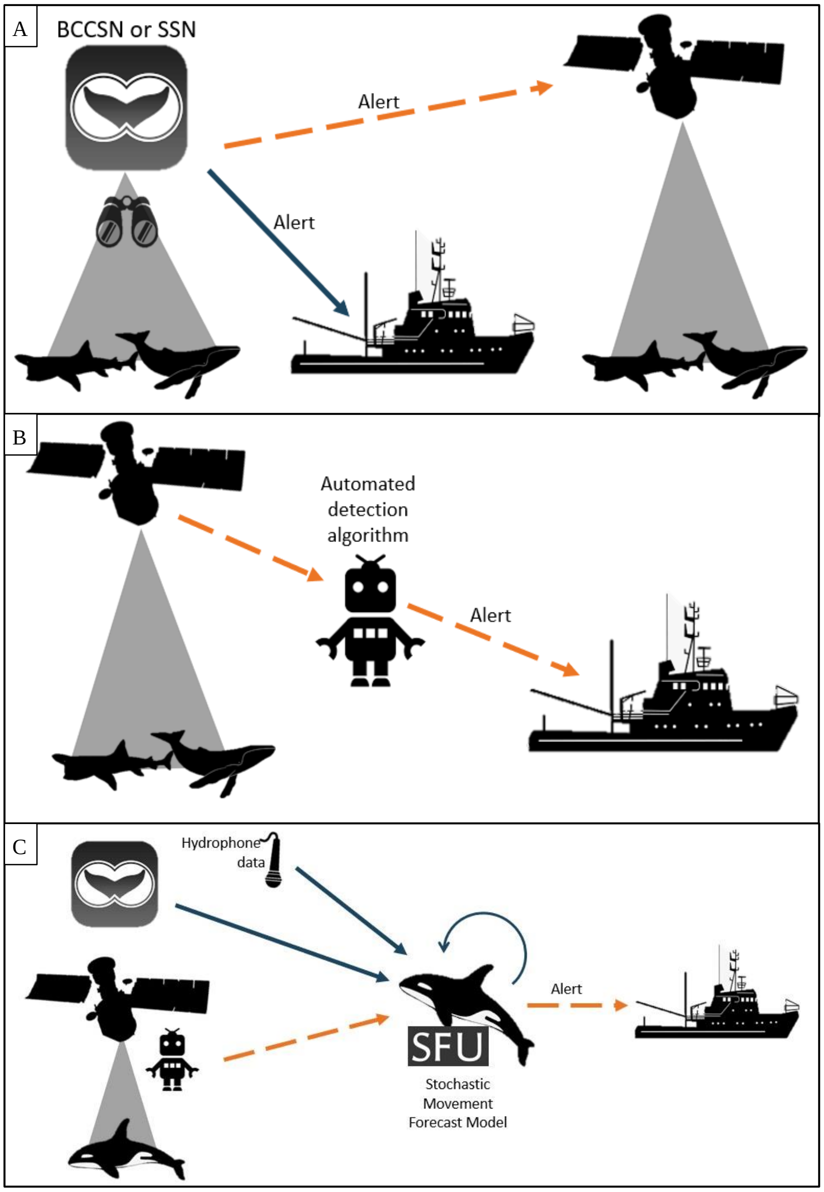

Figure 5: Diagram of possible real-time and/or forecasting systems (with existing pathways in solid blue and pathways in need of development in dashed orange) showing: A) a tip and cue using the pre-established BC Cetacean Sighting Network (BCCSN) and the DFO Shark Sighting Network (SNN); B) a satellite-based automated detection alert system; and, C) integrating a satellite-based automated detection system into a pre-existing forecast model for the southern resident killer whales developed at Simon Fraser University (SFU) by Dr. Ruth Joy and Dr. Marine Randon (Randon *et al*., 2022).

Conclusion

With the emergence of higher resolution satellite imagery in the 21st century, a variety of studies have showcased that VHR satellite imagery can be used to manually detect whales and other marine megafauna in a variety of regions across the globe (Abileah, 2001, 2002; Fretwell *et al.*, 2014, 2019; Cubaynes *et al.*, 2019, 2020; Corrêa *et al.*, 2020; Bamford *et al.*, 2020; Clarke *et al.*, 2021; Höschle *et al.*, 2021; Charry *et al.*, 2021; see Appendix A). Two automated detection algorithms have been developed for use with large whales and others are in development (Borowicz *et al.*, 2019; Guirado *et al.*, 2019), highlighting the potential use of this technology to detect megafauna into the future. In Canada, two large-scale initiatives - the SWAMM program and the smartWhales initiative - are using VHR satellite imagery to detect marine megafauna on the East Coast and in the Arctic, respectively. Although certain challenges like environmental conditions, imagery availability, costs, and species differentiation exist, researchers on the Pacific Coast would benefit from the initiation of 'pilot project(s)' and potentially the implementation of a VHR satellite-based marine megafauna monitoring program.

A few large databases of archived satellite imagery exist for the Pacific Coast of Canada, indicating that a marine megafauna detection project/program could be possible; however, additional work is needed to understand the limitations and costs associated with this imagery and to assess the viability of tasking imagery in certain regions. For the Pacific Coast (as with other regions), data collection using a semi- or fully-automated detection algorithm is needed, given the types of marine megafauna found on this coast and their specific characteristics. Species distribution models, past surveys on the locations of sightings and/or feeding grounds, information from sighting networks, and local and/or traditional ecological knowledge can all be woven together with information from satellites and other positional monitoring programs and systems, to focus efforts and address threats to megafauna. Detecting whales (and sharks) and classifying their images to the species level from VHR satellite imagery will also lead to understanding about how and why different species move, migrate, and aggregate. This sighting and movement information could be incorporated into species conservation and management at multiple spatial sales. Wide-ranging partnerships and collaborations across industry, academics, Indigenous groups, and government can and should be used to support a program on the Pacific Coast. This background report is a first step in exploring potential applications of this emerging science on the Pacific Coast of Canada and will ideally 'set the stage' for partnerships and collaborations that will enable the detection, monitoring, forecasting and protection of marine megafauna using space-based solutions in the future.

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Appendix A

Appendix A.1: Annotated Bibliography

Abileah, R. (2001) 'High-resolution imagery applications in the littorals', in Fujisada, H., Lurie, J.B., and Weber, K. (eds). International Symposium on Remote Sensing, Toulouse, France, p. 630. https://doi.org/10.1117/12.450711.

Abileah (2001) of SRI International, a non-profit scientific research institute, is the first to use satellite imagery to detect possible whales. Using IKONOS 2 imagery (1 m panchromatic resolution) of Maui, Hawaii, this paper outlines three different possible applications of using high-resolution imagery to: 1) map bathymetry, 2) monitor the health of coral reefs, and 3) census marine mammals. Abileah (2001) argues that satellite surveys are beneficial because of the fast acquisition time and ability to cover large and remote areas that aerial surveys cannot. However, the study highlights that satellite detection of whales remains difficult because whales have low radiance, which diminishes with depth and because uncalm sea state cause waves and whitecaps that can be misinterpreted as whales. For a more in-depth review of this work, see Abileah *et al.*, (2002).

Abileah, R. (2002) 'Marine Mammal Census Using Space Satellite Imagery', 52(3), pp. 709–724. PDFlink.

After Abileah (2001) first proposed the use of satellites for the detection of marine mammals, Abileah (2002) details the use of IKONOS 2 satellite imagery (1 m panchromatic resolution) to detect whales. The paper gives a brief history of the emergence of high-resolution satellite imagery and highlights some benefits and limitations of using high resolution satellite imagery compared to traditional aerial survey methods. The study presents that multiple possible whales were detected in the calm ocean waters of the Hawaiian Islands Humpback Whale National Marine Sanctuary in Maui and an orca was discernible in the amphitheater at Seaworld located in San Diego. Moreover, this paper simulates and injects an average-size whale (14 m) target into an IKONOS 2 image to measure the possible detectability of whales at different depths in rough waters. They implement two noise filtering methods to subtract ocean noise and find that even in strong wind conditions with whitecap clutter, the simulated whale target can be detected up to 20 m below the surface. However, because the spectral signal of the injected target was modelled using aerial imagery, the author highlights the need for *in situ* and satellite spectral measurements for future research.

Bamford, C.C.G. *et al.*, (2020) 'A comparison of baleen whale density estimates derived from overlapping satellite imagery and a shipborne survey', *Scientific Reports*, 10(1), p. 12985. https://doi.org/10.1038/S41598-020-69887-Y.

Bamford *et al.*, (2020) is the first and only to date (as of February 2022) to compare whale density estimates from traditional ship-based surveys to those determined using very high-resolution satellite imagery and the first to account for availability bias while using satellite imagery. To estimate and compare the densities of humpback whales in the Gerlache Strait of the Western Antarctic Peninsula, the authors acquired four Worldview 3 images (0.31 m panchromatic resolution) collected 7-10 days before a ship-based survey. They use data from dive-recording suction cup tag data of humpbacks to adjust for surface availability for both ship-based (approximated depth of detectability of 4-5 m) and satellite-based estimates (approximated depth of detectability of 1 m). They find that the corrected satellite estimates (0.13 whales per km^2) were lower than ship-based densities (0.33 whales per km^2). However, explain that the lower density estimates were expected because of the nature of satellite's instantaneous acquisition of imagery, the image resolution, the sea-state during acquisition, and most importantly, the temporal gap between surveys.

Borowicz, A. *et al.*, (2019) 'Aerial-trained deep learning networks for surveying cetaceans from satellite imagery', PLOS ONE. Edited by P. Pławiak, 14(10), p. e0212532. https://doi.org/10.1371/JOURNAL.PONE.0212532.

Browicz *et al*., (2019) developed a cetacean survey method using a convolutional neural network (CNN) to automate detection of whales in satellite imagery to minimize the labor requirements associated with manual detection. They train and tested two types of CNNs, ResNet and DenseNet, and two other kinds of traditional classifications methods known as ridge regression and C-SVC, using down-scaled (2 cm to 31 cm) aerial survey imagery of minke whales in European waters and Worldview 3 (0.31 m panchromatic resolution) imagery from Google Earth Pro of Peninsula Valdes, Argentina containing southern right whales and of humpback whales in Maui, Hawaii. First, they trained the models using a random subset of 90% of the imagery and use the remaining 10% to validate the trained algorithm and then repeated this process an additional 10 times. They found that both the CNN models outperformed the traditional classification methods. Out of the CNN models, the ResNet performed best and was able to classify all whales as whales and only misclassified 6.1% of water as whales (false positives) in the Worldview 3 imagery. They argue that this method is the first step to a fully automated detection system but remains a semi-automated method because the algorithms are not able to detect all whales and manual inspection is still needed to remove false positives.

Charry, B. *et al.*, (2021) 'Mapping Arctic cetaceans from space: A case study for beluga and narwhal', *PLOS ONE*, 16(8), p. e0254380. https://doi.org/10.1371/journal.pone.0254380.

This paper is the first to detect medium sized cetaceans (3-5 m) from satellite imagery. The authors assess the ability of Worldview 3 imagery (0.31 m panchromatic resolution) to detect belugas (Cumberland Sound) and narwhals (Tremblay Sound) in the Canadian Arctic. Imagery was tasked during calm sea-state and an allowance of 15% or less cloud coverage was given. Specifically, belugas are good candidates for detection via satellites due to their stark contrast with the surrounding waters and to a lesser extent Narwhals with their mottled white, black and grey coloration. A total of 292 beluga whales and 109 narwhals were detected through a visual inspection of the panchromatic band of the imagery. The authors also explore the ability of three different pansharpening methods to enhance whale detection: Fast Intensity-Hue-Saturation, Brovey Transform, and Additive Wavelet Transform. The authors found that Brovey Transformation performed best and noted that the visual interpreters preferred using 1, 2, 3 (coastal, blue, green); 1, 5, 8 (coastal, red and near-infrared); or 2, 3, 4 (blue, green and yellow) band combinations to visually interpret imagery. Authors note that although these methods show promise, visual interpretation of imagery is manually intensive and at this scale do not represent population wide estimates.

Clarke, P.J. *et al.*, (2021) 'Cetacean Strandings From Space: Challenges and Opportunities of Very High Resolution Satellites for the Remote Monitoring of Cetacean Mass Strandings', Frontiers in Marine Science, 8. https://doi.org/10.3389/FMARS.2021.650735.

Clarke *et al.*, (2021) is the second paper to outline and propose the use of very high-resolution satellite imagery to monitor cetacean mass stranding events, following Fretwell *et al.*, (2019). The authors review the current state of science for mass strandings focusing on the current methods, the present challenges, and the areas in need of more effort. Multiple different stranding networks currently monitor stranding incidences, but remote regions and economically impoverished areas remain logistically difficult to monitor. Following the mass stranding event that occurred in 2015 described by Fretwell *et al.*, (2019), Clarke *et al.*, (2021) present a brief case study where they identify the timing of a mass stranding event of sei whales in the remote Golfo de Penas, Chile in 2019. Moreover, the authors outline: the difference between tasking imagery and archived imagery, the cost of imagery, possible detection methods, the need for ground truth data, and the challenges of species differentiation. Finally, they lay out a road map for monitoring stranding events using satellite imagery. This road map includes the automation of detection, the need for data storage, sharing, and accessibility, the emergence of new satellite technology and includes a call for an interdisciplinary approach to this research. Although this paper focuses on cetacean mass stranding events, many of the claims are directly applicable to the use of VHR satellite imagery for live whale monitoring.

Corrêa, A.A. *et al.*, (2020) 'Use of satellite imagery to identify southern right whales (*Eubalaena australis*) on a Southwest Atlantic Ocean breeding ground', Marine Mammal Science, n/a(n/a), pp. 1–15. https://doi.org/10.1111/mms.12847.

Corrêa *et al*., (2021) compares the ability of very high (Pleiades 1A, 0.70 m resolution), high (RapidEye, 5 m resolution; Planet Scope, 3 m resolution) and medium (Sentinel 2, 10 m resolution; Landsat 8, 30 m resolution) resolution satellites to detect southern right whales in a breeding ground on the south-central coast of Santa Catarina, Brazil with aerial survey data. This is the first and only paper to date (as of February 2022) that compares satellite imagery detection of whales with aerial surveys. They used archived satellite imagery acquired within 2 days of aerial surveys for comparison. They manually interpreted imagery and found that it took approximately 2 hours per image to inspect an area of 15.8 km^2. No whales were identified in the Sentinel 2 and Landsat 8 imagery because of their coarse resolutions. Whales were detected in both the high and VHR imagery. Whale observations from all the images were pooled together and compared with the aerial surveys to see if any significant difference was found. No significance difference between the aerial imagery and satellite surveys were found (Mann-Whitney U test) between the number of whale groupings ($p = .841$, $n = 5$) and the total number of whales ($p = .222$, $n = 5$). Although the authors argue for the efficacy of this method because no significant difference is found, the low sample size/low statistical power of the test should be noted. A spatial analysis focused on the very high-resolution imagery found the locations of whales detected in the satellite imagery was positively correlated with the locations of whales detected in the aerial surveys (Mantel test; $r= 0.52$, $p=0.001$, $n= 13$), suggesting similar patterns of variation between them. Lastly, the authors tested two different types of unsupervised classification methods, a semi-automated classification plug-in (SCP) and Dzetsaka plug-in in QGIS, on the high-resolution imagery and found that the SCP method performed best and found 95.6% of the manually detected whales.

Cubaynes, H.C. *et al.*, (2019) 'Whales from space: Four mysticete species described using new VHR satellite imagery', Marine Mammal Science, 35(2), pp. 466–491. https://doi.org/10.1111/mms.12544.

This study is the first to use Worldview 3 (31 cm panchromatic resolution) imagery to detect whales from space. The authors chose four areas where 1) whales exist with morphological differences from other great whale species 2) the target species occur in high numbers, 3) a calm sea state is dominant and 4) no other megafauna are present that could be misconstrued as the target species. They present a manual method for counting whales with different levels of confidence that has been adapted by many researchers following the publication of this paper (Corrêa *et al*., 2021; Charry *et al*., 2021; Bamford *et al*., 2020) and give a broad overview of parameters to be considered when developing a satellite imagery-based approach to monitor whales. They find that it takes approximately 3 hours and 20 mins to visually interpret 100 km^2 of imagery and detected four different mysticete (whales of the suborder Mysticeti) species: fin whales in Ligurian Sea, Humpback whales in Hawaii, southern right whales in the Peninsula Valdes and grey whales in Laguna San Ignacio. The authors identify the unique visual characteristics that are able to differentiate species in satellite imagery such as the white head callosities of southern right whales and the long flippers present on humpback whales. However, they find that although the target species had slight differences in their coloration, their spectral profiles were relatively similar and difficult to differentiate from surrounding water highlighting the difficulty of using spectral characteristics in classification methods. Despite the difficulties in differentiating between spectral profiles, the authors urge for the development of automated or semi-automated detection in the future.

Cubaynes, H.C. *et al.*, (2020) 'Spectral reflectance of whale skin above the sea surface: a proposed measurement protocol', Remote Sensing in Ecology and Conservation, 6(3), pp. 411–423. https://doi.org/10.1002/rse2.155.

Cubaynes *et al.,* (2020) quantified the spectral signature of whales using samples from eight whale species: bowhead, minke, fin, sei, Bryde's, humpback, North Atlantic right, and sperm whales. Frozen integument (tough outer skin) samples were provided from previous stranding events and fresh samples were collected during the bowhead subsistence harvest by Inupiat first nations at Utqiagkvik, Alaska. To understand the impact of using previously frozen integument to measure spectral characteristics of whales, the bowhead whale's spectral reflectance was measured before and after freezing. The authors found that whale integument darkened the longer it stayed frozen and found no discernible difference between the spectral signatures of the 7 whales species measured, most likely due to using previously frozen samples. Although no spectral differences were found between species presented in this study, authors still argue for the creation of a spectral reflectance database for whales and suggest collecting measurements from unmanned aerial vehicles or during live stranding events. They note that whales do occur in a range of colours and previous work by Cubaynes *et al.*, (2019) and Abileah (2002) found differences in the spectral signatures among species, suggesting that live whales could be spectrally distinct enabling species discrimination when using satellite imagery, but more work is needed.

Cubaynes, H.C. and Fretwell, P.T. (2022) 'Whales from space dataset, an annotated satellite image dataset of whales for training machine learning models', Scientific Data, 9:245, https://doi.org/10.1038/s41597-022-01377-4

This paper highlights the importance of accurate automated systems to the detection of whales using very high-resolution satellite imagery. It also emphasizes the need for open source library(ies) containing examples of whales annotated in satellite images for the training and testing of automated systems. Presented in the paper are a dataset ('Whales from Space dataset') of 633 annotated whale objects created by surveying 6,300 km^2 of satellite imagery captured using WorldView-3, WorldView-2, GeoEye-1 and Quickbird-2 satellites in areas across the globe. Species covered are the southern right whale, humpback whale, fin whale, and grey whale. The dataset is available on the Natural Environmental Research Council (NERC) UK Polar Data Centre. Important notes regarding technical validation are included in the paper: (1) ground truthing, or the process of verifying on the ground what is observed in a satellite image, is not possible when attempting to detect a highly mobile 'object' like a whale, although it has been attempted via a number of methods (detailed and referenced in the paper); (2) a certainly level (one of 3) reflecting confidence in the detection of a whale was assigned to each detection based on a combination of criteria, and the authors recommend that only whales with a 'definite' certainty be used to train automated detection systems; and, (3) as species differentiation has not yet been tested when analysing satellite images, the authors reference the most likely species in their database.

Fretwell, P.T., Staniland, I.J. and Forcada, J. (2014) 'Whales from Space: Counting Southern Right Whales by Satellite', PLOS ONE, 9(2),https://doi.org/10.1371/journal.pone.0088655.

This paper is the second to use high resolution satellite imagery to detect whales and the first to use the Worldview series satellite imagery. The authors use a Worldview 2 image (50 cm panchromatic resolution, 113 km^2 coverage) to identify southern right whales in part of the world's largest breeding aggregation areas, the Golfo Nuevo, Peninsula Valdes in Argentina. Only southern right whales are seen in this area during July to November and they remain close to the surface to support their calves. This, accompanied by the area's characteristic calm sea state, make it a perfect area to test the ability of satellite imagery to detect whales. Through a manual count they were able to identify 55 probable whales, 23 possible whales using the pansharpened red, green and blue bands of the Worldview 2 imagery and another 13 possible whales using the coastal band of Worldview 2 which penetrates deeper into the water column. They note that for the manual classification the best overall results were retrieved using a combination of the red, near infrared, and coastal blue bands. Additionally, they compare a number of classification methods, maximum likelihood, isoData, k-means, and a simple thresholding method, to automatically detect whales and found that the thresholding method worked best. However, this method requires the largest amount of user input. This method found 84.6% of the manually classified whale-like objects, with a 23.7% false positive rate. They highlight that differentiation at this resolution between different baleen species is highly unlikely and that other possible confounding factors like subsurface rocks, seabird groups, boats and surface bubbles can be confused with whales in automation. This paper shows that satellite imagery can be used to detect whales but that more work is needed to assess its ability to determine population estimates and ascertain availability and perception bias.

Guirado, E. *et al.,* (2019) 'Whale counting in satellite and aerial images with deep learning', Scientific Reports, 9(1), p. 14259. https://doi.org/10.1038/S41598-019-50795-9

Published two days after the Barowicz *et al*., (2019) paper on using convoluted neural networks (CNN), this paper similarly explores the use of CNN to automate the detection of whales on a large scale. However, this paper focuses on using open access data and tools. The authors developed a two-step approach to first identify imagery where whales are present, and second to count and identify the locations of whales within the imagery. They built a training dataset using open-source data from Google Earth, free Arkive, NOAA photo library and NWPU-RESISC45 datasets and tested the model using 13,348 Google Earth imagery of ten marine mammal hotspots. They use F1, an index that evaluates the balance between precision and recall, to measure the performance of the models. In this specific case, precision was regarded as how many images were assigned to the right class and recall was the percentage of images that had whales that were classified correctly. A perfectly balance model would achieve a score of 100%. The models performed well, and the first model had an F1 measure of 81% ± 0.13% for presence detection and the second had a F1 measure of 94% ± 0.01% for locating and counting. They were able to identify and count 62 whales out of the 84 whales identified visually in the imagery. Along with developing the CNN models they analyzed the effect of whale behaviour on the models' performance and found that out of logging, breaching, spyhopping, blowing, peduncle, and submerged behaviours, that the lowest detectability occurred for submerged and spyhopping behaviours. These CNN-based models are easily transferable to other regions and imagery inputs thus show promise for future applications of automated whale detection. However, more work is still needed to differentiate species.

Höschle, C. *et al.,* (2021) 'The Potential of Satellite Imagery for Surveying Whales', Sensors, 21(3), p. 963. https://doi.org/10.3390/s21030963.

Hoschle *et al.,* (2021) present a review of the use of VHR satellite imagery to monitor whales. They define a broad framework for processing satellite imagery and discuss the current challenges with automated detection and scaling up satellite monitoring of whales. Some challenges they put forward are that archived imagery is mostly coastal and open ocean data is limited, commercial satellites are still cost prohibitive on a large scale, environmental conditions such as waves, clouds and swell remain an issue and automated detection software is still being developed for species specific use. They do however present future directions to concentrate effort such as building databases of imagery (aerial and satellite) to train systems, standardizing pre-processing workflows, refining automated detection to species level identification and understanding/accounting for limiting environmental factors. Like Clarke *et al.*, (2021) they call for an interdisciplinary approach to overcome the present challenges this field faces.

LaRue, M.A., Stapleton, S. and Anderson, M. (2017) 'Feasibility of using high-resolution satellite imagery to assess vertebrate wildlife populations', Conservation Biology, 31(1), pp. 213–220. https://doi.org/10.1111/cobi.12809.

LaRue *et al.*, (2017) provides a comprehensive literature review of the use of VHR satellite imagery to detect wildlife and identified criteria for its application. Their primary criteria are an open landscape, a colour contrast between the organism and the landscape, and a large enough body size to be detected (e.g., a polar bear of 2 m length and 1 m width). Their secondary criteria, highlights characteristics that increased the likelihood of detection by satellite imagery such as the ability to differentiate the organism from other features on the landscape, organisms having strong habitat associations, organism occupy specific areas at specific times, and organisms that congregate in large groups. Finally, they attempt to use Worldview 1 and 2 (60 cm panchromatic resolution) satellite imagery to detect muskoxen in the Canadian Arctic but are unsuccessful because of confounding features such as shadows, large rocks, and complex river deltas in the landscape that create a heterogenous background limiting visibility.

Personal Communications

Pisano, O. January 14, 2022. Smart Whales Consortium 2

Working in collaboration with Global Spatial Technology Solutions Inc. (GSTS), Olivia Pisano is a PhD student in the Marine Conservation lab supervised by Dr. Boris Worm at Dalhousie University. Pisano along with collaborators at the Ocean Frontier Institute (OFI), British Antarctic Survey, and the Bigelow Laboratory for Ocean Sciences (**Table S1**) goal is to develop a detection and management system that uses Artificial Intelligence models to automatically detect and identify NARWs with satellite imagery. This system would disseminate sightings and other valuable data to various stakeholders through an interactive platform. They are currently training automated detection algorithms using aerial data and will soon integrate and test the algorithm using satellite imagery. Although their algorithm is primarily built for detection of NARW, there are observations of basking sharks and other (non-NARW) baleen whales within the aerial imagery that could be used for species-specific training. Some challenges they have encountered on the East Coast that limit the ability to detect the NARW are cloud coverage, rough sea state, and low contrast between NARW and surrounding waters.

Tsui, O. January 14, 2022. Smart Whales Consortium 1

Olivier Tsui is the project manager for the Hatfield Consultant LLP (Hatfield) led smartWhales project. Hatfield oversee the consortium made up of collaborators from the University of New Brunswick, Dalhousie University, Duke University, AltaML and the Canadian Wildlife Federation (**Table S1**). Like the other consortiums in stream 1, they are developing a system that automatically detects NARW from very high-resolution satellite imagery using deep learning tools, specifically using cloud-computing modeling on the GEO Analytics Canada platform. They have procured satellite imagery from Cape Cod Bay in the US, Peninsular Valdez in Argentina, Baja peninsula in Mexico, Head of Bight in Australia, and the Antarctic and with this imagery have developed a preliminary whale detection model. They plan on improving this model by adding additional satellite-based training images of whales in 2022 and 2023. Additionally, they are currently exploring other deep learning methods to use images collected from drones and aerial platforms to augment the training dataset to aid with detectability. Some possible applications discussed were the development of a tip and cue system, where if a whale is detected in a specific area, then based on movement models, the surrounding areas could be cued for real-time collection of satellite imagery in order to attempt to monitor these detected whales.

Hodul, M. January 18, 2022. Smart Whales Consortium 3

Matus Hodul is a PhD student in Dr. Anders Knuby’s lab at the University of Ottawa and is a part of consortium led by Fluvial Systems Research Inc, in collaboration with INSARSAT Inc. and the Canadian Whale Institute (**Table S1**). Similarly to the other consortiums, they are currently working on developing an automated detection tool for

NARWs. Their large-scale goal is to develop a software that can ingest satellite imagery and detect NARWs in close to real-time in order to monitor and track their movements which will be used to minimize human/NARW interactions. They've developed a preliminary algorithm but are continuing to improve it. They have collected Worldview 3 imagery through MAXAR's HD technology program which enhances imagery from 31 cm panchromatic resolution to 15 cm resolution and collected SkySat (50 cm panchromatic) imagery from areas of known NARW distribution and will continue to task imagery in the future. Specifically, in the summer of 2021 they successfully obtained Worldview 3 imagery of NARWs in the feeding grounds of Cape Cod Bay, Massachusetts that coincided with an aerial survey. Thus, they have been able to make comparisons between these two methods.

Watt (Wheeler), C. January 18, 2022. DFO SWAMM Program

Dr. Cortney Watt is a research scientist with DFO in the Science Branch, Arctic and Aquatic Research Division, currently working on the Space Whales and Arctic Marine Mammals (SWAMM) program in the Canadian Arctic region. After the first publications had started to highlight the possibility of using of VHR satellite imagery to detect whales in the early 2010s, Watt started tasking imagery for a beluga population of special concern in collaboration with Dr. Marianne Marcoux (DFO), who tasked imagery for narwhals in the Canadian Artic in the summer of 2017. From that early work came a collaboration with the company Whale Seeker Inc. to manually detect these cetaceans in the imagery and led to the paper published by Charry *et al.*, in 2021 (summarized above). Following this work, they tasked Worldview 2 and 3 imagery across 11 different estuaries in the summer of 2020. Challenges they encountered when tasking imagery were the frequent presence of cloud, haze, and rough sea state in the Canadian Arctic. To assess imagery, they contracted MDA who developed a crowdsourcing approach using their Geohive platform. Drs. Watt and Marcoux are also currently collaborating on development of an automated detection algorithm. Furthermore, to aid with availability bias calculations they plan on using beluga cut-outs to measure the deepest depth at which a whale is visible in VHR satellite imagery (see **Figure S1, Appendix A.2**). A SARA Nature Legacy proposal provided funding in 2021 to support the procurement of satellite imagery for identifying and counting marine mammals in the Canadian Arctic in 2021, 2022 and 2023 and led to the official establishment of the SWAMM program. They successfully collected imagery in the summer of 2021, which is currently being processed, and have additionally tasked imagery in the overwintering grounds for belugas. Watt highlighted that for belugas they can use 30-50 cm resolution imagery due to their high contrast with water but can only use 30 cm resolution for narwhals. Through the development of this project, they are additionally working on detecting Walruses with Dr. Cory Matthews, a research scientist with DFO in the Arctic and Aquatic Research Division and have tasked imagery in Eastern Hudson Bay in an attempt to detect another endangered population of belugas with Dr. Arnaud Mosnier and Dr. Anne Provencher St-Pierre.

Joy, R. January 20, 2022. SRKW Forecasting Model

Dr. Ruth Joy is a professor in the School of Environmental Science at Simon Fraser University, where her lab focuses on computational and statistical tools to manage and minimize anthropogenic impacts on marine mammals and sea birds. Specifically, they are working on developing a real-time forecasting system for southern resident killer whales (SRKW) in the Salish Sea to minimize the occurrence of human/whale conflicts. They plan on using near-real time sightings and acoustic data in conjunction with historical information to make forecasts of future direction of travel for whales. These real-time data include sightings from the BCCSN, and acoustic data gathered from the BC Coast-Wide Hydrophone Network throughout the Salish Sea. These historic data include bathymetry, Chinook salmon distribution and abundance, SRKW density maps from historic records and biophysical ocean variables via the NEMO SalishSeaCast Environmental Research Division Data Access Program (ERDAPP) system such as temperature, salinity, currents, tides, phytoplankton, and zooplankton. The real-time forecasting system uses a directional correlated random walk to estimate the likelihood a pod would be found within a given area at up to two and a half hours after an observation has been made. Ruth has expressed interest in helping to build detection algorithms for imagery on the Pacific Coast of Canada and interest in the possibility of integrating observations made from VHR satellite imagery into their model in the future.

Appendix A.2: Supplemental Tables and Figures

Table S1: Summary of the 5 companies and their associated collaborators leading smartWhales projects in stream 1, focused on the development of automated detection algorithms for the NARW and stream 2 focused on prediction and modeling of NARW habitat. People that provided personal communications are included in parentheses beside their affiliated companies/universities. Table is adapted from Government of Canada, (2022).

Lead Company	Collaborators
Stream 1	
Hatfield Consultants (Olivier Tsui)	University of New Brunswick Dalhousie University Duke University AltaML Canadian Wildlife Federation
Global Spatial Technology Solutions Inc.	Dalhousie University (Olivia Pisano & Dr. Boris Worm) Ocean Frontier Institute British Antarctic Survey Bigelow Laboratory for Ocean Science
Fluvial Systems Research Inc.	INSARSAT Inc. University of Ottawa (Matus Hodul & Dr. Anders Knudby) Canadian Whale Institute
Stream 2	
Arctus Inc.	Takuvik (Laval University) Hatfield Consultants ACRI-ST Anderson Cabot Center for Ocean Life, New England Aquarium M-Expertise Marine Bigelow Laboratory for Ocean Sciences Merinov
William Sales Partnership (WSP) Canada Inc.	DHI Water & Environment Canadian Whale Institute Dalhousie University Institut des Sciences de la Mer de Rimouski

Figure S1: Image of beluga whale cut-outs from the SWAMM program which will be used to determine at which depth beluga whales can be seen in satellite imagery

Appendix A.3: Hyperlinks

Airbus (Price Drop) - https://apollomapping.com/blog/significant-price-drops-airbus-defense-space-imagery
Airbus, October 28, 2021 - https://www.intelligence-airbusds.com/newsroom/news/pleiades-neo-ready-for-launch/
Airbus, March 8, 2022 - https://www.intelligence-airbusds.com/newsroom/news/pleiades-neo-ready-for-launch/
Amazon Mechanical Turk. - https://www.mturk.com/
Arctus Inc. - https://arctus.ca/
BC Cetacean Sighting Network (BCCSN) - https://wildwhales.org/
Bioconsult SH - https://bioconsult-sh.de/en/
BioConsult, 2022 - https://bioconsult-sh.de/en/projects/spacewhale/
British Antarctic Survey, 2022 - https://www.bas.ac.uk/project/wildlife-from-space/
Cetalingua Project - https://cetalingua.com/about/
DigitalGlobe Core Imagery Product Guide - https://www.geosoluciones.cl/documentos/worldview/DigitalGlobe-Core-Imagery-Products-Guide.pdf
Discover (Airbus Platform) - https://discover.digitalglobe.com/
Dolphin (Zooniverse) - https://www.zooniverse.org/projects/cetalingua/dolphin-chat
European Space Agency - https://business.esa.int/projects/spacewhale-ii
Fluvial Systems Research Inc. (FSR) - https://www.mitacs.ca/en/partner/fluvial-systems-research-inc
Geo Wiki - https://www.geo-wiki.org/
Giraffes (Zooniverse) - https://www.zooniverse.org/projects/derekedwardlee/measuring-giraffes
Global Spatial Technology Solutions Inc. (GSTS) - https://gsts.ca/
Government of Canada, 2022 - https://www.asc-csa.gc.ca/eng/funding-programs/programs/smartearth/contributions-grants-contracts-awarded.asp
Hatfield Consultants Ltd. - https://www.hatfieldgroup.com/
HiDef Aerial Surveying Ltd. - https://bioconsult-sh.de/en/about-us/hidef-uk/
Humpback whale (Zooniverse) - https://www.zooniverse.org/projects/cetalingua/whale-chat
Indigenous Protected and Conserved Areas (IPCAs) - https://conservation-reconciliation.ca/about-ipcas
Image Hunter (Apollo platform) - https://imagehunter.apollomapping.com/
Kelp forests (Zooniverse) - https://www.zooniverse.org/projects/zooniverse/floating-forests
Kompsat (Price Drop) - https://apollomapping.com/blog/new-price-drops-on-kompsat-2-3-3a-satellite-imagery-get-a-new-price-list
Manatee (Zooniverse) - https://www.zooniverse.org/projects/cetalingua/manatee-chat
MAXAR HD Technology - https://explore.maxar.com/HD-Technology.html
MAXAR, 2022 - https://www.maxar.com/splash/it-takes-a-legion
MAXAR, January 07, 2019 - https://investor.maxar.com/investor-news/press-release-details/2019/Maxar-Technologies-Reports-Failure-of-its-WorldView-4-Imaging-Satellite/default.aspx
MAXAR's Geohive - https://geohive.digitalglobe.com/geohive/?utm_source=social&utm_medium=website
MegaMove Action - https://www.oceandecade.org/actions/megamove-overhauling-conservation-of-highly-migratory-marine-megafauna-at-global-scale/

MSC50 Wind and Wave Hindcast Model (DFO, 2022) - https://www.meds-sdmm.dfo-mpo.gc.ca/isdm-gdsi/waves-vagues/MSC50-eng.html
National Marine Conservation Areas (NMCAs; Parks Canada) - https://www.pc.gc.ca/en/amnc-nmca
Northern Sky Research, March 11, 2019 - https://www.nsr.com/nsr-report-finds-satellite-capacity-pricing-plunges-18-on-average-from-2018-2019/
Northern Sky Research, March 20, 2020 - https://www.nsr.com/satnews-satellite-capacity-pricing-index-report-now-available-from-nsr/
NRCAN, 2022 - https://www.nrcan.gc.ca/maps-tools-publications/satellite-imagery-air-photos/remote-sensing-tutorials/introduction/passive-vs-active-sensing/14639
Ocean Decade Regional Collaborative Center for the Northeast Pacific Ocean - https://oceandecadenortheastpacific.org/
Online (Planet sign up) - https://www.planet.com/get-started/
Penguins (Zooniverse) - https://www.zooniverse.org/projects/penguintom79/penguin-watch
Shark Pulse network - http://sharkpulse.cnre.vt.edu/
SPACEWHALES program - https://bioconsult-sh.de/en/projects/spacewhale/
The British Columbia daily regional wave height forecasts - https://weather.gc.ca/marine/marine_bulletins_e.html?Bulletin=fqcn23.cwvr
The British Columbia Geographic System 1:20,000 scale grid system - https://open.canada.ca/data/en/dataset/a61976ac-d8e8-4862-851e-d105227b6525
The DFO Shark Sighting Network (SSN) - https:/www.dfo-mpo.gc.ca/species-especes/sharks/report-eng.html
The NEMO SalishSeaCast Environmental Research Division Data Access Program (ERDAPP) - https://salishsea.eos.ubc.ca/erddap/index.html
BC Coast-Wide Hydrophone Network - https://www.bcwhales.org/bchydrophonenetwork
The Northern Shelf Bioregion (NSB) marine protected area network (MPAn) - https://mpanetwork.ca/bcnorthernshelf/
The Tula Foundation’s Quadra Center for Coastal Dialogue - https://quadracentre.org/
The Windy global wave, swell and wind forecast model - https://www.windy.com/?48.481,-123.317,5
UN decade of Ocean Science for Sustainable Development - https://www.oceandecade.org/
Wildlife from Space Program - https://www.bas.ac.uk/project/wildlife-from-space/
William Sales Partnership (WSP) Canada Inc.- https://www.wsp.com/en-CA
Zooniverse - https://www.zooniverse.org/