TECHNICAL NOTE

Satellite Remote Sensing for Wildlife Research in the Polar Regions

AUTHOR

Heather J. Lynch
Institute for Advanced Computational Science, Stony Brook University, NY
Department of Ecology & Evolution, Stony Brook University, NY

ABSTRACT

Wildlife research in the polar regions has historically been limited by the logistical constraints of site access, but recent developments in the use of satellite imagery for animal detection has unlocked new possibilities for pan-Arctic and pan-Antarctic monitoring of animal populations. A range of different sensor systems have been used for wildlife research, but most have focused on optical sensors that collect data in the visible spectrum and can be directly interpreted similar to a photograph. These include medium-resolution sensors like Landsat (30 m) and Sentinel-2 (10 m) and very high-resolution sensors such as Maxar's Worldview-2 (51 cm) and Worldview-3 (31 cm). These long-established satellite systems have been joined more recently by constellations of smaller satellites (so-called "Small Sats") that offer imagery of comparable spatial and spectral resolution to those operated by Maxar. This rapidly expanding portfolio of earth observation satellites offers the potential for a radical transformation of wildlife research in polar regions, but the sheer volume of data being collected now eclipses our capacity for manual imagery interpretation. To meet this challenge, researchers are now harnessing advances in computer vision that, coupled with improvements in computing capacity, promise to deliver a new era in our ability to monitor polar wildlife.

Keywords: satellite imagery, computer vision, penguins, seals, whales

Introduction

Satellite imagery has been in regular use for earth observation and monitoring for over 40 years, but much of this work has been focused on mapping the planet itself (ocean color, sea ice, forest cover, etc.) rather than the animals that live on it. Though the idea that we could use satellites to map polar seabirds was explored early on (Schwaller et al., 1984; Schwaller et al., 1989), the last decade has seen a major expansion of these efforts in step with a rapid increase in the number and variety of sensors now currently available for wildlife research.

Worldwide, satellite imagery has been used to survey everything from penguins and whales to cattle and elephants (see review by LaRue et al., 2017, and references therein). Though the potential for wildlife survey by satellite imagery is global, several factors have made the polar regions a leader in the technical development and operationalization of satellite-based monitoring. For one, the polar areas are exceptionally difficult and expensive to survey using more traditional means, so alternative methods provide not only a complement to but often the only feasible means of tracking wildlife over large spatial areas. Research in the polar regions, particularly the Antarctic, is also inherently international. The confluence of multiple earth observation programs operating in the polar regions provides the opportunity to compare and combine the strengths of different sensor programs. The absence of trees or other woody vegetation also facilitates the use of satellite imagery for animal survey, since the simplified landscape provides little cover that might obscure animals viewed from above. The polar areas also enjoy a geographical advantage, as polar orbiting satellites pass over the Arctic and Antarctic much more frequently than they do areas at lower latitudes and the development of very high-resolution digital elevation models for both the Arctic (Porter et al., 2018) and the Antarctic (Howat et al., 2019) have established in fine detail the coastline and bare rock areas on which wildlife are likely to be found. Finally, while some commercial satellite imagery remains very expensive, special licensing arrangements specific to polar science have facilitated the research needed to establish satellite-based surveys as technically feasible.

The distribution and abundance of wildlife can be tracked through satellite imagery in two different ways. In scenarios in which the size of the animal combined with the resolution of the sensor allows for the identification of individual animals, direct enumeration is possible. Though most directly comparable to traditional survey methods, direct census by satellite is currently only achievable for a small number of species using the very highest resolution sensors available for civilian research. Fortunately, it is often possible to observe the presence of animals even when individuals are not visible; large aggregations of animals may be directly visible, or they may leave by-products or modify their habitat in characteristic ways. The use of such indirect means to identify animals "in bulk" is often adequate for quantitative estimates of abundance and greatly expands the utility of these methods. While humans can easily switch between "animals-as-points" and "animals-as-polygons," these represent two distinct tasks for computer automation (classification vs. segmentation) and pose distinct challenges for the utilization of imagery for quantitative population estimates. Fortunately, neither direct nor indirect survey methods are particularly sensitive to the spectral characteristics of the imagery provided, and most applications require only a simple red-green-blue composite image or even a grayscale panchromatic image. This insensitivity to the specific absorption bands stands in contrast to many earth observation tasks in which the detailed nature of absorption in different wavelengths is key to classification, and it means that nearly all optical sensors of sufficient resolution are usable.

This technical note will describe the recent technical advances in the use of satellite imagery for wildlife surveys in the polar regions and some of the remaining challenges to the creation of fully automated data products for use in conservation and management. Though the focus of this piece will be on optical sensors that can be directly interpreted like a traditional photograph, some of the other sensor modalities available for wildlife census are noted briefly at the end.

Medium Resolution Sensors (10–30 m)

Some of the earliest exploration of satellite imagery for wildlife mapping was done using the Satellite pour l'Observation de la Terre satellites, which offered up to 10-m resolution imagery and were used early on to survey both Adélie (Bhikharidas et al., 1992) and king penguins (Guinet et al., 1995). More recent efforts, however, have focused on imagery provided by NASA's Landsat satellite series. The Landsat satellite program has been operational since 1972 (Goward et al., 2006) and currently includes three satellites in active operation (Landsat-7, Landsat-8, and the newly launched Landsat-9). While the spectral absorption bands have shifted slightly over the decades, the persistent coverage through time makes Landsat arguably the best long-term time series that we have available for wildlife research. In addition, Landsat imagery has been publicly available since 2008. Though the 30-m resolution precludes the direct census of animals, Landsat imagery has been used to survey Adélie penguins (Schwaller et al., 2013; Lynch & Schwaller, 2014), emperor penguins (Fretwell & Trathan, 2009), and Antarctic petrels (Schwaller et al., 2018), the first two of which are considered sentinel species for climate change and are regularly monitored as part of international efforts for Antarctic conservation. For penguins as well as flying birds such as the Antarctic petrel, the spectral characteristics of their guano allow for breeding colonies to be distinguished from other landscape features (e.g., Lynch et al., 2012; Rees et al., 2017). Because colony areal extent is highly correlated with population (Woehler & Riddle, 1998; Naveen et al., 2012; LaRue et al., 2014), the area within each guano-covered patch can be used to estimate the number of nests within. In addition, the spectral bands of Landsat have allowed researchers to estimate penguin diet from satellite imagery (Youngflesh, 2018). Offering higher spatial resolution than Landsat is Sentinel-2, which offers imagery at up to 10-m resolution. Sentinel-2 has been explored for the survey of emperor penguins (Fretwell & Trathan, 2021), but is arguably underutilized relative to its considerable potential.

Very-High Resolution Sensors (< 1 m)

Perhaps not surprisingly, the feasibility of directly enumerating individual animals using very high-resolution satellite imagery, such as Worldview or Quickbird, has generated considerable interest, and a large number of applications have been explored. These sensors typically provide a sub-meter resolution panchromatic image alongside a slightly lower resolution multispectral imagery. For example, Worldview-3 imagery is available with a 31-cm resolution panchromatic and eight bands in the visible and near-infrared at a 1.24-m resolution. Unlike Landsat, which collects imagery continually across a prespecified orbit pathway, Worldview imagery must be specifically tasked for imagery collection over target areas and is thus well suited for data collection over pre-specified locations (max area collected in a single pass is 67 km × 112 km) but does not easily accommodate regular repeated surveys over large contiguous areas. The University of Minnesota's Polar Geospatial Center (http://www.pgc.umn.edu) has played a pivotal role in supporting the use of commercial imagery for polar science; rapid growth in number of images available have allowed for nearly universal spatial coverage across the Arctic and terrestrial Antarctic and, in many key areas, a large number of repeated images that can be used to assess change over time (Figure 1).

In the Antarctic, crabeater seals (Gonçalves et al., 2020; Gonçalves et al., 2022; Figure 2a), Weddell seals (LaRue et al., 2011, 2021), fur seals (Foley, 2019), and southern elephant seals (McMahon et al., 2014; Fudala & Bialik, 2022) have all been enumerated in sub-meter commercial satellite imagery. Though imagery fusion methods can be used to create multispectral imagery at the higher resolution of the panchromatic (Witharana et al., 2016), seal

FIGURE 1

(a) Number of very-high resolution satellite image scenes over the Antarctic (a) and Arctic (b) available at the University of Minnesota's Polar Geospatial Center through April 2022. (c) The cumulative number of scenes available through time. Figure and data provided by Claire Porter, Polar Geospatial Center.

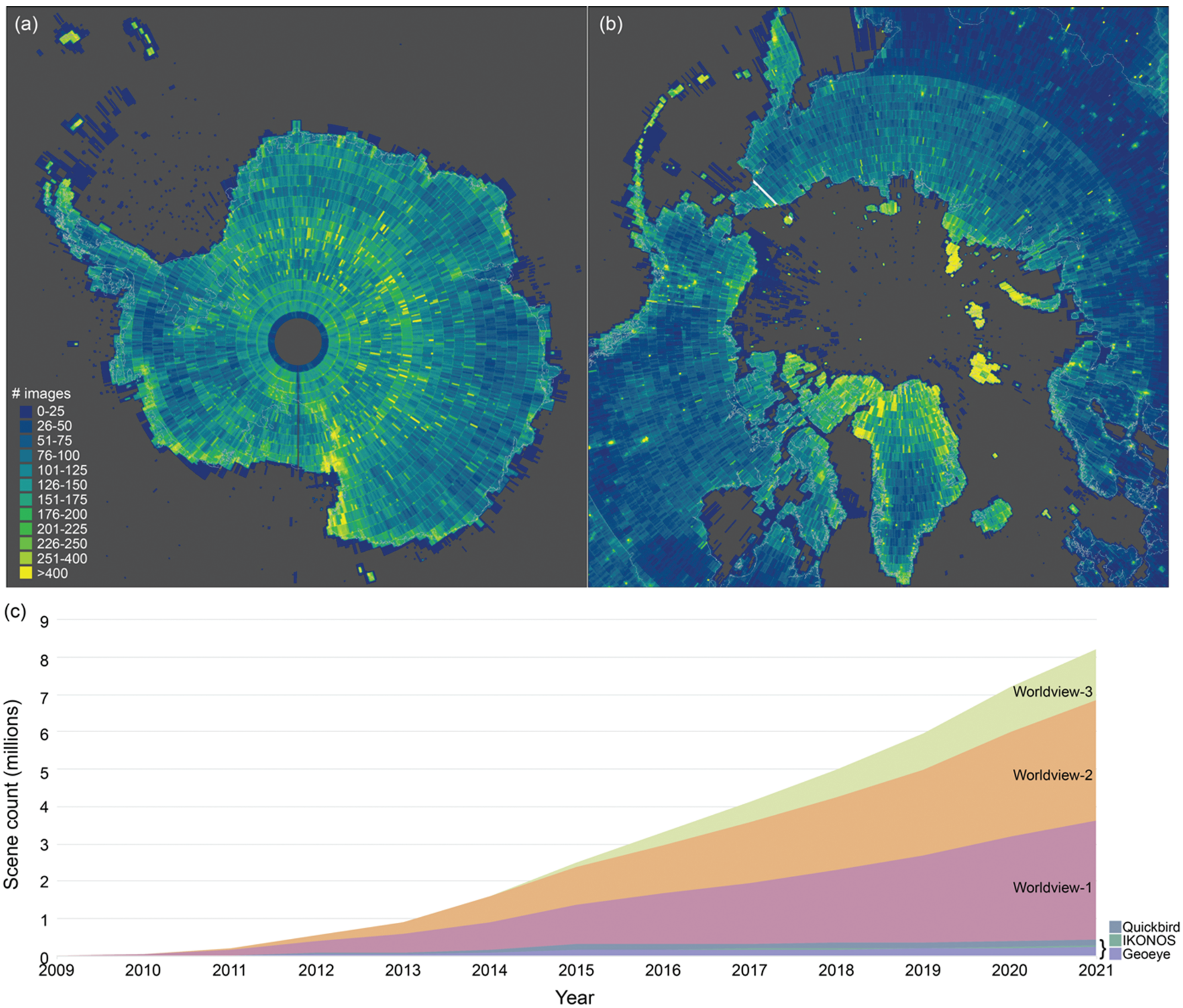
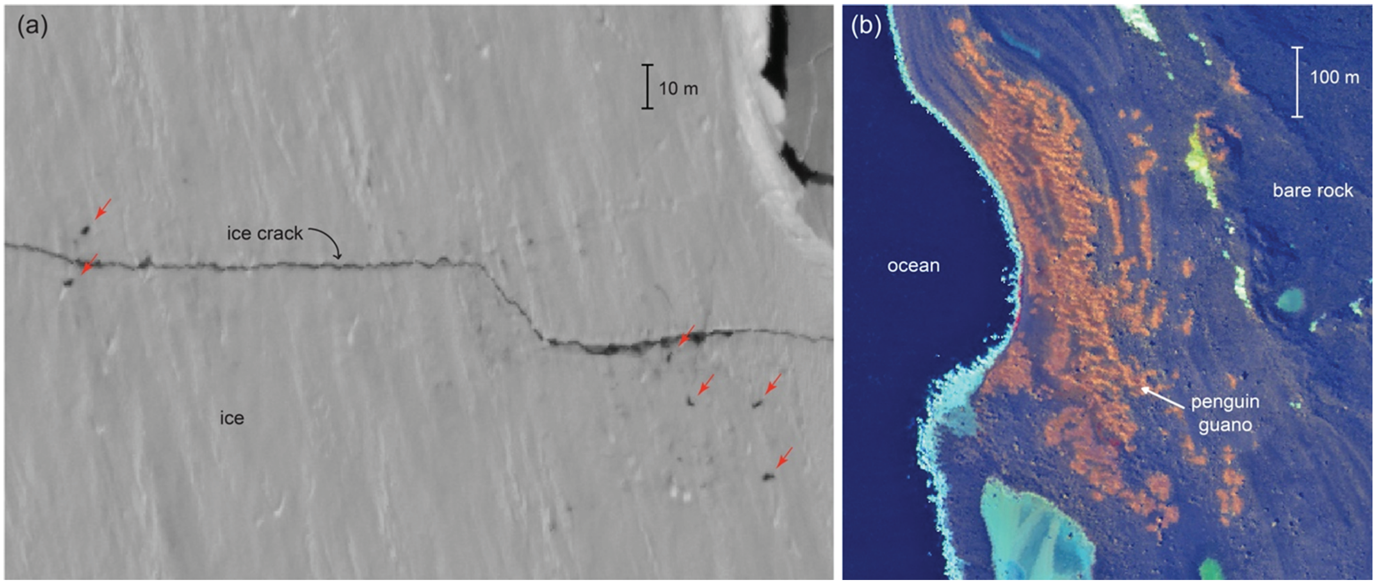


FIGURE 2

(a) Portion of a Worldview-3 scene from December 29, 2015, showing pack-ice seals clustered around a sea ice crack. Imagery copyright Maxar. (b) Portion of a Worldview-2 scene from February 18, 2016, showing the pinkish guano stain associated with breeding Adélie penguins at Inexpressible Island, Antarctica. Imagery copyright Maxar.



classification is largely insensitive to color information and usually the panchromatic image alone is sufficient. In the Arctic, applications have included walrus (Zinglersen et al., 2019) and polar bears (LaRue & Stapleton, 2018).

In addition to marine mammals that haul up on land or ice, satellite imagery has some capability of viewing animals in the water and, in this regard, nothing has generated more excitement than the possibility that satellite imagery could be used to survey whales (e.g., Fretwell et al., 2014). Many populations of whales were decimated by commercial whaling, and ship strikes and entanglements continue to pose severe threats (Clapham et al., 1999). Because whales are exceptionally difficult to survey, any cost-effective method to track populations in the open ocean would make a profound difference in our ability to monitor and protect these species. Early efforts to survey whales from satellite imagery have been challenged by the low frequency of encounter (most images do not, in fact, contain any whales) and surface waves that can obscure whales under the surface (Höschle et al., 2021). Nevertheless, pilot studies have demonstrated that whales can be observed in satellite imagery and can be detected using automated classification models (Borowicz et al., 2019; Guirado et al., 2019). The real challenge at this point is not technical but economic, since there is little incentive to capture imagery over the ocean at the spatial scales likely required for conservation-relevant population assessments.

Seabirds are another taxonomic group where high-resolution satellite imagery has proven effective for population monitoring. In the Antarctic, most of the work has focused on penguins (e.g., Barber-Meyer et al., 2007; Fretwell et al., 2012; Lynch et al., 2012; Lynch & LaRue, 2014; LaRue et al., 2014; Strycker et al., 2020). For the nest building brush-tailed penguins, the process of penguin identification proceeds similarly to that described for Landsat imagery except that the higher spatial resolution allows for a refined delineation of colony boundaries (Figure 2b). In all of these cases, there is a relationship between the area of the colony as observed in satellite imagery and the number of breeding pairs that allows for at least a rough estimate of abundance. This relationship is strongest and most robust for Adélie penguins (LaRue et al., 2014), as they pack in dense colonies that remain remarkably stable through time, and for this reason, Adélie penguins have been the easiest to survey using automated methods (Le et al., 2022). Emperor penguins are also visible where they gather at the colony, though the lack of nests and the shifting ice on which they breed means that colony locations are considerably more variable through time (LaRue et al., 2015), and estimates of abundance can be heavily influenced by factors such as the timing of imagery (both within the day and within the breeding season) and local weather conditions (Labrousse et al., 2022).

Though Worldview imagery has largely dominated the high-resolution landscape for polar wildlife survey, there is a growing portfolio of imagery providers capable of delivering imagery at these resolutions. Among them are constellations of so-called "Small Sat" sensors such as Planet (SkySat and PlanetScope) and Satellogic, which can deliver multispectral products at sub-meter resolution (Curnick et al., 2021). These newer products have not yet entered mainstream use for wildlife survey, but their technical specifications are well-suited to the task, and they are very likely to become an important component of future survey efforts.

Non-Optical Sensors for Wildlife Survey

While optical imagery has been the most promising satellite-based technology for wildlife survey, there has been some exploration of alternative data types. Radar imagery such as that provided by TerraSAR-X has been explored for penguin colonies, in the hopes that the height of penguins clustered at the colony might be distinguishable from the background substrate. Similar hopes are held for the newest generation of laser altimetry sensors, such as that on NASA's Icesat-2 satellite. While there has been some evidence that emperor penguins might be observable in this way (particularly during the winter when penguins are tightly packed together), efforts to observe colonies of the smaller nest building species have proven unsuccessful (Mustafa et al., 2012). Thermal infrared (TIR) imagery is another intriguing technology in the polar regions because it seems as though seabirds and marine mammals should be considerably warmer than their background environment and the relative scarcity of animals in the polar regions should minimize noise in the thermal signal. Unfortunately (in this context), the most promising target for thermal surveying is emperor penguins, and their body surface is actually a bit cooler than the surrounding air (McCafferty et al., 2013), and a recent study using drone imagery found no benefit in penguin abundance classification performance when including TIR data (Hinke et al., 2022). Though several polar species (e.g., polar bears, walrus, seals) have been surveyed successfully using airborne thermal sensors, satellite-based TIR imaging is captured at a much lower spatial resolution (e.g., 30 m on Landsat-8; 90 m on Terra) than optical imagery, and this sets a very high threshold for the smallest detectable aggregation.

Managing the Imagery "Firehose"

Until very recently, the use of satellite imagery for wildlife survey was characterized by small pilot studies to demonstrate feasibility with imagery interpretation dominated by tedious and time-consuming manual annotation. However, as the use of satellite imagery matures, there is a growing appreciation that scaling-up these approaches for repeated surveys over large areas will require new approaches. Though crowd-sourcing imagery interpretation has been explored and used successfully in some applications, considerable effort has been dedicated to machine-learning-based approaches that harness rapid advances in computer vision and computing power (Borowicz et al., 2019; Guirado et al., 2019; Gonçalves et al., 2020; Rodofili et al., 2022; Gonçalves et al., 2022). Though computer vision approaches, particularly convolutional neural networks (CNNs), have readily automated many tasks previously requiring human interpretation, wildlife surveys present some particular challenges. CNNs require large training data sets, but training data are often extremely limited, both because the imagery itself may be limited or because there are too few experienced image analysts to annotate the imagery that does exist. Licensing restrictions on commercial imagery greatly limit the availability of imagery to skilled computer vision experts, and the pace of development in computer vision makes it difficult for wildlife biologists to learn the skills needed to train and use new models. Except in rare circumstances in which imagery and ground data can be collected simultaneously, validation of wildlife surveys conducted using satellite imagery is difficult. This is particularly true for highly mobile organisms such as pack-ice seals and whales, whose presence in any particular image is almost impossible to validate independently. Finally, the rapid expansion of imagery collected poses challenges for imagery storage and distribution, and while cloud-based solutions (e.g., Amazon's EC2) can provide storage capacity beyond that available to any individual researcher or institution, the costs of imagery storage can be considerable.

Conclusions

The number of earth-observing satellite sensors has grown rapidly over the last several decades, and the resources available for space-based surveys of wildlife is sure to grow. In just the last decade, this field has witnessed a rapid transition from a handful of promising pilot studies to a fully fledged and increasingly well-established community of practitioners. Just as importantly, there is an increasing appreciation for the role that satellite imagery may play in Antarctic conservation and policy (LaRue et al., 2022). For those species large and exposed enough for satellite observation, we are rapidly moving toward automated approaches for imagery interpretation that will radically expand our capacity for regular, possibly even continuous, population assessment. While the release of even higher resolution imagery for civilian purposes would undoubtedly expand the utility and accuracy of satellite-based approaches, the imagery currently available is more than adequate for many polar species. Despite the promise of near-real time population estimates for some of the most closely monitored species on the planet, there are genuine sociotechnical hurdles to overcome if these approaches are to have their greatest impact on conservation. The costs of imagery acquisition will be absolutely prohibitive for all but the smallest areas, and every effort should be made to expand access to imagery for conservation purposes. Licensing restrictions on commercial imagery also preclude engaging with the larger computer vision community. The creation of species-specific publicly accessible training data sets would have a transformative impact on the pace of development and would greatly expand the number of computer vision experts engaged in wildlife applications. Finally, while the focus of recent efforts has been on the accurate classification of wildlife as captured in imagery, robust population monitoring will require greater effort to model the availability of animals and the propagation of all relevant uncertainties through to the final population estimate. Though critical work remains to bring this vision to reality, these pipelines should eventually provide wildlife "products" comparable to other environmental data sets such as sea ice and ocean temperature on which ecologists already rely so heavily.

Acknowledgments

I would like to thank Matt Schwaller for his ideas and suggestions on this manuscript and the National Science Foundation (NSF) EarthCube program (award 1740595) for funding my own work on satellite-based wildlife surveys. Geospatial support for much of the work described in this review was provided by the Polar Geospatial Center under NSF-Office of Polar Programs Awards 1043681 and 1559691.

References

Barber-Meyer, S.M., Kooyman, G., & Ponganis, P.J. 2007. Estimating the relative abundance of emperor penguins at inaccessible colonies using satellite imagery. Polar Biol. 30(12):1565–70. https://doi.org/10.1007/s00300-007-0317-8.

Bhikharidas, A.K., Whitehead, M.D., & Peterson, J.A. 1992. Mapping Adélie penguin rookeries in the Vestfold Hills and Rauer Islands, East Antarctica, using SPOT HRV data. Int J Remote Sens. 13(8):1577–83. https://doi.org/10.1080/01431169208904211.

Borowicz, A., Le, H., Humphries, G., Nehls, G., Höschle, C., Kosarev, V., & Lynch, H.J. 2019. Aerial-trained deep learning networks for surveying cetaceans from satellite imagery. PLOS ONE. 14(10):e0212532. https://doi.org/10.1371/journal.pone.0212532.

Clapham, P.J., Young, S.B., & Brownell, R.L., Jr. 1999. Baleen whales: Conservation issues and the status of the most endangered populations. Mamm Rev. 29(1):35–60. https://doi.org/10.1046/j.1365-2907.1999.00035.x.

Curnick, D.J., Davies, A.J., Duncan, C., Freeman, R., Jacoby, D.M.P., Shelley, H.T.E., … Pettorelli, N. 2021. SmallSats: A new technological frontier in ecology and conservation? Remote Sens Ecol Conserv. 8(2):139–50. https://doi.org/10.1002/rse2.239.

Foley, C. 2019. Long-term human impacts on sub-Antarctic ecosystems and mesopredator abundance. Ph.D. thesis, Stony Brook University.

Fudala, K., & Bialik, R.J. 2022. Seals from outer space—Population census of southern elephant seals using VHR satellite imagery. Remote Sens App: Soc Environ. 28:100836. https://doi.org/10.1016/j.rsase.2022.100836.

Fretwell, P.T., Staniland, I.J., & Forcada, J. 2014. Whales from space: Counting southern right whales by satellite. PLOS ONE. 9:e88655. https://doi.org/10.1371/journal.pone.0088655.

Fretwell, P.T., LaRue, M.A., Morin, P., Kooyman, G.L., Wienecke, B., Ratcliffe, N., … Trathan, P.N. 2012. The first global, synoptic survey of a species from space. PLOS ONE. 7(4):e33751. https://doi.org/10.1371/journal.pone.0033751.

Fretwell, P.T., & Trathan, P.N. 2009. Penguins from space: Faecal stains reveal the location of emperor penguin colonies. Glob Ecol Biogeogr. 18(5):543–52. https://doi.org/10.1111/j.1466-8238.2009.00467.x.

Fretwell, P.T., & Trathan, P.N. 2021. Discovery of new colonies by Sentinel2 reveals good and bad news for emperor penguins.

Remote Sens Ecol Conserv. 7(2):139–53. https://doi.org/10.1002/rse2.176.

Gonçalves, B., Spitzbart, B., & Lynch, H.J. 2020. SealNet: A fully automated pack-ice seal detection pipeline for sub-meter satellite imagery. Remote Sens Environ. 239:111617. https://doi.org/10.1016/j.rse.2019.111617.

Gonçalves, B., Wethington, M., & Lynch, H.J. 2022. SealNet2: Human-level fully-automated pack-ice seal detection. Remote Sens. 14(22):5655. https://doi.org/10.3390/rs14225655.

Goward, S., Arvidson, T., Williams, D., Faundeen, J., Irons, J., & Franks, S. 2006. Historical record of Landsat global coverage. Photo Eng Remote Sens. 72(10):1155–69. https://doi.org/10.14358/PERS.72.10.1155.

Guinet, C., Jouventin, P., & Malacamp, J. 1995. Satellite remote sensing in monitoring change of seabirds: Use of spot image in king penguin population increase at Ile aux Cochons, Crozet Archipelago. Polar Biol. 15:511–5. https://doi.org/10.1007/BF00237465.

Guirado, E., Tabik, S., Rivas, M.L., Alcaraz-Segura, D., & Herrera, F. 2019. Whale counting in satellite and aerial images with deep learning. Sci Rep. 9(1):14259. https://doi.org/10.1038/s41598-019-50795-9.

Hinke, J.T., Giuseffi, L.M., Hermanson, V. R., Woodman, S.M., & Krause, D.J. 2022. Evaluating thermal and color sensors for automating detection of penguins and pinnipeds in images collected with an unoccupied aerial system. Drones. 6(9):255. https://doi.org/10.3390/drones6090255.

Höschle, C., Cubaynes, H.C., Clarke, P.J., Humphries, G., & Borowicz, A. 2021. The potential for satellite imagery for surveying whales. Sensors. 21(3):963. https://doi.org/10.3390/s21030963.

Howat, I.M., Porter, C., Smith, B.E., Noh, M.-J., & Morin, P. 2019. The reference elevation model of Antarctica. The Cryosphere. 13(2):665–74. https://doi.org/10.5194/tc-13-665-2019.

Labrousse, S., Iles, D., Viollat, L., Fretwell, P., Trathan, P.N., Zitterbart, D.P., … LaRue, M. 2022. Quantifying the causes and consequences of variation in satellite-derived population indices: A case study of emperor penguins. Remote Sens Ecol Conserv. 8(2):151–65. https://doi.org/10.1002/rse2.233.

LaRue, M., Brooks, C., Wege, M., Salas, L., & Gardiner, N. 2022. High-resolution satellite imagery meets the challenge of monitoring remote marine protected areas in the Antarctic and beyond. Conserv. 15(4):e12884. https://doi.org/10.1111/conl.12884.

LaRue, M.A., Lynch, H.J., Lyver, P.O.B., Barton, K., Ainley, D.G., Pollard, A., … Ballard, G. 2014. A method for estimating colony sizes of Adélie penguins using remote sensing imagery. Polar Biol. 37(4):507–17. https://doi.org/10.1007/s00300-014-1451-8.

LaRue, M., Kooyman, G., Lynch, H.J., & Fretwell, P. 2015. Emigration in emperor penguins: implications for interpretation of long-term studies. Ecography. 38(2):114–20. https://doi.org/10.1111/ecog.00990.

LaRue, M.A., Rotella, J.J., Garrott, R.A., Siniff, D.B., Ainley, D.G., Stauffer, G.E., … Morin, P.J. 2011. Satellite imagery can be used to detect variation in abundance of Weddell seals (Leptonychotes weddellii) in Erebus Bay, Antarctica. Polar Biol. 34(11): 1727–37. https://doi.org/10.1007/s00300-011-1023-0.

LaRue, M.A., Stapleton, S.P., & Anderson, M. 2017. Feasibility of using high-resolution satellite imagery to assess vertebrate wildlife populations. Conserv Biol. 31(1):213–20. https://doi.org/10.1111/cobi.12809.

LaRue, M.A., & Stapleton, S. 2018. Estimating the abundance of polar bears on Wrangel Island during late summer using high-resolution satellite imagery: A pilot study. Polar Biol. 41(12):2621–6. https://doi.org/10.1007/s00300-018-2384-4.

LaRue, M.A., Salas, L., Nur, N., Ainley, D., Stammerjohn, S., Pennycook, J., … Rotella, J. 2021. Insights from the first global population estimate of Weddell seals in Antarctica. Sci Adv. 7(39):eabh3674. https://doi.org/10.1126/sciadv.abh3674.

Le, H., Samaras, D., & Lynch, H.J. 2022. A convolutional neural network architecture designed for the automated survey of seabird colonies. Remote Sens Ecol Conserv. 8(2):251–62. https://doi.org/10.1002/rse2.240.

Lynch, H.J., White, R., Black, A.D., & Naveen, R. 2012. Detection, differentiation, and abundance estimation of penguin species by high-resolution satellite imagery. Polar Biol. 35(6):963–8. https://doi.org/10.1007/s00300-011-1138-3.

Lynch, H.J., & Schwaller, M.R. 2014. Mapping the abundance and distribution of Adélie penguins using Landsat-7: First steps towards an integrated multi-sensor pipeline for tracking populations at the continental scale. PLOS ONE. 9:e113301. https://doi.org/10.1371/journal.pone.0113301.

Lynch, H.J., & LaRue, M.A. 2014. First global census of the Adelie penguin. Auk. 131(4):457–66. https://doi.org/10.1642/AUK-14-31.1.

McCafferty, D.J., Gilbert, C., Thierry, A.-M., Currie, J., Le Maho, Y., & Ancel, A. 2013. Emperor penguin body surfaces cool below air temperature. Biol Lett. 9(3):20121192. https://doi.org/10.1098/rsbl.2012.1192.

McMahon, C.R., Howe, H., van den Hoff, J., Alderman, R., Brolsma, H., & Hindell, M.A. 2014. Satellites, the all-seeing eyes in the sky: Counting elephant seals from space. PLOS ONE. 9(3):e92613. https://doi.org/10.1371/journal.pone.0092613.

Mustafa, O., Pfeifer, C., Peter, H.-U., Kopp, M., & Metzig, R. 2012. Pilot study on monitoring climate-induced changes in penguin colonies in the Antarctic using satellite images. Report No. (UBA-FB) 001611/E, Environmental Research of the Federal Ministry of the Environment, Nature Conservation and Nuclear Safety.

Naveen, R., Lynch, H.J., Forrest, S., Mueller, T., & Polito, M. 2012. First direct, site wide penguin survey at Deception Island, Antarctica, suggests significant declines in breeding chinstrap penguins. Polar Biol. 35(12):1879–88. https://doi.org/10.1007/s00300-012-1230-3.

Porter, C., Morin, P., Howat, I., Noh, M.-J., Bates, B., Peterman, K., … Bojesen, M. 2018. ArcticDEM, Version 3. Harvard Dataverse. V1. https://doi.org/10.7910/DVN/OHHUKH.

Rees, W.G., Brown, J.A., Fretwell, P.T., & Trathan, P.N. 2017. What colour is penguin guano? Antarct. 29(5):417–25. https://doi.org/10.1017/S0954102017000190.

Rodofili, E.N., Lecours, V., & LaRue, M. 2022. Remote sensing techniques for automated marine mammal detection: A review of methods and current challenges. PeerJ. 10:e13540. https://doi.org/10.7717/peerj.13540.

Schwaller, M.R., Lynch, H.J., Tarroux, A., & Prehn, B. 2018. A continent-wide search for Antarctic petrel breeding sites with satellite remote sensing. Remote Sens Environ. 210:444–51. https://doi.org/10.1016/j.rse.2018.02.071.

Schwaller, M.R., Olson, C.E., Jr., Ma, Z., Zhu, Z., & Dahmer, P. 1989. A remote sensing analysis of Adélie penguin rookeries. Remote Sens Environ. 28:199–206. https://doi.org/10.1016/0034-4257(89)90113-2.

Schwaller, M.R., Benninghoff, W.S., & Olson, C.E. 1984. Prospects for satellite remote-sensing of Adélie penguin rookeries. Int J Remote Sens. 5(5):849–53. https://doi.org/10.1080/01431168408948868.

Schwaller, M.R., Southwell, C.J., & Emmerson, L.M. 2013. Continental-scale mapping of Adélie penguin colonies from Landsat imagery. Remote Sens Environ. 139:353–64. https://doi.org/10.1016/j.rse.2013.08.009.

Strycker, N., Wethington, M., Borowicz, A., Forrest, S., Witharana, C., Hart, T., & Lynch, H.J. 2020. A global population assessment of the chinstrap penguin (Pygoscelis antarctica). Sci Rep. 10(1):19474. https://doi.org/10.1038/s41598-020-76479-3.

Witharana, C., LaRue, M.A., & Lynch, H.J. 2016. Benchmarking of data fusion algorithms in support of earth observation based Antarctic wildlife monitoring. ISPRS J Photogramm. 113:124–43. https://doi.org/10.1016/j.isprsjprs.2015.12.009.

Woehler, E.J., & Riddle, M.J. 1998. Spatial relationships of Adélie penguin colonies: Implications for assessing population changes from remote imagery. Antarct. 10(4):449–54. https://doi.org/10.1017/S0954102098000546.

Youngflesh, C. 2018. Ecological change in the Southern Ocean—Insights from Antarctic seabirds. Ph.D. thesis, Stony Brook University.

Zinglersen, K.B., Garde, E., Langley, K., & Mätzler, E. 2019. RemoteID: Identification of Atlantic Walrus at haul out sites in Greenland, using high-resolution satellite images. Technical report No. 111, Greenland Institute of Natural Resources, Greenland.