Eco-Social and Remote Sensing: Applications Across a New Era of Ecological Data

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Abstract of the Dissertation

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Field studies in ecology provide the basis for much of our insight into natural processes and the anthropogenic effects upon them. But the scale of inquiry, both spatial and temporal, and the speed with which questions can be posed and answered, is only partly driven by the processes themselves. Ecological inquiry, and thus conservation-oriented inquiry, is also controlled by logistical and bureaucratic constraints. Here I examine the application of opportunistic data and ‘found’ data, broadly available in an era of camera and mobile-sensor ubiquity, to ecological questions. I propose methods and applications to leverage these data and to combine them with satellites and unoccupied aerial vehicles. Using a series of case studies, I demonstrate methods and applications to augment, supplement, and complement traditional field studies, especially at the larger spatial scales. By combining imagery from modern unoccupied aerial vehicles, historical aerial surveys, and Landsat satellites, I estimate not only the current abundance and distribution of penguins in a previously unknown penguin hotspot known as the Danger Islands, but can establish the population dynamics of Adélie penguins (*Pygoscelis* *adeliae*) in the region across a nearly 60-year span. The population of Adélie penguins in the Danger Islands (751,527 breeding pairs) is larger than the rest of the Antarctic Peninsula region combined. This discovery has triggered a series of proposals to protect this tiny, but biologically critical, penguin hotspot.

Using contemporary aerial imagery as training data within a deep-learning framework, I also demonstrate the potential for automated analyses of very high-resolution satellite imagery as a means of surveying large cetaceans. Even at the finer temporal scale of within-season phenological processes, computer vision and ‘found’ data can augment and supplement existing field data. Combining field-collected images and observations of Weddell seals (*Leptonychotes weddellii*) with images sourced from the photo-sharing platform Flickr, I demonstrate the feasibility of photo-identification for among-year tracking in this species and provide evidence that Antarctic Peninsula Weddell seals molt earlier than Weddell seals elsewhere in Antarctica. Using similar methods, I provide the first description of Antarctic fur seal (*Arctocephalus gazella*) distributions on the Antarctic Peninsula and provide evidence for late-season dispersal and steady abundance over the last 25 years, despite dramatic declines at well-surveyed breeding colonies. The methods and applications I propose provide a framework for broadening both the spatial scale of ecological inquiry in many systems and deepening the pool of observations from which we may make inferences. In an era of rapid environmental change, making full use of data outside the realm of traditional field surveys can provide fuller and more rapid assessments of change and baseline states to improve the efficacy of conservation policy and practice.

Dedication

To islands.

the period of a low tide is about all men can endure

John Steinbeck, Log from the Sea of Cortez

For all about that Rock the Sea did flow.
And Danger well he wist long to continue there.

Edmund Spenser

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I am very grateful for the support my parents have shown during these years and their willingness to listen to my complaints about bureaucracy and the structures and politics of higher education, and to my sister, Lydia, whose research is far more interesting than my own.

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And many thanks to my advisors Heather Lynch and Lesley Thorne, and my committee members Stephen Baines and Douglas Krause, whose support, advice, and mentoring has made this dissertation much more interesting than what it set out to be.

1 Introduction

The Antarctic is a region with a highly variable climate, such that the regular extreme conditions in the form of cold air and water temperatures and polar light intervals are interrupted by variable temperatures, precipitation, and wind speed. The variability, which can occur within seasons, among years, or on decadal scales, is strong enough to complicate our ability to assess the strength and nature of anthropogenic climate change in the region. Despite decades of warming between the 1950s and early 2000s, (Turner et al. 2005; Thomas et al. 2013), recent cooling events, when viewed alongside the long-term ice record, demonstrate that at least some of the recent warming and co-incident ice loss on the Antarctic continent falls within the range of historical climate variability (Thomas et al. 2013; Turner et al. 2016a; Turner et al. 2016b).

The potential complications of spatial scale are pronounced on the Antarctic Peninsula, a body of land and its associated islands that span 1,200 km from the permanent land-fast sea ice in the south to the generally ice-fee coasts of the north. Much of Antarctic Peninsula research is conducted in the vicinity of permanent research stations. These provide a solution to the logistical challenges of conducting research in a polar environment but inherently limit the spatial extent of inquiry, leading to ‘central-place researchers.’ Moreover, their existence and origins point to the original impetus for Antarctic exploration and research, which has its roots in geopolitics and resource extraction (Dudeney & Walton 2012; Hemmings 2017) rather than reflecting a fundamental interest in elucidating Antarctic phenomena. The establishment of a permanent Antarctic research station is one of the methods for a state to declare its status within the Antarctic Treaty system (Hemmings 2017).

The result of a station-focused research program is clear when considering the Antarctic fur seal (*Arctocephalus gazella*). This species, hunted to near-extinction in the 19th century and effectively extirpated from the Antarctic Peninsula until the mid-20th century (O'Gorman 1961), has staged a remarkable recovery with very minimal human intervention aside from the cessation of hunting (Foley & Lynch 2020). The early periods of this recovery, however, which took place largely between the 1950s and 2000s, was, in many ways, overlooked by the station-based national research programs of the Antarctic until the 1990s. Occasional regional or sub-regional surveys (e.g., Aguayo 1978) and regular studies from Cape Shirreff, home of the largest seasonal breeding colony of Antarctic fur seals on the Peninsula, provide some insight into the trajectory of population growth. The effect of rapid population growth on the Antarctic Peninsula ecosystem and on the populations and behaviors of potential competitors remains effectively unknown because there has been little effort to understand this species at the spatial scale of its interactions with the surrounding environment.

Many pinnipeds, including the Antarctic fur seal, are highly mobile, exploiting vast foraging grounds of thousands of square kilometers of ocean (e.g., Arthur et al. 2017). Yet for the Antarctic fur seal and many other Antarctic species, much of our understanding comes from studies of the breeding season when they are least mobile. While focusing our efforts on quantifying the reproductive output and trajectory of a population provides valuable insight on the overall state of the Antarctic ecosystem, we must also investigate the broader region. By doing both, even if the regional data are patchy or opportunistic, we can pair the depth of station-based research with the breadth of wider observations and learn about the broader drivers of ecosystem change.

Highly-mobile species can have a profound impact on their environments, from the ecosystem-engineering effects of elephants (e.g., Pringle 2008) to the nutrients and propagules deposited on islands by seabirds (McCauley et al. 2012). Such species are of particular interest, as their movements put different, spatially discrete communities into contact, potentially broadening the scope of local environmental stressors. They also present particular challenges, both in terms of study logistics and for understanding larger ecosystem interactions, as their effect on communities is not consistent over space or time (Webb et al. 2017).

The interactions of highly-mobile species with habitats, species, and communities illustrate some of the challenges ecologists face in thinking about scale when examining ecological patterns and mechanisms. The scale of inquiry or, more directly, of study-design, can lead to vastly different or seemingly contradictory inferences (Thrush et al. 1996; Gotelli & Colwell 2001; Chase & Knight 2013), which complicates generalization and synthesis. As such, we should take particular note of instances in which our sole source of inference about a system or phenomenon comes from a single scale of inquiry, whether extent or grain, spatial or temporal.

With limited monitoring (i.e., a limited temporal extent), our ability to associate the overall population trend of highly-mobile species with potential environmental drivers is limited. To that point, better monitoring is needed, and a broader approach to formulating study designs in the face of a lack of historical data. To gain a broader spatio-temporal understanding of Antarctic Peninsula dynamics, innovation and imagination are required, especially given the logistical challenges of the region.

1.1 Rethinking Ecological Data

Given the complexity of ecological systems (Brown et al. 2002; Anand et al. 2010; Park & Talbot 2018) and the rapid change related to anthropogenic global climate change in many natural systems (Walther et al. 2002; Parmesan 2006; Kelly & Goulden 2008; Hoegh-Guldberg & Bruno 2010), there is an urgent and persistent need for ecological data to establish baselines and monitor change, yet many systems and regions suffer from wide data gaps. These gaps affect both our ability to understand the ecological processes that underpin the interactions of species with external stressors (Flather et al. 1997; Kaschner et al. 2012; Thurstan et al. 2015) and our ability to monitor and understand the effects of conservation interventions (Visconti et al. 2013).

While ecology as a discipline has accommodated technological innovation over the decades, its roots tap deeply into natural history (Dayton & Sala 2001; Bury 2006). The interplay of the methodological challenges of examining complex systems with the observational approach of the natural historian have and continue to create philosophical disagreement within the discipline (Weiner 1995; Bury 2006). And yet, with substantial data gaps across spatial, temporal, taxonomic, and systematic scales, imagination is needed for ecological inquiry to keep pace with anthropogenic disturbance, management, and policymaking.

Across the recent decades of this still-young discipline, innovation and technological advancement have opened new avenues of research, including entire scales of inquiry – from the microbiome to the global – that were previously inaccessible. While the technologies themselves have not necessarily been at the cutting edge – ecological research rarely explicitly *driving* the advancement of technology – new applications for technologies common in other fields have provided broad new insight when brought to bear on ecological questions. The appearance of birds in radar detections (Lack & Varley 1945) profoundly altered the scale at which bird populations could be studied, and the discovery of whale vocalizations (Payne & McVay 1971) had effects on both society and the study of cetacean populations and movements. There are such examples regularly across the discipline, whereby the adoption of a technology for a particular question provides an opportunity for others to imagine its potential applications, as with radiotracking and radiotelemetry for wildlife (Craighead & Craighead 1972; Cagnacci et al. 2010), field audio-recording (Mennill et al. 2006), aerial imaging (Rutz & Bluff 2008), biologging (e.g., Rutz et al. 2012), and molecular techniques (Andrew et al. 2013).

Across spatial ecology, there are frequently tradeoffs between analysis across a wide spatial extent, and the grain or resolution of the analysis (Fassnacht et al. 2006), and more broadly a mismatch between the scale of observation and the scale of the mechanism being studied (Turner et al. 1989; Levin 1992; Denny et al. 2004). The advent of aerial photography for ecology (Hempenius 1974; Zonneveld 1974) and satellite remote sensing (e.g., Work & Gilmer 1976; Rea & Ashley 1976), dramatically broadened the spatial extent of ecological analyses to the landscape scale, but by using data at a coarser grain (e.g., 1-km for Landsat-1). In the decades since, as sensor and transmission technology has improved, some satellite sensors can provide imagery with a resolution of 31 cm per pixel (WorldView satellites: Maxar Technologies).

As finer spatial grain becomes practicable at the same time as broad spatial extent, as with satellite remote sensing, we come closer to meeting Levin's (1992) challenge to observe at both the scale of the pattern and the scale of the mechanism. In the meantime, there exists a wide range of spatial and temporal scales that are poorly observed and which are essential for the creation of generalizable inference in the face of rapid change that itself proceeds differentially at different scales of observation.

In this vein, and with an eye to demonstrating opportunities that may be broadly applicable to other systems, regions, and taxa, I describe and demonstrate several methods that work across spatial and temporal scales to provide insight into patterns among Antarctic megafauna whose drivers may be local but whose effects are potentially regional. I use these methods to aggregate current and historical data to fill knowledge gaps, broadening the pool of ‘acceptable’ ecological data while expanding its spatial extent, and demonstrating the ability of deep-learning methods to supplement and augment traditional approaches to field research. Through these methods I provide some of the first information on regional-scale patterns of distribution and movement for two species of Antarctic pinniped and illuminate the potential scope of the problem of an insufficient spatiotemporal extent by documenting a previously un-surveyed Adélie penguin colony that represents half of the population of this species in the region and appears roughly stable over the last 60 years, despite considerable declines elsewhere. In each case, I describe the potential for future, broader applications to meet the challenges of the moment.

2 Multi-modal survey of Adélie penguin mega-colonies reveals the Danger Islands as a seabird hotspot

2.1 Abstract

Despite concerted international effort to track and interpret shifts in the abundance and distribution of Adélie penguins, large populations of Adélie penguins continue to be identified. Here we report on a major hotspot of Adélie penguin abundance identified in the Danger Islands off the northern tip of the Antarctic Peninsula (AP). We present the first complete census of *Pygoscelis* spp. penguins in the Danger Islands, estimated from a multi-modal survey consisting of direct ground counts and computer-automated counts of unmanned aerial vehicle (UAV) imagery. Our survey reveals that the Danger Islands host 751,527 pairs of Adélie penguins, more than the rest of AP region combined, and include the third and fourth largest Adélie penguin colonies in the world. Our results validate the use of Landsat medium-resolution satellite imagery for the detection of new or unknown penguin colonies and highlight the utility of combining satellite imagery with ground and UAV surveys. The Danger Islands appear to have avoided recent declines documented on the Western AP and, because they are large and likely to remain an important hotspot for avian abundance under projected climate change, deserve special consideration in the negotiation and design of Marine Protected Areas in the region.

2.2 Introduction

Monitoring populations is central to conservation strategies and to identifying threats to species. Indeed, central to the Convention on Biological Diversity (CBD 2017), as well as other key conservation measures (Agnew 1997; Southwell et al. 2017), is the assumption that we can measure such diversity and abundance. Numerous studies now suggest that Adélie penguin (*Pygoscelis adeliae*) populations are undergoing dramatic shifts in abundance, with marked declines along most of the Western Antarctic Peninsula (WAP) and associated sub-Antarctic Islands (Trivelpiece & Fraser 1996; Fraser & Patterson 1997; Sander et al. 2007; Forcada & Trathan 2009; Lynch et al. 2010; Lynch & LaRue 2014) and sharp increases in the Ross Sea and Eastern Antarctica (Lynch & LaRue 2014; Croxall et al. 2002; Ainley et al 2003; Jenouvrier et al. 2006; Lyver et al. 2014; Southwell et al. 2015; Che-Castaldo et al. 2017). While the causal drivers of these changes remain unknown and may in fact vary across the continent, several studies have linked Adélie penguin population trends to changes in sea ice extent and concentration as well as changes in air temperature and precipitation patterns and their possible effects on prey availability (Ainley et al. 2005; Forcada et al. 2006; Massom et al. 2006; Che-Castaldo et al. 2017). Understanding the population dynamics of sentinel species, such as Adélie penguins, will help illuminate the effects of climate change on less easily-studied components of the ecosystem (Trivelpiece et al. 1990; Ainley et al. 2002). Much of the concern regarding climate-driven changes has been focused on the WAP and South Shetland/South Orkney Islands, where Adélie penguin populations have declined sharply (~70%) over the last several decades

(Lynch et al. 2013; Humphries et al. 2017). Along the WAP, the northern end of Marguerite Bay (67° 30’ S) represents a clear boundary that divides areas of Adélie penguin population decline in the north from areas where abundances are either stable or increasing to the south (Casanovas et al. 2015). Far less is known of Adélie penguin populations along the northern and eastern portions of the AP, a region perhaps more closely tied to the Weddell Sea in terms of climate and sea ice production than to the dynamics of the WAP (Ducklow et al. 2007; Murphy et al. 2007).

The Danger Island archipelago is comprised of 9 islands stretching over approximately 35 km at the northernmost tip of the AP in the north-western Weddell Sea (Fig. 2.1). Despite their relative proximity to the WAP, which sees much of the tourist and fishing ship traffic in the Antarctic (CCAMLR 2016), pack ice is common around the Danger Islands even in austral summer (Comiso & Gordon 1998). In fact, due to the currents of the Weddell Sea, which drive sea ice northward, access to the islands is precluded in most years. Heroína Island, at the northeast end of the archipelago, is the most frequently visited of the Danger Islands and yet hosts a median visitation rate of only one ship landing per year (IAATO 2017). It is also the only island to date with a population estimate (285,000-305,000) derived from a ground survey of the island (Naveen et al. 2000; Lynch et al. 2008). While a previous geological expedition (Elliot et al. 1978) noted the presence of Adélie penguins on all of the Dangers Islands (with the exception of Darwin Island, which was not visited) and several others were photographed (by Melissa Rider and Steve Forrest, pers. comm.) from a passing vessel in 2008/09, the presence of Adélie penguins on several of these islands went largely unrecognized until a recent Landsat satellite survey of the Antarctic identified several islands, together supporting what appeared to be nearly 200,000 Adélie penguin nests (Lynch & Schwaller 2014). The (re)discovery of these populations, combined with evidence that the Danger Islands as a group supported a regionallysignificant population, motivated an expedition to the area. In this paper we report on the first comprehensive seabird survey of the Danger Islands and describe a heretofore unrecognized Adélie penguin hotspot. We document a novel a multi-modal survey approach comprised of ground surveys, and imagery from both satellites and unmanned aerial vehicle (UAV) photographic surveys and describe the cross-validation of these methods to accommodate the different sources of uncertainty introduced by each hotspot. We also discuss the critical implications of this seabird hotpot for the design of Marine Protected Areas in the Antarctic Peninsula region.

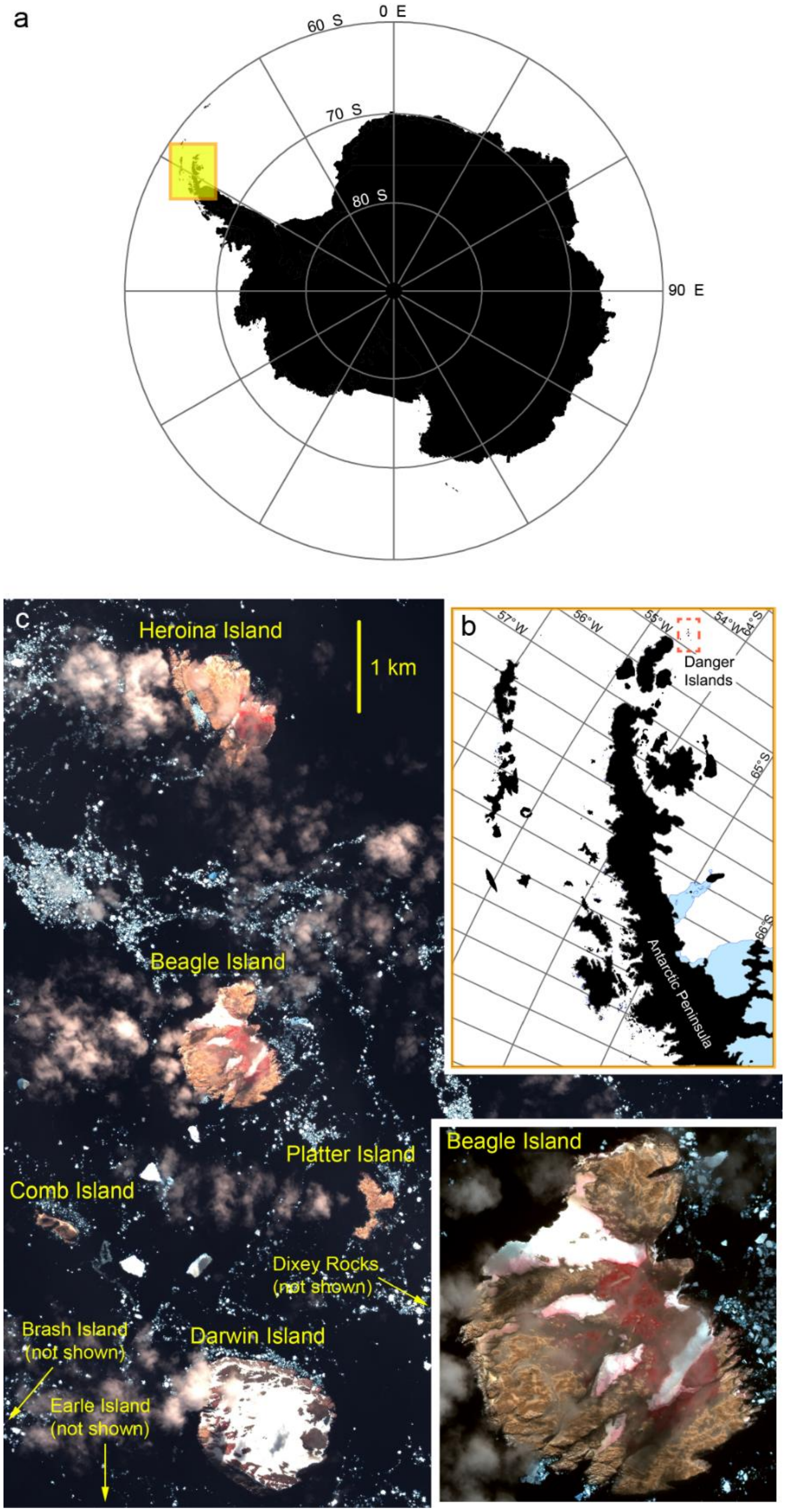

Figure 2.1: **a**, Map showing the location of the Antarctic Peninsula and **b**, The location of the Danger Islands group on the Antarctic Peninsula, both created using ESRI ArcMap 10.0 (http://desktop.arcgis.com/en/arcmap/). **c**, Quickbird image of the Danger Islands taken 22 January 2011 (Imagery copyright 2011 DigitalGlobe, Inc.).

We define the Danger Islands as including (from north to south): Brash Island, Heroína Island, Comb Island (also known as Peine Island), Beagle Island, Platter Island (Plato Island), Darwin Island, and Earle Island (Fig. 2.1). Dixey Rock and Scud Rock are also located in this area and were also surveyed. These islands range from generally low and flat (Platter Island), to sheer cliff faces (Darwin and Comb Islands), with most containing a mix of steep scree slopes, flat areas, and cliffs. The islands are composed of intrusive igneous rocks, predominantly feldspar-rich gabbro, that were formed during the late Cretaceous and are of similar age to the plutonic rock formations at the tip of the Antarctic Peninsula (Hamer & Hyden 1984). Data from this region are sparse, but during the last glacial maximum these islands may have been glaciated until around 6000 years before present (bp; Ingólfsson 2003). While the Holocene occupation history of penguins on the Danger Islands is currently undescribed, radiocarbon-dated remains from other northern Antarctic Peninsula breeding sites indicates a relatively recent (~600 bp) advent of breeding populations (Emslie et al. 2017).

2.3 Methods

2.3.1 Field survey

Surveys were conducted from the M/V *Hans Hansson* from December 9-18, 2015. We used a variety of survey methods on each island depending on conditions and time ashore, including one or more of the following methods: (1) manually counting individual nests, (2) counting individual nests in panoramic photos taken from the ground or the vessel, and (3) counting individual penguins from photographs captured by UAV. The combination of these methods allowed for efficient data collection with cross-validation of survey modes. The precision of census counts varied by island (Table 2.1), and island-specific error estimates were propagated to the archipelago-wide confidence intervals for total abundance.

Table 2.1 Census summary. ‘N1’: ≤5% error; ‘N2’±: 10% error; ‘N4’: ±50% error.

	Beagle	Brash	Comb	Darwin	Dixey Rock
Pygoscelis adeliae	284535‡ (N2)	94951‡ (N2)	12000# (N4)	5804# (N1)	0 (N1)
Pygoscelis papua	0 (N1)	2270 (N1)	186 (N1)	0 (N1)	0 (N1)
Pygoscelis antarctica	0 (N1)	0 (N1)	0 (N1)	0 (N1)	0 (N1)
Phalacrocorax atriceps					0 (N1)
Pygoscelis adeliae	Earle	Heroína	Platter	Scud Rock	
Pygoscelis papua	21071‡ (N2)	292363‡ (N2)	40803 (N1)	0 (N1)	
Pygoscelis antarctica	847 (N1)	999 (N1)	223 (N1)	0 (N1)	
Phalacrocorax atriceps	0 (N1)	27 (N1)	0 (N1)	0 (N1)	
Pygoscelis adeliae	156 (N1)			0 (N1)	

† First direct census of this location; ‡Count from drone imagery; # Count from ground or ship-based photography.

The timing of our expedition was ideal in terms of penguin phenology (Black 2016), and the surveyed colonies were dominated by individual penguins incubating well-established nests. Our estimates of abundance, therefore, represent a count of all 'actively' incubated nests on each island. Active nests were those occupied by a penguin, noting that the presence of eggs or chicks in the nest cannot be determined from aerial photography. To facilitate counting, islands were divided based on the natural boundaries between "sub-colonies," or naturally-occurring, discrete groups of penguin nests. For those sub-colonies too large to count accurately in their entirety, divisions were made based on natural markers within the sub-colony or, in their absence, using brightly coloured rope laid between nests; such subsections were counted individually. To ensure accuracy, each division was counted three times and these three counts were required to agree within 5% of their mean. If counts did not agree, divisions were further subdivided until three subsequent counts did agree within 5% of the mean. This 5% accuracy threshold corresponds to the 'N1' level of precision described by Croxall and Kirkwood (1979) and used regularly to report penguin abundance in the Antarctic (e.g., Woehler 1993; Naveen et al. 2000; Naveen et al 2012).

Full, site-wide counts for Adélie penguins were conducted at Platter and Earle Islands, the latter of which was also surveyed by UAV (Table 1). Manual counts of well-defined Adélie penguin sub-colonies were conducted at Heroína, Brash, and Beagle Islands as a validation of counts based on UAV photographs. Where present, we conducted site-wide counts of gentoo penguins and chinstrap penguins as well (Table 1). Adélie penguin populations at Comb and Darwin Islands were counted from images taken on the ground or from vessels offshore of the islands using Adobe Photoshop's count tool. On all islands, the presence of other bird or mammal species was noted opportunistically (Appendix Table A2.1).

2.3.2 UAV-based survey

UAV surveys were performed with a DJI Phantom 3 quadcopter using its stock 1.2 Megapixel camera. The UAV was flown either manually or automatically using the mission planning software Map Pilot App to generate image coverage of each island with at least 70% overlap between images. Following the suggestions laid out by Goebel and colleagues (2015), a minimum height above ground of 25 m was set for all flights to avoid disturbance to wildlife, and a maximum height above ground of 45 m was selected to maintain image quality for penguin identification. The geotagged imagery collected with the UAV was post-processed using the commercial photogrammetry software Photoscan (Agisoft LLC, St. Petersburg, Russia) which generated full, georeferenced orthomosaics, a top-down view of the island – in which each pixel corresponds to a fixed physical dimension – of the surveyed islands and their penguin colonies.

Brash, Earle, Beagle, and Heroína Islands were surveyed using composite panoramic images captured by the UAV (example in Fig. 2.2). The timing of our survey was ideal for capturing incubating penguins on the nest and the imagery was, in the overwhelming majority of cases, unambiguous with respect to penguins that were incubating versus walking through the colony or from the ocean. To automatically identify and count the number of occupied nests in the UAV orthomosaics we used a Deep Neural Network (DetectNet) implemented in the open source software NVIDIA DIGITS (NVIDIA Corporation, Santa Clara, CA). DetectNet is based on the GoogLeNet image classification framework (Szegedy et al. 2015) and is specifically designed to locate multiple objects of the same type within an image, making it well-suited to the task of detecting penguins in aerial imagery. The DetectNet network was trained to detect penguins using 512x512 sub-images selected from the orthophotos of the four islands being analysed and manually annotated with penguin locations. The images were split into two groups, one for training the network and one for validation, with 160 images and 1237 penguins in the training group and 93 images and 673 penguins in the validation group. The manually-labelled training data constituted 0.18% of the imaged area and 0.34% of the imaged penguins providing a massive decrease in manual labour required. Once trained, full island detection was performed by splitting the orthophotos into 512x512 sub-images which were run through the trained detector in DIGITS.

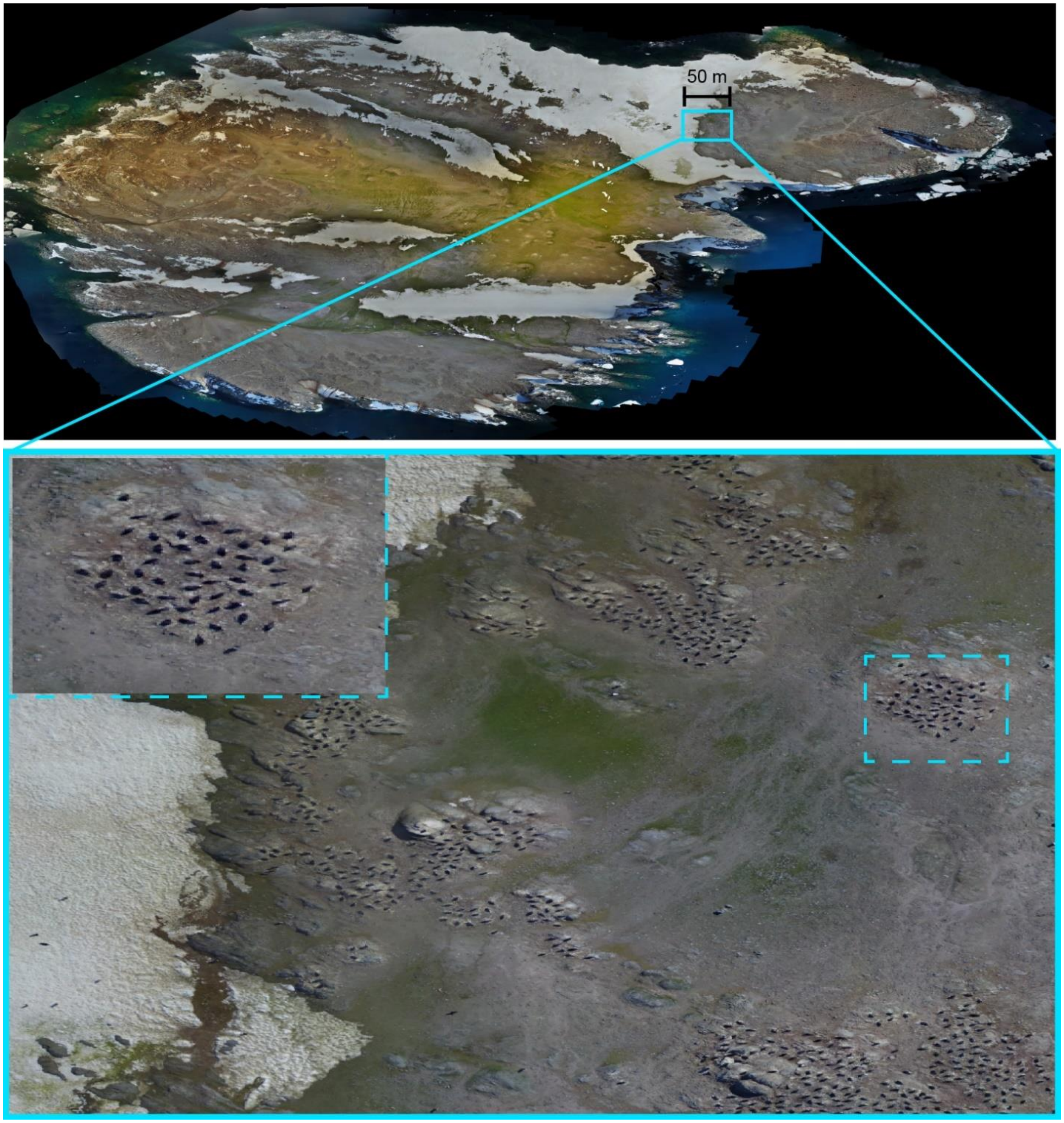

***Figure 2.2*:** UAV orthomosaic image of Brash Island (above), with examples of zoomed-in penguin rookeries (below).

False positives generated by this automated nest detection algorithm were comprised of both individual non-nesting penguins and artefacts, such as rocks and shadows, that appear visually similar to nesting penguins. While nesting penguins are highly spatially structured, with strong attraction between individuals (McDowall & Lynch 2017), the false positives are largely spatially unstructured. We therefore applied an additional spatial filter to the detections, retaining nests based on the distribution of nearest neighbors. Points passing through this spatial filter are classified as unambiguous penguin nests and are retained; points rejected at this stage are comprised of false positives and a much smaller number of isolated nests incorrectly rejected by the filtering process. We validated our nest detections by manually counting a selection of each of the four islands surveyed by UAV (Brash, Earle, Beagle, Heroína), and created a simple linear regression model to estimate the number of nests based on the number of nests manually counted and those counted with our automated method. These site-specific linear models allowed us to correct for any site-specific differences in the performance of the detection algorithm. Based on this analysis, we have classified our automated counts as $\pm 10\%$ accuracy (i.e., an ‘N2’ count), though we note that the average difference between the automated nest counting of UAV imagery and an *in situ* ground count of the same portion of the colony was only 0.6% and so our estimates may be even more precise than suggested by an ‘N2’ designation.

2.3.3 Historical aerial imagery

To understand the potential population trajectory of penguins in the Danger Islands region, the spatial extent of current penguin colonies can be qualitatively compared to historical aerial photographs (Fig. 2.3). We selected cloud-free photographs from the Falkland Islands and Dependencies Aerial Survey Expedition (FIDASE) for Heroína (FIDASE 1957a) and Brash

(FIDASE 1957b) islands. These islands were chosen as the FIDASE archive contained quality photographs shot nearly on nadir and both had been fully photographed by the UAV. The islands were photographed in black and white on Jan. 31, 1957 at an altitude of 4115 m to a scale of 1:27000, and digitally scanned by the U.S. Geological Survey. Both island frames were georeferenced to WorldView-2 satellite images and divided into polygons using segmentation algorithms tuned to provide a segment size reasonable for further analysis using Quantum GIS (QGIS; QGIS 2016). In both cases, segments were manually classified by a skilled observer as "guano" to designate recent guano deposition, "guano-like" to designate areas thought to be guano but with less certainly, "old guano" to designate areas of guano accumulation not necessarily associated with active nesting, and "non-guano," a classification encompassing rock, water, snow, and all other substrates not covered by guano (Fig. 2.3).

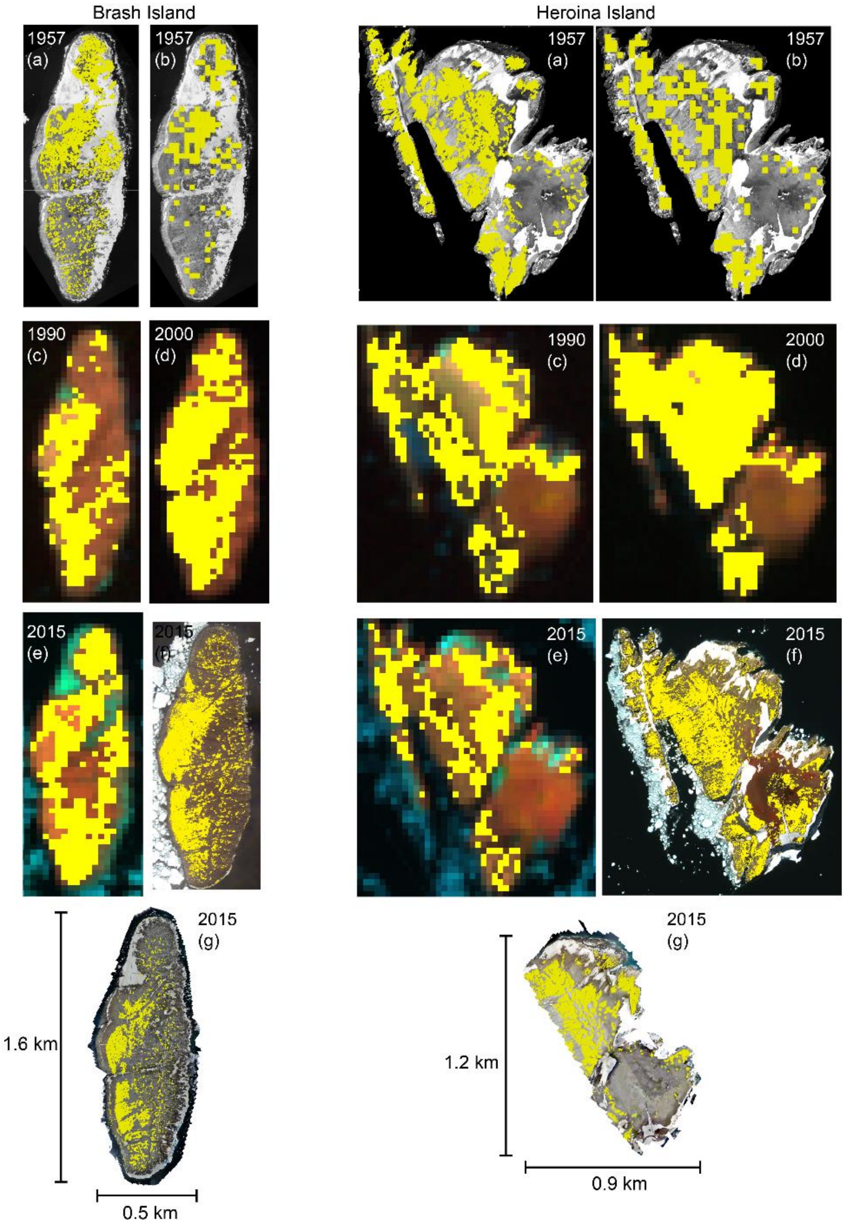

Figure 2.3**:** Guano areas (yellow) identified on Brash Island (at left) and Heroína Island (at right) from 1957 to present day. **a**, and **h**,: manually classified from aerial imagery from 1957; **b**, and **i**,: manually classified from aerial imagery from 1957 and reduced to 30 m cells for comparison with Landsat; **c**, and **j**,: Landsat-4 in 1990 classified as described in Methods; **d**, and **k**,: Landsat-7 in 2000 classified as described in the Methods; **e**, and **l**,: Landsat-8 in 2015 classified as described in the Methods; **f**, Worldview-2 image taken 19 February 2016 classified as described in the Methods (Imagery copyright 2016 DigitalGlobe, Inc.); **m**, Worldview-2 image taken 2 December 2015 classified as described in the Methods (Imagery copyright 2015 DigitalGlobe, Inc.); **g**, and **n**,: nests that were retained by the spatial filter marked as yellow dots overlaid on UAV imagery from ground survey described in this manuscript. Panels a, b, f, g, h, i, m, and n displayed using ESRI ArcMap 10.0 (http://desktop.arcgis.com/en/arcmap/); Panels c, d, e, h, k, and l displayed using ENVI 5.4 (https://www.harris.com/solution/envi).

2.3.4 Landsat satellite imagery analysis

Adélie penguin colonies identified in Fig. 2.3 were retrieved from Landsat imagery based on the algorithm described by Schwaller and colleagues (2013) and Lynch and colleagues (2014). The retrieval algorithm was originally developed for a single sensor and was modified in this case to operate on cross-calibrated data from Landsat-4 (imagery date 1990 in Fig. 2.3), -7 (2000) and -8 (2015). Cross-calibration among sensors was performed by calculating the mean difference of similar bands from Landsat-4 and -8 imagery compared to Landsat-7, and then adjusting the band values based on the mean differences in each spectral band. The algorithm was then applied to the cross-calibrated imagery to classify Adélie penguin colony areas.

2.3.5 High-resolution commercial imagery

Areas of guano staining were manually identified in high resolution satellite imagery (Fig. 2.3 panels f and m). A selection of unambiguous pixels within the guano stains were used to select other pixels (using Adobe Photoshop) similar in color, and areas were added and removed manually based on manual interpretation of the imagery combined with auxiliary information from the UAV imagery mosaics.

2.4 Results

Our survey found 751,527 (95^{th} CI = [710,103 – 792,443]) nesting pairs of Adélie penguins in the Danger Islands (Table 2.1) which we estimate (using the Mapping Application for Penguin Populations and Projected Dynamics; Humphries et al. 2017) is 55% of all Adélie penguins in subarea 48.1 as defined by the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) once our estimate is added. This subarea includes all of the western AP, the waters north of the AP to 60°S, and a portion of the north-western Weddell Sea west of 50°W. Without the Danger Islands it contains 606,526 (95^{th} CI = [322,477 – 990,402]) Adélie penguin pairs (Humphries et al. 2017).

Visual comparison of available aerial, satellite, and unmanned aerial vehicle (UAV) images, together spanning a 60-year period, suggests that the extent of the area occupied by Adélie penguin colonies on the Danger Islands has remained stable or has modestly-increased, though few data exist for the intervening years (Fig. 2.3). A previous ground-based estimate (Naveen et al. 2000) of 285,000-305,000 Adélie penguin nests on Heroína Island in 1996/97 is remarkably consistent with our updated estimate of 292,363 nests. The consensus of all the data considered in this analysis strongly suggests that the Danger Islands have remained roughly stable since the earliest records of the 1950s, in stark contrast to declines seen along the WAP.

In addition to Adélie penguins, we found several significant populations (>100 nests) of gentoo penguins (*P. papua*), particularly at Brash Island, and one small (27 nests) population of chinstrap penguins (*P. antarctica*) at Heroína Island. Additional information on flying birds and marine mammal observations collected during this survey are included in Appendix Table A2.1.

2.5 Discussion

This survey provides the first estimates of penguin abundance for this portion of the AP region and the first direct ground survey of the Dangers Islands with the sole exception of Heroína Island, which was last surveyed in 1996/97. Our estimate is more than three times the abundance estimated by an earlier survey (Lynch & LaRue 2014), largely because several colonies, not known to exist at the time, were missed entirely. We find the Adélie penguin colonies on Heroína Island and Beagle Island are the third and fourth largest Adélie penguin colonies in the world (Humphries et al. 2017), respectively, and represent the easternmost Antarctic colonies (54°W) of all three pygoscelid penguins until 45°E. Our ground- and UAV-derived survey provides important validation of satellite imagery as a tool for the discovery of new penguin colonies and demonstrates how satellite imagery and field expeditions can complement one another in our efforts to track penguin biogeography and long-term trends, given the challenge of long-term ground monitoring in the Antarctic. Our discovery of a major hotspot of abundance in the Danger Islands is important for our understanding of the global distribution of the Adélie penguin and should be considered in the development of future conservation measures such as Antarctic Specially Protected Areas (ASPAs) or Marine Protected Areas (MPAs).

At a regional scale this survey increases the total estimated abundance of Adélie penguins in CCAMLR subarea 48.1 by 68%. This dramatic increase in the number of known Adélie penguin breeding pairs radically changes our estimates of krill predation in the Northern Weddell Sea, in a portion of 48.1 that, notably, has not experienced the levels of krill fishing seen elsewhere along the Antarctic Peninsula (CCAMLR 2016; Nicol et al. 2012). The Adélie penguins found in the Danger Islands are among those penguins breeding north of the "Adélie gap," a stretch of the coast along the WAP roughly 400 km long from the Adélie colonies on the southwestern shore of Anvers Island to the south, to Nelson Island in the South Shetland Islands and nearly the tip of the AP to the north (Woehler 1993; Polito et al. 2011). This gap is devoid of breeding Adélie penguins and geographically differentiates those Adélie penguins to the south from those in the north in both summer and winter foraging habitat (Polito et al. 2011). The new abundance estimate for this northern component within subarea 48.1 highlights the spatial structure of predator abundance, demonstrating an area of high abundance distinct from those along the WAP. Accordingly, an updated understanding of predator distributions, particularly the location of major abundance hotspots, may have implications for the management of prey resources (Hinke et al. 2017a; Reid et al. 2004).

While our inference on past trends is unavoidably limited by the lack of prior ground surveys, our analysis of the available imagery suggests that Adélie penguin colonies in the Danger Islands have not suffered the net declines seen on the WAP, where some colonies have declined by an order of magnitude or have disappeared completely (Trivelpiece et al. 2011; Lynch et al. 2012; Che-Castaldo et al. 2017). Our findings are consistent with recent modelling work (Cimino et al. 2006) showing that the warming of the WAP has followed a west-to-east pattern, such that the Danger Islands have been largely spared the environmental changes experienced by the South Shetland Islands and the northern portion of the WAP. In particular, the Weddell Sea has not experienced the significant loss of sea ice that is seen in the Bellingshausen Sea, and instead shows slight gains over the past several decades (Parkinson 2002; Parkinson & Cavalieri 2012), providing more consistent foraging habitat for pagophilic species such as the Adélie penguin. We recognize, however, that while the evidence for stability from 1990-present is well supported by the available imagery, the evidence cannot rule out sequential and roughly compensatory periods of increase and decrease in the earlier period (1957-1990) as might be expected in any dynamic predator/prey system.

Given the large number of Adélie penguins breeding in the Danger Islands, and the likelihood that the northern Weddell Sea will remain suitable for Adélie penguins longer than the rest of the Antarctic Peninsula region, we suggest the Danger Islands should be strongly considered for further protection, either through an extension of the proposed Weddell Sea MPA that falls just to its south or by way of an MPA in the Western Antarctic Peninsula (Teschke et al. 2013; Teschke et al. 2016). Like the Ross Sea, the northern Weddell Sea represents an Adélie penguin hotspot of significant conservation value as a potential refugium relative to climate change. By establishing the distribution and abundance of penguins in this region, we hope to highlight its importance to regional and global populations and encourage more regular monitoring of the region.

3 Aerial-trained deep learning networks for surveying cetaceans from satellite imagery

3.1 Abstract

Most cetacean species are wide-ranging and highly mobile, creating significant challenges for researchers by limiting the scope of data that can be collected and leaving large areas un-surveyed. Aerial surveys have proven an effective way to locate and study cetacean movements but are costly and limited in spatial extent. Here we present a semi-automated pipeline for whale detection from very high-resolution (sub-meter) satellite imagery that makes use of a convolutional neural network (CNN). Our CNN was trained using down-scaled aerial imagery and tested on 31 cm-resolution imagery obtained from the WorldView-3 sensor. Satellite imagery was tiled and the trained algorithm was used to classify whether or not a tile was likely to contain a whale. Our model correctly classified 100% of tiles with whales, and 90% of tiles that contained only water. While the resolution of commercially-available satellite imagery continues to make this a challenging problem, our approach provides the means to efficiently eliminate areas without whales and, in doing so, greatly accelerates ocean surveys for large cetaceans.

3.2 Introduction

There is tremendous interest in understanding if and how cetacean populations are recovering following the cessation of intense commercial whaling, yet their extensive ranges and high level of mobility combine with the challenges of research at sea to leave them poorly studied in many regions. While many cetacean species favor shelf edges and other zones of deep-water upwelling across ocean basins (Hamazaki 2002; Yen et al. 2004; Moore et al. 2010; Bedriñara-Romano et al. 2018), most cetacean research is focused on coastal areas where populations may be concentrated at key times of the year and are logistically easier to survey. Far less work has been done to understand patterns of cetacean habitat use along distant continental shelf regions, and limited cetacean surveys in deep-water habitat may skew our understanding about preferred habitat (Kaschner et al. 2012). While data loggers and transponders have been employed for many species to track movements far outside the range of direct observation, providing data with high spatial and temporal resolution (Lesage et al. 2017; Weinstein & Friedlaender 2017; Bodey et al. 2018; Grecian et al. 2018; McKinnon & Love 2018), the cost of these devices often drastically limits the number of animals that might be tracked.

Broad-scale or basin-scale surveys are exceedingly challenging and costly, regardless of modality. Between 1975 and 2005, only 25% of the world's oceans were surveyed for cetaceans, with a high proportion of surveys falling inside the territorial waters of the United States (Kot et al. 2010; Kaschner et al. 2012). Basin-scale surveys are unavoidably multi-year efforts in which a region is surveyed in parts over consecutive years or involve extensive mark-recapture studies (Smith et al. 1999; Branch 2007; Branch 2011). Another approach has been to combine data from heterogeneous sources such as aerial and ship surveys (e.g., Branch 2011), strandings, and whaling data (Branch et al. 2007). However, these methods are expensive and the results are difficult to interpret due to large data gaps. New methods that complement existing tools and address these challenges of scale are required. While remote sensing has been used for decades to track coarse-grained changes in the environment (e.g., sea ice, land cover, urban development), the use of satellite imagery to directly survey animals is much more recent and hinges on the use of very high-resolution (sub-meter) imagery that can capture individual animals on the landscape (e.g., LaRue et al. 2011; Fretwell et al. 2012; Platonov et al. 2013; Lynch & LaRue 2014; Fretwell et al. 2017; Seymour et al. 2017). While the promise of direct surveys of wildlife from space is an exciting frontier for wildlife biology, the challenges in identifying animals, which are almost always rare and usually only a few pixels in size, remain formidable. In addition to the challenges inherent to classification, the volumes of high-resolution imagery that must be annotated for a comprehensive survey are enormous and require advances in computing, storage, and cyberinfrastructure.

Cetaceans remain a challenging taxon of study given their frequently broad ranges and marine life-history, but their size makes them an attractive target for the use of imagery-based surveys. Previous efforts to locate whales using high-resolution imagery (Abileah 2002; Fretwell et al. 2014; Cubaynes et al. 2019) have been largely successful yet face challenges in bringing the process to broader spatial or temporal scales given the time required for analysis (Cubaynes et al. 2019). Fretwell and colleagues (2014) successfully identified Southern Right whales (*Eubalaena glacialis*) near Peninsula Valdés, Argentina both manually and using a rule-based classification algorithm in WorldView-2 satellite imagery. This satellite sensor provides 8 spectral bands and a panchromatic band with a maximum resolution of 46 cm per pixel on-nadir. More recently, WorldView-3 imagery has become available, providing a maximum resolution of 31 cm per pixel on-nadir. Cubaynes and colleagues (2019) found that the spectral response of whales declines above the visible red band (630-690 nm). Because both manual and automated methods thus rely on only the visible bands, automated algorithms are easily validated by visual inspection.

Ocean basins are large, and the potential habitat of cetaceans may encompass vast areas, especially during times of migration. Without knowing where cetaceans are, far more imagery must be considered than can reasonably be annotated manually, particularly if surveys are going to be repeated with any regularity. With this increase in data volume, the only practical solution becomes a workflow that involves a high level of automation to accomplish the otherwise tedious task of manually examining millions of pixels constituting hundreds or thousands of square kilometers. Although contemporary machine learning algorithms have been in use for 20 years or more, their application to ecological datasets have only become commonplace in the past 5 – 10 years (Humphries et al. 2018). Machine learning applications involving computer vision are only now gaining traction as a means of managing large volumes of image data that are tedious to analyze manually, such as camera traps, aerial imagery, or time-lapse photography (Weinstein 2017). Such algorithms can automate the process of classifying individual features in images (e.g., Willi et al. 2009; Zhang et al. 2016) and counting or estimating abundance (e.g., Barber-Meyers et al. 2007; Seiferling et al. 2017). Driven by commercial applications, machine learning methods have progressed rapidly in the past decade, with particular interest being paid to deep-learning methods. Deep-learning algorithms have shown promise in the field of ecology, with applications in acoustic signal detection (Aodha et al. 2018), behavioral predictions (Browning et al. 2018), and camera trap classification (Nourouzzadeh et al. 2018), and have been adopted or proposed in numerous other fields such as medicine (e.g., Esteva et al. 2017), and traffic management (e.g., Lv et al. 2015).

We present a cetacean survey method, employing a convolutional neural network (CNN) to automate much of the satellite imagery interpretation. Our goal in this initial pilot study was not to develop a fully-automated method, but to identify images with a high probability of containing a whale and thereby minimize the labor required for expert annotation. Here we describe an initial pipeline for whale detection that makes substantial advances toward a fully-automated detection system up to and including the global scale.

3.3 Methods

3.3.1 Imagery

We pooled aerial imagery extracted from high-resolution video footage shot over various water bodies surrounding northern Europe and the United Kingdom by HiDef Aerial Surveying Ltd to create a training set of whale and water images (Fig 3.1). The native resolution of the aerial imagery was approximately 2 cm per pixel ground-sample distance, which we down-sampled to 31 cm per pixel using a bilinear resampling function in ImageJ (Schneider et al. 2012) to match the resolution of Worldview-3 imagery. During the aerial survey, the aircraft flies at 549 m above sea level with a speed of 222 km/h and captures multiple image frames of the same whale using four cameras. The two inner cameras cover a 129 m strip width and the outer cameras a 143 m strip width and are separated by a gap of about 20 m totaling to an effective transect width of 544 m (Weiß et al. 2016). We elected to retain these duplicate images, as each frame captures the whale at a slightly different angle or in a different body position and is therefore valuable in building the training data set. In total, we had 190 aerial images representing 17 individual minke whales (*Balaenoptera acutorostrata*).

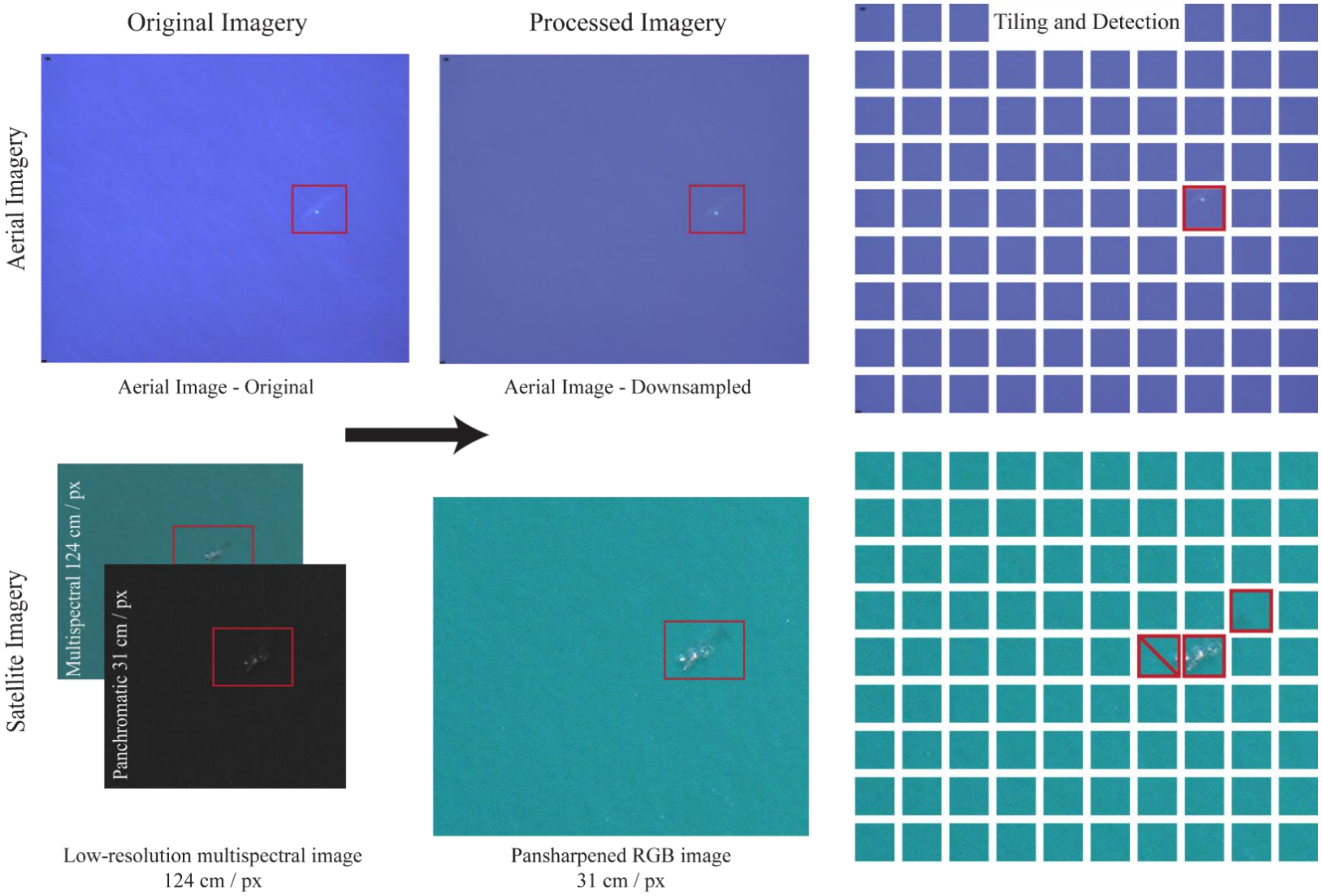

***Figure 3.1*:** The automated workflow. Aerial imagery (above) is down-sampled, tiled, and then used to train the model. Satellite imagery (below) is pansharpened and tiled before the model can detect whales. Satellite imagery courtesy of the Digital Globe Foundation.

All satellite imagery was collected at a resolution of 31cm per pixel (on-nadir) from DigitalGlobe's Worldview-3 sensor (Digital Globe, Westminster, Colorado; Appendix A3.1). This sensor records imagery in a variety of spectral bands in the visible and near-infrared range. Multi-spectral bands have a lower resolution (124 cm / pixel) than the panchromatic band, which incorporates a broad swath of the visible spectrum and is collected at 31 cm per pixel. To obtain very high-resolution multi-spectral imagery, we pansharpened the lower resolution multi-spectral bands using the higher resolution panchromatic band using the Gram-Schmidt algorithm implemented in ENVI (Exelis Visual Information Solutions, Boulder, Colorado). While pansharpening was conducted using all the available bands, we used only the red (630-690 nm), green (510-580 nm), and blue (450-510 nm) bands to approximate the RGB image captured during aerial survey.

Given that we required satellite imagery that definitely included whales, we surveyed known whale hotspots using Google Earth Pro and located imagery that contained visible Southern Right whales (*Eubalaena australis*) from Peninsula Valdés, Argentina and Humpback whales (*Megaptera novaeangliae*) from Maui, Hawaii (Fig 3.2). We also acquired cloud-free imagery of these regions based on times of the year where whales would be very likely to be present and active at the surface (Appendix A3.1). We excluded portions of the acquired imagery in which sea conditions prevented manual detection of whales.

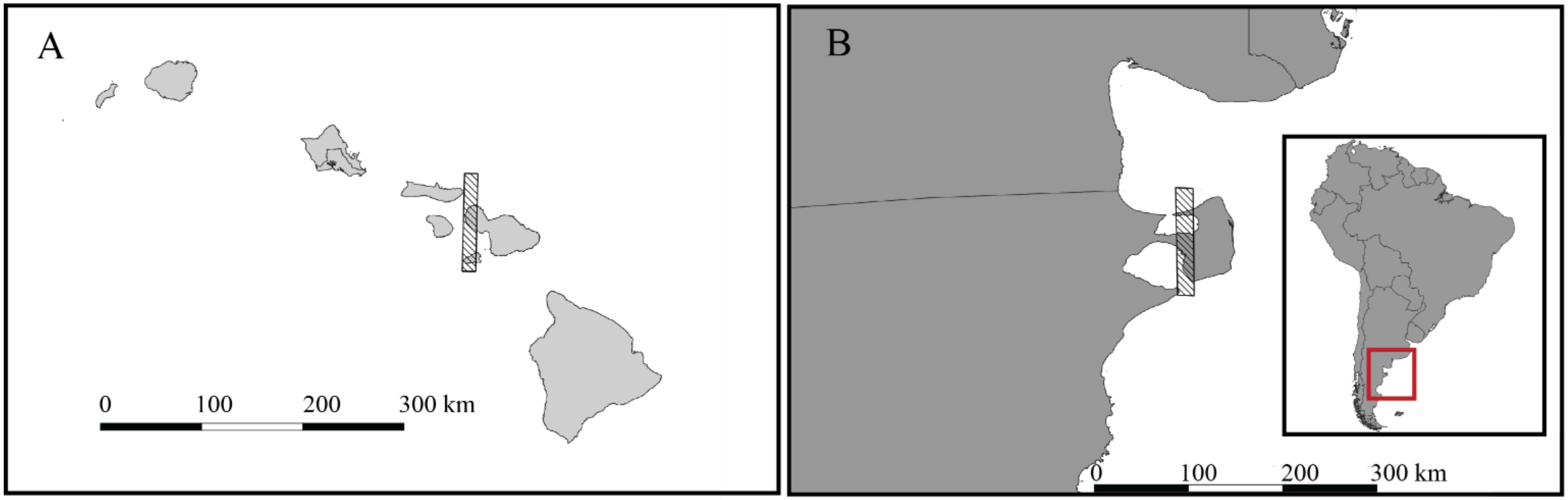

Figure 3.2: Locations of satellite imagery used**.** Maui, Hawaii (A) and Peninsula Valdes, Argentina (B).

3.3.2 Processing

To prepare imagery for use in model training, we split each image into small 32 × 32-pixel tiles each measuring 98.4 m² in area (Fig 3.1; S1 File). For both aerial and satellite imagery, tiles were manually separated into whale and water classes. We chose subsets of each satellite image for testing but retained all aerial water tiles for training, resulting in 40416 aerial tiles (water: n=39726; whale: n=690) and 40516 satellite tiles (water: n=40474; whale: n=42). Of the water satellite tiles, we randomly selected a subset (n=1390) to reduce testing time.

We selectively removed some aerial tiles prior to creating folds. These images contained a miniscule portion of a whale that was recognizable to a human observer only when put into context with the surrounding tiles. Given that these small whales were better captured by other neighboring tiles, we removed them from both training and testing to avoid confusion. Where whales were cleanly bisected by the border between tiles, such that at least 20% of the whale remained in the tile, we retained these images. The same procedure was adopted in with the satellite imagery to avoid false-negatives for whales that would already be captured by the model in another tile, reducing the number of satellite whale tiles used for testing from 42 to 32 (Fig 3.1).

3.3.3 Deep learning with convolutional neural networks

CNNs are extensions of traditional neural networks that work by summarizing patterns in images across many “hidden” layers through “convolutions” (i.e., complex data transformations; LeCun et al. 1998). Neural networks, the basis for CNNs, operate by simulating how neurons transmit information through the central nervous system (Rosenblatt 1962; Rumelhart et al. 1986). Information is input at a commencing node, which then passes information to several other nodes, which pass on to more nodes, until the output is translated at a terminal node. Each node adds some formulation to help decode the information passed into the commencing node. In CNNs, nodes are organized into “hidden” layers, where each layer applies a different image transformation (or convolution) to information from the previous layer. Transformations could include tasks such as stretching, skewing, splitting, or changing contrast of images. During training, the training images – or images containing only the target classes, whales and water – are fed to the model so that it can ‘learn,’ i.e., adjusting the network’s parameters to minimize the differences between the network’s outputs and the corrected labels. The model, once converged, can be validated using a test image subset that was withheld and not included in the training process. This form of machine learning minimizes the need for manually designing a rule-based classification scheme, but limits the interpretability of the model, which acts as a black box.

3.3.4 Model training

We trained our model using down-sampled aerial imagery. We separated 75% of aerial imagery for use in training, and 25% for use in validating the trained model, repeating this process to create a 4-fold validation system. We tested our model's classification performance by applying it to very high-resolution satellite imagery. Manually-annotated satellite imagery, in which whales and empty ocean were identified by expert annotators, was used as a standard against which the CNN's performance was compared. It is important to note that our model was naive to 'real' satellite imagery and was applied without further refinement following its development using the down-sampled aerial training and testing dataset.

We implemented our CNN using the Pytorch framework (Paszke et al. 2017), which makes it easy to implement, train, and adapt a model, and used the ResNet architecture with 18 layers (He et al. 2016). The network takes as input a 32×32 pixel image and outputs a vector of two elements, which represent the probability of the input image containing or not containing a whale, respectively. We use a ResNet-18 model that is pre-trained on the ImageNet dataset (Russakovsky et al. 2015) consisting of 1.28 million training images of 1000 classes. We modify the last layer of this model to train with our data, i.e., from outputting 1000 classes to outputting 2 classes. Pre-training the model on ImageNet has been known to reduce overfitting and training time.

Whales are inherently rare in imagery. The training architecture takes small batches of four images at a time and, given the rarity, would likely end up looking only at images of water much of the time, potentially creating an unreliable model. To overcome this, we implemented a weighted random sampler, which increases the probability that a whale image will appear in any given batch in proportion to the number of whale images in the overall training set. We used the set of images that were withheld from training to test the performance of each model. False positives and false negatives for each epoch were used to further tune model parameters and retrain models.

3.4 Results

Image tiling took approximately 15 seconds per km² on an Nvidia Tesla K80 GPU, though this relationship is unlikely to be linear. Model training took approximately one hour depending on the training set on our hardware. Our best model trained for 24 epochs and used a learning rate set at 0.0009, with a step size (a parameter that allows the learning rate to decay after a certain number of epochs) of 7 epochs, and a momentum of 0.9. We found that a higher learning rate often resulted in overfitting on the training data, wherein the first epoch of the model would perform reasonably well on satellite imagery (~80% of whales found) but would decline rapidly in subsequent epochs. On the opposite end, a learning rate of 0.00001 resulted in no learning (Table 3.1).

Table 3.1: Results of variation in learning rate (LR).

Model Results	**Precision**	**Recall**
LR = 0.0005	1.0000	0.7769
LR = 0.0009	**1.0000**	**0.9043**
LR = 0.0010	0.9990	0.7589
LR = 0.0011	1.0000	0.4510
LR = 0.0012	1.0000	0.7028

The standard measurement of performance in this case is precision, or the percent of positives (whale identifications) that are true positives, and recall, or the percent of whales that were found by the model. Precision was closely consistent among folds, ranging from 0.997 to 0.999, with slightly higher variation in recall from 0.930 to 0.989, suggesting that there was a small variation among the training images in the folds that was affecting model performance (Table 3.2). Our trained model correctly identified all whales in the WorldView-3 imagery presented to it, and 90.4% of water (Table 3.2), for a false-positive rate of about 9.6% (water misclassified as whale) and a false negative rate of 0% (whales misclassified as water).

Table 3.2 Results at the final epoch of 4-fold validation.

Aerial test fold	**N water training**	**N whale training**	**N water test**	**N whale test**	**Precision**	**Recall**
1	9230	179	3076	60	0.9989	0.9304
2	9230	179	3076	60	0.9970	0.9882
3	9231	179	3076	60	0.9989	0.9648
4	9229	180	3077	59	0.9983	0.9889

3.5 Discussion

Here we describe a functioning pipeline for identifying whales in high-resolution satellite imagery that can be immediately employed to reduce the time required to complete large-extent surveys. Like most machine learning applications, the model could be iteratively improved with the addition of correctly classified and verified whales from future imagery, and our current classification accuracy therefore represents a lower bound on the potential for satellite imagery to aid in cetacean surveys. As it stands, there is little open-water imagery available in DigitalGlobe’s archive of imagery as they do not collect continuously, instead tasking imagery collection for high-demand regions or in response to orders from customers. The current pricing structure for very high-resolution imagery would likely prevent many research applications from pursuing projects at basin-wide scales, but alternative pricing for non-profit organizations and education users is available. Encouraging the collection of open-water imagery in areas of interest and in areas of low competition is the first step in moving imagery-based methods to broad applicability. In the meantime, the pooling of aerial photographs with known ground-sample distance by different research groups could result in a more robust training image set, and users with large catalogs of aerial imagery for their specific taxa and regions could create bespoke local training sets to better classify cetaceans in their region of interest.

Given that our model is trained exclusively on minke whales, the smallest of the baleen whales, including more aerial photography of larger whale species would likely further improve performance. That said, it performed surprisingly well on whales that can reach double the size of a minke whale. The code could easily be modified to create overlapping tiles, which would eliminate problems arising from whales bisected by neighboring tiles. The addition of further classes representing objects such as boats, large ships, land, and rocks at the surface in the imagery would also help minimize the number of false positives in a cetacean survey. Such classes could be fine-tuned to the application at hand with training images added for the particular conditions found in a region, such as peculiar boat shapes or floating rafts of detritus.

Limitations inherent to this method are not dissimilar to those faced by any other survey methods. We did not attempt to use satellite imagery to locate whales in choppy water. Challenging sea-state conditions are common to boat- and aerial-based surveying (Barlow et al. 2001; DeMaster et al. 2001; Teilmann 2003; Hodgson et al. 2013) because waves and sea spray create a lot of "noise" which makes it difficult to separate a whale from the surrounding water. The collection of imagery also hinges on cloud cover, and future applications will need to pair this detection pipeline with appropriate statistical models for non-detection (Kéry & Schmidt 2008). Aside from environmental challenges, there are several satellites currently in orbit that could be used for cetacean surveying, such as previous iterations of WorldView and Pleiades. While this trained model may be robust to differences in spatial resolution among the various sensors available, we did not test imagery from other sensors. Sensor-specific models could easily be trained, as the aerial imagery can be down-sampled to any resolution desired.

This method could be used to improve cetacean research in several different ways. It provides a means of viewing and monitoring areas that are far from ports or are hazardous to access, such as polar regions, remote island chains, or open ocean. Moreover, it provides the potential to monitor these areas at a daily time scale, cloud-cover permitting. With enough imagery, it could be used to monitor the arrival of migrating species or examine fine-scale changes in foraging activity. Long-term studies on whale feeding and breeding grounds have provided critical information on the ecology and behavior of these animals but are poorly suited to answer basin-scale questions for species that range widely both within and among seasons. The arrival time of migrating whales at traditional feeding grounds, for example, has been used to understand links between habitat use and local environmental conditions (Ramp et al. 2015), but is unable to illuminate the existence of unmonitored areas that may serve as alternative feeding grounds. With the ability to rapidly and automatically detect whales in satellite imagery, boat or aerial surveys become valuable as ground-truthing rather than as the sole source of data on whale abundance and distribution, and researchers intent on instrumenting individuals or collecting individual-level data may be able to more accurately target their effort, saving time and expense. While far from a total replacement for other survey modalities, this method has promise to improve current survey methodology for large whales, increase the temporal resolution of surveys, expand the ocean surface area surveyed, minimize human risk, and increase the rate of data acquisition.

4 Eco-social sensors: Ecological opportunities in the era of camera ubiquity

4.1 Abstract

Expansive study areas, such as those used by highly-mobile species, provide numerous logistical challenges for researchers. Community science initiatives have been proposed as a means of overcoming some of these challenges but often suffer from low uptake or limited long-term participation rates. Nevertheless, there are many places where the public has a much higher visitation rate than do field researchers. Here we demonstrate a passive means of collecting community science data by sourcing ecological image data from a public photo-sharing platform – Flickr – using freely available Python packages and simple applications of convolutional neural networks. Using the Weddell seal (*Leptonychotes weddellii*) on the Antarctic Peninsula as an example, we use these data with field survey data to demonstrate the viability of photo-identification for this species, supplement traditional field studies to better understand patterns of habitat use, describe spatial and sex-specific signals in molt phenology, and examine behavioral differences between the Antarctic Peninsula's Weddell seal population and better-studied populations in the species' more southerly fast-ice habitat. While our analyses are unavoidably limited by the relatively small volume of imagery currently available, this pilot study demonstrates the utility of ad hoc wildlife photography, the value of geographic metadata for the

incorporation of such imagery into ecological analyses the remaining challenges of computer vision for ecological applications, and the viability of pelage patterns for use in individual recognition for this species.

4.2 Introduction

Marine mammals are highly mobile species that are inherently difficult to study, both because of the large spatial scales over which they interact with their environment, and because they spend the majority of their life underwater (Kaschner et al. 2012). Tracking studies of marine mammal movement are typically limited in sample size and this unavoidably constrains the types of questions that can be addressed (Sequeira et al. 2019). Surveys across vast landscapes are often expensive, requiring intensive dedicated field studies and large-scale collaborations, and frequently have lengthy intervals between visits (Calambokidis et al. 2001; e.g., Smith et al. 1999). Despite these challenges, understanding movement, habitat use, and connectivity at the scale of an individual's range is important for making conservation decisions (Runge et al. 2014), and thus there is substantial value in developing new approaches to solve this long-standing problem in marine ecology.

The distribution and migratory pathways of numerous species of marine mammal are poorly understood, and marine species inhabit a complex three-dimensional space that is difficult to observe. Community science (also called citizen science or participatory science) has been proposed as a means of crowd-sourcing the collection or analysis of data on marine mammal abundance, distribution, and habitat use (e.g., Cheeseman et al. 2017; LaRue et al. 2020), but this method also has some well-known challenges. Data quality is often raised as a shortcoming, though community-science projects can produce accurate datasets and should be assessed based on the specific details of each project's design and goals (Kosmala et al. 2016). Arguably, a greater challenge to community science's impact lies in the tiny fraction of the relevant population that formally participate in such projects; many more people encounter wildlife than can be motivated or trained to report or document them. This motivation gap makes it difficult to recruit community scientists and to keep them engaged over time (Nov et al. 2011) and creates an organizational barrier that can dissuade many professional researchers from setting up new projects. Here we explore the use of passively sourced images from the internet as a complement to both traditional field research and more formal community science efforts involving the active solicitation of data or analysis from the community. While passive collection of data misses the opportunity for sustained engagement with dedicated observers, it sidesteps the aforementioned motivation gap by capitalizing on people's desire to share information with their peers online, requires no setup, and leverages the ubiquity of high quality GPS-enabled cameras in most feasible environments.

We illustrate the potential for opportunistic photographs posted online to provide useful ecological inference and develop a "web crawler" to locate and acquire images from online platforms, using the Weddell seal (*Leptonychotes weddellii*), a species with a circumpolar Antarctic distribution, as a case study. While Weddell seals have been well studied in other parts of their range (Stirling 1969; Testa & Siniff 1987; Castellini et al. 1992; Burns et al. 1999; Hückstädt et al. 2017), Weddell seal life history and spatial ecology on the Antarctic Peninsula have received little attention to date. In continental Antarctica, Weddell seals are generally site-faithful, likely due to their reliance on holes in the sea ice that they use to enter the water to forage, mate, and breathe and their use of the ice surface for resting, nursing, and molting (Stirling 1969; Croxall & Hiby 1983; Cameron & Siniff 2004). It is unclear whether Weddell seals on the Antarctic Peninsula and sub-Antarctic islands demonstrate site-fidelity when there is no breathing hole to maintain, though in winter, sea ice does accumulate in bays and fjords. The large and increasing numbers of tourists visiting the Antarctic Peninsula (68,000 in 2019/20; IAATO 2020) provides an opportunity to capitalize on photographs collected and posted online by Antarctic visitors as a means of better understanding Weddell seal biology in this region. Photo-identification (photo-ID), the use of natural markings to identify individual animals, is a widely-used technique for studying the biology and habitat use of a wide range of both marine (e.g., Katona & Whitehead 1981; Bigg 1982; Yochem et al. 1990; Speed et al. 2007) and terrestrial species (e.g., Kelly 2001). Several species of phocid seal have been shown to retain the patterns of spots or streaks on their pelage between years (e.g., Forcada & Robinson 2006; Patterson & Redman 2013; Koivuniemi et al. 2016), and to date no work has yet confirmed this occurrence in Weddell seals.

By building an image catalog, photographs of Weddell seals can be used to assess both basic Weddell seal phenology and life-history diversity and their patterns of spatial habitat use. Here, we demonstrate the viability of Weddell seal pelage patterns for photo-ID and assess the utility of passively collecting community science data to supplement traditional field studies of Weddell seals. Further, we focus on three applications for images collected by biologists conducting field studies in the Antarctic Peninsula and internet-based photographic data from tourists visiting the region: (1) annual molting phenology and the potential for latitudinal differences, (2) haul-out site fidelity, and (3) spatial sex segregation. Together these applications demonstrate an alternative and cost-effective method for crowdsourcing previously existing data on social media platforms and harnesses the widespread use of high-resolution digital cameras with GPS.

4.3 Methods

4.3.1 Study Species

We demonstrate the applicability of this method using photographs of Weddell seals, a species frequently found in the regions of the Antarctic coast with fast ice, that is, permanent sea ice attached to land. Fast-ice regions are considered their primary habitat (Stirling 1969; Stirling 1977; LaRue et al. 2019), though Weddell seals are also found outside of fast-ice habitat. The most notable examples are the Antarctic Peninsula (Fig. 4.1), which has only seasonal sea ice – often as pack ice (loosely aggregated sea ice) – and as far north as Larsen Harbour, South Georgia (55° S; Vaughn 1968; Burton 2015), which has no regular sea ice.

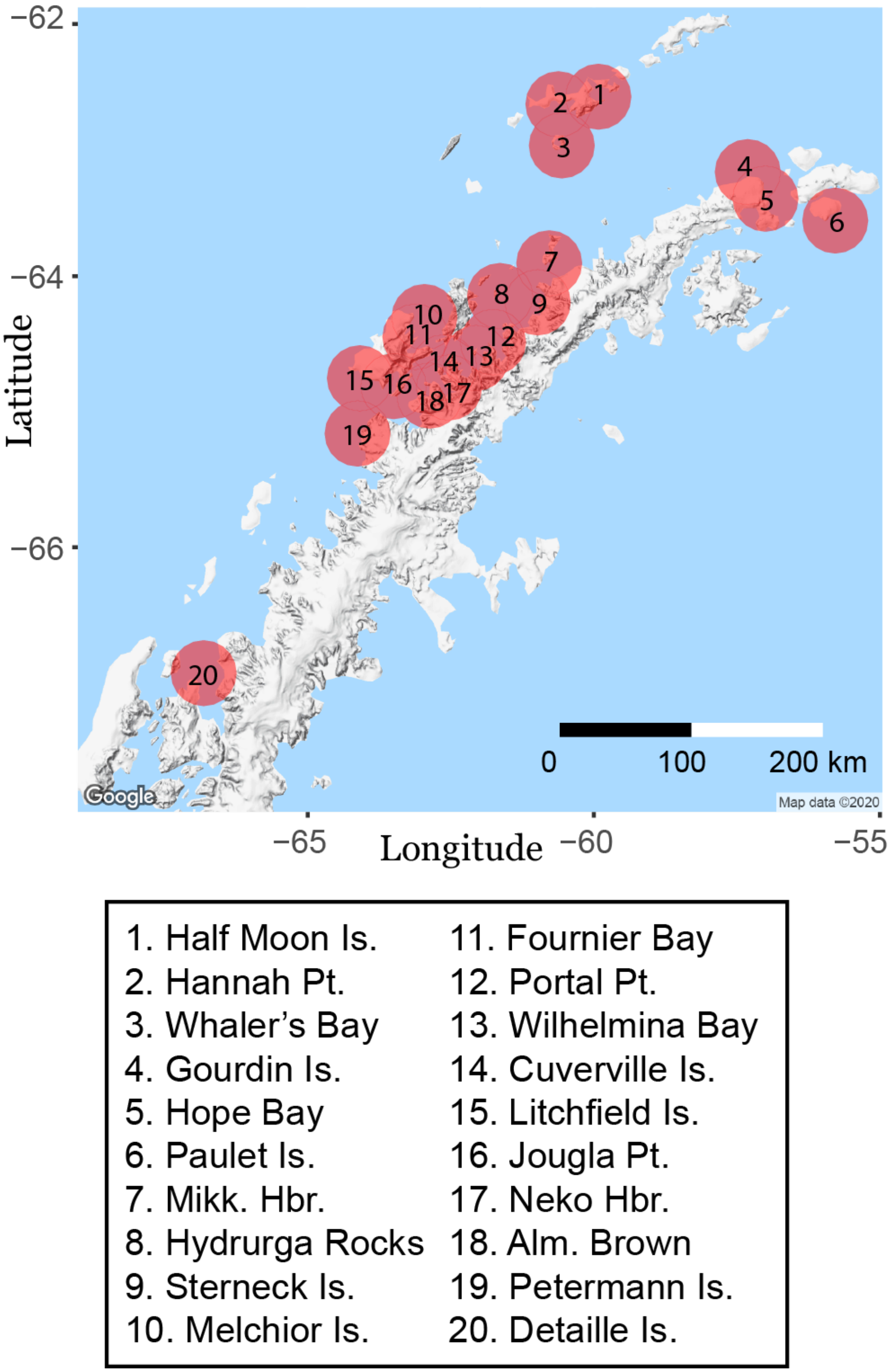

Figure 4.1: Locations and extent of web-crawler geographic queries on the Antarctic Peninsula. Circles have a radius of 32 km from the numbered site.

4.3.2 Web crawler and automated detection

We used an automated data-collection pipeline comprised of three stages: a web-crawler to locate and acquire publicly-shared images with relevant metadata such as location and date, a machine learning-based seal detector algorithm to remove images that are not seals and identify species, and a metadata scraper that isolates geo-tagged images (Fig. 4.2). Once manually verified, these images were added to photographs collected by scientists or actively submitted by community scientists to create a photo catalog ready for subsequent analysis.

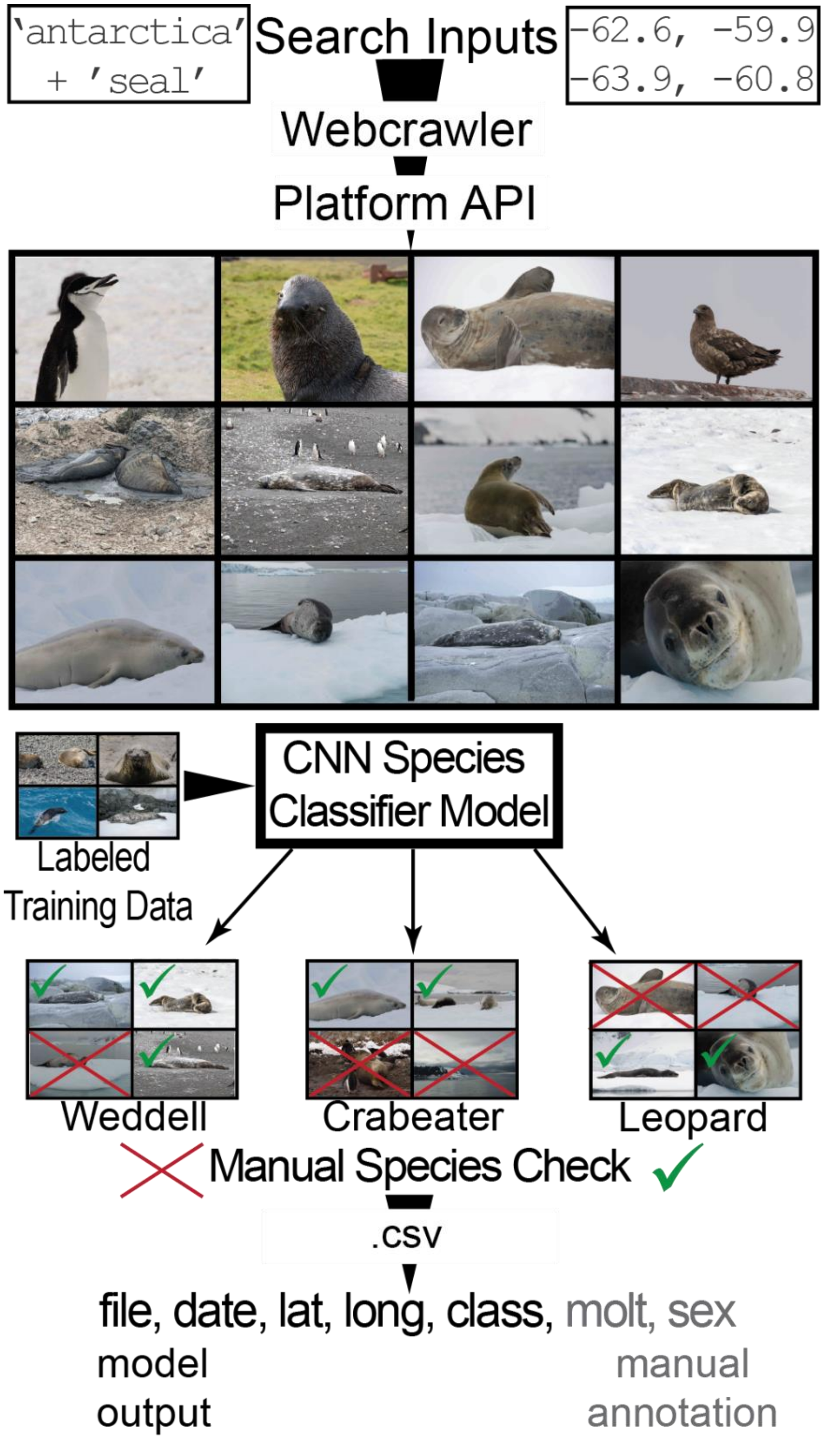

Figure 4.2**:** The workflow. Text and search terms are fed to the web-crawler, which interacts with the platform API (in this case, Flickr) to find images. Once downloaded, images are fed to the trained classifier which separates images by species. A manual verification step fixes misclassifications, and manual annotations such as molt and sex can then be added to the output dataset.

We implemented the web-crawler, written with the Python package *icrawler*, to scrape data from Flickr (Chen 2017). This web-crawler uses text-based search terms associated with image metadata, limiting the volume of imagery to analyze from all images to only those tagged, titled, or otherwise annotated with search terms specific to the questions of interest. To create a manageable test set of images and given the limitations of the Flickr application programming interface (API), we selected 20 sites spread across the western Antarctic Peninsula as search centroids (Fig. 4.1; Table S1). For each site, the web crawler searched for images tagged with the word 'seal' with geotags situated within a 32-km radius of the site (the maximum search radius within the Flickr API), and within the date range of Oct. 1, 2004 to Apr. 1, 2019, which roughly corresponded to our field-collected dataset. While the search regions overlapped (Fig. 4.1), images were recorded with their unique filenames from Flickr, such that duplicate photographs from overlapping searches were not included twice. The workflow also includes capability to search for all images using only text tags and to eliminate those images without a geotag, suitable for a broad survey that would be difficult to accomplish by specifying a geographic search (e.g., 'antarctica' + 'seal'). We used the search term 'seal,' which would capture seals of many species, rather than a more specific search term such as 'Weddell seal' so as to cast a wide net to avoid losing data due to misidentifications.

The web-crawler application locates and downloads images. At this stage, a Python-based image classifier determines whether the image contains a seal and then attempts to identify the species of seal. To build the classifier, we implemented two common convolutional neural network (CNN) model architectures, Resnet-50 (He et al. 2016) and Densenet-121 (Huang et al. 2017) within the PyTorch framework (Paszke et al. 2019) to isolate the best model for this application. CNNs are computer vision models that use an objective function (e.g., cross-entropy between predicted and ground-truth labels) to learn how to extract high-level representations of images that highlight important features. They then map those representations to class labels by learning from a set of labelled training images. Each of our models was trained on a training set of images annotated by experienced Antarctic seal researchers; images in which the species identification was ambiguous were excluded. A set of 4,261 images was used to train and validate the models. Further details of the CNN implementation can be found in Appendix A4.1

The output of the classification stage is a pared-down dataset ideally free of irrelevant images, but we included a final visual verification step to ensure the integrity of the data and to remove any irrelevant images the classifier may have missed. Throughout this process, the individual images are not changed, and all EXIF metadata (image file metadata) remains associated with the image. The optional final stage of dataset creation looks through the remaining images to isolate those images with geographic metadata, information that is automatically recorded by a smartphone and often included by more traditional cameras as well. The remaining dataset consists of directory of images of seals for each category with geographic metadata, and a .csv file listing the filename, date, and coordinates of the image.

4.3.3 Study Area

Our analyses are based on two streams of Weddell seal photographs: (1) images taken by trained observers during field work, and (2) “web-crawled” images taken by other Antarctic visitors. All images were collected along the portions of the Antarctic Peninsula (Fig. 4.1) visited most frequently by commercial cruise vessels, notably its western coastline and associated islands. Most of this region has only seasonal fast-ice formation and has variable and drifting concentrations of pack ice during the summer. Pack- and fast-ice provide potential haul-out locations for Weddell seals, but individuals also haul out on pebble, sand, and cobble beaches and on low-lying rock outcrops.

4.3.4 Field Collection of Weddell Seal Images

From Nov. 2015 to Mar. 2018, field biologists working on monitoring and research projects, along with a small number of Antarctic expedition guides, were asked to contribute photographs of Weddell seals, including images from prior field seasons. All researchers and guides were based on commercial tour vessels or occasionally on research expeditions around the Antarctic Peninsula and South Shetland Islands. Images were either associated with precise coordinates or assigned to a “site,” following the framework of other biodiversity mapping efforts on the Antarctic Peninsula that map seabird colonies to particular islands or beaches (Humphries et al. 2017). While this method of differentiating sites is not ideal for seals, which might be hauled out on ice floes or on islands or beaches without seabird colonies, most images mapped neatly onto named visitor sites or sites of continued penguin population monitoring (see Humphries et al. 2017) since Antarctic tourism is tightly regulated. For images with only site-level geographic data, we grouped images under a single set of coordinates for the site, and for those with more precise geographic information, we retained those finer coordinates.

4.3.5 Photo-Identification

Photographs from both the web crawler and field collection were processed to enhance the natural patterns on the pelage, primarily by altering brightness and contrast. We focused photo-identification efforts on the ventral region, as seals often lie on their side to sleep when hauled out (Fig. 4.3). While coat patterns are retained through molt, molt stage can impact the distinctiveness and visibility of the coat patterns, as old, worn fur can appear as one uniform gray or tan color that makes it harder to match a photograph to other photographs in the catalog. For images in which the pre-molt stage (Fig. 4.3A) substantially diminished the visible pattern, we made an effort to find a match but, in the absence of a match, did not include the image in the catalog as a new individual. To ensure that images in the catalog could be reliably used as “type specimens,” we assigned images ratings of quality and distinctiveness (Appendix A4.2). Images that exceeded a score threshold of 8 out of 15 when summed across ratings were not included in the catalog. A lower standard was considered for images to be matched against the catalog in order to locate additional observations of a previously-identified seal (i.e., an individual already in the catalog). If no match was found, such lower-quality images were retained separately in order to compare against the catalog again after new images were added. Images were excluded from all analyses if the ventral region was obstructed, the angle was extreme enough to prevent a view of the pattern, or resolution or irretrievable glare/shadows made the pattern unclear (Appendix A4.2).

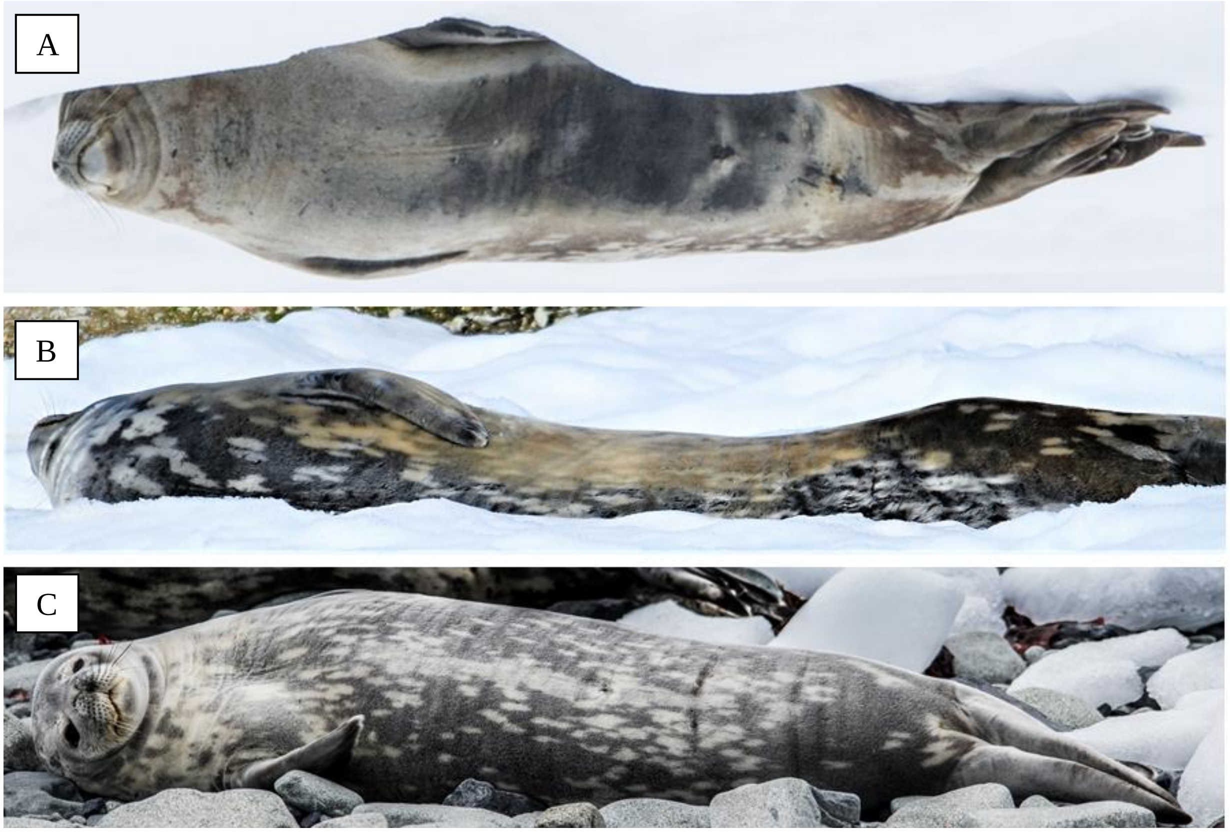

Figure 4.3: **(A)** A pre-molt individual showing heavy wear on the ventral surface. **(B)** A seal mid-molt. **(C)** A recently-molted individual.

Matching was completed manually by trained observers who either had prior photo-identification experience from other taxa or who had completed a training program and test-set of images. Initial matching was completed without any software support but was later migrated to the Discovery program (Gailey & Karczmarski 2012) which provided database integration and a means of including relevant metadata. Each image was compared to the catalog by two observers unless a match was found, when it was then verified by A. Borowicz. In every case, matches were verified by two people to ensure agreement.

4.3.6 Site Fidelity

Weddell seals in the fast-ice regions of their range frequently show site fidelity (Stirling 1969; Croxall & Hiby 1983; Cameron & Siniff 2004), though far less is known about site fidelity in areas without extensive or permanent fast ice. While our dataset does not yet contain enough records to map widespread movement along the Antarctic Peninsula, we were able to focus on two frequently-visited sites, Half Moon Island in the South Shetland Islands and Mikkelsen Harbour on Trinity Island (Fig. 4.1 Sites 1 and 7, respectively), given the popularity of these sites among tour operators. Together, these two sites hosted 24,517 passengers ashore in the 2018-19 season alone (IAATO 2020). We examined images collected by scientists, sent directly to us by passengers, and those obtained from the web-crawler to examine the degree of site fidelity exhibited in this region.

We also used the combined image catalog to track individual seals as a means of understanding their movement over time. Re-sightings of individuals provide important information about the use of haul-out sites in the Antarctic Peninsula by Weddell seals through the austral summer, particularly since the vast majority of haul-out sites in the Antarctic Peninsula have never been documented. This region is of particular interest, as it was excluded from a continent-wide remote-sensing survey for Weddell seals (LaRue et al. 2020), and thus remains poorly documented. Moreover, the potential prevalence of Weddell seals in non-fast-ice habitats is important to the understanding of population-level changes that might occur as ice habitats diminish with changing Southern Ocean climate dynamics (Siniff et al. 2008).

4.3.7 Spatial Sex-Segregation

As a simple example of the potential value of broad-scale image data, we also investigated spatial patterns of sex-segregation among Weddell seals. We annotated seal images based on sex, including an “unknown” category for those seals we were unable to rate. For this preliminary evaluation of differential sex distribution, we considered overall patterns based on latitude as well as the potential for individual haul-out sites to host different sex ratios of seals. We included all images of Weddell seals in this analysis, regardless of their suitability for photo-identification.

4.3.8 Molt Phenology

To examine molt phenology in Weddell seal photographs, each image from both the photo-identification catalog and the database of web-crawled images was qualitatively rated for molt progression as being (1) unmolted (having not yet started the molt process), (2) molting, or (3) fully molted (Fig. 4.3). Unmolted individuals were characterized by typically tan-brown (bleached) fur and indistinct patterning and occasionally showed heavy wear on their fur. Molting typically begins with the head, followed by a dorsal stripe, and the flanks (Beltran et al. 2019). Fully molted individuals displayed clear patterning with more gray and white coloration.

Actively-molting individuals were those with some characteristics of both unmolted and fully molted seals. We excluded any image lacking a date or location, and also removed images for which molt stage was unclear or the individual was young-of-the-year. Given that one of the first areas to molt is generally a dorsal stripe (Beltran et al. 2019) which is frequently out of view in our photographs, it is possible that some individuals were categorized as unmolted, but had in fact begun the process. The overall pattern of timing, however, should be unaffected.

As a preliminary means of exploring the potential drivers of molt phenology patterns, we considered all images (which allowed images with a timestamp but no geographic information to be used) and further separated images by sex and location. We then compared molt phenology within two regions of the Antarctic Peninsula, as a basic means of examining any link between latitude and phenology as has been indicated for other species within the Antarctic and without (Bonenfant et al. 2004; Herfindal et al. 2006; Lynch et al. 2012; McLean & Guralnick 2021). We subdivided the region into a northern component, including the South Shetland Islands and the Peninsula north of Trinity Island, and a Southern component, including the Peninsula and islands south of 63.5^o S latitude. Seals in the northern region have ready access to the deep water of the Bransfield Strait and, for seals in the South Shetland Islands, both the Strait and the relatively close shelf break to the north of the islands. In the southern region, the shelf break is considerably more distant, and the region is more likely to contain some sea ice into the summer.

4.4 Results

4.4.1 Image Collection

Across the 21 sites on the Antarctic Peninsula, our web search returned 978 images tagged ‘seal’ (Appendix A4.3). While all of these images were returned from a search that explicitly required a geo-tag, only 458 images contained coordinates, suggesting that the other photographs were tagged with a location within Flickr and that this information was not written to the image metadata. Of those geo-tagged images, 149 were verified as containing a Weddell seal and were used in subsequent analyses (Fig. 4.4A). From our field-based efforts, we collected 148 Weddell seal images around the Antarctic Peninsula (Fig. 4.4A).

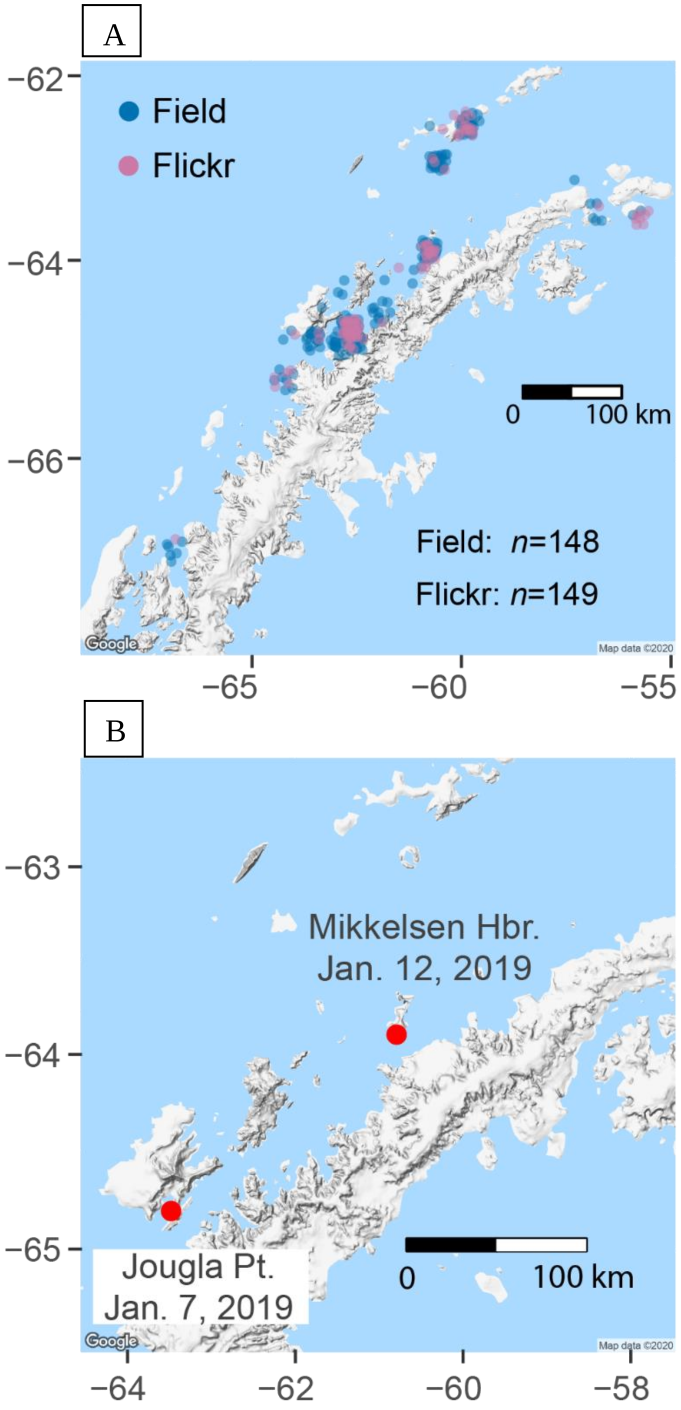

Figure 4.4: ***(A)*** Locations of field-collected and web-scraped Weddell seal images. **(B)** Longest within-season travel for an individual, from Jougla Point in the south to Mikkelsen Harbour in the north (167-km straight-line distance).

Of the two classifiers evaluated, the ResNet-50-based classifier performed best, but required substantial verification. The overall recall of the model (true positives ÷ [true positives + false negatives]) was 48.7%, while the precision (percent true positive out of all images labelled as positive) was 52.6% (Table 4.1). As a result, nearly half of all web-scraped images, in nearly all classes, had to be reclassified manually.

Table 4.1: Precision and recall outcomes for different image classes from both CNN classifiers, and the overall weighted macro precision and recall for each model.

	DenseNet-121		**ResNet-50**	
Class	**Precision**	**Recall**	**Precision**	**Recall**
Crabeater	0.62	0.37	0.68	0.24
Southern Elephant	0.46	0.38	0.55	0.41
Antarctic Fur	0.55	0.50	0.45	0.53
Leopard	0.49	0.29	0.53	0.49
Non-Seal	0.47	0.76	0.53	0.78
Weddell	0.34	0.25	0.37	0.25
Overall Weighted Macro	*0.49*	*0.47*	*0.53*	*0.49*

4.4.2 Photo-Identification

From the 148 Weddell seal images collected during our field effort, we amassed a catalog of 96 individuals, 16 of which were resighted at least once. After the manual verification of the CNN classifier, we examined the resulting 149 web-scraped Weddell seal images; seventy-two did not meet the quality standards for photo-identification. Of the remaining 79 usable images, we determined that there were 41 unique seal sightings, increasing the size of our photo-ID catalog by 28% to 189 images. In several cases, multiple photographs had been taken concurrently of the same seal, and in others multiple seals appeared in a single photograph. In this scheme, two individuals within the same photograph are considered two sightings.

4.4.3 Site Fidelity

Our dataset from Half Moon Island (Fig. 4.1, site 1) comprised 15 seal sightings (Table 4.2) collected between 2005 to 2015. At Mikkelsen Harbour (Fig. 4.1, site 7) our dataset consisted of 33 sightings (Table 4.1) from 2015 to 2019. At both sites, some individuals were re-sighted in the same season and some in different years. At Half Moon Island, 7 individuals were seen only once, while the remaining 8 images were re-sightings at either Half Moon Island or at another site. Only 7 individuals at Mikkelsen Harbour were seen only once.

Table 4.2**:** Images from two sites of focus for photo-identification.

Site	**Images Field-Collected**	**Images Web-Scraped**
Half Moon Island	12	3
Mikkelsen Harbour	29	4

While broad inference about travel and site fidelity within and among years at a large spatial scale will require further data collection, the data collected thus far provide an interesting preliminary view into Weddell seal movement. More than half of all individuals (Flickr and catalog; n=93 individuals) were photographed only once (65%; n=115), even at frequently visited sites. Eighteen individuals (13% of all individuals) accounted for all 51 re-sightings (i.e., 29% of photographs were re-sightings). Of those re-sightings, 13 individuals were resighted across different research seasons and 13 were resighted within the same research season. Overall, 16 were resighted at the same site and only 8 individuals at different sites; only one individual was *only* resighted at a different site.

Aside from re-sightings at the same location, the shortest within-season distance observed was 2.5 km (straight-line distance) from Mikkelsen Harbour to the Tetrad Islands, which occurred over four days. The longest within-season distance was 167 km over 5 days in 2019 between Jougla Point and Mikkelsen Harbour (Fig. 4.4B). More interesting, perhaps, is another seal that made a 150-km trip between Mikkelsen Harbour (26 Dec 2015) and Half Moon Island (27 Dec 2015) over the course of one day (Appendix A4.4). This is notable both for the distance and speed, but also because a suggestive (but low-quality) image from Georges Point was taken the day before (25 Dec 2015). If the same individual, this seal would have made a further 125-km trip from Georges Point to Mikkelsen Harbour. While that image does not meet our quality standards, it is a striking possibility because another seal was positively identified at both Georges Point and Mikkelsen Harbour on 25 and 26 Dec 2015, respectively (Appendix A4.4). The confirmed Mikkelsen-Half Moon sighting is also notable in that it is of the most frequently sighted individual in the catalog, seen 7 times between 2017 and 2019, though all other sightings are from Mikkelsen Harbour.

Mikkelsen Harbour, a small bay on the southern shore of Trinity Island, was commonly used by resighted seals. Of seals seen in at least two different locations, all but one was observed at Mikkelsen Harbour at least once. While this could be an artifact of the popularity of this site with tour operators, and the resulting high number of photographs obtained from this site, resighting rates were much lower at Half Moon Island, another frequently-visited site at which Weddell seals are nearly always present during the tourist season (Naveen & Lynch 2011).

4.4.4 Sex Segregation

Of all 232 geo-tagged Weddell seal images from all sources (inclusive of images unsuitable for identification), 127 could be sexed (60 males, 67 females), while 105 could not be sexed (Fig. 4.5A). Broadly, seals were distributed evenly across a latitudinal gradient (Fig. 4.5B). Our results suggest a pattern of site-specific sex-segregation, though substantially more data are required to investigate this trend in more detail (Fig. 4.5C). Whaler’s Bay (Fig 4.1, site 3) and Half Moon Bay (Fig. 4.1, site 1), for example, showed a roughly 2:1 female-to-male ratio, while Mikkelsen Harbour and Neko Harbour (Fig. 4.1, sites 7 & 17) showed more even sex ratios, though we did not investigate the potential for different patterns to emerge in different years.

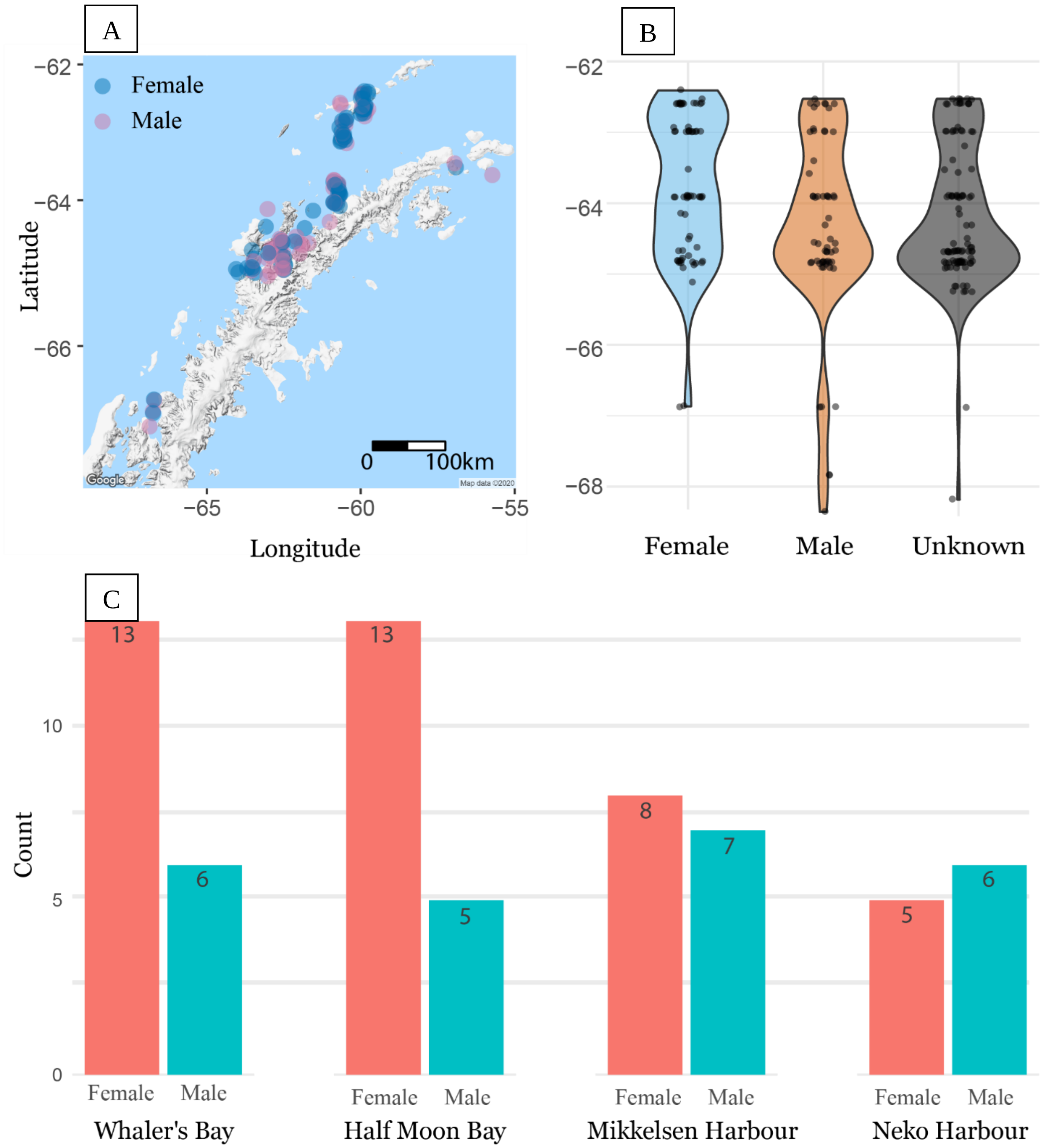

Figure 4.5: **(A)** Male/female distribution across the region. **(B)** Latitudinal distribution by sex. **(C)** Site-level sex ratios.

4.4.5 Molt Phenology

We were able to rate molt stage for 169, or 73%, of the 232 geo-tagged images. The dataset included roughly similar numbers of images for each molt stage, with 57 unmolted seals, 66 molting, and 46 fully molted. Their distribution across the season showed a clear seasonality to molt phenology (Fig. 4.6). While our observations of both the unmolted and fully-molted categories are necessarily curtailed by the challenges of navigating in early- and late-season sea ice and the bounds of the field season, the summary statistics from this work demonstrate seasonal patterns. The mean date of observations of seals in the molting stage was January 15 (s.d. = 22 days), and the earliest date that a molting seal was observed was December 14. While the earliest date of an unmolted sighting and the latest day of a fully-molted sighting are artifacts of the start and end of the research and tourism seasons, the latest unmolted sighting (March 16) and earliest fully-molted sighting (January 25) give us some insight into temporal patterns of molt. The latest unmolted individual falls almost 3 standard deviations from the mean date of a molting sighting, which suggests that this individual may have had some underlying condition – whether related to disease or body condition – that prevented molt from beginning or delayed initiation.

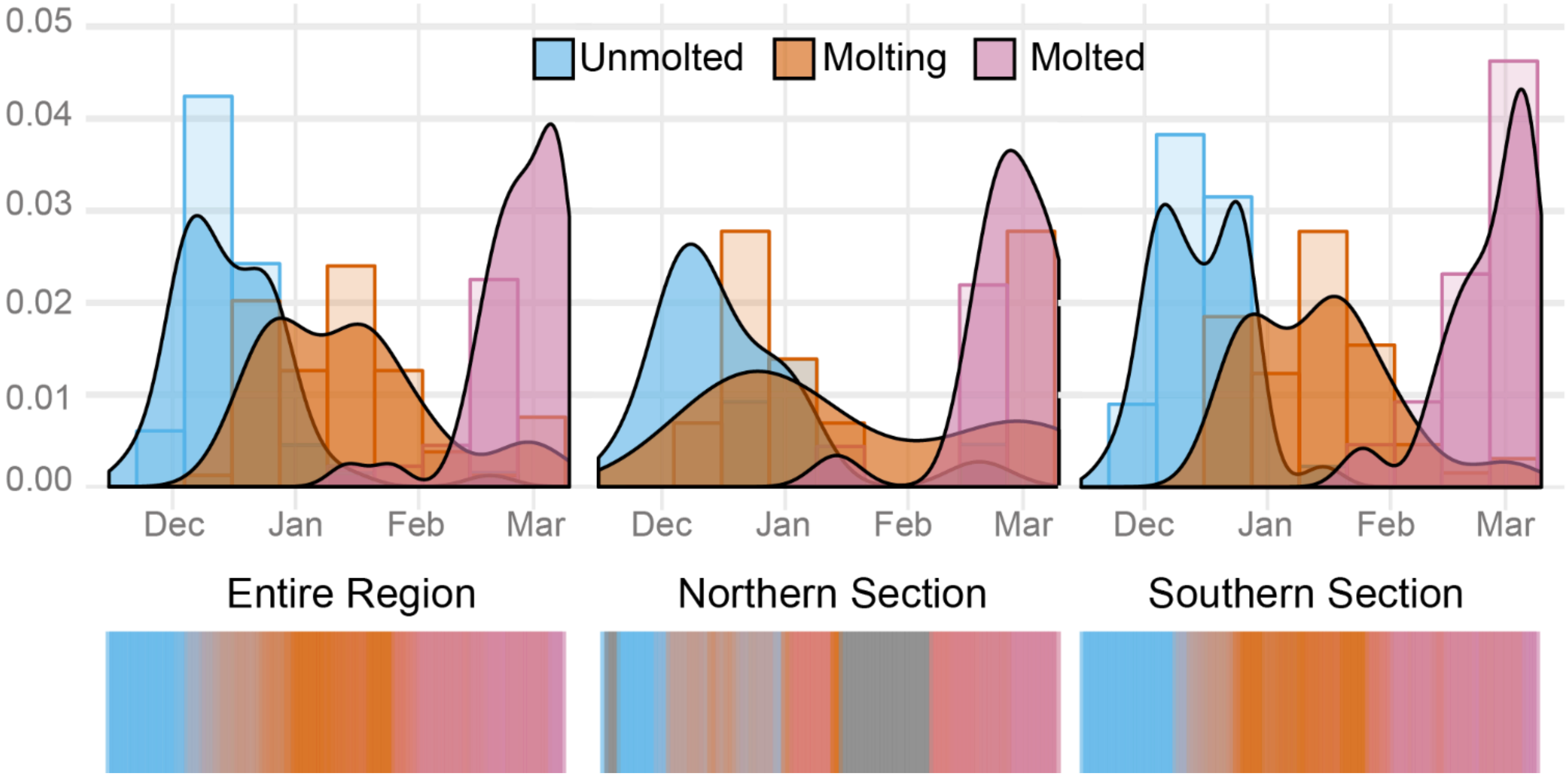

Figure 4.6: The seasonal progression of Weddell seal molt. Histogram data in 12-day bins, and kernel density estimates for each stage. The northern region lies north of 63.5º S while the southern region lies south of this latitude.

The northern region included 49 images in which molt stage could be rated, while the southern region included 120 images. The mean date of observations for molting seals was January 17 in the north, and January 14 in the south. The aforementioned late molter doesn't allow us to make any meaningful inference about differences in timing for starting molt, but there was a gap of 11 days between the earliest date a seal was observed as fully-molted in the North (Jan 14; mean date of being molted = Feb 26, s.d. = 13 days) and South (Jan 25, mean = Mar 4, s.d. = 13 days), though the relatively fewer images associated with the northern sector essentially make this gap between dates unreliable (Student's t-test for difference in mean date: $t = 1.721, df = 40.05, p = 0.093$).

4.5 Discussion

'Traditional' community science has produced valuable insights by radically expanding the scope of data collection in some applications (e.g., Lodi & Tardin 2018; Poisson et al. 2020) and has, as an additional benefit, promoted science knowledge and data literacy among participants (Cronje et al. 2011; Jordan et al. 2011; Haywood 2015; Dean et al. 2018). However, the active solicitation of data from the public is not well-suited to all applications and is only one possible means of engaging non-scientists in data collection. For better or worse, members of the public are consistently pressed into service as unwitting sensors, providing passive data on traffic conditions, patterns of movement, and commercial behaviors (Baruh & Popescu 2015). Meanwhile, they *intentionally* share other information with their friends, family, and the public at large, at the scale of 4 million Flickr posts and more than 100 million Instagram posts per day (Thornley-Brown 2019; Aslam 2020). While the former data stream is fraught with complexities surrounding privacy and choice, the latter provides an opportunity for the public and planet to benefit from data that are already being intentionally and willingly shared online.

Here we have used Flickr, a photography-sharing website hosting tens of billions of photographs, to gain insight into one species, the Weddell seal, at its range limits and in one of the most remote regions of the world. Using freely-available Python packages, we have collected image data from the Antarctic Peninsula, classified images to the species level, and extracted basic geographic and temporal information. While the images often do not meet the standards we typically set for fieldwork, they provide an ancillary data stream beyond what our field team is able to produce.

Even with a limited dataset from both field expeditions and tourist photographs, we have demonstrated the viability of photo-identification in this species for the first time and have identified several patterns of interest for further, targeted investigation. While Weddell seals in more southerly fast-ice habitats are site-faithful to breathing holes (Stirling 1969; Croxall & Hiby 1983; Cameron & Siniff 2004), there is less obvious need for such a behavior in the perennially ice-free regions of the Antarctic Peninsula. Nevertheless, we have demonstrated that these seals are regularly seen both within and among seasons at the same site. At the same time, we have documented long-distance travel in the same species. The degree to which site-fidelity is plastic among or within seals is worth further investigation. Even aside from these patterns, leveraging photo-sharing platforms has allowed us to create a rough distributional map of all seal species on the Antarctic Peninsula (Appendix A4.5). A field program to collect even these rough presence-only data with the level of detail demonstrated here would be logistically infeasible.

As for sex-segregation, there is evidence for substantial segregation among other Antarctic pinnipeds (Santora 2013). Physiological needs for a post-partum female and a post-mating male are likely different, which could drive sex-specific habitat use during and after the mating season (Beltran 2018). Our preliminary examination of sex-based patterns of distribution did not suggest a robust latitudinal trend, though the small sample size limits our inference. We were unable to sex nearly half of the seal images, though our inability was largely due to physical obstructions or photography than to anything specific to the seal being photographed. As a result, unsexed individuals are, given the evidence available, missing at random. At the scale of individual sites however, there is some evidence that males and females prefer different haul-outs, and perhaps different foraging grounds. More dedicated effort monitoring these sites within seasons would demonstrate whether patterns of sex segregation are random, permanent, or shift over the season.

Notably, January 15 was the mean of the dates in which we recorded a visibly-molting seal, the same date that Beltran et al. (2019) assess as the mean molt initiation date in the McMurdo Sound area, a region at a much higher latitude and with a more extreme fast-ice climate. Because the period over which one can observe a molting seal is longer than the period over which one can observe the initiation of molt, these findings suggest that molt may initiate earlier for Weddell seals on the Antarctic Peninsula than for those further south, which would align with the suggestion that molt timing is linked to ambient conditions as seals' thermoregulatory costs associated with molting are roughly double those prior to the onset of molting (Walcott et al. 2020). The climate of the Antarctic Peninsula is notably warmer than that of the Ross Sea however, where Beltran et al. (2019) and Walcott et al. (2020) based their research, so it is unclear the degree to which thermoregulatory cost-saving is an important driver of phenology in the Antarctic Peninsula region. Our first observation of a molting individual however, December 14, is close to but later than the observed earliest molt-initiation date from Beltran et al. (2019). It is possible that this is an artifact of the small sample size and inconsistent effort, but this could also suggest that phenology is less clearly defined on the Peninsula than in other regions. More consistent sampling, especially in areas with consistent Weddell seal presence, would resolve this question.

This underlying question of the linkage between behavioral and phenological responses both in extreme environments (such as the fast-ice habitat of McMurdo Sound and the Ross Sea) and in less-extreme environments (such as the ice-free regions of the Antarctic Peninsula), deserves somewhat more attention, given the possibility of warming temperatures in many polar environments due to anthropogenic global climate change. The phenological and behavioral differences between McMurdo Sound Weddell seals and their more northerly Antarctic Peninsula cousins could provide insight into the ability of Weddell seals and other Antarctic pinnipeds to adapt to changing physical conditions in their respective environments. What little evidence we have suggests that diminishing sea ice in the Antarctic Peninsula region could result in migration or population decline (Siniff et al. 2008).

While our implementation of a ResNet CNN was minimally helpful, requiring substantial manual intervention to achieve a reliable dataset, such classification algorithms would likely be more successful with other study species. Phocid seals have broadly similar body plans, which we expect made differentiating between species challenging. More training data would likely alleviate some of this problem and improve the model performance, though the classification problem is challenging and an area ripe with opportunities for the computer vision community. Images from tourists come from many different angles, distances, and lighting conditions, and the cues used by biologists and naturalists to identify a seal on an ice floe from a distance may be subtle. The characteristic body shape of a seal species may be visible to an observer who can deduce how a seal is angled and rolled, but an algorithm is naïve to the third-dimensional characteristics of an image; body position, roll, and the blubber layer combine to create a deformable surfaces problem.

ResNet correctly classified roughly half of our images but also missed half. Those mis-classified images were fairly evenly distributed across the major classes of image with some exceptions. Antarctic fur seals and Southern elephant seals are both abundant in the South Shetland Islands (Hucke-Gaete et al. 2004; Gil-Delgado et al. 2012), especially in several well-visited areas with unique orange-tinted rocks. The misclassification of several landscape photographs as these seals, and of fur seals as elephant seals, suggests that the algorithm may have cued on the color values more than the shapes of the seals. On the other hand, of Antarctic seals, elephant and fur seals are the only two species to regularly position their bodies upright, another potential area of confusion. In a two-dimensional sense, a Weddell seal occupies a form that many of the other seal species included could adopt and this could explain why the Weddell seal class had the lowest precision among the classes (Table 4.1). Where CNN performance is concerned, the answer is nearly always more training data.

For species with more distinct shapes or coloration, a paired web-crawler/classification algorithm approach will likely be very successful at differentiating a study species from the other photographs of a region available on photo-sharing websites. Areas such as national parks have far more visitors than biologists and many tourists are focused on wildlife at these locations. For example, Flickr hosts over 10,000 geo-tagged images labelled ‘elk,’ and over 29,000 labelled ‘buffalo’ or ‘bison.’ While small, timid, or nocturnal species may not be a good fit for this approach, megafauna would be ideal candidates. A combined approach of fieldwork and the shared data of wildlife enthusiasts as passive "citizen sensors" has the opportunity to dramatically increase the size of ecological datasets, at the expense of some data quality. We are heartened by the fact that such an approach can work in the Antarctic, which suggests areas with higher volumes of visitation may have even more success with such a method.

5 Spatial & temporal use patterns of Antarctic fur seals (*Arctocephalus gazella*) on the Antarctic Peninsula

5.1 Abstract

Following extirpation from the Antarctic Peninsula in the 1820s, and exhaustive hunting in South Georgia, the Antarctic fur seal (*Arctocephalus gazella*) has experienced a dramatic recovery in the 20th and 21st centuries. However, this recovery appears to have been driven largely by the breeding population on South Georgia, which appears to have recovered beyond its historic baseline. In contrast, the Antarctic Peninsula's population remains nearly an order of magnitude below the abundance just prior to the sealing era. Here we examine the current state of knowledge of fur seals around the Antarctic Peninsula and, using field survey data alongside data sourced from social media records of Antarctic tourist encounters, try to synthesize the spatiotemporal patterns and drivers of fur seal distributions on the Peninsula. Surveys across the region and supporting community-science evidence demonstrate that site-wise fur seal abundance has not noticeably increased in the last 25 years, but that seals – and especially males and subadults – disperse widely in the region following the breeding season. We describe the remaining gaps in our knowledge and the questions of relevance to management decision-making and regional ecology.

5.2 Introduction

Among species driven to near-extinction, the Antarctic fur seal (*Arctocephalus gazella*) is one of few examples of robust recovery, and one of fewer that have recovered without substantial intervention beyond the cessation of direct hunting. On South Georgia, where fur seals were hunted from the 18th to 20th centuries, there is evidence that the population has reached a level similar to its pre-exploitation abundance (Boyd 1993; Hodgson et al. 1997), though more recent estimates provide evidence to the contrary (e.g., Foley & Lynch 2020). On the Antarctic Peninsula only one breeding colony, at Cape Shirreff on Livingston Island, has recovered to a substantial degree.

Recovery at Cape Shirreff has been rapid, with only 11 individuals reported in 1959 but around 20,000 in the early 2000s (O'Gorman 1961; Hucke-Gaete et al. 2004), though the most recent estimates suggest a population that remains an order of magnitude lower than that prior to exploitation (Hucke-Gaete et al. 2004). At Bird Island on South Georgia, pup production was around 10,000 pups per year in the 1960s and approximately 90,000 in the mid-1970s (Payne 1977). Over that period, the population growth rate actually slowed, declining from 16.8% yr^{-1} (Payne 1977) from the 1950s through the early 1970s to 9.8% yr^{-1} from the 1970s through 1990s (Boyd 1993). Current estimates suggest a population of around 2.5 million females overall on South Georgia (Foley 2019) that continues to expand to new areas of the island (Trathan et al. 2012). Previous estimates of the South Georgia population suggest an abundance of 3 million (Barlow et al. 2002) or 4.5-6.2 million individuals in 1999 (Hofmeyr 2016). Bird Island, the site of the most regular fur seal research in South Georgia, hosts a population of around 100,000 individuals (Barlow et al. 2002), though this population appears to be in decline (Forcada & Hoffman 2014).

At a broader scale, rapid population recovery of such an abundant marine predator, following over a century of exploitation, may combine with anthropogenic climate change to effect important shifts in the region's food web. At South Georgia, during population growth in the 1970s fur seals were establishing new breeding colonies on less-populated beaches (Payne 1977). More recently there is evidence that South Georgia fur seals are now out-competing Macaroni penguins (*Eudyptes chrysolophus*) for Antarctic krill (*Euphausia superba*), a key prey species across the Southern Ocean (Barlow et al. 2002). Under a changing Antarctic climate, disruptions to krill production are likely to be more common, and in years of low krill abundance, such competition may depress reproduction or survival among other krill predators.

The abundance and distribution of Antarctic fur seals across the Antarctic Peninsula region is not well understood outside of the breeding colonies in the Cape Shirreff region. But fur seals have the potential to be important predators in the region, with substantial dietary overlap with penguins, whales, seals, and other taxa. Antarctic fur seals appear to be more generalist predators than some species in the region, but across most of the Antarctic Peninsula, appear to favor krill (Casaux et al. 2003a, 2003b; Garcia-Garin 2020). Some regional or geographic variation is evident however, with fish such as myctophids playing an important role in diet in some areas (Casaux et al. 1998; Casaux et al. 2003a). Notably however, the lack of studies considering diet across the region means that the geographic differences evident from point studies in different decades could be driven by changes in prey availability among years rather than clear differences in diet among areas. In the South Shetland Islands for example, two studies separated by three years found fish and krill to be most important, respectively (Casaux et al. 1998; Casaux et al. 2003a). Regardless of temporal or spatial variation, overlap with other predators is clear, and a clearer understanding of the use of the region by Antarctic fur seals is important to determine the interactions among species and the potential effects of seasonal immigration in the system on their populations.

5.2.1 A brief review of the Antarctic fur seal around the Antarctic Peninsula

The history of the Antarctic fur seal is closely tied to the early exploration of Antarctica, with commercial sealers arriving in the South Shetland Islands in 1819. This period of sealing lasted only a few short years before fur seals were largely extirpated from the region, with nearly 100 ships collecting over 320000 fur seal pelts (O'Gorman 1961). Further sealing in the 1870s effectively destroyed the colonies that were in the process of reestablishment, though the period between then and more concerted scientific expeditions in the 1920s is rife with unreliable narratives (O'Gorman 1961).

Those early surveys of the Antarctic Peninsula demonstrate the scale of recovery in the current era. Expeditions between the 1920s and 1950s did not report any fur seals, and a study at Cape Shirreff, Livingston Island in 1959 documented only 10 individuals, including only one breeding female with a pup (O'Gorman 1961). In 1965-66, a wide-ranging coastal survey of the South Shetland Islands and part of the northern Antarctic Peninsula discovered Antarctic fur seals only on Livingston Island (~ 200 individuals) and the Elephant Island group (~ 250 individuals), though both islands included small breeding populations (Aguayo & Torres 1967). By 1972-73, the observed population at Livingston Island had risen to over 3000 individuals, including some 400 at King George Island (first recorded in 1969-70), such that the over 6000 total individuals were censused in the region (Aguayo 1978).

In the 1980s, the population continued to rise and to expand to new haul-outs and breeding beaches in the region. Fur seals were first reported at Deception Island only in 1986-87, at which point there were over 500 males, but no females, observed (Bengtson et al. 1990). The Livingston Island population had increased to over 11000 individuals around this time, including nearly 3000 pups (Bengtson et al. 1990). The most recent estimates from Cape Shirreff place this population around 20000 individuals (Hucke-Gaete et al. 2004), though declining pup production over the last 15 years (~ 1200 pups in 2010/11; Goebel et al. 2011) suggests that the overall population may have declined.

Without detailed data on abundance and distribution, it is challenging to infer the mechanisms by which the population grew during those time periods. As there are no other documented source populations on the Antarctic Peninsula from that era, and given that Cape Shirreff remains the largest breeding population in the region by far, it is reasonable that such increases may be the result of rapid intrinsic growth plus a large pulse of immigrants or migrants from South Georgia.

Current evidence for potential broad-ranging dispersal (e.g., Boyd et al. 1998; Arthur et al. 2017; Lowther et al. 2020; Bester 2021) supports the idea that immigration from South Georgia and elsewhere could have spurred resurgence among colonies in the South Shetlands. Genetic evidence provides a different story however, with distinct populations detected for the South Shetland Islands, South Georgia, and Bouvet Island to the east (Humble et al. 2018). While this suggests that the recovery seen in different localities is primarily a product of reproduction rather than immigration, there is some evidence for limited gene flow to the South Shetland Islands from South Georgia (Bonin 2012; Hoffman et al. 2018; Humble et al. 2018).

While Antarctic fur seals amass in the tens of thousands on beaches during the breeding season, they disperse widely in other seasons (Santora 2013; Arthur et al. 2017; Hinke et al. 2017a; Lowther et al. 2020). Fur seals are income breeders, which limits the travel of lactating females during this season to foraging grounds close to their colonies (Boyd et al. 2002). As harem breeders however, most males are not successful at mating, and so are released from colony attendance at some point (Arnould & Duck 1997), though even successful males abandon the colony earlier than females who must still attend pups (McCann 1980). This difference in reproductive activity leads to potentially broad differences in post-breeding dispersal, such that males and females interact with different environments and different communities.

Female fur seals at Cape Shirreff have been documented at winter foraging grounds near the South Orkney Islands and offshore of the Chilean coast, demonstrating a potential winter foraging range of thousands of kilometers (Arthur et al. 2017) while, conversely, there is evidence that male fur seals from South Georgia and the South Orkney Islands make a reverse trip, travelling south to the Antarctic Peninsula (Santora 2013; Lowther et al. 2020). Such wide-ranging dispersal allows disparate populations to come into contact, with potential intraspecific dynamics that are unrelated to within-population demographics. Around the Antarctic Peninsula, for example, an influx of subadults and adult males from South Georgia in late summer (Santora 2013) potentially coincides with the period in which female fur seals from local colonies are rebuilding energy stores post-weaning, though tracking studies (e.g., Arthur et al. 2017; Hinke et al. 2017a; Lowther et al. 2020) suggest that the foraging distributions of these two groups may not overlap spatially to a significant degree. Further interspecific competition can arise since pygoscelid penguins are simultaneously provisioning their chicks in the region.

While breeding populations may be largely distinct, populations do regularly overlap at the regional scale outside of the breeding season, when individuals disperse to winter foraging grounds. For example, females from South Georgia frequently remain near the continental shelf of the island (Boyd et al. 1998; Staniland et al. 2012) and, while females from Cape Shirreff have a wide range of potential winter foraging grounds, some of these individuals also travel to South Georgia, especially as more southerly foraging grounds are occluded by winter sea ice (Arthur et al. 2017). While there is extreme natal philopatry for breeding sites among female Antarctic fur seals, at least some individuals also have strong preference for foraging sites as well, creating the potential for regular overlap among populations (Arthur et al. 2015).

This potential overlap during the non-breeding seasons introduces the potential for highly-local environmental factors in foraging grounds to drive similar population trends in subsets of distinct breeding populations. Most studies of foraging and dispersal however have focused on female movements, but an increase in the at-sea abundance of male fur seals around the Antarctic Peninsula in late summer (Santora 1998) suggests that the dispersal of non-breeding or post-breeding fur seals from other populations could overlap with the local foraging grounds of lactating females from the South Shetland Islands. Indeed, while many instrumented males from the South Orkney Islands used the waters south of the South Shetland Islands, some were recorded in the waters north of Cape Shirreff (Lowther et al. 2020). Regardless of potential foraging overlap among disparate fur seal populations, there is clear overlap among these seals and other local krill predators such as penguins (e.g., Kokubun et al. 2010 Miller et al. 2010; Korczak-Abshire et al. 2021), crabeater seals (*Lobodon carcinophaga*; Burns et al. 2004) and baleen whales (e.g., Dalla Rosa et al. 2008; Secchi et al. 2011; Johnston et al. 2012) The lack of a broad survey effort across the Antarctic Peninsula and South Shetland Islands limits our ability to understand the ecological significance of Antarctic fur seal movement, seasonal immigration, and resource use and the wider implications for conservation and management in this changing region.

To begin to address this lack of survey effort and to understand how and wherethe dynamics of Antarctic fur seals use the broaderon the Antarctic Peninsula, we review the state of knowledge surrounding their movements and habitat use in the region, with a particular focus on spatial and temporal trends in distribution and site-wise abundance since the 1990s inferred through an examination of multiple data sources. These include 1) seal sightings obtained from scientific surveys; 2) georeferenced tourist photographs posted to Flickr; and 3) records from the iNaturalist observation platform filed with the Global Biodiversity Information Facility (GBIF).

Our exploratory examination was structured to address three key questions: 1) Do the observed occurrences of Antarctic fur seals in the Antarctic Peninsula region reflect population-dynamic patterns seen at breeding colonies in Antarctica or South Georgia? Has the abundance of Antarctic fur seals in the Antarctic Peninsula region increased over the study period, similar to increases observed on South Georgia?; 2) Has the summertime geographic distribution of fur seals changed on the Peninsula?; and 3) Are there clear patterns of Antarctic fur seal distribution in space and time on the Peninsula?

5.3 Methods

5.3.1 Data

We used three datasets to examine the spatiotemporal distribution of Antarctic fur seals around the Antarctic Peninsula and to identify data gaps for future assessments. Records from field surveys conducted as part of the Antarctic Site Inventory (ASI; Naveen & Lynch 2011) or following ASI protocols contained fields indicating fur seal presence, and a field to provide notes. In some cases, these notes contained specific counts of fur seals and in others estimates such as “hundreds” or “more than 100.” Field surveys (n = 2055) were conducted from 1994-2020 and each record corresponds to a *Pygoscelis* spp. penguin nesting colony (or suspected colony) or an Antarctic shag (*Leucocarbo bransfieldensis*) nesting colony. Sites were visited during the seabird nesting season, which runs from October through March, but were primarily visited on an opportunistic basis by researchers working off passenger cruise ships. As a result, some sites have many records and other, more remote or less popular sites have few or no records. Within the ASI data, we considered both presence/absence and abundance. More records contain observations of presence/absence ($n = 266$) than of abundance ($n = 135$).

A presence-only dataset was also collected from publicly-available tourist photographs posted to Flickr. Following Borowicz et al. (2021), the Flickr Application Programming Interface was queried with the term “seal” and a radial geographic search parameter that captured most of the Antarctic Peninsula visited by tourists and yielded only images with geographic metadata (all images: n = 984). Once records were located, the corresponding images were downloaded and classified using a convolutional neural network to separate images containing different species (Borowicz et al. 2021). A final manual check corrected misclassifications, and the relevant metadata – including species and location – was recorded in a dataset (fur seal images: n = 98).

A second presence-only dataset was collected from the Global Biodiversity Information Facility (GBIF 2021). GBIF aggregates data from a variety of sources, and in the Antarctic, most records of fur seal presence are collected from iNaturalist, a citizen-science platform in which users can photograph organisms and upload them to the platform, where a community of knowledgeable users attempt to identify the species. We collected a dataset of only iNaturalist observations (n = 1782), excluding all observations from other sources. Only records of Antarctic fur seals for which, at a minimum, two users had agreed on the species, and overall two thirds of identifications agreed, were considered evidence of presence in the data aggregated by GBIF (iNaturalist 2021; n = 72).

Both GBIF and Flickr data cannot be easily corrected for effort, and any increase across years could be a function of increased adoption of those platforms by users, rather than an increase in abundance. These data are more suited to assessing phenology by collapsing the data across years.

5.3.2 Presence

The Antarctic Site Inventory dataset is the most comprehensive source of data available for the distribution of fur seals in the Antarctic Peninsula region and it includes records in which no seals were recorded. Such absence data are difficult to infer from databases like GBIF, which include only records of presence. Using these presence/absence data, we modeled a crude encounter rate using logistic regression estimated in a Bayesian framework and implemented with Stan (Stan Development Team 2021). In this model,

$$Y_i \sim Bern(p_i)$$

$$logit(p_i) = \alpha + \beta_1 \times Year_i + \beta_2 \times Latitude_i + \beta_3 \times Week_i$$

where Y_i represent the presence or absence of seals at a site visit ($0 = absence, 1 = presence$), and the probability of presence p_i is modeled as a function of Year, Latitude, and Week. Here we consider Year to be a ‘seasonal’ year, such that the year 2004 would encompass the months of Nov. and Dec. in calendar year 2004, as well as Jan., Feb., and Mar. in calendar year 2005, and Week as the number of weeks since the first week of January. Repeated observations of a site within a season are considered independent observations. Priors for the α and β terms were uninformative Normal.

To validate our observations about encounter probability, we also examined the basic encounter rate from iNaturalist observations and Flickr images. We parameterized this model identically to the ASI model, but excluded Year as a covariate, since the volume of iNaturalist observations uploaded to the site has approximately doubled each year since the platform’s launch (iNaturalist 2020), and similar changes in Flickr user effort are likely to confound temporal trends without a robust detection model.

While the timeframe associated with iNaturalist data is roughly similar to the survey dataset (first record: 1989), the iNaturalist platform was not created until 2008, such that these earlier records were added retroactively rather than uploaded in real or near-real time. To investigate whether these observations might be biased, we considered two variables: latitude and user. If iNaturalist photographs are primarily uploaded by tourists, early images with more restricted geographies might indicate that they came from Antarctic scientists, who might be biased toward certain geographies or species. Likewise, if most images were uploaded by only one or several users, those users' personal biases might have an undue influence on the data.

While there was some difference between the spatial distribution of observations before and after 2008 (Fig. 5.1A), the pre-2009 images were heavily skewed toward a single user (Fig. 5.1B). We elected to remove that entire period to ensure some level of data integrity by adhering only to the period in which users could upload in real time.

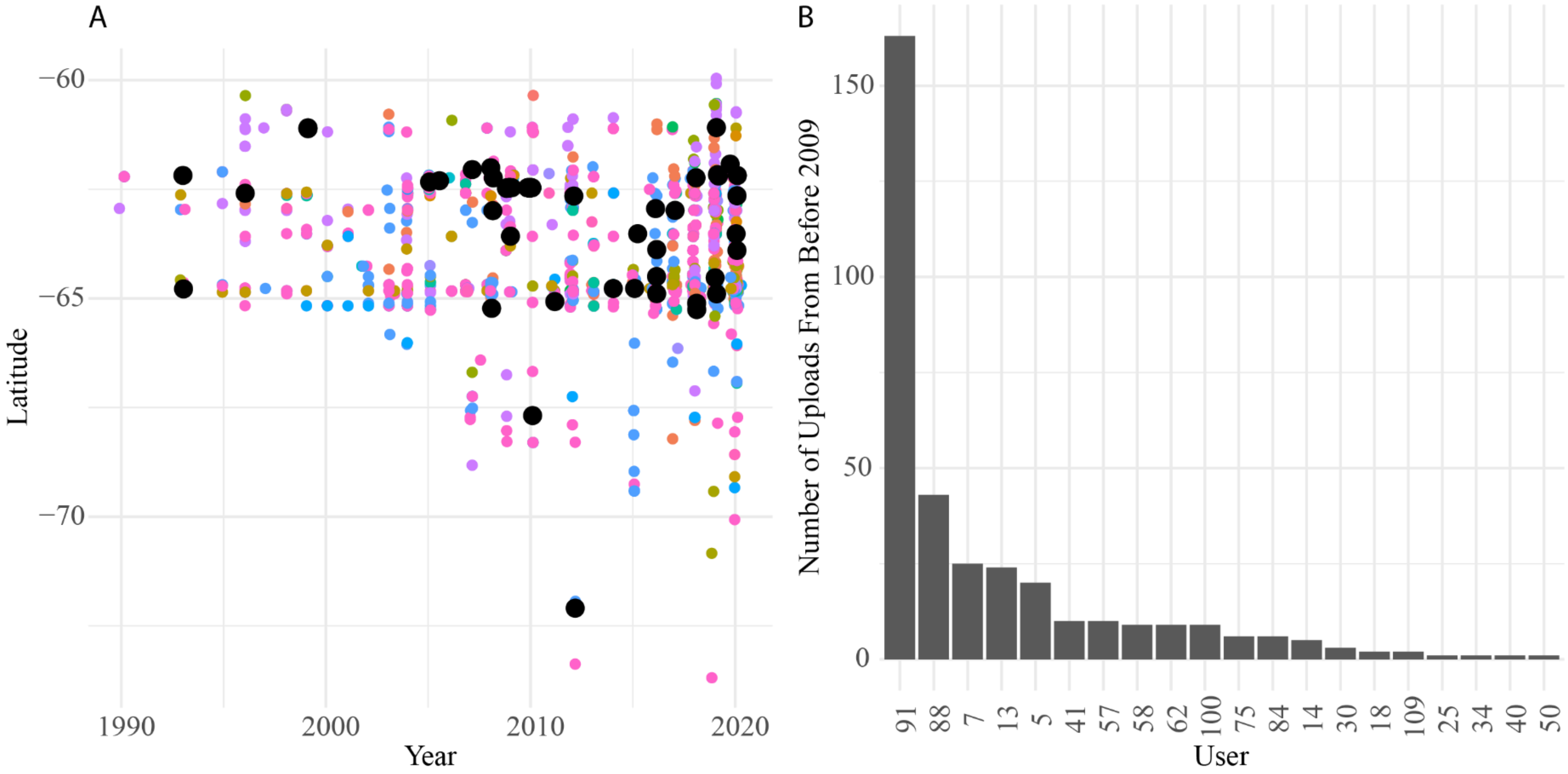

Figure 5.1: Assessment of the iNaturalist dataset. **A**) Latitudinal distribution of Antarctic uploads over time. Colors denote different families of taxa. Black dots represent fur seals. **B**) Per-user contribution of pre-2009 photographs (Users denoted by numbers). One user is responsible for most images prior to 2009.

5.3.3 Site-wise Abundance

Not all records contain abundance estimates for fur seals, and some contain rough estimates (e.g., ‘more than 100’). In the case of a record of ‘more than’ some number, we included that lower bound as the abundance. Where the record contained a range (e.g., ‘10-12 fur seals’) we took the mean (11). We excluded records indicating ‘many fur seals’ or a similar, non-quantitative statement from abundance estimates. In the case of entries with ‘a few’ or ‘a couple’ of fur seals, we assumed that these estimates were 2 or 3 seals. For records in which absence was explicitly stated, we recorded abundance as 0 which provided some information about absences.

Because the abundance data were over-dispersed (mean $=$ 60.8; s.d. $=$ 228), we first modelled abundance using the Negative Binomial distribution. This model was unable to capture the large number of observations in which seal abundance was very small ($<$ 5 individuals). Instead, we found modelling abundance using a Gamma distribution, as:

$$Y_i \sim Gamma\left(shape, \frac{shape}{\lambda_i}\right)$$

$$\log(\lambda_i) = \alpha + \beta_1 Year_i + \beta_2 Latitude_i + \beta_3 Day_i$$

was a better fit to the observations. In this model, Y_i represents the number of fur seals observed in the i^{th} site visit. We used weakly informative Normal priors for α and for each β coefficient, and an uninformative exponential prior for the shape parameter. We estimated model posteriors using the last 1000 of 2000 samples across each of 4 chains implemented in Stan (Stan Development Team 2021).

5.3.4 Sentinel-species Comparison

Given the frequent use of Adélie penguins as sentinels of change in the Southern Ocean (Miller & Davis 1993; Ainley 2002; Boersma 2008) and similar diets among fur seals and *Pygoscelis* spp. penguins in the Antarctic Peninsula region, we compared the encounter rate from the ASI data with an estimated reproductive index for Adélie penguins modelled primarily from ASI site surveys. The goal of this analysis was to understand whether this species, already well-observed, could act as a useful proxy for fur seal habitat use. For this analysis, we collapsed the data into wide regions: the South Shetland Islands (including all islands north of the Bransfield Strait), the Northeast Antarctic Peninsula (which includes the northern tip of the Peninsula, its associated islands, and all colonies on the eastern side of the Peninsula), the Central-west (which includes all sites on the western side of the Peninsula south to approximately 65ºS), and the Southwest (all sites south of 65ºS). To investigate whether declines in Adélie penguins might co-occur with fur seal declines, we modelled their relationship with a simple Bayesian linear regression implemented in Stan (Stan Development Team 2021), both for each region independently and for the entire Peninsula.

5.4 Results

5.4.1 Data

Overall, the Antarctic Site Inventory data contained 2058 survey records across 242 sites and provided 266 records of presence (13% of records). There were 135 records (7%) that also contained an explicit abundance estimate, or 869 records (92%) when considering pseudo-absences as a 0 abundance estimate. Fur seals were recorded in every year from 1995-2020. There were 96 sites (40%) that had at least one record of fur seal presence, 56 sites (23%) that had at least one abundance estimate, or 217 sites (90%) including pseudo-absence abundance.

We included 1331 records from iNaturalist, which comprised 71 species from 2009-2020. Of these, 47 (4%) were records of Antarctic fur seals. After excluding records without date or location data, the Flickr dataset included 458 records, of which 61 (13%) included fur seals.

5.4.2 Presence

There was only a weak positive relationship between fur seal encounter rate and year (Fig. 5.2A) in our survey-based model, but a strong relationship with seasonality (Fig 5.2C), such that probability of encountering a fur seal increased substantially later in the season (Table 5.1). While the 95% credible intervals for the Year parameter do not include zero, they are only fractionally above. Encounters were also more likely in northern than southern latitudes, especially at the latitudes of the South Shetland Islands (Fig. 5.2 B). Posterior distributions (Fig. A5.1) and posterior chains (Fig. A5.2) are provided in Appendix A5.1.

Table 5.1: Estimates and 95% credible intervals for β parameters in each logistic model.

Covariate	**Survey Data Model**	**Community Data Model**
Intercept	$-7.88\ (-50.98, 36.13)$	$9.92\ (1.12, 19.33)$
Year	$0.03\ (0.00, 0.05)$	NA
Latitude	$0.87\ (0.74, 1.00)$	$0.21\ (0.07, 0.36)$
Week	$0.37\ (0.32, 0.42)$	$0.23\ (0.19, 0.28)$

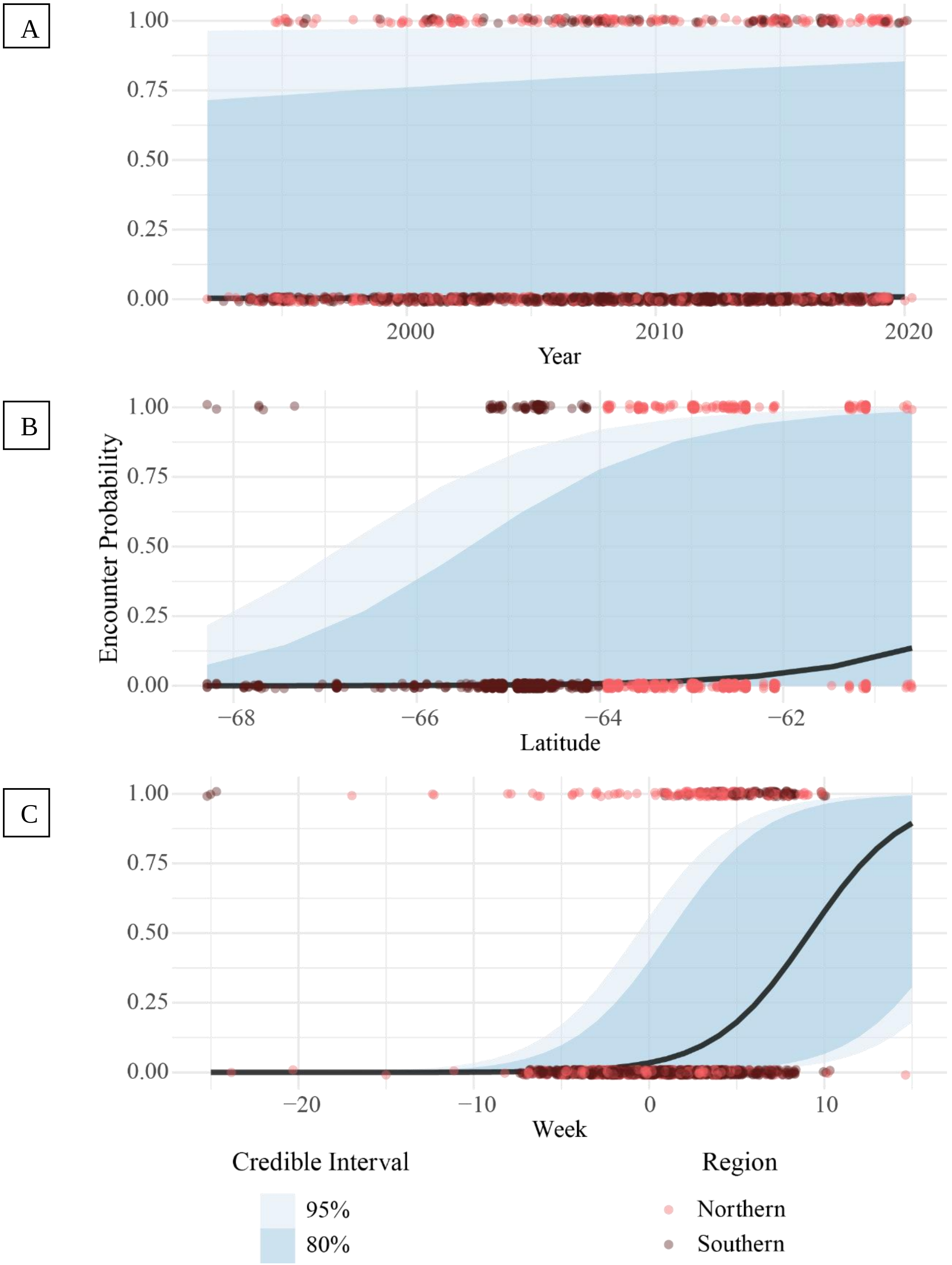

***Figure* 5.2**: Posterior estimates and Bayesian credible intervals of the logistic model. The northern and southern regions separate sites north and south of -64ºS. The northern region encompasses the South Shetland Islands and a small amount of the Antarctic Peninsula.

Using the combined Flickr and iNaturalist data and repeating the same procedure, we arrived at slightly different parameter estimates. For Week and Latitude, the effect on encounter rate was positive, similar to the ASI data, but it did not show the same strength of effect, with parameter values smaller than those from the ASI model (Table 5.1). Nevertheless, both covariates match the pattern from the ASI model, with increasing encounter probability to the north and later in the season. Posterior distributions (Fig. A5.3) and chains (Fig. A5.4) are provided in Appendix A5.1.

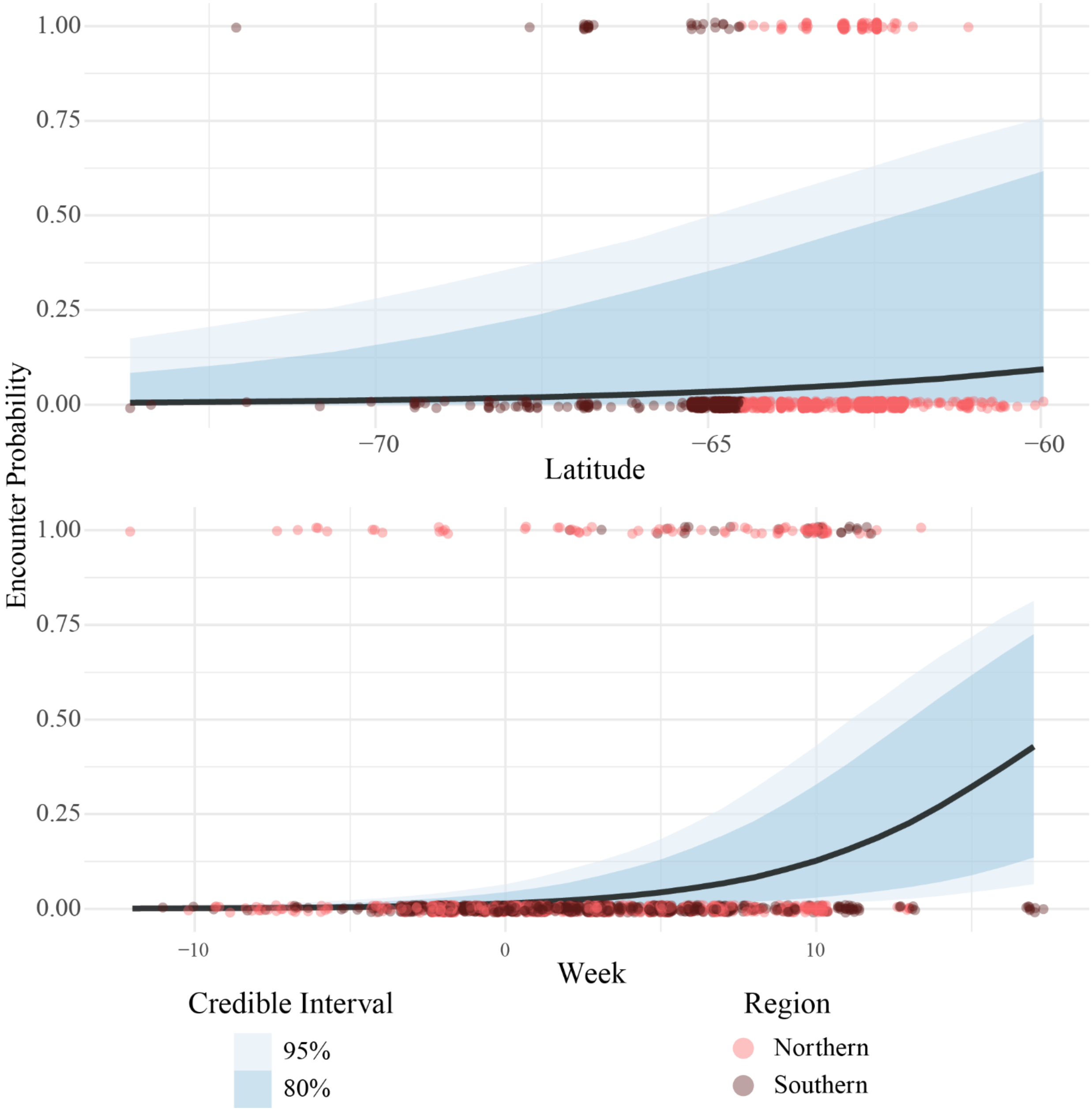

Figure 5.3: Posterior estimates and Bayesian credible intervals of the community science logistic model (Flickr & iNaturalist). As previously, the northern and southern regions refer to sites north and south of 64ºS.

5.4.3 Site-wise Abundance

Similar to the logistic models, latitude and week both had positive effects on abundance (Table 5.2). More northerly latitudes had higher abundances (Fig. 5.4B), and abundance increased over the course of a season (Fig. 5.4C). In more northerly latitudes and towards the end of the summer (February and March), our uncertainty grows, as the data present a wide range of abundances (Fig. 5.4B,C). Our estimate for the effect of year indicated a small increase over time (Fig 5.4A; Table 5.2). Posterior distributions (Fig. A5.5), model fit (Fig. A5.6), and posterior chains (Fig. A5.7) are included in Appendix A5.1.

Table 5.2*:* Estimates and 95% credible intervals for parameters in the Gamma abundance model.

Covariate	**Coefficient Estimate**
Intercept	$-101.06\ (-186.50 - 16.47)$
Year	$0.08\ (0.03, 0.12)$
Latitude	$0.83\ (0.69, 0.98)$
Week	$0.47\ (0.02, 0.71)$

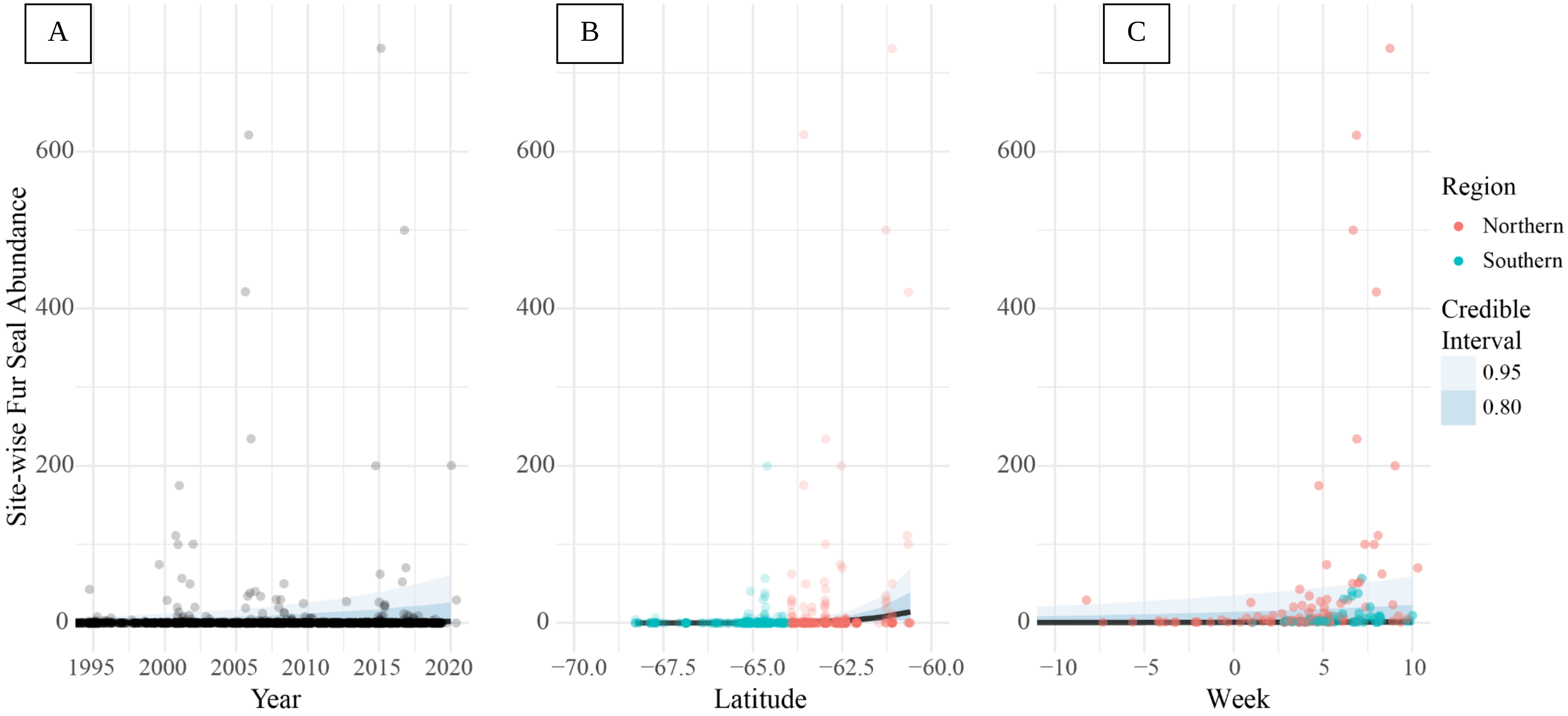

Figure 5.4: Gamma model outcomes for each parameter. Each dot represents a survey of a site during which abundance was recorded. Blue dots in panels B and C refer to sites north of -64ºS, and red dots south of that latitude. The northern region encompasses the South Shetland Islands and a portion of the northern Antarctic Peninsula. For panel C, Week 0 begins on Jan. 1.

Two outliers – the only two records of abundance in excess of 1000 – were removed from the final models as they exerted substantial control over the parameter estimates, particularly for Year, as both outliers came from 2004. With outliers included, there is a negative effect of Year, suggesting that abundance has declined since the 1990s (95% C.I.: -0.06, 0.02; Appendix Table A5.1), though the credible intervals overlap with zero. Without the outliers, the estimate for this parameter remains slightly positive. The sign for the other coefficients remains the same, though the effect of week becomes smaller, and latitude becomes stronger (Table A5.1). Posterior distributions (Figure A5.8), model fit (Figure A5.9), and posterior chains (Figure A5.10) are provided in Appendix A5.2 for comparison.

5.4.4 Sentinel-species Comparison

Across the entire region, our linear model found a weak negative relationship between penguin reproductive success and fur seal encounter probability (Table 5.3), however the 95% credible intervals substantially overlapped with zero. At the level of individual regions, all models were equivocal, with credible intervals overlapping zero. The estimate of the slope for both the Northeast and Southwest was negative, the South Shetland Islands slightly positive, and the Central West positive (Figure 5.5).

Table 5.3: Linear model comparing Adélie penguin reproductive success and fur seal encounter probability.

Model	**Slope Posterior Estimate**
Peninsula-Wide Model	$-0.08\ (-0.38, 0.24)$
South Shetland Islands	$0.00\ (-0.51, 0.47)$
Northeast	$-0.20\ (-0.61, 0.21)$
Central West	$0.13\ (-0.41, 0.78)$
Southwest	$-0.14\ (-1.00, 0.90)$

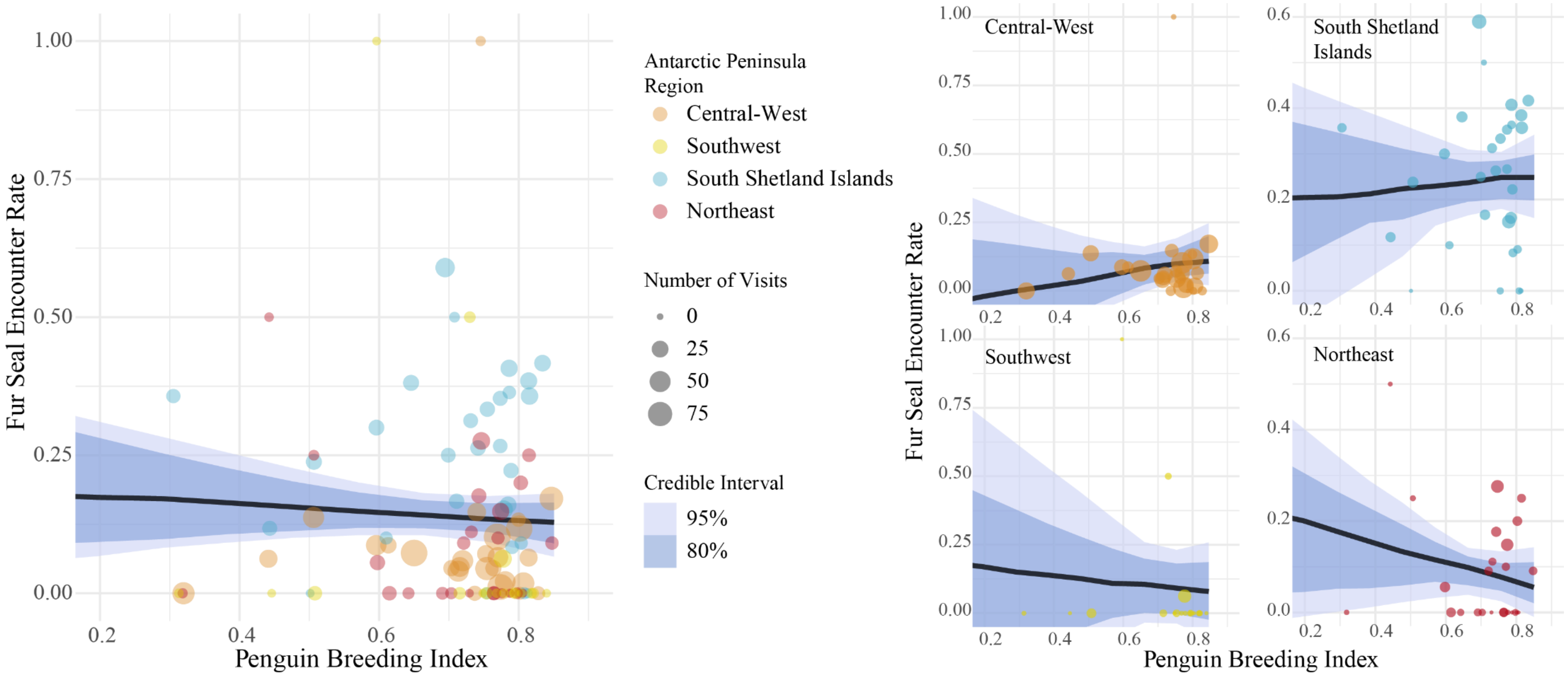

Figure 5.5: Fur seal encounters as a function of Adélie penguin reproductive success.

5.5 Discussion

The recovery of the Antarctic fur seal has coincided with the formalization of marine resource management in the Southern Ocean (Bonner 1990). The Convention for the Conservation of Antarctic Marine Living Resources (CCAMLR) provides management for Antarctic resources such as the Antarctic krill fishery and sets policy for other taxa based on treaty documents such as the Convention for the Conservation of Antarctic Seals (Bonner 1990). At the same time, the regional distribution and density of Antarctic krill has changed (Atkinson et al. 2004; Atkindson et al. 2019), such that an increase in a krill predator population has in some places coincided with a substantial prey reduction (Trathan & Hill 2016). From the South Georgia population alone, total annual krill consumption could be as high as 6.8 million tons (Trathan & Hill 2016). The spatial and temporal patterns of abundance of both predators and krill are complex. Given the challenges of disentangling these relationships, improving the spatial extent of monitoring for many krill-predator species is warranted.

While Antarctic fur seal population declines are evident at Cape Shirreff and Bird Island, there is poor documentation for the population trajectory of other breeding colonies in either the Antarctic Peninsula or South Georgia. The notable difference in density between colonies on South Georgia (Staniland et al. 2011; Foley 2019), suggests that lessons from Bird Island may not be readily generalizable across South Georgia though there is evidence to suggest that the mechanisms of decline across the South Shetland Islands are similar among sites (Krause & Hinke 2021).

Our data contained two outliers where abundance was significantly higher than expected based on the other data available; notably, both outliers came from the same day and from sites only 28 km from one another. These observations suggest that fur seals may occasionally congregate in very high numbers but that such haul-out sites may be difficult to find in areas that are not frequented by tourists. While two data points are inconclusive, they suggest that the distribution and especially the site-wise abundance of fur seals may be highly pulsed and variable, such that a consistent sampling effort may be required to understand these patterns. Fur seals are visible in sub-meter satellite imagery (Foley 2019), which makes future surveys of the Antarctic coastline for such haul-outs feasible.

Tay Head on Joinville Island off the northern coast of the Antarctic Peninsula, one of the two sites with outlier counts, lies in an area with limited survey effort and only appears in ASI records 5 times in 28 years. In late February 2002, the ASI recorded an estimated 1500 seals at this site. Of the 5 total surveys at Tay Head, however, 3 occurred in 2002, less than a month apart; on January 25, we recorded 14 seals, and on February 4, 20 seals. There are more observations for the second outlier site – Paulet Island – though the raw data are similarly suggestive, pointing to at least some years in which the abundance of fur seals increases dramatically towards the end of the summer. Timelapse camera surveys of such sites, such as those already common for penguin colony monitoring (Youngflesh et al. 2020), may be another means of improving our understanding of the temporal patterns of such aggregations.

While there is evidence for strong natal philopatry at breeding colonies (Hoffman & Forcada 2012) and fidelity to broad foraging regions (Arthur et al. 2015), there is little to no evidence to support or refute the idea that Antarctic fur seals show haul-out site fidelity outside the breeding season. The pulses recorded in these surveys may be fleeting or may be permanent late-season features. Given the ability of these outlying data points to exert some control over our understanding of an annual trend in abundance, our finding of a slight increase should be interpreted in light of our weak understanding of post-breeding season behavior in this species.

The regions in which our surveys detect the highest encounter rates are also frequently adjacent to areas that are rarely or never surveyed (Figure 5.6). As most sites in the ASI database are of nesting seabird colonies and it is reasonable to assume that fur seals and nesting penguins have different onshore habitat requirements, it is possible that large areas of fur seal haul-out habitat remain un-surveyed. The limitations of this dataset suggest that further evidence for abundance increases or range expansion could be missed. Moreover, the focus towards penguin censuses within this dataset presents several potential biases, which we have not tested here: 1) the potential for observers to avoid estimating abundance when it is large (i.e., not enough time to count, not enough confidence to estimate), and 2) the potential for observers to avoid estimating when abundance is small (i.e., low abundance is normal and unremarkable, larger aggregations are interesting and worth counting). Given the turnover of observers over time, such biases are not necessarily consistent across the dataset and make estimating detection probability more difficult.

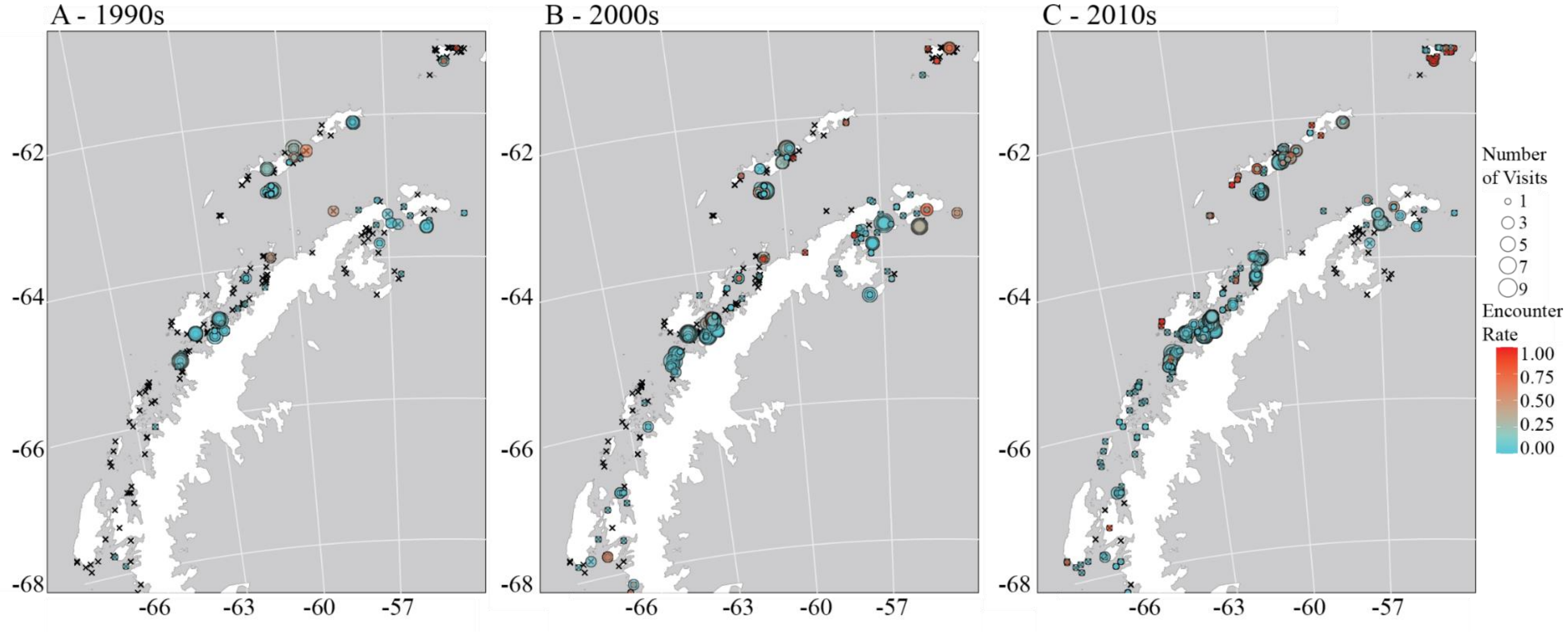

Figure 5.6: Encounter rate from ASI surveys over the decades. X denotes a site that was not surveyed during that decade.

Of particular note, we found little evidence of a relationship between Adélie penguin reproductive success and fur seal encounter rate. While the two statistics measure different processes, they each hint at the population dynamics of the species. Penguins are frequently cited as “sentinels” of change in the Southern Ocean (Miller & Davis 1993; Ainley 2002; Boersma 2008), but our inconclusive results suggest that caution is warranted in the degree to which we can infer the population trends of other species based upon a single or several well-observed species. Given recent and long-term changes in the populations of Antarctic fur seals in the Antarctic Peninsula and South Georgia, the lack of a strong relationship provides further evidence that monitoring of spatiotemporal patterns of use in this species is needed to fully understand the dynamics of this system.

Recent declines in pup production at both Bird Island in South Georgia (Forcada & Hoffman 2014) and Cape Shirreff in the South Shetland Islands (Goebel et al. 2011) point to several independent drivers of change. Declines in pup production (Forcada et al. 2005) and female abundance (~35% decline; Forcada & Hoffman 2014) at Bird Island coincided with positive sea surface temperature anomalies around South Georgia, potentially altering prey availability (Forcada et al. 2005), particularly for Antarctic krill (Forcada & Hoffman 2014). At Cape Shirreff, following a peak in the early 2000s, pup production declined by around 13% yr^{-1} through 2011 (Goebel et al. 2011), with further overall population decline in the years since (Krause & Hinke 2021). Similarly, first-year survival has remained low in recent decades (Schwarz et al. 2013).

Beyond changes to prey availability, increases in the abundance of fur-seal predators may also play a role in the observed population declines at both sites. In South Georgia, the increase in the population of northern (*Macronectes halli*) and southern (*M. giganteus*) giant petrels is thought to be related to the decades-long increase in the population of Antarctic fur seals (Poncet et al. 2019), whose pups are a source of prey during the breeding season (Nagel et al. 2021). In the South Shetland Islands, predation on fur seal pups is also an important source of first-year mortality. An increasing abundance of leopard seals (*Hydrurga leptonyx*) in the area has resulted in a commensurate increase in predation (Boveng et al. 1998; Goebel et al. 2011; Krause et al. 2015), though as reproductive output has decreased, so too has the availability of fur seal pups as prey for this generalist predator (Krause et al. 2020). Density-dependent pup mortality, such as trampling, also plays some role (Doidge et al. 1984; Reid & Forcada 2005), though the degree to which it is exacerbated by declining prey availability (i.e., starvation), or ameliorated by declining pup production is less clear, with some evidence for negative density dependence due to predation in South Georgia (Nagel et al. 2021). Evidence for inbreeding at Bird Island (Humble et al. 2020), increasing heterozygosity among younger cohorts (Forcada & Hoffman 2014), and sex-specific differences in immigration to Livingston Island (Bonin 2012), suggests further lines of inquiry.

While the data presented herein represent the fullest picture of fur seal distribution and movement around the Antarctic Peninsula to date, the real power of this field survey and ‘found data’ approach has been to highlight gaps in our understanding about how fur seals interact with the Antarctic Peninsula ecosystem. Antarctic fur seals, as an abundant predator, represent just one such species, but the fact of their apparent seasonal southward expansion could have important effects on the post-fledging success of penguins in the region or on migratory baleen whales, all potential competitors for Antarctic krill and fish species. Such an interaction can go both ways; the recovery of Humpback whales in the region (Pallin et al. 2018; Zerbini et al. 2019) may be exerting downward pressure on other krill predators. What little evidence exists for resource partitioning among sympatric krill predators focuses primarily on the partitioning of spatial resources, as when Humpback and Antarctic minke whales (*Balaenoptera bonaerensis*) occupy differential strata of the water column but target the same prey (Friedlaender et al. 2009), though evidence for partitioning by prey species does exist for some predators (e.g., Herr et al. 2016). Such evidence suggests some level of competition among krill predators, but it remains unclear at what scale competition operates in the region. Without better knowledge of the spatial and temporal distribution and overlap among species, assessing this competition, and predicting future resource use under changing Antarctic conditions, will remain elusive.

Despite the remaining mechanistic questions about interactions among populations and species in this region, our models demonstrate that even web-scraped or community-science data such as that collected from Flickr or iNaturalist can help confirm natural patterns when data are sparse or incomplete, even if they are unsuitable for analysis on their own merits. Even in data-poor regions or those as remote as Antarctica, occasional observations of species can provide additional information to reinforce existing knowledge or modelling efforts (e.g., Dahood et al. 2019) or open new questions. Given the rapid pace of environmental change in many systems, such data should not be ignored.

6 Conclusions

Ecological data abound, though often in forms unusual from the perspective of traditional ecological inquiry. In this dissertation I have developed the means to find and acquire such data and the methodological considerations for employing them in an ecological context. I have done so with a view to how such data can be used to augment existing data (i.e., build upon existing datasets), supplement our data (i.e., elucidate patterns not captured by our protocols), and complement our data (i.e., by giving us confidence in the patterns we have uncovered or by demonstrating that patterns exist at scales outside of our scales of inquiry). I have applied these methods principally with an interest in elucidating the patterns of distribution for Antarctic krill predators across scale but with an eye to their broad applicability across regions, systems, and taxa. By focusing on a small and overlooked archipelago off the northern tip of the Antarctic Peninsula in Chapter 2, I have demonstrated the breadth of insight available when combining historical aerial and satellite remote sensing with contemporary UAV-aerial and ground censuses and employing machine-learning classification techniques. This site-specific work substantially broadened the landscape of Adélie penguin population dynamics by effectively doubling the known population of this species in the region of the Antarctic Peninsula. To Levin's (1992) point, I have established that the mechanisms driving Adélie penguin population declines (e.g., Emslie et al. 1998; Lynch & LaRue 2014; Hinke et al. 2017b) are not necessarily operating universally at the regional scale, despite considerable discussion of regional phenomena since declines have been documented (Cimino et al. 2014; Lynch & LaRue 2014; Cimino et al. 2016).

More recent work has indicated that growth rates for penguin colonies are highly stochastic among years (Che-Castaldo et al. 2017) and that the temporal scale of analysis has an important effect on the shape of the drivers of decline for this species (Iles et al. 2020).

For other taxa, information is entirely absent in some regions. This is true of cetaceans across much of the ocean but especially the high seas and polar regions (Kaschner et al. 2012). Even when attempting to aggregate surveys to improve power, the variability among survey methods and species does not clearly improve global insight (Jewell et al. 2012). I have proposed and demonstrated a method in Chapter 3 by which consistent surveys of large cetaceans could be conducted by combining the spatial extent provided by modern satellite sensing platforms with the classification power of deep learning. As a proof-of-concept, this method is already successful and can only improve in both its classification accuracy and is scalability.

In an effort to work across grain and extent – specifically to provide a ground-level view across the regional scale – I have developed methods for incorporating data from ‘eco-social sensors’ – those collecting data for social purposes (i.e., sharing with friends and family) rather than for research – into existing analyses and datasets in Chapters 4 and 5. These data, even in the polar regions, can broaden inference and expose new patterns. By pairing web-crawling applications with convolutional neural networks for image classification, we move closer to a ‘computer vision for ecology’ as proposed by Weinstein (2017) and can handle much larger volumes of data than is possible using manual methods. Such AI-powered techniques are essential when incorporating information from ‘big data’ sources such as social media platforms, since much of the information contained within such platforms is irrelevant to our focused ecological questions.

In this way, the complications of an AI and social-sensor approach become evident as well. When giving up control of how the data are generated, we must be open to the many ways in which the data generators – people – may bias or misrepresent the data they create. There are few assumptions that can reasonably be made with such ‘found’ data, and so those assumptions that are made must be carefully wrought and intentional. By failing to understand found data and the processes by which deep-learning algorithms classify data, we can create *new* biases and reinforce existing biases (Turner Lee 2018; Panch et al. 2019; Sap et al. 2019).

Data cast in this light is the milieu for data science, yet domain knowledge, especially that of the natural history of a region of interest, is difficult to extract with observations only of images of far-away places. Such an approach as I have proposed here, and its natural extensions in which analyses may be conducted entirely with web-scraped or social-sensor data, require careful and intentional effort in which the data scientific approach is regularly interrogated for its biases and any lack of consistency with an intentional observation of a system (Leonelli 2016). Considerations such as data privacy (Di Minin et al. 2021) and data infrastructure (Farley et al. 2018) may be new in many areas of ecology and conservation biology, but solutions should similarly be developed alongside applications.

Ecology as a big data and data science realm is already showing promise and is emerging as a point of collaboration among disparate fields toward a shared goal of developing better conservation data streams (e.g., Berger-Wolf et al. 2017). Such approaches can provide a path around the potential diminishing returns of investment in expansive field studies for conservation planning (Grantham et al. 2008), substantially reducing the cost of data collection by augmenting and supplementing fieldwork. But more broadly, imaginative approaches create new opportunities for global inquiry and synthesis, and promise for timeliness in an era of rapid change.

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Appendix A2

This appendix relates supplementary material from Chapter 2: Multi-modal survey of Adélie penguin mega-colonies reveals the Danger Islands as a seabird hotspot.

Table A2.1*: P - species present, N - species present and nesting, A - absent, '--' - not observed*
** Given the reports of hybridization between Brown skuas (S. antarcticus) and south polar skuas (S. maccormicki) (Ritz et al. 2006), we did not attempt to assess the species of skua present.*

Species	**Beagle**	**Brash**	**Comb**	**Darwin**	**Dixey Rock**	**Earle**	**Etna**	**Heroina**	**Platter**	**Scud Rock**
Birds										
Adélie penguin (*Pygoscelis adeliae*)	N	N	N	N		N	N	N	N	
Gentoo penguin (*Pygoscelis papua*)		N	N			N		N	N	
Chinstrap penguin (*Pygoscelis antarctica*)		A	A			A		N	A	
Antarctic shag (*Phalacrocorax atriceps*)		--	--			N			N	
Skua species (*Stercorarius spp.*)*		P	P			N			P	
Southern giant petrel (*Macronectes giganteus*)		P	--			--			P	
Cape (pintado) petrel (*Daption capense*)		--	--			--			N	
Snow petrel (*Pagodroma nivea*)		--	N			P			--	
Wilson's storm petrel (*Oceanites oceanicus*)		N	--			--			P	

Kelp gull (*Larus dominicanus*)		N	P			P			P	
Snowy sheathbill (*Chionis albus*)		N	N			N			N	
Antarctic tern (*Sterna vittata*)		--	P			--			--	

Species	**Beagle**	**Brash**	**Comb**	**Darwin**	**Dixey Rock**	**Earle**	**Etna**	**Heroina**	**Platter**	**Scud Rock**
Plants										
Antarctic hairgrass (*Deschampsia antarctica*)		--	--			--			--	
Seals										
Weddell seal (*Leptonychotes weddelli*)		--	P			P			P	

Appendix A3

This appendix relates supplementary material from Chapter 3: Aerial-trained deep learning networks for surveying cetaceans from satellite imagery

Table A3.1

We acquired imagery from Digital Globe's WorldView-3 sensor via the Digital Globe Foundation. See https://discover.digitalglobe.com/ for details on individual scenes and a preview.

Scene ID	**Location**	**Date**
1040010003121A00	Peninsula Valdes, Argentina	14 Oct. 2014
1040010029924200	Maui, Hawaii, USA	13 Feb. 2013

Appendix A4

6.1 Appendix A4.1

The full training set included southern elephant seals (n=614), crabeater seals (n=464), Antarctic fur seals (n=533), harp seals (n=30), leopard seals (n=518), Ross seals (n=45), Weddell seals (n=743), an ‘other’ seal category (n=140) for those seals not captured by the previous categories, and a non-seal category for anything else (n=1174). While our focus was on Weddell seals, including classes for other species that are likely to be encountered in the imagery should improve the performance of our classifier. For example, including a harp seal class – a species found only in the northern hemisphere – seemed prudent given the possibility of mistaking Arctic and Antarctic regions. Even absent any of these seals in the data, this extra class provides the model with more certainty about how the species of Antarctic seal differ visually from other species. For example, other species of non-Antarctic seal are far more similar to Weddell seals than they are to the many different ways an image could be ‘non-seal’ (e.g., an iceberg).

The training set for building the CNN classification model comprised a mix of images provided from the authors’ own collections as well as those collected from a Google Image search for Antarctic seals. Our intent was to capture roughly the types of photographs likely to be shared by visitors to Antarctica, including seals at different angles and distances and images of whales, landscapes, penguins, and other types of non-marine mammal seals, such as Navy SEALs or the singer Seal (Fig S1A). To validate our models, we retained a roughly similar number of randomly-selected images from all the above categories.

Figure A4.1: Examples of images obtained from a web-crawler search for ‘Antarctica+seal’. An Antarctic landscape, a Weddell seal tagged correctly, Robin Williams at the Happy Feet premier (a plot summary included the word ‘seal’). Photographs courtesy Flickr users kthypryn (CC BY 2.0), Gregory Smith (CC BY-SA 2.0), Eva Rinaldi (CC BY-SA 2.0)

6.2 Appendix A4.2

To be included in the catalog as a new individual, images must meet standards of quality. The focus, resolution, contrast, lighting, angle, and visibility of the ventral region must not reasonably prevent a future match from being made. Distinctiveness, a separate measure, is primarily a measure of molt stage in this scheme, as individuals with old, worn fur have indistinct patterning. Individuals with nearly solid coloration (i.e., very minimal patterning) may also be rated as indistinct.

Individuals with distinctiveness ratings of 3/3 are not included in the catalog since it is unlikely that we can positively match them without distinctive features. Individuals with summed quality ratings ≥ 8 are not included in the catalog. As such, an image with a perfect score in 3 categories but the worst score, 5/5, in another category will not be included.

Focus and clarity

Here we focused on the sharpness of the seal in the image and the resolution. An out-of-focus image (or an image in which the focus is on something other than the seal) would receive a low rating, as would an image of a seal in the distance such that, when zoomed in, the resolution of the seal was poor. Images were rated from 1 (best) – 5 (worst) on this scale.

Examples:

Figure A4.2: After zooming in to this image, much of the pattern is still visible, but the detail is less clear. In this category, it rates at 2/5.

Figure A4.3: Poor focus. Some detail is visible which might allow this seal to be matched to an image in the catalog, but is not sufficient to be introduced as a new individual. 4/5

Contrast and Lighting

In this category, we consider whether the lighting creates conditions which prevent matching. This could be strong shadows or glare which cannot be recovered using photo-editing software or over- or under-exposure.

Examples:

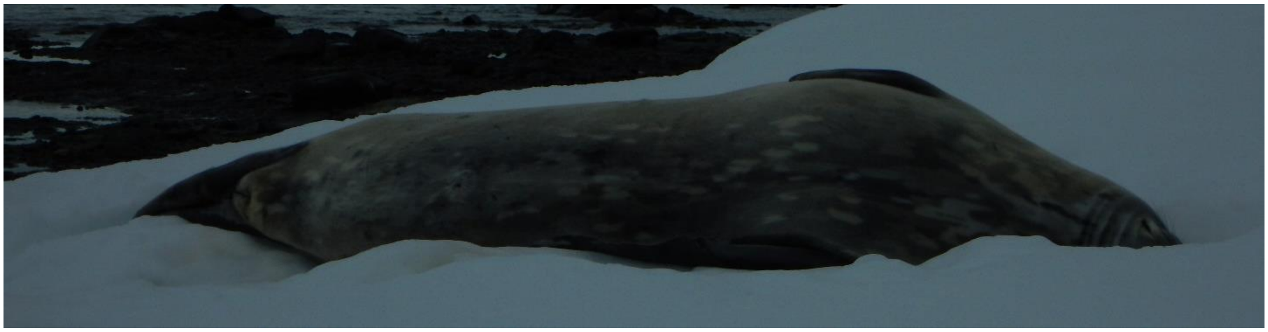

Figure A4.4: An underexposed image. Much of the pattern is still visible, but subtle shading differences can't be assessed. 4/5

Figure A4.5: Bright glare on the flank of the seal is outside of the main ventral area of interest, but removes some detail. 3/5

Angle

Extreme angles can both obscure our view of the relevant area and make both human and machine methods unreliable for matching.

Examples:

Figure A4.6: *An extreme angle means much of the ventral region is out of view. 4/5*

Figure A4.7: A seal at a roughly 45-degree angle. Some of the neck region is out of view, but much of the pattern is visible. 3/5

Visibility of the ventral region

The ventral region can be obscured from a variety of sources. Seals resting for long periods of time may sink into slowly-melting holes, flippers may cover the region, rocks and snow piled up in front of the seal can block the region from view. Similarly, seals resting on their ventral region can obscure the region.

Examples:

Figure A4.8: A seal lying on its front. Only a small section of the ventral region is visible. 5/5

Figure A4.9: Only a portion of this seal was included in the photograph. The pattern on the neck may be sufficient to match an individual to the catalog, but it is insufficient for inclusion as a new individual. 4/5

Figure A4.10: Ice and snow on this iceberg obscure half of the seal. 4/5

EXAMPLE RANKINGS:

Figure A4.11: Focus/Clarity: 1/5; Light/Contrast: 1/5; Angle: 1/5; Ventral: 2/5; Distinctiveness: 3/3. Nearly perfect, however the seal is about to molt and much of the fur is worn, obscuring the patterning. Q: 5, D: 3

Figure A4.12: Focus/Clarity: 1/5; Light/Contrast: 2/5; Angle 1/5; Ventral: 4/5. Dist: 1. The image is sharp but much of the seal is obscured and there are shadows and glare. Q: 8, D: 1

Figure A4.13: Focus/clarity: 1/5; Light/contrast: 3/5; Angle: 1/5; Ventral: 1/5. Dist: 1/5. The glare and exposure create some limitations. Q: 6, D: 1

Figure A4.14: Focus/clarity: 2/5; Light/contrast: 4/5; Angle: 2/5; Ventral: 3/5. Dist: 1/5. The exposure, resolution, and ventral visibility combine to make this a difficult image. Q: 11, D: 1.

6.3 Appendix A4.3

Table A4.3: Flickr web crawler queries. Each site was queried with a minimum and maximum date (in Unix timestamps), coordinates for the center of a radial geographic search, the radius of the search in kilometers, and the search term “seal.” The number of images returned are noted. Such a search excludes all images that are not geo-tagged.

Site Code	Max Date Unix	Min_Date_Unix	Lat	Long	Radius (km)	# of images	Search term	Full site name
HALF	1554076800	1096588800	-62.59	-59.92	32	139	seal	Half Moon Island
HANN	1554076800	1096588800	-62.65	-60.62	32	103	seal	Hannah Point
WHAL	1554076800	1096588800	-62.98	-60.56	32	44	seal	Whaler's Bay
GOUR	1554076800	1096588800	-63.19	-57.31	32	0	seal	Gourdin Island
HOPE	1554076800	1096588800	-63.4	-57	32	8	seal	Hope Bay
PAUL	1554076800	1096588800	-63.57	-55.78	32	14	seal	Paulet Island
MIKK	1554076800	1096588800	-63.9	-60.78	32	79	seal	Mikkelsen Harbour
HYDR	1554076800	1096588800	-64.15	-61.64	32	3	seal	Hydrurga Rocks
STER	1554076800	1096588800	-64.2	-60.98	32	4	seal	Sterneck Island
MELC	1554076800	1096588800	-64.31	-62.96	32	21	seal	Melchior Islands
FournierBay	1554076800	1096588800	-64.46	-63.12	32	7	seal	Fournier Bay
POPT	1554076800	1096588800	-64.5	-61.76	32	4	seal	Portal Point
WilhelminaBay	1554076800	1096588800	-64.62	-62.06	32	289	seal	Wilhelmina Bay
CUVE	1554076800	1096588800	-64.69	-62.62	32	0	seal	Cuverville Island
LITC	1554076800	1096588800	-64.77	-64.09	32	20	seal	Litchfield Island
JOUG	1554076800	1096588800	-64.83	-63.5	32	24	seal	Jougla Point
NEKO	1554076800	1096588800	-64.84	-62.53	32	41	seal	Neko Harbour
ALMI	1554076800	1096588800	-64.9	-62.87	32	0	seal	Almirante Brown Station
PETE	1554076800	1096588800	-65.18	-64.13	32	152	seal	Petermann Island
DETA	1554076800	1096588800	-66.88	-66.82	32	26	seal	Detaille Island

6.4 Appendix A4.4

Individual 1 was sighted at Georges Point on 25 Dec. 2015, and at Mikkelsen Harbour on 26 Dec. 2015 (125 km straight-line distance).

Figure A4.15: Image of Seal 1 at Georges Pt. on 25 Dec 2015

Figure A4.16: Image of Seal 1 at Mikkelsen Hbr. on 26 Dec 2015

Individual 2 may have travelled between Georges Point and Mikkelsen Harbour (125 km straight-line distance). Both were photographed at Mikkelsen Hbr. on the same day, and may have both been photographed at Georges Point the day before.

Figure A4.17: Suggestive of Seal 2, but an inconclusive image from Georges Point on 25 December 2015

Figure A4.18: Image of Seal 2 at Mikkelsen Harbour on 26 Dec 2015

Figure A4.19: Image of Seal 2 at Half Moon Island on 27 Dec 2015

6.5 Appendix A4.5

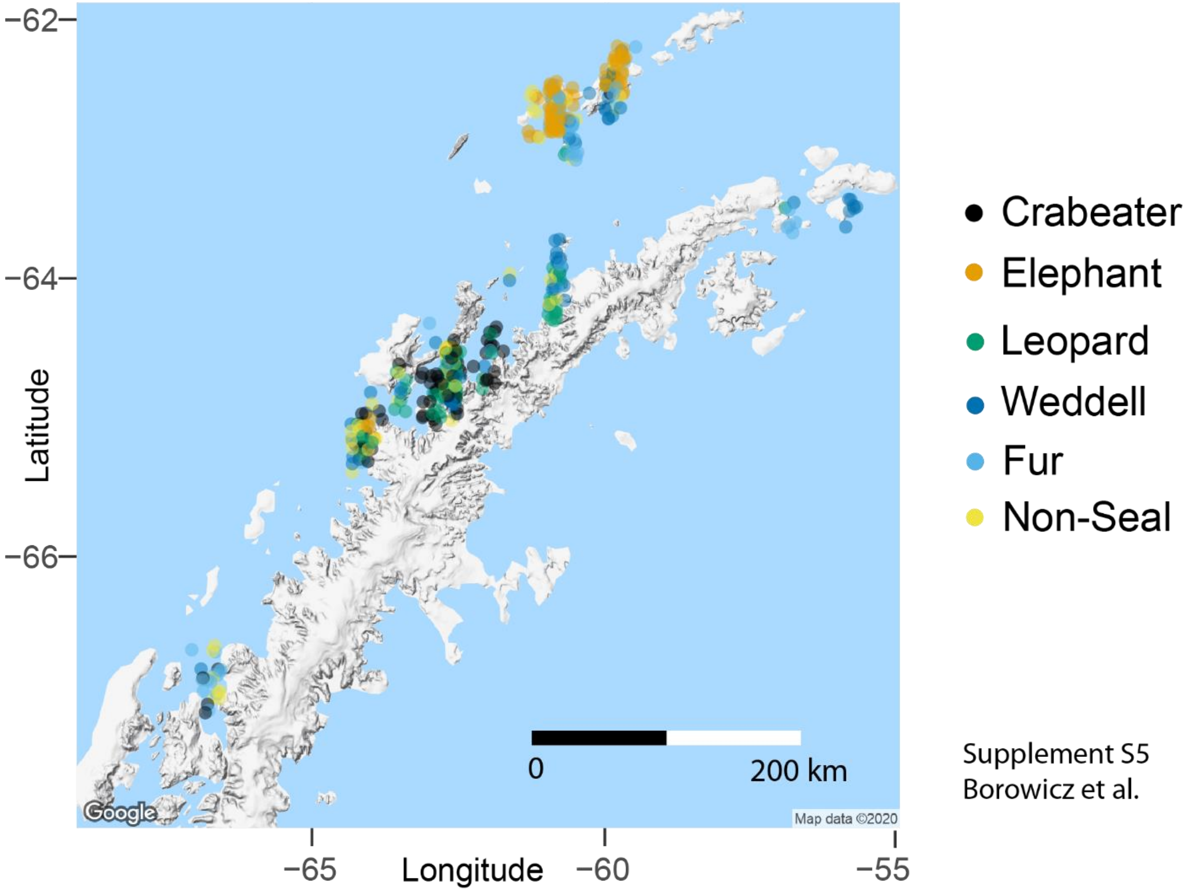

Figure A4.20: Distributional map of Antarctic pinnipeds, drawn from Flickr images.

Appendix A5

6.6 Appendix A5.1

Posterior estimates and model fits.

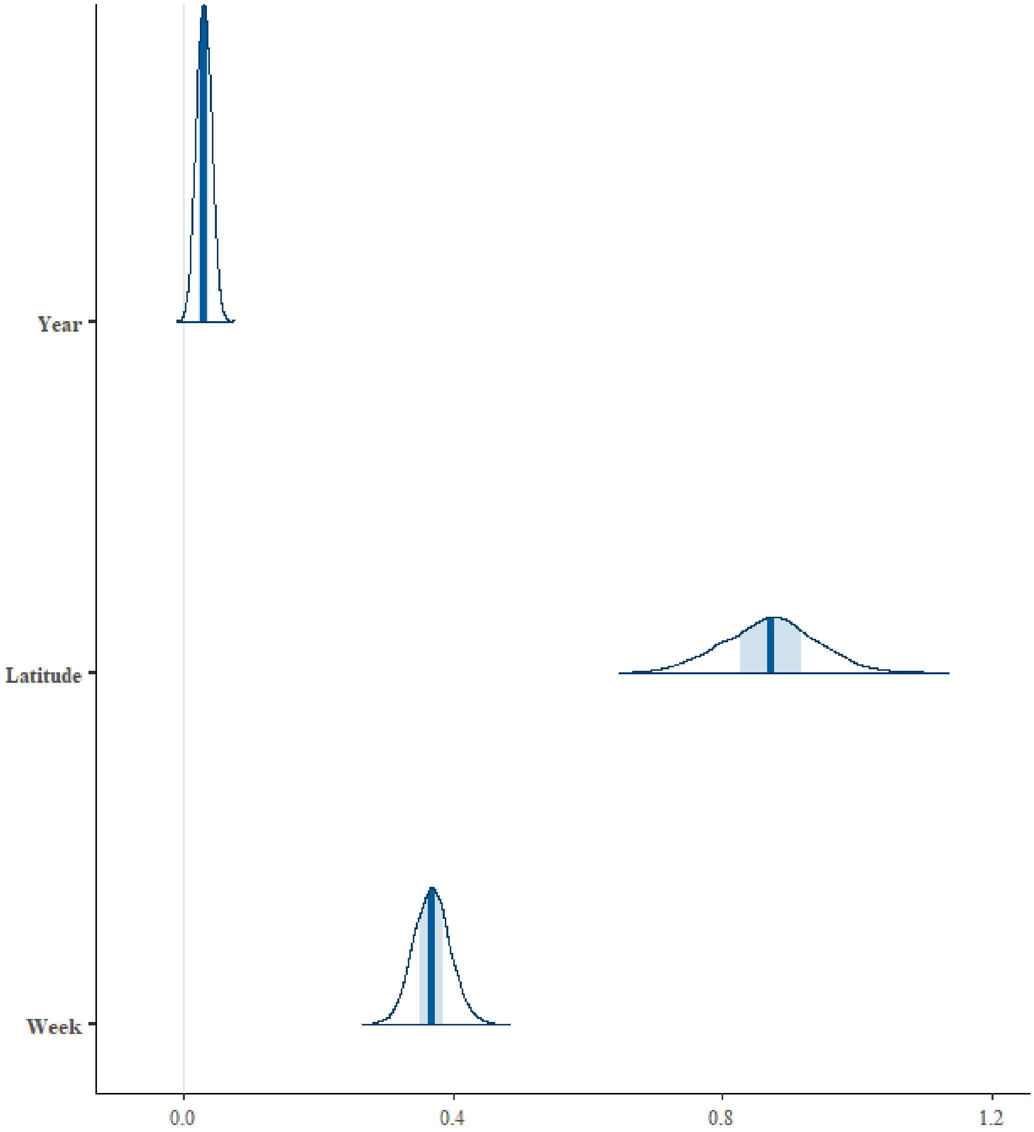

Figure A5.1: Posterior parameter distributions from the logistic model using ASI data. Dark blue bands represent the 50% credible intervals, and light blue bands the 90% credible intervals.

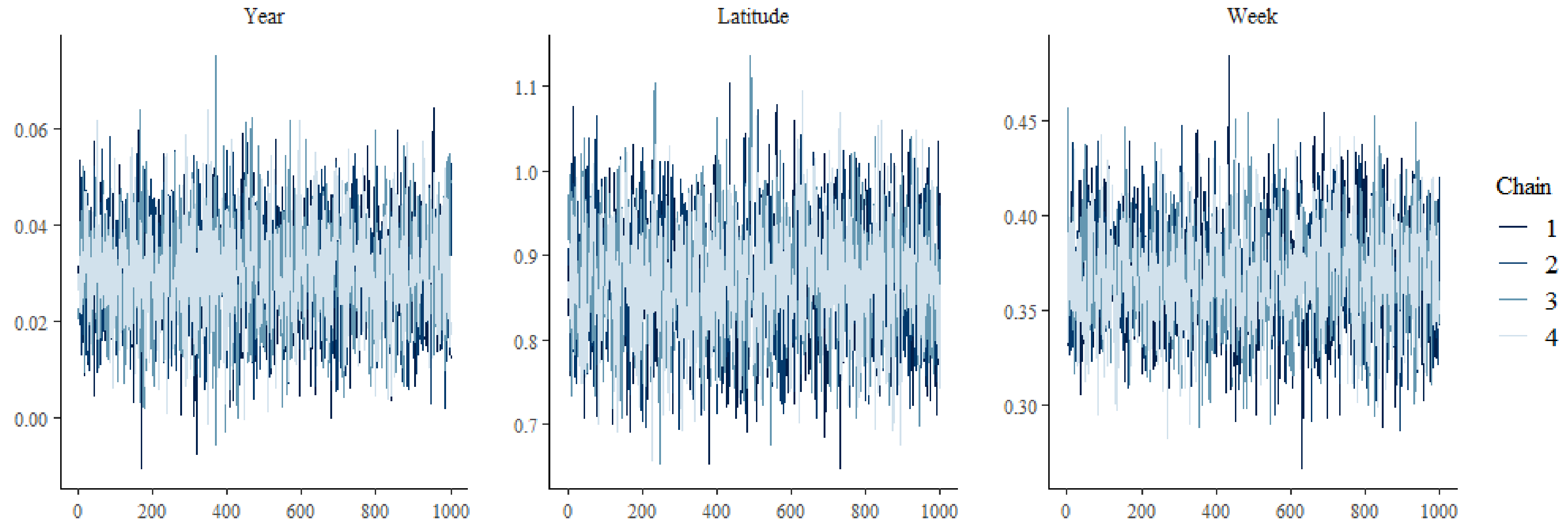

Figure A5.2: Posterior chains from the logistic model using ASI data.

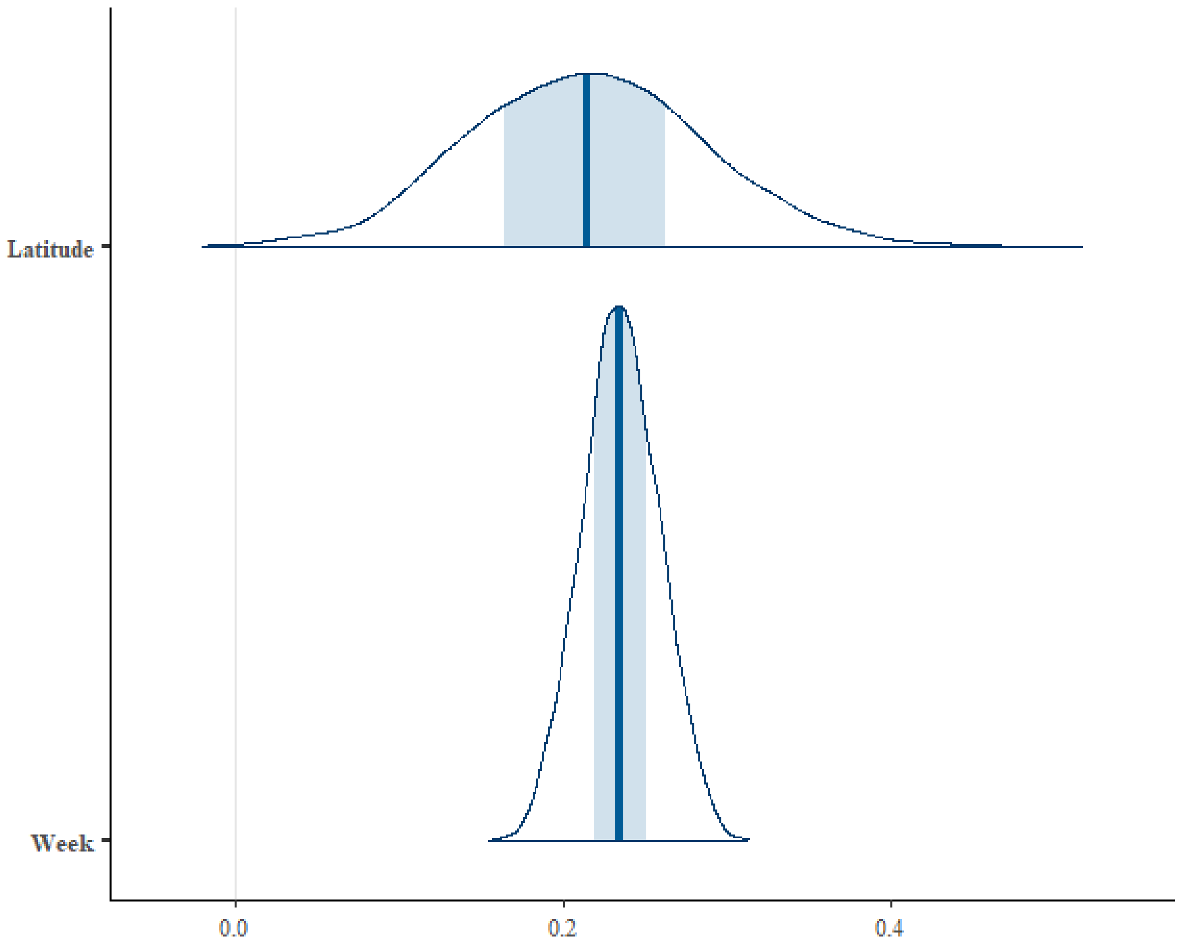

Figure A5.3: Parameter posterior distributions from the logistic community science (Flickr & iNaturalist) model. Dark blue lines represent the 50% credible intervals and light blue bands the 90% credible intervals.

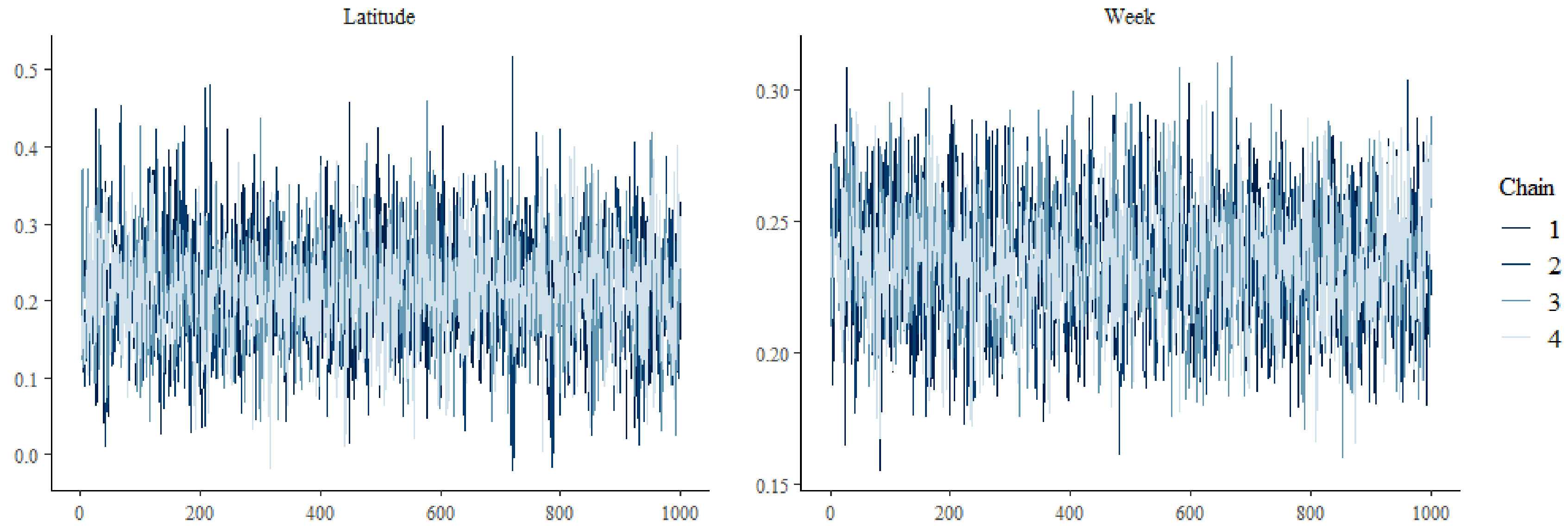

Figure A5.4: Posterior chains from the logistic model using community science data (Flickr & iNaturalist).

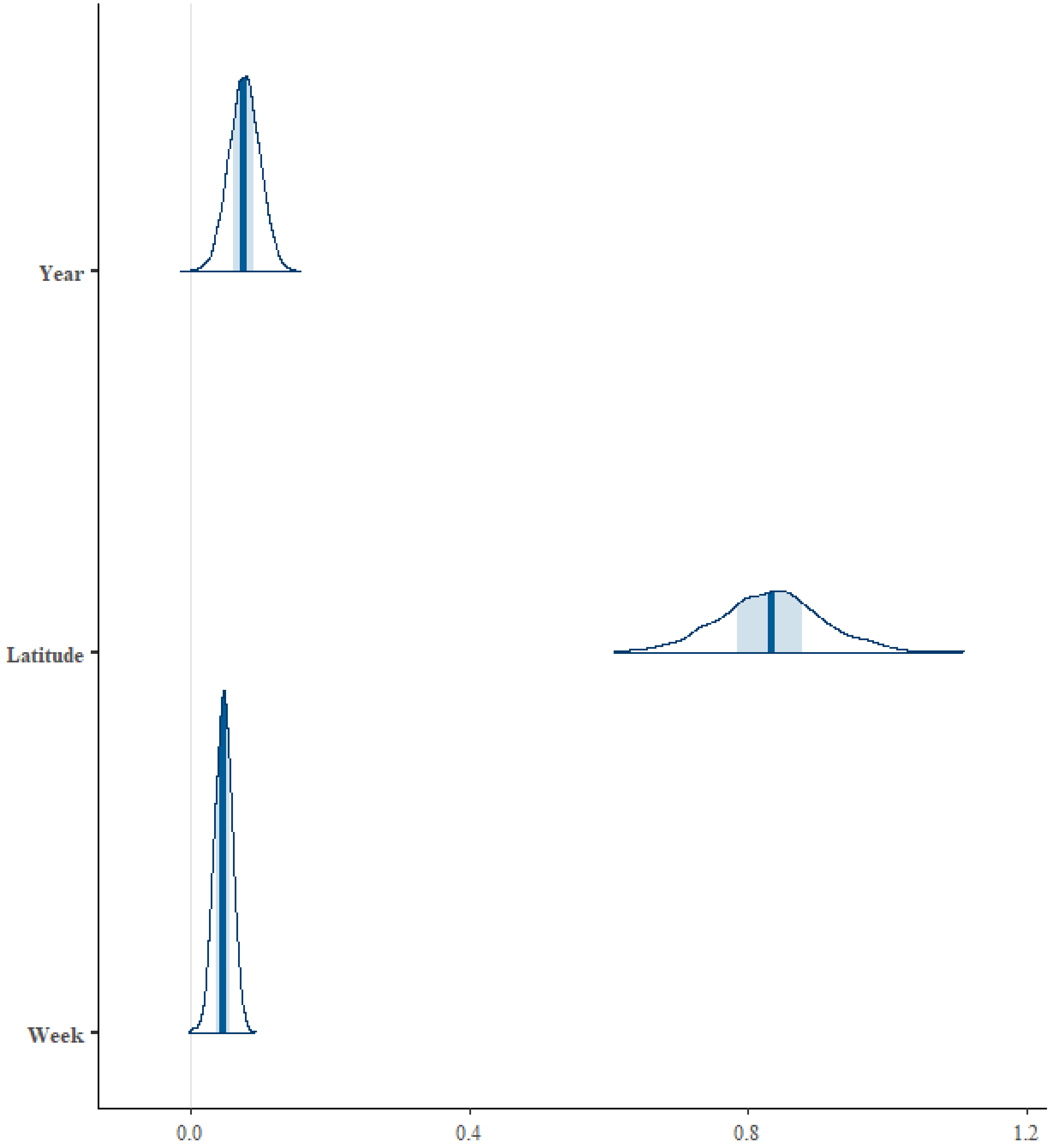

Figure A5.5: Posterior distributions for parameters from the Gamma abundance model. Dark blue bands represent 50% credible intervals, and light blue bands represent 90% credible intervals.

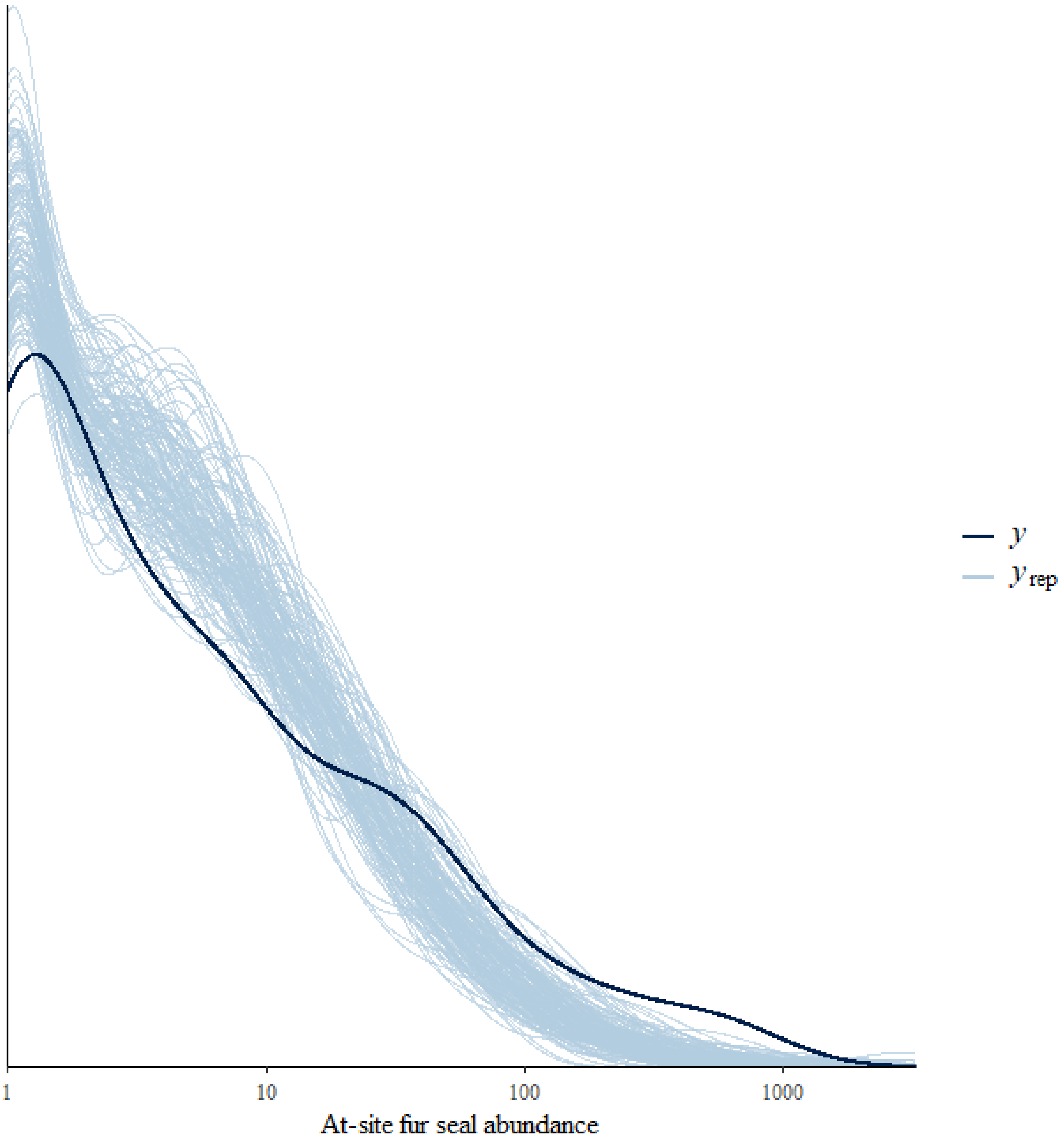

Figure A5.6: Gamma GLM fit for fur seal site-wise abundance. Blue lines represent posterior draws; the black line is the ASI data.

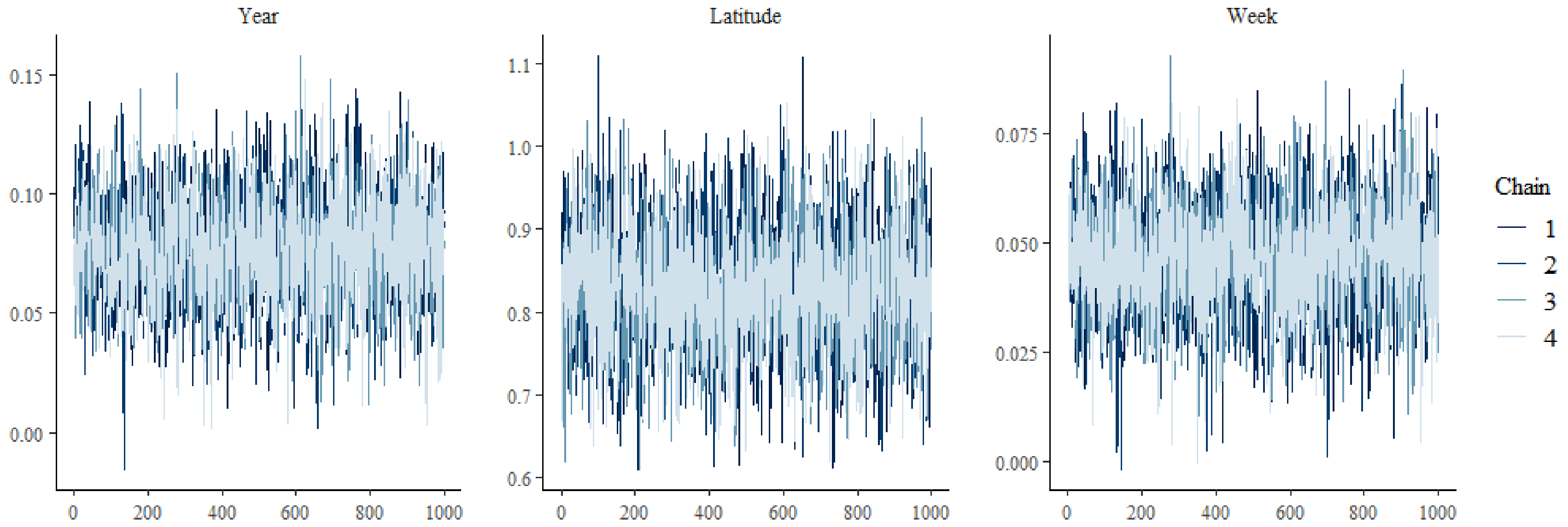

Figure A5.7: Posterior chains from the Gamma abundance model.

6.7 Appendix A5.2

Posterior estimates from the Gamma model when two outliers are included.

Table A5.1: Posterior coefficient estimates for the Gamma abundance model with and without outliers.

Covariate	**Coefficient Estimate (With Outliers)**	**Coefficient Estimate (Without Outliers)**
Intercept	$17.44\ (17.44, 194.46)$	$-101.06\ (-186.50, 16.47)$
Year	$-0.02\ (-0.07, 0.02)$	$0.08\ (0.03, 0.12)$
Latitude	$0.94\ (0.78, 1.09)$	$0.83\ (0.69, 0.98)$
Week	$0.03\ (0.00, 0.05)$	$0.47\ (0.02, 0.71)$

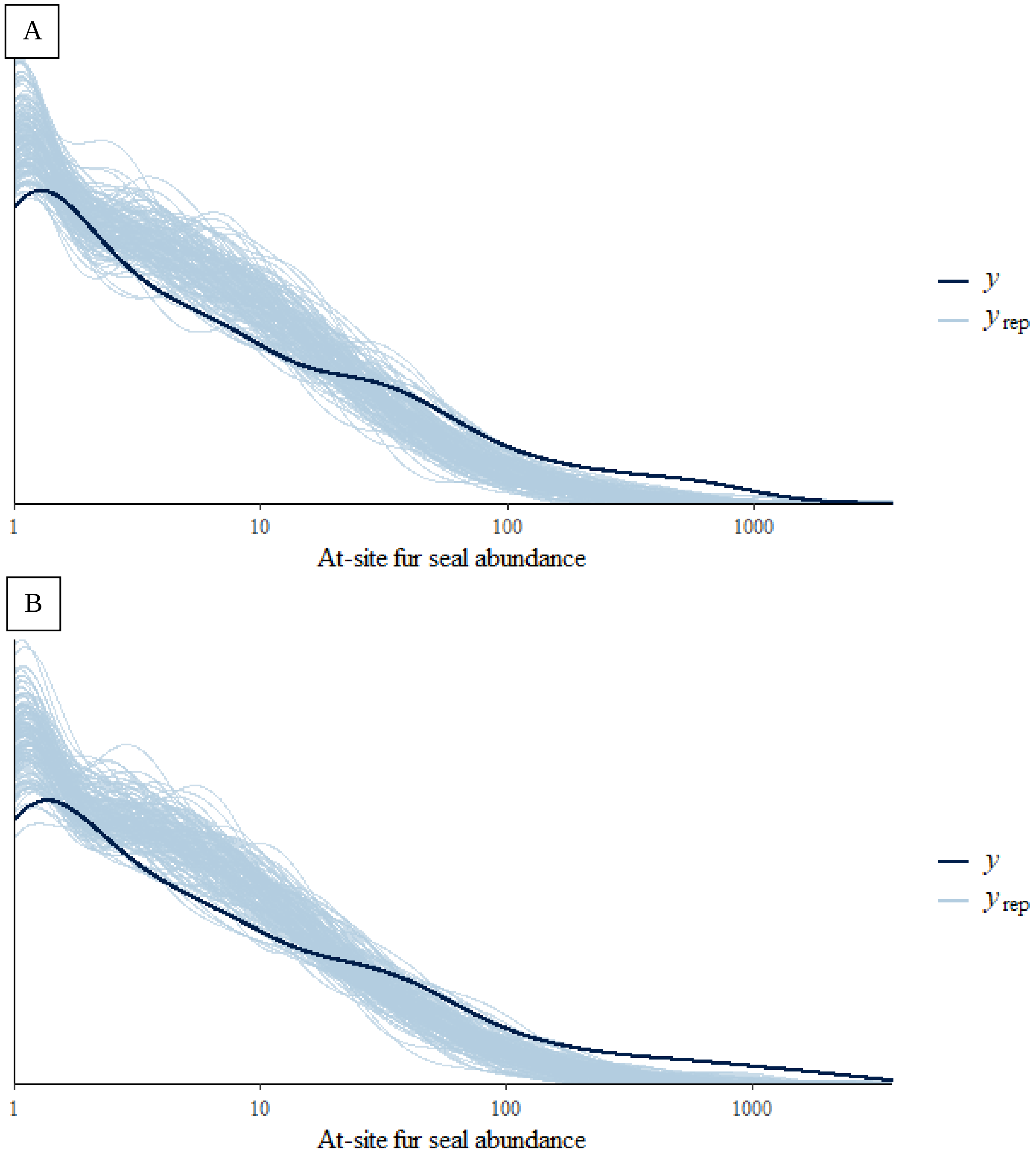

Figure A5.8: Model fits for the Gamma model when outliers are excluded (A) or included (B).

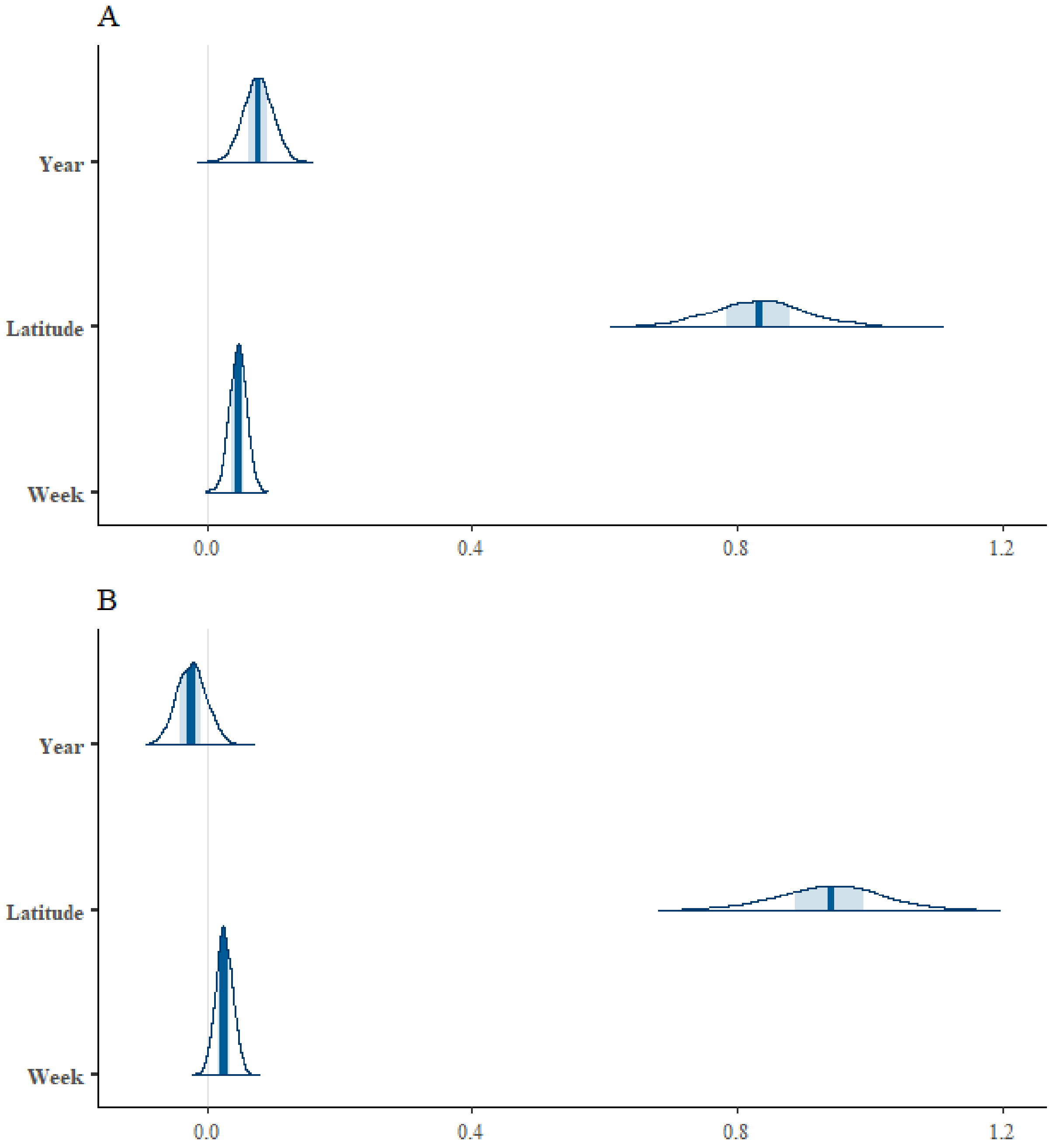

Figure A5.9: Posterior distributions from the Gamma abundance model when (A) outliers are excluded or (B) included.

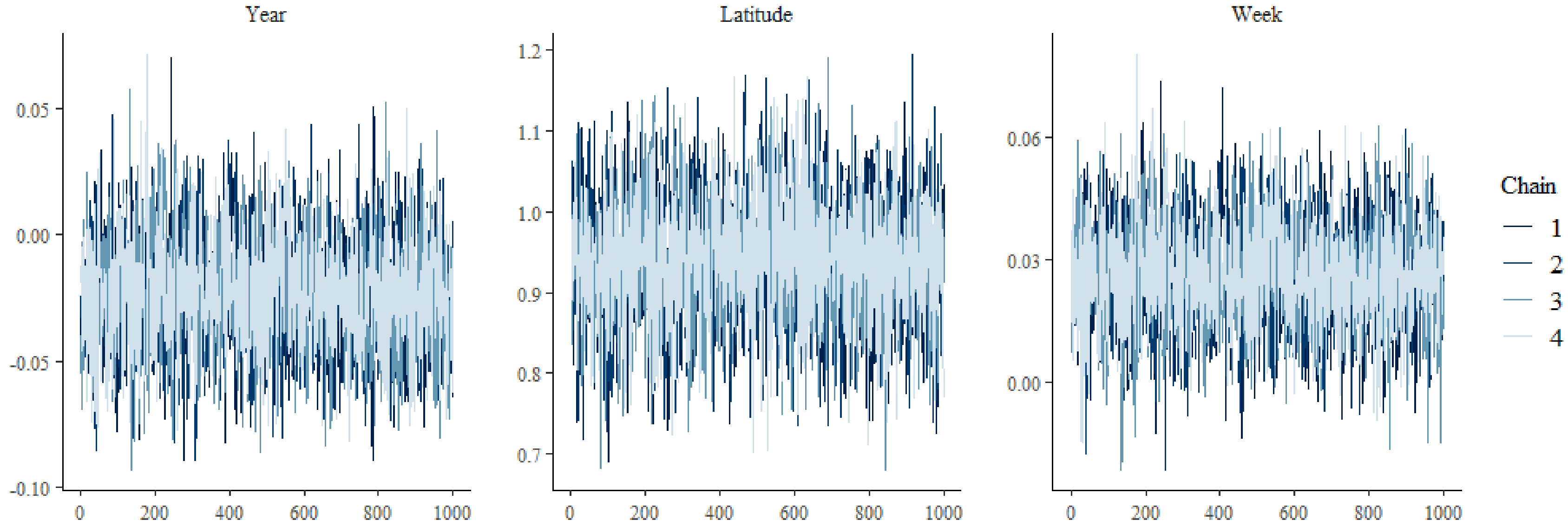

Figure A5.10: Posterior MCMC chains from the Gamma abundance model when outliers are included.

Hay, hermanos, muchísimo que hacer.

César Vallejo

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