Using Bioacoustics to Examine the Effects of Industrial Disturbance on Owls and their Prey

by

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Abstract

Anthropogenic disturbance is known to have negative population consequences and alter animal behaviour, and a growing body of research on the effects of anthropogenic noise is finding similar negative impacts on wildlife. Noise in natural environments can mask important acoustic signals used for animal communication. Owls use vocal communication to attract mates and defend territories, and rely on acoustic cues to locate their prey. Industrial noise has been shown to negatively affect owl hunting success and reduce foraging efficiency by affecting their ability to detect prey, but whether this results in reduced habitat suitability for owls in areas near industrial noise sources is largely unknown. It is also not known if the abundance of small mammals, the primary prey of owls, is affected by industrial noise. Communication between small mammals is unlikely to be directly affected by noise because they primarily communicate using olfactory rather than vocal signals, but small mammals could be indirectly affected through altered predation dynamics. I sought to determine if owls avoid the areas surrounding chronic industrial noise sources, if prey availability is affected by chronic industrial noise, and the relative importance of noise compared to other types of disturbance resulting from industrial development on owl habitat use. I used autonomous recording units and automated recognizers to survey for owls and scan recordings for owl vocalizations, to assess the impacts of disturbance from industrial development on owls in northeastern Alberta, a region that has seen increased development in the oil and gas industries in recent years. I found that barred owls (*Strix varia*), great horned owls (*Bubo virginianus*), and boreal owls (*Aegolius funereus*) were equally likely to occupy noisy sites compared to sites with no noise, indicating that site-level occupancy (representing a home range scale) was unaffected by the presence of noise sources on the landscape. I found no difference in abundance or activity of red-backed voles (*Myodes gapperi*) and deer mice (*Peromyscus maniculatus*), indicating that these important prey species are not strongly affected by noise. Finally, I found each owl species responded differently to the different disturbance types. Barred owls were less likely to be present in areas with greater proportions of human footprint and roads, whereas great horned owls were more tolerant to disturbance and were more likely to be present in areas with greater proportions of soft linear features (e.g. seismic lines, pipelines), though they did avoid areas with large industrial facilities. Boreal owl presence was more strongly affected by forest composition than disturbance; they prefer more coniferous forests, and it was less clear if they were sensitive or relatively tolerant to disturbance. Assessing the relative impacts of multiple types of disturbance and how the accumulation of disturbances can impact wildlife is important in understanding species declines and can help focus conservation efforts. My thesis contributes to research on the impacts of anthropogenic disturbance and suggests the effect of noise on barred owls, great horned owls, and boreal owls is minimal at the spatial scales I looked at. Similarly, the effect of noise on abundance and activity of red-backed voles and deer mice was weak, suggesting similar prey availability for owls. For the owl species I studied, forest composition and other types of disturbance on the landscape are more likely to influence their habitat use.

Preface

This thesis is an original work by Julia Shonfield. Field methods were approved by the University of Alberta Animal Care Committee (AUP00001055).

Chapter 2 of this thesis was published in 2017 as J. Shonfield and E. Bayne, "Autonomous recording units in avian ecological research: current use and future applications", *Avian Conservation and Ecology*, vol. 12, issue 1, article 14. I was responsible for concept formation, reviewing the literature and writing the manuscript. E. Bayne provided input and feedback on concept formation and writing of the manuscript.

Chapter 3 of this thesis was published in 2018 as J. Shonfield, S. Heemskerk, and E. Bayne, "Utility of automated species recognition for owl acoustic monitoring", *Journal of Raptor Research,* vol. 52, issue 1, pages 42-55. I was responsible for concept formation, data collection, analysis and writing the manuscript. S. Heemskerk was an undergraduate student I supervised conducting a BIOL 499 independent research project in 2016-2017, and contributed to data collection, analysis and writing the manuscript. E. Bayne provided input and feedback on concept formation, analysis, and writing of the manuscript.

Chapter 4 of this thesis was published in 2017 as J. Shonfield and E. Bayne "The effect of industrial noise on owl occupancy in the boreal forest at multiple spatial scales", *Avian Conservation and Ecology*, vol. 12, issue 2, article 13. I was responsible for data collection, analysis and writing the manuscript. E. Bayne provided input and feedback throughout concept formation, field work, analysis, and writing of the manuscript.

Chapter 5 of this thesis has been submitted to the *Journal of Mammalogy* as J. Shonfield and E. Bayne "Investigating the effects of industrial noise on small mammal abundance and activity" and is currently in review. I was responsible for concept formation, data collection, analysis and writing the manuscript. E. Bayne provided input and feedback throughout concept formation, field work, analysis, and writing of the manuscript.

Chapter 6 of this thesis is being prepared for journal submission.

In addition, based on work I did during my PhD on owl habitat use and vocal activity, I submitted a manuscript for inclusion in the conference proceedings of the World Owl Conference in September 2017 to be published in the Portuguese avian journal *AIRO* as J. Shonfield and E. Bayne "Using bioacoustics to study owl vocal behaviour and habitat use" and is currently in review.

Dedication

I dedicate this thesis to my grandparents, Violet Shonfield (1921-2017) and Morris (Shonny) Shonfield (1921-2014). They played an integral role in my education, and supported me financially during my BSc degree at McGill University. Without their support I may not have gone on to a PhD degree. I wish they could be here to share this accomplishment with me.

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company in the lab and learning about your projects. I had some fantastic fellow PhDs to share office space with during my degree. Janet Ng was my office mate, rock climbing partner, and closest friend during my PhD degree. She taught me many skills throughout my degree including how to network, how to be a good supervisor to undergraduate students, and how to have a good work-life balance. Janet got me involved in various volunteer opportunities and introduced me to Colonel Slade (the barred owl). Elly Knight was a great addition to the office in 2015, and it was extremely helpful to have someone to talk about details of recognizers, bioacoustics, and various analyses. The process of completing a PhD degree without my wonderful office and lab mates would not likely have been nearly enjoyable as it was.

Thanks to Eric Neilson for always being willing to drop his own work and fix whatever problem I had in my R code, and for numerous helpful discussions about occupancy models. Thanks to Jess Haines for many helpful tips for teaching ornithology and the field ecology course. Many other graduate students and faculty contributed to a positive experience during my degree: the Biol 603 crew, the Boutin lab crew, the BioSci innertube waterpolo team, people who attended Wednesday nighters, and many others. Thanks to Frances Stewart for being an excellent companion at many different conferences during our PhD degrees. I thank Hedwig Lankau for organizing the field recordings and maintaining the database; Monica Kohler and Brandi Mogge for coordinating lease access. Thanks to Beaverhill Bird Observatory, especially Amelie Roberto-Charron and Meghan Jacklin for giving me the chance to learn more about owls during my degree through banding saw-whet owls. Finally, I'd like to thank my family for all their love and support. Thanks especially to Geoff Sherman for his love and patience; the end of this degree feels a bit like the end of a chapter, and I'm looking forward to the next chapter of our lives together.

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Chapter 1. Introduction

Anthropogenic disturbance

Anthropogenic disturbance can have negative effects on species populations and can alter the behaviour of individuals. Assessing impacts of anthropogenic disturbance is important for wildlife conservation and management, and a large body of research has been working on understanding potential impacts across taxa and the underlying mechanisms at multiple scales (e.g. Northrup and Wittemyer 2012; Neilson and Boutin 2017; Scrafford et al. 2017; Tucker et al. 2018). Anthropogenic disturbances can be grouped into two broad categories: physical disturbance leading to alteration of habitat from the landscape (e.g. clearing vegetation to extract natural resources), and sensory disturbance (e.g. noise, light, and other forms of pollution) that can permeate through landscapes. Habitats that may appear intact can be degraded by sensory disturbance if it causes animals to avoid those areas or negatively impact individuals inhabiting those areas.

All landscapes have natural ambient noise levels, caused by various abiotic (e.g. wind and rain) and biotic factors (e.g. animal vocalizations). Noise from anthropogenic sources is increasingly affecting natural areas (Barber et al. 2011) due to an increasing human population, and subsequent increases in transportation, urban sprawl and industrial development. A recent study found that anthropogenic noise (from transportation, development and extractive land use) doubled the background sound levels in 63% of protected area units in the United States (Buxton et al. 2017), highlighting the need for the management of noise pollution in protected areas. Recently, there has been a growing awareness that acoustic environments (i.e. natural soundscapes) have both an ecological and social value, and can have important benefits to humans as well as ecological communities (Dumyahn and Pijanowski 2011, Francis et al. 2017). In the terrestrial ecology literature, there is a growing concern that noise pollution from anthropogenic sources can degrade ecosystem integrity.

Anthropogenic noise disturbance can range from acute or infrequent noise, which may trigger startle responses in animals, to frequent or chronic noise that could interfere with signal detection (Francis and Barber 2013). In the process of animal communication, a sender sends a signal, which is then perceived and influences the behaviour of a receiver (Marler 1967). Noise can affect signal perception by reducing the ability of a receiver to detect a signal over background noise levels and affect their ability to discriminate one signal from another (Brumm and Slabbekoorn 2005). Noisy environments can pose problems for animals that communicate vocally because of 'acoustic masking', where an increase in amplitude of background noise leads to a reduction in a receiver's ability to detect the communication signal (Francis et al. 2011a). Acoustic masking depends on the relative amplitude of the signal and background noise (i.e. signal-to-noise ratio), but also depends on the degree of overlap in the frequencies of the signal and the noise.

Anthropogenic disturbance is known to have negative population consequences and alter animal behaviour, and a growing body of research on the effects of anthropogenic noise is finding similar negative impacts on wildlife (reviewed in Brumm and Slabbekoorn 2005, Barber et al. 2010, Francis and Barber 2013). Not surprisingly, this research has predominantly focused on species that rely on vocal communication for important components of their life history (e.g.

to attract a mate or defend a territory). A substantial portion of the research in this field, and many of the earliest studies, were done in aquatic environments on marine mammals (reviewed in Shannon et al. 2016). In terrestrial environments, the focus has been on songbirds (Habib et al. 2006, Bayne et al. 2008, Francis et al. 2011a, 2011b, Shannon et al. 2016), and several studies have found negative effects of noise on songbird abundance and diversity (Bayne et al. 2008, Francis et al. 2009, McClure et al. 2013). Studies on terrestrial mammals have found negative effects on foraging behaviour in bat species that hunt by listening for prey-generated sounds (Siemers and Schaub 2011, Bunkley and Barber 2015), and increased vigilance in squirrels that rely on vocal communication to warn of predators (Shannon et al. 2014). Most studies have focused on vertebrates (Shannon et al. 2016); however, at least one study on terrestrial arthropods found noise-induced changes to abundance (either negative, positive or neutral) for different families of arthropods (Bunkley et al. 2017). The evidence to date suggests that anthropogenic noise can have negative impacts on individuals and has the potential to impact entire ecological communities by affecting biodiversity, abundance, and behaviour of a wide range of species across taxonomic groups.

Species or individuals that continue to inhabit noisy areas may have altered their vocal signals in an effort to overcome difficulties communicating. There are several ways to minimize acoustic masking and increase the signal-to-noise ratio including 1) increasing the amplitude, 2) adjusting the frequency to minimize overlap, and 3) calling longer and/or more often so that the signal is more likely to reach the receiver (Slabbekoorn 2004, Patricelli and Blickley 2006). There is evidence of noise-induced changes to the vocalization signals of several songbird species (e.g. Slabbekoorn and Peet 2003; Francis et al. 2011b; Luther and Derryberry 2012).

Songbirds most commonly shift the frequencies of their signals upwards (Roca et al. 2016), reducing the masking effect by predominantly low-frequency (Hz) anthropogenic noise and improving detection by the receiver (Pohl et al. 2012). In other birds and some anurans, the timing of the vocalization signal is altered in noisy conditions (Fuller et al. 2007, Cunnington and Fahrig 2010, Dominoni et al. 2016). However, not all species appear to be able to alter their vocal signal (Francis et al. 2011a), and avoidance of noisy areas may be the only option. While altering signals can improve perception, it can also compromise vocal performance (Luther et al. 2016), which could result in fewer mating opportunities and more challenges in defending a territory. There is evidence that songbirds living in noisy areas have reduced pairing success (Habib et al. 2006) and reduced fitness (Halfwerk et al. 2011, Schroeder et al. 2012). Species that are present in noisy areas may still experience negative consequences to their fitness and reproductive success due to the noise regardless if they have altered their vocalization signals.

One approach to studying the impacts of anthropogenic noise on wildlife is to use existing noise sources on the landscape (e.g. compressor stations) as treatment sites and similar locations without noise sources as control sites (Bayne et al. 2008, Francis et al. 2009, 2011a). An experimental approach involves introducing anthropogenic noise in controlled playback experiments (Blickley et al. 2012, McClure et al. 2013, Rosa et al. 2015, Ware et al. 2015). The experimental approach allows for the study of the impacts of noise in isolation from other confounding variables; however, there are few real-world examples of an anthropogenic noise disturbance without an associated physical disturbance to the landscape, especially in the case of chronic noise sources. For some species the effect of noise may be less important compared to the effects from other types of disturbance. Recent studies have shown a small effect of noise on grassland songbirds compared to other types of disturbance such as the physical industrial infrastructure (Bernath-Plaisted and Koper 2016, Nenninger and Koper 2018). Another study on tawny owls (*Strix aluco*) found a small effect of urban noise and a larger effect of habitat loss and fragmentation (Fröhlich and Ciac 2017). Thus, research aiming to assess the impacts of noise should also asses the relative importance of other types of disturbance on the landscape.

Studying a single type of disturbance in isolation ignores the potential for cumulative effects of multiple disturbance types. The concept of cumulative effects is that while each disturbance or land use change on its own may result in a small or negligible effect on wildlife, the accumulation of disturbances, or changes over time/within a region can result in a major impact on wildlife (Theobald et al. 1997). Evaluating cumulative effects of disturbance is important for resource management and wildlife conservation (Burton et al. 2014), and can indicate the relative importance of different types of disturbance or different combinations of disturbance types. This knowledge can lead to more effective mitigation strategies and help us to understand what is driving declines in species that are at risk.

Owls and disturbance

Owls (Strigiformes) use vocal communication to attract mates and defend territories, and when hunting at night they rely on prey-generated acoustic cues (Payne 1971, Martin 1990). The reliance of owls on acoustic signals for communication and acoustic cues to locate prey could make them particularly susceptible to anthropogenic noise. Noise from industrial operations, which is generally low in frequency (< 1 kHz), is likely to mask owl calls, which are also low in frequency (~ 0.2 - 1.2 kHz, see Figures 1.1-1.3), and has the potential to interfere with detecting cues from prey. Owl density and occupancy of sites has been found to decrease with increased proximity to roads and increased traffic volume (Hindmarch et al. 2012, Silva et al. 2012), which may be related to the masking effect of traffic noise that could impact intraspecific communication or hunting ability. However, roads have several factors other than noise (e.g. vehicle collisions and pollution) that can negatively affect animal abundance and distribution (Fahrig and Rytwinski 2009), making it difficult to attribute observed effects solely to noise.

Recent experiments using playbacks of anthropogenic noise revealed that increasing industrial noise levels negatively affect the hunting success of northern saw-whet owls, *Aegolius acadicus* (Mason et al. 2016), and traffic noise reduces the foraging efficiency of long-eared owls, *Asio otus*, and short-eared owls, *Asio flammeus* (Senzaki et al. 2016). There is other evidence to suggest that owls may be sensitive to noise; spotted owls (*Strix occidentalis)*, for example will flush from nests more frequently with increased proximity to a temporary noise stimulus (Delaney et al. 1999). Studies on physiological stress responses of spotted owls to temporary anthropogenic noise stimuli found mixed results; in one case noise resulted in elevated fecal glucocorticoids (Hayward et al. 2011), but another found no detectable increase in fecal corticosterone in response to noise (Tempel and Gutiérrez 2003). Owls may be sensitive to noise disturbance, but owl distribution and behaviour around noisy infrastructure has not been well studied (but see Scobie et al. 2016), and little is known about how owls may respond to chronic noise sources on the landscape.

Given the evidence that chronic industrial noise can mask the sounds of owl prey and impair owl hunting, optimal foraging theory (Charnov 1976) would predict that owls should avoid industrial noise sources because of the increased search time needed to locate small mammals. However, if prey densities are lower near noisy areas this could also cause owls to avoid these areas. Small mammal densities could be lower if the noise makes them more vulnerable to predation leading to lower survival. This could occur either because the attention of small mammals could be compromised from distraction from the noise (the 'distracted prey hypothesis', Chan et al. 2010, Chan and Blumstein 2011), or the sound of movements by approaching predators could be masked by the noise. Owls are unlikely to gain any hunting advantage from the noise because they are silent predators (Sarradj et al. 2011), but land predators who primarily use scent to detect prey may benefit by the sound of their approach being masked.

Bioacoustics

Most owl species are difficult for human observers to detect visually due to their nocturnal habits, cryptic colouration, and occurrence at low densities. Owls are effectively detected by their calls, and for this reason acoustic surveys are commonly used to determine presence or abundance of owls (Goyette et al. 2011, Rognan et al. 2012). Owls vocalize to attract mates and defend territories from conspecifics during the breeding season in early spring (Johnsgard 2002, Odom and Mennill 2010a), so detecting these calls is a reliable indicator that a species is occupying a territory. Using territorial vocalizations to determine presence of owls is useful for estimating patch occupancy and obtaining information on owl habitat use and distribution across a landscape. Acoustic surveys for owls often broadcast a recorded owl call (Clark and Anderson 1997. Sater et al. 2006, Grossman et al. 2008, Kissling et al. 2010), to increase the probability of detecting an owl by eliciting territorial individuals to call back (Kissling et al. 2010). However, there are several drawbacks to call-broadcast surveys: 1) they can draw owls in from a distance (Zuberogoitia et al. 2011), which could affect conclusions about habitat associations of owls, and 2) detection from call-broadcast surveys may vary with different equipment and can also affect detection of other owl species (Bailey et al. 2009, Wiens et al. 2011), which could be problematic for studies targeting multiple owl species. Depending on the research objective, passive surveys for owls using recent bioacoustic technology may be a better approach.

Bioacoustics is the study of sound produced by animals. Bioacoustics as a research field has gained momentum in recent years with technology able to record sound autonomously in many different environments. Autonomous recording units (ARUs) enable passive surveys to be conducted for owls, as opposed to having field personnel out listening at night for owls. Several different models of ARUs are commercially available and have been tested for conducting avian surveys (Acevedo and Villanueva-Rivera 2006, Holmes et al. 2014, Zwart et al. 2014). Using ARUs to conduct passive acoustic surveys may be effective for surveying vocalizing species that are rare or difficult to detect by other methods. The ability to record animal vocalizations is nothing new, but what really sets these units apart is that they can be programmed to record on a pre-determined schedule and left out in the field to passively record vocalizations. Using ARUs for nocturnal owl surveys has the benefit that they can be set up at any time and programmed to record at night, minimizing safety risks of nocturnal field work and reducing observer bias.

Bioacoustics research relies on technological advances. Prior to ARU technology, the ability to visualize sounds by generating a spectrogram is considered to have been revolutionary in the field of bioacoustics and the study of bird vocalizations (Marler 2004). ARUs are increasingly used to research and monitor birds because of the benefits of reduced observer bias and the ability to collect data over longer time scales (Buxton et al. 2013, Frommolt and Tauchert 2014). At the same time, ARUs have the drawback that the volume of recordings collected can be very time consuming to process. However, automated species recognition can potentially assist in the processing of recordings and is emerging as a valuable tool in the field of bioacoustics. In general, the process of automatically detecting acoustic signals involves matching recording segments to a template (often termed a 'recognizer') derived from training data and registering a hit when a similarity threshold is reached. A few different approaches have been developed, and some are more easily accessible through commercial or open software. Automated recognition has been tested in a few different bird and amphibian species (Buxton and Jones 2012, Taff et al. 2014, Holmes et al. 2015, Brauer et al. 2016), and has the potential to efficiently process a large volume of recordings within a manageable timeframe (Knight et al. 2017).

Thesis overview

In the boreal forest of northern Alberta, chronic noise from industrial operations could affect habitat suitability of the surrounding area for owls, causing them to avoid the area. My thesis aims to use bioacoustic approaches to assess the impacts of industrial disturbance on owls and their prey in northern Alberta, a region that has seen increased development in the oil and gas industries in recent years (Alberta Biodiversity Monitoring Institute 2017). In chapter 2, I review the use of ARUs in avian ecological research and synthesize current knowledge of the benefits and drawbacks of this recent technology. In chapter 3, I test the utility of automated recognition for territorial calls of three owl species: the barred owl (*Strix varia*), the boreal owl

(*Aegolius funereus*), and the great horned owl (*Bubo virginianus*). I assess the performance of each recognizer and compare the results to listening to a subsample of the recordings. In chapter 4, I use these bioacoustic approaches to survey for owls and assess the impact of industrial noise on owls by determining if owls avoid the areas surrounding chronic industrial noise sources. In chapter 5, I evaluate the impacts of industrial noise on prey availability by determining whether small mammal abundance and activity is affected by chronic industrial noise using mark-recapture methods. In chapter 6, I assess the cumulative effects of industry on owls by evaluating the relative importance of various types of disturbance resulting from industrial development (including noise-producing facilities, linear features, and other types of forest clearings that vary in the amount of human activity and infrastructure present) on owl habitat use. Finally, in chapter 7, I synthesize the results and ideas from the preceding chapters, discuss management implications, and provide suggestions for future research directions.

Study species

At the outset, this research was not targeting any owl species in particular. I used a passive survey approach to collect data on any owl species vocalizing. After the first field season of data collection in 2013, preliminary data processing identified three owl species that were detected the most frequently during the surveys (in decreasing order): great horned owl (*Bubo virginianus*), boreal owl (*Aegolius funereus*), and barred owl (*Strix varia*). I continued to analyze data on these three owl species to answer my research questions. Other species detected infrequently (in decreasing order) include the northern saw-whet owl (*Aegolius acadicus*), great gray owl (*Strix nebulosa*), long-eared owl (*Asio otus*), northern hawk owl (*Surnia ulula*), and the northern pygmy owl (*Glaucidium gnoma*).

The great horned owl is a large and heavy owl, with the most extensive distribution of any owl in North America, and found in South America as well (Johnsgard 2002). They have prominent ear tufts and large yellow eyes. Great horned owls are formidable predators and have a broad diet, though mammals (small rodents and lagomorphs) make up the majority of their diet (Cromrich et al. 2002). They are non-migratory and are found in such a wide range of habitats that it can be difficult to characterize habitat requirements for the species, though they require trees for nesting and roosting (Johnsgard 2002). In Alberta, they are found throughout the province in the prairies and in the northern boreal. Fittingly, they are Alberta's provincial bird. Like all owls, they do not build their own nests, and primarily nest in stick nests built by corvids or diurnal raptors (Johnsgard 2002). Great horned owls give a territorial vocalization consisting of 4 or 5 hoots (Kinstler 2009; Figure 1.1). Both the male and female will produce this vocalization and will call back and forth in duets (Kinstler 2009). The male's voice is slightly lower pitched than the female's voice. This call is primarily heard during the breeding season in late winter/early spring.

Boreal owls are small owls found in forested areas throughout the boreal region in Canada and parts of the Rocky Mountains in the U. S. (Johnsgard 2002), and in northern Europe where they are known as Tengmalm's owl after Swedish naturalist Peter Gustaf Tengmalm. Boreal owls are non-migratory, generally found in older mixedwood and coniferous forests (Hayward et al. 1993, Lane et al. 2001), and nest in old woodpecker cavities (Johnsgard 2002). Breeding dispersal is more extensive in females, whereas males tend to remain on their breeding territory each year (Korpimäki et al. 1987). They prey primarily on small rodents; one study in the northern Rocky Mountains in the U.S found the southern red-backed vole (*Myodes gapperi*) was the most frequent prey item of boreal owls (Hayward et al. 1993). Boreal owl males produce a 'staccato call' that consists of a trill of fairly uniform frequency (Figure 1.2) that is used for territorial defence and mate attraction (Bondrup-Nielsen 1984). The boreal owl call closely resembles the winnowing noise of the common snipe (*Gallinago gallinago*) but can be distinguished by the constant pitch and short duration of the trill, unlike the snipe winnow that is longer and increases and then decreases in frequency (Bondrup-Nielsen 1984). Duets between males and females are not known to occur in this species, and I found no evidence of duets in the acoustic data I collected. Boreal owl males call frequently and consistently during the breeding season in late winter/early spring (Bondrup-Nielsen 1984).

Barred owls are large owls that are non-migratory. They have no ear tufts and dark eyes. They were historically distributed in the forests east of the Great Plains in North America, but have expanded their range westward over the past century (Livezey 2009a). In Alberta, the earliest reliable record of a barred owl is from 1934 (Priestley 2004, Livezey 2009a). Barred owls are currently listed as a 'sensitive' species in Alberta, and have been since 2000. The westward expansion of barred owls is primarily attributed to increases in the number of trees facilitated by fire suppression and the decline of bison in the Great Plains following displacement of Native North Americans and settlement of Europeans (Livezey 2009b). Barred owls are generally found in older mixedwood forests, and feed on a variety of prey including rodents (Johnsgard 2002, Priestley 2004, Livezey 2007). They exhibit high territory fidelity (Olsen 1999), and nest primarily in cavities (Priestley 2004, Livezey 2007). The main predator of barred owls is considered to be the great horned owl. However, a review of studies on diet of great horned owls did not include barred owls as prey (Cromrich et al. 2002), though barred owls have been found to avoid great horned owls when their territories overlap (Laidig and Dobkin 1995). Barred owls have a large vocal repertoire and produce a variety of calls (Odom and Mennill 2010a). Their territorial vocalization is the two-phrased hoot consisting of two sets of four notes (Figure 1.3) and is commonly referred to by the popular mnemonic 'Who cooks for you? Who cooks for you all?' Both males and females will give the two-phrased hoot, and will also call back and forth in duets using this call as well as the one-phrased hoot and the ascending hoot (Odom and Mennill 2010a).

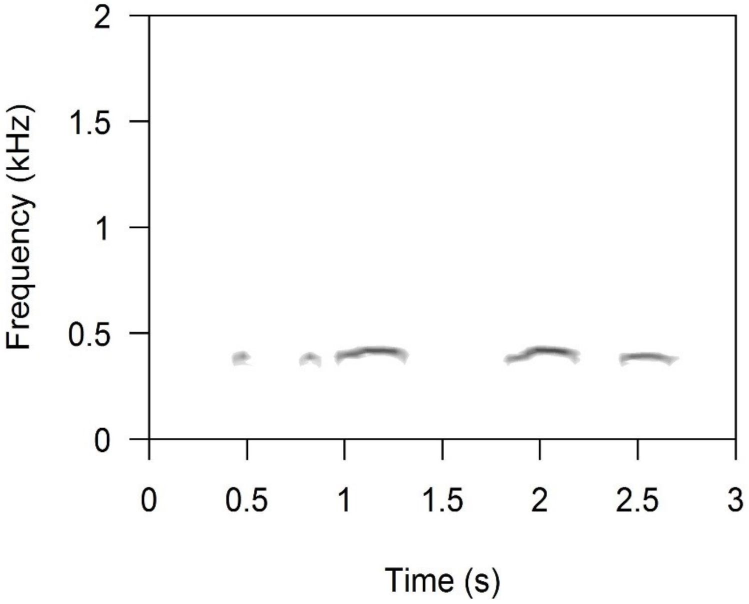

Figure 1.1 Spectrogram of a great horned owl territorial call consisting of 5 hoots.

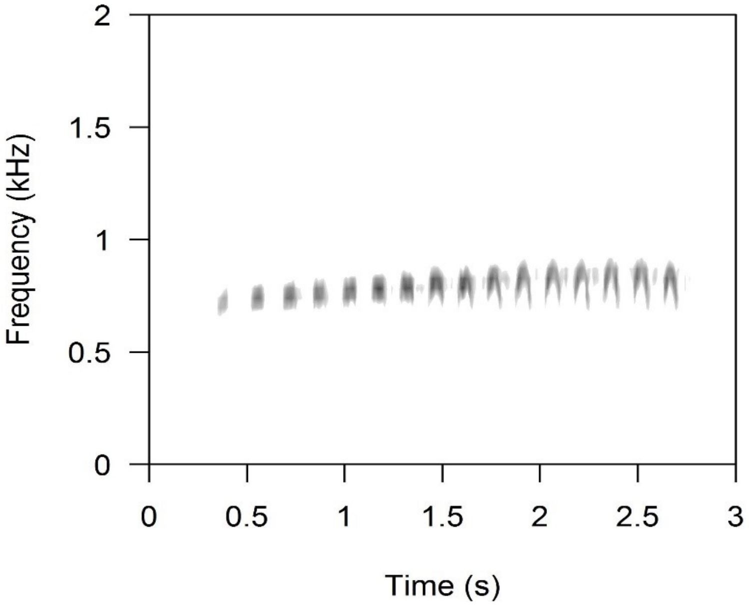

Figure 1.2 Spectrogram of a boreal owl territorial call, known as the ‘staccato song’.

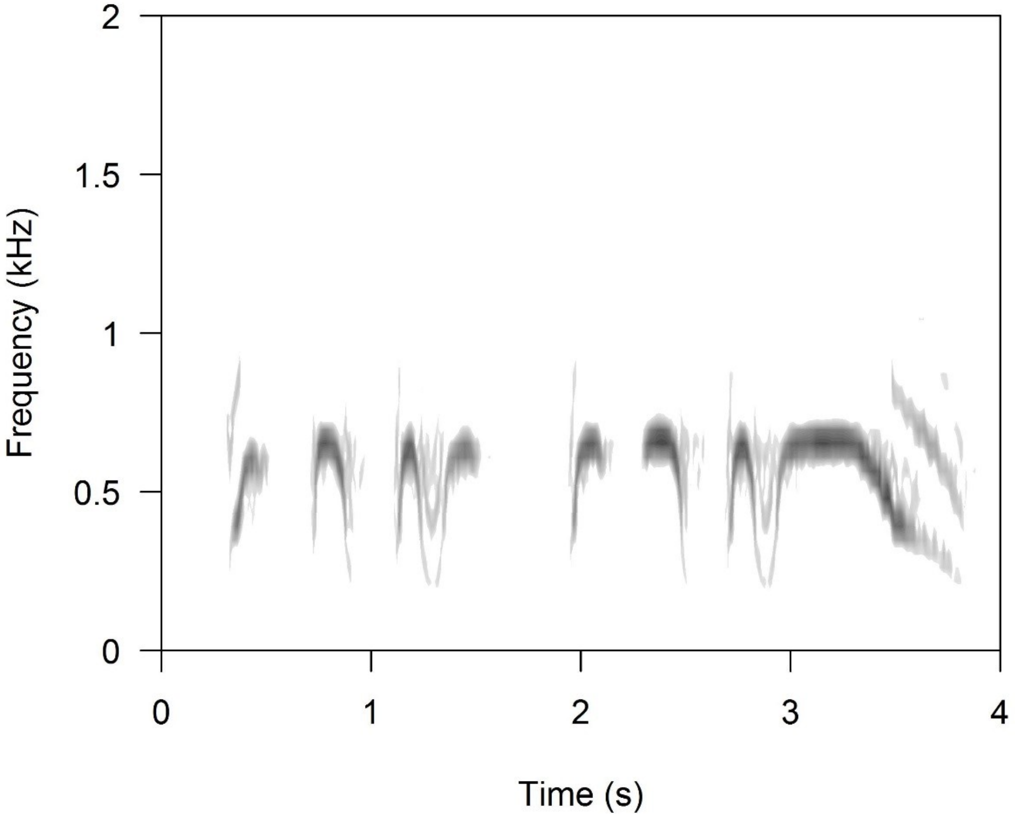

Figure 1.3 Spectrogram of a barred owl territorial call, the two-phrased hoot.

Chapter 2. Autonomous Recording Units in Avian Ecological Research: Current Use and Future Applications

INTRODUCTION

Acoustic surveys are widely used to sample avian communities or target species for ecological research, conservation and monitoring. Many bird species vocalize reliably, and thus acoustic surveys can be used to estimate abundance, density or occupancy (Dawson and Efford 2009, Marques et al. 2013, Lambert and McDonald 2014, Sovern et al. 2014, Drake et al. 2016). Surveys repeated on an annual basis are useful for long-term monitoring (e.g. Furnas and Callas 2015). Acoustic surveys can employ playbacks by broadcasting vocalizations from a speaker to provoke a response (e.g. for owl surveys: Hayward et al. 1993, Laidig and Dobkin 1995), or they can be completely passive, simply listening for vocalizing species. Avian point counts are a commonly used type of passive acoustic survey, where a human observer identifies birds in the field from vocalizations and potentially some visual detections (Rosenstock et al. 2002). Point counts have long been used to survey birds because many species are easier to detect from vocalizations, and apart from an experienced observer, they require no specialized equipment, and are easy to implement across a range of conditions. This is changing, however. Relatively new technology is becoming increasingly available to record sound in the field autonomously using units programmed to turn on and record on a set schedule unattended in the field. We refer to these as autonomous recordings units (ARUs) and we encourage future studies to maintain consistency and use this same terminology.

While the idea and ability to record animal vocalizations is not new, the prevalence of autonomous recording technology has increased in recent years in avian ecological research. We conducted a literature search to document the rate of increase of this technology in avian research. We conducted a search of peer-reviewed literature in the Web of Science database in January 2017 using the following search terms: acoustic recording, autonomous recording unit, autonomous recorder, autonomous recording, automated digital recording system, bioacoustic monitoring, and passive acoustic monitoring. We retained only primary research articles on avian species that used recording units that could function autonomously. We identified 61 articles in 32 peer-reviewed journals from 2006 to 2017 (Appendix 1, Table A1.1). There was a noticeable increase in the number of articles published using ARUs for avian research from 2014 to 2016 (Figure 2.1) and we expect this trend to continue in 2017. ARUs are being lauded as a useful tool for monitoring species that are elusive, rare, or otherwise difficult to detect using point counts (Blumstein et al. 2011, Holmes et al. 2015), though there are drawbacks. In this review, we summarize the current use of ARUs in avian ecological research and synthesize the current knowledge of the benefits and drawbacks of using ARUs. We also discuss techniques for processing and analyzing recordings and highlight future research applications. ARUs have lots of potential but are under-utilized in avian research. This review aims to stimulate future avian research to use ARUs in innovative ways.

Advantages and disadvantages of ARUs in the field

A primary consideration for using ARUs for avian research and monitoring is how their performance compares to surveys with human observers in terms of species detections. We identified 21 studies in the peer-reviewed literature that compared field surveys with human observers to recordings, from either non-autonomous or autonomous recording units, and summarized the results (Table 2.1). The majority of the studies we identified surveyed for birds using traditional point counts, where a human observer records all birds heard and seen at a fixed location within either a specified or unlimited radius. Other methods used to survey birds included using a playback for a target species (McGuire et al. 2011, Sidie-Slettedahl et al. 2015), walking a survey route (Zwart et al. 2014), and a timed area search (Wimmer et al. 2013). Five studies, including some of the earliest, used portable non-autonomous recorders (Haselmayer and Quinn 2000, Hobson et al. 2002, Celis-Murillo et al. 2009, 2012, Campbell and Francis 2011), while the remainder used ARUs (Table 2.1). Four studies had unequal sampling effort between methods, with longer sampling periods for ARUs (Acevedo and Villanueva-Rivera 2006, McGuire et al. 2011, Wimmer et al. 2013, Holmes et al. 2014), and 2 of these studies found ARUs performed better than human observers according to the metrics used (Table 2.1). Of the remaining 17 studies with equal sampling effort, ARUs performed better than humans in three studies, performed equally in eight studies, and performed less well than humans in six studies based on the metric used in each study (Table 2.1). Most studies used species richness as the metric for comparison, though other metrics for comparison included species composition, abundance, presence/absence, call counts and detection probabilities (Table 2.1).

Several studies that found humans performed better than ARUs acknowledged their advantages over point counts and reported that they could be an effective method for certain objectives or target species (Borker et al. 2015, Klingbeil and Willig 2015, Sidie-Slettedahl et al. 2015, Leach et al. 2016). Several studies also suggested that using both methods in combination could be more effective than either method alone (Celis-Murillo et al. 2009, 2012, Tegeler et al.

2012, Digby et al. 2013, Holmes et al. 2014, Alquezar and Machado 2015, Van Wilgenburg et al. 2017). Only one study where humans performed better reported that ARUs were not cost-effective compared to point counts, but acknowledged the utility of a permanent record and recommended the use of portable recorders when conducting point counts (Hutto and Stutzman 2009). In several cases where ARUs detected fewer species or fewer individual birds than humans, this was attributed to humans being able to detect birds at greater distances (Hutto and Stutzman 2009, Venier et al. 2012, Sedláček et al. 2015, Sidie-Slettedahl et al. 2015). Two papers in this special issue demonstrate methods to correct for differential detectability of birds between ARUs and human point counts, using paired sampling (Van Wilgenburg et al. 2017) and playback experiments (Yip et al. 2017b). Some studies attributed fewer species detections by ARUs to visual detections of birds in the field (Hutto and Stutzman 2009, Klingbeil and Willig 2015, Leach et al. 2016), but in other studies humans detected few species by visual cues only during point counts (Tegeler et al. 2012, Alquezar and Machado 2015). ARUs may not always be able to 'hear' as far as humans, but this will depend on the sensitivity of the ARU model and microphones (Rempel et al. 2013, Turgeon et al. 2017). Differences in the number of species detected could also be due to how recordings are processed back in the lab, for example the quality of headphones used when listening (Campbell and Francis 2011), the volume at which the recordings are listened to, or variability among observers processing the recordings (Rempel et al. 2005). We argue that the evidence to date indicates that ARUs are generally comparable to avian point counts with human observers, offer a number of advantages over human observers in the field, and can be effective for surveying birds.

Acoustic recordings provide a permanent record, an advantage recognized by researchers before recording equipment became autonomous. Recordings can be reviewed by multiple observers, reducing observer bias and enabling researchers to assess detection probability and analyze factors that could affect detection (Campbell and Francis 2011). Recordings are preferable to use when species richness is high (Hobson et al. 2002, Campbell and Francis 2011), particularly during the dawn chorus (Haselmayer and Quinn 2000), because of the ability to listen multiple times. A downside to this is the increased amount of time spent listening to recordings; however, a permanent record can be important for verifying species identification of uncommon or rare species (Jones et al. 2007, Swiston and Mennill 2009). In addition, a permanent record enables comparisons of contemporary to historical vocalizations. For example, Luther and Derryberry (2012) found the songs of white-crowned sparrows (*Zonotrichia leucophrys*) increased in minimum frequency over a 37-year period in San Francisco concurrent with rising levels of traffic noise using archived audio recordings. A disadvantage is that storage requirements for audio recordings can rapidly become overwhelming and require considerable planning and expense to maintain. Nevertheless, permanent audio records are likely to be an important data source for tracking changes in species distributions and animal vocalizations over time, including documenting biodiversity changes in areas with increasing anthropogenic disturbance.

Fully autonomous recording units have some distinct advantages in the field over avian point counts and non-autonomous recording equipment. ARUs can be set up or taken down in a matter of minutes, and while they require a minimum of two visits by field personnel, they require less field time in total compared with point counts in some cases (e.g. Holmes et al.

2014). ARUs can be programmed to record for a similar duration as point counts (e.g. 3-10 minutes), but can make several recordings per day and multiple surveys can be done over several days or months (e.g. Goyette et al. 2011, Tegeler et al. 2012). The increased temporal effort makes ARUs a useful tool for studying rare or elusive species that vocalize infrequently (Rognan et al. 2012, Holmes et al. 2014, 2015, Zwart et al. 2014, Campos-Cerqueira and Aide 2016). A downside is if an ARU fails to record, the loss of data could go unnoticed for a long time, making it imperative to check units before deployment. Another disadvantage of ARUs is that there can be a trade-off between temporal coverage and spatial coverage. Initial purchase costs of ARUs are high, and there are ongoing maintenance costs for replacing batteries and damaged microphones. Achieving similar spatial coverage as point counts would require either a large number of ARUs (a considerable cost) or moving them often.

ARUs can be deployed at a time that is convenient, and be programmed to record at a suitable time for target species. This flexibility could be advantageous for surveying returning migratory birds, some of which have begun migrating earlier due to climate change (Cotton 2003), as ARUs can be deployed before the birds arrive. This flexibility also makes ARUs an attractive option for surveying remote locations and conducting nocturnal surveys (e.g. Goyette et al. 2011, Digby et al. 2013, Sidie-Slettedahl et al. 2015). A pilot project by Environment and Climate Change Canada used ARUs to survey northern boreal bird species near the northern limit of their breeding range in the Northwest Territories, a region largely inaccessible because of few all-season roads. By taking advantage of winter roads to communities and diamond mines, they deployed ARUs in the winter, programmed them to turn on and record migratory birds in the spring, and retrieved the data the following winter when the roads were open again

(S. Haché, pers. comm.). ARUs will likely prove useful in other cases where accessibility for conducting surveys is a limiting factor.

Observers conducting point counts may introduce bias to the data collected if their presence affects a bird's behaviour or if the observer cannot reliably detect all species. An observer's ability to detect vocalizations can vary with experience, but with ARUs, less experienced observers with access to reference recordings can obtain similar accuracy to more experienced personnel while listening to audio recordings in the lab (Goyette et al. 2011). Acoustic detections from both point counts and ARU-based surveys are subject to the observer's hearing ability, but with ARUs it is possible to reduce this bias by being able to adjust the volume and having multiple observers listen to recordings. A disadvantage is that multiple-observer modeling approaches may overestimate the number of species due to identification errors (Campbell and Francis 2011). Observers conducting point counts in the field may disturb and influence the behaviour of birds. Birds may flush upon the arrival of an observer, and the approach distance can be influenced by clothing colour of the observer for some species (Gutzwiller and Marcum 1997). Another study in a different bird community found no effect of observer presence on bird behaviour (Campbell and Francis 2012). Field personnel setting up an ARU may influence the behaviour of birds while they are present, but this disturbance is temporary and the recordings will occur without the observer present, so it is less likely that timid or shy birds are negatively affected.

Techniques for processing recordings

ARUs can reduce field time but significantly increase processing time in the lab by generating large datasets that can be challenging to work with. Listening to recordings is a common processing approach and is probably still the best option for studies on avian community composition. Several factors can influence species detection during listening, such as headphone quality, multiple listeners, and repeated listening to a recording. Projects should establish a standardized listening protocol before processing acoustic data to minimize potential bias from these factors. Spectrograms are frequently used during listening to enhance species detection and identification. For studies targeting one or a few species of interest, manual scanning of spectrograms without listening can be an efficient processing method if the vocalizations are visually distinctive and recognizable (Swiston and Mennill 2009). Software for generating spectrograms and sound editing is readily available, as either freeware (e.g. Audacity) or commercial software (e.g. Adobe Audition). In addition, Obrist et al. (2010) identify several programs dedicated to bioacoustic use, and some are equipped with tools for sound analysis and automated species recognition to facilitate processing recordings.

Recent advances in automated species recognition is likely to increase the efficiency of processing large volumes of acoustic recordings for avian research and monitoring. In general, the process involves matching recording segments to a template (often termed a ‘recognizer’) derived from training data and registering a hit when a similarity threshold is reached. A few different approaches have been developed, including band-limited energy detectors (Mills 2000), binary point matching (Katz et al. 2016), decision trees (Acevedo et al. 2009, Digby et al. 2013), random forest (Ross and Allen 2014), spectrogram cross-correlation (Katz et al. 2016), hidden

Markov models (Wildlife Acoustics 2011), and most recently deep learning through convolutional neural networks (Salamon and Bello 2017). Only a few of these approaches are incorporated into commercial or open source software including Song Scope (Wildlife Acoustics Inc., Maynard, MA, USA), Raven Pro (Cornell Laboratory of Ornithology, Ithaca, NY, USA), and R package 'monitoR' (Hafner and Katz 2017), making them more easily accessible to avian researchers. It is important to note that species recognition is rarely completely automated for any of these approaches or programs, as it is usually necessary to have human observers check automated output results to filter out the false positives (Buxton and Jones 2012, Zwart et al. 2014, Colbert et al. 2015, Sidie-Slettedahl et al. 2015). False negatives are also a concern with recognizers, and usually involve listening or manual scanning to identify vocalizations on the recordings the computer missed (Buxton and Jones 2012, Zwart et al. 2014, Holmes et al. 2015). Nevertheless, a recognizer can be useful in detecting rare or elusive species and can make data processing more efficient and manageable.

Processing recordings using a recognizer can be effective and efficient, but is not always a straightforward process. There are examples in the literature of successful (Buxton and Jones 2012, Taff et al. 2014, Zwart et al. 2014, Holmes et al. 2015) and less successful attempts (Colbert et al. 2015, Sidie-Slettedahl et al. 2015) to build recognizers to identify species calls on recordings. One issue is that abiotic noise on the recordings, from heavy wind or rain for example, can cause a lot of false positives (Buxton and Jones 2012, Zwart et al. 2014) and increase the rate of false negatives (Buxton and Jones 2012, Willacy et al. 2015). Another issue is that overlapping calls from other species on recordings can result in failure to detect the target species calls (Buxton and Jones 2012). Ultimately, the effectiveness of a recognizer will depend on the research question. If the goal is to determine if a species is present, then a recognizer is useful if it reliably detects a species when it is present. To study calling behaviour, a large majority of the vocalizations on recordings need to be detected. One of the problems with comparing performance of recognizers is there are no established standard assessment metrics or detection thresholds, and there are few comparisons of performance across approaches or software programs (but see Acevedo et al. 2009). The need for a common framework in the development and assessment of recognizers for automated species recognition has been identified (Blumstein et al. 2011) and some progress has been made toward this goal (Potamitis et al. 2014), but more collaborative work is still needed in this area.

Automated species recognition is not the only recent advance in tools for processing acoustic recordings. There are now several packages available in R (R Core Team 2017) that can import sound files and offer various sound analysis functions. The R package ‘seewave’, for example, has functions for time, amplitude and frequency analyses, as well as generating sounds for playback experiments (Sueur et al. 2008). The ‘soundecology’ package has functions to implement acoustic indices to characterize animal acoustic communities and soundscapes from the physical attributes of sound on recordings (Villanueva-Rivera and Pijanowski 2016). In addition to automated species recognition, the ‘monitoR’ package has functions to rename recordings and isolate shorter segments in long recordings, which can be useful if using an ARU with limited scheduling capabilities (Katz et al. 2016). The recently developed ‘warbleR’ package builds off ‘seewave’ and ‘monitoR’ functions to streamline analyses of acoustic signal structure by measuring signal parameters (frequency, time and amplitude), pairwise acoustic dissimilarity, and performing pairwise spectrogram cross-correlations (Araya-Salas and Smith-

Vidaurre 2017). Another type of advance in bioacoustics processing is the development of an automated monitoring network that combines hardware and software to record sound in the field, send the recordings to a data server in real time for processing, and includes tools for data management and automated species recognition (Aide et al. 2013). Advances in bioacoustic processing will no doubt continue to improve the efficiency of processing large volumes of acoustic recordings.

Statistical approaches to analyzing ARU data

Statistical analyses of acoustic data collected with ARUs presents several possibilities and challenges. Estimating species density or abundance per unit area is important for conservation research, monitoring programs and wildlife management planning. ARUs are basically unlimited distance point counts, making it problematic to estimate density because the detection radius and consequently the area surveyed can change across species and habitats (Yip et al. 2017a, 2017b). One approach is to estimate a detection radius for each species by broadcasting calls at varying distances from the ARU and calculating a radius based on what observers can hear from a set of sounds known to have occurred at set distances (Yip et al. 2017a). Another similar approach is to use theoretical sound transmission and playback trials to determine a threshold volume (dB) of the calls within a certain radius. Lambert and McDonald (2014) determined that Australian bell miners (*Manorina melanophrys*) within a 50-m radius of the ARU would be louder than 70 dB, and were able to calculate density within this radius. A problem with these approaches is that the output volume of bird vocalizations has rarely been measured, making it difficult to determine an appropriate volume for the playback. An inappropriate playback volume could either underestimate or overestimate the detection radius, and there remains considerably more work to do in this area.

Distance sampling has been lauded as a useful tool to estimate density from point counts (Rosenstock et al. 2002). Distance sampling estimates the rate of missed detections based on the distance between observers and detected animals by fitting a detection function that corrects for individuals missed during a species count (Buckland et al. 2001). If it were possible to reliably estimate distance of species heard on ARU recordings (e.g. using amplitude or a measure of signal strength), distance sampling to estimate density could be feasible, but more work is still needed in this area. A more promising approach is to use arrays of passive detectors and spatially explicit capture-recapture methods to estimate density from locations of individuals (Efford et al. 2009). This approach has been extended to estimate bird densities from an array of acoustic recorders, and was more precise than mist-netting (Dawson and Efford 2009). The key with this approach is that individuals must be able to be identified from vocalizations, though individuals do not need to be localized, the models instead estimate call density from the spatial pattern of detections (Efford et al. 2009). This approach holds promise for estimating bird densities using ARUs, but it will require considerable investment in equipment and time spent analyzing acoustic data before researchers can implement it.

Estimating occupancy from acoustic surveys may be a more feasible alternative to estimating density. Occupancy modelling uses repeat observations at sites to estimate detectability and account for imperfect detection when estimating the probability of a species occupying a site or patch (MacKenzie et al. 2002). Acoustic data collected with ARUs are well suited for this approach because of the ease of increasing the number of observations, or 'visits', with no additional field time required. Increasing the number of visits and sampling sites improves the accuracy and precision of occupancy estimates (MacKenzie et al. 2002). Automated species recognition from ARUs can be an efficient method to obtain data from acoustic recordings for occupancy modeling (Campos-Cerqueira and Aide 2016). An issue with estimating occupancy is that interpreting the biological meaning of the results requires some knowledge of species movement and home range size. For example, if a species movement rate is low and they have a small home range size, then a single ARU is appropriate to determine occupancy of that species because it is unlikely to move in and out of the area surveyed and thus meets the assumption of closure. Violations of the assumption of closure can lead to overestimates of the probability of occupancy (Rota et al. 2009). For species with larger home ranges than the area surveyed by a single ARU, an occupancy modelling approach may still be used, but interpreted as the probability of the species using an area during the sampling season as opposed to occupancy. Assessing occupancy in such a context and using it to provide an index of abundance may require multiple ARUs to define a sampling unit.

The occupancy modelling approach is quite flexible and has been adapted to deal with a variety of different sampling scenarios. The original model estimates occupancy of a single species during a single season (MacKenzie et al. 2002). Multi-season or dynamic models estimate colonization and local extinction of sites or patches by a single species over multiple seasons (MacKenzie et al. 2003). Co-occurrence models account for interactions between species on occupancy and detection (MacKenzie et al. 2004), and have been used to investigate competitive exclusion between northern spotted owls (*Strix occidentalis caurina*) and barred owls (*Strix varia*) in Oregon (Bailey et al. 2009). It is possible to allow for both false negative and false positive error rates when modeling site occupancy (Royle and Link 2006). Occupancy models developed to use data from multiple detection methods could prove useful for surveys that use human observers and ARUs in combination to be able to make inferences about method-specific detection probabilities (Nichols et al. 2008). There are also Bayesian approaches to occupancy modeling (Royle and Kéry 2007, Kéry and Royle 2008). Many of the occupancy models mentioned above can be implemented using the R package 'unmarked' (Fiske and Chandler 2011), and are an important statistical tool for analyzing and interpreting acoustic data collected with ARUs.

A future challenge of analyzing acoustic data from ARUs is integrating data that was collected differently and over different lengths of time. This will be a challenge for biodiversity monitoring programs that may change recording technology as new models of ARUs become available. A practical solution is for monitoring programs to have a period of overlap between older and newer ARU models to be able to make direct comparisons between units (Rempel et al. 2013). Recording schedules within a monitoring program may also change from year to year as methods become more refined or as different species become important targets for conservation. One of the main challenges with analyzing ARU data is determining the unit of replication, and this can be particularly problematic if the sampling effort at a point is inconsistent between years. In addition to changes in sampling effort (i.e. recording schedule), the microphones can degrade and lose sensitivity with field use (Turgeon et al. 2017), and the settings used for the audio recordings can differ, all of which can affect the number of species that are detected. Occupancy modelling can provide some solutions to these issues, as differences in detection probability between methods can be estimated (e.g. different models of ARUs) and the models can handle missing data if some visits are missed, which may occur if the ARU fails to record at a particular point in time. Nevertheless, research and monitoring programs using ARUs will need to consider these issues and should have a system of quality control to ensure that microphones and ARUs are meeting a set standard each time they are deployed.

Current and future applications

ARUs have the potential to be used in innovative ways in avian ecological research beyond simply being a substitute for a human observer. We highlight some examples of applications of ARUs that fall into three general research categories: biological monitoring, animal movement, and communication behaviour. ARUs can be an effective method for tracking presence/absence of multiple taxa for monitoring and conservation. ARUs can monitor the success of conservation programs (e.g. activity at seabird colonies after invasive predator eradication, Buxton and Jones 2012). Monitoring can continue uninterrupted if ARUs are serviced and batteries and data storage are replenished. ARUs can be deployed at the same location for several weeks to record at the optimal time for multiple taxa. ARUs deployed in temperate regions, for example, can detect owls calling in early spring followed by amphibians and songbirds as the season progresses. The timing of biological surveys for monitoring is important to determine whether a species is present with some certainty, and the ability of ARUs to record over an extended period can facilitate getting the timing right.

Bioacoustic monitoring may extend beyond species counts to acoustic habitat mapping and soundscape monitoring in the future. In a recent paper, Dumyahn and Pijanowski (2011) argued that soundscapes have value worthy of conservation. Data processing methods have recently been established to characterize sounds from different sources (e.g. biotic, abiotic and anthropogenic) for acoustic habitat monitoring to detect changes in soundscapes (Merchant et al. 2015). In addition, various acoustic indices have recently been developed to characterize animal acoustic communities and soundscapes from the physical attributes of sound (Sueur et al. 2014). The Acoustic Complexity Index (Pieretti et al. 2011) for example, was tested to detect shifts in songbird phenology and was an effective, though coarse metric to detect the arrival of migrating songbirds (Buxton et al. 2016). While these acoustic indices do not provide information about which species are present, studies have suggested that some indices may be useful in estimating diversity (Depraetere et al. 2012), calling activity (Farina et al. 2011, Buxton et al. 2016), and directing the selection of recordings to process (Towsey et al. 2014). More rigorous testing and research on acoustic indices and their interpretation is needed, and avian studies can benefit and make important contributions to this research (Gasc et al. 2017). Newly developed tools in bioacoustics, such as acoustic habitat mapping and acoustic indices, may prove useful for bioacoustic monitoring, as well as habitat and biodiversity assessments.

Recording animal vocalizations using ARUs is a non-invasive method to collect data on animal movement patterns and habitat use on both large and small scales. At a large scale, ARUs can be used to study migration pathways and time of arrival of migratory birds (Farnsworth and Russell 2007, Sanders and Mennill 2014, Buxton et al. 2016). At a small scale, time-synced ARUs arranged in an array can allow for localization of individuals within their home range using time difference of arrival of acoustic signals (Mennill et al. 2006, 2012, Campbell and Francis 2012, Frommolt and Tauchert 2014). In addition to studying habitat use, localization can be used to estimate density (Lambert and McDonald 2014) using standard distance sampling methods (Buckland et al. 2001), and to study behavioural patterns associated with vocalizations (e.g. function of songbird duets, Mennill and Vehrencamp 2008). For some species it is possible to identify individuals using song discrimination techniques (Ehnes and Foote 2015, Petrusková et al. 2016), which could be useful for estimating return rates between breeding seasons and for behavioural studies tracking individuals throughout the breeding season. Localization can be used on any vocalizing species regardless of their size (unlike VHF tags), without capturing and handling them. A disadvantage of localization is that it increases data processing time substantially. Even with recently developed software (Wilson et al. 2014), this method is still very time consuming because each sound needs to be manually processed to calculate the time difference of arrival. Localization will be effective only for species that vocalize regularly and for species with individually unique vocal characteristics that persist over time (Mennill 2011), but can provide movement data for species that may be difficult to capture or too small for any other type of tracking technology.

ARUs have the ability to collect detailed data on vocalizing behaviour. Data on daily or seasonal vocalization patterns (e.g. Goyette et al. 2011, Sosa-López and Mennill 2014) can enable researchers to study communication and the effects of neighbourhood social context on vocal behaviour (e.g. Taff et al. 2014). New ARUs that can be attached to an animal (referred to as 'on-animal' devices or acoustic tags) can address different behavioural ecology questions than ARUs deployed in the environment. Acoustic tags have primarily been used in studies on marine mammals (Mellinger et al. 2007, Johnson et al. 2009), but were recently attached to common nighthawks (*Chordeiles minor*) in a study in northern Alberta (E. Knight pers. comm.). Acoustic tags have the benefit that they can record both intentional and unintentional vocalizations. Feeding noise is an example of an unintentional vocalization, and has been used to quantify daily time budgeting of mule deer (*Odocoileus hemionus*) (Lynch et al. 2013). Acoustic tags could prove useful for a wider variety of avian studies assuming the size of the technology decreases in coming years. Recording animal vocalizations from an ARU in the environment or attached to an animal provides an opportunity to address questions about vocalization characteristics, calling behaviour, foraging, movement, and effects of sound in the environment (including from anthropogenic sources) on animal behaviour.

CONCLUSION

ARUs have a number of benefits for avian ecological research including the ease of repeat sampling across spatial and temporal scales, reduced observer bias, reduced field time, and a permanent record of the survey. ARUs have comparable species detection rates compared with avian point counts using human observers, though there are some cases with lower detection rates for ARUs. Understanding the sampling distance of ARUs and how this varies relative to humans, other ARU types, and in different environments is a crucial area of research that is required to get the most from ARUs. Other drawbacks to be aware of include difficulty processing large amounts of data, storage capacity for the audio files, differences in recording schedules and settings between years, and potential recording problems as equipment ages. The drawbacks are not necessarily an issue if the equipment is properly maintained, the ecological question is appropriate for the use of ARUs, and careful thought goes into the study design. Much of the avian research using ARUs to date has focused on comparing species detection data from ARUs to human observers. While this is important to test for any new technology before using it more extensively, the results have demonstrated that ARUs are comparable. ARUs have the potential to be used in more innovative ways than simply as a substitute for a human observer in the field and we are excited to see how this new technology will provide fundamental insights into the ecology of vocalizing birds.

Table 2.1 Summary of studies that evaluated the performance of autonomous and non-autonomous acoustic recorders compared to traditional avian point counts with a human observer in the field. Studies were considered to have equal effort between the two methods if each method sampled for the same cumulative amount of time.

References	Recorder type	Effort	Metric	Performance
Acevedo & Villanueva-Rivera 2006	Autonomous	Unequal	Species richness	Recorder better
Alquezar & Machado 2015	Autonomous	Equal	Species richness Species composition	Equal
Borker et al. 2015	Autonomous	Equal	Single species call counts	Humans better
Campbell & Francis 2011	Non-autonomous	Equal	Species richness	Equal
Celis-Murillo et al. 2009	Non-autonomous	Equal	Species abundance Species richness Species composition Detection probability	Recorder better[1]
Celis-Murillo et al. 2012	Non-autonomous	Equal	Species richness Species composition Detection probability	Equal
Digby et al. 2013	Autonomous	Equal	Single species call counts	Equal[2]
Haselmayer & Quinn 2000	Non-autonomous	Equal	Species richness	Equal
Hobson et al. 2002	Non-autonomous	Equal	Species richness	Equal[3]

			Species abundance Species composition	
Holmes et al. 2014	Autonomous	Unequal	Presence/absence of 3 target species	Equal[4]
Hutto & Stutzman 2009	Autonomous	Equal	Species richness	Humans better
Klingbeil & Willig 2015	Autonomous	Equal	Species richness Species composition	Humans better
Leach et al 2016	Autonomous	Equal	Species richness Species composition	Humans better
McGuire et al. 2011	Autonomous	Unequal	Presence/absence of a target species	Equal
Sedlácek et al. 2015	Autonomous	Equal	Species richness Species abundance Species composition	Equal[5]
Sidie-Slettedahl et al. 2015	Autonomous	Equal	Abundance of 3 target species Detection probability	Humans better
Tegeler et al. 2012	Autonomous	Equal	Species richness	Equal
Van Wilgenburg et al. 2017	Autonomous	Equal	Detection probability	Equal[6]
Venier et al. 2012	Autonomous	Equal	Species richness Species abundance	Humans better[7]
Wimmer et al. 2013	Autonomous	Unequal	Species richness	Recorder better

Zwart et al. 2014	Autonomous	Equal	Presence/absence of a target species	Recorder better

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[1] Similar number of species were detected for both methods, but there were differences in species composition between methods. Probability of detecting birds was higher when listening to recordings, and the data from recordings yielded more reliable estimates of detection probability and abundance than human point count data.

[2] Human observers detected more calls, but both methods produced the same results for the most important conservation information from the survey: the annual change in calling activity of little spotted kiwi (*Apteryx owenii*).

[3] Human observers detected a few more species, but the species composition was very similar and species abundance estimates did not differ between methods.

[4] Using an automated recognition approach to detect target species on recordings worked as well as point counts with human observers for Acadian flycatcher (*Empidonax virescens*) and cerulean warbler (*Setophaga cerulea*), but point counts outperformed recordings for prothonotary warbler (*Protonotaria citrea*).

[5] Species richness was not significantly different between methods, and species composition was similar. Although there was a strong correlation between species abundance for the two methods, the recorders underestimated abundance for several bird species.

[6] Most species in this study did not show a bias in detection probability between methods and raw counts were comparable between methods, though a few species did show substantial bias.

[7] Humans performed better compared to an autonomous recording unit (Song Meter SM1 by Wildlife Acoustics) and this comparison was the primary objective of the study, but a non-autonomous recorder (E3A by River Forks) also included in the study performed equally compared to humans.

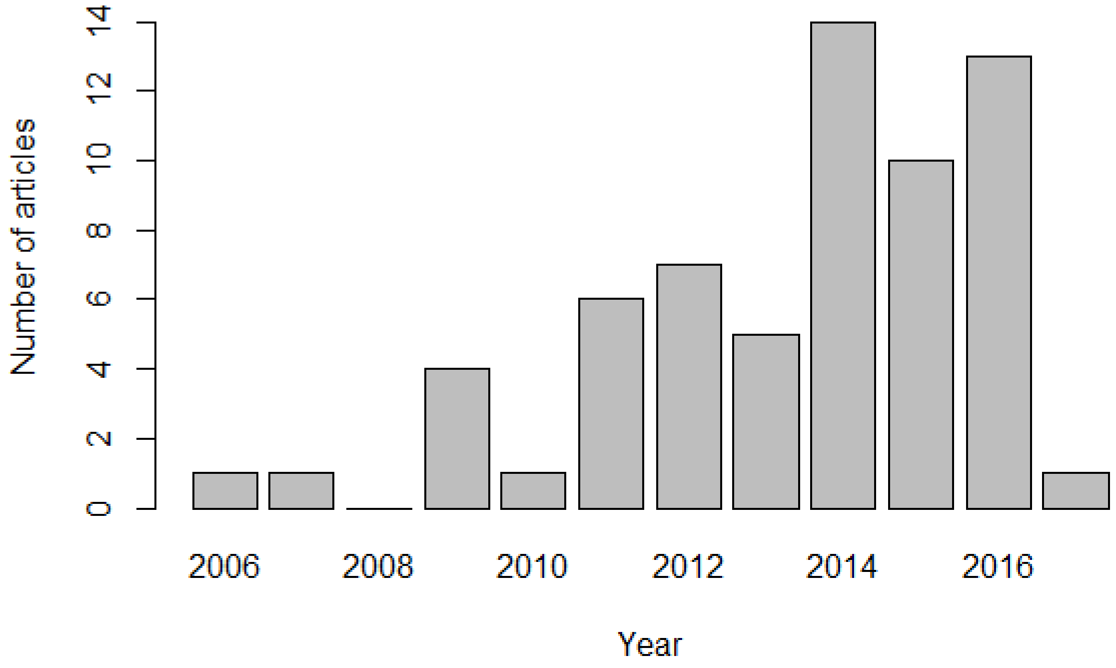

Figure 2.1 Original research articles published in peer-reviewed journals per year that used autonomous recording units for avian research. See Appendix 1, Table A1.1 for a list of all articles included in this figure.

Chapter 3. Utility of Automated Species Recognition for Owl Acoustic Monitoring

INTRODUCTION

Most owl species are difficult for human observers to detect visually due to their nocturnal habits, cryptic colouration, and occurrence at low densities. Owls are more effectively detected by their calls, and as a result, monitoring and research projects frequently use acoustic surveys to determine presence or abundance of owls (Goyette et al. 2011, Rognan et al. 2012). Owls use territorial vocalizations to attract mates and defend territories from conspecifics during the breeding season in early spring (Johnsgard 2002, Odom and Mennill 2010b), so detecting these calls is a reliable indicator that a species is occupying a territory. Tracking presence of owls using their territorial vocalizations can enable research and monitoring programs to estimate patch occupancy, and obtain information on owl habitat use and distribution across a landscape.

Acoustic surveys for owls often broadcast a recorded owl call (Clark and Anderson 1997, Sater et al. 2006, Grossman et al. 2008, Kissling et al. 2010). Broadcasting owl calls can increase the probability of detecting an owl by eliciting territorial individuals to call back (Kissling et al. 2010). The rationale for using call-broadcast surveys is that owl calling rates are thought to be low. Although a broadcast call can increase detection of owls, there are drawbacks. Call-broadcast surveys can draw owls in from a distance (Zuberogoitia et al. 2011), which could affect conclusions about habitat associations of owls. Detection from call-broadcast surveys may vary with different equipment, and can also affect detection of other owl species (Bailey et al. 2009, Wiens et al. 2011), which could be problematic if the survey is targeting multiple owl species. Depending on the study objective, passive acoustic surveys may be a less biased method for surveying owls.

Passive acoustic survey methods for owls do not broadcast calls. They can be implemented with field personnel as a traditional point count or with autonomous recording units (ARUs) that can be programmed to record on a set schedule and passively record owls calling. Traditional point counts are relatively time-consuming, and because the calling behaviour of owls may be affected by a variety of environmental factors including time of season, temperature, weather, and lunar phase (Clark and Anderson 1997, Kissling et al. 2010), this can constrain the timing of field surveys. Passive acoustic surveys using ARUs are increasingly used in avian research (Shonfield and Bayne 2017a) and can be useful for surveying rare and elusive species (Holmes et al. 2014, 2015, Campos-Cerqueira and Aide 2016) and for conducting nocturnal surveys for a variety of species including owls (Rognan et al. 2012). An important benefit of using ARUs for nocturnal owl surveys is that the units can be set up at any time and left out for extended periods. This reduces the challenges and constraints of planning surveys during optimal weather conditions, reduces observer bias, and eliminates many of the safety concerns for field personnel conducting nocturnal field work during the late winter/early spring.

The probability of detecting an owl is an important consideration when selecting a survey method because false absences (i.e. failure to detect an owl when present) can lead to biased estimates and misleading inferences. At first glance, call-broadcast surveys may seem preferable because if the probability of detecting an owl is increased compared to a passive survey, then this should lead to fewer false absences. However, an ARU can increase the cumulative detection probability of owls because it can record on a set schedule for several days or weeks. Thus, an ARU can reduce the problem of lower detection probabilities of passive surveys and increase the utility of the survey data by increasing the number of sampling occasions while still only requiring two visits by field personnel. For these reasons, using ARUs for passive acoustic surveys appears to be a promising new approach for studying and monitoring owls.

Acoustic datasets collected with ARUs over extended time periods can be large and daunting to process. Automated species recognition of animal vocalizations is changing this. This process involves matching recording segments to a template (often termed a “recognizer”) derived from training data and registering a hit when a similarity threshold is reached. A few different approaches have been developed, including band-limited energy detectors (Mills 2000), binary point matching (Katz et al. 2016), decision trees (Acevedo et al. 2009, Digby et al. 2013), random forest (Ross and Allen 2014), spectrogram cross-correlation (Katz et al. 2016), hidden Markov models (Wildlife Acoustics 2011), and most recently deep learning through convolutional neural networks (Salamon and Bello 2017). A few are easily accessible to researchers through commercial or open source software, including hidden Markov models in Song Scope (Wildlife Acoustics Inc., Maynard, MA U.S.A.), cluster analysis in Kaleidoscope (Wildlife Acoustics Inc., Maynard, MA U.S.A.), band-limited energy detectors in Raven Pro (Cornell Laboratory of Ornithology, Ithaca, NY U.S.A.), and spectrogram cross-correlation in R package ‘monitoR’ (Hafner and Katz 2017), Avisoft SASLab Pro (Avisoft Bioacoustics, Berlin, Germany), and Xbat (Cornell Laboratory of Ornithology, Ithaca, NY U.S.A.). Automated recognition and programs that can implement this approach are likely to be useful for a variety of projects using acoustic monitoring.

Previous studies have used automated recognition techniques to process acoustic recordings more efficiently for birds and amphibians (Buxton and Jones 2012, Frommolt and Tauchert 2014, Taff et al. 2014, Colbert et al. 2015, Holmes et al. 2015, Brauer et al. 2016). Automated recognition techniques perform poorly when there are a lot of overlapping calls (Buxton and Jones 2012, Digby et al. 2013) either from conspecifics or heterospecifics, and may also perform poorly if there is a lot of abiotic noise on the audio recordings. The effect of noisy recordings on the performance of automated acoustic recognition is important to assess because natural noise is present everywhere and anthropogenic noise is becoming increasingly prevalent in natural areas.

Owl calls are potentially well-suited to automated species recognition. The calls are unlikely to overlap with conspecifics (except for some minimal overlap during male–female duets in some species), and few other species are present or vocally active at the same time, as owls call nocturnally in late winter/early spring. In the acoustic data we have collected, it is rare to hear two or more owl species calling on the same audio recording (about 1 in 100 recordings, J. Shonfield unpubl. data). Conducting passive acoustic surveys with ARUs and combining this approach with automated species recognition may be an efficient method of increasing the probability of detecting owls during passive surveys, and subsequently increasing the statistical power to detect trends and habitat specific differences in abundance. There is interest in using automated recognition of owls for acoustic surveys, and we are aware that this approach is being tested for surveys of spotted owls (*Strix occidentalis*; J. Higley, Hoopa Tribal Forestry, pers.

comm.; M. Hane, Weyerhauser, pers. comm.); however, there is a gap in the literature on whether this is effective for other species of owls.

In this study, we used ARUs to conduct acoustic surveys for owls in northeastern Alberta. Our main objective was to test the utility of automated computer recognition techniques to process acoustic data collected with ARUs to determine presence/absence of owls at survey locations. We chose three owl species found throughout Canada and the United States: the barred owl (*Strix varia*), the boreal owl (*Aegolius funereus*), and the great horned owl (*Bubo virginianus*). We built templates (hereafter "recognizers") for each species to scan through our large acoustic dataset and automatically identify the territorial calls of these owls. We built two different recognizers for barred owls using different parts of their territorial call because it is longer and more complex than the calls of the other two species. To evaluate the utility of the recognizers we did two comparisons of results; first, we compared the results of owl detections obtained from the recognizers to the results of detections obtained from listening to a subsample of the recordings. Second, we compared the results of the two barred owl recognizers to evaluate the effect of using different templates to identify different parts of the call. For both comparisons, our specific objectives were: (1) to assess the performance of each recognizer by evaluating the precision (probability of a recognizer match being a true match), total processing time, and false negatives; (2) to assess whether noise level on recordings affects the precision of a recognizer; and (3) to compare results of owl habitat associations based on different survey methods using occupancy models.

METHODS

Study area

We selected study sites in upland forested areas of the Lower Athabasca planning region in northeastern Alberta, located south of Fort McMurray, north of Lac la Biche and northwest of Cold Lake (Figure 3.1). Forests in the study area were composed primarily of trembling aspen (*Populus tremuloides*), white spruce (*Picea glauca*), and black spruce (*Picea mariana*) trees. All sites were >3 km apart. We surveyed 45 sites with varying levels of industrial noise that were selected based on the type of industrial noise present. Chronic noise sites (*n* = 13) had either an *in-situ* oil processing plant facility or a compressor station present at the center of the site, both of which produced continuous noise at a loud level. Intermittent noise sites (*n* = 17) were positioned with a road bisecting the site, and had intermittent traffic noise but no chronic noise present. Control sites (*n* = 15) did not have a road or industrial infrastructure present and thus had no industrial noise. The area surveyed at each site (256 ha) approximated the home-range size of pairs of barred owls and great horned owls during the breeding season (Mazur et al. 1998, Bennett and Bloom 2005, Livezey 2007). The estimates for boreal owl home-range sizes during the breeding season vary widely between studies (Hayward et al. 1993, Santangeli et al. 2012), but are likely smaller than our sites.

Acoustic surveys

We conducted passive acoustic surveys for owls using a commercially available ARU: the SM2+ Song Meter (Wildlife Acoustics Inc., Maynard, MA U.S.A.). We programmed each ARU to turn on and record in stereo format for 10 min at the start of every hour at 44.1 kHz with a 16-bit resolution. Recording files were stored in .wac format, a loss-less audio compression format that is proprietary to Wildlife Acoustics. We recorded in stereo format to have a backup channel in case one of the microphones failed or was damaged in the field. We tested each ARU and both microphones prior to deployment to identify any units with non-responsive channels or degraded microphones. We used gain settings of 48 dB for both the left and right channel microphones. We installed ARUs at each site for approximately 2 weeks between 21 March 2014 and 6 May 2014, which is when owls are actively calling (Clark and Anderson 1997, Kissling et al. 2010). We attached ARUs at a height of approximately 1.5 m on trees with a diameter smaller than the width of the ARU (18 cm). At intermittent noise sites and control sites, we deployed five ARUs in a square formation, with one at each corner spaced 1.6 km apart, and one in the center positioned 1.2 km from each corner. At chronic noise sites, we deployed six ARUs per site with the sixth ARU on an adjacent or opposite side of the noise source a minimum of 200 m from the central ARU. We assumed the detection radius of a single ARU would be reduced in noisy areas, so the additional ARU was deployed to increase the area surveyed near noise sources and to increase our sample size of the number of locations we surveyed with loud noise. In total, we deployed ARUs at 238 locations across 45 sites; however, one ARU failed to record completely, so we effectively surveyed 237 locations.

For comparison to the recognizers, we listened to a subsample of recordings by randomly selecting four dates for each site, and listening to the midnight recordings (each recording was 10 min in duration) on those dates from each ARU deployed at that site. We used Adobe Audition CS6 (Adobe Systems Inc., San Jose, CA U.S.A.) to visualize each recording as a spectrogram to help locate and identify vocalizations while listening to recordings. Four trained researchers identified owls calling on the recordings, and assessed industrial noise on each recording based on the following index: no noise (noise code 0), low and distant (noise code 1), moderate (noise code 2), and very loud and close (noise code 3). We took the modal noise index from the four 10-minute recordings and used that as the noise-level ranking at that ARU location. Researchers also kept track of the amount of time it took to listen and transcribe the data from each recording to keep track of processing time for listening. Researchers were trained using sample owl clips and practiced listening of 25 example recordings prior to data collection. Any detections that they could not confidently identify were checked by a researcher with 2 years of experience identifying owls on recordings (JS); JS also conducted random checks of recordings to ensure accuracy.

Building recognizers

We used the program Song Scope 4.1.3A (Wildlife Acoustics Inc., Maynard, MA U.S.A.) to build recognizers to detect the territorial calls of three owl species: the two-phrased hoot of the barred owl (Odom and Mennill 2010a), the trill of the boreal owl (also known as the staccato song, Bondrup-Nielsen 1984), and the territorial hoot of the great horned owl (Kinstler 2009). For the barred owl call, we created two different recognizers, one for the entire two-phrased hoot and one for the terminal two notes of the two-phrased hoot (Figure 3.2). We used several clips from the field recordings of good quality calls we identified from listening and annotated them in Song Scope to be used as training data to build each recognizer (Appendix 2, Table A2.1). We considered calls to be “good quality” if they were produced near the microphone (i.e. had little attenuation) and were not masked by acoustic signals from other animals or abiotic noise. We used good quality calls from as many different locations within our study area as possible, rather than using many annotations from the same recording because increasing the number of locations can have a positive effect on the precision of a recognizer (Crump and Houlahan 2017). We used 51 annotations of the entire two-phrased hoot of the barred owl from 17 locations, 26 annotations of the terminal two notes of the barred owl two-phrased hoot from nine locations, 42 annotations of the boreal owl trill from seven locations, and 83 annotations of great horned owl territorial hoots from eight locations (Appendix 2, Table A2.1).

When building a recognizer, the user can adjust the settings in Song Scope to improve signal detection of the annotated clips. We kept the sample rate, background filter, Fast Fourier Transform (FFT) window size, and overlap settings consistent across all recognizers (Appendix 2, Table A2.1). Based on the call properties of each species, we adjusted the minimum and maximum frequency and timing settings (maximum syllable length, gap between syllables, and maximum song length) to constrain the program to only identify candidate signals within these settings (Appendix 2, Table A2.1). Song Scope uses hidden Markov models to match recording segments to a recognizer template derived from training data and registers a hit when a similarity threshold is met (Wildlife Acoustics 2011). For each detected vocalization, Song Scope provides two values: a quality value (between 0.0 and 99.9) that indicates where the vocalization fits within a statistical distribution of parameters from the training data used to build the recognizer, and a score value (between 0.00 and 99.99) indicating the statistical fit of the vocalization to the recognizer model (Wildlife Acoustics 2011). The user sets a minimum quality and minimum score threshold each time a recognizer is run through a set of acoustic data. Lower thresholds lead to more hits and more false positives, but higher thresholds can lead to more false negatives. The choice of whether to minimize false positives or false negatives should depend on the study objective (Crump and Houlahan 2017). We aimed to use the data to determine presence/absence of owls, so we wanted to minimize false positives while still detecting owls at all locations where we detected them by listening to recordings. From test runs on a small subset of our acoustic dataset, we settled on using a minimum quality setting of 50 and a minimum score setting of 60, and used these values for all four recognizers when scanning all recordings collected in 2014. Though we recorded in stereo, Song Scope scans one channel at a time, so we scanned the left channel only because there was no damage in the field to any of the microphones.

Processing recognizer results

The results output from each recognizer had a number of false positives (i.e. hits that were not the target owl species), so five trained researchers verified all hits generated by the program before compiling the data. As with the listening data, detections that researchers could not confidently identify were checked by JS, who also conducted random checks to ensure accuracy. To address our first objective, we quantified true positives and false positives to calculate the precision of each recognizer as the proportion of true positive hits out of the total number of hits. We quantified false negatives by determining the number of locations where owls were detected by listening but missed by the recognizers. We quantified false negatives at two spatial scales: at the scale of an individual ARU location, and at the scale of a site by pooling detections from all ARUs within a site. To estimate processing time, observers kept track of the time to verify the hits for a subset of the data processed by the recognizers (a minimum of 13 sites for each recognizer). We estimated for each recognizer how many hits can be verified per minute of observer processing time, and used this rate to calculate the total processing time of each recognizer based on the total number of hits generated by Song Scope. We then compared the total processing time of the recognizers to the total time spent listening to recordings.

To address our second objective to assess whether noise level on recordings affects the precision of a recognizer, we assigned a noise index ranking for each ARU location by using the modal noise index from our assessment while listening to recordings. For each noise-level rank, we calculated the average number of all hits per ARU location. We also calculated the proportion of true hits (i.e. the target species) weighted by the total number of all hits per ARU location for each noise-level rank. This weighted average is the average precision, and we compared these values between noise levels for each recognizer to assess whether increasing noise on recordings led to a decrease in precision of a recognizer. We also checked the noise levels of the locations where owls that were detected from listening to recordings were missed by the recognizers.

Occupancy analysis

Occupancy modelling uses repeated observations at sites to estimate detectability and account for imperfect detection when estimating the probability of species occurrence (MacKenzie et al. 2002). To address our third objective, to compare results of owl habitat associations based on different survey methods, we ran single-species single-season occupancy models for each owl species separately using the package ‘unmarked’ (Fiske and Chandler 2011) in R version 3.3.3 (R Core Team 2017) using RStudio version 1.0.143 (RStudio Team 2017). For the occupancy models, we compiled detection histories from the data obtained from listening and the data from the recognizers. The listening data consisted of four recordings from each ARU at a site, so we compiled a detection history for each ARU location from these four “sampling occasions.” For the data obtained from the recognizers, we used each day as a separate “sampling occasion.” All ARUs were deployed for a minimum of 13 days, so we compiled a detection history of each ARU location for 13 sampling occasions, each consisting of a 24-hr period. ARUs with complete recording failures were not included in the dataset (*n* = 1). ARUs that failed at some point during the deployment (*n* = 12) and did not record for all 13 days were indicated in the detection history as "missed surveys" on days that they did not record. Occupancy modeling can deal with these "missed surveys" if they are indicated in the detection history. Owls are unlikely to be found consistently within the area around an ARU due to movement, so occupancy models at this scale represent use of the area as opposed to occupancy per se. Hereafter, we use the term "use," to represent the probability of an owl using the area we surveyed with an ARU during the breeding season.

We ran occupancy models with forest composition as a continuous predictor variable of the occupancy parameter (i.e. seasonal use) to compare results of owl habitat use across methods (data extracted from listening or using a recognizer). We ran separate models for each species and for each extraction method. We extracted data on forest composition in ArcGIS 10.3.1 (Environmental Systems Research Institute, Inc., Redlands, CA U.S.A.) by calculating the proportion of coniferous forest weighted by area from the Alberta Vegetation Inventory (AVI) within an 800-m-radius buffer around each ARU location. We used an 800-m radius buffer because this approximated the maximum detection radius of an ARU to detect owls calling (Yip et al. 2017). For barred owls, we included a quadratic term for proportion coniferous forest, because previous research indicates they prefer mixedwood forests (Mazur et al. 1998, Russell 2008). For boreal owls and great horned owls, we did not include a quadratic term for proportion coniferous forest, as boreal owls prefer coniferous forests (Hayward et al. 1993, Lane et al. 2001) and great horned owls are found in a wide variety of forest types (Johnsgard 2002). We compared the estimates of use in response to forest composition between the listening and recognizer acoustic datasets. We ran occupancy models for each of the barred owl recognizer templates and compared them to determine if different biological inferences would be drawn about barred owl habitat use based on different methods of data collection. We did not include forest age as a covariate in our models, because initial analyses with forest age extracted from the AVI layer suggested it was not a good predictor of occupancy for any of the three owl species. This was likely due to limited sampling in young forest stands. Mean forest age around each ARU ranged from 21–153 years (overall mean of 92 years), but 96% of stations were surrounded by mature forest (>50 years old), and 84% of stations were surrounded by old forest (>80 years old).

RESULTS

We listened to a total of 944 recordings, approximately 157 hours of audio data. Each 10-minute recording took an average of 11 minutes to listen and record data, and from this we estimated that listening took approximately 174 hours in total. Song Scope scanned 84,516 recordings (approximately 14,086 hours of audio data), and this scanning process was repeated for each of the four recognizers. The amount of processing time required for trained observers to check the output results varied among the recognizers due to differences in verification rate (the number of hits observers could check per minute) and the total number of hits (Table 3.1). Each of the recognizers generated true positives and false positives and the precision of each recognizer varied widely. Both barred owl recognizers had the highest number of total hits and the lowest precision, whereas the great horned owl and boreal owl recognizers had fewer hits and greater precision (Table 3.1). Total verification time for each recognizer, calculated by dividing the verification rate by the total number of hits, was lowest for the great horned owl recognizer and highest for the boreal owl recognizer (Table 3.1). The total verification time summed across all four recognizers is approximately 30 hours, which was substantially less than the 174 hours spent listening to a small subset of the total recordings collected.

We compared the locations where each owl species was detected by listening to where they were detected by the recognizers to determine false negatives. The recognizers increased the number of locations where barred owls and great horned owls were detected, but detected boreal owls at slightly fewer locations compared to the listening data (Table 3.2). The recognizers for barred owls (full two-phrased hoot) and great horned owls detected these owls at all sites where they were detected by listening to the recordings; however, the boreal owl recognizer failed to detect this species at four sites where they were detected by listening. All recognizers missed owls at some ARU locations, but for barred owls (full two-phrased hoot) and great horned owls there were few locations missed, whereas for boreal owls the number of locations missed was 8 times higher (Table 3.2).

The two barred owl recognizers performed similarly when compared to the data from listening. The terminal note recognizer detected barred owls at one more site and ARU location than the full two-phrased hoot recognizer, but had lower precision (Table 3.2). Despite the similarity of the total number of sites and ARU locations with barred owl detections, when the results of the two recognizers were directly compared, it became evident that the two recognizers did not detect the target species at all the same locations (Table 3.3). When the results of both recognizers were pooled, this yielded the highest number of locations with barred owl detections (Table 3.3).

Of the locations we surveyed with ARUs, 101 had no noise (noise level index 0), 79 had low noise (noise level index 1), 32 had moderate noise (noise level index 2), and 25 had loud noise present on the recordings (noise level index 3). For all four recognizers, there were few hits in total at loud locations (noise index of 3; Figure 3.3). For the two barred owl recognizers, the greatest number of hits occurred at ARU locations with low levels of noise (index of 1); however, for the boreal owl and great horned owl recognizers, there was little difference in the number of hits regardless of whether there was no noise or moderate noise on the recordings (Figure 3.3). The average precision for the two barred owl recognizers was slightly lower at locations with low noise compared to locations with no noise (Figure 3.4). There were no detections of barred owls at any ARU locations with moderate or loud noise (Figure 3.4). The average precision of the boreal owl recognizer was consistent between locations with no noise and moderate noise (noise indices 0 to 2), and there were no hits at all at locations with loud noise (noise index 3; Figure 3.4). The great horned owl recognizer also had consistent precision between locations with no noise and moderate noise (Figure 3.4). Oddly, the great horned owl recognizer had higher precision at locations with loud noise (Figure 3.4). Closer inspection of these results revealed that there were only two ARU locations at this noise level with hits from the recognizer, and for all of them the calls of a great horned owl were clearly audible despite the loud noise. Of the three locations where the recognizers missed barred owls and great horned owls where they were detected from listening to recordings (Table 3.2), two had no noise and one had low noise. Of the 24 ARU locations where boreal owls were missed (Table 3.2), 16

ARU locations had no noise, four ARU locations had low noise, and four ARU locations had moderate noise. Of the four sites where the recognizer missed boreal owls, three were sites with a chronic noise source and one was a site with no noise.

We compared the results of the occupancy models from the recognizer and listening data for each species with forest composition as a covariate to assess whether conclusions drawn about owl habitat use were consistent across acoustic methods. For barred owls, we found similar patterns of habitat use across proportion coniferous forest for the two recognizer templates (Figure 3.5). From both recognizers, we found that barred owl habitat use is highest for forests with a mix of deciduous and coniferous trees (Figure 3.5). In contrast, the results from the listening data show a less clear pattern and much lower estimates of probability of use (Figure 3.5). For boreal owls, we found a similar pattern of increasing habitat use as forests increase in the proportion of coniferous trees for both the recognizer and listening data; however, the listening data had consistently higher overall estimates of probability of use (Figure 3.5). Great horned owls had similar estimates of probability of use across the range of forest composition, but we saw a dramatic difference in the precision of these estimates between the recognizer data and listening data (Figure 3.5). The 95% confidence intervals for the listening data are large, and this is likely due to low detection of great horned owls by listening to recordings and few repeat detections at the same ARU location.

DISCUSSION

Using ARUs to conduct passive surveys facilitates collecting acoustic data over longer time scales but leads to large volumes of data that can be very time-consuming to process.

Recognizers can potentially provide a solution by scanning the data to search for and identify calls of a target species. For large monitoring projects, it would not be feasible to listen to more than a few recordings per location, leading to a small sample size. Using recognizers allows more recordings to be processed, which can increase the sample size and the number of detections of the target species. Before recognizers can be employed in monitoring or research projects, it is important to test their performance. Our overall objective was to test the utility of recognizers for detecting three owl species found in North America. The first step was to assess performance of recognizers based on precision, false negatives, and processing time. Out of all hits generated by the great horned owl and boreal owl recognizers, 72% and 99% were the target species calls, respectively. This precision is within the range of precision reported for other recognizers for bird and amphibian species using the same software (Buxton and Jones 2012, Brauer et al. 2016). For both barred owl recognizers, ~2-3% of all hits were barred owl calls. These recognizers had lower precision than the other two owl species recognizers, but that precision was similar to a recognizer built to identify wild turkey (*Meleagris gallopavo*) calls using the same Song Scope software (Colbert et al. 2015). At first glance, the barred owl recognizers may seem less useful because of their low precision and high number of false positives. Precision is useful in comparing different recognizers (Crump and Houlahan 2017), but is not necessarily the best metric to assess performance of a recognizer. If recognizers are very precise then they have few false positives but potentially more false negatives.

Quantifying the number of false negatives is important to assess recognizer performance because it indicates what the recognizer is missing. Listening and/or visually scanning recordings are currently the best options to determine what the recognizer is missing (Buxton and Jones

2012, Brauer et al. 2016, Campos-Cerqueira and Aide 2016, Crump and Houlahan 2017). However, it can be difficult to objectively assess when a recognizer has truly missed a vocalization. For example, a study on several seabird species visually scanned recordings but only considered decent-quality calls not detected by the recognizer as false negatives (Buxton and Jones 2012). Our general impression is that the signal-to-noise ratio likely influences the rate of false negatives, although we did not examine each missed vocalization to assess if it was faint. Our objective was to evaluate the utility of using automated recognizers to assess owl presence or absence at each survey location, so knowing the number of locations where recognizers missed owls was more important than determining how many recordings or how many calls on the recordings were missed. Given this objective, the recognizers for barred owls and great horned owls performed well considering only three locations were missed for each species. The boreal owl recognizer did not perform as well and detected this species at fewer locations than listening, an example of the trade-off between precision and false negatives (Crump and Houlahan 2017). If a recognizer is less precise, then it will generate more false positives but potentially fewer false negatives, which was the case for the barred owl recognizers. The great horned owl recognizer appeared to balance this trade-off, because it had high precision and few false negatives. To reduce the false negatives for the boreal owl recognizer, we could try decreasing the score threshold, but this would likely decrease the precision and increase processing time. Another option would be to combine the two approaches, e.g. use the recognizer first and then subsequently listen to a subset of recordings at ARU locations where boreal owls were not detected by the recognizer. Despite some shortcomings, the benefit of using the recognizers to determine presence/absence of owls was that we were able to process many more recordings and obtain a much larger dataset of owl detections than would have been possible with either listening to recordings only or conducting owl field surveys without using ARUs.

The recognizers differed by more than 2.5 times the estimated processing time required for trained researchers to check the output results (Table 3.1), due in part to the ratio of true positives to false positives. Currently, the best way to deal with false positives is to have trained researchers review the computer output to filter them out before analyzing the data (Holmes et al. 2014, Colbert et al. 2015, Celis-Murillo et al. 2016). We were able to process the output in a reasonable amount of time (4 to 12 hours per recognizer), and it took substantially less time than listening to a small subset of the recordings. However, our estimate of processing time does not take into account the time required for the computer to scan the recordings. It was not always possible to know when the software finished scanning without monitoring it regularly, and the amount of time was dependent on the processing capability of the computer used. We used multiple computers with different processing capabilities, making it difficult to provide an estimate of the time spent scanning. However, it took a substantial amount of time to scan the data collected with the recognizers (on the order of several weeks), and this process had to be repeated to obtain results from all recognizers. Although it took much longer to listen to a subset of recordings, it was possible to obtain data on all owl species heard calling from listening to each recording only once. Listening to recordings was also necessary to obtain good quality clips of owl calls before starting the process of building a recognizer. For small audio datasets (<40 hours of recordings), it can be more efficient to listen to recordings, but this advantage disappears once datasets are larger than 40 hours (Knight et al. 2017). Our results indicate that for such a large dataset (approximately 14,086 hours of recordings) there is a significant benefit of using recognizers in terms of processing time.

There is a general perception that noisy recordings can be problematic for automated species recognition, but few studies have attempted to address this directly. We surveyed for owls in areas with varying levels of industrial noise and found that for the barred owl and great horned owl recognizers, no sites were missed and the ARU locations missed had low levels of industrial noise or none at all. The boreal owl recognizer missed some ARU locations with moderate and low noise, but the majority of ARU locations missed had no noise on the recordings. However, most of the sites missed for boreal owls were sites with chronic noise sources. The precision of the recognizers did not appear to be strongly affected by the presence of industrial noise. Industrial noise on the recordings was predominantly below 1000 Hz, which overlaps substantially with the frequency range of all three owl species calls. There were no detections of barred owls from the recognizers at locations with moderate or loud noise; this could be due to difficulties of the recognizers in detecting the calls, but we did not detect them from listening to recordings either, and thus barred owls may not be present in noisy areas. Similarly, boreal owls may not be present in areas with loud noise, which could explain the lack of detections from the recognizer or listening to recordings. Boreal owls were missed at several locations with moderate noise, indicating that they were sometimes present and calling in moderately noisy areas and the recognizer was not always able to detect them in these areas, potentially due to the frequency overlap with industrial noise. Great horned owls were detected in very noisy areas, and the recognizer appeared to be able to detect them despite the noise overlapping their calls. Overall, our results suggest recognizers can function in non-ideal recording environments to some extent.

We found that the two different recognizer templates we tested to detect barred owl calls performed similarly. We initially thought that because of the length and variability of the two-phrased hoot of the barred owl, that using the full call as the template might be less effective for automated recognition. The recognizer using the terminal two notes of the call had lower precision, and the increased number of false positives led to a greater total processing time. Both recognizers detected barred owls at a similar number of locations, but interestingly these locations did not completely overlap and each recognizer detected owls at a few different locations. Nevertheless, compared to the listening data both recognizers had few false negatives, and had nearly identical estimates of habitat use across a range of forest composition. These results suggest that biological inference on habitat use by owls is robust to changes in the template used to build a recognizer. Automated recognition approaches are still relatively new, and because there is no established methodology for building recognizers, it is important to explore potential differences in biological inferences from different methods. Other studies that have sought to identify best practices in building recognizers in Song Scope have focused on score threshold (Brauer et al. 2016), amount of training data, and temporal/spectral settings (Crump and Houlahan 2017). Our work contributes to this field, and suggests that for species with long vocalizations using a template of the entire vocalization does not negatively influence the effectiveness of automated recognition.

Acoustic surveys are often used to determine habitat associations of vocalizing species. So, for owl monitoring programs it is important to determine if the results of owl habitat use from automated recognition is consistent with results based on listening to recordings. Barred owls tend to be found most frequently in mixedwood forests (Mazur et al. 1998, Russell 2008), and our results of habitat use from both recognizers are congruent with the literature; however, the preference for mixedwoods was less apparent with the results from the listening data. Boreal owls tend to be found in more coniferous forests (Hayward et al. 1993, Lane et al. 2001), and we found a similar pattern of increasing habitat use in more coniferous forests for both the recognizer and listening data. Although the estimates of the probability of use by boreal owls is higher from the listening data across the range of forest composition, the trend is similar for the recognizer data and thus we would make similar conclusions of preferred habitat from either dataset. Great horned owls are habitat generalists and use a wide variety of different habitats across North America (Laidig and Dobkin 1995, Bennett and Bloom 2005, Grossman et al. 2008). So, it is not that surprising that our results suggest that great horned owls are equally likely to use areas across a range of forest composition. Although the estimates of habitat use were similar for both methods for great horned owls, the precision of the estimates from the occupancy models was much better using the recognizer dataset. Our results suggest that using automated recognition can lead to similar biological inferences in terms of owl habitat use, and can be preferable to obtain more precise estimates when using occupancy models for owls.

The recognizers we built for the different owl species worked well, and in our opinion their performance was adequate to determine presence or absence of owls within a study area. Our approach could assist in scanning recordings to assess fine-scale habitat preferences and estimate density by localizing individuals in microphone arrays, where each ARU is synchronized using the time on a Global Positioning System (GPS) attachment (Mennill et al. 2012). We used a particular software to test the utility of automated recognition of owl calls, but there are several other software options available (e.g. the R package monitoR (Katz et al. 2016), Raven Pro by the Cornell Lab of Ornithology). New software and new techniques are likely to be developed as the field of bioacoustics progresses, so we stress that this study is not to demonstrate the utility of the particular software that we used. We argue that given the low detection rates of owls by listening to recordings, using an automated recognition approach is likely to be highly useful for monitoring and studying owls. However, the output needs to be verified to remove false positives in the data. Despite the time needed to verify the output, we have clearly demonstrated the efficiency that can be gained by using recognizers for these owl species and we suggest that similar increases in efficiency could be obtained with recognizers built for other owl species.

Table 3.1 Output results from Song Scope for each owl recognizer, and the time necessary to verify the output.

Recognizer	Total Hits	True Positive Hits	Precision[1]	Verification Rate (Hits/min)	Total Verification Time (min)
Barred owl (full two-phrased hoot)	10,361	282	0.27	27	384
Barred owl (terminal two notes)	19,794	317	0.16	42	471
Boreal owl	6932	6862	0.99	10	693
Great horned owl	3069	2223	0.72	12	256

[1] Precision is calculated as the number of true positive hits divided by the total number of hits generated by each recognizer.

Table 3.2 Assessment of false negatives of owl recognizers detecting calls recorded on autonomous recording units (ARUs) deployed at 237 locations within 45 sites surveyed in the spring of 2014. Numbers in brackets are the percentages of sites and locations surveyed with detections. Sites and ARU locations missed by the recognizer had detections from listening, and sites and ARU locations added by the recognizer were not detected from listening to a subset of recordings.

Recognizer	Listening		Recognizer		Missed by Recognizer		Added by Recognizer	
	No. Sites	No. ARU Locations	No. Sites	No. ARU Locations	No. Sites	No. ARU Locations	No. Sites	No. ARU Locations
Barred owl (full two-phrased hoot)	7 (16%)	12 (5%)	19 (42%)	40 (17%)	0	3	12	31
Barred owl (terminal two notes)	7 (16%)	12 (5%)	20 (44%)	41 (17%)	1	4	14	33
Boreal owl	29 (64%)	71 (30%)	26 (58%)	63 (27%)	4	24	1	16
Great horned owl	16 (36%)	25 (11%)	40 (88%)	129 (54%)	0	3	24	107

Table 3.3 Comparison of the performance of the two barred owl recognizers based on the number of sites and autonomous recoding unit (ARU) locations where this species was detected using each recognizer. Numbers in brackets are the percentages of sites and locations surveyed with detections. Sites and ARU locations missed by each recognizer had detections from the other recognizer.

Recognizer	Sites with Detections	ARU Locations with Detections	Sites Missed	ARU Locations Missed
Barred owl (full two-phrased hoot)	19 (42%)	40 (17%)	4	12
Barred owl (terminal two notes)	20 (44%)	41 (17%)	3	11
Total locations with barred owl detections	23 (51%)	52 (22%)		

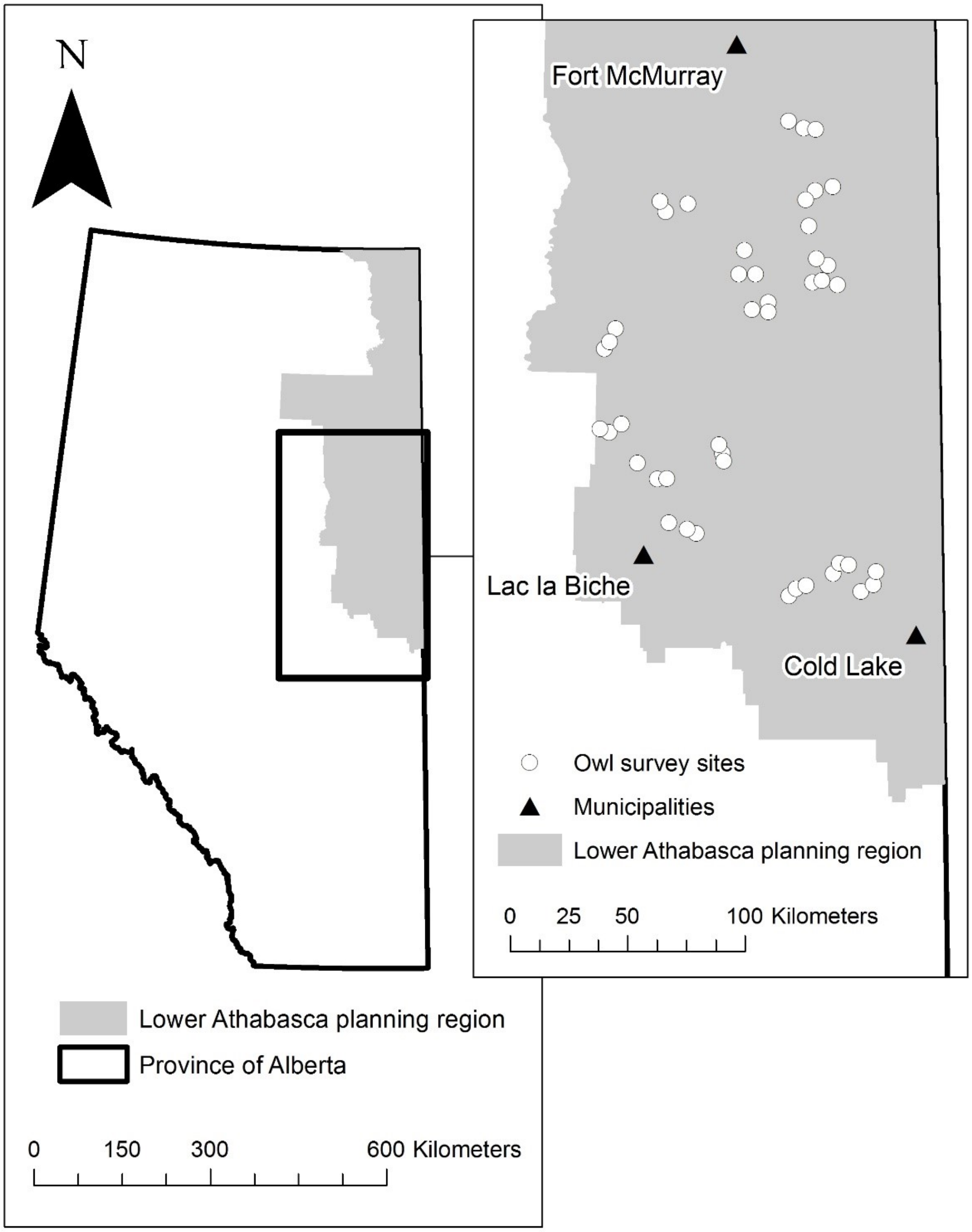

Figure 3.1 Owl survey sites within the Lower Athabasca planning region in Northeastern Alberta. We used autonomous recording units deployed at 45 sites to survey for owls between 21 March and 6 May 2014.

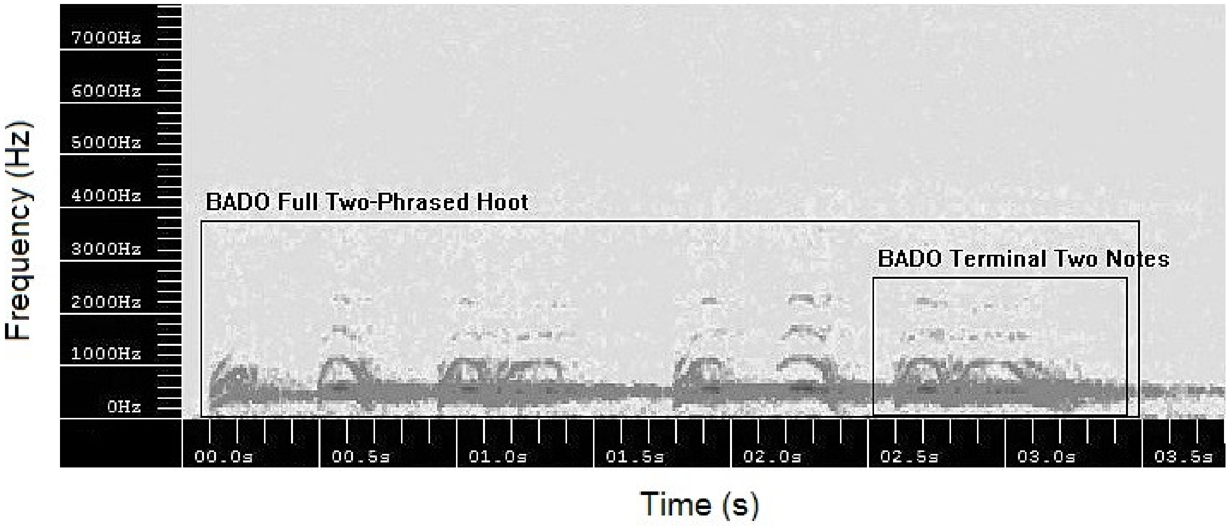

Figure 3.2 Example of annotated clips in Song Scope of the barred owl (BADO) territorial call for the full two-phrased hoot recognizer and the terminal two notes recognizer.

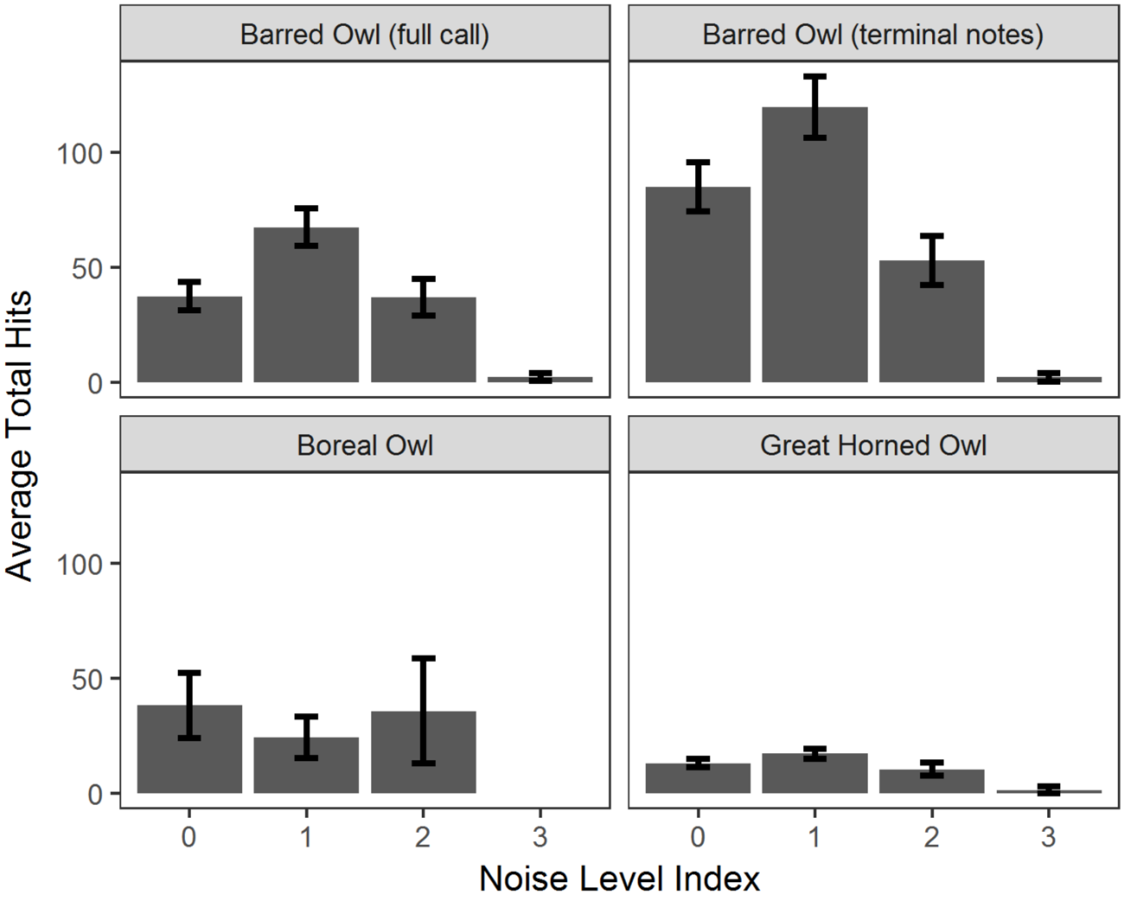

Figure 3.3 Average total hits per survey location (mean ± SE) for each owl recognizer across different noise levels. Total hits include both true positives (owl calls) and false positives. Noise levels were assessed while listening to a subset of recordings using the following index: (0) no noise, (1) low and distant, (2) moderate, and (3) very loud and close noise.

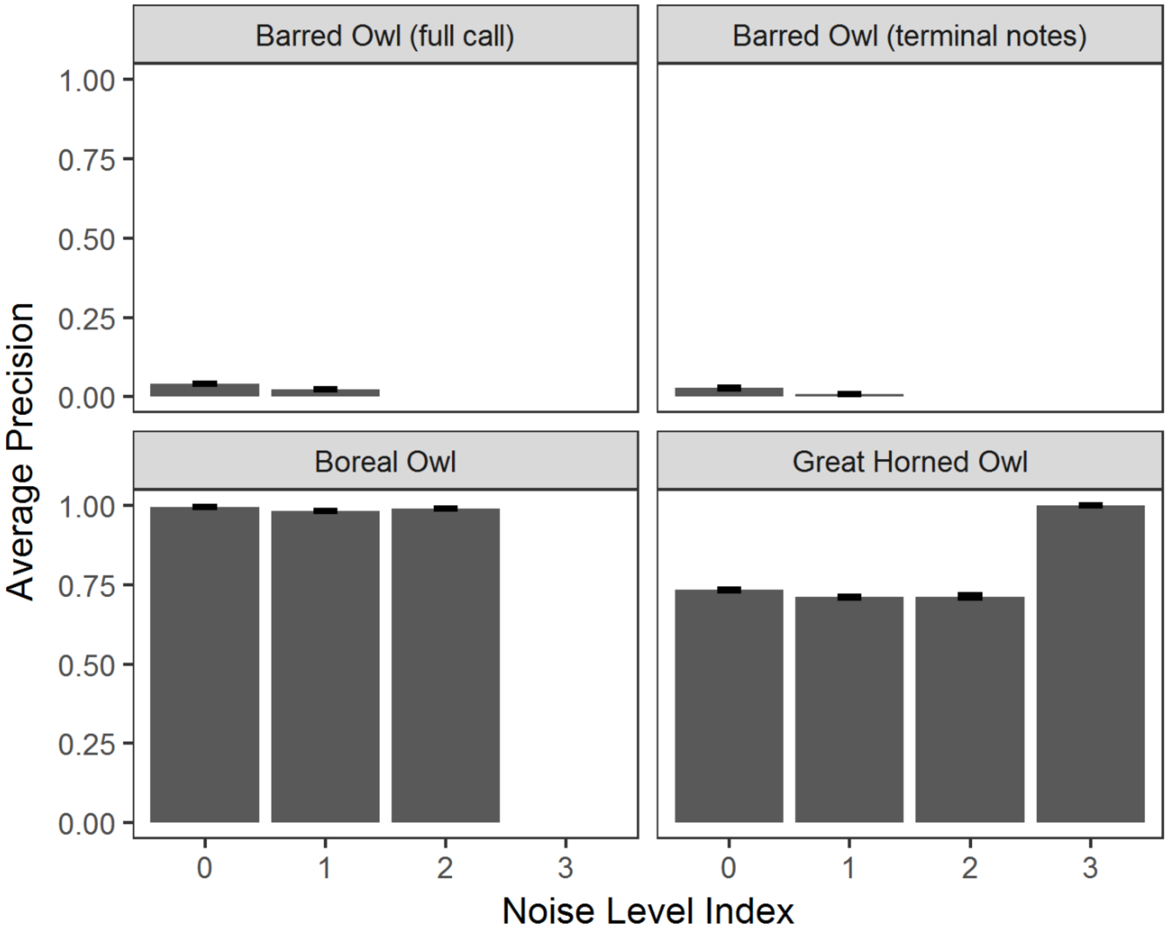

Figure 3.4 Average precision (weighted mean ± SE calculated using Cochran 1977 formula) across noise levels for each owl recognizer. See Fig. 3.3 for explanation of noise level index codes.

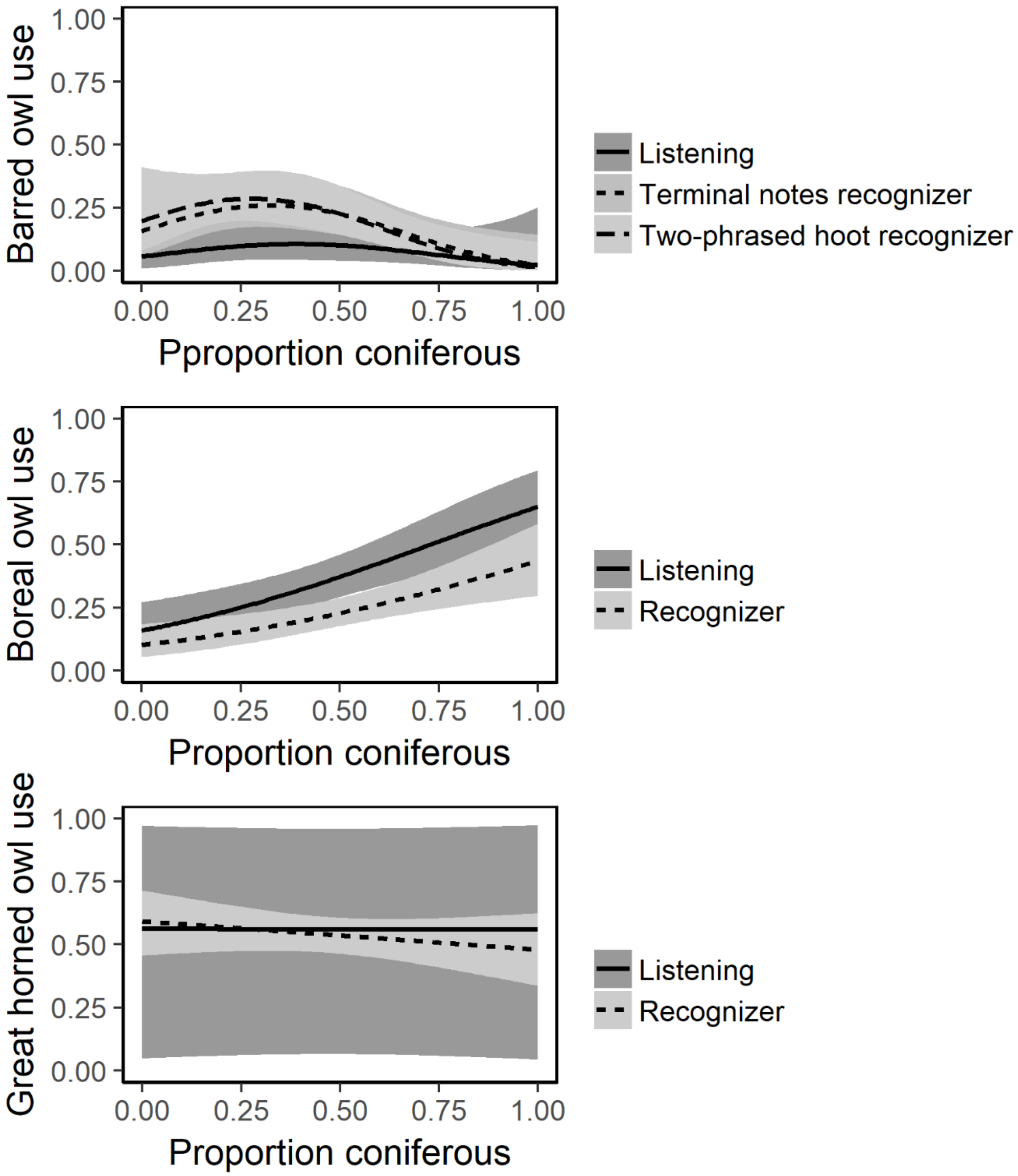

Figure 3.5 Estimates of probability of use by owls from occupancy models with forest composition (proportion coniferous forest) as a covariate, with separate models for the different methods (listening and recognizers). The solid or dashed lines are the estimates from each model and the shaded gray bands are the 95% confidence intervals.

Chapter 4. The Effect of Industrial Noise on Owl Occupancy in the Boreal Forest at Multiple Spatial Scales

INTRODUCTION

Noise in an environment can affect animal communication by reducing a receiver's ability to detect important signals as background noise increases, a phenomenon known as 'acoustic masking' (Francis et al. 2011a). One source of acoustic masking is anthropogenic noise; increased transportation, urban sprawl and industrial development are all contributing to create noisier landscapes. Noise can be infrequent and may trigger startle responses in animals, or noise can be chronic and potentially interfere with signal detection (Francis and Barber 2013). A growing body of research seeks to understand the effects of anthropogenic noise on animals (reviewed in Brumm and Slabbekoorn 2005, Barber et al. 2010, Francis and Barber 2013). The majority of studies have documented effects of noise (Shannon et al. 2016), including noise-induced changes to animal signals (Slabbekoorn and Peet 2003, Francis et al. 2011b) and decreases in animal abundance and diversity (Bayne et al. 2008, Francis et al. 2009, McClure et al. 2013). This suggests that communication is strongly affected by noise, causing some species to alter their signals and some to avoid noisy areas altogether.

Owls (Strigiformes) use vocal communication to attract mates and defend territories. When hunting at night, owls also use acoustic cues made by prey, such as rustling leaves, to aid in prey capture (Payne 1971, Martin 1990). Increasing industrial noise levels negatively affect the hunting success of northern saw-whet owls, *Aegolius acadicus* (Mason et al. 2016), and reduce the foraging efficiency of long-eared owls, *Asio otus*, and short-eared owls, *Asio flammeus*

(Senzaki et al. 2016). However, a study on the nocturnal space use of western burrowing owls, *Athene cunicularia hypugaea*, found they did not avoid areas affected by anthropogenic noise (Scobie et al. 2016). A study on spotted owls, *Strix occidentalis*, found they will flush from nests more frequently with increased proximity to a noise source (Delaney et al. 1999). Two other studies on physiological responses of spotted owls to anthropogenic noise found elevated fecal glucocorticoids (Hayward et al. 2011), but no detectable increase in fecal corticosterone (Tempel and Gutiérrez 2003). These studies on spotted owls applied temporary noise stimuli (e.g. helicopters, chainsaws, or motorcycles), so it is not known how owls respond to a permanent noise source on the landscape. Increased proximity to roads and increased traffic volume has been found to decrease owl density and occupancy of sites (Hindmarch et al. 2012, Silva et al. 2012), which may be at least partially due to the masking effect of traffic noise. However, roads have several factors other than noise (e.g. vehicle collisions and pollution) that can negatively affect animal abundance and distribution (Fahrig and Rytwinski 2009), making it difficult to attribute observed effects to noise per se. Owl distribution around noisy infrastructure has not been well studied, and little is known about how chronic noise may affect the distribution of owls on the landscape. In addition to interfering with an owls' ability to detect cues from prey, industrial noise may mask owl calls, both of which are low in frequency. In the boreal forest of northern Alberta, chronic noise from industrial operations could affect habitat suitability of the surrounding area for owls, causing them to avoid the area.

Surveys to determine presence or abundance of owls often broadcast a recorded owl call to elicit a response (Clark and Anderson 1997, Grossman et al. 2008, Kissling et al. 2010). Although broadcast-call surveys can increase the probability of detecting an owl by eliciting territorial individuals to respond (Kissling et al. 2010), they are also known to draw owls into areas they might not otherwise use (e.g. Zuberogoitia et al 2011). This could affect conclusions drawn from the results of whether an owl was using the area of interest. In addition, whether call-broadcast surveys are as effective in noisy areas in terms of whether the owls could hear the playback has not been evaluated. Passive acoustic surveys employing autonomous recording units (ARUs) set to record on a predetermined schedule, are becoming increasingly prevalent in avian research (Shonfield and Bayne 2017a). ARUs have been found to be useful for surveying owls (Rognan et al. 2012) as well as other rare and elusive species (Holmes et al. 2014, 2015, Campos-Cerqueira and Aide 2016). ARUs can be left unattended in the field for extended periods, and by increasing the amount of time surveyed at a location, the likelihood that an owl occupies an area but goes undetected is reduced. Combining passive acoustic surveys with statistical methods that account for imperfect detection (occupancy models: Mackenzie et al., 2002) has been shown to be an effective approach for improving species distribution estimates for rare or threatened species (Campos-Cerqueira and Aide 2016). Because passive surveys are a less biased method to assess habitat use, using them in combination with occupancy models to estimate and correct for detection probability is likely the best approach for estimating owl occupancy in noisy locations.

We hypothesized that owls avoid areas near chronic industrial noise sources because they are less suitable habitat. We conducted passive acoustic surveys by deploying several ARUs per site in spring during owl breeding season in northeastern Alberta, and used automated species recognition to identify owl calls on the recordings. We estimated occupancy of barred owls (*Strix varia*), great horned owls (*Bubo virginianus*), and boreal owls (*Aegolius funereus*) during the breeding season at sites with and without noisy infrastructure to test the prediction that occupancy is lower at noisy sites compared to quieter control sites that are unaffected by industrial noise. We tested the effect of noise on owl occupancy at two spatial scales: at the site level (larger scale), and at the level of individual ARU stations (smaller scale).

METHODS

Study area

The study area was located in the boreal forest of northeastern Alberta, within the Lower Athabasca planning region (LAPR). Specifically, study sites were in upland forested areas south of Fort McMurray, north of Lac la Biche and northwest of Cold Lake (Figure 4.1). The LAPR has seen increased development in the oil and gas industry in recent years (Alberta Biodiversity Monitoring Institute 2017), and subsequent increases in the number of industrial noise sources on the landscape, making it a suitable area to research the potential effects of industrial noise on wildlife.

Sites were selected based on the industrial infrastructure present and grouped into three noise categories: chronic noise, intermittent noise, and no noise (Table 4.1). For chronic noise sites, the infrastructure present was either an in-situ oil processing plant facility or a compressor station (Table 4.1). The processing plants produce continuous noise at a loud level and have a large cleared area for the facilities. Compressor stations, used to pressurize oil and natural gas pipelines, produce chronic noise at a similarly loud level to the processing plants (Table 4.1), but have a smaller cleared area (2-4 ha). Intermittent noise sites contained a well pad connected by a permanent access road, they had traffic noise but no industrial noise, and a similar amount of cleared forest as compressor stations. Sites with no noise contained a well pad accessed by a pipeline (there were no permanent access roads within these sites), they had no traffic or industrial noise, and a similar amount of cleared forest to the intermittent noise sites. Forest interior sites were not chosen as controls, because it would then be difficult to separate the effect of noise from the effect of edge habitat associated with cleared areas.

Acoustic surveys

Acoustic surveys for owls were conducted using SM2+ Song Meters (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA), a commercially available autonomous recording unit (ARU). We conducted passive surveys without broadcasting calls to avoid drawing in owls. We programmed each ARU to turn on and record in stereo format for 10 minutes at the start of every hour at 44.1 kHz with a 16-bit resolution. Recording files were compressed and stored on the SD cards of the ARUs in .wac format, a loss-less audio compression format proprietary to Wildlife Acoustics. We tested each ARU and both microphones prior to deployment to identify any units with non-responsive channels or degraded microphones. We used gain settings of 48 dB for both the left and right channel microphones. We attached ARUs at a height of approximately 1.5 m on trees with a smaller diameter than the width of the ARU (18 cm). ARUs were installed at each site for approximately two weeks in the spring, when owls are most actively calling. We surveyed 54 sites in 2013 between March 18 and May 18, and 18 sites in 2014 between March 21 and May 6, for a total of 72 sites. Each site consisted of 5-6 survey stations with an ARU deployed at each, with the center station closest to the noise source or well pad clearing, but still located within the forest (Figure 4.2). The area enclosed by the ARU survey stations at each site

(256 ha) approximated the home range size of pairs of barred owls and great horned owls during the breeding season (Mazur et al. 1998, Bennett and Bloom 2005, Livezey 2007; Appendix 3).

Sites with intermittent noise, and sites with no noise each had five ARU stations (Figure 4.2). To address the issue of reduced detection in noisy areas, we deployed a 6th ARU near the center at sites with chronic industrial noise (processing plants and compressor stations; Table 4.1). The additional center ARU station was on an adjacent or opposite side of the noise source from the first center ARU station. We deployed the additional ARU 200-500 m from the center ARU to increase the area surveyed near the noise source. The variation in spacing was due to different configurations of the industrial infrastructure at each site. We assumed the detection radius of a single ARU would be reduced in noisy areas. In addition to this additional ARU, a separate experiment was conducted to estimate the detection radius of ARUs in noisy and quiet areas to compare the total area surveyed. The experiment used a speaker to simulate owls calling at increasing distances from an ARU set up near a noise source to compare the effective detection radius (Yip et al. 2017a) to an ARU set up in a quiet area (see Appendix 4 Table A4.1 for more details).

Extracting acoustic data

We used automated species recognition to efficiently process acoustic recordings to detect territorial vocalizations of barred owls, great horned owls, and boreal owls. Owl calls are well-suited to automated recognition because of little heterospecific overlap, because few other species are present or vocally active during the time of night and season when owls are calling. These three owl species were heard frequently on recordings and it was possible to obtain several representative clips of their calls. We annotated clips from field recordings in Song Scope (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) to build templates or ‘recognizers’. We used 51 annotations of the 2-phrased hoot of the barred owl (Odom and Mennill 2010a) from 22 field recordings, 83 annotations of great horned owl territorial hoots (Kinstler 2009) from 10 field recordings, and 42 annotations of the boreal owl trill from 8 field recordings (Bondrup-Nielsen 1984) (Appendix 2, Table A2.1). To build each recognizer, we adjusted the settings in Song Scope to improve signal detection of the annotated clips (Wildlife Acoustics 2011). We kept some settings of the recognizers consistent for all three owl species (e.g. sample rate, background filter, FFT size and overlap; Table A2.1), but other settings were adjusted based on the specific call properties of each species (e.g. frequency and timing settings; Table A2.1). See Chapter 3, for additional details on the performance of these three recognizers. We scanned all recordings collected in 2013 and 2014 with the 3 species-specific recognizers we built. Though we recorded in stereo, Song Scope scans only one channel (the left channel by default), so there are no duplicate detections resulting from detecting owl calls on each channel. Trained listeners verified all hits generated by the program to filter out false positives.

We assessed industrial noise at each ARU station using two different methods. First, we listened to recordings and ranked industrial noise on each recording based on the following index: no noise (noise code 0), low and distant (noise code 1), moderate (noise code 2), and very loud and close (noise code 3). We listened to the midnight recordings from 3-4 randomly selected dates for each station, and assigned the modal noise index for each station. Second, we measured the relative noise level on recordings in dB using the maximum power measurement tool in Raven Pro version 1.5 (Cornell Laboratory of Ornithology, Ithaca, NY U.S.A.). We made measurements on both the left and right channels on one or two recordings from each station (n = 609 recordings measured) where there were no species vocalizing and no wind or rain on the recordings.

Landscape variables

We extracted forest composition and human disturbance variables in ArcGIS 10.3.1 (Environmental Systems Research Institute, Inc., Redlands, California, USA) to account for differences between sites. We used an 800-m radius buffer around each ARU station (201 ha), approximating the maximum detection radius of an ARU to detect owls calling (Yip et al. 2017a). For forest composition, we calculated the proportion of coniferous forest present weighted by area from the Alberta Vegetation Inventory (AVI) within each 800-m buffer. We also calculated mean forest age weighted by area from the AVI layer, but did not include it in our models because initial analyses suggested it was not a good predictor of occupancy for any of the three owl species. This was likely due to limited variation in forest age at the locations surveyed, mean forest age around each ARU ranged from 21 to 153 years (overall mean of 93 years), 97% of stations were surrounded by mature forest (50+ years old), and 84% of stations were surrounded by old forest (80+ years old). For human disturbance, we calculated the proportion of human footprint in the buffer area from Alberta Biodiversity Monitoring Institute's Human Footprint layer 2012 version 3 (http://www.abmi.ca/home/data/gis-data). Disturbances in this layer include linear features (roads, seismic lines, pipelines, transmission lines and railways), industrial and resource extraction features (well pads, compressor stations, processing plants, mines and other facilities), and recent forest cut blocks. For analyses at the site level, the landscape variables were extracted over the total area (861 ha) covered by the 800-m buffers around each station.

Analysis

Presence/absence data derived from the automated recognizers was compiled into detection histories for each ARU station. We defined each 'sampling occasion' in our detection history as a 24-hour period (a total of 24 ten-minute recordings processed by the recognizers). We had a total of 9 occasions in our detection history because ARUs were deployed for a minimum of 9 days. We analyzed data for each species separately at two spatial scales. The site level scale approximates an owl home range, and the station level is a smaller area surrounding an ARU. Stations with ARUs that had no acoustic data due to complete recording failures were eliminated from the dataset (n = 9); there were no sites where more than one ARU failed. Stations with ARUs that failed at some point during the deployment (n = 5) and did not record for all 9 days were indicated in the detection history as 'missing observations' on days that they did not record. An advantage of occupancy modeling is that it can account for 'missing observations' (MacKenzie et al. 2002). At the site level, we pooled the detection histories of all ARUs within the site. At the station level, the two center ARU stations were pooled and treated as a single unit in the analysis.

Owl occupancy was modeled using 'single species single season' occupancy models (MacKenzie et al. 2002) using the package 'unmarked' (Fiske and Chandler 2011) in R version 3.3.1 (R Core Team 2017) with R studio version 0.99.903 (RStudio Team 2017). At the site level, we included noise category of each site as a categorical predictor variable in both the occupancy parameter and the detection parameter to assess the relative importance of industrial noise to explain both occupancy and detection probability of owls. Processing plants and compressor station sites had comparable noise levels and were both included in the ‘chronic noise’ category (Table 4.1). The analysis at the site level included 72 sites: 21 chronic noise sites, 28 intermittent noise sites, and 23 sites with no noise (Table 4.1). At the station level, we ran models with noise level as a continuous predictor variable for both the occupancy parameter and the detection parameter. Initially, we ran models using the noise index, but then ran models with relative noise level measured in Raven Pro, likely a less subjective measure of noise. We present the results from the models with the relative noise level, but also discuss how these compared to results with using the noise index. Because owls are unlikely to be found consistently within the area around a single ARU station due to movement, and the same owl could be found at more than one station within a site on different sampling occasions, the occupancy estimates from models at the station level are an estimate of owl ‘use’ (MacKenzie 2006). At the station level, a total of 353 stations were included in the analysis.

We included proportion coniferous forest and proportion of the area disturbed by humans as continuous predictor variables for the occupancy parameter at both scales to account for differences in forest composition and landscape disturbance. For barred owls, we included a quadratic term for proportion coniferous forest, because previous research indicates they prefer mixedwood forests (Mazur et al. 1998, Livezey 2007, Russell 2008). For boreal owls and great horned owls, we did not include a quadratic term for proportion coniferous forest because boreal owls prefer coniferous forests (Hayward et al. 1993, Lane et al. 2001) and great horned owls are found in a wide variety of forest types (Johnsgard 2002). In the occupancy modelling literature, time of day is often included as a survey-specific variable in the detection parameter to account for differences in detectability at different times of day. We did not include time of day in our models at either scale because we surveyed during all hours of the night and then pooled the detections on a daily basis.

We ran 16 candidate models for each owl species at each spatial scale, and used Akaike's Information Criteria for model selection (Burnham and Anderson 2002). We included a null model (with no variables), a global model (with all variables), and models fitted for all possible combinations of variables (proportion coniferous, proportion disturbed, and noise category/relative noise level) without interactions. We ranked models using Akaike's Information Criteria for small sample sizes (AIC_c), and made model-averaged predictions using the R package 'MuMIn' (Barton 2017). Model averaging of top models can be a robust method to obtain parameter estimates and predictions, and is recommended when the weight of the top model is less than 0.9 (Grueber et al. 2011). There are various recommendations for choosing the top model set for model averaging, for example using a cut-off of 2 ΔAIC_c (Burnham and Anderson 2002), a cut-off of 6 ΔAIC_c (Richards 2008), or a cut-off of 10 ΔAIC_c (Bolker et al. 2009). Our primary interest was to estimate the impact of noise on owl occupancy and detection, so we chose a cut-off of 4 ΔAIC_c as our top model set to try to ensure that a noise variable was included in one of the models in the top model set while not including too many models.

RESULTS

Site occupancy

Barred owls were detected at 29 out of 72 sites, a naïve occupancy of 40%. The top ranked model for barred owls at the site level was our global model with all variables tested (Table 4.2). The second ranked model differed by less than 2.5 ΔAIC_c and did not include noise category in the occupancy parameter (Table 4.2), suggesting that the noise category of sites did not have a strong effect on occupancy. The predicted occupancy estimates for each category appear to differ, but the 95% confidence intervals are large and overlapping (Figure 4.3). The occupancy estimates are higher than we might have expected, based on the fact that barred owls were detected at only 40% of sites. This overestimation of occupancy and the large confidence intervals likely resulted from low detection probability of barred owls (less than 0.3; Figure 4.3). The top two models both included noise category in the detection parameter (Table 4.2), but the predicted detection probability was only slightly lower for chronic noise sites than the other two noise categories and the 95% confidence intervals overlapped (Figure 4.3).

Great horned owls were detected at 58 out of 72 sites, a naïve occupancy of 81%. The null model was the top-ranked model for great horned owls, and none of the top models with a ΔAIC_c less than 4 included noise category as a factor in either the occupancy or detection parameter (Table 4.2). To compare great horned owl occupancy across noise categories to the other owl species, we predicted occupancy from the next ranked models that included noise category as a factor in the occupancy and in the detection parameter (Table 4.2). Because these models had a low weight of evidence, it was not surprising that we found no effect of noise category of the site on great horned owl occupancy or on detection probability (Figure 4.3).

Boreal owls were detected at 28 out of 72 sites, a naïve occupancy of 39%. Noise category of the site was included as a factor in the occupancy parameter for only one of the top models (Table 4.2), and we found that the predicted occupancy of sites by boreal owls was similar across noise categories (Figure 4.3). Noise category was included in the detection parameter in all the top models (Table 4.2), and the predicted detection probability for boreal owls was highest for sites without noise and lowest for sites with chronic noise (Figure 4.3).

Forest composition varied between sites from 0.10 to 0.94 proportion coniferous forest with a mean of 0.48, and proportion of the area disturbed by humans ranged from 0.02 to 0.71 with a mean of 0.23. For barred owls, proportion coniferous forest and proportion of the site disturbed were important predictors of site occupancy and were included the top ranked models (Table 4.2). Barred owls were most likely to occupy a site when the forest composition was a mix of deciduous and coniferous trees, with about 25-50% coniferous trees, and less likely to occupy sites with a greater proportion of disturbance by humans (Figure 4.4). There was no effect of forest composition or human disturbance on site occupancy by great horned owls or boreal owls (Figure 4.4).

Station occupancy

Barred owls were detected at 47 stations (13%) across 29 sites, of these 12 sites had 2 or more stations with detections. The relative noise level of stations where barred owls were detected ranged between 63.5 dB to 92.6 dB, with a mean (± standard error) of 74.6 dB ± 1.1 dB. The top ranked model for barred owls at the station level did not include noise level as a factor for occupancy, but did contain noise level as a factor for detection probability (Table 4.3). We found no effect of relative noise level on station level occupancy (i.e. use), and only a slight decline in detection probability for barred owls as the relative noise level increased (Figure 4.5). This differed from the model results using noise index, where we found a decline in station occupancy at higher noise indices. This relationship may have been primarily driven by the fact that no barred owls were detected at stations with a noise index of 2 (moderate noise) or 3 (loud noise). Though we found no effect of relative noise level on station occupancy, it is worth noting that no barred owls were detected at any stations with an estimated relative noise level more than 93 dB.

Great horned owls were detected at 144 stations (41%) across 58 sites, of these 42 sites had 2 or more stations with detections. The relative noise level of stations where great horned owls were detected ranged between 57.8 dB to 110.8 dB, with a mean (± standard error) of 77.2 dB ± 0.8 dB. The null model was not the top model for great horned owls but had similar support as the top model (Table 4.3). There was no effect of relative noise level on station level occupancy (i.e. use) or on detection probability for great horned owls (Figure 4.5). Boreal owls were detected at 58 stations (16%) across 28 sites, of these 17 sites had 2 or more stations with detections. The relative noise level of stations where boreal owls were detected ranged between 65.3 dB to 110.8 dB, with a mean (± standard error) of 77.8 dB ± 1.3 dB. Only one of the top models for boreal owls included relative noise level as a factor for occupancy, and had similar support as other models that did not include noise level (Table 4.3). We found no effect of noise level on station level occupancy by boreal owls (Figure 4.5). The top models for boreal owls all included relative noise level as a factor for detection probability (Table 4.3), and we found that detection probability decreased with increasing noise levels (Figure 4.5). For both great horned owls and boreal owls, our model results using noise index were consistent with the results presented above, we found no effect of noise index on station occupancy.

From the playback experiment, we found the effective detection radius for an ARU located near a chronic noise source was roughly half the distance of an ARU in a quiet area (Appendix 4, Table A4.1). Although we deployed a second center ARU at chronic noise sites to increase the area sampled, it was not equal to the area sampled by ARUs in quiet areas (Appendix 4, Table A4.1). This indicates that at the station level as noise level increased, the area sampled decreased. Industrial noise levels were highest for center stations that were closest to industrial noise sources, the relative noise level (mean ± standard error) at center stations at chronic noise sites was 93.4 ± 2.5 dB, whereas stations at the four corners of chronic noise sites were 79.7 ± 0.8 dB. The relative noise level at center stations at intermittent noise sites was 78.1 ± 2.3 dB, and the relative noise level at the corner stations of intermittent noise sites was 76.4 ± 1.0 dB. Not surprisingly, stations at sites with no noise had the lowest relative noise level, 74.2 ± 0.8 dB.

Forest composition varied between stations from 0 to 1 for proportion coniferous forest with a mean of 0.48; proportion of the area disturbed by humans varied from 0 to 0.94 with a mean of 0.18. Station level occupancy of barred owls was highest when the forest was a mix of deciduous and coniferous trees and declined with increasing disturbance by humans (Figure 4.4). Similar to the site level analysis, forest composition and human disturbance had no effect on great horned owl station level occupancy (Figure 4.4). There was no effect of human disturbance on station level occupancy of boreal owls, but there was a slight increase in use in more coniferous forests, though this effect was not strong (Figure 4.4).

DISCUSSION

We found no evidence that occupancy of sites at a home range scale by barred owls, great horned owls or boreal owls was affected by the presence of industrial noise sources or roads. We had predicted that owls would avoid noisy areas due to potential problems communicating and hunting in the presence of industrial noise, but our results indicate that owls do not avoid these areas at this large scale. This could be explained by the fact that the noise level at the edges of chronic noise sites and intermittent traffic sites was reduced to the point that in some areas it was almost inaudible, which would likely have little impact on owl communication and hunting success. In addition, there was no effect of noise from either a chronic noise source or intermittent traffic on detection probability for barred owls and great horned owls, though detection probability was slightly higher at sites with no noise for boreal owls. These three owl species do not appear to avoid noise sources at the home range scale, but occupancy at this scale does not indicate how owl use is distributed within a site. For all three species, we found that between 30-60% of sites had detections at only a single station. The noisy area in the middle of a site could create a donut shape of space use where the center is avoided, or the noise could act as a barrier where owls are only using a portion of the site.

At the station level, we found that use did not decline with relative noise level for all three owl species. Detection probability for barred owls and great horned owls was not affected by noise level, but for boreal owls there was a decline in detection with increased noise. Although owl use did not decline with increased noise, the area surveyed with ARUs declined because of the decreased effective detection radius. We attempted to reduce the bias of detecting fewer owl calls in noisy locations by including noise as a factor for detection probability in our models, deploying two ARUs at the center of chronic noise sites to increase the area sampled, and by estimating the detection radius of ARUs in noisy areas. The effective detection radius in noisy areas was roughly half that of quiet areas, so even with two ARUs deployed at the center of the site, the sampled area was not equal to that of an ARU in a quiet location. We assumed that if owls were using noisy areas that they would move into the detection radius of the ARU and call at some point during the nine sampling days. Although not conclusive, we have some hints that barred owls may be more sensitive than the other species. We found that great horned owls and boreal owls were heard calling at stations with higher noise levels compared to where barred owls were heard calling. This is unlikely to be due to increased masking of barred owl calls from the industrial noise, because their calls are slightly higher in frequency than great horned owl calls but lower in frequency than boreal owl calls. We also found that barred owl use declined with increased human disturbance resulting in the loss of forest cover. The species we studied do not appear to be avoiding noisy areas, but whether these owls are tolerant of noise is not clear given that the area surveyed was smaller at noisy stations, and chronic noise seemed to differentially influence detectability between species. We may not be able to conclusively determine to what extent owls are using noisy areas at this scale unless we track their movements using other methods (e.g. transmitters).

Two recent studies have estimated hunting success and hunting efficiency of owls in the presence of anthropogenic noise (Mason et al. 2016, Senzaki et al. 2016). The conclusions of both these studies were that noise levels corresponding to 120 m from a road and 200 m from a compressor station results in reduced detection of prey (Senzaki et al. 2016) and lower capture success of prey (Mason et al. 2016). These estimates of the distance of the noise effect could explain why we did not find lower occupancy of sites by owls at either sites with intermittent traffic noise or chronic noise sources, because a small proportion of the site would be within these distances from a road or industrial noise source, thus there are likely areas within a site where owls are able to hunt. Our results indicate that industrial noise does not preclude owls from occupying territories adjacent to noise sources. It would be an interesting area of future research to evaluate if occupancy rates are more variable at territories adjacent to noise sources from year to year. We found no evidence that owls are avoiding noisy areas on a smaller scale, contrary to what we would expect given the results of these studies on owl hunting success under noisy conditions (Mason et al. 2016, Senzaki et al. 2016). However, owls are unlikely to vocalize while hunting, so it is not likely we detected them in noisy areas while they were trying to hunt. A study tracking western burrowing owls with transmitters found that nocturnal space-use was not affected by industrial noise (Scobie et al. 2016). Future research tracking these three species of owls found in the boreal forest will be necessary to understand how these species' behaviour and movement is influenced by noise sources.

The sites we surveyed varied in the amount of deciduous and coniferous forest, and in the amount of disturbance by humans. At both spatial scales, barred owls were more likely to be found in mixedwood forest, and less likely to be found in areas with increased disturbance by humans resulting in the loss of forest cover. Barred owls are associated with older mixedwood forests in the northern boreal forest (Mazur et al. 1998, Russell 2008), and have been found to be most likely to occur in landscapes with >66% forest cover (Grossman et al. 2008). Our results are in support of barred owls being habitat specialists and preferring mixedwood forests, and suggest they are sensitive to human disturbance that results in the loss of forest cover, though they do not appear to be sensitive to noise specifically. For great horned owls, forest composition and human disturbance had no effect on the probability of occupancy at either scale. Great horned owls are generalists and are known to use a wide range of habitat types throughout North America (Johnsgard 2002). They may be more tolerant to disturbance, as they are often associated with heterogeneous landscapes and prevalent in landscapes with intermediate levels of forest cover (Grossman et al 2008). Our results are in support of great horned owls being habitat generalists and tolerant to human disturbance. For boreal owls, we found no effect of forest composition on occupancy of sites, and a weak trend for boreal owls to use areas with more coniferous trees. Boreal owls inhabit mixed-conifer, spruce-fir and Douglas fir forests in western Montana, Idaho, and northwestern Wyoming (Hayward et al 1993), and mixedwood upland forest stands in Minnesota (Lane et al 2001). There was no effect of human disturbance on the occupancy of boreal owls at either scale.

This study is the first to look at the impact of chronic industrial noise on the distribution of three owl species in the boreal forest. Literature reviews on the effects of anthropogenic noise on wildlife have found the majority of studies documented effects from noise and suggest that noise presents a threat to species and ecosystems (Barber et al. 2010, Shannon et al. 2016). A comparative study on avian sensitivities (primarily passerines) to anthropogenic noise found that species with lower frequency vocalizations, and species with animal-based diets were more sensitive to noise (Francis 2015). Owls certainly fit this description, but at the spatial extent we assessed there was no evidence of noise effects on owls. Species that do not show avoidance may still be negatively affected from chronic noise, for example impacts on passerines include reduced pairing success (Habib et al. 2006) and reduced fitness (Halfwerk et al. 2011, Schroeder et al. 2012). Spotted owls nesting near noisy roads have been found to fledge fewer young than owls nesting near quiet roads (Hayward et al. 2011). Future research should assess the reproductive success of owls living in noisy areas to determine if chronic industrial noise has other negative impacts. Our research contributes to the literature on effects of anthropogenic noise, but suggests the effect on occupancy of barred owls, great horned owls and boreal owls is minimal.

Table 4.1 Details of the different types of sites surveyed for owls. Noise levels were first assessed while listening to a subset of recordings using the following noise index: (0) no noise, (1) low and distant, (2) moderate, and (3) very loud and close noise. A modal noise index was determined for each station, and a mean noise index was calculated for sites surveyed with different industrial infrastructure. Noise level was also assessed for each station by measuring the relative noise level (dB) on recordings with no species vocalizing, no wind, and no rain.

Noise category	Infrastructure present	Noise source	Mean noise index	Relative noise level (mean ± SE)	No. of sites
Chronic noise	Oil processing plants	Facilities	1.88	82.9 ± 1.5 dB	7
Chronic noise	Compressor stations	Facilities	1.61	82.3 ± 1.3 dB	14
Intermittent noise	Well pad on road	Road traffic	0.99	76.8 ± 0.9 dB	28
No noise	Well pad on pipeline	None	0.48	74.2 ± 0.8 dB	23

Table 4.2 Comparison of occupancy models for owls at the site level (n = 72 sites). Occupancy (psi) and detection probability (p) are modeled with noise category (NC) (chronic, intermittent or no noise) as a factor. Proportion coniferous forest (Con) and proportion of the area disturbed by humans (Dist) were included as factors to account for differences in forest composition and disturbance. The number of parameters is represented by K. Models were evaluated based on differences between AIC_c scores (Δ_i) and AIC_c weights (w_i). Only the first six models with the lowest Δ_i are reported here, Δ_i is the difference between the observed model (i) and the best model as determined by the lowest AIC_c.

Species	Model	K	AIC_c	Δ_i	w_i
Barred owl[1]	Psi(NC + Con + Con^2 + Dist),p(NC)	9	341.77	0.00	0.71
	Psi(Con + Con^2 + Dist),p(NC)	7	344.26	2.49	0.20
	Psi(NC + Con + Con^2 + Dist),p(.)	7	346.93	5.16	0.05
	Psi(Con + Con^2 + Dist),p(.)	5	348.69	6.93	0.02
	Psi(NC + Con + Con^2),p(NC)	8	351.84	10.07	<0.01
	Psi(Con + Con^2),p(NC)	5	353.02	11.25	<0.01
Great horned owl	Psi(.),p(.)	2	710.16	0.00	0.39
	Psi(Con),p(.)	3	711.88	1.72	0.16
	Psi(Dist),p(.)	3	712.00	1.84	0.15
	Psi(Con + Dist),p(.)	4	712.97	2.81	0.09
	Psi(NC),p(.)	4	714.23	4.07	0.05
	Psi(.),p(NC)	4	714.34	4.18	0.05
Boreal owl	Psi(.),p(NC)	4	430.47	0.00	0.45
	Psi(Con),p(NC)	5	432.72	2.25	0.15

Psi(Dist),p(NC)	5	432.75	2.28	0.14
Psi(NC),p(NC)	6	433.05	2.58	0.12
Psi(Con + Dist),p(NC)	6	435.10	4.63	0.04
Psi(NC + Con),p(NC)	7	435.45	4.98	0.04

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[1] Models for barred owl included a quadratic term for proportion coniferous forest (Con^2) because they are known to prefer mixedwood forests.

Table 4.3 Comparison of occupancy models for owls at the station level (n = 353 stations). Occupancy (psi) and detection probability (p) are modeled with the relative noise level (NL) measured in Raven Pro as a factor. Proportion coniferous forest (Con) and proportion of the area disturbed by humans (Dist) were included as factors to account for differences in forest composition and disturbance. The number of parameters is represented by K. Models were evaluated based on differences between AIC_c scores (Δ_i) and AIC_c weights (w_i). Only the first six models with the lowest Δ_i are reported here, Δ_i is the difference between the observed model (i) and the best model as determined by the lowest AIC_c.

Species	Model	K	AIC_c	Δ_i	w_i
Barred owl[1]	Psi(Con+Dist),p(NL)	6	584.30	0.00	0.64
	Psi(NL+Con+Dist),p(NL)	7	586.30	2.00	0.24
	Psi(NL+Con+Dist),p(.)	6	588.10	3.81	0.10
	Psi(Con+Dist),p(.)	5	591.33	7.03	0.02
	Psi(Con),p(NL)	5	598.54	14.25	<0.01
	Psi(NL+Con),p(SL)	6	600.49	16.20	<0.01
Great horned owl	Psi(Dist),p(.)	3	1659.27	0.00	0.16
	Psi(.),p(.)	2	1659.67	0.40	0.13
	Psi(.),p(NL)	3	1660.23	0.96	0.10
	Psi(Dist),p(NL)	4	1660.34	1.07	0.09
	Psi(Con+Dist),p(.)	4	1660.65	1.38	0.08
	Psi(NL+Dist),p(.)	4	1661.06	1.79	0.07
Boreal owl	Psi(Con),p(NL)	4	958.88	0.00	0.34
	Psi(NL+Con),p(NL)	5	959.67	0.79	0.23

Psi(Con+Dist),p(NL)	5	960.81	1.93	0.13
Psi(.),p(NL)	3	961.40	2.52	0.10
Psi(NL+Con+Dist),p(NL)	6	961.69	2.81	0.08
Psi(NL),p(NL)	4	962.76	3.88	0.05

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[1] Models for barred owl included a quadratic term for proportion coniferous forest (Con^2) because they are known to prefer mixedwood forests.

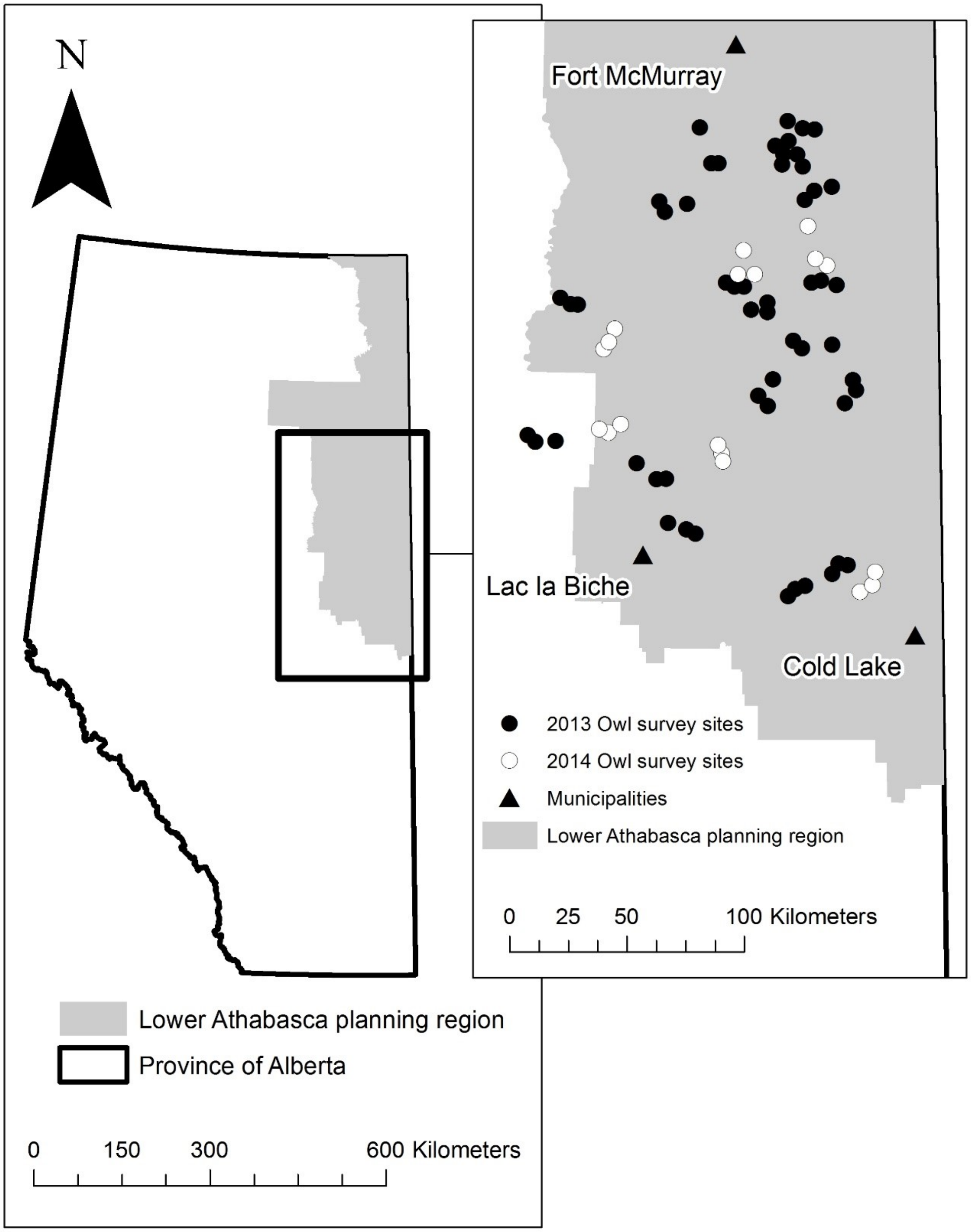

Figure 4.1 Map of owl site locations within the Lower Athabasca Planning Region in Northeastern Alberta. Sites were located >3 km apart.

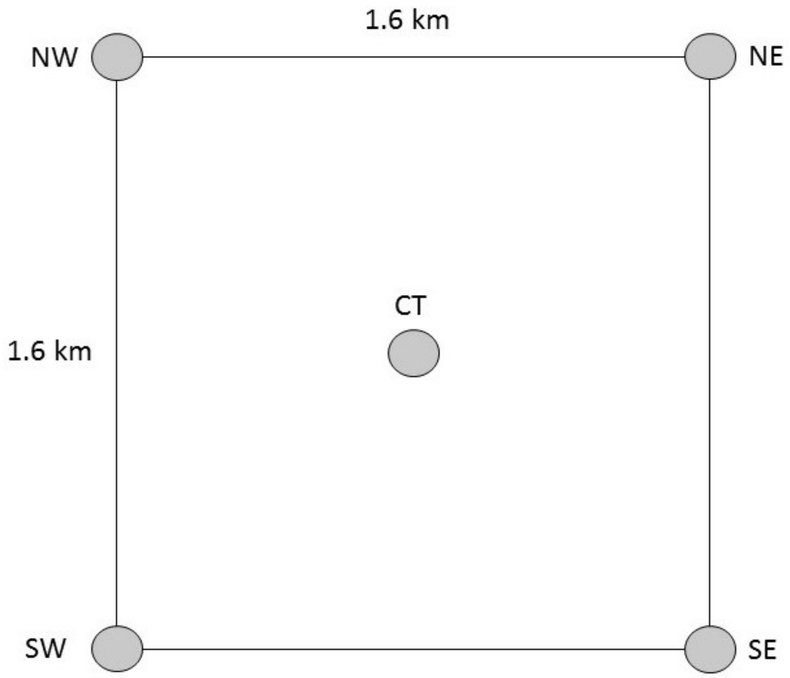

Figure 4.2 Configuration of stations within each site. One autonomous recording unit (ARU) was deployed at each station to survey acoustically for owls for approximately two weeks in the spring in 2013 and 2014. ARUs were programmed to turn on and record for ten minutes at the start of every hour. For the two types of chronic noise sites (processing plants and compressor stations) an additional ARU (not shown) was deployed on an adjacent or opposite side of the noise source from the center (CT) ARU.

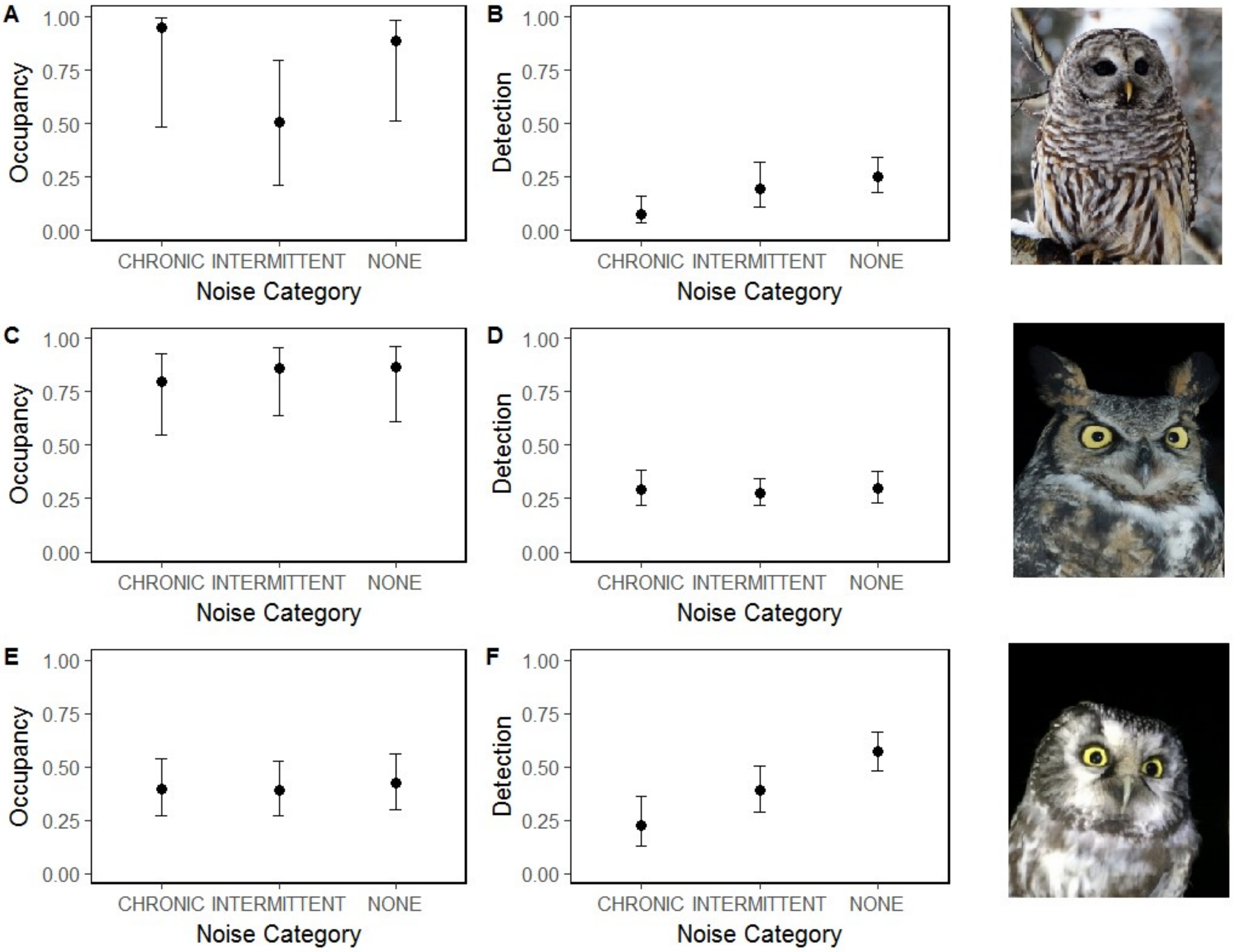

Figure 4.3 Site level model predictions of occupancy (left panels) and detection probability (right panels) for barred owls (A, B), great horned owls (C, D), and boreal owls (E, F) for the three noise categories of sites. Predictions are averaged from models within 4 ΔAIC_c of the top model (Table 4.2). For great horned owls, none of the models within 4 ΔAIC_c contained noise category as a factor for either the occupancy or the detection parameters. So we made predictions based on the highest ranked models containing noise category as a factor for either the occupancy or the detection parameters (Table 4.2). The error bars are 95% confidence intervals. Owl photos taken by J. Shonfield.

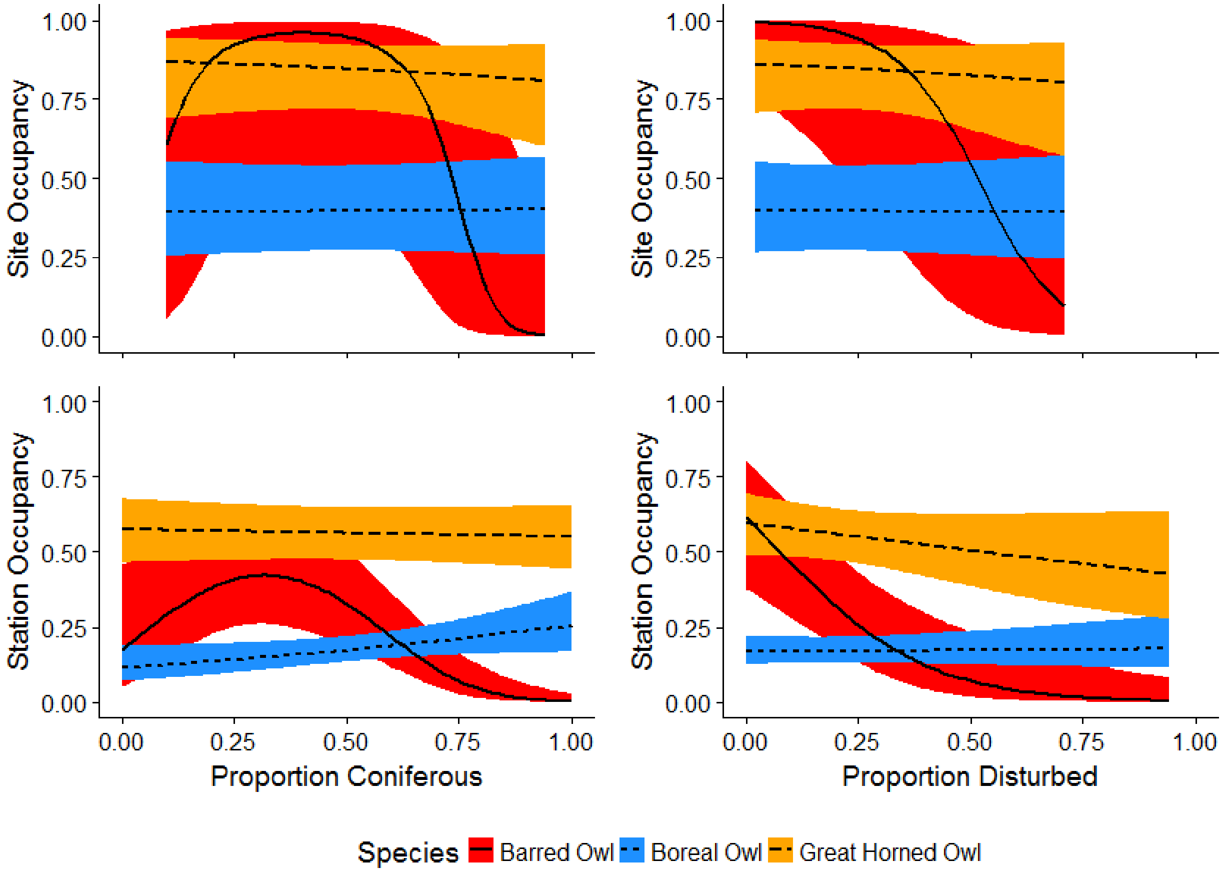

Figure 4.4 Model averaged predictions (models within 4 ΔAICc of the top model; Table 4.2, Table 4.3) for all three owl species for occupancy at two spatial scales: at the site level (top panels), and at the station level (bottom panels) as a function of forest composition (proportion coniferous forest) and landscape disturbance (proportion of the area disturbed by humans resulting in loss of forest cover). The solid or dashed lines are the model averaged predictions and the coloured bands are the 95% confidence intervals.

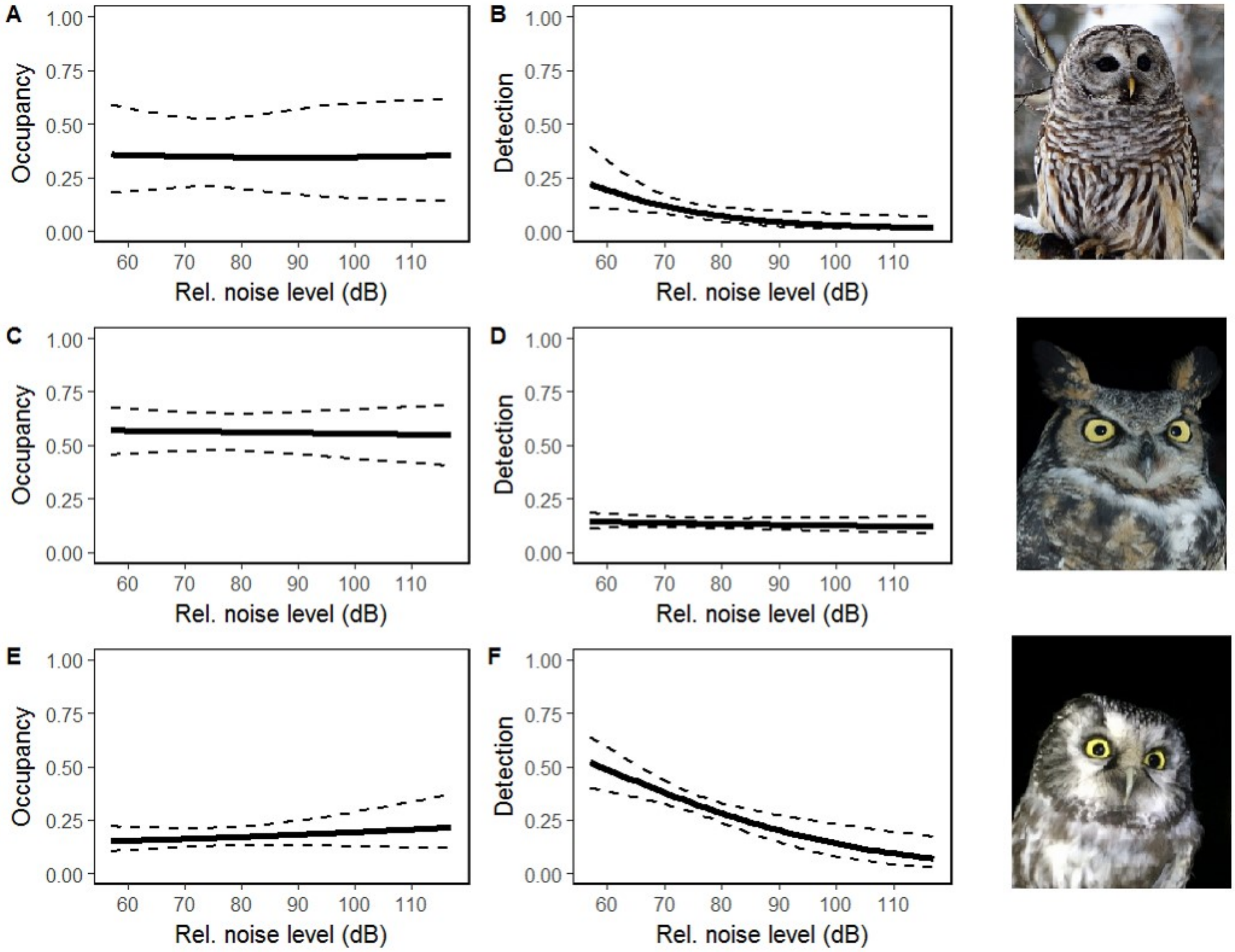

Figure 4.5 Station level model predictions of occupancy (left panels) and detection probability (right panels) for barred owls (A, B), great horned owls (C, D), and boreal owls (E, F) across relative noise levels. Predictions are averaged from models within 4 ΔAIC_c of the top model (Table 4.3). The solid lines are the model averaged predictions and the dashed lines are 95% confidence intervals. Owl photos by J. Shonfield.

Chapter 5. Investigating Effects of Industrial Noise on Small Mammal Abundance and Activity

INTRODUCTION

All landscapes contain some level of natural noise, caused by various abiotic (e.g. wind and rain) and biotic factors (e.g. animal vocalizations). Ecosystems are being increasingly affected by anthropogenic noise (Barber et al. 2011) due to an increasing global human population, and subsequent increases in transportation networks, urban sprawl and resource extraction (Buxton et al. 2017). A growing body of research seeks to understand the effects of anthropogenic noise on communication, behaviour, distribution, and reproduction of species that rely on vocal communication for important components of their life history (reviewed in Brumm and Slabbekoorn 2005, Barber et al. 2010, Francis and Barber 2013). Noise can affect signal perception and is defined as any factor that reduces the ability of a receiver to detect a signal or to discriminate one signal from another (Brumm and Slabbekoorn 2005). Noise disturbance can range from acute or infrequent, which may trigger startle responses in animals, to frequent or chronic noise that could potentially interfere with signal detection (Francis and Barber 2013).

In terrestrial environments studies have focused on songbirds (Habib et al. 2006, Bayne et al. 2008, Francis et al. 2011a, 2011b, Shannon et al. 2016). Songbirds use vocalizations to attract mates and defend breeding territories, and decreases in songbird abundance and diversity (Bayne et al. 2008, Francis et al. 2009, McClure et al. 2013) suggest there are negative impacts due to noise. There are fewer studies on terrestrial mammals, and these have focused on species that rely on auditory communication or auditory cues. For example, bat species that hunt by listening for prey-generated sounds (Siemers and Schaub 2011, Bunkley and Barber 2015), Mt. Graham red squirrels (*Tamiasciurus hudsonicus grahamensis*) that use vocalizations to defend territories (Chen and Koprowski 2015), and prairie dogs (*Cynomys ludovicianus*) that use vocalizations to warn conspecifics of predators (Shannon et al. 2014). There has been little research on potential effects of anthropogenic noise on mammalian species that do not rely heavily on vocal communication.

Many species of small rodents do not generally rely on acoustic signals for intraspecific communication. Olfaction plays a large role in intraspecific communication for many rodent species; for example, studies on kin recognition and kin discrimination in rodents have focused on the importance of odours (Mateo 2003). Small mammals serve an important function in terrestrial ecosystems as prey for mammalian and avian predators (Livezey 2007, Andruskiw et al. 2008), predators of songbird nests (Bayne and Hobson 1997), predators of seeds and arthropods (Martell and MacAulay 1981, Schnurr et al. 2002), and dispersers of fungal spores (Maser et al. 1978, Martell 1981). For this reason, many studies have focused on evaluating the impacts of various types of anthropogenic landscape disturbance and the resulting edges on small mammal communities (e.g. Adams and Geis 1983; Bayne and Hobson 1998; Moses and Boutin 2001; Hadley and Wilson 2004). We are not aware of any studies to date on impacts of noise on small mammals. While it is unlikely that small mammals are directly affected by anthropogenic noise through changes in intraspecific communication, they may be indirectly affected through predation.

Small mammals may be indirectly negatively affected by noise in an environment if it causes them to be more vulnerable to predation. This could occur for two reasons: 1) the attention of small mammals could be compromised by distraction from the noise (the 'distracted prey hypothesis', Chan et al. 2010, Chan and Blumstein 2011), and 2) the sound of movements by approaching predators could be masked by the noise. Small mammals are prey for a variety of terrestrial and aerial predators, and their ability to detect approaching predators is important for their survival. Small mammals exhibit defensive behaviours in response to the calls of avian predators (Hendrie et al. 1998). Though most avian predators do not vocalize while hunting, the reduction in activity and increased use of burrows by small mammals after the predator call would appear to serve to reduce their probability of detection by avian predators (Hendrie et al. 1998). Small mammals are presumably also listening for sounds that could indicate an approaching predator, and an inability to detect these acoustic cues could impact their survival. If small mammals are more vulnerable to predation due to the noise, then this could result in decreased activity. Field and lab-based studies found activity of *Microtus* and *Myodes* voles was lower under increased predation risk (Norrdahl and Korpimäki 1998, Trebatická et al. 2008). In general, the reduced activity of prey species is thought to reduce the probability of an encounter with a predator, and thus the movement behaviour or activity of the prey can provide an indication of perceived predation risk.

Alternatively, anthropogenic noise may have a positive effect on small mammal abundance if it provides a refuge from disturbance-sensitive predators (e.g. Francis et al. 2009). Industrial noise from compressor stations has been shown to mask the noise of scurrying mice and decrease the odds of prey detection, strike behaviour, and the overall hunting success of northern saw-whet owls *Aegolius acadicus* (Mason et al. 2016). Studies on other acoustic predators, two species of bats that hunt arthropods using prey-generated sounds, found search time for prey increased in the presence of traffic and industrial noise stimuli (Siemers and Schaub 2011, Bunkley and Barber 2015). These studies provide evidence that noise can negatively impact the foraging efficiency of acoustic predators, which could result in noisy areas serving as a refuge for prey, but whether this change in predator foraging success is sufficient to alter prey abundance or activity is unknown.

Our study objective was to assess the impact of industrial noise on small mammal abundance and activity. We used mark-recapture methods to estimate abundance of small mammals at sites adjacent to chronic noise sources, sites adjacent to roads, and sites without noise. We hypothesized that small mammal abundance could be positively affected by noise if it provides a refuge from predators, but alternatively small mammal abundance could be negatively affected if noise causes them to be more vulnerable to predators. We used the maximum distance moved between recaptures of individual small mammals as a measure of spatial extent of activity, and tested whether noise had an impact on small mammal activity. We hypothesized that animals would move less under greater perceived predation risk, because increased mobility can increase the chance of encountering a predator. Finally, we considered that effects of noise could be occurring over a more localized scale by altering the magnitude of edge effects, so we analyzed the number of individuals caught at varying distances from a noisy or quiet forest edge.

METHODS

Study area

The study area was located in the boreal forest of northeastern Alberta, within the Lower Athabasca Planning Region (LAPR). Specifically, study sites were in upland forested areas north and south of Fort McMurray, north of Lac la Biche and northwest of Cold Lake (Figure 5.1). The LAPR has seen increased development in the oil and gas industries in recent years (Alberta Biodiversity Monitoring Institute 2017), and subsequent increases in traffic volume and industrial noise sources, making it a suitable area to research the potential effects of industrial noise on wildlife. Sites were a minimum of 1 km apart, in mixedwood forest stands composed primarily of trembling aspen (*Populus tremuloides*) and white spruce (*Picea glauca*). Other tree species that were sometimes present included black spruce (*Picea mariana*), balsam poplar (*Populus balsamifera*), jack pine (*Pinus banksiana*), white birch (*Betula papyrifera*), balsam fir (*Abies balsamea*), and tamarack (*Larix laricina*). The most common species in the shrub layer included prickly wild rose (*Rosa acicularis*), Labrador tea (*Rhododendron groenlandicum*), green alder (*Alnus crispa*), beaked hazelnut (*Corylus cornuta*), and willow (*Salix spp*.).

Sites were selected based on the industrial infrastructure present and grouped into three noise categories: chronic noise, intermittent noise, and no noise (Table 5.1). All sites had one forest edge where the tree canopy ended at an open clearing. The clearings differed in the presence or absence of industrial infrastructure and a noise source. Chronic noise sites were situated adjacent to clearing with a compressor station. Compressor stations are used to pressurize oil and natural gas pipelines and produce noise continuously at a loud level. Intermittent noise sites were situated adjacent to a permanent access road and were subject to intermittent traffic noise. Control sites were situated adjacent to a square forest clearing (wellpads with no noise or infrastructure) and had no permanent access roads, and thus no traffic, no infrastructure, and no industrial noise sources. Control sites with no noise source were at least 1 km away from a road or any other industrial noise source. Sites in each noise category were distributed throughout the study area (Figure 5.1).

To obtain an estimate of noise levels for each noise category we used a handheld sound level meter (Sper Scientific 840018) to take sound pressure measurements at 5 sites in each of the three noise categories (chronic, intermittent and no noise). In 2015, we took two instantaneous measurements of the maximum sound level (dBA) during a 10-second period at all four corners of the small mammal trapping grid at each site at a height of 1 m from the ground. We calculated the average noise level for each site, and the average noise level for each noise category.

Trapping design

To estimate abundance at each site, we conducted small mammal live-trapping using standard mark-recapture methods from the beginning of July to the end of August in 2014 and 2015. This period reflects when small mammal abundance is likely at the peak, as young born that spring would have already emerged from their natal nests, and is often when surveys for small mammals in the boreal forest are done (e.g. Bayne and Hobson 1998; Fauteux et al. 2012). One trapping grid was set up at each site within forested areas, with one edge of the grid along the forest edge adjacent to the forest clearing (either from a compressor station, a road or an isolated forest clearing). Grids were 1.05 ha in size, with traps spaced at 15-m intervals, making an 8 x 8 grid with 64 traps. We trapped 14 sites for small mammals in the summer of 2014. In summer 2015, we trapped 12 of the same sites from 2014 and 11 new sites for a total of 23 sites trapped (Table 5.1). We did not return to two sites in 2015 due to access restrictions.

We used Longworth live traps (13.8 cm x 6.4 cm x 8.4 cm) baited with a handful of black oil sunflower seeds (*Helianthus spp.*), a small piece of apple for hydration, and polyester fiber for bedding. Traps were set between 16:00 and 20:00, and checked in the mornings starting at 06:00 for four consecutive days. Traps were locked open in the middle of the day. Small mammals captured were transferred from the trap to a mesh handling bag and identified to species. Individuals were sexed, weighed to the nearest gram with a Pesola spring balance (Pesola, Baar, Switzerland), and marked with a uniquely numbered metal ear tag (National Band and Tag Co.) before being released at the point of capture. Live-trapping and handling protocols followed guidelines of the American Society of Mammalogists (Sikes et al. 2011) and were approved by the University of Alberta Animal Care Committee (AUP00001055) and the Government of Alberta (Wildlife Research Permit No. 54843 in 2014, and No. 56196 in 2015).

Vegetation sampling

We targeted areas of mixedwood forest with aspen and white spruce as the dominant stand type in an attempt to control for forest composition, though there was still some heterogeneity across sites. At all grids trapped in 2015, we conducted vegetation sampling at a subsample of trap locations within each grid to quantify vegetation characteristics. In each of the 23 grids trapped, we sampled vegetation at 16 trap locations per grid, for a total of 368 trap locations across all grids. We sampled vegetation on every other trapline in each trapping grid, and at every other trap location. At these trap locations, we estimated percent canopy cover and conducted a 15-m radius visual scan for tree species composition, tree size class, and relative density and size class of downed woody debris greater than 5 cm in diameter. We assessed tree size class and downed woody debris size class as follows: over 50% of trees/logs within a 15-m radius of the trap location smaller than 10 cm diameter, 10-20 cm diameter, and >20 cm diameter. We assessed relative density of downed woody debris using the following categories: low (1-5 logs within a 15 m radius of the trap location), medium (5-10 logs within 15 m), and high (>10 logs within 15 m).

At the same trap locations, we visually estimated the percent cover of shrubs within a 2-m radius of the trap location, and classified dominant ground cover using the following categories: bare ground, grass, sedge, forb, litter, moss, or lichen. All vegetation data was collected in 2015. We summarized vegetation characteristics at each site by determining the modal category for downed wood debris density class, downed wood debris size class, dominant ground cover type, and tree size class. We calculated the average of the continuous vegetation variables for each site: canopy cover, shrub cover, and forest composition (proportion coniferous trees).

Analysis

All analyses were performed using R version 3.4.3 (R Core Team 2017) in RStudio version 1.1.383 (RStudio Team 2017). To evaluate the difference in sound pressure level across noise categories of sites, we calculated the average sound pressure level for sites where we took measurements in the field at the four corners of the trapping grid. We used an analysis of variance (ANOVA) and a Tukey post-hoc test to determine if the sound pressure level was different between the three noise categories.

We report the abundance of small mammals as the number of unique individuals captured per 100 trap-nights. When calculating the number of trap-nights, we used a correction factor of half a trap-night subtracted for each trap sprung (Nelson and Clark 1973, Beauvais and Buskirk 1999). This corrects for closed traps that reduce the number of animals that can be captured, and this method is applicable to any trapping device that becomes inoperative when sprung (Nelson and Clark 1973). We conducted a two-factor ANOVA to determine if the noise category of sites influenced the abundance of small mammals among years. We performed an ANOVA on the abundance of all rodent species combined, and separate ANOVAs for the two most abundant species: southern red-backed voles (*Myodes gapperi*) and deer mice (*Peromyscus maniculatus*). Abundance data were not normally distributed, so were log(x + 1)-transformed prior to analysis. We added 1 to the abundance of each site to allow transformation, because we had some sites where no deer mice were caught. Initially, the interaction between year and noise category was included in the ANOVA model, but was removed if not significant. We then fitted a more complex linear model with year, noise category, and vegetation variables that had significant effects on abundance (based on $\alpha = 0.05$) to account for differences between sites in vegetation characteristics. This analysis did not include two sites because of missing vegetation data, these were trapped in 2014 but not in 2015 when vegetation data was collected. To test for significant effects of vegetation on small mammal abundance, we ran univariate linear models with each of the following vegetation variables: wood debris density class, downed wood debris size class, dominant ground cover type, tree size class, canopy cover, shrub cover, and forest composition.

To answer the question of whether industrial noise affected the movement of individuals, we calculated the maximum distance moved between recapture events during the 4-day trapping session for individuals that were recaptured at least once, as a measure of the spatial extent of activity by small mammals. We included deer mice and southern red-backed voles only in this analysis because we caught few individuals and had very few recaptures of any other species (Table 5.2). Maximum distance moved was not normally distributed and was log(x + 1)-transformed prior to analysis. We added 1 m to all distances to allow transformation when the maximum distance moved was 0 m. This occurred for individuals that were only ever caught at the same trap location. The log maximum distance moved by each individual was our response variable, and we included noise category, year, species and sex as fixed effects in our model to test for an effect of noise while controlling for other variables that we had reason to believe could affect movement behaviour based on previous studies. All fixed effect variables in the model were categorical: noise category (chronic, intermittent or no noise), year (2014 or 2015), species (deer mouse or red-backed vole), and sex (male or female). Initially, all two-way interactions were included in the model. We used a backward stepwise model simplification to eliminate non-significant interactions. We initially ran a linear mixed effects model using the R package lme4 (Bates et al. 2015), and included site as a random intercept to account for possible differences in movement behaviour across different sites. However, the random effect of site explained little variance and did not improve the model, so we simplified the analysis to a linear model with only fixed effects.

To answer the question of whether an effect of noise was occurring at a smaller scale than the size of the trapping grids, we calculated a relative distance of each trap to the forest edge of the clearing. Traps on the first line of the trapping grid closest to the forest edge were assigned a distance of 0 m, and the distance increased in 15 m increments. We were interested in testing for an edge effect on the number of individual small mammals caught, but more importantly whether the edge effect differed between noisy forest edges and quiet forest edges. At this scale, an increase in the number of individuals caught could be due to increased abundance and/or changes in behaviour of small mammals. We determined the number of individuals caught across traplines located the same distance from the edge at each site separately. There were 8 traplines per site, thus our sample size for this analysis was 296 traplines across both years. Our response variable, number of individual rodents captured per trapline during the 4-day trapping session, showed overdispersion (i.e. the variance was larger than the mean), so we used a mixed effects model with a negative binomial distribution using a log-link function in the 'glmmADMB' package in R (Skaug et al. 2016). Exploratory analyses suggested that the relationship between number of individual rodents caught and distance to the forest edge was not linear, so a model with a term for inverse distance (1/distance) was fit to the data. This functional form provided a better fit based on comparing models using Akaike Information Criterion (AIC; Burnham and Anderson 2002). We included year as a fixed effect to account for large differences in small mammal abundance between years. Our final statistical model included number of individual rodents captured per trapline as the response variable, fixed effects of year, inverse distance to the forest edge, noise category, the interaction between distance and noise category, and site as a random intercept to account for differences in small mammal abundance and vegetation characteristics between sites.

RESULTS

We recorded 1,531 small mammal captures during 8,484.5 trap-nights, and we caught and tagged a total of 674 individuals. Abundance of small mammals was higher during the summer of 2014 (13.7 individuals per 100 trap-nights) than in 2015 (5.4 individuals per 100 trap-nights). Although we trapped more sites in 2015, we only captured 292 individuals during 5,473 trap-nights, compared to 382 individuals during 3,011.5 trap-nights in 2014. Directly comparing sites trapped in both years, the number of individuals caught decreased in 2015 for 11 out of the 12 sites trapped. Seven species of rodents were captured (Table 5.2), but 98% of all captures and 96% of all individuals caught were southern red-backed voles (n = 956 captures, 450 individuals) and deer mice (n = 544 captures, 200 individuals). We caught red-backed voles at 100% of sites trapped and deer mice at 68% of sites trapped across both years.

The sound pressure level measured at grid corners 1 m from the ground varied from 31.0 to 61.6 dBA. Average sound pressure level varied across sites from 31.7 to 54.4 dBA. Average sound pressure level at sites was significantly different between noise categories ($F_{2,12} = 11.69$, $p = 0.0015$). A Tukey post-hoc test revealed that the chronic noise sites (50.70 ± 2.01 dBA) were significantly louder ($p = 0.01$) than the intermittent noise sites (40.34 ± 2.57 dBA) and significantly louder ($p = 0.002$) than the control sites (36.82 ± 1.70 dBA). There was no difference between the intermittent noise and control sites ($p = 0.49$). The change in sound pressure level at chronic noise sites decreased by 6.6 dB on average from the side of the grid closest to the noise source to the side furthest from the noise source. This difference was smaller at intermittent noise sites, a decrease of 1.97 dB in sound pressure level from the side of the grid closest to the road to the side furthest from the road.

Abundance of small mammals (all rodent species pooled) differed between years (Figure 5.2; $F_{1,33} = 11.64$, p-value = 0.002), but did not differ between noise categories (Figure 5.2; $F_{2,33} = 1.30$, p-value = 0.29). Abundance of red-backed voles differed between years ($F_{1,33} = 9.77$ p-value = 0.004), but did not differ between noise categories ($F_{2,33} = 1.68$, p-value = 0.20). The interaction between year and noise category approached significance ($F_{2,31} = 3.01$, p-value = 0.06). We caught twice the number of red-backed vole individuals per 100 trap-nights at chronic noise sites in 2015 compared to other sites, whereas we caught similar numbers of red-backed vole individuals across noise categories in 2014 (Figure 5.2). Abundance of deer mice did not differ between years ($F_{1,33} = 2.01$, p-value = 0.17), and did not differ between noise categories ($F_{2,33} = 0.48$, p-value = 0.62). For the vegetation characteristics that we summarized for each site, we found significant effects of forest composition ($F_{1,33} = 7.20$, p-value = 0.01), dominant ground cover ($F_{2,32} = 5.57$, p-value = 0.008), and canopy cover ($F_{1,33} = 6.54$, p-value = 0.02) on the abundance of all rodent species pooled. However, there was no effect of noise category on small mammal abundance (for all rodents pooled, red-backed voles, and deer mice) when these three vegetation variables were added to the models with year and noise category, and for this reason we chose to only present the results of the simpler models (see above) without the vegetation variables.

We calculated the maximum distance moved during a trapping session for each individual red-backed vole (n = 283) and deer mouse (n = 160) recaptured at least once. The analysis included a total of 443 individuals, 257 individuals in 2014, and 186 individuals in 2015. The range of maximum distance moved between recaptures during a 4-day trapping session varied between 0 m and 129 m, with a mean maximum distance (± SE) of 33.8 m. The mean maximum distance moved was 31.8 ± 1.53 m in 2014 and 36.4 ± 2.06 m in 2015, but this difference was not significant between species (Table 5.3). We found no effect of noise category of the site on the maximum distance moved by individuals during a trapping session (Figure 5.3; Table 5.3). The mean maximum distance moved (± SE) by deer mice was 38.5 ± 2.36 m, and for red-backed voles it was 31.1 ± 1.39 m, but this difference was not significant (Table 5.3). We found a significant effect of sex on mean maximum distance moved (Table 5.3), where males (n = 207 individuals) moved 38.4 ± 1.95 m on average, and females (n = 236 individuals) moved 29.7 ± 1.55 m on average. The effect of sex was primarily due to red-backed vole females moving less than males.

In our analysis on effects of noise within the trapping grids, we tested whether the number of individuals caught varied with inverse distance to the forest edge, and whether this effect differed between noisy edges and quiet edges. Our analysis included 296 traplines (8 per grid), and the number of individual rodents caught on a trapline varied from 0 to 16, with a mean of 3.7 individuals. We found a significant effect of year (Table 5.4), but the interaction between inverse distance to the edge and noise category was not significant (Table 5.4). We ran the model without the interaction term and found the effect of year was highly significant, but there was no significant effect of inverse distance or noise category on the number of individual rodents.

DISCUSSION

There was little evidence that industrial noise had an impact on the abundance of small mammals. Small mammal abundance could have been negatively affected by noise if it caused them to be more vulnerable to predation, or they could have been positively affected if noise provided a refuge from predators. There is a possibility that both of these opposite effects could be operating at the same time, leading to no detectable difference in abundance of small mammals between noise categories. This could occur if predators that use auditory cues to hunt prey avoid noisy areas, while predators using olfaction or vision are attracted to noisy areas with more susceptible prey. Unfortunately, there are few studies that have looked at how predators respond to anthropogenic noise. Three species of owls in northern Alberta were found to be equally likely to occupy sites with industrial noise sources compared to sites without noise (Shonfield and Bayne 2017b). A study in New Mexico found a negative effect of industrial noise on species richness of nesting songbirds, but those species that did nest in noisy areas had higher success due to lower nest predation. This occurred because western scrub-jays (*Aphelocoma californicus*), the primary nest predator in the study area, were avoiding noisy areas (Francis et al. 2009). More research into how the predator community is responding to industrial noise is necessary to untangle these potential effects on prey. Nevertheless, the net result appears to be that there is no difference to the small mammal community in our boreal forest system. Presumably this means that for at least some predators that prey on small mammals, they are able to tolerate hunting in noisy environments. This assumes that predators can have regulating effects on small mammal populations, but there is experimental evidence that predators can drive the population cycles of *Microtus* voles in western Finland (Korpimäki et al. 2005).

We used maximum distance moved by individuals as a measure of activity by small mammals. We found considerable variation in the maximum distance individuals moved, ranging from effectively no movement for individuals caught in a single trap, to individuals moving up to 129 m diagonally across the trapping grid. A study tracking movement of two

Microtus spp. using radio telemetry to locate individuals twice a day also found considerable variation in movement, voles moved between 2 and 62 m between consecutive fixes (Norrdahl and Korpimäki 1998). Red-backed voles in our study moved a mean maximum distance of 31.1 m, which is comparable to another live-trapping study on this species with the same trap spacing, where voles moved 26 m during a 3-day trapping session (Vanderwel et al. 2010). We found the maximum distance individuals moved between recapture events was not affected by industrial noise, but did differ between sexes. We predicted that movement, as an indicator of activity, would be influenced by predation risk based on the results of previous studies (Norrdahl and Korpimäki 1998, Hegab et al. 2015). Our results indicate that small mammal movement was similar regardless of the presence of industrial noise, suggesting perceived predation risk was similar across sites. That male voles moved more than females was similar to a study on grey-sided voles (*Myodes rufocanus*) and bank voles (*Myodes glareolus*) that found males moved more than females and consequently were more exposed to predation risk (Trebatická et al. 2008).

The chronic noise sites had higher noise levels than the intermittent and no noise sites. We did not detect a difference in noise level at intermittent noise sites near roads compared to sites with no noise. The intermittent nature of traffic noise makes it difficult to assess noise levels in the field without continuous acoustic monitoring, and the measurements we made in the field did not always capture trucks passing by. Presumably the traffic volume at our sites was insufficient to create any kind of noise effect on small mammals, but also suggests that road mortality or edge effects caused by roads were no different than those caused by wellpads or industrial sites with compressor stations. The grids we trapped were small, just over a hectare, yet there was an audible decrease in noise level at chronic noise sites from one side of the grid to the other. Despite the fact that we found no difference in small mammal abundance at the grid level, we considered that there may be an edge effect occurring over a short distance. However, our results indicated that there was no interaction between distance from the edge and presence of a noise source on the number of individuals caught. We also found no evidence of an edge effect on small mammal abundance. Reviews of studies on edge effects have generally shown mostly neutral effects of edges on small mammals (Ries et al. 2004, Darling 2008). Edge effects can be positive if they result in habitat enhancement, for example if species are attracted to different resources available in each habitat, as edges are the ideal location to gain access to spatially separated resources (Ries et al. 2004). Edge effects are more likely to be negative if they result in transitional habitat that lacks important resources for some species, or if they result in higher predation risk or mortality.

Research on effects of anthropogenic noise on wildlife has tended to show mostly negative effects, or effects that we interpret as having potential negative consequences. Numerous studies have found lower abundance of certain species and that biodiversity is lower in noisy areas (Bayne et al. 2008, McClure et al. 2013, Bunkley et al. 2017). Other studies have found individuals living in noisy areas have offspring with lower body condition and survival, leading to reduced fitness (Schroeder et al. 2012, Kleist et al. 2018). More recently, studies have shown that noise may have a small effect compared to other types of disturbance such as physical industrial infrastructure (Bernath-Plaisted and Koper 2016, Nenninger and Koper 2018), and habitat loss and fragmentation (Fröhlich and Ciac 2017). The negative effects of noise seem to be primarily caused by masking of important signals (Bee and Swanson 2007, Grade and Sieving

2016) used in intra-specific acoustic communication. Our results suggest that for species primarily using non-auditory signals for communication, the effects of noise are minimal and unlikely to be key drivers of population dynamics or behaviour.

Impacts of anthropogenic disturbance on wildlife can differ between taxonomic groups. For example, the literature on the effects of roads has shown mainly negative effects on the abundance of birds, reptiles and large mammals, but for small mammals the effects on abundance are either neutral or positive (Fahrig and Rytwinski 2009). Our understanding of the impacts of noise on different species and taxonomic groups continues to evolve and further work on small mammal communities and their response to noise is warranted, but should be done in conjunction with studies on predator behaviour near noisy areas.

Table 5.1 Number of small mammal sites trapped in each year in each noise category.

Noise category	Infrastructure present	Noise source	2014	2015	Total unique sites
Chronic noise	Compressor station	Facilities	5	7	8
Intermittent noise	Road	Road Traffic	5	8	8
No noise	None	None	4	8	9
Total sites			14	23	25

Table 5.2 Number of individuals caught, and number of individuals recaptured at least once during the 4-day trapping session for each species in each year. Live-trapping was done in July and August of each year, and each site was trapped once.

Species	Scientific name	Individuals caught in 2014	Individuals recaptured in 2014	Individuals caught in 2015	Individuals recaptured in 2015
Southern red-backed vole	*Myodes gapperi*	258	172	192	110
Deer mouse	*Peromyscus maniculatus*	109	85	91	76
Meadow vole	*Microtus pennsylvanicus*	10	1	5	1
Northern flying squirrel	*Glaucomys sabrinus*	2	1	1	0
Red squirrel	*Tamiasciurus hudsonicus*	2	0	0	0
Meadow jumping mouse	*Zapus hudsonius*	1	0	2	1
Least chipmunk	*Tamias minimus*	0	0	1	0
Total small mammals		382	259	292	188

Table 5.3 Results of a linear model explaining log transformed maximum distance moved by individual rodents between traps during a 4-day trapping session. Effects are reported as the effect of the level in parenthesis (e.g. chronic) relative to the reference category. In this case the reference categories are no noise for the noise category, 2014 for year, females for sex, and deer mice (*Peromyscus maniculatus*) for species. Significant p-values are in bold (significance level α = 0.05).

Effect	Estimate ± SE	t	p
Intercept	2.97 ± 0.15	20.11	**<0.0001**
Noise category (chronic)	-0.21 ± 0.15	-1.44	0.15
Noise category (intermittent)	-0.03 ± 0.16	-0.19	0.85
Year (2015)	0.08 ± 0.12	0.67	0.50
Sex (male)	0.35 ± 0.12	2.84	**0.005**
Species (southern red-backed vole *Myodes gapperi*)	-0.01 ± 0.13	-0.10	0.92

Table 5.4 Results of a negative binomial generalized linear mixed model (GLMM) explaining number of individual rodents caught per trapline during 4-day trapping sessions. Effects are reported as the effect of the level in parenthesis (e.g. chronic) relative to the reference category. In this case the reference categories are no noise for the noise category, and 2014 for year. Significant p-values are in bold (significance level α = 0.05).

Fixed effect	Estimate ± SE	Z	p
Intercept	1.60 ± 0.22	7.29	**<0.0001**
Year (2015)	-0.80 ± 0.08	-10.29	**<0.0001**
Noise category (chronic)	0.07 ± 0.31	0.23	0.82
Noise category (intermittent)	-0.12 ± 0.31	-0.40	0.69
Inverse distance to edge	-0.10 ± 0.17	-0.60	0.55
Noise category (chronic) × Inverse distance to edge	0.40 ± 0.22	1.81	0.07
Noise category (intermittent) × Inverse distance to edge	0.27 ± 0.24	1.16	0.25
Random effect	**Variance**	**SD**	
Site	0.356	0.597	

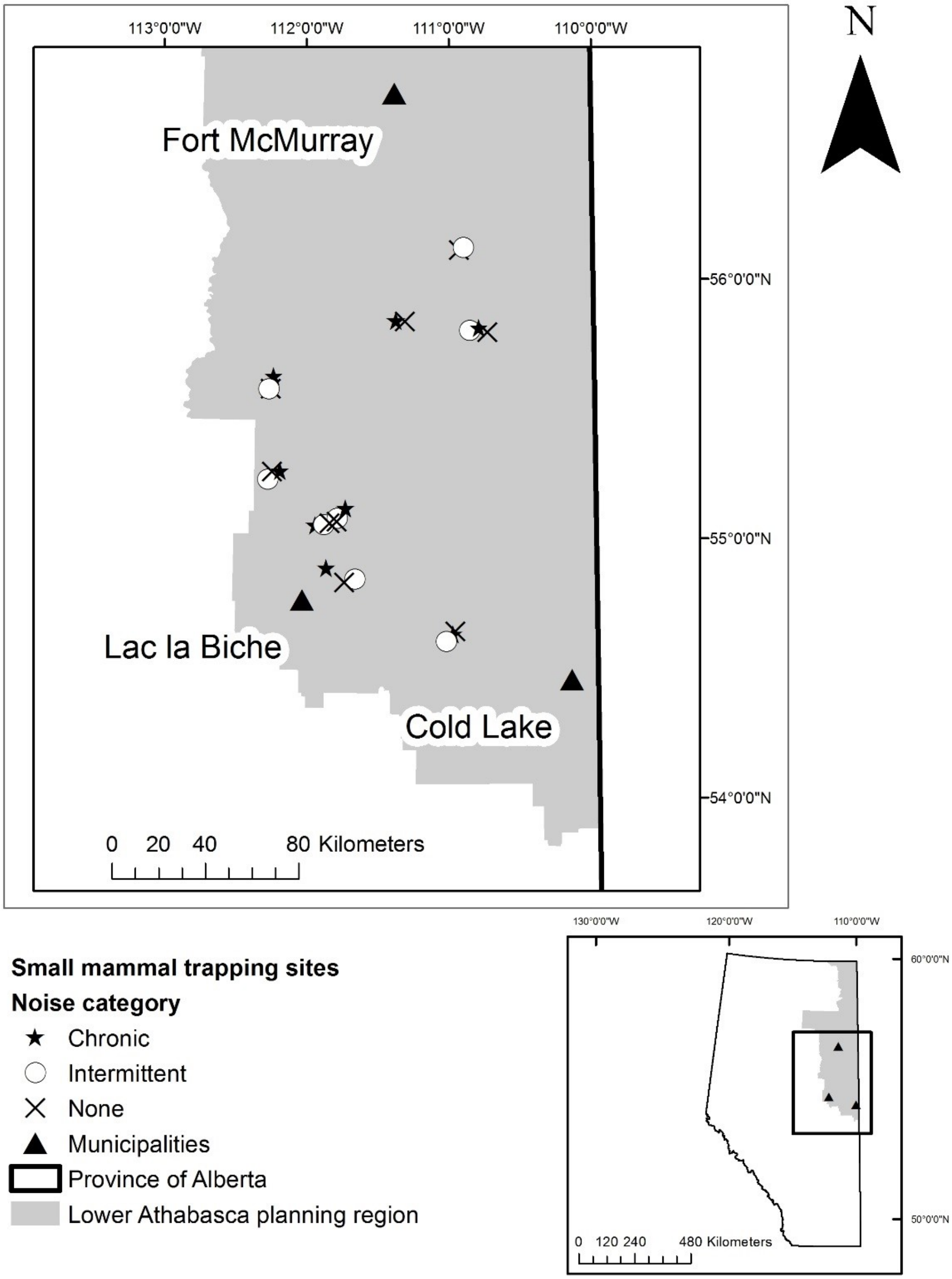

Figure 5.1 Map of the study area located within the Lower Athabasca planning region of northeastern Alberta (bottom right inset) and locations and noise categories of sites where small mammals were live-trapped.

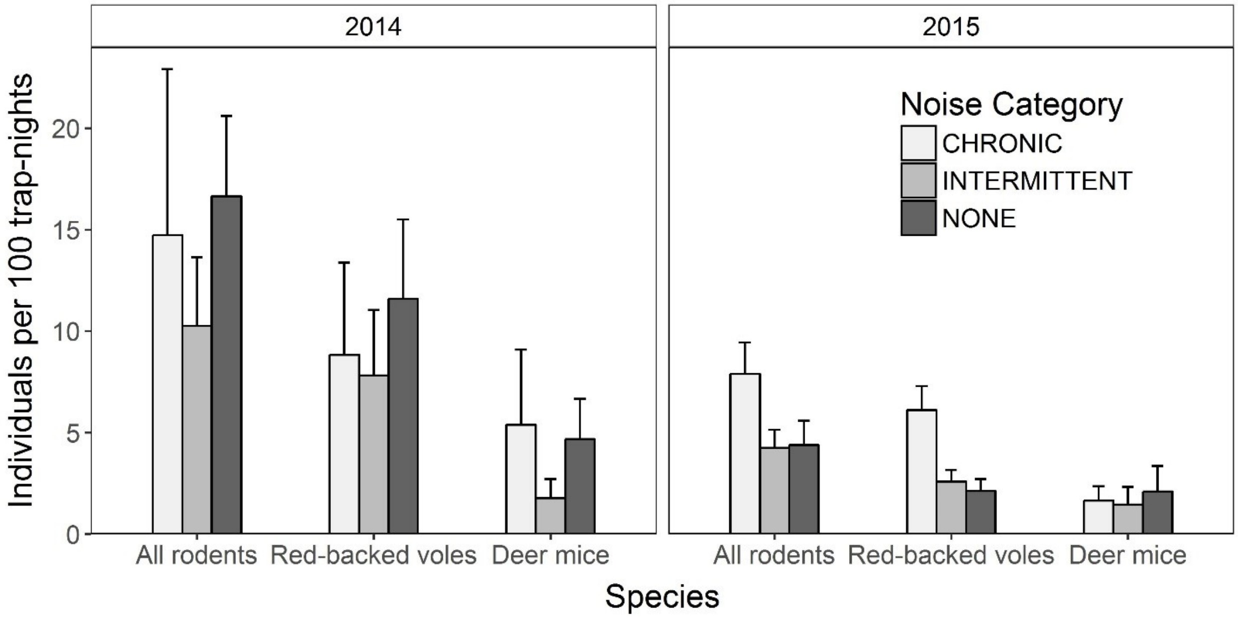

Figure 5.2 Abundance of small mammals for each year in each noise category (mean number of individuals per 100 trap-nights ± 1 SE). In 2014, 14 sites were trapped (left panel) and in 2015, 23 sites were trapped (right panel). Chronic noise sites were adjacent to compressor stations, intermittent noise sites were adjacent to a road, and no noise sites were adjacent to forest clearings away from roads or facilities.

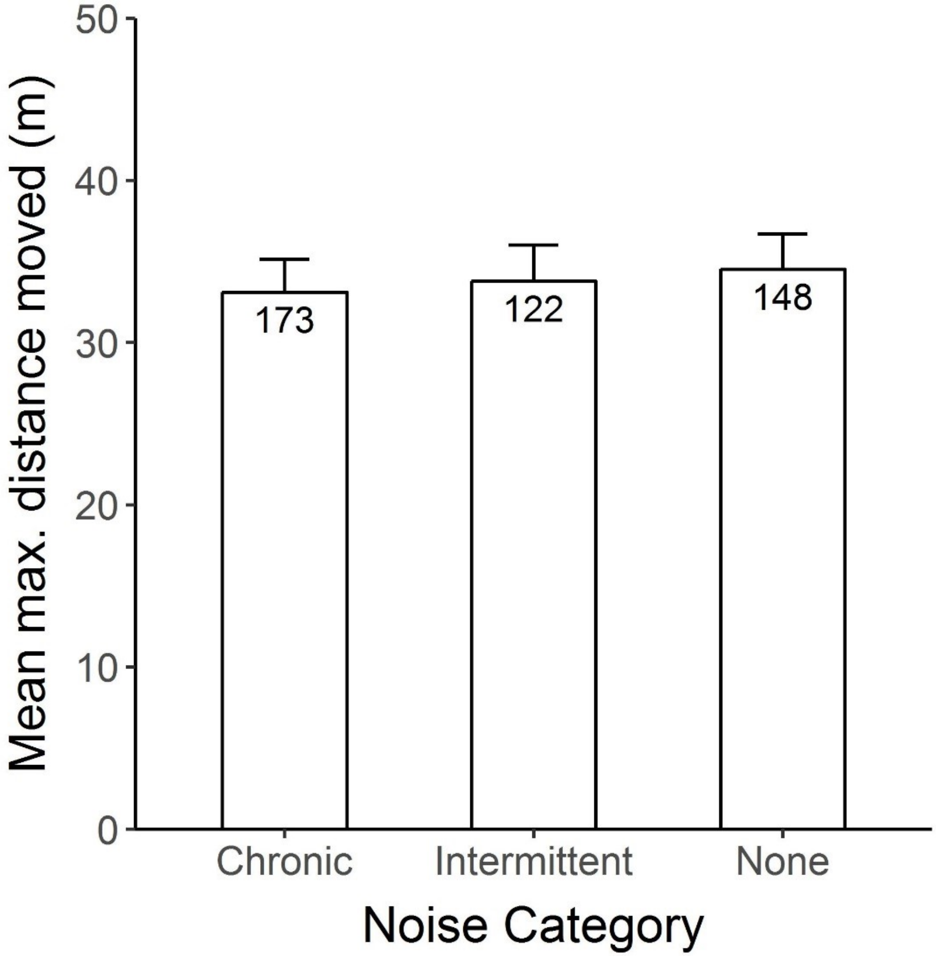

Figure 5.3 Mean maximum distance moved (mean ± 1 SE) between traps by small mammals (deer mice and red-backed voles only) during 4-day trapping sessions for each noise category. Chronic noise sites were adjacent to compressor stations, intermittent noise sites were adjacent to a road, and no noise sites were adjacent to forest clearings away from roads or facilities. Numbers in the bars indicate the sample size (i.e. number of individuals caught at least twice).

Chapter 6. Cumulative Effects of Industrial Disturbance on Owls in the Boreal Forest

INTRODUCTION

There is a large and growing body of research on the impacts of anthropogenic disturbance on wildlife. Anthropogenic disturbances can be grouped into two broad categories: physical disturbance leading to an alteration or removal of habitats on the landscape (e.g. clearing vegetation, building structures), and sensory disturbance (e.g. light, noise, and other forms of pollution) that can permeate through landscapes. For example, logging creates a physical disturbance in the form of cutblocks, but the process of logging a forest also involves heavy machinery and the noise generated is a sensory disturbance. In many cases, a physical disturbance on the landscape also produces a sensory disturbance that effectively extends the zone of influence of that type of disturbance (e.g. industrial facility with infrastructure that produces chronic noise), which increases the functional amount of habitat lost for many species.

Animals are likely to exhibit a negative response to anthropogenic disturbance if it results in loss of their habitat, and if it poses a higher predation risk. Wolves use natural edges between forest and open areas for hunting (Bergman et al. 2006), and have been found to use anthropogenic linear features to travel (Dickie et al. 2016), so linear features and disturbances that create forest edges may be areas of higher predation risk for prey species. Risk of human-caused mortality can also lead to negative responses to anthropogenic disturbance, for example numerous species avoid roads, and many are vulnerable to road mortality (Fahrig and Rytwinski 2009). While anthropogenic disturbances can negatively affect wildlife, this is not always the case. Seismic lines and other linear features are used as travel corridors and enable faster travel speeds for wolves (*Canis lupus*) in Alberta's boreal forest (Dickie et al. 2016). Wolverines (*Gulo gulo*) in northwestern Alberta strongly selected forestry cutblocks during active harvest, which is hypothesized to be due to foraging opportunities as prey may be displaced by the sensory disturbance (Scrafford et al. 2017). Positive responses in one species to anthropogenic disturbance may be related to negative responses in another closely competing species, e.g. decline in numbers of African lions (*Panthera leo*) due to human disturbance resulted in an increase in spotted hyenas (*Crocuta crocuta*) (Green et al. 2017). These examples highlight that certain types of disturbance are favoured by some species if they provide foraging opportunities, reduce competition, or facilitate movement.

Reductionist approaches often focus on assessing the impact of a single type of disturbance on wildlife. Research on the effects of anthropogenic noise, for example, has seen a steady increase in the number of studies published in the last two decades (Shannon et al. 2016). Some studies on the effects of anthropogenic noise have conducted controlled playback experiments where noise is introduced in isolation of other forms of anthropogenic disturbance (McClure et al. 2013, Rosa et al. 2015, Ware et al. 2015). This experimental approach allows for the study of the impacts of noise in isolation from other confounding variables, but there are few real-world examples of an anthropogenic noise disturbance without an associated physical disturbance to the landscape, especially in the case of chronic noise sources. More recent studies have shown that noise can have a small effect compared to other types of disturbance such as the physical industrial infrastructure (Bernath-Plaisted and Koper 2016, Nenninger and Koper 2018), and habitat loss and fragmentation (Fröhlich and Ciac 2017). Studying a single type of disturbance in isolation ignores the potential of additive or synergistic effects of multiple disturbance types. The concept of cumulative effects is that while each disturbance or land use change on its own may result in a small or negligible effect on wildlife, the accumulation of disturbances, or changes over time/within a region can result in a major impact on wildlife (Theobald et al. 1997). Evaluating cumulative effects of disturbance is key to resource management and wildlife conservation (Burton et al. 2014), and can help us to understand what is driving declines in species that are at risk.

Owls (*Strigiformes*) are important components of the ecosystems they inhabit as top aerial predators present year-round, and may be more likely to encounter anthropogenic disturbances because they are highly mobile and inhabit large territories. Studies on the effects of anthropogenic disturbance on owls have focused specifically on roads, as well as habitat loss from physical disturbances. Roads are a well-studied type of disturbance and have been found to have negative effects on a wide variety of species (Fahrig and Rytwinski 2009), and owls are no exception. Increased proximity to roads and increased traffic volume has been found to decrease owl density and occupancy of sites (Hindmarch et al. 2012, Silva et al. 2012), and traffic volume has been attributed to decreased fledging rates in northern spotted owls (*Strix occidentalis caurina*) (Hayward et al. 2011). A study on tawny owls (*Strix aluco*) in an urban region found noise from roads decreased the probability of occurrence, but this effect was small compared to a much stronger positive effect of the size of wooded areas on owl occurrence (Fröhlich and Ciac 2017). Northern saw-whet owls (*Aegolius acadicus*) have lower foraging efficiency and reduced reproductive success in areas with high levels of habitat loss and fragmentation (Hinam and St. Clair 2008).

Conversely, some forms of anthropogenic disturbance have the potential to provide good habitat for owls. Some species of owls are known to inhabit and nest in urban areas (White et al. 2018), where prey can be abundant, and there can be numerous nesting opportunities (e.g. corvid nests and nest boxes). Some owl species have become closely associated with human-built structures, for example the barn owl (*Tyto alba*) commonly nests in barns and other old buildings (Johnsgard 2002). Thus, anthropogenic disturbance has the potential be both beneficial and detrimental for owls depending on the species and type of disturbance. In areas where multiple types of anthropogenic disturbance exist (e.g. roads, cutblocks from forestry operations, and oil processing facilities from the energy sector) it is important to assess the potential for cumulative effects of these disturbances on owls, and whether certain types are influencing where owls are found on the landscape to a greater degree than other types of disturbance. Our objective for this study is to evaluate potential cumulative effects and assess the relative importance of different types of anthropogenic disturbance on habitat use of three owl species in boreal Alberta: the barred owl (*Strix varia*), the boreal owl (*Aegolius funereus*), and the great horned owl (*Bubo virginianus*).

METHODS

Study area

This study was located in the boreal forest of northeastern Alberta, within the Lower Athabasca Planning Region (LAPR). The LAPR has seen increased development in the oil and gas industry in recent years, and there are forestry operations in the region (Alberta Biodiversity Monitoring Institute 2017), making it a suitable area to research potential cumulative effects of different types of anthropogenic disturbance on wildlife. The amount of human footprint in the LAPR is highly variable, some areas are quite intact while other areas have a patchwork of different disturbances clustered closely together (Figure 6.1). We surveyed for owls at locations in forested areas in the LAPR, specifically within an area south of Fort McMurray, north of Lac la Biche, and northwest of Cold Lake (Figure 6.1). Survey locations were selected to sample across a gradient of total disturbance, and were spaced a minimum of 1.2 km apart.

Acoustic surveys

Passive acoustic surveys for owls were conducted using commercially available ARUs (SM2+ and SM4 Song Meters by Wildlife Acoustics, Inc., Maynard, Massachusetts, USA). We surveyed for owls during four spring breeding seasons from 2013-2016. ARUs were deployed each season between March 8 and May 7, when owls are actively calling. ARUs were deployed for a minimum of 9 days at each survey location. We programmed each ARU to record in stereo format at 44.1 kHz with a 16-bit resolution. Recording files were stored in .wac format on SM2+ units and .wav format on SM4 units. We tested each ARU and both microphones prior to deployment to identify any units with non-responsive channels or degraded microphones. We used gain settings of 48 dB for both the left and right channel microphones. We attached ARUs at a height of approximately 1.5 m on trees with a smaller diameter than the width of the ARU (18 cm for SM2+ units, and 12 cm for SM4 units). Over the four spring seasons of deploying ARUs, there were 22 ARUs that had complete recording failures that were not included in the final dataset, most of these failures occurred in 2013 in the first year of deployment, and in the three subsequent years only 7 ARUs failed.

Each location we surveyed had a single ARU deployed. ARUs were deployed to detect owls during the breeding season from March to May, but some ARUs were left out longer with the intent of surveying other vocalizing species (e.g. songbirds and amphibians) for other projects. ARUs were deployed specifically to detect owls in 2013, 2014 and 2015 and were set to record for 10 minutes at the start of every hour. ARUs that were deployed for longer periods had a reduced recording schedule to extend the battery life. A subset of ARUs deployed in 2013 were on a reduced schedule set to record for 10 minutes 8 times per day: at midnight, sunrise, 1 hr after sunrise, 2 hrs after sunrise, 6 hrs after sunrise, 2 hrs before sunset, 1 hr before sunset, and at sunset. All ARUs deployed in 2016 were on a reduced schedule, and were set to record 14 times per day for either 3 or 10 minutes at a time. ARUs recorded for 10 minutes at midnight and a ½ hr after sunrise, and for 3 minutes at 1am, 2am, 1.5 hrs before and after sunrise, ½ hr before sunrise, at sunrise, 2.5 hrs after sunrise, at noon, at 3pm, 1 hr before and after sunset, and at sunset.

Extracting acoustic data

We used automated species recognition to efficiently process acoustic recordings to detect territorial vocalizations of barred owls, great horned owls, and boreal owls. We previously demonstrated that using an automated recognition approach is an efficient method to obtain detections of owl calls from large volumes of audio recordings (Shonfield et al. 2018). We annotated clips from field recordings in Song Scope (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) to build templates or ‘recognizers’ for each of these three owl species. For details on how these recognizers were built and how well they performed, refer to chapter 3 of this thesis or see Shonfield et al. (2018). For all recordings collected from 2013 to 2016, we scanned them using the three owl recognizers to automatically detect the three target owl species. Trained observers verified all hits generated by the program to filter out false positives. Once verified, we compiled the owl detection data to determine presence/absence of each owl species at each location surveyed.

Landscape variables

We extracted data on human disturbance from existing spatial database resources using Geographic Information System (GIS) tools in ArcGIS 10.3.1 (Environmental Systems Research Institute, Inc., Redlands, California, USA) from Alberta Biodiversity Monitoring Institute's (ABMI) Human Footprint layer 2014 version 2 (http://www.abmi.ca/home/data-analytics). This polygon vector layer includes all types of anthropogenic disturbance across the province of Alberta, categorized into 115 feature types. These feature types include various linear features (e.g. roads, seismic lines, pipelines, transmission lines and railways), industrial and resource extraction features (e.g. well pads, compressor stations, processing plants, mines and other facilities), and recent forest cutblocks. We grouped and re-categorized all 115 feature types into the following six disturbance categories: facilities, cutblocks, low activity clearings, high activity clearings, hard linear features, soft linear features (Table 6.1). We also included an additional category for total human footprint, which was all feature types combined (Table 6.1). We based our decisions on assigning feature types to the new disturbance categories on the descriptions provided in the metadata file for the ABMI human footprint. See Table A5.1 in Appendix 5 for names and descriptions of all feature types in the ABMI human footprint layer and the new disturbance category we designated.

We extracted variables on human disturbance, as well as forest composition and forest age in ArcGIS 10.3.1, using an 800-m radius buffer around each ARU station (an area of 201 ha), approximating the maximum detection radius of an ARU to detect owls calling (Yip et al. 2017). For each of the six categories of human disturbance (Table 6.1), we calculated the proportion disturbed in the buffer area from the ABMI human footprint layer. For forest composition, we calculated the mean proportion of coniferous trees present within forested areas from the Alberta Vegetation Inventory (AVI) for each 800-m buffer. We also calculated mean forest age within forested areas in each 800-m buffer from the AVI layer.

Analysis

We used boosted regression trees (BRTs) to assess the relative importance of human disturbance and other landcover variables in explaining presence of owls on the landscape. BRTs are a type of machine learning technique, and they are well-suited to modelling complex ecological data because they can handle different types of predictor variables, accommodate missing data, can fit complex nonlinear relationships, and automatically handle interaction effects between predictors (Elith et al. 2008). We chose to use BRTs because we wanted to explore non-linear effects and interactions between disturbance types as part of a cumulative effects analysis. We compiled presence/absence data for each of our three owl species for each location surveyed with an ARU from the recognizer data. We assumed that the presence of an owl species at a location indicated that the species was using the area surrounding the ARU, and that this area contained at least some characteristics necessary for survival.

We ran BRTs in R version 3.4.3 (R Core Team 2017) using RStudio version 1.1.383 (RStudio Team 2017), implemented in the 'gbm' package (Ridgeway 2017) and 'dismo' package (Hijmans et al. 2017). A ten-fold cross validation method was used to identify meta-parameter settings and to build models. To determine the optimal settings for the BRTs, we examined all possible combinations of a range of learning rates (0.005, 0.001, 0.0005, 0.0001) and tree complexity values (2, 3, 4 and 5) following Elith et al. (2008), and this was done for each of the three owl species. The learning rate determines how much each successive tree contributes to the overall growing model, while tree complexity controls the depth of interaction between the explanatory variables. For each species, we selected the model with the combination of learning rate and tree complexity with the lowest residual deviance and at least 1,000 trees, as recommended by Elith et al. (2008). We used a bag fraction of 0.75 for all models. The number of trees was determined by the lowest residual deviance across ten cross-validation folds. The output generated from the final model was used to examine the relative importance of the predictor variables for each owl species. We plotted the six predictor variables with the highest relative influence for each owl species, to examine the direction of the effects of the predictor variables with the strongest influence. We examined pairwise interactions between predictor variables and report those with an interaction strength greater than one.

For all three owl species, we included all six disturbance variables in the BRT model as well as the forest composition and forest age variables. For barred owls, we also included a variable for the presence/absence of great horned owls as a potential competitor and predator that could influence the distribution of barred owls. For boreal owls, we included variables for the presence/absence of barred owls and great horned owls as both these larger owls may be potential predators. For great horned owls we did not include variables for the presence/absence of the other two owl species because we assumed that great horned owls would be dominant over the other species.

RESULTS

We compiled recordings from ARUs at 452 locations in the LAPR in northern Alberta from 2013 to 2016. Our final dataset included 153 locations surveyed in 2013, 104 locations in

2014, 134 locations surveyed in 2015 and 51 locations in 2016 (Figure 6.1). Barred owls were detected at 83 (18%) of locations, with the earliest detection on March 21 and the latest detection on May 30. Great horned owls were detected at 227 (50%) of locations, with the earliest detection on March 16 and the latest detection on June 24. Boreal owls were detected at 94 (21%) of locations, with the earliest detection on March 12 and the latest detection on June 11. We used owl presence in our analysis without correcting for detection probability, but given the length of time we surveyed during the period when owls are actively calling, we are confident that our methods would detect owls if they were present in each location. The locations surveyed varied in the proportion of the different types of human disturbance, as well as proportion coniferous forest and mean forest age within an 800-m radius of the ARU (Table 6.2). Facilities were the least common type of disturbance and only present at about 23% of locations surveyed, whereas soft linear features were nearly everywhere (at 99.8% of locations surveyed, Table 6.2). Proportion coniferous forest and mean forest age were within the top four most influential variables in the BRT models for all three species, whereas the types of disturbance with strong influence differed between owl species.

For each owl species, the final BRT model used a learning rate and tree complexity that resulted in the lowest residual deviance and at least 1,000 trees. For barred owls, we used a learning rate of 0.0001 and a tree complexity of 3 (Table 6.3). The final model had 8800 trees, and explained 13% of the variation in the data (Table 6.3). The strongest variable influencing presence of barred owls was proportion coniferous forest (relative influence 34.4%). Partial dependency plots show a positive marginal effect on barred owl presence in forests with 0% to 70% coniferous trees (i.e. deciduous and mixedwood forests), and a negative marginal effect on barred owl presence once the forest composition exceeded 70% coniferous trees (Figure 6.2). The second strongest variable influencing presence of barred owls was the proportion of hard linear features (relative influence 17.2%), followed closely by proportion of total human footprint (relative influence 16.1%). Partial dependency plots indicate that barred owl presence decreased with increasing proportion of hard linear features and with increasing total human footprint (Figure 6.2). Interactions between variables were weak; only four two-way interactions had a multiplicative strength greater than one, and the strongest interaction was between proportion coniferous forest and total human footprint (Table 6.4). This interaction had a positive effect on barred owl presence in more deciduous and mixedwood forests with low proportions of total human footprint. Other disturbance types (soft linear features, cutblocks, low and high activity clearings) had low relative influence (between 2.8% and 7%) on the presence of barred owls. The proportion of industrial facilities had the weakest influence of all the disturbance types (relative influence 0.8%), and the presence of great horned owls had the weakest influence of all the variables tested on the presence of barred owls (relative influence 0.06%).

For great horned owls, we used a learning rate of 0.0005 and a tree complexity of 2 (Table 6.3). The final model had 3300 trees, and explained 9% of the variation in the data (Table 6.3). The strongest variable influencing presence of great horned owls was the proportion of soft linear features (relative influence 25.8%). Partial dependency plots showed that great horned owl presence increased as the proportions of soft linear features increased (Figure 6.3). The second strongest variable influencing presence of great horned owls was the proportion of industrial facilities (relative influence 17.8%), followed closely by mean forest age (relative influence 16.8%), and proportion coniferous forest (relative influence 15.7%). Partial dependency plots indicate a negative effect of increasing proportion of facilities on presence of great horned owls (Figure 6.3). Forest age showed a sharp positive marginal effect of forests 75 years and older on great horned owl presence, and proportion coniferous forest showed a sharp negative marginal effect of forests greater than 80% coniferous on great horned owl presence (Figure 6.3). Interactions between predictor variables were weak; the only two-way interaction with a multiplicative strength greater than one was between mean forest age and proportion of soft linear features (Table 6.4). This interaction had a positive effect on great horned owl presence in older forests with moderate proportions of soft linear features.

For boreal owls, we used a learning rate of 0.001 and a tree complexity of 2 (Table 6.3). The final model had 5500 trees, and explained 30% of the variation in the data (Table 6.3). The strongest variable influencing presence of boreal owls was forest composition (relative influence 17.5%). Partial dependency plots indicate that boreal owls are more likely to be present as the proportion coniferous forest increased (Figure 6.4). The second strongest variable was the mean forest age (relative influence 16%), followed closely by proportion of low activity clearings (relative influence 15%) and the proportion of high activity clearings (relative influence 14.6%). The effect of forest age shows a fluctuating pattern between 60 and 120 years old (Figure 6.4). There were few locations surveyed in very young or very old forests, most locations surveyed (87%) had a mean forest age between 60 and 120 years, and most locations (67%) were in mature forest between 80 and 110 years old. Low and high activity clearings show positive effects at very low proportions of these disturbances but with a sharp negative effect as the proportion of these disturbances increases (Figure 6.4). The majority (97%) of survey locations had less than 10% disturbed by low activity clearings, and similarly 95% of locations had less than 10% disturbed by high activity clearings.

The relative influence of great horned owl presence was 12.6% and there was a negative marginal effect on boreal owl presence when great horned owls were absent, and a positive marginal effect on boreal owl presence when great horned owls were present (Figure 6.4). Great horned owls were present at 70% of the locations where boreal owls were present. The presence of barred owls had the weakest influence of all the variables on the presence of boreal owls (relative influence 0.06%). Interactions between variables were weak, only 2 two-way interactions had a multiplicative strength greater than one, and the strongest interaction was between mean forest age and proportion of soft linear features (Table 6.4). This interaction had a positive effect on boreal owl presence in more coniferous forests with low proportions of soft linear features.

DISCUSSION

We evaluated potential cumulative effects of anthropogenic disturbance on barred owls, great horned owls, and boreal owls by assessing the relative importance of disturbance types on the presence of owls. The variance explained by the model for each species was never higher than 30%, which may indicate that the overall importance of anthropogenic disturbance is low in its effect on where these owl species are found. However, since we used presence/absence data for owls, we cannot say whether anthropogenic disturbance affects survival or reproduction of these owl species. We found little evidence for additive effects of disturbance on the presence of the three species studied. The two-way interactions between predictor variables were weak, and the strongest interactions were not between disturbance types, and instead were between forest composition/age and a disturbance type. We had hypothesized that owls could be sensitive to anthropogenic disturbance because they are highly mobile with large territories, and therefore may be more likely to encounter disturbance. However, it is possible that these same traits allow them to tolerate disturbance by being able to move to less disturbed areas within their territories. The fact that the models did not explain more than 30% of the variance in the data is problematic if we were using these models to predict where owls are found on the landscape, but that was not the intention of this study. If it had been, we would have considered including additional variables describing vegetation characteristics and climatic conditions. The abundance of prey is likely an important factor explaining presence of owls that we did not include, and though we collected data on small mammal abundance in our study area (see chapter 5), this was done at only a small number of locations where owls were surveyed.

Facilities that produce chronic noise were present within an 800-m radius at less than a quarter of the locations surveyed for owls. The proportion of oil/gas facilities had low influence on the presence of barred and boreal owls, but it was the second most influential variable on the presence of great horned owls. We previously assessed the effect of chronic industrial noise on occupancy of barred owls, great horned owls, and boreal owls and found no evidence of avoidance of noise sources in northern Alberta (Shonfield and Bayne 2017b). The results in the present study for great horned owls are contrary to what we would expect based on our previous work. This may be explained by the fact that we did not take into account the size of the facilities in the previous study (Shonfield and Bayne 2017b), and the results here indicate the effect of facilities on great horned owl presence is negative only when the proportion of the area occupied by the facilities is ~15% of the area. Other studies have shown that the effect of noise may not be as important compared to other types of anthropogenic disturbance (Bernath-Plaisted and Koper 2016, Fröhlich and Ciac 2017, Nenninger and Koper 2018), and the results of this work provide further evidence that this generally appears to be the case for the three owl species in our study area as well.

Soft linear features, such as seismic lines, occupy a small area on the landscape but high densities of these features contribute to forest fragmentation and increase the amount of edge habitat (Pattison et al. 2016). They are ubiquitous in our study area in northern Alberta and were found nearly everywhere we surveyed. The proportion of soft linear features did not have a strong influence on the presence of barred and boreal owls, but did have a strong influence on great horned owl presence. Interestingly, we found a positive effect of proportion of soft linear features on the presence of great horned owls. We attribute this effect to favourable hunting areas on seismic lines, pipelines and transmission lines. The vegetation on soft linear features is similar to meadows, and small mammals favouring this type of habitat, such as meadow voles (*Microtus pennsylvanicus*), are abundant on linear features in the boreal forest (Darling 2008). Great horned owls employ a perch-and-wait hunting style, and soft linear features would provide multiple perch locations for them to hunt from.

We included both roads and railways as hard linear features in our analysis, but there was only a single rail line in our study area, so we attribute any effects of hard linear features primarily to roads. The proportion of hard linear features had low influence on great horned and boreal owl presence, but had a strong influence on barred owl presence. Our results suggest that a higher proportion of roads has a negative effect on the presence of barred owls. Owls are frequently killed on roads (Bishop and Brogan 2013) and road mortality of barred owls has been found to increase on roads with higher speed limits and on roads in areas of higher habitat suitability (Gagné et al. 2015). A study in Portugal found that density of tawny owls (*Strix aluco*), a closely related species to the barred owl, was lower near major roads (Silva et al. 2012).

Other types of disturbance included cutblocks, low and high activity clearings, and total human footprint. Forestry cutblocks were some of the largest disturbances, occupying up to 70% of the area at some survey locations. Cutblocks had a low influence on the presence of the three owl species, but areas with high proportions of total human footprint usually included cutblocks. We found proportion of total human footprint negatively influenced barred owl presence, similar to our previous results showing a negative effect of total human footprint on occupancy of barred owls within the same study area (Shonfield and Bayne 2017b). Results presented here provide additional evidence that barred owls are sensitive to all disturbances that result in the removal of trees from the landscape.

Forest composition had an influence on the presence of all three owl species, but this was strongest for barred owls and boreal owls. Similar to what we previously found for barred owls in this study area (Shonfield and Bayne 2017b), they were more likely to be present in deciduous and mixedwood forests, a habitat preference that is well documented in the boreal region (Mazur et al. 1998, Olsen 1999, Russell 2008). Boreal owls showed a positive effect as proportion coniferous forest increased. This preference for coniferous forests and mixedwood forests is supported by other studies on boreal owl habitat use (Hayward et al. 1993, Lane et al. 2001). Forest age had a moderate influence on the presence of all three owl species. Most locations surveyed were in mature forest, with few locations in very young or very old forest. Multiple studies have shown that barred owls and boreal owls generally prefer older forests (Hayward et al. 1993, Mazur et al. 1998, Olsen 1999, Russell 2008), there is little evidence of great horned owls showing any preference for forest age but presumably they would require larger trees for nesting. We found a positive effect of forest age on barred owl and great horned presence. For boreal owls, we found a positive effect of very old forests but a negative effect of mature forests with a mean age between 80 and 110 years old. A study of boreal owls in Finland (known in Europe as Tengmalm's owl), found their survival increased with greater cover of old forest (> 80 years), though the mean extent of old forest within owl territories was only about 12% (Hakkarainen et al. 2008). This suggests that older forest is important to boreal owls, but perhaps using the mean forest age was not the best metric for explaining presence of boreal owls.

We included the presence of other owl species to account for possible spatial avoidance of larger owls as predators and competitors of the smaller owls, but we did not find any evidence of spatial avoidance between the three owl species studied. The presence of barred owls had little influence on the presence of boreal owls, and there was a similar lack of effect of great horned owl presence on barred owls. Barred owls and great horned owls have been found to have overlapping home ranges where both species occur, but there may be avoidance through temporal partitioning (Laidig and Dobkin 1995). The presence of great horned owls had some influence on the presence of the boreal owls, but it was the opposite of what we had predicted, presence of great horned owls had a positive effect on the presence of boreal owls. This does not necessarily imply boreal owls are attracted to areas with great horned owls, but it suggests boreal owls are not spatially avoiding great horned owls. Great horned owls are habitat generalists

(Johnsgard 2002) and were present at a large majority of the locations where boreal owls were present, so great horned owls may be occupying habitats with adequate prey and suitable nesting and roosting sites, that can also be suitable habitat for boreal owls. It is possible that boreal owls can reduce predation risk by short-term behavioural avoidance of great horned owls in areas where both species are present.

The results of this study contribute to our understanding of how anthropogenic disturbances influence where these three owl species are present on the landscape in northern Alberta. The three owl species studied differed in their sensitivity to human disturbance. We found further evidence that barred owls are sensitive to human disturbance, with roads and total human footprint having negative effects on their presence. In contrast, great horned owls are relatively tolerant of human disturbance and our results indicated that soft linear features have a positive effect on their presence. For boreal owls, our results did not provide clear evidence that they are either sensitive or tolerant to human disturbance. We found some evidence for cumulative effects of disturbance on barred owls from the result that total human footprint had a negative effect on their presence. However, the evidence for cumulative effects in the other two owl species was minimal. Total human footprint was not a strong predictor of presence of either great horned owls or boreal owls, and we did not find strong interacting effects between disturbance variables. Evaluating cumulative effects can be difficult, but a boosted regression tree analysis enabled us to assess the relative importance of different types of disturbance, and explore interactions between disturbance types as part of a cumulative effects analysis. Assessing the relative impacts of multiple types of disturbance and how the accumulation of disturbances can impact wildlife can help focus conservation efforts.

Table 6.1 Descriptions of the types of human disturbance included in the analysis, and the features included in each type (for more details on features included see Table A5.1 in Appendix 5).

Disturbance category	Description	Features included
Facilities	Noise-producing industrial facilities for energy extraction	compressor stations, oil/gas plants
Cutblocks	Areas with trees removed by forestry operations	clearcuts, selective harvest, salvage logging
High activity clearings	Clearings with high levels of human activity	active well pads (oil or gas), industrial camps, other clearings with industrial infrastructure
Low activity clearings	Clearings with low levels of human activity	inactive or abandoned well pads (no infrastructure)
Hard linear features	Linear features with an impermeable surface	paved and gravel roads, railways
Soft linear features	Linear features with a vegetated surface	seismic lines, transmission lines, pipelines
Total human footprint	All features combined	All of the above features

Table 6.2 Predictor variables included in the boosted regression tree models. Means and ranges of each variable are based on values of the variable within an 800-m buffer around each of the 452 locations included in the analysis. Locations present is the percent of locations surveyed with each disturbance type present (not applicable for forest age and forest composition). Locations were surveyed for owls between 2013 and 2016 using autonomous recording units.

Variable	Mean	Range	Locations present
Facilities (proportion)	0.01	0.00 – 0.45	22.6%
Cutblocks (proportion)	0.08	0.00 – 0.74	51.5%
High activity clearings (proportion)	0.02	0.00 – 0.45	62.2%
Low activity clearings (proportion)	0.01	0.00 – 0.31	63.9%
Hard linear features (proportion)	0.02	0.00 – 0.16	57.7%
Soft linear features (proportion)	0.03	0.00 – 0.14	99.8%
Total human footprint (proportion)	0.18	0.00 – 0.78	99.8%
Forest age (mean of forested area in years)	91.8	21.0 – 153.5	NA
Forest composition (proportion coniferous)	0.52	0.00 – 1.00	NA

Table 6.3 Details of the final boosted regression tree model (BRT) for each owl species. For each owl species, the final BRT model used a learning rate and tree complexity that resulted in the lowest residual deviance and at least 1,000 trees. The percent of variation in the data explained by each model is calculated as the residual mean deviance divided by the total mean deviance.

Species	Tree complexity	Learning rate	Bag fraction	Number of trees	Total mean deviance	Residual mean deviance	Percent of variation in data explained by model
Barred owl	3	0.0001	0.75	8,800	0.954	0.827	13%
Great horned owl	2	0.0005	0.75	3,300	1.386	1.262	9%
Boreal owl	2	0.001	0.75	5,500	1.022	0.717	30%

Table 6.4 Pairwise interactions between predictor variables in boosted regression tree models for barred owls, great horned owls, and boreal owls. Interaction size is reported as multiplicative strength, only those interactions greater than one are reported here.

Species model	Variable 1	Variable 2	Interaction size
Barred owl	Forest composition	Total human footprint	4.72
	Forest composition	Hard linear features	3.25
	Forest composition	Soft linear features	1.51
	Forest age	Hard linear features	1.30
Great horned owl	Forest age	Soft linear features	1.26
Boreal owl	Forest composition	Soft linear features	4.18
	Forest age	Forest composition	2.54

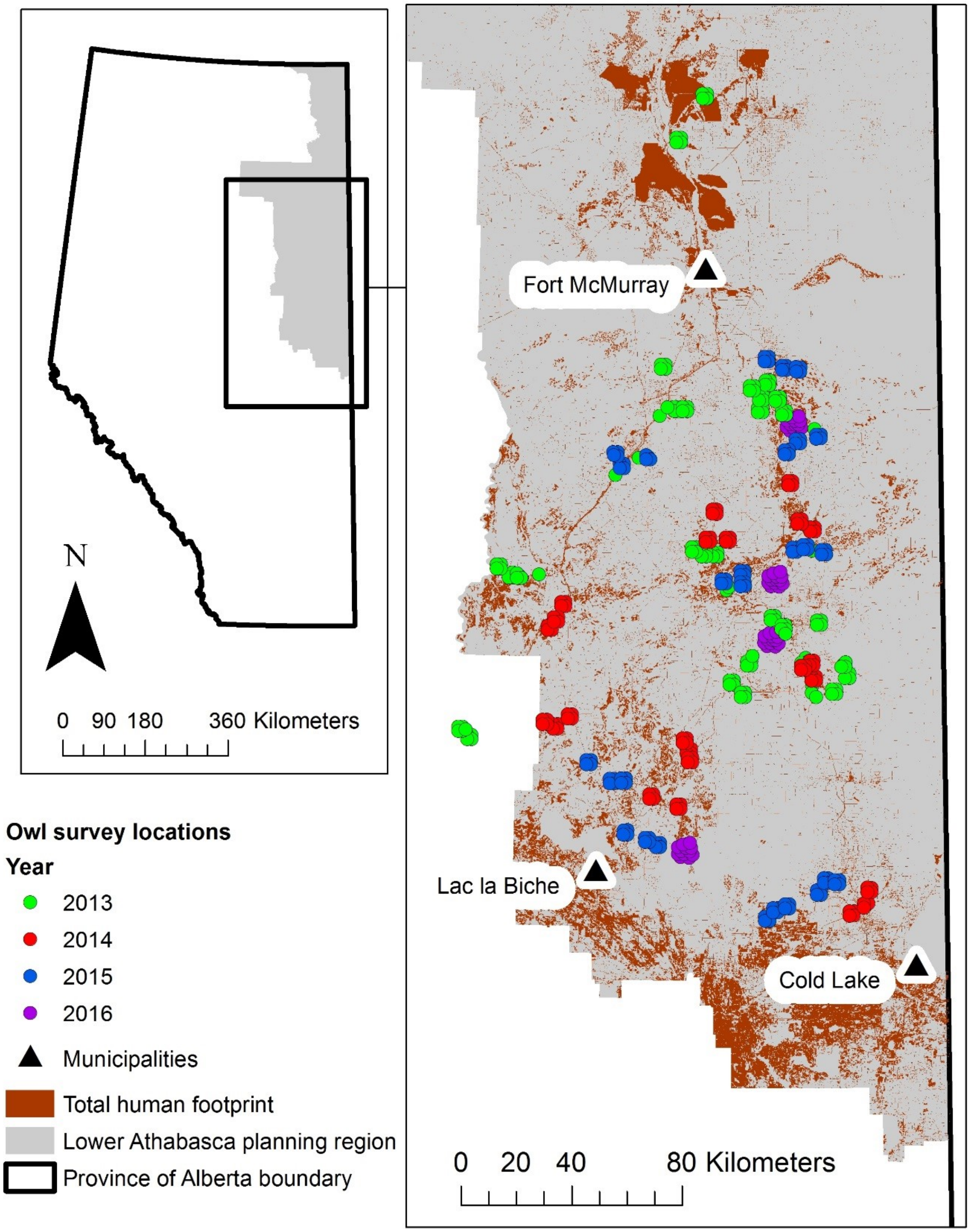

Figure 6.1 Locations surveyed for owls using autonomous recording units between 2013 and 2016 and included in the boosted regression tree analysis (n = 452).

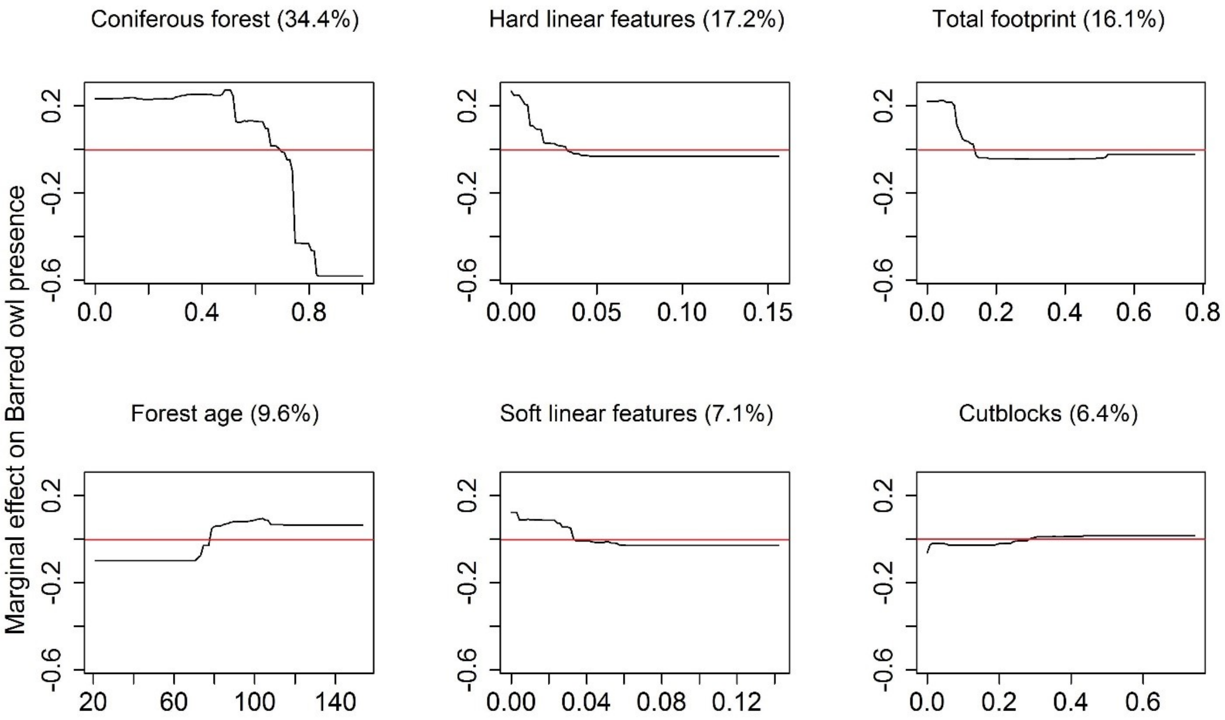

Figure 6.2 Partial dependency plots showing the top six predictors from the boosted regression tree model for the presence of barred owls. Y axes are on the logit scale and show the effects of proportion coniferous forest, proportion of hard linear features (roads and railways), proportion of total human footprint, mean forest age (in years), proportion of soft linear features (e.g. seismic lines, transmission lines, pipelines), and proportion of cutblocks from forestry logging within an 800-m radius of the survey location on barred owl presence. Numbers in parentheses show the relative contribution of each variable to the model. The red horizontal lines indicate a marginal effect of zero.

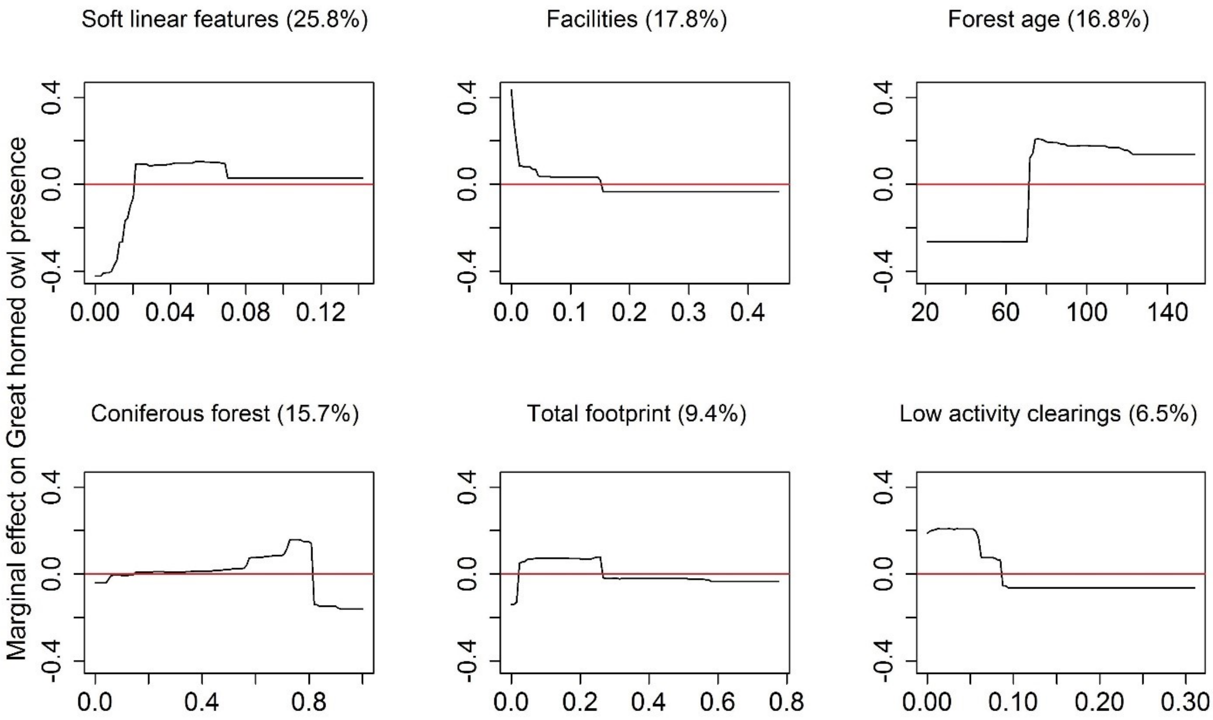

Figure 6.3 Partial dependency plots showing the top six predictors from the boosted regression tree model for the presence of great horned owls. Y axes are on the logit scale and show the effects of proportion of soft linear features (e.g. seismic lines, transmission lines, pipelines), proportion of industrial facilities, mean forest age (in years), proportion coniferous forest, proportion of total human footprint, and proportion of low activity clearings within an 800-m radius of the survey location on great horned owl presence. Numbers in parentheses show the relative contribution of each variable to the model. The red horizontal lines indicate a marginal effect of zero.

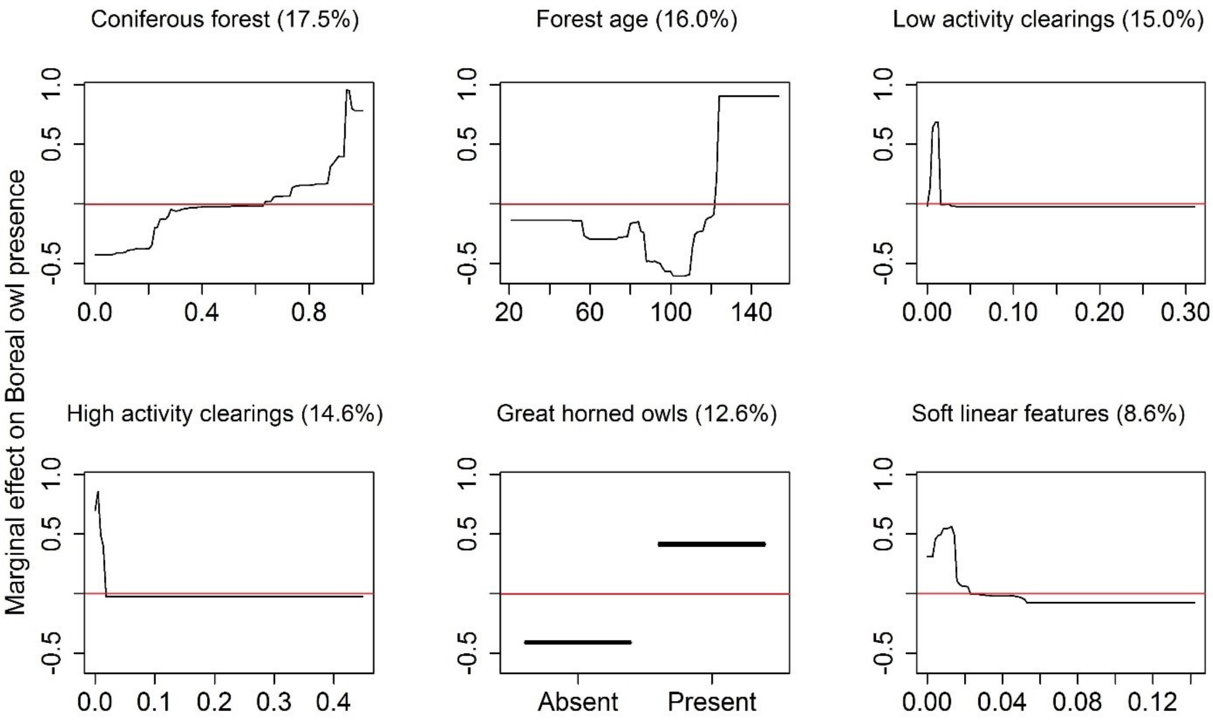

Figure 6.4 Partial dependency plots showing the top six predictors from the boosted regression tree model for the presence of boreal owls. Y axes are on the logit scale and show the effects of proportion coniferous forest, mean forest age (in years), proportion of low activity clearings, proportion of high activity clearings, presence/absence of great horned owls, and proportion of soft linear features (e.g. seismic lines, transmission lines, pipelines) within an 800-m radius of the survey location on great horned owl presence. Numbers in parentheses show the relative contribution of each variable to the model. The red horizontal lines indicate a marginal effect of zero.

Chapter 7. Discussion

The research presented in this thesis used bioacoustics approaches to assess the impacts of industrial disturbance on owls and their prey in northern Alberta. Part of my thesis aimed to test and demonstrate the utility of bioacoustic technology for studying owls. Bioacoustic tools have the potential to lead to significant advances in avian ecological research. In chapter 2, I reviewed the use of autonomous recording units (ARUs) in avian research and found that many studies are using this technology simply as a substitute for human observers in the field. I highlighted future applications of ARUs, and called on researchers to use ARUs in more innovative ways than simply as a substitute for a human observer in the field. Since publishing this review (Shonfield and Bayne 2017a), a paper came out using ARUs and occupancy modeling to monitor dates of peak vocal activity of passerines (Furnas and McGrann 2018). I anticipate that future studies will continue to find new and innovative ways of using ARUs to collect data that would otherwise be very difficult or very time consuming to collect without ARUs. In this thesis, I used ARUs to survey for owls and collected data over much longer time scales (daily and seasonally) than what would typically be collected by human observers conducting nocturnal point counts for owls in the field.

I developed automated recognizers to detect calls of barred owls, great horned owls, and boreal owls, and I evaluated their performance in chapter 3. These recognizers became an integral part of the research in this thesis. Over the course of my research, I deployed 1,356 ARUs to survey owls over 4 years (2013-2016). I used recognizers to automatically scan a massive dataset of recordings, e.g. I estimate that I collected 125,844 10-minute recordings in

2013, 84,518 10-minute recordings in 2014, and 53,791 10-minute recordings in 2015. Considering time needed to learn the recognizer program and build the recognizer, it has been estimated for Song Scope that once the dataset is larger than 26 hours of recordings, it is faster to process the data with a recognizer than human listening (Knight et al. 2017). I found that the amount of time needed to check the output of the recognizers was manageable and much more efficient than listening to a small subset of the total recordings collected. Without the use of recognizers, I would only have been able to process a small proportion of the recordings I collected and would have ended up with a much smaller dataset of owl detections. In chapter 3, I demonstrated that the number of locations where owls were detected increased substantially when using recognizers compared to when listening to recordings, and the number of locations where owls were missed was low. Recognizers to detect owl calls could be a very useful tool for monitoring and management, for example for trend analysis for species of concern. Using new bioacoustics tools (ARUs in combination with recognizers) was effective and efficient in conducting passive surveys for the three owl species I studied, and this approach is likely to be useful for studying other owl species that vocalize frequently.

This research makes a novel and important contribution in understanding animal responses to anthropogenic noise. An understanding of how noise and other forms of anthropogenic disturbance affect owl behaviour and prey abundance is important to better predict habitat loss for owls. In chapter 4, I found minimal effects of noise on owl occupancy at two different spatial scales. Barred owls, great horned owls, and boreal owls were all equally likely to occupy areas approximating a home range size with a noise source present as compared to areas without a noise source. In chapter 5, I found small mammal abundance was not strongly affected by industrial noise, the main prey of the owl species I studied (Hayward et al. 1993, Cromrich et al. 2002, Livezey 2007). Prior to this research, there were no studies on the impacts of industrial noise on the small mammal community. There was also little known about the effects of noise on owls, except for a study on nocturnal space use of western burrowing owls around oil and gas infrastructure (Scobie et al. 2016), and a few studies on spotted owls that looked at effects of temporary noise (e.g. from helicopters, chainsaws, or motorcycles) on flushing behaviour (Delaney et al. 1999) and stress hormone levels (Tempel and Gutiérrez 2003, Hayward et al. 2011). The results from these two chapters of my thesis indicate that industrial noise sources have not degraded the surrounding habitat to the extent that entire owl home ranges are unoccupied, and there continues to be prey available for owls and other predators.

It may seem counterintuitive to rely on the ability to hear owls calling to determine if they are avoiding noise sources. However, using passive acoustic surveys allowed me to sample many sites over a large area, and to systematically sample chronic noise sources, sites with intermittent traffic noise, and control sites with no noise. The nature of bioacoustics data is that it informs us about the behaviour of the animal in terms of their calling activity and their presence within the detection radius of the ARU. It does not provide fine-scale data about specific locations used inside the detection radius, or about behaviours that are not associated with vocal signals. Owls do not vocalize while hunting, so ultimately the data in this thesis cannot inform us about what areas owls are using to hunt. Tracking owl movements with GPS or radio-telemetry tracking devices would provide this type of information and this study could have been stronger if owls were tracked in addition to the acoustic surveys. Samples sizes for telemetry tracking are often small, e.g. other projects have typically tracked 20 or fewer individual owls when using tracking devices (Carey et al. 1990, Olsen 1999, Bennett and Bloom 2005, Hinam and St. Clair 2008), though notably one study caught and tracked 32 individual barred owls (Russell 2008). However, if a small number of owls had been tracked, and this data was collected in addition to the extensive bioacoustic surveys we conducted, these two approaches could be complimentary and together could have provided more insight on owl behaviour than from the acoustic surveys alone.

Research on the effects of anthropogenic noise is important to understand and quantify the impact of this type of disturbance on various aspects of an animal's biology. Understanding impacts of noise pollution has been touted as a critical step in developing effective policies for conserving wildlife (Blickley and Patricelli 2010). In addition, little is known about how noise affects predator-prey relationships, and this is particularly relevant to acoustic predators like owls. Two studies on the impacts of noise on hunting behaviour of owls (Mason et al. 2016, Senzaki et al. 2016), found prey detection and strike success decreased with increased noise. The conclusions of both these studies were that noise levels corresponding to 120 m from a road, and 200 m from a compressor station, were likely to impair owl hunting behaviour. These estimates of the distance of the noise effect could explain why I did not find lower occupancy of sites by owls at sites with intermittent traffic noise or sites with chronic noise sources, because a small proportion of the site would be within these distances from a road or industrial noise source, thus there are likely areas within a site where owls are able to hunt.

Some of the strongest negative effects of anthropogenic noise have been documented in birds. For example, traffic noise decreased lek attendance by male greater sage-grouse

(*Centrocercus urophasianus*) by 73% (Blickley et al. 2012), and decreased abundance of all birds by 28% (McClure et al. 2013). A study on four species of secondary cavity nesting songbirds found nest box occupancy was negatively affected by noise from compressors, and that noise was a better predictor of occupancy than forest cover (Kleist et al. 2017). Many studies that find negative effects call for minimizing anthropogenic noise as an important conservation priority (e.g. Francis et al. 2011). An important question though, is how widespread are these negative effects of noise across taxa? The majority of studies published on the impacts of anthropogenic noise are on birds and aquatic mammals, we know far less about the effects of noise on terrestrial mammals, reptiles, amphibians, fish, and invertebrates (Shannon et al. 2016). As with any type of disturbance, there are likely to be some species that are sensitive and some that are tolerant, and this information can influence management decisions for mitigating noise. There are various options for mitigating noise produced by industry. For example, sound barrier walls can reduce noise levels by up to 70% (Francis et al. 2011c). While it is possible to retroactively reduce noise levels at existing compressor stations, the same investment could have a bigger effect on increasing habitat for wildlife by using it to replant trees on wellpads (Bayne et al. 2008). Going forward, it will be important to consider the effects of noise in light of the potentially larger effects of physical habitat loss on species, and to plan mitigation strategies accordingly.

Assessing the impact of a single type of disturbance on wildlife can be useful to determine whether a type of disturbance has either a negative or positive effect. However, this approach disregards the fact that multiple disturbance types are often present, and it is rare for a single type of disturbance to occur in isolation. Documented negative effects of noise may not be solely due to the noise, and while some examples indicate that noise is a strong predictor of an observed response (Kleist et al. 2017), other examples indicate the effect of noise can be small compared to other factors (Bernath-Plaisted and Koper 2016, Fröhlich and Ciac 2017, Nenninger and Koper 2018). These studies highlight the importance of considering relevant environmental variables, and studying multiple disturbance types to better understand the potential for cumulative effects. In chapter 6, I evaluated potential cumulative effects using a boosted regression tree analysis to assess the relative importance of different types of anthropogenic disturbance on owl habitat use compared to variables describing forest characteristics, and to compare these effects between species.

The three owl species I studied each responded slightly differently to the different disturbance types. In chapters 3 and 6, I found that barred owls were less likely to be present in areas with greater proportions of human footprint, suggesting they are sensitive to any disturbance that results in the removal of forest cover. Great horned owls were more tolerant to disturbance: in chapter 3 their occupancy of sites was not affected by the proportion of total human footprint, and in chapter 6 I found they were more likely to be present in areas with greater proportions of soft linear features (e.g. seismic lines, pipelines), though they were more likely to be absent in areas with large industrial facilities. Boreal owl presence was mostly driven by forest composition: results in chapters 3 and 6 indicated that they prefer more coniferous forests, and it was less clear if they are sensitive or tolerant to disturbance. Assessing the relative impacts of multiple types of disturbance and how the accumulation of disturbances can impact wildlife is important in understanding species declines and can help focus conservation efforts.

By studying three different owl species in this thesis, I was able to compare species-specific responses to noise and industrial disturbance. There are often management imperatives to understanding the responses of multiple species to disturbance, because some species can be sensitive and others more tolerant to disturbance (Francis et al. 2011a, Francis 2015). In addition, larger owl species can be predators or dominant competitors of smaller owls (Sergio and Hiraldo 2008, Zuberogoitia et al. 2008), so patterns of occurrence in one species could be influenced by the presence of other species (Bailey et al. 2009). However, in chapter 6 I did not find evidence of spatial avoidance of larger owl species. It is possible that smaller owls can reduce predation risk by short-term behavioural avoidance of larger owls in areas where species co-occur. Future research should focus on determining whether smaller owls show short-term behavioural avoidance of larger owls, and whether this behaviour is influenced by owl sensitivity to human disturbance.

A review of the impacts of unconventional energy sources on wildlife found that most documented effects of unconventional oil and gas extraction are predominantly negative (Northrup and Wittemyer 2012). There has been a concern in the Lower Athabasca planning region about disturbance from oil extraction influencing predator-prey dynamics. This work has primarily focused on large mammal predator-prey systems, for example woodland caribou and wolves (Dickie et al. 2016), and moose and wolves (Neilson and Boutin 2017). The research in this thesis provides some insight about the impacts on a different predator-prey system between owls and their small mammal prey. My thesis demonstrates that there is only a marginal zone of influence surrounding chronic industrial noise sources for owls and their small mammal prey. The three owl species I studied did not avoid the areas surrounding noise sources, and small mammal abundance and activity were unaffected by the noise. Small mammals are an important prey source for numerous avian and terrestrial predators, and we know little about how predators respond to chronic noise and whether they can hunt in these noisy areas. Future work should focus on the behaviour of predators near noisy areas to further our understanding of how human disturbance can alter predator-prey relationships.

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Appendix 1. Summary of Peer-Reviewed Primary Research Articles that used Autonomous Recording Units for Avian Research

Table A1.1. Primary research articles published in peer-reviewed journals included in Figure 2.1 that used autonomous recording units (ARUs) for avian research, sorted by year published. To locate articles, we searched the Web of Science database in January 2017 using the following search terms: acoustic recording, autonomous recording unit, autonomous recorder, autonomous recording, automated digital recording system, bioacoustic monitoring, and passive acoustic monitoring. Only articles on avian species that used recording units that could function autonomously were retained. See Bibliography for full references.

Authors	Year	Journal
Acevedo et al.	2006	Wildlife Society Bulletin
Jones et al.	2007	The Wilson Journal of Ornithology
Acevedo et al.	2009	Ecological Informatics
Hutto & Stutzman	2009	Journal of Field Ornithology
Rognan et al.	2009	The Journal of Wildlife Management
Swiston & Mennill	2009	Journal of Field Ornithology
Odom & Mennill	2010	The Condor
Baldo & Mennill	2011	Journal of Field Ornithology
Farina et al.	2011	Ecological Informatics
Goyette et al.	2011	Journal of Field Ornithology
McGuire et al.	2011	South Australian Ornithologist
Osmun & Mennill	2011	Ethology

Buxton & Jones	2012	Journal of Field Ornithology
Campbell & Francis	2012	Journal of Field Ornithology
Depraetere et al.	2012	Ecological Indicators
Mennill et al.	2012	Methods in Ecology and Evolution
Rognan et al.	2012	Northwestern Naturalist
Tegeler et al.	2012	Wildlife Society Bulletin
Venier et al.	2012	Wildlife Society Bulletin
Buxton et al.	2013	The Auk
Cerqueira et al.	2013	Diversity and Distributions
Digby et al.	2013	Methods in Ecology and Evolution
Rempel et al.	2013	Journal of Field Ornithology
Wimmer et al.	2013	Ecological Applications
Borker et al.	2014	Conservation Biology
Frommolt & Tauchert	2014	Ecological Informatics
Holmes et al.	2014	Wildlife Society Bulletin
Oppel et al.	2014	Nature Conservation
Perrault et al.	2014	Ornithology
Potamitis et al.	2014	Applied Acoustics
Ross & Allen	2014	Ecological Informatics
Sanders & Mennill	2014	Canadian Field Naturalist
Smith et al.	2014	PLoS One
Sosa-López & Mennill	2014	Journal of Ornithology
Taff et al.	2014	Proceedings of the Royal Society B

Towsey et al.	2014	Ecological Informatics
Wilson et al.	2014	Bioacoustics
Zwart et al.	2014	PLoS One
Alquezar & Machado	2015	The Wilson Journal of Ornithology
Borker et al.	2015	Wildlife Society Bulletin
Colbert at al.	2015	Wildlife Society Bulletin
Ehnes & Foote	2015	Bioacoustics
Figueira et al.	2015	Biological Conservation
Furnas & Callas	2015	The Journal of Wildlife Management
Holmes et al.	2015	Canadian Field Naturalist
Klingbeil & Willig	2015	PeerJ
Sedlácek et al.	2015	Ostrich
Sidie-Slettedahl et al.	2015	Wildlife Society Bulletin
Alvarez-Berríos et al.	2016	Tropical Conservation Science
Celis-Murillo et al.	2016	Journal of Ornithology
Celis-Murillo et al.	2016	Animal Behaviour
Cerqueira et al.	2016	Methods in Ecology and Evolution
Cragg et al.	2016	Wildlife Society Bulletin
Drake et al.	2016	Wildlife Society Bulletin
Dufour et al.	2016	Ecological Informatics
La & Nudds	2016	Ecosphere
Leach et al.	2016	Emu
Pryde & Greene	2016	New Zealand Journal of Ecology

Rempel et al.	2016	Ecological Indicators
Sandoval et al.	2016	Journal of Ornithology
Zhang et al.	2016	Bioacoustics
Yip et al.	2017	Condor

Appendix 2. Details for the Automated Computer Recognizers Built in Song Scope

Table A2.1. Details of the settings, annotations, and performance statistics of the automated computer recognizers built in Song Scope (Wildlife Acoustics Inc., Maynard, Massachusetts, USA) to detect calls of barred owls (*Strix varia*), great horned owls (*Bubo virginianus*), and boreal owls (*Aegolius funereus*).

Recognizer settings	Barred owl (Full Two-phrased Hoot)	Barred owl (Terminal Two Notes)	Great horned owl	Boreal owl
Min. quality[1]	50	50	50	50
Min. score[2]	60	60	60	60
Sample rate (Hz)	16,000	16,000	16,000	16,000
Max. complexity[3]	32	32	31	32
Max. resolution[4]	7	7	10	7
FFT size[5]	512	512	512	512
FFT overlap[6]	0.5	0.5	0.5	0.5
Frequency minimum (Hz)	312.5	312.5	187.5	468.75

Frequency range (Hz)	1250	1250	1125	1250
Amplitude gain (dB)	0	0	0	0
Background filter (sec)[7]	1	1	1	1
Max. syllable length (ms)	784	288	496	288
Max. syllable gap (ms)	928	240	1008	400
Max. song length (ms)	4016	800	3040	4048
Dynamic range (dB)[8]	10	10	15	15
Algorithm	2.0	2	2.0	2.0
No. of annotations used	51	26	83	42
Sources for annotations	22 field recordings from 17 different point locations in NE Alberta	15 field recordings from nine different ARU locations in NE Alberta	10 field recordings from 8 different point locations in NE Alberta	8 field recordings from 7 different point locations in NE Alberta
Recognizer performance statistics				
Cross training (% ± SE)	74.49 ± 4.96	75.51 ± 5.12	79.78 ± 3.07	80.07 ± 5.97
Total training (% ± SE)	74.16 ± 3.43	57.77 ± 3.16	79.98 ± 2.88	81.71 ± 4.98

Model states	27	29	23	23
State usage	11 ± 6	7 ± 3	8 ± 2	5 ± 3
Feature vector	7	7	10	7
Mean symbols (n)	30 ± 24	12 ± 4	21 ± 8	19 ± 11
Syllable types	8	8	7	8
Mean duration of syllable (s)	2.64 ± 0.67	0.50 ± 0.10	2.06 ± 0.35	1.20 ± 0.30

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[1] Quality values indicate where a signal fits within a statistical distribution of parameters from the training data used to build a recognizer (range 0–99.9)

[2] Score values indicate statistical fit of the signal with the recognizer model (range 0–99.99)

[3] Number of states used to generate the model for the recognizer

[4] Length of feature vectors in the recognizer, controls the maximum number of dimensions that can be modelled

[5] Controls the spectrogram by adjusting the temporal and spectral bin size through the Fast Fourier Transform algorithm

[6] Amount of overlap between each Fast Fourier Transform bin

[7] Sets the time used to calculate average background noise and remove it from the spectrogram (range 0–5 sec)

[8] Limits the decibel range of signals that will be detected when compared to the strongest signal (range 10–90 dB)

Appendix 3. Comparing Barred Owl Detection Locations from ARUs and GPS Tracking Technology

In the spring of 2014, the Government of Alberta caught and attached backpack GPS locators on several barred owls in northern Alberta as part of a separate project studying the habitat use of barred owls. In collaboration with government personnel, I was able to deploy ARUs surrounding two of the barred owls with GPS locators while out in the field that season. The two sites were 8.5 km apart and were both located north of Lac la Biche near the community of Heart Lake, Alberta. I used SM2+ Song Meters (Wildlife Acoustics, Inc., Maynard, Massachusetts, USA), programmed to turn on and record in stereo format for 10 minutes at the start of every hour at 44.1 kHz with a 16-bit resolution. Recording files were stored in .wac format, and we used gain settings of 48 dB for both the left and right channel microphones. I attached ARUs at a height of approximately 1.5 m on trees with a smaller diameter than the width of the ARU (18 cm).

The ARUs were spaced 800 m apart, and were in 3 x 3 grids of 9 spanning an area of 256 ha, the same area as the owl survey sites in Chapter 4. The grids were centered over the location where each of the two barred owls were caught. ARUs at the first site were deployed on April 18, 2014 and picked up on May 3, 2014. The barred owl at that first site had 30 GPS fixes logged between April 10 and July 15, 2014 (Figure A3.1). ARUs at the second site were deployed on April 22 and picked up on May 5, 2014. The barred owl at the second site had 10 GPS fixes logged between April 14 and May 8, 2014 (Figure A3.2). The barred owl locations from the GPS fixes are mainly within the area covered by the ARUs, providing further evidence that the size of the owl survey sites used in Chapter 4 approximates the size of the home range of a barred owl.

I scanned the recordings collected with the barred owl recognizer in Song Scope using the same methods described in Chapters 3 and 4. At the first site, a barred owl was heard calling at 6 out of the 9 ARUs (Figure A3.1). At the second site, a barred owl was heard calling at 4 out of 9 ARUs (Figure A3.2). Generally, the locations where ARUs detected barred owls calling was in agreement with where I would have expected to detect barred owls based on locations of the GPS fixes (Figures A3.1 and A3.2).

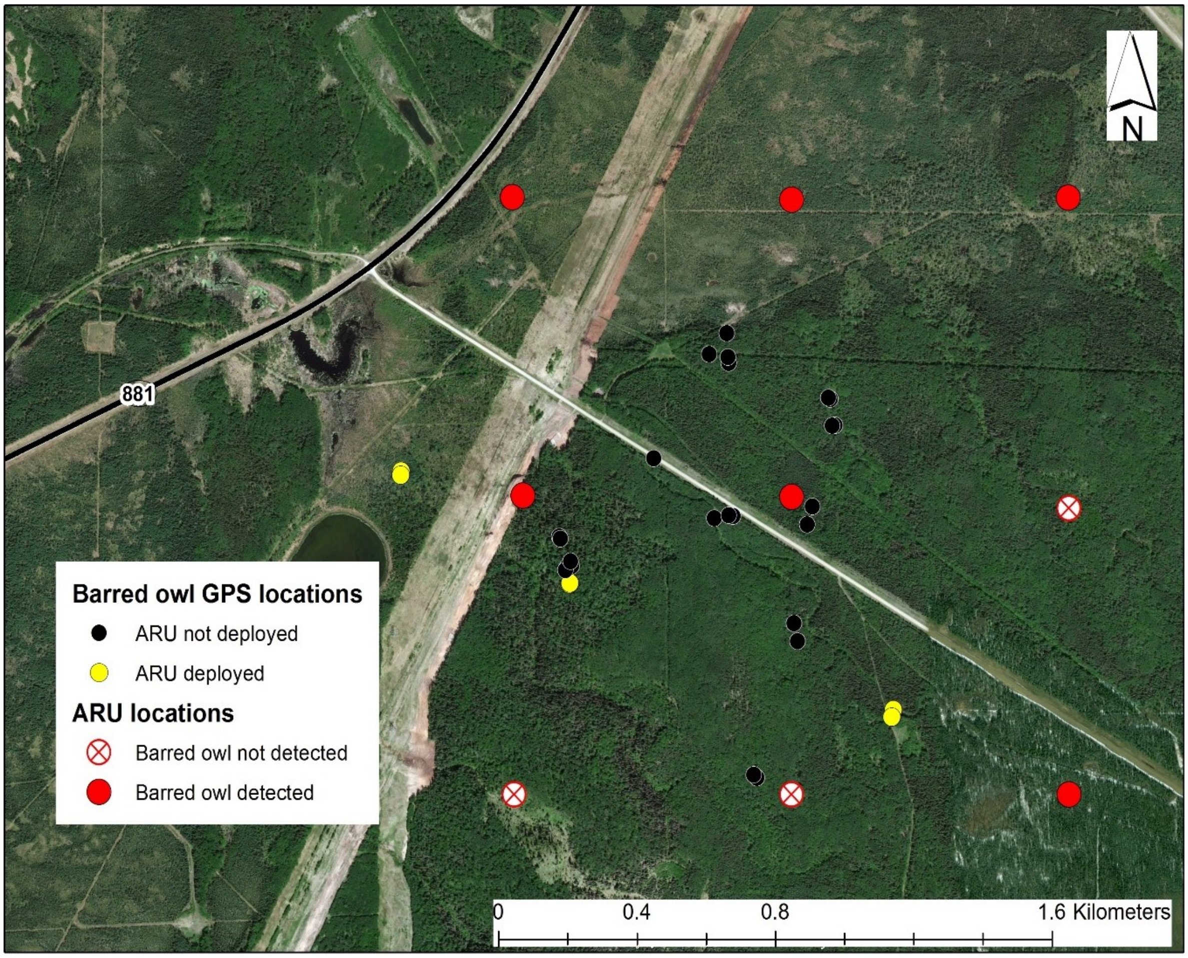

Figure A3.1. Locations of barred owl detections at site 1. Autonomous recording units (ARUs) were deployed from April 18 to May 3, 2014. GPS locations are divided between fixes that occurred during the range of dates when the ARUs were deployed, and fixes that occurred outside that range of dates.

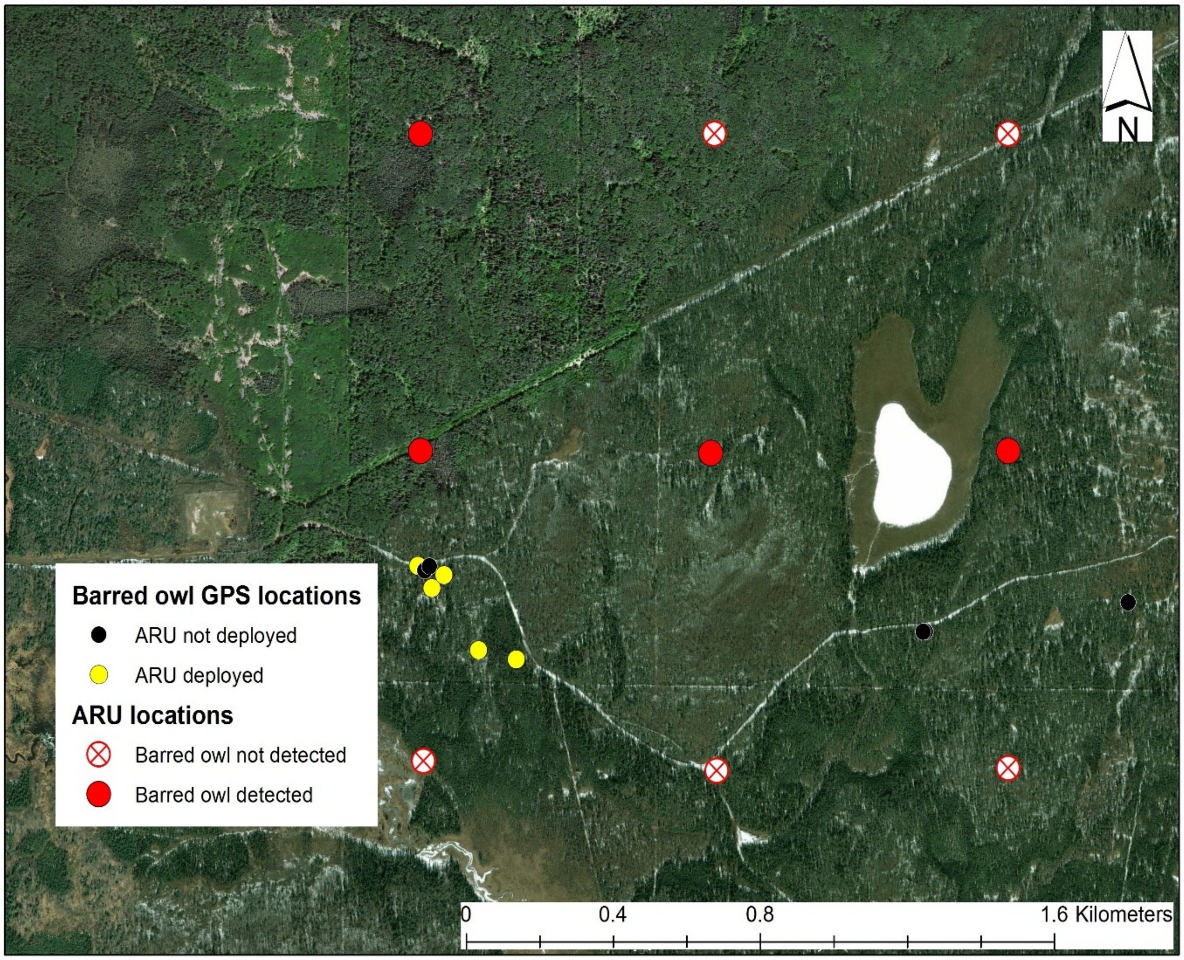

Figure A3.2. Locations of barred owl detections at site 2. Autonomous recording units (ARUs) were deployed from April 22 to May 5, 2014. GPS locations are divided between fixes that occurred during the range of dates when the ARUs were deployed, and fixes that occurred outside that range of dates.

Appendix 4. Estimating the Effective Detection Radius for Autonomous Recording Units under Noisy Conditions

Playback methods

To estimate how far we could hear owls on autonomous recording units (ARUs) in noisy areas compared to quiet areas, we broadcast owl calls from a speaker at different distances from the ARU along 5 control transects and 5 noisy transects between November 25 and December 5, 2014. Control transects were in forested areas unaffected by road or traffic noise. Noisy transects extended away from a compressor station. Using the same methods and equipment as Yip et al. (2017a) we broadcast recorded owl calls using an Alpine digital CD Receiver (CDE-122) connected to an Alpine 6.5-inch speaker and tweeter set (SPR-60) contained within a wooden box (25 cm x 29 cm x 38 cm). The speaker was attached to a tripod at a height of 1.5 metres, a height similar to other avian playback studies (Koloff and Mennill 2013, Sandoval et al. 2015). The speaker faced the ARU and broadcast calls at 30 standardized distances ranging from 12 to 1,312 meters measured using a handheld GPS unit (GARMIN GPSmap 78, accuracy ± 3 m). For both noisy and quiet transects, a single ARU (an SM2+ Song Meter by Wildlife Acoustics, Inc., Maynard, Massachusetts, USA) was attached at a height of approximately 1.5 m on trees with a smaller diameter than the width of the ARU (18 cm). The ARU was set to record continuously in stereo format at 44.1 kHz with a 16-bit resolution. The ARU remained stationary and the speaker was moved to each distance interval to simulate an owl calling from increasing distances from the ARU. For noisy transects the ARU was positioned approximately 100 m from a compressor station.

Owl calls were broadcast in the following order: northern saw-whet owl (*Aegolius acadicus*), boreal owl (*Aegolius funereus*), great gray owl (*Strix nebulosa*), long-eared owl (*Asio otus*), and barred owl (*Strix varia*). We used a two second interval between calls to avoid signal overlap. This sequence was broadcast at a sound pressure level of 90dB (re 20 µPa) which we normalized using Adobe Audition CS6 (Adobe Systems Inc., San Jose, California, USA) and calibrated using a handheld sound level meter (Sper Scientific 840018) by measuring a 1000Hz pure tone 1 m from the speaker (based on fast-time A-weighting). We used Adobe Audition CS6 to generate the 1000Hz pure tone. Although we broadcast owl calls at 90dB, we do not know how closely this reflects the real sound level of owl calls. This information is difficult to obtain and there is little published on this for any avian species, thus we acknowledge that this method can only determine relative differences in detection distances between noisy and quiet areas.

Sound Processing

Recorded playbacks were extracted from recordings using Adobe Audition CS6. Owl calls from each sequence were clipped into individual sound files (n = 1070) using an automated script and the ‘textgrid’ function in Praat V5.4.06 (Boersma and Weenink 2015). These clips were randomized and joined together in sets of 10 sounds with 2 second spacing to create a single sequence of randomized sounds using an automated batch script. These sequences were given to 2 trained observers who identified sounds by listening to the recordings at standardized volume levels and from visually scanning spectrograms in Adobe Audition CS6 (window type: Blackman-Harris; window length: 2048). Volume levels were selected to maximize amplitude and detections while avoiding any risk of hearing damage. Fifteen percent of sounds were blank ambient background sound consisting of low levels of wind and vegetation noise normally present in recordings to control for false positive identifications. Randomization of sounds removed an observer's ability to predict which sounds would occur in what order although observers were aware of all possible species that could be presented.

We used a half-normal detection function to calculate Effective Detection Radius (EDR) using the same approach as Yip et al. (2017a). EDR is the parameter, τ, in the half-normal detection function: $p(d) = \exp(-d^2/\tau^2)$. EDR is defined as the distance at which number of individual birds detected outside τ is equal to the number of missed individuals within τ. We ran generalized linear models (GLMs) with a fixed intercept at 0, complimentary log-log link function, and binomial distribution. Interaction with distance was included in models for all parameters of interest but main effects were excluded to accommodate a fixed intercept. This allowed us to calculate EDR using a linear modelling framework. We transformed distance to $x = -d^2$ before modelling so that distance was a linear predictor. We estimated EDR for all species (Appendix 3, Table A3.1) by summing the beta coefficients of variables related to distance in our best models (β). We calculated EDR using: $\tau = (1/\beta)^{0.5}$.

Table A4.1. Estimated effective detection radius (EDR), lower and upper 90% confidence intervals (CI) and the estimated area sampled by an autonomous recording unit (ARU) for the territorial calls of five species of owls in loud and quiet conditions.

Species	Conditions	EDR (m)	Lower 90% CI	Upper 90% CI	Area sampled (ha)
Barred owl	Loud	221.54	185.49	261.38	15.42
	Quiet	491.68	391.57	609.35	75.95
Boreal owl	Loud	179.81	146.51	211.75	10.16
	Quiet	468.64	375.90	576.41	69.00
Great gray owl	Loud	203.61	167.79	239.40	13.02
	Quiet	675.69	517.15	936.22	143.43
Long-eared owl	Loud	189.95	158.62	219.33	11.34
	Quiet	390.83	313.52	473.48	47.99
Northern saw-whet owl	Loud	277.22	232.39	338.04	24.14
	Quiet	442.88	346.39	543.15	61.62

Appendix 5. Details of the Disturbance Features in the ABMI Human Footprint Layer

Table A5.1. Descriptions of the disturbance features in the ABMI human footprint layer and their newly assigned disturbance category (see Table 6.1 in chapter 6 for a description of the new disturbance categories)

Feature	Disturbance category	ABMI Code	ABMI sublayer	Feature description from ABMI metadata
AIRP-RUNWAY	High activity clearing	301	03 Roads	An active landing facility for aircraft, usually associated with paved and lighted runways, an operating control tower, and services for aircraft and passengers
BORROWPIT-DRY	High activity clearing	204	02 Borrow Pits, Sumps, Dugouts, Lagoons	Includes pits dug to build forestry and well-site roads. They are usually associated with a road or another structure. No presence of water.
BORROWPITS	High activity clearing	203	02 Borrow Pits, Sumps, Dugouts, Lagoons	Includes pits dug to build forestry and well-site roads. They are usually associated with a road or another structure.

BORROWPIT-WET	High activity clearing	205	02 Borrow Pits, Sumps, Dugouts, Lagoons	Includes pits dug to build forestry and well-site roads. They are usually associated with a road or another structure. Presence of water confirmed by visual interpretation.
CAMPGROUND	High activity clearing	1101	11 Other vegetated facilities and recreation	Disturbed vegetation with frequently changing facilities of RVs and tents used for overnight stay. Most often comprised of several individual clearings surrounded by vegetation and gravel or concrete roads connecting clearings.
CAMP-INDUSTRIAL	High activity clearing	801	08 Industrial sites	Building used for temporary residence by employees on or in close proximity to an industrial activity such as mining, forestry, or oil and gas activities.

CLEARING-UNKNOWN	Low activity clearing	802	08 Industrial sites	A human-made clearing with unknown purposes and contains no visible buildings, fences or equipment
CLEARING-WELLPAD-UNCONFIRMED	Low activity clearing	803	08 Industrial sites	Roughly square in shape clearing, roughly 90-120 m wide (approx. 1 ha). Not confirmed as a well pad by available reference sources.
COUNTRY-RESIDENCE	High activity clearing	1501	15 Urban and rural residential	Rural developments (10 - 100 buildings per quarter section).
CROP	Low activity clearing	1701	17 Cultivation	Agricultural areas used for cultivation.
CULTIVATION_ABANDONED	Low activity clearing	1704	17 Cultivation	Agricultural land that has been formally seeded and tilled, but no evidence of present day production use. Landscape appears to have a heterogeneous mix of vegetation and closely resembles natural cover.

CUTBLOCK	Cutblock	1801	18 Harvested areas	Areas where forestry operations have occurred (clearcut, selective harvest, salvage logging, etc.)
DISTURB_VEG	High activity clearing	2101	21 Disturbed vegetation	Disturbed vegetation that does not fit any other category of human footprint.
DUGOUT	High activity clearing	207	02 Borrow Pits, Sumps, Dugouts, Lagoons	Excavations typically associated with agriculture and rural residence, constructed to catch run off water for use by livestock.
FACILITY-OTHER	Facility	804	08 Industrial sites	Industrial facility characterized by large non-residential buildings most often surrounded by concrete for parking purposes. The purpose of the facility is not disclosed.
FACILITY-UNKNOWN	Facility	805	08 Industrial sites	Industrial facility characterized by large non-residential buildings most often surrounded by concrete for parking purposes. The purpose of the facility is unknown.

GRVL-SAND-PIT	High activity clearing	701	07 Mine sites	An area of surface disturbance for the purpose of extracting sand and/or gravel consistently open and/or expanding over multiple years, usually close to lakes or rivers.
LAGOON	High activity clearing	201	02 Borrow Pits, Sumps, Dugouts, Lagoons	Artificial holding or treatment ponds for industrial, agricultural or municipal wastewater. Human made water and sewage lagoons used for municipal purposes.
LOW-IMPACT-SEISMIC	Soft linear feature	2001	20 Seismic lines	A polygon feature class derived from a 1.5-meter buffer (3 meter total width) of a pre-low-impact-seismic centerline.
MINES-OILSANDS	High activity clearing	703	07 Mine sites	Heavy industry use with bare and/or vegetated ground and low human density for the purpose of oil sands mining.
MISC-OIL-GAS-FACILITY	Facility	807	08 Industrial sites	Industrial facility used for the purpose of oil and gas.

OIL-GAS-PLANT	Facility	808	08 Industrial sites	Industrial facility used for oil production.
OPEN-PIT-MINE	High activity clearing	705	07 Mine sites	An area of surface disturbance for the purpose of mining (with the exception of sand and/or gravel), consistently open and/or expanding over multiple years, usually close to lakes or rivers.
PIPELINE	Soft linear feature	1901	19 Pipelines	A line of underground and over ground pipes, of substantial length and capacity, used for the conveyance of petrochemicals.
PRE-LOW-IMPACT-SEISMIC	Soft linear feature	2001	20 Seismic lines	A polygon feature class derived from a 3-meter buffer (6 meter total width) of a pre-low-impact-seismic centerline.
RECREATION	High activity clearing	1104	11 Other vegetated facilities and recreation	Urban/rural greenspace and recreation that does not fit into other categories (e.g. grave yards, baseball diamonds, parks, shelterbelts, ski hills, clearings from old industrial activity

				that is now vegetated). This layer was also used to identify green-space features that do not fit into other categories such as storage areas and parking lots.
RIS-BORROWPITS	High activity clearing	206	02 Borrow Pits, Sumps, Dugouts, Lagoons	Identifies an area disturbed for the purpose of extraction of aggregate materials including gravel pits.
RIS-CLEARING-UNKNOWN	High activity clearing	810	08 Industrial sites	Identifies all areas where vegetation has been removed for the purposes of preparing the land for drainage, soil removal, overburden removal, mining, etc. but where soil has been left mostly intact and relatively undisturbed. May include any or all of: tree removal, shrub removal, and/or grubbing (stump removal). Identifies areas cleared for by other industry

				and not for the purposes of forest harvesting or for oil sands development.
RIS-DRAINAGE	High activity clearing	707	07 Mine sites	Identifies surface disturbance for the purpose of managing surface water features.
RIS-FACILITY-OPERATIONS	High activity clearing	811	08 Industrial sites	Designated for areas which are not part of the plant site, e.g., may include laydown areas not integrated with the main plant site(s), tailings lines, water lines, compressor station, buildings away from the main plant site, flare stack, communications tower.
RIS-FACILITY-UNKNOWN	High activity clearing	812	08 Industrial sites	Identifies areas where the reclamation liability associated for the disturbance is currently held by another industry operator.
RIS-MINES-OILSANDS	High activity clearing	708	07 Mine sites	Identifies areas where overburden removal has commenced for the purposes of preparing an

				area for open pit mining and all mine pit features.
RIS-OILSANDS-RMS	High activity clearing	709	07 Mine sites	Identifies reclamation material stockpiles (RMS). Each RMS may have several material types and corresponding volumes.
RIS-RECLAIMED-PERMANENT	High activity clearing	713	07 Mine sites	Identifies polygons which meet the definition of permanent reclamation - land is considered permanently reclaimed when landform construction and contouring, clean material placement (as required), reclamation material placement and revegetation has taken place.
RIS-RECLAIMED-TEMP	High activity clearing	714	07 Mine sites	Identifies polygons which meet the definition of temporary reclamation – areas being managed where vegetation has been seeded, planted, or ingressed, where there is an expectation that future disturbance may occur

				at that location. This does not include cleared areas (planned for future disturbance) that have naturally revegetated through ingress.
RIS-ROAD	Hard linear feature	304	03 Roads	Identifies roads that are not specifically part of other disturbed features.
RIS-SOIL-SALVAGED	High activity clearing	716	07 Mine sites	Identifies areas where soil salvage is occurring but where overburden removal has not commenced.
RIS-TAILING-POND	High activity clearing	717	07 Mine sites	Identifies all areas associated with tailings including toe berms, dykes, beaches, ponds and drying areas.
RIS-TRANSMISSION-LINE	Soft linear feature	1302	13 Transmission lines	Include the right of way area designated for the powerline.
RLWY-SGL-TRACK	Hard linear feature	404	04 Railways lines - hard surface	A road or track for trains, consisting of parallel steel rails, supported on wooden crossbeams.

				The single track consists of one parallel sets of tracks.
ROAD-GRAVEL-1L	Hard linear feature	305	03 Roads	A roadway surfaced with gravel and constituted as a main access route. The road surface is about 6 metres in width, and the road clearing is about 20 metres or greater in width. The surface, ditches, bridges and intersections are in good condition.
ROAD-GRAVEL-2L	Hard linear feature	306	03 Roads	A roadway surfaced with gravel and constituted as a main access route. The road surface is 7 metres or greater in width, and the road clearing is 30 metres or greater in width. The surface, ditches, bridges and intersections are in good condition.
ROAD-PAVED-DIV	Hard linear feature	314	03 Roads	A major roadway, which is paved with asphalt or concrete, and consists of two (2) roadbeds

				separated by a median. Each road bed usually consists of two (2) or more lanes.
ROAD-PAVED-UNDIV-1L	Hard linear feature	315	03 Roads	A roadway, paved with asphalt or concrete, consisting of one (1) lane, and usually found servicing rural acreages that are close to large urban centres.
ROAD-PAVED-UNDIV-2L	Hard linear feature	316	03 Roads	A roadway, paved with asphalt or concrete, and consisting of two (2) adjacent lanes, with no median to separate them.
ROAD-UNCLASSIFIED	Hard linear feature	318	03 Roads	A temporary coding for an unknown class of road, that will be updated after a field check or verification. (Source: road_album_2.ppt)
ROAD-UNIMPROVED	Hard linear feature	319	03 Roads	A roadway surfaced with dirt and constituted as a minor access route. The road surface is up to 7 metres in width, and the road clearing is up to 20 metres in width. The surface and

				ditches are poorly maintained, and the bridges are narrow.
ROAD-WINTER-ACCESS	Soft linear feature	322	03 Roads	A clearing that is vehicular accessible in winter only.
ROUGH_PASTURE	Low activity clearing	1703	17 Cultivation	Cleared land for purpose of livestock grazing.
RURAL-RESIDENCE	High activity clearing	1502	15 Urban and rural residential	Rural developments (less than 10 buildings per quarter section).
SUMP	High activity clearing	201	02 Borrow Pits, Sumps, Dugouts, Lagoons	Artificial holding or treatment ponds for industrial wastewater.
SURROUNDING-VEG	High activity clearing	1106	11 Other vegetated facilities and recreation	Disturbed vegetation surrounding an airport runway and other industrial features.

TAILING-POND	High activity clearing	721	07 Mine sites	Body of water on/in close proximity to an oil sands mine comprised of acids, benzene, hydrocarbons, residual bitumen, fine silts, and water.
TAME_PASTURE	Low activity clearing	1702	17 Cultivation	Farmlands planted with cultivated grasses or legumes.
TRAIL	Soft linear feature	2003	20 Seismic lines	A polygon feature class derived from a 2-meter buffer (4 meter total width) of a pre-low-impact-seismic centerline.
TRAIL-ATV	Soft linear feature	323	03 Roads	A trail primarily used for ATV activities.
TRANSFER_STATION	High activity clearing	1002	10 Landfill	Small area of land, less than one hectare, usually fenced with a U-shaped road and two entry ways. One small rectangular building. Used primarily for garbage drop-off and

				located close to municipalities or present in rural areas.
TRANSMISSION-LINE	Soft linear feature	1301	13 Transmission lines	A utility corridor >10 m wide with poles, towers and lines for transmitting high voltage electricity (voltage greater than 69 kV).
TRUCK-TRAIL	Soft linear feature	324	03 Roads	A roadway surfaced with dirt or low vegetation and constituted as a minor access route. The road clearing is 6 metres or greater in width. Streams are generally forded, and ditches are few.
URBAN-RESIDENCE	High activity clearing	1503	15 Urban and rural residential	Urban residence (>100 buildings per quarter section).
VEGETATED-EDGE-RAILWAYS	Hard linear feature	602	06 Vegetated surfaces of roads, trails and railways	Disturbed vegetation alongside railway edges.

VEGETATED-EDGE-ROADS	Hard linear feature	601	06 Vegetated surfaces of roads, trails and railways	Disturbed vegetation alongside road edges
WELL-ABAND	Low activity clearing	1601	16 Well sites abandoned	Ground cleared for an oil/gas well pad where the well is currently abandoned.
WELL-BIT	High activity clearing	902	09 Well sites active	Well site - ground cleared for a bitumen well pad.
WELL-CASED	High activity clearing	903	09 Well sites active	Well site - ground cleared and well cased.
WELL-CLEARED-NOT-DRILLED	High activity clearing	905	09 Well sites active	Well site - confirmation of the boundary outline are provided by reference sources.
WELL-GAS	High activity clearing	907	09 Well sites active	Well site - ground cleared for a gas well pad.
WELL-OTHER	High activity clearing	908	09 Well sites active	Well site - clearing, purpose is unknown.