Improving train detectability to reduce collisions with wildlife

by

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Abstract

Collisions of motorized transport with wildlife impact a wide range of species and can cause injuries and economic losses to people. On roads, vehicle collisions with animals have been studied extensively, resulting in mitigation measures that reduce collisions by segregating animals and vehicles, warning drivers about animals, or encouraging animals to be more wary of vehicles. Wildlife–train collisions have received less attention despite documented impacts to species of conservation concern. In addition, characteristics of railways may limit the feasibility of using mitigation measures designed for roads. As part of a larger initiative studying grizzly bear (*Ursus arctos*) mortality from train collisions in Banff and Yoho National Parks (Alberta and British Columbia, Canada), the aim of this dissertation was to determine how collisions might be reduced, particularly for grizzly bears and at locations where collisions have occurred in the past.

I considered the problem of wildlife–train collisions as a complex systems failure at the interface of the animal, train, and railway environment systems. Within a hierarchy of causal mechanisms, I identified potential for reducing collisions by improving animal awareness of approaching trains. I approached this problem with three specific objectives: (1) to understand better the availability of acoustic signals that indicate train approach, (2) to design a warning system to alert wildlife about approaching trains, and (3) to test whether that system causes animals to leave the track earlier when a train approaches.

For the first objective, I measured the audibility of approaching trains along sections of railway track to determine if train audibility could be predicted from features of the track environment, and I tested if poor audibility was associated with the density of recorded animal collisions. I showed that raised topography

within track curves might reduce train audibility around curves. Differences in train speed and in the sound power emitted by locomotives contributed more consistently to differences in audibility within sites, while background noise from adjacent roads and rivers appeared to create differences among sites. Where the audibility of trains was lower, collisions occurred at higher densities on average. Using a physics-based model to predict train audibility along the entire railway, I found that clusters of collisions only sometimes coincided with locations of low predicted audibility; this result suggested that low train audibility is not a necessary condition for the occurrence of collision clusters.

For the second objective, I tested multiple low-cost sensors in two configurations for their ability to detect trains, leading to the invention of an electronic system to promote wildlife avoidance of trains via associative learning. I showed that magnetic and vibration sensors could reliably detect trains as they passed, enabling my design of a warning system in which warning signals are triggered wirelessly by distant train detectors.

For the third objective, I built working prototypes of this warning system, and I used remote cameras triggered by train approach to measure the responses of wildlife to trains where warning signals were and were not provided. I demonstrated that animals that were provided with warning signals left the track earlier than those that were not: on average, 62% earlier for larger animals (coyotes, *Canis latrans*, and larger) and 29% earlier for smaller animals.

Together, my results suggest that the risk of wildlife–train collisions may be high where trains are difficult for animals to hear, that this risk could be mitigated with a train-triggered warning system, and that such a system increases the time interval between wildlife leaving the track and a train arriving at their location. With the increasing overlap between vulnerable populations of wildlife and frequent, fast-moving trains, this approach to reducing wildlife–train collisions could help to protect diverse species in locales around the world.

Preface

This dissertation is an original work by Jonathan Backs. The research project embodied in Chapter 4 of this dissertation received research ethics approval from the University of Alberta Animal Care and Use Committee, project name "University of Alberta Grizzly Bear Mitigation Project," AUP00000438_AME1, June 17, 2016.

Chapter 2 of this dissertation is a manuscript in preparation with authors J.A.J. Backs, J.A. Nychka, and C.C. St. Clair. I was responsible for the study design, data collection, analysis, and manuscript preparation with substantial feedback and ideas from J.A. Nychka and C.C. St. Clair.

Chapter 3 of this dissertation has been published as J.A.J. Backs, J.A. Nychka, and C.C. St. Clair, *Warning systems triggered by trains could reduce collisions with wildlife,* Ecological Engineering, vol. 106 (2017), pages 563–569. Appendix C of this dissertation was included with this publication as supplementary material. I was responsible for the study design, equipment design and manufacture, data collection, analysis, and manuscript preparation with substantial feedback and ideas from J.A. Nychka and C.C. St. Clair.

Chapter 4 of this dissertation is a manuscript in preparation with authors J.A.J. Backs, J.A. Nychka, and C.C. St. Clair. I was responsible for the study design, equipment design and manufacture, data collection, analysis, and manuscript preparation with substantial feedback and ideas from J.A. Nychka and C.C. St. Clair.

To those who didn't make it

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Chapter 1

General introduction

Transportation networks and their associated infrastructure affect wildlife in complex ways. For instance, the widespread effects of roads have received substantial attention in recent decades (Fahrig & Rytwinski 2009; Benıtez-López et al. 2010; Rytwinski & Fahrig 2012). Roads may attract some species with opportunities for habitat (e.g., Li et al. 2010), travel (e.g., DeMars & Boutin 2018), and foraging (e.g., Martinig & Mclaren 2019). Roads may also harm animals through noise (Parris 2015) and chemical pollution (Folkeson et al. 2009), and can form barriers to animal movement, with potential to fragment habitat and isolate populations (Jaeger et al. 2005; Rytwinski & Fahrig 2012). Roads can also encourage predatory access by humans (Nielsen, Herrero, et al. 2004) or other species (DeMars & Boutin 2018). For some species, attractive and harmful effects of roads may act together to create ecological traps (Nielsen, Stenhouse, et al. 2006; Barrientos & Bolonio 2009; Penteriani et al. 2018).

Direct mortality from collisions with vehicles is among the most visible effects of roads on wildlife. The loss of animals to vehicle collisions has had measureable impacts on populations, notably of endangered species including the Iberian lynx (*Lynx pardinus*; Ferreras et al. 1992), Florida panther (*Puma concolor couguar*; Schwab & Zandbergen 2011), and red wolf (*Canis rufus*; Fazio 2007), suggesting the potential of collisions to alter community composition and ecosystem dynamics (van der Ree et al. 2015b). These mortalities also impact humans because utility and intrisic values of animals are lost (Schneider 2019). For example, hunting and tourism revenues are often used to quantify the economic value of animals lost to collisions (K.J. Boyle & Bishop 1987; Conover 1997). Collisions with large animals on roads (e.g., ungulates) also result in substantial economic costs to society in the form of human injuries or fatalities as well as damage to property (Conover 1997; Huijser, Duffield, et al. 2009). Wildlife–vehicle collisions also occur for other transportation modalities, with potentially similar effects for wildlife and people (Lima, Blackwell, et al. 2015; Blackwell, DeVault, Fernández-Juricic, et al. 2016). Collisions with watercraft endanger manatees (*Trichechus manatus latirostris*; reviewed by Rycyk et al. 2018) and right whales (*Eubalaena glacialis*; Nowacek et al. 2004). In aviation, 194 000 collisions with birds and terrestrial animals were reported in the United States between 1990 and 2017 (Federal Aviation Administration 2018), damaging aircraft and creating substantial danger for pilots and passengers.

Trains on railways also collide with and kill animals, and their associated infrastructure may exert similar effects on ecosystems to those of roads (Borda-de-Água et al. 2017; Barrientos, Ascensão, et al. 2019). Railway collisions appear to exert demographic effects on populations (van der Grift 1999), have been documented to kill endangered species including Asian elephants (*Elephas maximus*; Dasgupta & Ghosh 2015) and red-headed vultures (*Sarcogyps calvus*; Khatri et al. 2019). Train-caused mortality may also threaten vulnerable populations of leopards (*Panthera pardus*; Joshi 2010) and elk (*Cervus canadensis*; Popp, Hamr, et al. 2018). Train collisions may sometimes kill more animals than adjacent roads (Huber et al. 1998; COST 341 Management Committee 2000; Waller & Servheen 2005). Despite these effects, railway ecology has garnered less attention than road ecology (Popp & S. Boyle 2017), perhaps because human health and property are less at risk than for road or air transportation. However, derailments and human injuries have been documented, especially outside of North America (e.g., Langbein 2011; Morse et al. 2014; NDTV 2018).

In this dissertation, I focused on the context of train collisions with grizzly bears (*Ursus arctos*) and other animals in Banff National Park, Alberta, Canada (hereafter, Banff). Grizzly bears, though not globally endangered, are a threatened species in Alberta, and in Banff suffer human-caused mortality from a number of sources including removal by wildlife officials for conflict management, road collisions, and railway collisions (Bertch & Gibeau 2009). Between 2000 and 2019, 14 train-caused grizzly bear mortalities were confirmed and another seven bears were reported to have been struck (but no carcasses were found) on the Canadian Pacific railway that runs through Banff. This rate of mortality represented a sharp increase from previous decades and a substantial number for a local population near 60 individuals (St. Clair et al. 2019) with one of the lowest reproductive rates in North America (Garshelis et al. 2005). The railway was the largest direct source of human-caused grizzly bear mortality between 1990 and 2008 (Bertch & Gibeau 2009). These facts have led to ongoing public scrutiny of railway management within Banff, including concerns about spilled grain that can attract grizzly bears and other species to the track (St. Clair et al. 2019). Despite the public focus on grizzly bears and other large carnivores (e.g., wolves (*Canis lupus*); CBC News 2016), a wide range of species are killed by trains in Banff ranging in size from moose (*Alces alces*) and black bears (*Ursus americanus*) to small birds and squirrels (*Tamiasciurus hudsonicus*) (Parks Canada, unpublished data). Elk and deer (*Odocoileus* spp.) are the species most frequently killed by trains in Banff, on the order of dozens of individuals per year (Parks Canada and Canadian Pacific, unpublished data).

This work was part of a larger project undertaken in cooperation with the Parks Canada – Canadian Pacific Joint Initiative for Grizzly Bear Conservation. In 2010, Canadian Pacific announced one million dollars in research funding to address the problem of grizzly bear mortality from train collisions in Banff and neighbouring Yoho National Park, British Columbia, Canada. A portion of this funding was awarded in 2012 to the research lab of Colleen Cassady St. Clair at the University of Alberta, and later matched by a Collaborative Research and Development Grant provided by the Natural Sciences and Engineering Research Council of Canada (NSERC). Research was undertaken to measure the presence of bear attractants along the railway (Pollock, Nielsen, et al. 2017), grain deposition rates along the railway (Gangadharan et al. 2017), and use of the railway and railway-associated forage by grizzly bears (Hopkins III et al. 2014; Murray et al.

2017; Pollock, Whittington, et al. 2019, A. Friesen, unpublished data). Research also sought to determine if mitigation on the adjacent Trans-Canada Highway had affected patterns of railway mortality (Gilhooly et al. 2019) and if the caching behaviour of red squirrels enhanced availability of spilled grain to bears (Put et al. 2017). Other research projects were also funded to fit multiple grizzly bears in Banff with telemetry collars (Parks Canada, unpublished data), to observe the responses of bears to trains with train-mounted cameras (Burley 2015), and to enhance natural travel and escape routes for wildlife along the railway (I.G. Pengelly and J.D. Hamer, unpublished data). In the context of these works by others, which largely examined the factors that lead bears and other animals to encounter trains, I sought to understand the circumstances that lead to collisions within the context of animal–train encounters. I also sought to determine if collisions could be reduced with interventions designed for this context.

1.1 Problem analysis

The Canadian Pacific railway was Canada's first transcontinental railway, connecting the ports of Montreal and Vancouver with a route that crosses the Rocky Mountains of Alberta and British Columbia. The railway parallels the Trans-Canada Highway as well as the secondary Bow Valley Parkway through much of Banff. An average of 19 trains per day (Chapters 2, 4) travel through Banff, carrying mainly agricultural products and natural resources west and manufactured goods east from the port of Vancouver to the rest of Canada with a small proportion of passenger traffic. The highways and railway connect centres of human use including the Banff and Lake Louise townsites as well as numerous campgrounds and trail systems throughout the Bow River valley.

Tending to follow the valley bottom, this major transportation corridor bisects some of the most productive wildlife habitat in Banff. In the eastern half of the park, the montane ecoregion is characterized by wetlands, grasslands, and mixed forest of white spruce (*Picea glauca*) and trembling aspen (*Populus tremuloides*), while at higher elevations in the west, sub-alpine forests of lodgepole pine (*Pinus* *contorta*) dominate (Holland & Coen 1983). A diversity of wildlife coexist within this ecosystem, including large carnivores like grizzly bears, black bears, wolves, and cougars (*Puma concolor*) as well as ungulates such as elk, deer, and moose. Many species favour the productive habitat at the valley bottom, and were struck by vehicles on the Trans-Canada Highway until fencing of the highway followed its twinning through the park from east to west between 1981 and 2014 (Clevenger et al. 2001; Gilhooly et al. 2019). This fencing was accompanied by the construction of 44 wildlife crossing structures that support connectivity of wildlife populations across the highway (Parks Canada 2017).

Animal access to the adjacent railway was not restricted. For wildlife in Banff, the railway appears to be one of few continuous routes with low levels of human use through the area of dense human use around the Banff townsite in the east and through the increasingly rugged topography in the west. Grizzly bears, for example, are known to travel along the railway within Banff (Pollock, Whittington, et al. 2019). These bears may also take advantage of enhanced vegetative forage at the edge of the right-of-way (Pollock, Nielsen, et al. 2017), forage on agricultural products spilled from trains (Gangadharan et al. 2017), and opportunistically gain access to rail-killed ungulates (Murray et al. 2017). Ungulates, birds, and other species appear to use the railway for similar purposes (Chapter 4).

It is within this context that trains encounter and sometimes collide with animals when moving through Banff. A growing body of literature has examined the features of railways and their adjacent landscapes that tend to increase the probability of collisions in space and time. Collisions appear to be more frequent where the track curves (Popp, Hamr, et al. 2018; Jasińska et al. 2019) and where vegetative forage occurs near the track (Gundersen, Andreassen & Storaas 1998), sometimes resulting in high spatial collision densities (hereafter, hotspots; cf. Bıl, Andrášik, Dul'a, et al. 2019). However, little is known within the road or railway contexts about the conditions that determine whether a given animal–vehicle encounter will result in a collision (Lima, Blackwell, et al. 2015).

Animal–train collisions might logically be viewed as a problem occurring at the interface of three entities: the animal, the train (including train operator), and the railway environment. These entities may be viewed as complex systems, each made up of interacting component parts that together produce emergent behaviours that can be difficult to predict (Hitchins 2007; Meadows 2008). This framing is a common analytical approach in the safety and human factors literature, where accidents that at one time may have been ascribed to errors on the part of individual people are better understood in terms of the complex sociotechnical systems that create conditions from which accidents emerge (Salmon et al. 2015). This perspective helps to avoid narrow framing when identifying mechanisms that create deviations from the desired systems performance (i.e., failures; Berk 2009). I chose this approach with the intent to systematically identify opportunities for countermeasures that could reduce the likelihood of animal–train collisions.

As one approach to examining the animal–train–environment interface, I conducted a fault tree analysis (Appendix A). Fault tree analysis is one common approach to deducing possible causes for failures in complex systems (Vesely et al. 2002; Berk 2009). A fault tree analysis begins by identifying the undesired event and proceeds to identifying the "immediate, necessary, and sufficient causes" for the event that are related to each other with logical operators such as AND or OR (Vesely et al. 2002, pg. 47). These causes are similarly broken down until the desired level of detail is reached. I defined the top event of my fault tree as "the injury or death of a large mammal in a collision with a train" and restricted the scope of the fault tree to the train (including train operator), a single animal, and their immediate environment. Although the fault tree I produced was too large to include in this dissertation, the process was valuable for providing a systematic way to think about possible causes. I noted that many of the possible causes I identified related to a failure of the train (including the train operator) and the animal to exchange information early enough for either of these agents to avoid a collision. In this discussion, I focus on the animal's response to the train because heavy freight trains cannot change direction or slow quickly enough to avoid collisions unless animals are detected well in advance.

As others have suggested, an animal's response to a vehicle may be viewed as a three-stage process: detection of the vehicle, assessment of the vehicle as a threat, and evasion of the vehicle (Lima, Blackwell, et al. 2015). Success in all three stages is necessary to avoid a collision (Lima, Blackwell, et al. 2015), and delays in detection or threat assessment might logically constrain the time of an animal's evasion response. This conceptual model seemed plausible in light of video footage of grizzly bear collisions shown to us early in the project by project partners at Canadian Pacific. Locomotive-mounted cameras revealed that bears appeared to retreat suddenly from the train, as if surprised, and were struck after being overtaken by the train as they fled from the train between the rails. Other work has observed similar responses to trains by ungulates (Rea, Child, et al. 2010). When surprised by a train, bears and other animals may see the flat, open railway track as their most efficient escape route, especially where deep snow (Becker & Grauvogel 1991; Rea, Child, et al. 2010), steep topography, bodies of water, or dense vegetation restrict escape from one or both sides of the right-of-way. Even if other escape routes are available, the acute stress that animals might experience during a train encounter is known to adversely affect decision-making (Mobbs & Kim 2015). Maladaptive flight responses might then be prevented if the conditions that lead to surprise could be prevented.

Although it may seem unlikely that animals could fail to detect vehicles as large and loud as trains (Lima, Blackwell, et al. 2015), conditions present in the track environment might plausibly delay an animal's detection and assessment of a train to the point where surprise were possible. Given the speed at which trains often travel, animals likely rely on their senses of vision and hearing to detect them. In a mountainous protected area like Banff, the railway corridor often curves around regions of dense vegetation and raised topography that limit visibility of oncoming trains (as has been found elsewhere; Hamr et al. 2019; Jasińska et al. 2019). Despite these issues with visibility, I have personally been surprised by trains in Banff that I was able to see before I could hear them, leading me to suspect that audibility of trains could also be an issue for animals (as described in Chapter 2). That collisions have been found to occur more frequently near track curves suggests that spatial features of the track environment might contribute mechanistically to wildlife collisions (Popp, Hamr, et al. 2018; Jasińska et al. 2019). Features of the environment that change in time may also contribute, including light level and weather effects (fog, precipitation, wind) (reviewed by Steiner et al. 2014). However, related work on roads has shown that the most dangerous locations and times for animals may not coincide with collision hotspots if populations are locally suppressed by collisions (Eberhardt et al. 2013; Ascensão et al. 2019) or if animal use is simply low for other reasons (Neumann et al. 2012).

To mitigate the risk of wildlife–vehicle collisions, especially in the road context, a diverse suite of tools has been developed. These measures work by (1) reducing animal–vehicle encounters, (2) modifying the behaviour of vehicle operators, or (3) modifying the responses of animals to vehicles. For method (1), physical exclusion of animals from transportation corridors with fencing and crossing structures appears to be the most consistently effective method of reducing collisions (Clevenger et al. 2001; Huijser, Duffield, et al. 2009). Related methods seek to remove animals from the vicinity of roads or reduce the attractiveness of roads, including population culls (Doerr et al. 2001), vegetation removal (Jaren et al. 1991; Andreassen et al. 2005), or scent deterrents (Bıl, Andrášik, Bartonička, et al. 2018). For method (2), static wildlife warning signs and reduced speed limits are low-cost measures but largely ineffective if ignored by drivers (Huijser, Mosler-Berger, et al. 2015). Active measures seek to improve driver responsiveness by providing more specific information in space and time, for example with wayside (Huijser, McGowen, et al. 2006) and in-vehicle (Forslund & Bjärkefur 2014) animal detection systems. However, this method seems more practical on roadways than on railways, where heavy freight trains cannot change direction or slow quickly on time scales required to avoid collisions. Collision mitigation for trains has consequently focused on method (3), encouraging animals to avoid incoming vehicles. On roads, passive wayside deterrents have been devised that reflect the headlights of incoming vehicles to scare animals away from the road (D'Angelo et al. 2006); active deterrents detect approaching vehicles and provide light-and-sound stimuli to frighten animals (Mulka 2009). Little published evidence supports the effectiveness of these methods on roads (D'Angelo et al. 2006), though new methods are emerging (Riginos et al. 2018). Vehicle-mounted sonic deterrents seem similarly ineffective on roads (Valitzski et al. 2009), but they may be more effective on railways (Muzzi & Bisset 1990; Shimura et al. 2018). Perhaps because of these mixed results, collision mitigation via animal deterrents or warnings has received less attention than either driver warning or animal separation methods.

Reasons for the ineffectiveness of some passive animal deterrents are unclear. Perhaps the visual or auditory stimuli are too weak to reach the target animals (e.g. from deer whistles or headlight reflectors; D'Angelo et al. 2006; Valitzski et al. 2009). It may also be that the stimuli lack the temporal and spatial specificity to convey the intended meaning—for animals, via a process of associative learning (Domjan 2005). Habituation to the stimuli may also occur if animals receive no unconditioned stimulus that reliably follows the deterrent (Rankin et al. 2009; Blumstein 2016), as is known to occur for systems intended to scare animals away from crop fields or livestock (Koehler et al. 1990). An active warning system designed to cause a learned association, e.g., between arbitrary conditioned stimuli and the unconditioned aversive experience of the close passage of a train, could bridge the information gap between train and animal (Chapter 3). Similar approaches have shown promise in limited tests elsewhere, though the success of this test was attributed to the use of warning signals composed of naturally aversive sounds (Babińska-Werka et al. 2015).

Two central questions emerge from this discussion. First, why are animals vulnerable to train collisions? Spatial and temporal factors in the railway environment are known to increase collision risk, but the processes that determine retreat behaviour during an animal–train encounter remain difficult to study (Lima, Blackwell, et al. 2015). Towards an answer to this first question, I chose to explore the relationship between train audibility and features of the railway environment, as poor train audibility could affect how animals respond to trains. Second, what can be done to reduce collisions? Could collisions be reduced without excluding animals or trains from the system? Towards an answer to this second question, I chose to design, build, and test an animal warning system capable of creating learned associations between warning stimuli and train passage. If animals were able to interpret the information about train approach that such a system would be intended to convey, perhaps they would be less frequently surprised by approaching trains and thereby more likely to choose an appropriate escape response.

1.2 Scope of this work

The broad aims of this dissertation were to understand if problems with train audibility could contribute to wildlife–train collisions in Banff and to determine if an active warning system could effectively intervene to increase train detectability and collision avoidance for animals. In answering these research questions, I aimed to generate insights that could be generalized to other parts of the world where wildlife are struck and killed by trains.

The dissertation is organized into three data chapters. In Chapter 2, I used self-contained weatherproof sound recorders to measure the audibility of trains at 10 locations along the railway in Banff. I used these data to test hypotheses about the relationship between track curvature, topography within track curves, and audibility with regression and physics-based models. I also compared measured and simulated audibility data with historical data on the locations of wildlife–train collisions in Banff. In Chapter 3, I proposed a design for an animal warning system that would be capable of creating learned associations between arbitrary stimuli and train passage according to the principles of associative learning. I built and tested two low-cost methods for detecting approaching trains that did not interfere with railway infrastructure, which I saw as a key requirement for adoption by railway companies like Canadian Pacific. In Chapter 4, I developed a working prototype of this animal warning system and tested its ability to modify the responses to trains of wild, free-ranging animals. I used self-contained weatherproof cameras triggered by approaching trains to observe the behaviour of animals before and during train approaches at locations where I alternated the provision and omission of warning signals. I measured the time between each animal's flight initiation and the arrival of the train at the location where it fled. I compared results for trains approaching from straight and curved track sections to additionally test for a relationship between train detectability and the effect of the warning system on the flight initiation times of animals.

The dissertation concludes with a general discussion in Chapter 5. Appendices for each data chapter are included, including complete designs for the warning systems as built for Chapters 3 and 4.

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Chapter 2

Low audibility of trains may contribute to increased collisions with wildlife*

2.1 Abstract

Transportation collisions with wildlife are a global issue, causing mortality of animals and creating risk of injuries and economic losses for people. Measures for mitigating the risk of collisions sometimes focus on enhancing the detectability of vehicles to animals, a strategy that might be most effective on low-use roads and railways in locations where detection failures are most likely. Some literature suggests that detection is impeded by lack of visibility, but the audibility of vehicles to animals is rarely explored in this context. We sought to test the hypotheses the audibility of trains could be obscured by raised topography within track curves and that reduced audibility could contribute to the mortality of wild animals from train collisions within Banff National Park, Alberta, Canada. We measured the relative audibility of trains via the ratio of train approach sound to background sound (signal-to-noise ratio) as trains approached at 10 locations with raised topography within track curves. We compared relative audibility measurements to the history of train collisions with wildlife at these locations and, via simulation from a physical model, along 45.6 km of the railway through our study area. Mean relative audibility was negatively associated with the historical number of collisions at our

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10 measurement sites and a similar association was found for the lowest quartile of simulated train audibilities across our study area. Topography within curves reduced train audibility by an average of 3.2 dB per 6.2 m of topography height above track grade, but high variance in these estimates produced marginal *p*-values. Train audibility was also reduced by 1.9 dB for every 8.6 $\mathrm{km\,h^{-1}}$ increase in train speed and by at least 2.0 dB for every 4.7 dB reduction in train sound power. Speeds were lower and sound powers were higher for trains moving west rather than east through Banff, suggesting locomotives were in higher throttle states when climbing the elevation gradient through the park. Comparisons of three physical models with our measured audibilities similarly suggested that train speed and sound power could be at least as influential as topography. Variation in background noise among (mean range 52.0 dB to 66.8 dB SPL) and within (SD range 1.8 dB to 11.8 dB) sites may have been most influential, and included noise from nearby road traffic, a river, and weather effects. Although audibility may be only one of several factors that contribute to collision risk, measurement of vehicle audibility may help conservationists and transportation managers to better-understand and mitigate wildlife collisions on railways and roads.

2.2 Keywords

Acoustics; hearing; vehicles; detection; railway; strikes; mortality; learning

2.3 Introduction

Transportation networks and their associated infrastructure alter the natural systems in which they exist. Although some organisms thrive in these altered systems (Fahrig & Rytwinski 2009; Morelli et al. 2014), many species are affected negatively. On land, roads fragment landscapes and degrade habitat while the vehicles that traverse them collide with and kill animals (reviewed in van der Ree et al. 2015a). When large animals are struck, people can be injured and vehicles can be damaged (Bissonette et al. 2008). Railways and trains appear to exert similar effects (reviewed by van der Grift 1999; Dorsey et al. 2015; Barrientos, Ascensão, et al. 2019). Despite the continued expansion of railways worldwide (Dulac 2013), documented impacts to species of conservation concern (e.g., Roy & Sukumar 2017), and risks of injury to passengers and damage to trains (Morse et al. 2014; NDTV 2018), wildlife collisions on railways remain understudied (Popp & S. Boyle 2017).

Mitigation of terrestrial wildlife collisions has been a focus of research for decades, producing a suite of tools applicable to both roads (van der Ree et al. 2015a) and railways (Borda-de-Água et al. 2017). The most consistently effective methods reduce or prevent animal access to rights-of-way, typically with fences accompanied by crossing structures that reduce barrier effects for wildlife (Clevenger et al. 2001; Glista et al. 2009). Other strategies seek to modify the behaviour of vehicle operators with some combination of speed reduction and advanced warning (Huijser, Mosler-Berger, et al. 2015). In contrast, operators of trains (especially heavy freight trains) have no ability to change direction and limited ability to slow safely on the time scales necessary to avoid collisions with wildlife. Hence, recent work on railway mitigation has focused on helping animals to avoid trains (Babińska-Werka et al. 2015; Backs et al. 2017; Seiler & Olsson 2017).

Roadside and trackside mitigations may be strategically deployed in locations where collisions with wildlife occur most frequently (hereafter, hotspots; e.g., Bıl, Andrášik, Dul'a, et al. 2019), though danger can exist where hotspots do not (Eberhardt et al. 2013; Ascensão et al. 2019). The spatial distribution of hotspots can often be correlated to local features of the road or railway environment (e.g., Gundersen, Andreassen & Storaas 1998; Gunson, Mountrakis, et al. 2011; Jasińska et al. 2019). Some features may increase the probability of encounters between animals and vehicles, such as forested habitat adjacent to a roadway that promotes animal use of the area (Gunson, Mountrakis, et al. 2011). Other features may increase the probability of a collision once an encounter has occurred, where the same vegetation that attracts animals to a roadway can limit visibility for drivers and reduce the time available for drivers to avoid animals (Bashore et al. 1985).

The ability of animals to detect and respond to vehicles might also be affected by the local environment of the road or railway (reviewed by Lima, Blackwell, et al.

2015). To detect a fast-approaching vehicle, animals are likely to rely on vision and hearing, but visibility to animals of oncoming vehicles can be obstructed where a transportation corridor curves around vegetation or rugged topography (Hamr et al. 2019; Jasińska et al. 2019). While low visibility of vehicles to animals is rarely suggested as a collision mechanism on roads, visibility of vehicles for human pedestrians is known to be important (reviewed by Ulrich et al. 2014), and low visibility of trains has been proposed to contribute to the clustering of wildlife collisions near curves on railways (Dorsey et al. 2015; Popp, Hamr, et al. 2018; Jasińska et al. 2019). Where the visibility of trains is obstructed, animals might logically rely on hearing to detect approaching trains. However, audibility to animals of oncoming vehicles could also be reduced by topography within curves, and to some extent by dense forest (F.M. Wiener & Keast 1959; Yip et al. 2017), as earthen berms have long been used for noise abatement along transportation corridors (reviewed by Ekici & Bougdah 2003). In other contexts, greater collision risk has been found where road vehicle audibility is reduced for human pedestrians (e.g., Ulrich et al. 2014) and where train audibility is reduced for vehicle drivers (Lipscomb 1995) or pedestrians (Mortimer 1994; Lichenstein et al. 2012). While studies have examined the audibility of vehicle-mounted acoustic deterrents (e.g., Valitzski et al. 2009; Shimura et al. 2018), the audibility of vehicles themselves is rarely considered in the context of terrestrial animal–vehicle collisions (excepting Huber et al. 1998; Vidya & Thuppil 2010; Heske 2015).

The purpose of this study was to determine if animals might be more vulnerable to collisions where vehicles are more difficult to hear, especially where visibility is obstructed by topography and vegetation within curves in the transportation corridor. On a railway through a mountainous protected area where visibility is frequently obstructed, we used sound recorders to measure sound from trains (25 s to 35 s before train arrival) and background sound (5 min to 90 min before train arrival) using as a relative measure of train audibility the ratio of train sound to background sound (signal-to-noise ratio, SNR). We measured SNR at 10 sites where track that curved around raised topography met a straight section of track, allowing us to compare train approaches from curved and straight track within each site. Within each site, we simultaneously recorded train sound at two distances from the track to determine if the availability of train sound to animals differed within the width of the cleared right-of-way. Using these data, we sought to test the hypothesis (1) that low train audibility contributes to an increased rate of animal–train collisions, predicting that historical counts of animal–train collisions at each site would be negatively correlated with (a) the mean measured SNR at each of our 10 sites and (b) the SNR across the study area simulated by a physical model of the interaction of train sound with topography. We then sought to test the hypothesis (2) that raised topography impedes the transmission of train sound around curves in the track, predicting that (a) trains approaching from track curves would be less audible on average than trains approaching from straight sections of track, that (b) topography height would be negatively correlated with SNR for trains approaching from around curves, and that (c) a physical model accounting for the interaction of sound with topography would more accurately and precisely predict our measured SNR data than simpler physical models that did not account for the presence of topography.

2.4 Methods

2.4.1 Study area and period

We recorded train sounds along the Canadian Pacific railway in Banff National Park, Alberta, Canada (hereafter, Banff). Here, train collisions are a leading cause of mortality for wildlife, including elk (*Cervus canadensis*), deer (*Odocoileus* spp.), wolves (*Canis lupus*), black bears (*Ursus americanus*), and the provincially threatened grizzly bear (*Ursus arctos*; Bertch & Gibeau 2009; Gilhooly et al. 2019). The ballast-covered portion of the railway extends 3 m to 5 m from the track centreline, beyond which lie sub-alpine forests of lodgepole pine (*Pinus contorta*) in the western half of Banff and montane wetlands, grasslands, or mixed forests of white spruce (*Picea glauca*) and trembling aspen (*Populus tremuloides*) in the eastern half of Banff (Holland & Coen 1983). Vegetation and topographical features tend to abut the track along its length, limiting visibility around curves. Parallel to the railway through much of Banff are the four-lane Trans Canada Highway (0.0 km to 1.2 km from the railway in the eastern half of Banff) and the two-lane Bow Valley Parkway (0.0 km to 0.9 km away in the eastern half), following the Bow River (0.0 km to 2.4 km away in the eastern half) through the Canadian Rocky Mountains.

Sound recordings were made over two multi-day recording sessions during the summer of 2016 (27 June–1 July, 2–5 August). Coinciding with peak tourist season in Banff, mean traffic volumes on the Trans Canada Highway were 33 290 vehicles per day (range 24 972 to 41 349 vehicles per day), far above the daily average for 2016 of 22 769 vehicles per day (counted 1.6 km west of Banff park gates; Alberta Transportation 2019). The mean ambient temperature was 15.4 °C (range 3.1 °C to 28.2 °C) with occasional winds from the southeast or northwest gusting up to 44 $\mathrm{km\,h^{-1}}$. Total rainfall was 0.7 mm but weather varied across the study area (Environment and Climate Change Canada 2019).

2.4.2 Survey design

We restricted recordings to a 45.6 km portion of the railway in the eastern half of Banff, where the highest densities of wildlife–train collisions within Banff occured in recent decades (Gilhooly et al. 2019). Within this region, we selected 10 sites where the railway curved around topography with areas higher in elevation than the adjacent track bed (determined from a digital elevation model for Banff viewed with geographic information systems (GIS) software) and where this curve met a straight section of track greater than 300 m in length (Table 2.1; Table B.1). We recorded sound at up to three sites concurrently, changing sites after 1–2 days to distribute recording time among the 10 sites.

We measured train audibility at two locations per site as well as train speed by placing three sound recorders (SM2+GPS, Wildlife Acoustics, USA) in an array configuration (Fig. 2.1[a]). On the inside of each track curve where the straight-away began, one recorder was mounted on a tripod near the track (trackside recorder), a second where vegetative cover abutted the right of way (forest edge recorder), and a third 100 m along the straightaway from the trackside recorder (speed recorder). To ensure that trains passed both recorders simultaneously, the trackside and forest edge recorders were placed on a line perpendicular to the track using a length of string, a plumb bob, and a tape measure (e.g., Brouwer et al. 1985). Recorder positions were marked with stakes to support identical placement where sites were revisited for multiple recording sessions. Once positioned, the trackside and forest edge recorders were aligned with their microphones oriented parallel to the track (Fig. 2.1[a]) by sighting across spirit levels placed on top of the recorder housings.

We equipped the trackside and forest edge recorders with two microphones each (SMX-II, Wildlife Acoustics, USA) to allow train direction to be determined from the audio recordings, while we used a single microphone on the speed recorder. Sound recorders were programmed to record continuously (59 minutes on, 1 minute off every hour due to hardware limitations) in uncompressed WAV format at a sample rate of 96 kHz. To allow recorded sound levels to be compared across different microphones, we calibrated each microphone with a 1 kHz, 94 dB SPL (re 20 µPa) signal (SM-CAL1, Amprobe, USA) at the beginning (entry calibration) and end (exit calibration) of each recording session. Entry calibrations were used exclusively for the audio analysis, but no pair of entry and exit calibration levels differed by more than 3.0 dB. The timing of events could be compared across recordings because sound recorders automatically synchronized with global positioning system (GPS) time signals to within 1 ms for most recordings.

2.4.3 Audio analysis

We examined recordings in Audacity software version 2.1.2 (Audacity Team 2016). A single observer determined the times of train arrival at each trackside and speed recorder to within 0.2 s typically by comparing the recording spectrogram with audible playback to find the centre of the Doppler shift created by the passage of the front wheelset on the lead locomotive. Train passages were excluded from further analysis if this moment of arrival was not captured by all recorders at a site (e.g., if any recorder in the array was in the inactive portion of its hourly cycle).

We catalogued from the recordings the direction of travel for each train (by ear) and other events including recorder setup, calibrations, and passages of non-train track vehicles.

Because recording took place at up to three sites concurrently, individual trains were recorded 1–3 times as they travelled through the study area. Trains typically proceeded through the study area without stopping and could be identified unambiguously across sites by comparing arrival times, direction of travel, length, and distinctive acoustic features (e.g., locomotive timbre, wheel flats). Each unique train was assigned an identification code (hereafter, train identity).

Train speeds were measured to within $3\,\mathrm{km\,h^{-1}}$ typically by comparing the time difference of train arrival at the trackside and speed recorders (Table 2.1). We excluded from further analysis all trains with speed less than $30\,\mathrm{km\,h^{-1}}$ because these trains exhibited excessive rail squeal, a type of train sound generated disproportionately by slow trains on track curves (M. Rudd 1976). This noise would have obscured our tests of hypotheses about topography and curvature because rail squeal appears to propagate well through the track rails (Rose et al. 2004). For trains with measured speeds that exceeded the posted speed by more than $10\,\mathrm{km\,h^{-1}}$, we confirmed our measurements by estimating the width of the Doppler shift as their locomotives passed (e.g., Young et al. 2004); speed measurements were corrected for two trains at Site G by this method, where GPS time synchronization was temporarily lost.

To convert the root-mean-square (RMS) of a set of sample values (from a recorded WAV file) to the equivalent RMS value in pascals, we derived from each entry calibration a conversion factor for each recording session:

$$F_{\mathrm{Cal}} = \frac{P_{\mathrm{Cal}}}{\bar{s}_{\mathrm{Cal}}}, \tag{2.1}$$

where $P_{\mathrm{Cal}} = 94\,\mathrm{dB\,SPL} = 1.002\,\mathrm{Pa}$ is the calibration sound pressure and $\bar{s}_{\mathrm{Cal}}$ is the RMS of the sample values recorded during a microphone calibration.

As an indicator of train audibility, we measured the signal-to-noise ratio (SNR) in decibels (dB) of approaching trains 25 s to 35 s before arrival (hereafter, the approach interval). Previously, we speculated that 20 s before arrival was a key time for animals to detect the approach of the train if they were to leave the track safely (Backs et al. 2017); this time has also been identified as minimum warning interval for human safety at railway level crossings (Richards & Heathington 1990). We chose 25 s to 35 s before arrival for our audibility measurements after observing that trains were usually audible above the background noise in this interval. Further, we found that trains travelling at the measured mean speed (61.2 km h^{-1}) took approximately 30 s to fully traverse track curves at our recording sites, suggesting the 25 s to 35 s interval would be likely to expose an effect of topography if one existed. We used the decibel scale for SNR as an indicator for audibility because the sound pressure levels from which SNR is calculated are perceived (by humans) on an approximately logarithmic scale (Barron 2002).

Train passages were excluded from further analysis if any portion of the approach interval was not recorded by both the trackside and forest edge recorders, or if excessive noise (e.g., recorder setup, thunder, train horns, motorcycles, aircraft) or microphone artifacts (from rain, wind) were present during the approach interval. Within each 10 s approach interval, we calculated the RMS of the audio samples (from a recorded WAV file) for overlapping 1 s sub-intervals every 0.5 s, multiplied each of these 19 values by the calibration conversion factor F_{Cal} from (2.1), then calculated the mean of the resulting sound pressures (hereafter, the approach sound level). Background sound levels were calculated similarly for the 5 min to 90 min before each train arrival (hereafter, the background interval), excluding from each background interval regions of interference from recorder setup, other trains, and non-train track vehicles. Every background sound level was calculated from at least 5 minutes of interference-free recording. We converted mean sound pressure values for the approach interval $\bar{P}_{\mathrm{approach}}$ to decibel (dB) sound pressure levels (SPL) L_{approach} using

$$L_{\mathrm{approach}} = 20 \log_{10} \frac{\bar{P}_{\mathrm{approach}}}{P_{\mathrm{ref}}}, \tag{2.2}$$

where $P_{\mathrm{ref}} = 20\,\mu\mathrm{Pa}$ is the SPL reference pressure (Barron 2002). $L_{\mathrm{background}}$ was found similarly. We then defined the SNR in dB as

$$\mathrm{SNR}_{\mathrm{dB}} = L_{\mathrm{approach}} - L_{\mathrm{background}}. \tag{2.3}$$

We note this definition of SNR departs from convention because L_{approach} (the "signal" in SNR) is not measured independently of the background sound:

$$\bar{P}^2_{\text{approach}} = \bar{P}^2_{\text{train}} + \bar{P}^2_{\text{background}}, \tag{2.4}$$

where $\bar{P}_{\text{train}}$ is the RMS sound level due to the train alone and we assume $\bar{P}_{\text{background}}$ during the approach interval is the same as it was during the background interval. This implies that $\text{SNR}_{\text{dB}} = 3\,\text{dB}$ when the sound from the train and background contribute equally to the approach sound level, but allows us to retain data where the measured $\text{SNR}_{\text{dB}} < 0\,\text{dB}$ (i.e., where the sound level during the approach interval is less than during the background interval).

We also estimated the sound power emitted by each train using sound level measurements when the train was close to the recorder. We calculated the mean sound level as before, but using the interval 1.0 s to 2.0 s before train arrival (or up to 6.5 s to 7.5 s before arrival if necessary to avoid train horns). Assuming that background sound and topography effects were negligible, and treating the train as a point source of sound over perfectly reflective ground, we expected the near-distance measured sound level $\bar{P}_{\text{near}}$ to relate to the sound power level in dB $\text{SWL}_{\text{train}}$ based on the inverse square of the distance r_{near} (Barron 2002):

$$\text{SWL}_{\text{train}} = 20\log_{10}\frac{\bar{P}_{\text{near}}}{P_{\text{ref}}} - 10\log_{10}\frac{Q}{4\pi r^2_{\text{near}}}, \tag{2.5}$$

where $Q = 2$ is the directivity factor over flat, perfectly reflecting ground (Barron 2002). r_{near} was found using the measured train speed.

2.4.4 Animal collision data

We used a mortality database collected by Parks Canada Agency spanning 1981 to 2016 that provided locations of wildlife–train collision events within our study area ($n = 1062$). Events in this dataset included collisions where mortality was confirmed by Parks staff (94%) as well as reported collisions where the fate of the animal was not confirmed (6%). Multi-animal collisions (4%) were counted as single events to ensure that each counted event was independent. Precision of recorded locations changed over time, as collisions prior to the mid-1990s were recorded to the nearest mile marker (i.e., within 0.8 km) while collision locations were later recorded with handheld GPS units. We used a version of the database where the accuracy of locations was enhanced where possible by interpretation of descriptive notes from the original data (Gilhooly et al. 2019). Consistency of reporting also improved from 1998 onwards, when Parks Canada Agency standardized the reporting of collisions (Gilhooly et al. 2019). The directions of train travel for collision events were not available.

Because coordinates provided with each event only approximately aligned with a GIS layer of the railway track (Canadian Pacific, unpublished data), we snapped the location of each collision event to the nearest point on railway layer. We used for subsequent analyses the number of collision events within a 400 m length of track centred on each measurement site (Table 2.1). This method reflected our estimate of the length of track over which a train traversing the curve could have its sound level at 30 s farther along the track affected by the topography within that curve. This length also provided robustness against the imprecision of recorded locations for collision events.

2.4.5 Association of measured audibility with collisions

We tested for an association between the audibility of trains (indicated by the measured SNR values in dB) and collision counts (response variable) at our 10 measurement sites using a Poisson generalized linear model (GLM) with a logarithmic link (Zuur, Ieno, Walker, et al. 2009). Because train directionality was not available for the collision data, measured SNRs were averaged across trains approaching from both directions within sites before conversion to decibel units. We assessed model fit with a likelihood-ratio χ^2 test comparing the model of interest with the null model (Dunn & Smyth 2018). We used Wald z-statistics and associated p-values to assess the importance of each parameter in the model (Murtaugh 2014a,b) with the understanding that Wald statistics may be conservative due to the small sample size (Dunn & Smyth 2018). Because the model fit suggested that our recorder position had no effect on the association between collision count and audibility, all subsequent analyses used data from the trackside recorders only.

2.4.6 Linear tests of topography and curvature

Topography and curvature were quantified for the curved approach direction within each site. A train travelling at the mean speed of our analyzed trains (mean ± SD = (63.7 ± 8.6) km h^{-1}) would be 531 m along the track curve from the recorder at 30 s before arrival (half-way through the approach interval). In GIS software, we drew a polygon for each site from the trackside recorder, along the 531 m of track between the recorder and the train, then along a straight line back to the recorder. The maximum elevation within this polygonal area minus the mean elevation along the 531 m length of track was used to represent this topographical feature (hereafter, the topography height). Elevations were from light detection and ranging (LiDAR) data for all sites except Site J, where only a lower-resolution DEM was available (Parks Canada, unpublished data). Track curvature was quantified by taking the ratio of the recorder–train straight-line distance and the 531 m on-track distance (hereafter, the track curvature ratio).

We tested our hypotheses about the effects of track curvature and topography on measured SNR by developing a single regression model for each hypothesis (Harrell 2015; Ver Hoef & Boveng 2015): one to test for a difference between audibility of train approaches from straight vs. curved track, a second to test for effects of topography height and degree of curvature on the audibility of trains approaching around curves, and a third to test for a potential confound of audibility with train direction of travel. In each case, a linear mixed-effects model was used (Zuur, Ieno, Walker, et al. 2009) with the measured SNR (in dB) of each train observation as the response. To account for the conditional independence of samples measured within each of our 10 sites and within up to 89 unique trains, each of which was recorded at between one and three sites as it travelled through the study area, we included crossed random intercepts of site and train identity in each model (Gelman & Hill 2007; Zuur, Ieno, Walker, et al. 2009; Zuur, Ieno & Elphick 2010). We compared trains approaching from straight vs. curved track and from east vs. west using all train observations (hereafter, the all approaches dataset); we compared by-site values of topography height and track curvature ratio using trains approaching from curved track only (hereafter, the curved approaches dataset). In each model, we controlled for the measured by-train speed and sound power level. We assessed each model fit with respect to a null (intercept-only) model with the same random effects structure using a conditional F-test with the Kenward-Roger correction for degrees of freedom (df; Kenward & Roger 1997; J.C. Pinheiro & D.M. Bates 2000; Halekoh & Højsgaard 2014; D. Bates et al. 2015). We used Wald t-statistics with Kenward-Roger corrected df (Halekoh & Højsgaard 2014; Kuznetsova et al. 2017) and associated p-values to assess the importance of each parameter in each model (Murtaugh 2014a,b). We also assessed relationships among train speed, sound power, and direction of travel using Welch's unequal variance t-tests (Ruxton 2006) and the Pearson correlation coefficient.

2.4.7 Development of physical predictions

Although our linear statistical model allowed a straightforward test of our hypotheses, we suspected that it would not detect effects of topography and curvature because it did not account for the complex relationship between these variables and the sound level at the recorder. We derived a set of three progressively more sophisticated models to approximate the acoustical physics of our experiment, and we tested each model for its ability to predict the measured SNRs. To distinguish these physics-based models from the statistical models with which we tested them, we refer hereafter to the physics-based models as physical predictions.

In the simplest case, we supposed that the approaching train contributed negligibly to the the sound level at the recorder 25 s to 35 s before arrival, meaning the SNR would simply be equal to one (i.e. 0 dB; hereafter, the *background* prediction; Fig. 2.1(b)):

$$\mathrm{SNR}_{\mathrm{dB}} = L_{\mathrm{approach}} - L_{\mathrm{background}} = 0\,\mathrm{dB}, \tag{2.6}$$

where L_{approach}, $L_{\text{background}}$, $\bar{P}_{\text{approach}}$, and $\bar{P}_{\text{background}}$ are as from (2.2). Given (2.4), the *background* prediction is equivalent to stating $\bar{P}^2_{\text{train}} = 0$.

To improve the prediction, we included the sound from the train L_{train} in the predicted approach sound level. Rearranging (2.5), replacing both $\bar{P}_{\text{near}}$ and r_{near},

$$L_{\text{train}} = 20\log_{10}\frac{\bar{P}_{\text{train}}}{P_{\text{ref}}} = \text{SWL}_{\text{train}} + 10\log_{10}\frac{Q}{4\pi r^2_{30\text{s}}}, \tag{2.7}$$

where $Q = 2$ as before. $r_{30\text{s}}$ is the straight-line distance between the train and sound recorder at 30 s before arrival (half-way through the approach interval), found using the measured train direction, train speed, and a GIS layer of the railway track to estimate the position of the train along the track 30 s before arrival. We added this train sound to the background sound to obtain the *background & train* prediction (Fig. 2.1(c)):

$$\text{SNR}_{\text{dB}} = 10\log_{10}\left(\frac{\bar{P}^2_{\text{train}}}{\bar{P}^2_{\text{background}}} + 1\right). \tag{2.8}$$

To include the effect of topography, we approximated the topography within the curve as a rectangular acoustic barrier (hereafter, the equivalent barrier; Fig. 2.1(d); Maekawa 1968). Sound was not allowed to transmit through the barrier, but was allowed to diffract over the top and around a vertical edge placed near the railway. The attenuation imposed by this barrier on the sound from the train is termed the insertion loss IL in dB (Barron 2002), allowing us to construct the *background & train & barrier* prediction (Fig. 2.1(d)):

$$\text{SNR}_{\text{dB}} = 10\log_{10}\left(\frac{\bar{P}^2_{\text{train}}}{\bar{P}^2_{\text{background}}} \cdot 10^{\frac{-\text{IL}}{10}} + 1\right). \tag{2.9}$$

An expression for the insertion loss of the equivalent barrier was adapted from the work of others (Maekawa 1968; Kurze & Anderson 1971; Lam 1994; Muradali & Fyfe 1998) and simplified by ignoring interference effects (cf. the energy summation approach Lam 1994):

$$\text{IL} = M_1 + 10\log_{10}\left[\frac{4}{4 + 2\cdot\frac{10^{\frac{-M_5}{10}}}{10^{\frac{-M_1}{10}}}}\right]. \tag{2.10}$$

Here, M_i refers to the value of an empirical relation called the Maekawa curve (Maekawa 1968; Kurze & Anderson 1971), which relates the value of the Fresnel number $N_i = \frac{2}{\lambda}(d_i - d_o)$ and the attenuation of a diffracted path $i \in (1, ..., 8)$, where $i = 1$ corresponds to the two-segment linear path overtop of the equivalent barrier, $i = 5$ corresponds to the two-segment linear path around one vertical edge of the equivalent barrier, and subscript o corresponds to the direct path without any barrier (*sensu* Muradali & Fyfe 1998). For this model, we assumed a single wavelength $\lambda = \frac{f}{c_s}$ for the train sound, using a frequency $f = 74.3\,\mathrm{Hz}$, a typical value for the strongest frequency component of locomotive sound in our measured train samples (cf., Remington & M.J. Rudd 1976), and a speed of sound $c_s = 340.5\,\mathrm{m\,s^{-1}}$, the value for dry air at 15 °C (Rumble 2019), within the ambient temperature range during our study. We adapt our definition of M_i as follows (Lam 1994; Muradali & Fyfe 1998):

$$M_i = \begin{cases} 0, & N_i \leq -0.3 \\ 5, & N_i = 0 \\ 5 + 20\,\mathrm{sgn}(N_i)\log_{10}\left[\frac{\sqrt{2\pi|N_i|}}{\tanh\sqrt{2\pi|N_i|}}\right], & \text{otherwise} \end{cases} \tag{2.11}$$

This expression shows that the contribution to the total attenuation of a given diffracted ray path i increases with the path length difference $(d_i - d_o)$, which depends not only on the height of the topography within the track curve but also its nearness to the train and the recorder.

We determined the size and location of each equivalent barrier from a linear topographical profile between the recorder position, which was the same for all trains at a given site, and the train position, which was derived from the speed of each train. At 1000 evenly spaced points along a line between the recorder and train, we bilinearly interpolated the value of elevation from LiDAR data for all trains except a subset at Site G and all at Site J where we used a lower-resolution DEM (as above). We projected lines along this profile from the train and recorder points that were allowed to touch the topography only once; where these lines met was the top of the equivalent barrier (hereafter, the Maekawa point; Maekawa 1968). If no topography obstructed line of sight between the train and recorder points, a Maekawa point was chosen from the available topography that yielded the smallest absolute value of the Fresnel number, indicating that the selected topographical feature might interact most strongly with the train sound. To find the horizontal extent of the equivalent barrier, a line was drawn from the Maekawa point perpendicular to the train–recorder line towards the railway track; the horizontal extent of the barrier was terminated 5 m from the track, or half the distance between the Maekawa point and the track if this distance was less than 5 m.

2.4.8 Tests of physical predictions

We compared our three physical predictions using one fixed- and one mixed-effects linear model for each, yielding a total of six models. In each model, the measured SNR (in dB) of each train was used as the response variable and one of the three sets of physical predictions was used as an offset variable such that the only estimated fixed effect in each model was the intercept (Dunn & Smyth 2018). Thus, for fixed-effects models, the intercept parameter was equal to the mean of the difference of the measured SNRs and the physically predicted SNRs (hereafter, the physical residuals). For the mixed-effects models, crossed random intercepts for site and train identity were also estimated, yielding physical residuals that were estimated in light of the conditional independence of the observations (Gelman & Hill 2007; Zuur, Ieno, Walker, et al. 2009). Parameter-specific t-statistics were derived exactly for the intercept parameters of the fixed-effects models (Dunn & Smyth 2018), while Wald t-statistics were used for mixed-effects models with Kenward-Roger corrected df (Halekoh & Højsgaard 2014; Kuznetsova et al. 2017). p-values indicated the degree to which each intercept was statistically different from zero (Murtaugh 2014a,b; Dunn & Smyth 2018). We contrasted the accuracy and precision of the physical predictions by the distance from zero and SE values of each estimate of the physical residuals.

2.4.9 Simulation of physical predictions

The statistical power of our test for an association between measured audibility and collision counts may have been limited by our measurement of train audibility at only 10 sites. To increase the spatial scope of this test, we applied the *background & train & barrier* physical predictions to the entire railway within our study area. We generated points every 10 m along the railway track ($n = 4523$), then simulated trains approaching from both directions at each point according to (2.9). Because we had no recordings at most of these locations, we assumed a constant background sound level of 61.2 dB SPL and a sound power level for all trains of 132.4 dB, each equal to the mean values measured for data used in our previous analyses. We also assumed that trains travelled at the posted train speed for each location (Table 2.1; Canadian Pacific, unpublished data).

2.4.10 Association of simulated audibility with collisions

We tested for an association between the simulated SNR values (in dB) and collision counts (response variable) within 200 m of each simulated point using a Poisson GLM with logarithmic link (Zuur, Ieno, Walker, et al. 2009) for each direction of train travel. To test for a suspected association at only low values of audibility, we fitted similar models only for data in the lowest quartile of the simulated SNR for each direction. We computed Wald z-statistics for each parameter, but the inherent spatial correlation present in these data likely yielded anti-conservative p-values (Zuur, Ieno & Elphick 2010). Therefore, we did not rely on p-values for inference and only compared each model's predicted difference in the collision count over the range of simulated SNR values.

All analyses were performed in R version 3.5.1 (R Core Team 2018) except where noted above. Statistical analyses are summarized in Table 2.2.

2.5 Results

Recorder arrays were active for 281.5 hours in total (mean [SD] = 28.2 [7.4] hours per site) over which 222 train passages were captured (104 unique trains), suggesting that 18.9 trains per day (SD 2.7) passed through Banff during the study period (using site as the unit of replication and weighting by number of hours sampled). The average passing speed for recorded trains was 61.2 $\text{km}\,\text{h}^{-1}$ (SD

12.6), though this differed substantially among sites and by direction within site with some trains substantially faster and slower than the posted speed (Table 2.1). After exclusion of train samples for incompleteness of approach and background intervals (8 trains), for interference from noise in the approach interval (42 more trains), and for passing speeds less than $30\,\mathrm{km\,h^{-1}}$ (9 more trains), 163 train passages remained. Train audibilities appeared to vary substantially both among and within sites (Fig. 2.2), and background sound levels preceding each of these train approaches differed widely among sites from 52.0 (SD 1.8) dB SPL at Site J to 66.8 (SD 3.1) dB SPL at Site H (Table 2.1).

2.5.1 Association of measured audibility with collisions

Wildlife–train collisions were more frequent where we measured that trains were harder to hear (Fig. 2.3). Our Poisson GLM fit the data better than the null model (df = 3, $\chi^2 = 99.4$, $p < 0.001$) and suggested that train audibility at the trackside recorders was strongly correlated with collision count (mean SNR (dB) parameter, Table 2.3). For forest edge recorders, the model predicted a slightly weaker correlation but this difference was not statistically significant (interaction parameter, Table 2.3).

2.5.2 Linear tests of topography and curvature

We found no difference in audibility (as indicated by SNR) between trains approaching from straight versus curved track. The linear mixed-effects model comparing straight and curved approaches was an improvement over a null model with the same random effects structure (df = (4, 109.4), $F = 8.7$, $p < 0.001$), but the parameter for straightaways vs. curves was not different from zero regardless of whether we controlled for effects of train speed and train sound power and regardless of whether we included a suspected interaction with train speed (*straight vs. curve*, Table 2.4). Train speed and sound power emerged as stronger predictors of audibility, with audibility decreasing as train speed increased (Fig. 2.4(a)) and audibility increasing as train sound power increased (Fig. 2.4(b)).

For train approaches from curves alone, we found a possible effect of topography on audibility. Our model incorporating track curvature ratio and topography height was only a marginal improvement over the null model (df = $(5, 12.8)$, $F = 2.0$, $p = 0.152$). The model fit showed a marginal effect of topography height, a non-significant effect of track curvature ratio, and a non-significant interaction (*within curves*, Table 2.4). Although we caution against their interpretation due to the marginal or non-significant p-values, the directions of these effects in the fitted model suggested that topography had a more pronounced effect on audibility for sharper track curves (Fig. 2.5).

We also explored the effect of train travel direction on audibility in addition to our hypothesis about approach curvature. Our model incorporating train direction was an improvement over the null model (df = $(3, 129.9)$, $F = 11.8$, $p < 0.001$), but the parameter for train direction was not significant when we controlled for effects of train speed and sound power (*eastbound vs. westbound*, Table 2.4). This result was plausible because westbound trains travelled more slowly on average than eastbound trains (Welch's t-test: df = 116.1, $t = 5.3$, $p < 0.001$) and westbound trains emitted more sound power than eastbound trains (Welch's t-test: df = 148.9, $t = -10.3$, $p < 0.001$). Train speed and train sound power were nevertheless uncorrelated (Pearson's $r = -0.31$).

2.5.3 Tests of physical predictions

Comparing the three sets of physical predictions, we found the *background & train* and the *background & train & barrier* predictions were similar in their ability to predict the measured data (Fig. 2.6). Mixed-effects models on each set of physical predictions estimated intercepts that were similarly distant from zero for the *background & train* and the *background & train & barrier* predictions, with the intercept for the *background & train & barrier* predictions being nearest to zero in absolute value (1.8 dB difference) and smallest in SE (0.7 dB difference; Table 2.5). Fixed-effects models yielded similar results, although the *background & train* estimate was instead closest to zero (−1.6 dB difference; Table 2.5). Both mixed- and fixed-effects model sets showed that the *background* predictions substantially underestimated the SNR of measured trains (intercept larger than zero), while the *background & train* predictions tended to overestimate (intercept smaller than zero) and the *background & train & barrier* predictions tended to underestimate the same data. The residual SD was smallest among the mixed-effects models for the *background & train* predictions (3.3 dB difference) while the residual SD was smallest among the fixed-effects models for the *background & train & barrier* predictions (4.4 dB difference).

2.5.4 Associations of simulated audibility with collisions

Applied along the railway through the study area, the *background & train & barrier* model predicted regions of low train audibility (indicated by SNR) that appeared to coincide with regions of high collision count; regions of high collision count also appeared to exist with no corresponding region of low audibility (Fig. 2.7). The simulated data revealed a baseline-like structure visible in the simulated SNR (Fig. 2.7[a]), corresponding to the SNR value expected for flat, straight track. This baseline showed that the predicted audibility decreased as the speed of the simulated trains increased. Local decreases of near 1 dB in the simulated SNR occurred where simulated trains were approaching from around track curves with no interposing topography, while larger local decreases of 2 dB to 4 dB occurred where the track curved around larger topographical features. The simulated SNRs did not agree closely with measured values at our 10 sites (Table 2.1).

Poisson GLMs comparing the collision counts to the corresponding simulated audibilities found only a small association overall (Table 2.6, all SNR datasets; Fig. 2.8, long black lines). Over the range of SNRs for simulated westbound trains (0.25 dB to 6.06 dB), the westbound model predicted a difference of 5.1 animal collisions—only 12% of the largest strike count observed within 200 m of a simulation point. For simulated eastbound trains, we found a similar difference of 4.9 collisions over the 0.49 dB to 5.93 dB of predicted SNR. Over just the lowest quartile of simulated audibilities (Table 2.6, SNR lowest quartile datasets; Fig. 2.8, short red lines), regressions revealed a larger difference in the number of predicted collisions over a smaller SNR range. The westbound model predicted a difference of 18.3 collisions (44% of largest strike count) over 0.25 dB to 4.31 dB of predicted SNR. The eastbound model predicted a difference of 6.2 collisions (15% of largest strike count) over 0.49 dB to 4.31 dB of predicted SNR. All tested relationships were statistically significant, but we did not interpret the *p*-values further due to the spatial correlation inherent in these data.

2.6 Discussion

Animals might routinely use acoustic cues to detect and avoid vehicles like trains, especially in protected areas where visibility can be limited by dense vegetation and rugged topography. Yet, the availability of these acoustic cues to animals and the corresponding effects on animal–vehicle collision risk are not well understood. In measuring and modelling the audibility of trains in Banff, we found evidence consistent with our first hypothesis in that animal–train collisions occurred more frequently at locations with low train audibility. The evidence was not clearly consistent with our second hypothesis about the effect of raised topography on attenuating the sound of approaching trains. While train audibility was perhaps affected by site-specific variables like track curvature and topography, it was more clearly associated with train-specific variables like train speed and sound power. We also found substantial variation in train audibility among and within sites that could make train detection more difficult for animals.

As our first hypothesis, we suspected that low train audibility would contribute to an increased rate of animal–train collisions. We predicted that higher counts of animal–train collisions would be associated with low train audibility, and this association was evident for the measured data at our 10 sites. In contrast, one previous study found no significant mean difference in train audibility between collision and random locations, although the method for assessing train audibility was not described (Huber et al. 1998). We found no other quantitative studies relating audibility of terrestrial vehicles to collision risk, despite existence of literature identifying aircraft sound as a factor in the behavioural responses to aircraft terrestrial mammals and birds as well as responses to watercraft of marine mammals (reviewed by Lima, Blackwell, et al. 2015). In our study, because we measured audibility using the SNR, the loudness of both background and train approach sounds necessarily contributed to the observed association. Among the 10 measured sites, the two sites with the lowest mean SNRs and highest collision counts also had the highest mean background levels. Road traffic was the primary source of background noise at these sites, and traffic noise can increase or decrease the distance at which some species flee in response to approaching predators or humans (Barber et al. 2010; Shannon et al. 2016; Petrelli et al. 2017). Yet in the simulated data across the study area, where differences in background noise were ignored, the lowest simulated audibilites were also associated with collision counts. This result suggests that the approach sound level may be as important as the background sound level when determining train audibility, as has been found for humans (Lipscomb 1995). The similar associations found for the trackside and forest edge recorders likely stem from the close proximity of these recorders (3 m to 13 m; Table B.1) relative to the scale of the topographical features involved in the acoustical diffraction process, which were on the order of 500 m.

As our second hypothesis, we suspected that raised topography within track curves impedes the transmission of train sound. We predicted that trains would be less audible when they approached from around curves with topography than from straightaways and that the obstructing effect of topography would explain this difference. However, we found no difference on average between the audibilities of trains approaching from curves and straightaways. Strong differences in audibility nevertheless existed between sites and among curved and straight approaches within some sites, suggesting that the existence of a track curve alone was not enough to explain differences in audibility among trains. Previous studies have found that curvature sometimes does and sometimes does not correlate with locations of animal–vehicle collisions (on roads, cf. Gunson, Chruszcz, et al. 2005; Gunson, Mountrakis, et al. 2011; on railways, cf. Huber et al. 1998; Popp, Hamr, et al. 2018; Jasińska et al. 2019), perhaps because methods varied for measuring curvature and for accounting for potential confounds. Looking within curved approaches, our analysis revealed a strong but marginally significant effect of topography height and no significant effect of track curvature ratio. Given that raised topography is routinely used for noise abatement along transportation corridors (Ekici & Bougdah 2003), we suggest this analysis does not rule out the existence of a topography effect, which despite its marginal significance was of a direction and strength consistent with our hypothesis. Our detection of a marginal effect could be attributed to limitations of our study design, including the low number of uncorrelated degrees of freedom available to test the topography and curvature effects (Kenward & Roger 1997) and the simplistic measure of topography used (maximum height within the curve). Variation in background sound levels could also be more important than topography in determining train audibility, as even the largest expected effect of topography from the *background & train & barrier* predictions (5.7 dB; Fig. 2.7) was less than the variation in background sound level within some sites (SD values ranged from 1.8 dB to 11.8 dB; Table 2.1). The comparison of our physical predictions also appeared not to support or rule out a topography effect, as we found that predictions accounting for (*background & train & barrier*) and not accounting for (*background & train*) topography were different from each other but a similar distance from the measured data on average. Future tests of this hypothesis might be improved using models that accounted for the full topographical profile of the railway environment (e.g., Karantonis et al. 2010) as well as potential confounding interactions with the atmosphere, the ground, and vegetation (F.M. Wiener & Keast 1959; Embleton 1996; ISO Technical Committee ISOK 43, Acoustics, Subcommittee SC 1, Noise 1996).

We measured and controlled for train speed and train sound power in our statistical models to isolate potential effects of topography, curvature, and approach direction. However, speed and sound power emerged as similar in strength to the topography effect and their parameters were more statistically significant. The comparison of physical predictions similarly suggested that train speed and sound power were comparably important to topography in generating the data. All analyses indicated that trains emitting more sound power were generally more audible and that faster-moving trains were generally less audible. These results seem reasonable given that fast trains are further from the recorder than slow trains at 30 s before arrival and given that sound pressure at a receiver is inversely proportional to the squared distance from the source (see (2.7) for *background & train*). Our statistical model suggests that halving a train's speed from 66 $\mathrm{km\,h^{-1}}$ to 33 $\mathrm{km\,h^{-1}}$ would increase its SNR at 30 s before arrival from 7.2 dB to 14.4 dB (straight approaches; Table 2.4, *straight vs. curve*), in close agreement with (2.7) (*background & train*) and equivalent to more than double the approach sound level. Other studies have suggested that reduced train speed reduces risk of collisions for animals (Becker & Grauvogel 1991; Gundersen & Andreassen 1998; Visintin et al. 2018), and increased audibility could be one mechanism by which this occurs. Further, we found that westbound trains were generally more audible because they moved more slowly and emitted more sound power on average. As elevation increases along the railway within Banff from east to west, westbound locomotives may be in higher throttle states that emit more noise (Remington & M.J. Rudd 1976) and may travel at a lower speeds while climbing. Train sound power (via throttle state) is likely also affected by variables we did not measure including train length and loading, which can vary by direction in our study area (e.g., Gangadharan et al. 2017), as well as conditions of excessive wheel–rail squeal known to be caused by a combination of low train speed and high track curvature (M. Rudd 1976) for which we excluded most westbound trains at Site H.

Although we found that collisions occurred more frequently where trains were consistently less audibile, we speculate that the wide variation in train audibility among trains and locations could increase the collision risk even where audibility is not often low. For instance, we observed that trains were sometimes audible (especially via horn sounds) up to 10 minutes before they arrived. Instances like these might plausibly lead animals to ignore sounds of train approach because the sounds are not promptly reinforced by the aversive stimulus of a close approach of a train (i.e., habituation; Rankin et al. 2009). Animals at locations with normally consistent audibility might learn avoidance responses for trains that are audible well before they arrive (as in a discriminated avoidance procedure; Domjan 2005). An animal used to highly audible trains might be more likely to respond maladaptively (e.g. Rea, Child, et al. 2010) if it were surprised by an unusually fast and quiet train at the same location (e.g., Sites A, F, and J; Fig. 2.2) or by a train with a lower audibility at a different location (e.g., Sites I vs. J; Fig. 2.2).

Under ideal conditions, it seems unlikely that animals could be surprised by vehicles as large and loud as trains. Low train audibility might more plausibly increase vulnerability to collisions when other stimuli demand an animal's cognitive resources (Owen, Swaisgood, et al. 2017). The threshold sound level required for detection of a sound and for recognition of the same sound may differ (as for humans, Lipscomb 1995; cf. threat assessment, Lima, Blackwell, et al. 2015). While the minimum detectable difference in loudness between two sounds is near 1 dB depending on the loudness and frequency (Florentine et al. 1987), train sounds must be at least 10 dB louder than background noise to reliably provoke an alerting response in vehicle drivers at road–rail level crossings (Mortimer 1994; Lipscomb 1995). Further, it may be that only when the train stimulus is intense enough does it elicit a response from an animal because of the inherent cost to responding (Frid & Dill 2002). Animals might underestimate the cost of not responding if they are habituated to train stimuli (Lima, Blackwell, et al. 2015; Blumstein 2016) and perhaps especially if they are accessing resources within the railway corridor including spilled grain (Gangadharan et al. 2017), enhanced vegetative forage (Pollock, Nielsen, et al. 2017), rail-killed ungulates (Murray et al. 2017), or rodent prey (J. Backs, personal observation). Foraging and other distractions may also increase the amount of train stimulus required to elicit a response (Lima & Bednekoff 1999), analagous to inattentional deafness in humans (Mack & Rock 1998). Reducing the presence of attractants in a transportation corridor may reduce collisions (e.g., Grilo et al. 2012; Murray et al. 2017), though the mechanism of distraction has not been tested in this context (Lima, Blackwell, et al. 2015). Distracted human pedestrians have more difficulty hearing simulated approaching vehicles (Davis & Barton 2017).

Looking at maps of the largest collision clusters in our study area, we observed that multiple factors known to increase collision risk appeared to exist at each cluster location (Appendix B.2). As we acknowledged in our study design, visibility of trains is already limited around curves where vegetation and raised topography abut the track. In this work, we found that the same topography along with high background noise (e.g., from nearby roads) may reduce train audibility for animals at some collision clusters. The same steep embankments, along with adjacent water bodies and highway fencing present near some collision clusters, seem likely to reduce the ability of animals to escape collisions with trains (e.g., Hamr et al. 2019). These same features could also create situations where animals are compelled to use the railway to travel between habitat patches amidst the otherwise high density of human activity in the Bow River valley (Pollock, Whittington, et al. 2019). The co-occurrence of these issues with detectability, escapability, and attraction appear to be implicit in the design of the railway corridor for this mountainous area: to limit track grades, the track tends to follow topographical contours. Because the co-occurrence of these issues may have confounded our ability to attribute collision risk to train audibility, future efforts to model collision risk in this and other mountainous areas should strive to be comprehensive in their accounting for risk factors. To facilitate future research in this area, we further recommend that railway companies and wildlife managers rigorously record not only the precise locations of wildlife–train collisions but also the direction of travel for the train that struck each animal.

We observed during the course of our study three other phenomena that affected our auditory detection of trains but that we did not examine. First, large transport trucks and motorcycles on the nearby Trans-Canada Highway convincingly imitated train sounds to the point that we were occasionally fooled into leaving the railway track as per our safety protocol; the effect of this regular exposure was to reduce our willingness to leave the track when train sounds were heard (i.e., a secondary source of habituating stimuli). Second, we occasionally experienced illusory localizations of train sound that led us to believe that a train was approaching from the opposite of its actual approach direction. This effect can result when the reflected path (e.g. off nearby topography or vegetation) from a sound source to a receiver is louder than the direct path that might be additionally obscured by topography within a track curve (von Békésy 1949). Third, we observed that both ultrasound (up to 48 kHz) and infrasound (suggested by the subtle shake of buildings over 500 m from the track) were excited by trains, but we had limited ability to measure either with our sound recorders. Ultrasonic signals from approaching trains were sometimes recorded well before human-audible train sounds, and both ultrasound (transmitted through track rails; (Rose et al. 2004; Backs et al. 2017)) and infrasound (transmitted through the ground; Thompson 2009, Chapter 12) are likely unaffected by track curvature or topography. Yet, diverse species are able to hear sounds that humans cannot (e.g. ultrasound for deer, H. Heffner & H.E. Heffner 2010; infrasound for elephants (e.g., *Elephas maximus*), R.S. Heffner & H.E. Heffner 1982), and measurements of train audibility within multiple frequency bands may yield insights that our total spectrum measurements did not.

If the acoustic detectability of trains contributes to collision risk, this source of risk might be mitigated not only by improving train audibility but perhaps also by reducing the variance in train audibility. These objectives might be practically achieved in locations of high collision risk with targeted reductions in train speed, with consistent use of train horns, and potentially with trackside wildlife warning signals. Our results showed that trains are audible at a longer time before arrival at lower speeds, and speed reductions appear to be effective in reducing collisions (Visintin et al. 2018). Reduced variation in train speed may also reduce instances of surprise from low-audibility outliers. Train horns also increase the audibility of trains, consistent with requirements in Canada and elsewhere that horns be blown whenever approaching road–rail crossings (Transport Canada 2018) and evidence for their benefit to drivers as well as pedestrians (Mortimer 1994; Lipscomb 1995). Wildlife warning signals deployed along the railway track would emit light and sound stimuli at a consistent time before train arrival, allowing animals to learn to associate the signals with train approach because the signals are always provided at the same intensity and only to animals within the high risk location (Babińska-Werka et al. 2015; Backs et al. 2017). Similarly, warning signals are used worldwide to protect drivers and pedestrians at road–rail crossings (reviewed by Caird et al. 2002). For locations with the highest collision risk, changes in the design of the railway corridor might be necessary that either exclude wildlife (e.g. fences and crossing structures; Clevenger et al. 2001) or reduce the confluence of risk factors such as proximity with roads and rivers, obstructing vegetation, and steep topography.

In summary, we showed that train audibility and background noise varied among sites along a railway through a mountainous protected area, and that low train audibility was correlated with the history of wildlife collisions at those sites. We attempted to predict train audibility with both linear statistical and nonlinear physical models incorporating measures of topography within track curves, which suggested increases in audibility with decreased train speed and increased train sound power. The effect of topography generally was unclear due to poor model fits, and when applied across the study area, the nonlinear physical model incorporating topography effects correlated with collisions only at locations in the lowest quartile of predicted audibility. We conclude that more research is warranted about train audibility and its effect in animal–train collisions, and recommend the use of more sophisticated models to explore both background noise and train audibility in the acoustic context of the surrounding landscape. Increased attention to vehicle audibility may increase understanding of collision mechanisms and increase options for mitigating the risk of wildlife–train collisions with potential application to wildlife–vehicle collisions on roads.

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2.8 Supporting Information

1. Table B.1: Site locations, straightaway lengths, and recorder placements
2. Appendix B.2: Features of cluster and measurement sites

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2.10 Tables

Table 2.1: Summary of train sound measurements and related features at 10 sites along the Canadian Pacific railway within Banff National Park, Alberta, Canada. Within each train direction (Train dir.), we contrast the number n of trains recorded (for which "Measured speed" is reported to within $3\,\mathrm{km\,h^{-1}}$ typically) with the number of trains analyzed (for which background levels and signal-to-noise ratios [SNR] are reported) after exclusion of slow trains (speed < $30\,\mathrm{km\,h^{-1}}$) and noisy approaches (from weather or horn presence). The *background & train & barrier* physical predictions are used for "Predicted SNR" (see Methods). We provide the number of animal collisions recorded within 200 m of each site (Colls.), the direction from recorders to each track curve (Dir. to curve), the track curvature ratio where values closer to one are more straight (Curve ratio), the maximum height of topography above the mean track grade (Topo. height), and the nominal maximum speed of trains at each site (Posted speed; Canadian Pacific, unpublished data). Locations, straightaway lengths, and recorder separations are given in Table B.1.

Site	Name	Colls.	Train dir.	Dir. to curve	Curve ratio	Topo. height (m)	Posted speed ($\mathrm{km\,h^{-1}}$)	n recorded, analyzed	Measured speed ($\mathrm{km\,h^{-1}}$)	Background level (dB)	Measured SNR (dB)	Predicted SNR (dB)
A	Castle East	4	W	E	0.986	7.5	80	8, 8	58 (10, 50–75)	59.0 (4.5)	10.0 (5.4)	8.3 (3.0)
			E		–	–		9, 6	76 (20, 25–97)		8.0 (3.5)	4.4 (4.1)
B	Johnston Canyon	2	W	W	–	–	80	11, 4	47 (6, 38–59)	62.3 (11.8)	21.3 (3.9)	16.8 (3.5)
			E		0.984	3.3		11, 7	77 (4, 71–82)		12.9 (4.7)	7.0 (3.8)
C	Hillsdale West	12	W	E	0.967	24.3	64	9, 7	45 (13, 28–63)	64.0 (4.6)	6.8 (4.5)	1.6 (1.1)
			E		–	–		13, 4	58 (9, 41–67)		5.5 (2.7)	1.6 (0.7)
D	Muleshoe	7	W	E	0.983	2.4	64	9, 7	61 (6, 49–65)	53.0 (3.2)	13.6 (3.5)	15.5 (2.8)
			E		–	–		10, 10	63 (3, 58–68)		14.7 (3.4)	14.4 (3.6)
E	Five Mile A	16	W	E	0.957	12.9	64	13, 11	59 (3, 54–64)	58.9 (9.6)	9.9 (4.0)	8.7 (3.2)
			E		–	–		12, 3	63 (2, 61–65)		13.1 (3.1)	12.9 (4.5)
F	Five Mile S	8	W	E	0.918	3.1	64	7, 7	62 (4, 52–65)	60.0 (4.4)	16.4 (2.9)	11.2 (4.1)
			E		–	–		16, 11	64 (2, 60–68)		8.1 (6.2)	7.1 (3.7)
G	Five Mile C	6	W	W	–	–	64	5, 3	57 (11, 39–63)	61.5 (3.8)	13.0 (4.4)	10.6 (2.8)
			E		0.915	7.9		13, 9	61 (5, 52–67)		4.3 (3.8)	2.6 (1.9)
H	Stables	33	W	E	0.875	13.1	64	13, 1	28 (12, 19–64)	66.8 (3.1)	8.1 (1.5)	2.8 (0.8)
			E		–	–		15, 12	62 (5, 55–72)		3.9 (4.6)	2.7 (2.0)
I	Anthracite	28	W	W	–	–	72	14, 10	62 (9, 48–73)	64.9 (2.2)	7.5 (3.0)	4.6 (1.6)
			E		0.98	1.8		18, 16	67 (4, 62–77)		4.8 (4.5)	0.6 (0.5)
J	Carrot East	4	W	W	–	–	72	14, 11	66 (8, 53–78)	52.0 (1.8)	19.5 (2.7)	16.1 (3.4)
			E		0.967	5.4		16, 16	71 (3, 68–77)		15.6 (3.2)	6.0 (2.0)

Table 2.2: Summary of statistical models used in this work. Response variables were modelled as a function of the fixed and random effects, depending on the model type (see Methods). Model types included generalized linear models (GLMs; all Poisson-distributed with logarithmic links), linear mixed-effects models (LMEs), and linear fixed-effects models (LFEs). Each model included a fixed intercept. Fixed effects marked with "(offset)" were included in the model with no estimated parameter. ":" indicates interaction effects. Each model used the all approaches dataset, except for the *within curves* model (as indicated).

Analysis, *model name* (all approaches dataset)	Model type	Response	Fixed effects	Random effects
Association of measured audibility with collisions	GLM	Collision count	Measured SNR	
Linear tests of topography and curvature				
Straight vs. curve	LME	Measured SNR	Approach direction, train speed, train sound power, direction:speed	Site, train ID
Within curves (curved approaches dataset)	LME	Measured SNR	Topography height, track curvature ratio, train speed, train sound power, height:curvature	Site, train ID
Eastbound vs. westbound	LME	Measured SNR	Train direction, train speed, train sound power	Site, train ID
Tests of physical predictions				
Fixed, background	LFE	Measured SNR	*Background* SNR (offset)	
Fixed, background & train	LFE	Measured SNR	*Background & train* SNR (offset)	
Fixed, background & train & barrier	LFE	Measured SNR	*Background & train & barrier* SNR (offset)	
Mixed, background	LME	Measured SNR	*Background* SNR (offset)	Site, train ID
Mixed, background & train	LME	Measured SNR	*Background & train* SNR (offset)	Site, train ID
Mixed, background & train & barrier	LME	Measured SNR	*Background & train & barrier* SNR (offset)	Site, train ID
Associations of simulated audibility with collisions	GLM	Collision count	*Background & train & barrier* SNR	

Table 2.3: Parameter estimates (Est.), standard errors (SE), and Wald z statistics for a Poisson GLM with logarithmic link comparing wildlife collision counts (response variable) with measured signal-to-noise ratios (SNR) in decibels (dB), recorder position (trackside or forest edge), and their interaction. SNRs were averaged by direction (westbound and eastbound) within each of ten measurement sites (Table 2.1) separately for sound recorders positioned at the trackside and at the forest edge. Reference categories (ref.) are indicated in parentheses. ":" indicates interaction effects.

Parameter	Est.	SE	z	p
Intercept	4.20	0.24	17.3	<0.001
Mean SNR (dB)	-0.18	0.03	-6.7	<0.001
Recorder position (forest edge, ref. trackside)	-0.42	0.32	-1.3	0.188
SNR:Forest edge	0.04	0.04	1.1	0.291

Table 2.4: Parameter estimates (Est.), standard errors (SE), and Wald t statistics from three linear mixed-effects models for which the response variable was signal-to-noise ratio (SNR) of approaching trains in decibels. All models included crossed random intercepts for site and train identity. Reference categories (ref.) are indicated in parentheses. ":" indicates interaction effects. Degrees of freedom (df) were approximated using the Kenward-Roger method. Boldface lines (excluding intercepts) indicate statistical significance at $\alpha = 0.05$. Straight vs. curve and eastbound vs. westbound models used data for trains approaching from both directions, while the within-curves model used data only for trains approaching from track curves. Continuous variables were centered and scaled to aid interpretation: for the bi-directional data, train speed (original mean [SD] = 63.7 [8.6] $\mathrm{km\,h^{-1}}$), train sound power (original mean [SD] = 129.0 [4.7] dB); for the within-curves data, topography height above track (original mean [SD] = 7.1 [6.2] m), track curvature ratio (original mean [SD] = 0.962 [0.026] dB), train speed (original mean [SD] = 63.6 [8.7] $\mathrm{km\,h^{-1}}$), train sound power (original mean [SD] = 128.3 [5.1] dB).

Model name (dataset)	Est.	SE	df	t	p
Straight vs. curve (all approaches)					
Intercept	7.6	1.6	11.5	4.7	<0.001
Approaching from curve (ref. straight)	-0.4	0.6	85.3	-0.7	0.473
Train speed ($\mathrm{km\,h^{-1}}$, scaled)	-1.9	0.5	111.5	-3.5	<0.001
Train sound power (dB, scaled)	2.0	0.5	134.4	4.3	<0.001
Curve:speed	0.3	0.7	91.1	0.4	0.711
Within curves (curved approaches)					
Intercept	7.8	1.7	5.9	4.6	0.004
Topography height above track (m, scaled)	-3.2	1.7	7.1	-1.9	0.096
Track curvature ratio (scaled)	0.3	1.4	7.0	0.2	0.847
Train speed ($\mathrm{km\,h^{-1}}$, scaled)	-1.9	0.9	67.2	-2.2	0.035
Train sound power (dB, scaled)	3.1	1.2	48.0	2.6	0.014
Topography:curvature	1.3	1.9	10.0	0.7	0.519
Eastbound vs. westbound (all approaches)					
Intercept	6.9	1.6	13.8	4.2	<0.001
Train moving westbound (ref. eastbound)	1.2	1.4	126.2	0.8	0.416
Train speed ($\mathrm{km\,h^{-1}}$, scaled)	-1.6	0.5	138.5	-3.5	<0.001
Train sound power (dB, scaled)	1.8	0.5	113.1	3.6	<0.001

Table 2.5: Parameter estimates (Est.), standard errors (SE), and Wald t statistics for linear models comparing physical predictions with measured values for the signal-to-noise ratio (SNR) in decibels (dB). Each model has the measured SNR as the response and the physical predictions as an offset variable; the intercept in each case estimates the mean of the physical residuals (measured SNR minus predicted SNR). We contrast estimates of the residuals among each set of physical predictions (model name) for linear mixed models using crossed random intercepts of train ID and site with linear models using only fixed effects. We report for comparison the estimated standard deviations (SD) of the random intercepts for mixed models and residual SDs for all models.

Model type: *model name*	Est.	SE	df	t	p
Fixed: *background*					
Intercept	8.4	0.6	162	15.1	<0.001
Residual SD	7.1				
Fixed: *background & train*					
Intercept	-1.6	0.4	162	-4.1	<0.001
Residual SD	4.8				
Fixed: *background & train & barrier*					
Intercept	2.1	0.3	162	6.1	<0.001
Residual SD	4.4				
Mixed: *background*					
Intercept	7.7	1.4	12.0	5.4	<0.001
Train ID (random effect SD)	5.6				
Site (random effect SD)	4.0				
Residual SD	2.9				
Mixed: *background & train*					
Intercept	-2.1	1.0	9.6	-2.1	0.054
Train ID (random effect SD)	2.0				
Site (random effect SD)	2.9				
Residual SD	3.3				
Mixed: *background & train & barrier*					
Intercept	1.8	0.7	9.7	2.3	0.042
Train ID (random effect SD)	1.7				
Site (random effect SD)	2.1				
Residual SD	3.5				

Table 2.6: Parameter estimates (Est.), standard errors (SE), and Wald z statistics for four Poisson GLMs with log links comparing wildlife collision counts (response variable) with simulated signal-to-noise ratios (SNR) in decibels (dB). SNRs were simulated using the *background & train & barrier* physical predictions. GLMs were regressed on either the full set of data within a train direction (all SNR; n = 4523) or the lowest quartile of the SNR data within a train direction (SNR lowest quartile; n = 1131).

Train direction (dataset)	Est.	SE	z	p
Westbound (all SNR)				
Intercept	2.620	0.021	126.2	<0.001
Simulated SNR (dB)	-0.082	0.004	-19.0	<0.001
Westbound (SNR lowest quartile)				
Intercept	3.275	0.023	139.7	<0.001
Simulated SNR (dB)	-0.345	0.007	-46.8	<0.001
Eastbound (all SNR)				
Intercept	1.680	0.026	63.5	<0.001
Simulated SNR (dB)	0.114	0.005	21.4	<0.001
Eastbound (SNR lowest quartile)				
Intercept	2.580	0.033	79.2	<0.001
Simulated SNR (dB)	-0.191	0.010	-20.1	<0.001

2.11 Figures

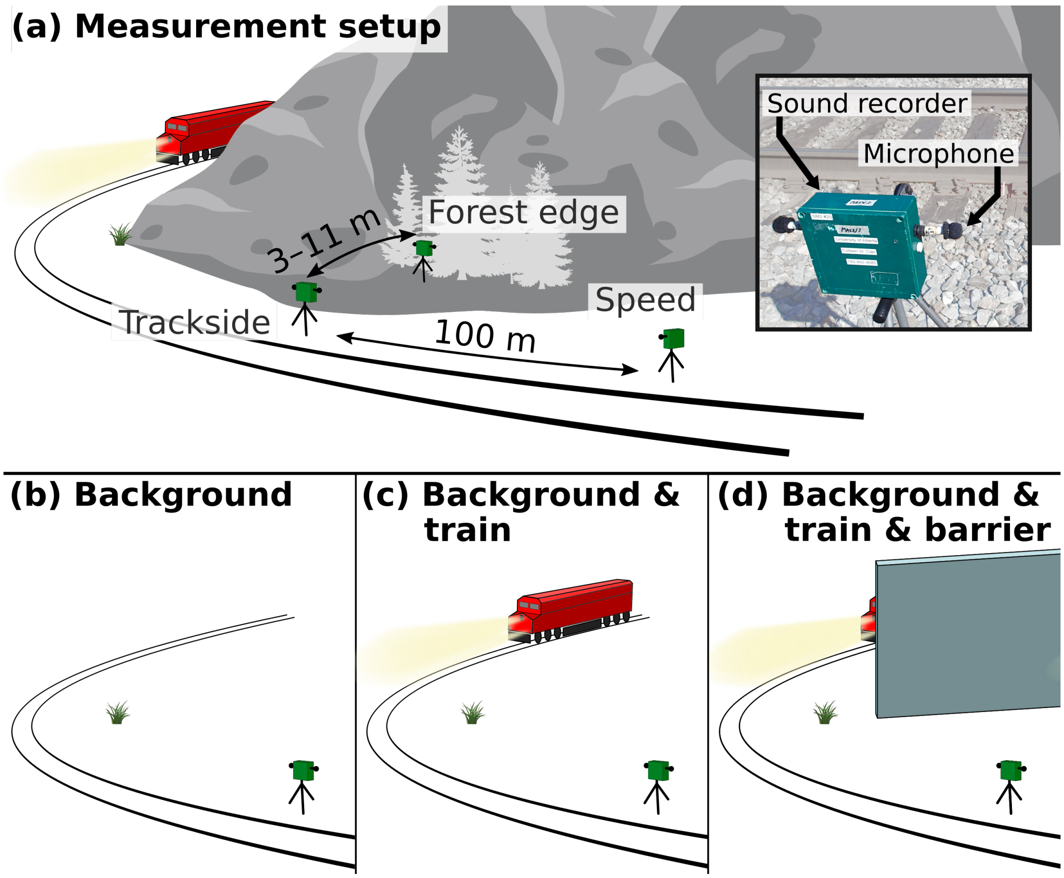

Figure 2.1: Illustration of the experimental setup and physical predictions. (a) Sound recorders were mounted on tripods near the track (trackside recorder), at the edge of vegetative cover (forest edge recorder), and 100 m along the straight section of track (speed recorder) on the inside of track curves around raised topography. Topography height and track curvature varied by site (Table 2.1). Inset: Photograph of a trackside recorder. (b) The *background* physical predictions assumed that background noise was the dominant factor determining the sound level at the recorder. (c) The *background & train* physical predictions added sound from the train to the *background* predictions, supposing the topography between the train and recorder had no effect on train sound. (d) The *background & train & barrier* predictions were developed using an equivalent acoustic barrier to estimate the attenuating effect of the raised topography within the track curve.

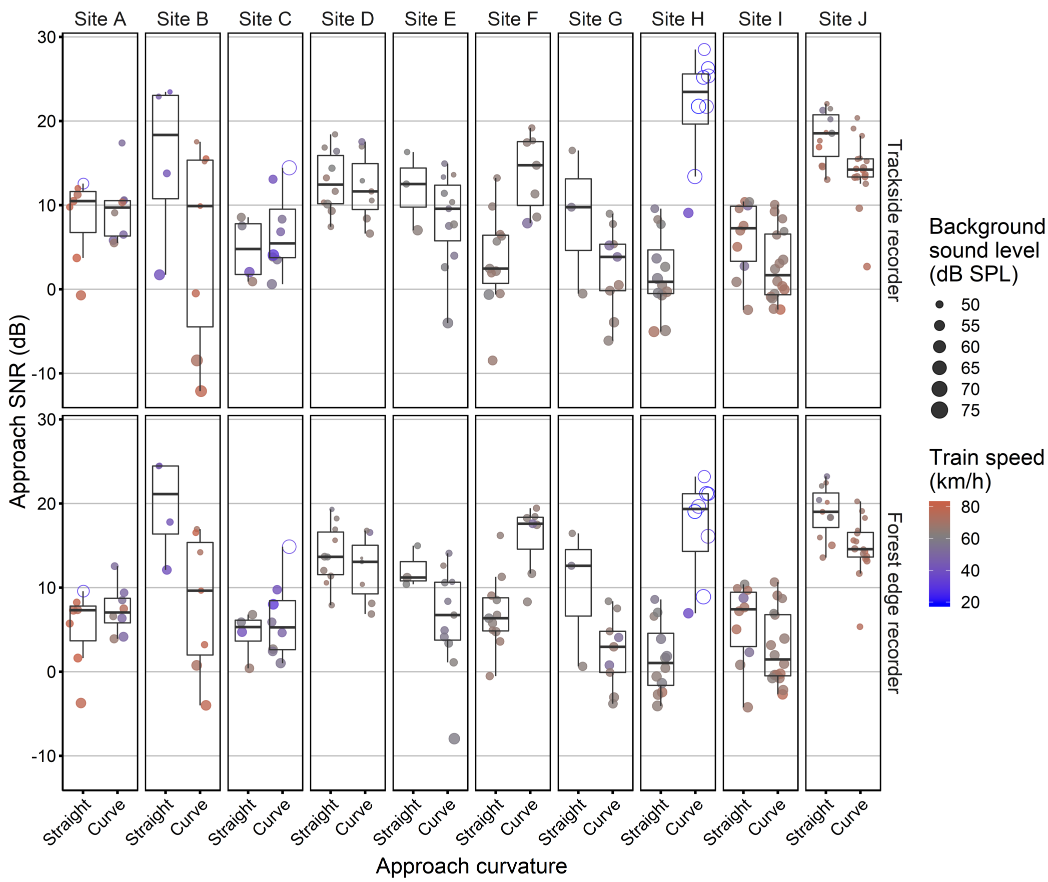

Figure 2.2: Comparison of measured train audibilities by site and direction of approach for trackside (upper panel) and forest edge recorders (lower panel). Audibilities were measured as signal-to-noise ratios (SNRs) and calculated by dividing the approach sound level 25 s to 35 s before each arrival by the background level 5 min to 90 min before each arrival. Trains with passing speeds less than 30 km h^{-1} are shown as open circles but were not included in subsequent analyses. Box plots show medians, first and third quartiles, and range to 1.5 times the interquartile range.

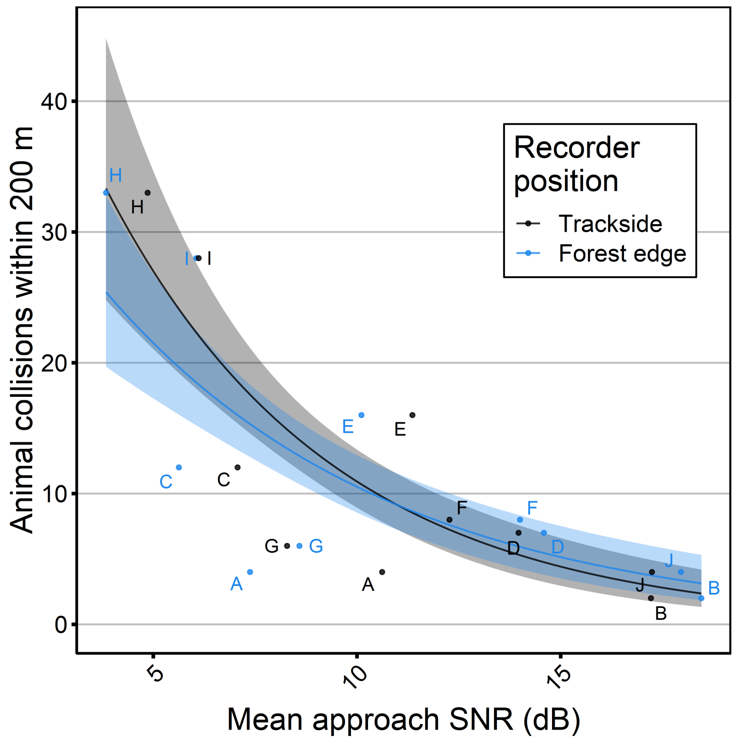

Figure 2.3: Comparison of measured signal-to-noise ratio (SNR, in dB; response variable) for approaching trains and historical counts of animal–train collisions. SNRs were averaged by direction (westbound and eastbound) separately for sound recorders positioned at the trackside and at the forest edge. Lines show fitted values for collision count within 200 m of the sound measurement location (with 95% point-wise confidence band on the predictions; Dunn & Smyth 2018) for the model of Table 2.3. Mean SNRs for each site and recorder are indicated with points labelled by site (Table 2.1).

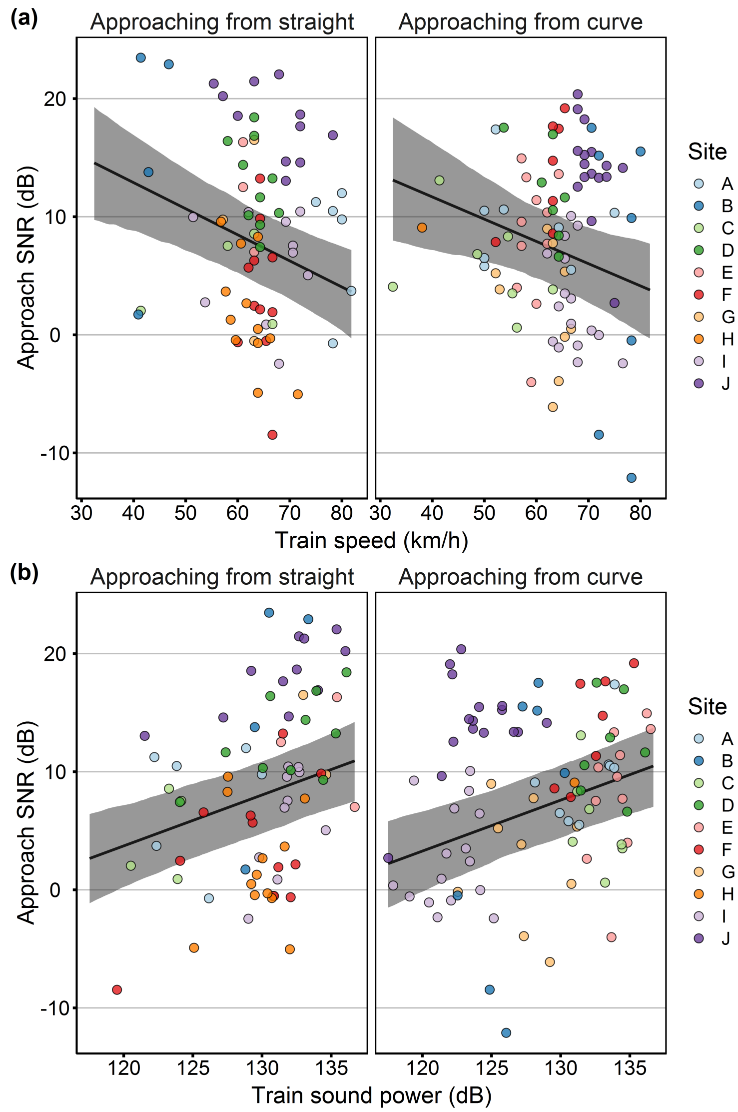

Figure 2.4: Comparison of train audibilities as indicated by signal-to-noise ratio (SNR, in dB; response variable) for trains approaching from track curves and straightaways. (a) Comparison across train speeds. (b) Comparison across train sound powers. Lines with shaded regions show mean predicted values and 95% prediction intervals at the population level for the *Straight vs. curve* model (Table 2.4). Point-wise 95% confidence bands on the population-level predictions were computed by bootstrap resampling (D. Bates et al. 2015; Knowles & Frederick 2018) using for (a) the mean train sound power of 129 dB and for (b) the mean train speed of 63.7 km h^{-1}.

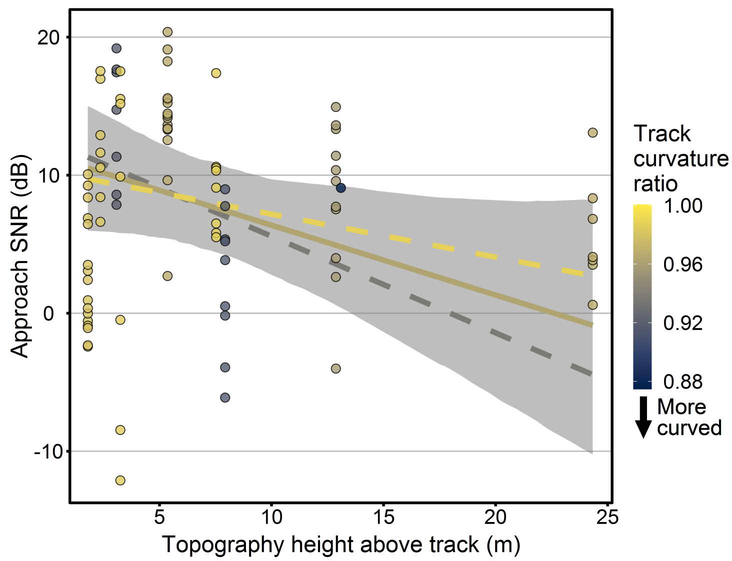

Figure 2.5: Comparison of train audibilities as indicated by signal-to-noise ratio (SNR, in dB; response variable) with topography height and track curvature for trains approaching from curves only. The solid line and shaded region show mean predicted values and point-wise 95% confidence bands at the population level for the *within curves* model (Table 2.4) computed by bootstrap resampling (D. Bates et al. 2015; Knowles & Frederick 2018) using the mean value of track curvature ratio (0.962) for the curved approaches dataset. Track curvature ratios approaching 1.0 indicate straight track and lower values indicate greater curvature. Dashed lines (reflecting statistical non-significance of curvature effects; Table 2.4) show model-predicted values for track curvature ratios of 0.937 (darker dashes) and 0.988 (lighter dashes).

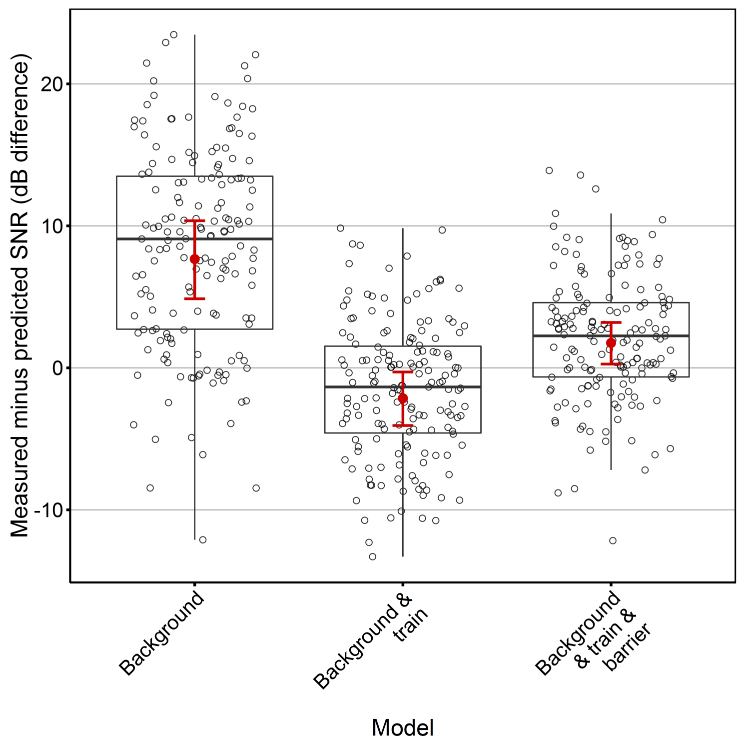

Figure 2.6: Comparison of three physical predictions modelling the signal-to-noise ratio (SNR) of an approaching train at 30 s before arrival. Residual values (measured SNR minus predicted SNR) are shown for each data point in our experiment. Boxplots show medians, first and third quartiles, and ranges to 1.5 times the inter-quartile range. Larger points with error bars show estimates and 95% CIs on the predictions at the population level computed by bootstrap resampling (D. Bates et al. 2015; Knowles & Frederick 2018) for the mixed-effects models of Table 2.5.

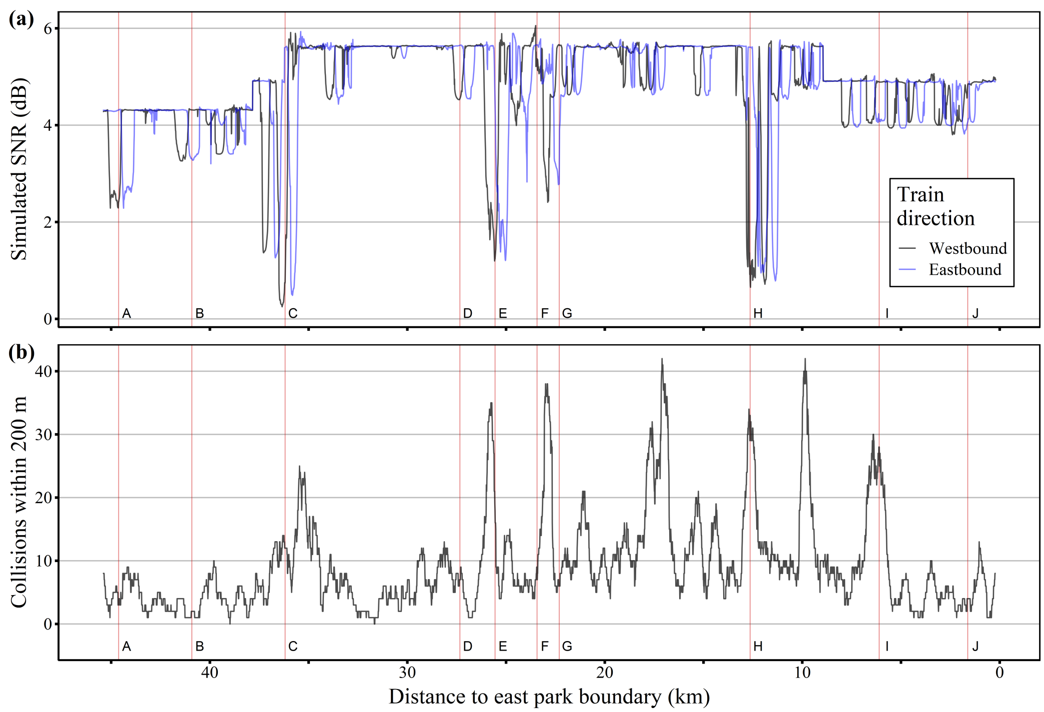

Figure 2.7: Comparison of animal collision count and simulated train audibilities as indicated by signal-to-noise ratio (SNR) along the railway through the east half of Banff National Park, Alberta, Canada. (a) Train SNRs from the *background & train & barrier* physical predictions using a constant background noise level of 61.2 dB SPL. The horizontal axis, shared with panel (b), indicates the position of a listener on the railway towards which westbound or eastbound trains are approaching. (b) Count of animal collision events recorded from 1981–2016 (Parks Canada, unpublished data) measured with a sliding window of 400 m length. Red vertical lines correspond to sites where sound measurements were taken (Table 2.1).

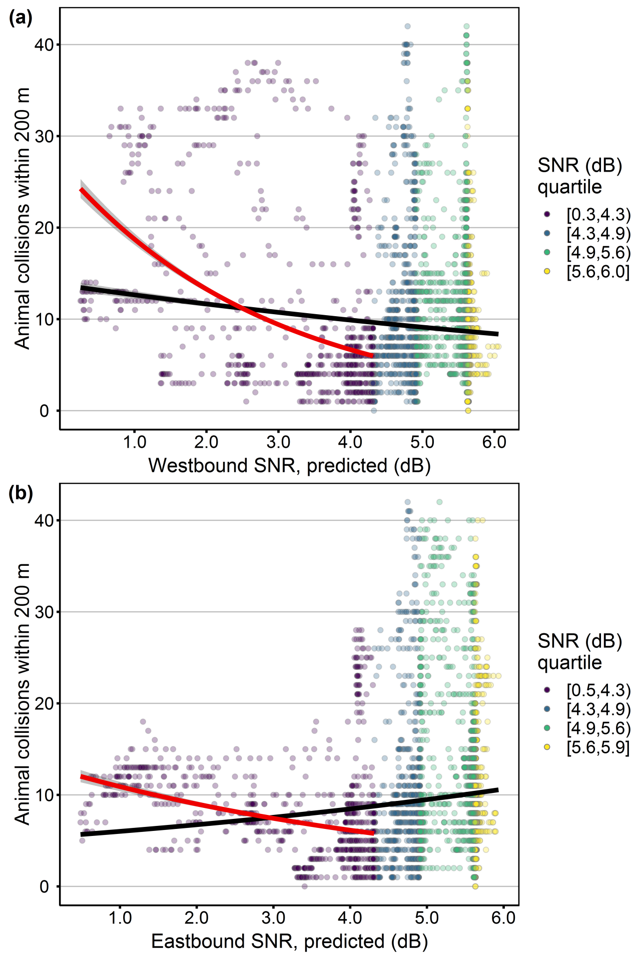

Figure 2.8: Comparison of collision counts (response variable) with simulated train audibilities as indicated by signal-to-noise ratio (SNR, in dB) for eastbound and westbound trains. Long black lines represent predictions for models regressed on the full set of simulated SNRs within each train direction (all SNR models; Table 2.6), while short red lines represent predictions for models regressed on the lowest quartile of simulated SNRs within each train direction (SNR lowest quartile models; Table 2.6). Point-wise 95% confidence bands are shown for each prediction line but are often narrower than the depicted lines.

Chapter 3

Warning systems triggered by trains could reduce collisions with wildlife*

3.1 Abstract

Ecosystems are degraded by transportation infrastructure partly because wildlife mortality from collisions with vehicles can threaten the viability of sensitive populations and alter ecosystem dynamics. This problem has attracted extensive study and mitigation on roads, but little similar work has been done for railways despite the occurrence of wildlife–train collisions worldwide. We propose a method for reducing wildlife losses on railways by providing animals with warning signals that are triggered by approaching trains, particularly in areas of high strike risk. Analogous to the warning signals provided for people at road–rail crossings, our system emits flashes of light and bell sounds approximately 20 seconds before train arrival at the location where the system is deployed. Learning theory predicts that animals will associate these warning signals with train arrival if the warning signal (conditioned stimulus) consistently precedes train arrival (unconditioned stimulus). We tested two designs for a warning system: one that detects passing trains and wirelessly relays this information to warning devices further along the track, and one that integrates detection of trains at a distance with warning signals in a single device. The most reliable design detected passing trains with magnetic

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or vibration sensors and relayed the information to warning devices. We have developed an affordable and publicly available prototype of this design that can be built for a material cost of US$225. With refinement, this technology could become an inexpensive means of protecting wildlife and people around the world from fatal train strikes wherever strike risk is known or predicted to be unusually high.

3.2 Keywords

Railway; strikes; animals; associative learning; train detection; sensors; vibration; infrared; magnetism; machine learning

3.3 Introduction

Wild animals interact with transportation networks in complex ways. Through habitat loss, fragmentation, and degradation as well as direct mortality, the abundance of many species is reduced near roads (Fahrig & Rytwinski 2009; Benıtez-López et al. 2010; Rytwinski & Fahrig 2012, reviewed by) with potential to alter community composition and ecosystem dynamics (van der Ree et al. 2015b). Although the effects of roads on wildlife are typically negative, some species have been found to increase in abundance near roads (e.g., Fahrig & Rytwinski 2009; Morelli et al. 2014) while others are attracted to the vicinity of roads despite high risk of mortality (e.g., Nielsen, Stenhouse, et al. 2006). Strikes on railways have received less attention, perhaps because they present less risk to people (Langbein 2011; Morse et al. 2014) or because railways are less prevalent than roads (Dulac 2013). Nevertheless, train strikes have been associated with population effects (reviewed by van der Grift 1999; Seiler, Helldin, et al. 2011; Dorsey et al. 2015) and animals are sometimes struck more often on railways than on adjacent roads (Huber et al. 1998; COST 341 Management Committee 2000; Waller & Servheen 2005). Additional incentive for strike reduction on railways applies for sensitive or threatened populations and charismatic, keystone, or culturally-important species.

The best methods for reducing wildlife–vehicle collisions on roads are often impractical on railways. Collision reduction is increasingly achieved through the installation of wildlife exclusion fencing and crossing structures, which can reduce the frequency of wildlife–vehicle collisions by up to 80% (Clevenger et al. 2001) while maintaining habitat connectivity (reviewed by Glista et al. 2009). These road mitigation measures are costly, however, and despite the consumptive, passive-use, and management values of animals killed by vehicles (K.J. Boyle & Bishop 1987; Conover 1997; Schwabe & Schuhmann 2002), mitigations may be less cost-effective on railways where strikes typically do not damage human assets (cf. Huijser, Duffield, et al. 2009). Exclusion fencing may also reduce animal access to beneficial foraging (Wells et al. 1999; Dorsey 2011), travel (H.H. Kolb 1984; S. Hedeen & D. Hedeen 1999), and habitation (Moroń et al. 2014; Kaczmarski & Kaczmarek 2016) opportunities along railways, and exclusion from these opportunities may be unnecessary where traffic intensity on railways is dramatically lower than on a typical road. As an alternative to exclusion fencing, road vehicle operators can sometimes avoid wildlife strikes by detecting animals and slowing down, especially if driver awareness is improved with warning signs or animal detection systems (Huijser, McGowen, et al. 2006). In contrast, train operators cannot change course and require minutes of warning time to slow safely. Systematic speed reductions reduce stopping distances and can often reduce wildlife strikes on both road (Gunson, Mountrakis, et al. 2011) and rail (Gundersen & Andreassen 1998). However, unless the speed reduction is drastic it may be ineffective (Rea, Child, et al. 2010), especially where deep snow, steep topography, or adjacent water bodies encourage animals to retreat along the track (e.g., Becker & Grauvogel 1991).

An alternative approach to reducing wildlife–train collisions is to increase the probability that animals will leave the track after detecting an approaching train. For people and other animals, failure to detect an oncoming train can lead to a collision directly or via a maladaptive escape response (Lima, Blackwell, et al. 2015), perhaps induced by panic. Such detection failures are especially likely if the visual or acoustic cues of an approaching train are obscured by vegetation, topography, or deep snow, especially around track curves, or if the cues are masked by competing stimuli from nearby roads and rivers (Figure 3.1(a)). When these conditions occur in areas used frequently by animals, heightened collision risk presumably results. The risk of detection failures in these areas (hereafter, strike zones) might be reduced if warning signals were provided in advance of train arrival in a way that could not be obscured or masked. Animals could learn to associate these warning signals with train approach if the signals were provided at a consistent time relative to train arrival and if the signals differed from stimuli that occur in other contexts (Domjan 2005). The warning signal need not be aversive because the close approach of a vehicle is, itself, an aversive unconditioned stimulus (e.g., Rea, Child, et al. 2010). Similar behavioural principles govern the logic behind road–railway crossing signals for people and were recently applied in a wildlife warning system (Babińska-Werka et al. 2015). Although effective, these systems rely on close integration with railway infrastructure and require expensive proprietary hardware. Lower-cost wildlife warning devices used on roads, such as headlight reflectors and deer whistles, are largely ineffective (D'Angelo et al. 2006; Valitzski et al. 2009). This may be because reflectors and whistles lack the spatial and temporal precision of association between the conditioned warning stimuli and the unconditioned stimulus of close approach by a vehicle.

Here, we describe an electronic system for reducing wildlife–train collisions that combines the precise signaling of active warning systems (e.g., road–railway crossing signals) with the flexibility of installation and affordability of passive warning systems (e.g., headlight reflectors). We tested two designs for such a system (Figure 3.1(a)–(c)). One is based on paired but spatially separated devices in which the first device detects a passing train and relays that information to a distant warning device positioned within the strike zone (hereafter, the passing relay). The other is based on a single device positioned within the strike zone that predicts train arrival time from a distance and activates integrated warning stimuli at the desired time (hereafter, the approach detector). Both methods can be implemented with low-cost, off-the-shelf components, assembled with basic electronics tools, and installed without affecting railway infrastructure or operations.

3.4 Methods

3.4.1 Study area

The two methods were tested on a freight railway owned and operated by Canadian Pacific within Banff National Park, Alberta, Canada (hereafter, Banff) and Yoho National Park, British Columbia, Canada (hereafter, Yoho). This railway bisects the two parks, runs alongside the four-lane Trans-Canada Highway, and was the largest single source of direct human-caused mortality for grizzly bears (*Ursus arctos*) within Banff between 1990 and 2008 (Bertch & Gibeau 2009). Black bears (*Ursus americanus*), wolves (*Canis lupus*), elk (*Cervus canadensis*), and moose (*Alces alces*) are also struck (Parks Canada Agency, unpublished data).

Road–rail crossing signals in our study area generally activate near 20 s before train arrival (cf. Richards & Heathington 1990). To mimic the effectiveness of these signals, we chose a target warning time for our tests of (20 ± 5) s. Both of the methods we propose can provide longer warning times if desired.

3.4.2 Passing relay

The passing relay comprises two types of devices placed along a railway track: sensing devices are placed at a distance from either side of a strike zone to detect trains that pass them, and warning devices are placed within the strike zone to provide warning signals along the length of the zone (Figure 3.1(b)). When a sensing device detects a train, it transmits a wireless radio signal that activates all warning devices within the strike zone. Sensing devices are placed far enough from the strike zone that a train moving at average speed takes 20 s to reach the centre of the strike zone.

Seven commercially available sensors were used to detect trains at close range (Table 3.1): a digital compass, an infrared rangefinder, an infrared motion detector, an accelerometer, and three vibration switches designed to trigger on weak, medium, and strong vibrations. Each sensor was placed in a plastic enclosure and attached with a magnet to the outside web of the track rail (vibration sensors) or laid flush with the ballast rock between the track rails (infrared sensors and compass). Data from each sensor were logged continuously (Arduino Uno and Data Logging Shield, Adafruit Industries, USA) for a minimum of ten train passages over one or more recording sessions. An adjacent stereo audio recorder (SM2+GPS, Wildlife Acoustics, USA) measured the time of each train arrival according to its internal clock, which was synchronized with the Global Positioning System (GPS). All recordings were made at a single site within Banff.

Train arrival times were estimated from spectrograms of the audio recordings to within ± 0.2 s. Sensor data were then examined for changes coinciding with train arrival. Thresholds could be set part-way between the noise floor and the train signal, yielding no false positives or negatives for most sensors (Table 3.1). Each sensor's data were then searched by computer for signals exceeding the corresponding threshold (hereafter, a detection), skipping six minutes of data after each detection to allow trains to pass. Detections were matched to train arrivals from the audio recordings if their times coincided within 60 s. Detections with no matching arrival were recorded as false positives; arrivals with no matching detection were recorded as false negatives. Other track vehicles (e.g., maintenance trucks) were treated identically because most sensors had no trouble detecting them.

We were unable to closely synchronize the internal clock of the data logger with that of the audio recorder, and this limited our ability to compare detection accuracy among the sensors. While the clocks were within 10 s of each other at the beginning of every recording session, the actual value changed each time the data logger was reprogrammed. Further, the compass and rangefinder recordings used a different internal clock that drifted by 10 s per day. We assumed a model for these effects where the detection times from each recording session were given an unknown offset and an offset that changed with time. To recover detection precision, we linearly regressed the difference of detection and arrival times against the recording time for each recording session. For recording sessions whose models had a significant slope ($p < 0.05$), we report the regression residuals, rather than the raw differences of detection and arrival times; for recording sessions with non-significant models, we report the differences of detection and arrival times with the mean value subtracted. Recording sessions comprising less than three detections were excluded. This transformation of the data reflects the loss of information about sensor accuracy (systematically early or late detection) caused by the clock synchronization problem (but see Discussion).

Hypothetical warning times were estimated from this measure of detection precision. Since train detections can be relayed from the sensing device to the warning device in a negligibly short time, a highly precise sensor would provide an equally precise warning time only at the centre of the strike zone and only if train speeds in the area were always the same. If a particular train had a higher speed than average, the passing relay would provide a warning time shorter than the target time. Moreover, an animal nearer to the train than the strike zone centre would perceive a warning time shorter than the target time. To simulate these effects, speed was measured for each train detected by the accelerometer using a pair of GPS-synchronized audio recorders (SM2+GPS, Wildlife Acoustics, USA) placed 200 m apart along the track. A hypothetical strike zone of 200 m length (12 s at 60 $\mathrm{km\,h^{-1}}$) was then centred 20 s away from the sensor at the average speed of this sample of trains. For each train, a hypothetical animal was placed randomly within the strike zone. Assuming each train maintained its speed, the warning time provided to the animal was the time elapsed between train detection by the accelerometer and train arrival at the animal.

3.4.3 Approach detector

The approach detector is a standalone device placed within the strike zone that detects trains at a distance (Figure 3.1(c)). When a detected train is determined to be 20 s from the device, integrated warning signals are activated. Each approach detector detects trains and activates independently.

To detect trains at long range, we chose to use the train-generated vibrations that travel long distances in track rails. Rail vibrations cannot be obscured by vegetation or topography because they are confined to and guided by the track rails. Moreover, noise from rivers or roads near the track (Figure 3.1(a)) cannot vibrate the rails, allowing rail-attached vibration sensors to achieve a higher signal-to-noise ratio than in-air microphones. Similar vibrations are commonly used to detect defects in track rails (Loveday 2012), and train-generated vibrations have been observed over 2 km ahead of train arrival (Rose et al. 2004), but to our knowledge they have never been used to predict train arrival time.

Piezoelectric film sensors (polyvinylidene fluoride film printed with silver ink for shielding; Table 3.1) were used as contact microphones to transduce rail vibrations into electrical signals. The sensors were adhered with epoxy (Speed Set Epoxy, LePage, Canada) or cyanoacrylate glue (Super Glue Gel Control, LePage, Canada) to neodymium magnets (BY0X02, K&J Magnetics, USA). This enabled secure attachment to the outer web of the track rails while the stiffness of the cured adhesive and magnet allowed for acoustic transmission from the rail to the sensor. Signals from these sensors were received by a custom preamplifier (Appendix C.2) and recorded (SM2BAT and SM2BAT+, Wildlife Acoustics, USA) at sample rates of 192 kHz or 384 kHz, allowing us to measure acoustic signals from 10 Hz to 48 kHz for all recordings (Mandal & Asif 2007).

To sample a range of conditions that could affect the generation and transmission of rail vibrations, trains were recorded with the piezoelectric sensors at six sites along the railway within Banff and Yoho and as well as one site along the Canadian Pacific railway south of Edmonton, Alberta, Canada. Sites and recording times were selected to sample many possible track conditions, including curved and straight track, the inside and outside rails on curves, and locations near to and far from track joints and rail lubrication equipment. For Banff and Yoho sites, recordings were collected at winter and summer temperatures.

Because we could not discern any clear threshold from vibration spectrograms to indicate when trains were 20 s away, we chose to automate the classification of patterns with machine learning. We first split recordings for each train approach into smaller intervals (Appendix C.3). Each interval was then assigned a class of “true” or “false” to indicate whether the interval fell within 20 s of train arrival.

Classification models were trained with 10-fold 10-repeat cross-validation (using Kuhn et al. 2015; R Core Team 2015) on a data set containing all intervals from a site-stratified random sample of 80% of approach recordings (the training set). One model was trained for all sites together and another model for each site alone. The random forest classifier (using Liaw & M. Wiener 2002; R Core Team 2015) was chosen for its robustness to overfitting (Breiman 2001). Approaches of non-train track vehicles were excluded from this analysis to optimize the models for train detection.

Warning times provided by this method were estimated from the predictions of the trained models on the remaining 20% of approach recordings (the test set). The first interval a model classified as "true" gave the time at which an approach detector would have activated its warning signal. Activation times more than 60 s before train arrival were recorded as false positives; approaches for which the model did not predict a trigger were recorded as false negatives.

3.5 Results

For the passing relay, we compared 183 combinations of seven sensor types and 105 unique vehicle passages (103 trains and 2 other track vehicles) to arrival times from the audio recordings. As expected, the slopes in the linear models to remove clock drift were statistically significant (at $p < 0.001$) only for the compass and infrared rangefinder; means were subtracted for the other sensors (with two extreme outliers excluded from the mean for the infrared motion detector). Five of the seven sensors detected every passage and did so with high precision (85–100% within 2 s of the mean; Figure 3.2). Of these, only the compass and accelerometer achieved no false detections and precision within ± 2 s for all detections, but the compass achieved this with triple the sample size. The single false positive reported for the infrared rangefinder (Figure 3.2) may have been caused by the passage of an animal. The other two sensors were so imprecise (less than 50% within ± 2 s for the medium switch) or missed so many passages (82% missed by the strong switch) that we did not consider them further.

Warning times provided by the passing relay were simulated using the speeds of the 13 trains detected by the accelerometer (mean and standard deviation: $(61.7 \pm 2.4)\,\mathrm{km\,h^{-1}}$) and 13 random animal locations within a hypothetical 200 m strike zone (range: −99 m to +95 m). This simulation yielded a range of values largely within or very near to the target interval ((20 ± 5) s; Figure 3.3, left).

For the approach detector, we assessed 430 combinations of up to four simultaneous recording locations and 116 unique train passages. On average, site-specific classification models detected 80% of train approaches in its test set. These models provided a median warning time 1.8 s earlier than the 20 s target and an interquartile range (i.e., the middle 50% of values) of 15.9 s (Figure 3.3, centre). The model incorporating all sites detected more approaches from the same test set (88%) but with reduced accuracy and precision: The median warning time was 4.7 s earlier than the target with an interquartile range of 18.5 s (Figure 3.3, right). In spectrograms of the approach recordings, we could see vibration signals from approaching trains at least 20 s and sometimes as much as 210 s before arrival. However, background noise from other frequency bands was often strong enough that these signals did not affect the time-average signal level until 5 s to 10 s later.

Comparisons of the accuracy, precision, and false detection rates of the two wildlife warning methods (Figure 3.3) clearly favour the passing relay.

3.6 Discussion

Our results show that a highly precise train detector can be built with simple, off-the-shelf components. The passing relay missed no trains and triggered only when trains passed, and the timing of triggers was highly precise for both the compass and accelerometer sensors. The model of the approach detector built with data from all sites achieved fewer false detections than models built with data from each site alone, but with less accuracy and precision. Even with variations in train speed and animal location, the passing relay provided warning times largely within the target interval and did so far more consistently than the approach detector.

Three of the remaining passing relay sensors performed nearly as well as the compass and accelerometer. For instance, the infrared rangefinder yielded similar precision—apart from the single false positive—and was tested far longer than accelerometer. However, the mechanisms of detection for the infrared sensors are inherently different: the passage of animals could easily trigger false positives in both infrared sensors but not in the compass or accelerometer. Furthermore, the infrared motion detector has an activation time threshold of 80 s (Table 3.1). The extra distance the train would travel during this time means that communication between the sensing and warning devices would require signal repeaters that would increase the cost and complexity of the system.

For all five sensors presented, our use of linear regression or mean subtraction to transform the data could have removed real differences in the median detection times among the sensors. However, one could easily compensate for any such differences by changing the spacing between the sensor and the strike zone. Train speed and animal location will more strongly affect the warning times.

Because true positive and true negative signals are so similar in train approach recordings, approach detection is much harder than passage detection. This similarity in signals is likely driven by variation in train speed; differences in how well rail sections transmit vibration; and the complex interactions of train wheels, rail surface, car mass, train speed, and track curvature that produce the vibrations (Remington 1976; M. Rudd 1976). Our visual comparison of spectrograms derived from the train recordings suggested that the time before train arrival of each first observable signal was related to the train speed as well as the proximity of track lubrication equipment. Moreover, the in-rail acoustic train signals detectable at the greatest distances were exclusively ultrasonic (typically 20 kHz to 40 kHz), but lower in frequency than the 40 kHz to 80 kHz range expected from other work (Rose et al. 2004) (Appendix C.4).

Our >80% detection rates are nonetheless promising for a first use of in-rail acoustic signals to detect trains, and the approach detector could be improved with further effort. Alternative data processing strategies could separate the approach signal into frequency bands before computing mean signal levels. Such strategies might be identified automatically using unsupervised feature learning algorithms on large datasets (Coates et al. 2011). At the cost of including a more sophisticated computer in each device, approach detectors could iteratively improve their accuracy and precision with each train passage via online machine learning techniques (Shalev-Shwartz 2011). The cost of such technology continues to decline.

If the approach detector could be improved, it would have four advantages over the passing relay. First, the classification model may (with sufficient training sample size) learn to account for variations in train speed. Second, independent triggering of each warning system within the strike zone would increase the warning time consistency experienced by nearby animals, as long as the warning stimuli of nearby devices are more salient than those of distant devices. Third, the approach detector does not require separate sensing devices, allowing the system to accommodate small strike zones at the same cost per metre as large zones. Fourth, the approach detector should be more reliable because all devices in the zone would be fully redundant and would not depend on wireless communication.

Meanwhile, the passing relay results are strong enough to warrant implementation and further testing for the purpose of wildlife warning. The choice of sensor among compass, accelerometer, and weak vibration switch will depend on factors other than precision of detection, including not only cost (Table 3.1) but also power requirements and durability (Table C.2, Appendix C.5). Similar multi-dimensional comparisons must be made to select a controller; a wireless communication system; a warning signal; a power source; and a means of protecting the components from water, dust, ultraviolet degradation, and mild impact (e.g., shifting ballast rock). The parts for our prototype cost US$100 for the sensing device and US$125 for the warning device (Appendix C.5). These costs could be reduced with design refinement and mass production.

The passing relay design is ideal for protecting short sections of track (e.g., 200 m or less for train speeds near 60 $\mathrm{km\,h^{-1}}$) with a history or predicted risk of high strike rates. Ideally, multiple warning devices should be placed on the track within a strike zone (one every 50 m) with a sensing device placed 20 s (at average train speed) from the strike zone center to detect trains approaching from either direction. Greater lengths of track could be protected by repeating this pattern on adjacent track sections, as long as care were taken to limit warning times to the same (20 ± 5) s within each consecutive protected zone. An ideal approach may be to combine these warning systems with short sections of fencing, excluding wildlife from the most dangerous areas while also mitigating strike risk at the fence ends (cf. Lehnert & Bissonette 1997; M. Olsson pers. comm.). Strike risk could be further reduced if these measures were combined with reductions in train speed (Rea, Child, et al. 2010), especially in areas of high strike risk.

The use of train-triggered warnings for the reduction of wildlife–train strikes makes two assumptions that require further study. First, it assumes that the inconsistent availability of train approach signals increases the risk of animals being struck. Second, it assumes that a warning signal will change animal behaviour so as to reduce their risk of being struck. In a recent test of another train-triggered wildlife warning system, animals reacted to trains earlier and were more likely to leave the track when a precisely timed acoustic warning was provided (Babińska-Werka et al. 2015). This study did not determine whether the success of the system was driven by the temporal consistency of the warning signal, the choice of animal distress calls as warning sounds, or both. However, wildlife are prone to habituate to warning signals that are not followed by reinforcement or punishment (Ujvari et al. 1998; Gilsdorf et al. 2002), suggesting that learning plays a role in the success of this train-triggered warning system (Babińska-Werka et al. 2015). Associative learning in this context requires that the warning stimuli are salient, uniquely associated with trains, and consistently timed relative to train arrival (Domjan 2005). Learning of this type, especially as part of an avoidance learning process, has been demonstrated in wild animals using auditory and visual cues (Vollrath & Douglas-Hamilton 2002; Kloppers et al. 2005) as well as olfactory stimuli (Baker et al. 2007). Seemingly-similar wildlife warning technologies, such as wildlife warning reflectors (D'Angelo et al. 2006) and deer whistles (Valitzski et al. 2009), have had a limited effect on collision rates, potentially because the warning stimuli could not be associated specifically enough with the unconditioned aversive stimulus of close approach by a vehicle.

Although aversiveness of conditioned stimuli is not a requirement for associative learning (Domjan 2005), the literature offers incomplete guidance on the design of non-aversive warning stimuli for animals (Appendix C.5). Optical and acoustic signals are natural choices because they can be turned on and off quickly and are easily produced with low-cost, low-power technologies such as light-emitting diodes and piezoelectric speakers. Visual and auditory perceptual ranges have been measured for some wild mammals (e.g., white-tailed deer, D'Angelo et al. 2008; H. Heffner & H.E. Heffner 2010; Cohen et al. 2014), but data are incomplete or unavailable for many other species (for reviews see Fay 1988; Ahnelt & H. Kolb 2000; Jacobs 2010). Additional work is needed to explore the effects of flashing versus steady light (but see Blackwell & Seamans 2009), the effects of light colour on night vision (in humans, Mertens 1955), or the interaction of light colour with a possible magnetoreceptive sense (cf. Poot et al. 2008; Niessner et al. 2016).

Ultimately, this work allows confident selection of a train detection method for train-triggered wildlife warning systems. Our system potentially achieves the temporal and spatial specificity required for associative learning while limiting the financial, logistical, and technical barriers that might apply to similar technology. Warning systems based on our train detection methods may have further application outside of the wildlife protection and train contexts. For instance, pedestrians on railway tracks are sometimes struck while distracted by headphones (Lichenstein et al. 2012), and a visual warning may reduce the frequency of these events. For this application, we recommend the approach detector over the passing relay, because the self-contained approach detector can be deployed at lower densities over larger areas. We expect the inconsistency of warning time of the approach detector to be less of a problem for humans than for wildlife. However, the passing relay could be used by railway workers in countries around the world as a portable, precise, and inexpensive train warning system. The passing relay may also be useful for providing warnings to wildlife and pedestrians on roads, as road vehicles would be detectable with infrared and magnetic sensors: non-train track vehicles were detected flawlessly by these sensors. Vibrations in the road created by vehicles may also be detectable with the accelerometer and piezoelectric sensors, potentially enabling an approach detector. Importantly, vibration-based and magnetic sensing remain reliable under diverse weather and lighting conditions—a distinct advantage over optical headlight detection that has been used previously (Mulka 2009). This work offers a new way to help wildlife and people coexist with transportation networks worldwide.

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3.8 Supplementary material

1. Appendix C.1: Purchasing information for sensors tested
2. Appendix C.2: Preamplifier for the piezoelectric sensor
3. Appendix C.3: Details of the machine learning algorithm for the approach detector
4. Appendix C.4: Characteristics of recorded spectrograms and the railway track
5. Appendix C.5: Design of a passing relay prototype

3.9 References

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3.10 Tables

Table 3.1: Sensors tested in this work, including the sensing modality and chosen detection thresholds. Costs may be significantly lower for parts purchased in bulk. (See Appendix C.1 for suppliers, manufacturers, and part numbers.)

Sensor	Method	Mode of train detection	Threshold chosen	Cost (US$)
Digital compass	Passing relay	Residual magnetization of train steel	Vector magnitude of signal > 700 arb. units	10
Infrared rangefinder	Passing relay	Intensity of infrared light reflected	Rolling mean of 5 readings > 100 arb. units	15
Infrared motion detector	Passing relay	Motion of heat source	"On" duration > 80 s	10
Accelerometer	Passing relay	Slow rail vibrations	Vertical signal < 800 arb. units	15
Vibration switch, weak	Passing relay	Weak rail vibrations	Activation rate > 5 Hz	1
Vibration switch, medium	Passing relay	Moderate rail vibrations	Activation rate > 2 Hz	1
Vibration switch, strong	Passing relay	Strong rail vibrations	Activation rate > 1 Hz	1
Piezoelectric film, shielded	Approach detector	Fast rail vibrations	Random forest model	30

3.11 Figures

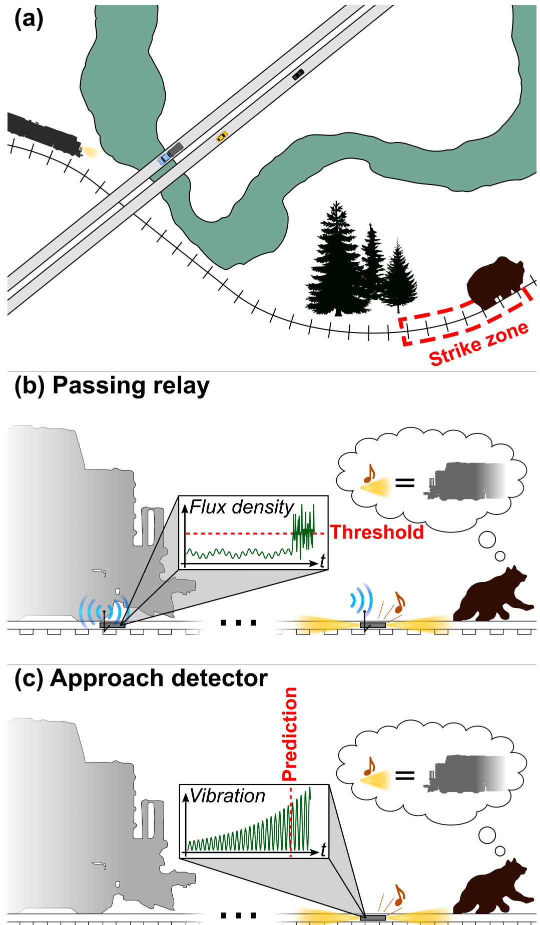

Figure 3.1: Concept for a train-triggered wildlife warning system. (a) Warning signals produced by trains are inconsistently available at some locations: light and sound from the train can be obscured, distorted, masked, or imitated by the surroundings. As a result, wildlife may be unaware of approaching trains or confused by the stimuli and become surprised when the train is very near. (b) The passing relay uses a sensing device to detect trains and relay triggers to a remote warning device. (c) The approach detector uses in-rail vibrations to detect trains at a distance and trigger integrated warning signals. For both warning systems, we rely on animals to associate the warning signals with train approach. Animals that have learned this association leave the track when the warning activates.

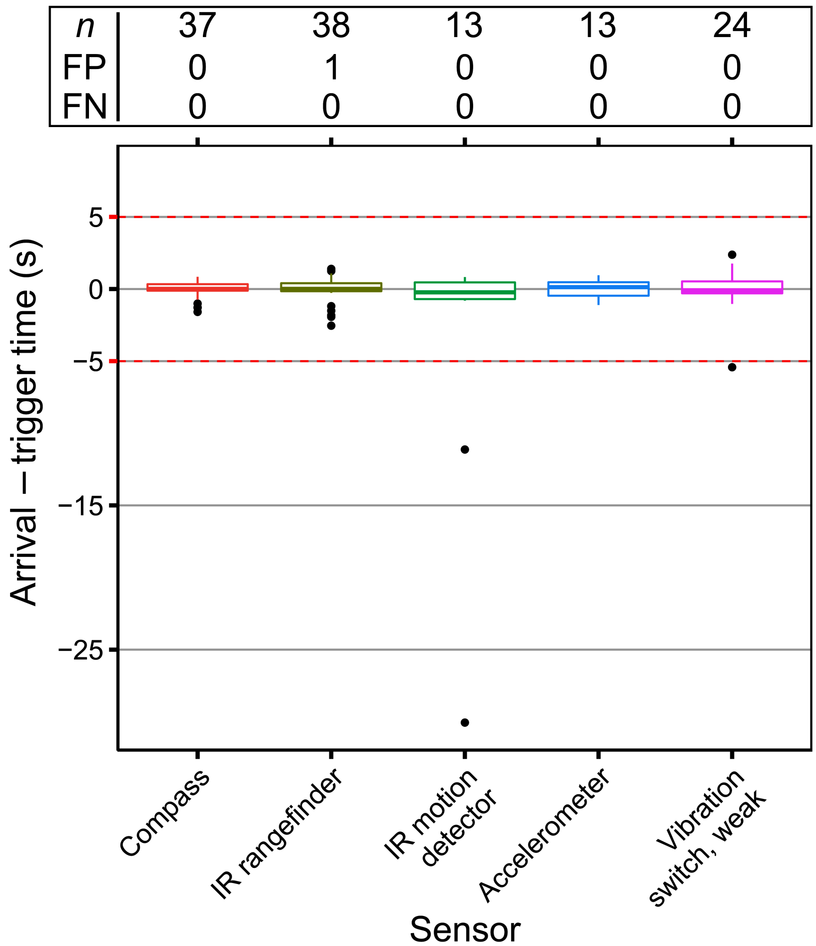

Figure 3.2: Train detection precision was similarly high for five of the sensors tested. Clock synchronization errors are removed from the arrival and detection time differences shown. Box plots indicate medians, first and third quartiles, and range to 1.5 times the interquartile range. Outliers are shown as black dots. The above table shows the number of trains and other track vehicles (*n*), false positives (FP), and false negatives (FN) recorded for each sensor.

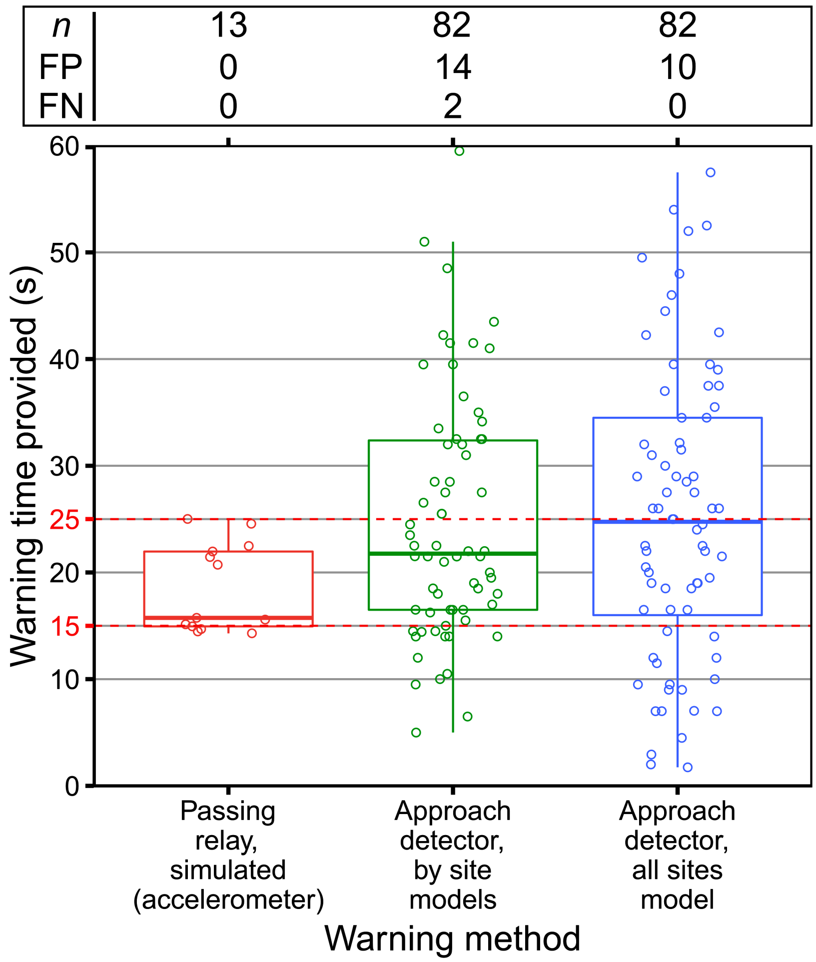

Figure 3.3: Simulated warning times provided by the passing relay (left) were more accurate and precise than those provided by the approach detector. Approach detector classification models were trained and tested separately on data from each site (center) or on data from all sites together (right). All data points are shown (open circles). Box plots indicate medians, first and third quartiles, and range to 1.5 times the interquartile range. The above table shows the number of trains (n), false positives (FP), and false negatives (FN) recorded for each method.

Chapter 4

Warning systems triggered by trains increase flight-initiation times of wildlife*

4.1 Abstract

1. Trains on railways collide with and kill animals, incurring economic costs for railway operators and impacting species of conservation concern. Few solutions have been demonstrated to mitigate collision risk on railways, especially solutions that could economically target locations where collisions occur most frequently. We proposed to address this problem with train-triggered warning signals, consisting of flashing lights and bell sounds emitted in the 30 seconds leading up to train arrival, that could teach animals to avoid encounters with trains.

2. We installed our warning systems at four test sites located adjacent to track curves on an active railway. We used remote cameras to observe the behavioural responses of wild animals up to 45 s before train arrival in alternating treatment periods with and without warning signals. We contrasted the observed flight initiation times when warning signals were and were not provided and when trains approached from straight versus curved sections of track, predicting that trains approaching from curves would be harder for animals to detect.

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3. When warning signals were provided, animals larger than and including coyotes (*Canis latrans*) initiated a flight response from the track an average of 62% earlier, from 10.5 s (SE = 1.2) to 17.0 s (SE = 1.5), while animals smaller than coyotes initiated flight responses an average of 29% earlier from 11.3 s (SE = 1.6) to 14.6 s (SE = 1.9). For trains approaching from curves, animals in both species groups fled earlier on average in the presence of warning signals, but there was no statistical difference between treatment and control periods. The treatment effects were substantially larger for trains approaching from straightaways.

4. *Synthesis and applications.* Our work shows that non-aversive warning systems could be an effective means for reducing the likelihood of train collisions by providing additional time for animals to adopt an effective escape trajectory. Additional work could demonstrate the generality of this approach for the benefit of wildlife, and perhaps people.

4.2 Keywords

Collisions; behaviour; deterrents; learning; mortality; railway; railroad; technology

4.3 Introduction

Transportation networks create complex challenges for the management of adjacent natural systems. Roads now influence ecosystems around the world (van der Ree et al. 2015a) and have extensive effects on wildlife populations (Benıtez-López et al. 2010; Rytwinski & Fahrig 2012; Morelli et al. 2014) that include the provision of foraging opportunities (Barrientos & Bolonio 2009; Martinig & Mclaren 2019), promotion of animal movement (DeMars & Boutin 2018), and collisions of vehicles with animals (reviewed by Fahrig & Rytwinski 2009). Railways seem to exert similar effects on wildlife (Borda-de-Água et al. 2017), but their ecological effects have garnered much less attention (Popp & S. Boyle 2017). This dearth of information is unfortunate because railways may sometimes kill more animals than adjacent roads (Huber et al. 1998; COST 341 Management Committee 2000; Waller & Servheen 2005), with potential for demographic effects and damage to species of conservation concern (van der Grift 1999; Dorsey et al. 2015; Borda-de-Água et al. 2017). One reason for the lack of attention is that wildlife–train collisions rarely harm people (in contrast with wildlife collisions on roads; e.g., Bissonette et al. 2008), although derailments are sometimes caused by collisions with large animals (e.g., Langbein 2011; Morse et al. 2014). Wildlife–train collisions may nevertheless incur economic costs when mortalities affect threatened species or species with a high value to people (K.J. Boyle & Bishop 1987; Conover 1997; Huijser, Duffield, et al. 2009).

Despite the problems posed by wildlife–train collisions, few practical mitigation options exist. Wildlife exclusion fencing, an effective means of separating terrestrial animals from vehicles on roads (Clevenger et al. 2001), may not be cost-effective for railways where collisions are of little risk to human safety (Huijser, Duffield, et al. 2009). Fencing may also exacerbate low habitat connectivity and population viability unless the barrier includes gaps in the fence (potentially risking entrapment; e.g., Lehnert & Bissonette 1997) or wildlife crossing structures (at great expense, reviewed by Glista et al. 2009). An alternative to wildlife exclusion on roads is to create opportunities for vehicle operators to detect and avoid animals (Huijser, McGowen, et al. 2006), but this is not practical for trains, which cannot slow down safely on short notice or change direction to avoid animals. Systematic reduction of train speed has been shown to reduce collision risk (Gundersen & Andreassen 1998; Visintin et al. 2018), but reduced speed could reduce the economic advantages of railway transport including high throughput and energy efficiency (AREMA 2003). Animal collisions on railways, as on roads, are also more prevalent in some areas (collision hotspots) than others (e.g., Gundersen, Andreassen & Storaas 1998; Popp, Hamr, et al. 2018; Jasińska et al. 2019).

The problem of reducing wildlife–train collisions motivated our previous development of a train-triggered, track-mounted warning system which signals, via a flashing light and bell sound, the impending arrival of a train (Backs et al. 2017).

The system works by (1) detecting a train as it passes a device containing magnetic and vibration sensors and (2) relaying that information wirelessly to (3) trigger the warning devices installed on a nearby section of track where collision risk is to be mitigated. The relative positions of the train detector and warning devices are determined by prior measurements of train speed to generate a consistent warning time of 30 s. The stimuli generated by the warning devices are assumed to be more predictable in time and space than the sound, light, or vibrations generated by the train itself, which we found to be highly variable both in time and space (J. Backs, unpublished data). Importantly, this system does not attempt to provide an aversive stimulus to deter animals from the area comparable to some similar systems (Babińska-Werka et al. 2015; Shimura et al. 2018; cf. Seiler & Olsson 2017), only to alert them to the impending arrival of a train and to do so with greater temporal and spatial specificity than can be achieved by vehicle-mounted whistles (Valitzski et al. 2009) or wayside headlight reflectors (D'Angelo et al. 2006).

Here, we tested the ability of this warning system to modify the responses of animals to trains. We used remote cameras to observe wild, free-ranging animals on a live railway track at locations where the warning system was installed (treatment) or not (control) for periods of 2–4 weeks and then reversed treatment assignments. Based on the hypothesis that animals would learn to associate warning signals with trains, passages of which we assumed were already aversive, we predicted that animals would leave the railway track sooner (relative to train arrival) when warning signals were provided. Increasing this escape time would be expected to reduce the risk of collisions, particularly if earlier departures lessened the likelihood of panic-like responses or erratic flight paths (Lee et al. 2010; Rea, Child, et al. 2010; Mobbs & Kim 2015). If the presence of intervening topography or vegetation made it more difficult to detect approaching trains, we predicted that animals would flee later (during controls) and exhibit greater responsiveness to the warning signals (during treatments) when trains were approaching from around curves in the track. To facilitate this comparison, warning systems were installed at the intersections of curves and straightaways, such that trains approached from straight track in one direction and curved track in the other direction.

4.4 Methods

4.4.1 Study area

We conducted the study on the Canadian Pacific main line railway, which bisects the Bow river valley within Banff National Park, Alberta (hereafter, Banff) in the Canadian Rocky Mountains. In the western half of Banff, the railway runs adjacent to subalpine forests dominated by lodgepole pine (*Pinus contorta*); in the eastern half, the lower-elevation montane eco-region is characterized by wetlands, grasslands, and mixed forests dominated by white spruce (*Picea glauca*) and trembling aspen (*Populus tremuloides*) (Holland & Coen 1983). The railway parallels the four-lane Trans-Canada Highway (TCH) as well as the two-lane Bow Valley Parkway through much of Banff. Traffic volumes on the TCH averaged near 23 000 vehicles per day in 2016–2017, ranging from less than half of this average in November 2016 to more than double this average over the July 2017 long weekend (measured 1.6 km west of Banff park gates; Alberta Transportation 2019). This traffic, together with the nearby Bow River and the mountainous terrain, exposed the railway corridor and adjacent forest to diverse conditions of acoustic noise (J. Backs, unpublished data). The ballast-covered portion of the right-of-way typically extended 3 m to 5 m from the track on both sides, outside of which vegetation and topography often limited visibility around curves. Ambient temperatures during our study ranged from −36.7 °C (January 2017) to +31.4 °C (July 2017) with snow accumulation present but varying in depth from November 2016 to April 2017 with a maximum of 39 cm in March 2017 (Environment and Climate Change Canada 2019); wind and precipitation conditions often changed hourly. Snow on the railway track was plowed routinely and melted earlier (via sun exposure) on the dark-coloured rails and ballast rock than in the surrounding forest.

In Banff, collisions with trains have become a major source of mortality for grizzly bears (*Ursus arctos*; Bertch & Gibeau 2009), a threatened species in Alberta. Trains also kill annually up to several dozen individuals of other species of mammals including black bears (*Ursus americanus*), wolves (*Canis lupus*), elk (*Cervus canadensis*, moose (*Alces alces*), and deer (*Odocoileus* spp.; Gilhooly 2016; Gilhooly et al. 2019) as well as smaller mammals and birds.

4.4.2 Site choices

We chose test sites on the eastern half of the railway within Banff (from the eastern park boundary to Castle Junction, 45.6 km west), where train collisions with wildlife are most common (Gilhooly et al. 2019). Using a digital elevation model, we identified all sites within this region where the railway curved around an area of raised topography and where this curve ended in a long straightaway (>300 m). These sites were expected to have the greatest contrast in train detectability by direction because trains arriving from around such a curve are often obscured by both vegetation and topography. Of ten such sites identified within the study area, we chose a subset of four where we expected to observe animals on the track most frequently (Table 4.1; P. Busse, Canadian Pacific, December 2016 pers. comm.; S. Cherry, A. Forshner, D. Gummer, and J. Whittington, Parks Canada, December 2016 pers. comm.).

4.4.3 Experiment design

Each warning system comprised four types of self-contained electronic devices connected through a wireless radio-frequency network, which we termed train detectors, warning devices, camera controllers, and signal repeaters (Appendix D.1; Backs et al. 2017). These devices were deployed along the railway track to coordinate the activation of warning signals and cameras (for observing animal responses) with the arrival of a train. We targeted a warning time of (30 ± 5) s, in contrast to our previous work that targeted (20 ± 5) s (Backs et al. 2017), based on our desire to ensure that conditioned (warning) stimuli were typically presented to animals before unconditioned (train) stimuli (Domjan 2005).

At each site, a 200 m length of track was designated for our experimental treatment (hereafter, the test zone), which began at the point where the curved track met the straightaway and continued 200 m along the straightaway (Fig. 1). Train detectors were mounted on the track 40 s away at mean train speed (measured previously with sound recorders) in both directions from the test zone center. When a train moving towards the test zone passed a detector, this device sent a radio signal to all other devices in the network. This signal was received by camera controllers (two per site) mounted in trees on either side of the test zone, where they triggered trail cameras (HP900 with external trigger, Reconyx, USA) facing the test zone to take 90 photographs at up to two frames per second, yielding at least 45 s of footage. The radio signal was also received by warning devices (four per site) within the test zone, which emitted the warning signals (flashing amber lights and bell sounds; Appendix D.1) after a 10 s delay for a period of 35 s (30 s before and 5 s after train arrival at the test zone center). Signal repeaters were placed as needed (one to four per site) between the train detectors and camera controllers to ensure network connectivity. Following activation, all devices were programmed to wait six minutes while the train passed.

We deployed warning systems at two sites (treatment pair 1, Table 4.1) for the first six treatment rotations (November 2016–February 2017) and expanded to the remaining sites (treatment pair 2, Table 4.1) for the remaining six rotations (February 2017–July 2017). At any given time, only one of the sites in each treatment pair was deployed with warning devices (hereafter, the treatment condition), while the other site was deployed without warning devices (hereafter, the control condition). The treatment and control conditions were swapped within treatment pairs every 2–4 weeks to control for seasonal effects. Warning systems were inactive between experimental periods when the batteries in the devices were depleted.

4.4.4 Image analysis

We recorded calibration images at each site where the experimenters were standing at known locations within the test zone. These images provided references for the locations of animals and trains captured in subsequent image sequences. Location references remained accurate enough throughout the experiment to identify the near edge of the test zone to within 5 m. These references further allowed estimation of train speed to within ± 4 $\mathrm{km\,h^{-1}}$ to ± 10 $\mathrm{km\,h^{-1}}$ (Appendix D.2).

For sites under the treatment condition, we verified the correct operation of the warning signals by observing the flashing warning lights in camera images (Fig. 2(b)). Occasionally, flashes were not observed in a treatment sequence because of snow accumulation in front of the lights or because the capture rate of the cameras was similar to the flash rate of the warning lights. In these cases, we judged that the treatment was likely delivered (even if only aurally) when sequences recorded before and after the sequence in question showed flashing lights. If this condition was not met, we excluded the sequence from further analysis because the treatment was likely not delivered (e.g., when batteries were depleted).

To support analysis and interpretation, we recorded several environmental variables that could have affected the responses of animals to trains. These included weather conditions (rain, snow, and wind), light level (dawn, day, dusk, night), and foliage presence (off, emerging, on) that might have visually or aurally obscured train approaches and snow cover (none, light, moderate, heavy) that can affect the retreat behaviours of animals (e.g., Rea, Child, et al. 2010).

4.4.5 Behavioural coding

A team of observers reviewed images retrieved from the cameras. In each sequence of 90 images, we recorded the number of animals visible for each species present. We identified duplicate events from opposing cameras to prevent double counting. A single observer then reviewed all sequences with animals to eliminate inter-observer variation in the interpretation of behaviours.

We designated the first animal to flee (regardless of species) within the field of view of either camera at a site as the focal animal (Fig. 2(a)). We classified the initial behaviour of this animal as one of foraging (small, occasional movements with head down), travelling (steady movement along the track), alert (head up, ears erect, face oriented towards the train), flight (fast movement along or away from the track), crossing/approaching/leaving (movement perpendicular to the track), or unknown (behaviour not discernable). Image numbers were recorded where this animal changed its behaviour to alert (if observed) and flight. We did not consider further the timing of alert responses because too few clear alert responses were observed. We also excluded sequences where an animal was initially fleeing. To increase the sample size for larger species, we chose a large animal as focal over an earlier-fleeing small animal if independence of the flight response seemed likely (e.g., substantial interposing vegetation and distance).

When the focal animal displayed flight behaviour, we noted the position of the animal, and the image for which the train was closest to this position. The time stamp of this image revealed the time between the initiation of the animal's flight response (Fig. 2(c)) and train arrival at the location where retreat began (Fig. 2(d)). We termed this time difference the flight initiation time t_{FIT}, related to the more common flight initiation distance d_{FID} (reviewed by Stankowich & Blumstein 2005) as

$$d_{\mathrm{FID}} = v_{\mathrm{T}}\, t_{\mathrm{FIT}} \tag{4.1}$$

where v_{T} is the train speed. We excluded treatment sequences from further analysis where the flight response was observed before the warning signals were active (i.e., within 8 s of the first image in the sequence). We also excluded sequences where flight behaviour did not have a discrete beginning, where flight did not lead an animal to leave the ballast (rock-covered) area or to seek cover within the ballast area without stopping its movement, or where the animal returned to the ballast area within the same image sequence.

We only used animal sequences for our analyses where we were confident that we had correctly coded the flight response, that the warning signals activated (during treatment periods), and that a flight response did not occur before we expected the warning signals to activate (during treatment periods; together, the high-confidence criteria). To increase our sample size, we did not exclude sequences where the focal animal began within the test zone as long as the sequences otherwise met the high-confidence criteria. We chose not to analyze small animal sequences recorded after April 20, 2017 because a sufficient sample of small animals was obtained from earlier months.

4.4.6 Statistical analysis

We tested our hypotheses on two groupings of the data: coyotes and larger animals (hereafter, large animals) and animals smaller than coyotes (hereafter, small animals). Although we were primarily interested the effect of treatment on large animals, for which mortality records are kept by both Parks Canada and Canadian Pacific, many more samples were obtained for small animals. We also expected large and small animals to respond differently to trains based on expected differences in their perceptual ranges (Mech & Zollner 2002; Blumstein 2006).

For each species group, we developed a regression model for flight initiation time testing for the effects of treatment and track curvature while controlling for potential confounding factors (Gelman & Hill 2007; Harrell 2015; Ver Hoef & Boveng 2015). Our experimental design suggested the inclusion of a random effect of test site (Zuur, Ieno, Walker, et al. 2009), but the severe imbalance of high-confidence samples among sites caused singularity in mixed model fits where test site was included as a random effect (D. Bates et al. 2015). Sites were instead pooled for large animals as the smaller sample permitted the inclusion of at most three parameters (Harrell 2015), while for the larger sample of small animals test site was included as a fixed factor (i.e., no pooling; Gelman & Hill 2007, pg. 275). Generalized linear models (GLMs) were fitted with Gamma-distributed errors due to the positive continuous nature of the response (Zuur, Ieno, Walker, et al. 2009) and with an identity link function for convenience of interpretation. We report Wald t-statistics for each parameter estimate with the understanding that they are generally conservative (Dunn & Smyth 2018), and we infer importance of the parameters to the model fit using the corresponding p-values (Murtaugh 2014a,b). Model fits were assessed by likelihood ratio F-tests comparing the model of interest with the null model (Dunn & Smyth 2018). Where averaged comparisons between factor levels were desired, contrasts were calculated by estimating the marginal means (Lenth 2019) with significance estimated with Wald t-statistics (Dunn & Smyth 2018). Dispersion estimates for our models were generally greater than recommended for the use of Wald statistics (Dunn

& Smyth 2018, pg. 277), but parameter values and standard errors nevertheless agreed closely with estimates obtained by other techniques (e.g., bootstrapping; Appendix D.3).

For large animals we modelled treatment, approach curvature, and their interaction only. For small animals, we modelled these effects while controlling for train speed (centered and scaled to zero mean and unity SD) and Boolean effects of noise-generating weather, snow cover, and animals beginning their sequences foul of the track (i.e., within 1.2 m of the nearest rail; Canadian Pacific 2010). We excluded from further analysis variables with under-represented categories (initial behaviour of the focal animal, whether the focal animal crossed the track during its flight, whether vision-obscuring weather was present) or that showed collinearity with treatment (number of days since start of experiment; Zuur, Ieno & Elphick 2010). We excluded from all analyses the small number of samples for which train speeds were less than $45\,\mathrm{km\,h^{-1}}$, both to prevent their undue influence on the small-animals regression (Harrell 2015, pg. 90) and because slow trains traversing curves tend to emit loud, high-frequency noise (M. Rudd 1976) that would likely change their acoustic detectability for animals.

All statistical analyses were performed in R version 3.5.1 (R Core Team 2018).

4.5 Results

Sampling for a total of 520 site-days, we recorded 1.6 million images in 17679 sequences capturing 9628 unique events with and without animals present, suggesting that an average of 19 trains passed each site per day. Animals were visible in 838 sequences (711 unique events; 90 large animals, 619 small animals, 2 of unknown size) involving 1942 individual animals (Appendix D.4), predominantly deer, elk, red squirrels (*Tamiasciurus hudsonicus*), and unidentified birds. No animals were visibly struck by trains, and all animals (where the train did not obscure the camera view before the animal retreated) were observed to flee in response to train approach. Of the 711 unique events in which animals were visible, 280 were interpretable with our behavioural coding: e.g., our cameras recorded the focal animal initiating a flight response as well as the train reaching the animal's position of first flight. Retaining from these only high-confidence sequences (27 large, 157 small) with train speeds greater than 45 $\mathrm{km\,h^{-1}}$ (see Methods), $n = 25$ large animal sequences and $n = 149$ small animal sequences remained.

Large animals displayed earlier flight initiation times in the presence of warning signals (Fig. 3). Our model fit was better than the null model (df = (3, 24), $F = 4.9$, $p = 0.010$) and suggested that the treatment parameter had a strong effect on flight initiation time with marginally significant but large parameters for track curvature and its interaction with treatment (Table 4.2). The model predicted a mean increase in flight initiation time of 6.5 s (SE = 1.9, $t = -3.4$, $p = 0.003$) from 10.5 s (SE = 1.2) for control to 17.0 s (SE = 1.5) for treatment, averaged across curved and straight approaches. The mean difference between flight initiation times for trains from curves and straightaways was negligible (est. 0.8 s lower for straightaways, SE = 1.92, $t = -0.4$, $p = 0.695$), but the treatment effect was substantially weaker when considering only trains approaching from curves (est. 2.7 s earlier flight for treatment, SE = 2.8, $t = -0.9$, $p = 0.34$).

Small animals also displayed earlier flight initiation times in the presence of warning signals, but to a lesser degree than large animals (Fig. 3). Our model fit was better than the null model (df = (10, 148), $F = 2.5$, $p = 0.010$) and suggested a small but important effect for track curvature, a marginally significant effect of treatment, and no significant interaction (Table 4.2). Averaged over levels of all other variables, the model predicted that treatment increased flight initiation time of small animals by 3.3 s (SE = 1.5, $t = -2.2$, $p = 0.03$) from 11.3 s (SE = 1.6) for control to 14.6 s (SE = 1.9) for treatment. The model also predicted a decrease in average flight initiation time from straightaways at 14.9 s (SE = 1.9) to curves at 11.1 s (SE = 1.7) (difference of 3.9 s, SE = 1.4, $t = 2.7$, $p = 0.007$). The model predicted a small and statistically marginal decrease in the ability of the treatment to increase flight initiation times for trains approaching from curves (2.4 s greater for treatment, SE = 1.6, $t = -1.5$, $p = 0.137$) compared to straightaways (4.2 s greater for treatment, SE = 2.4, $t = -1.7$, $p = 0.085$).

4.6 Discussion

Wildlife mortality from collisions with trains might be reduced without train speed reductions or animal exclusion measures if animals more consistently left the track before trains arrived. We tested a track-mounted wildlife warning system designed to encourage the avoidance of trains by animals. We expected that animals would have earlier flight initiation times in response to warning signals, especially when trains were otherwise difficult to detect, which we assumed to apply when trains approached from curves. When warning signals were present, animals had earlier flight initiation times on average, but contrary to our prediction, the effect was most pronounced when trains approached from straight sections of track. If flight initiation time is related to collision risk, our results suggest that train-triggered warning systems could mitigate collision risk for wildlife and offer insight into where warning systems may be most useful.

When we provided warning signals, both large and small animals retreated earlier from trains than when signals were not provided. Averaged across trains approaching from curves and straightaways, large animals retreated 6.5 s earlier and small animals retreated 3.3 s earlier. Although apparently small, these differences represent 62% and 29% increases over the mean flight initiation time with no warning signals, respectively. At the mean train speed in our analyzed sample (60.5 $\mathrm{km\,h^{-1}}$), these time differences correspond to increased separations between animal and train of 110 m (large animals) and 55 m (small animals) at the moment of flight initiation. Perhaps the most comparable study to date used a track-side warning system that emitted a sequence of animal alarm calls and predator vocalizations for 60 s leading up to train arrival (Babińska-Werka et al. 2015), in contrast to the 30 s warning time targeted in our study. These authors achieved a larger increase in escape time from control to treatment conditions (26 s for roe deer), although the variation they measured in escape time under the treatment condition (mean ± SD = (35.0 ± 38.3) s) was much larger than in the present study (mean ± SD = (17.3 ± 6.0) s for large animals). This difference could be attributable to the larger interval between stimulus onset and train arrival

(60 s versus 30 s in this work; Babińska-Werka et al. 2015) or the use of aversive warning stimuli (Babińska-Werka et al. 2015). Our warning stimuli appeared to cause earlier retreats without the use of aversive stimuli (Backs et al. 2017).

Track curvature had differing effects for large and small animals. For large animals, flight initiation times for curves and straightaways did not differ meaningfully; for small animals, the mean decrease in flight initiation time from straightaways to curves was 3.9 s, comparable to the mean difference between treatment and control for the same species group. The small animals difference appears to be consistent with our prediction that animals would respond later to trains approaching from curves. Studies of wildlife–vehicle collisions on both roads and railways have highlighted the association of collisions with curves (Gunson, Mountrakis, et al. 2011; Popp, Hamr, et al. 2018; Jasińska et al. 2019), citing visibility as an issue for drivers (Bashore et al. 1985) and potentially animals (Hamr et al. 2019), and recommending vegetation clearing as a potential means of reducing collision risk (Andreassen et al. 2005). Acoustic detectability of trains might also be reduced where the track curves around steep topography (J. Backs, unpublished data). Contrary to our expectation, both large and small animal models revealed decreases in the effect of treatment for curves compared to straightaways. We speculate that this could occur if animals were more likely to initiate early flight responses when both warning signals and train stimuli were presented together, which would in general occur earlier for trains approaching from straightaways. Animals appear to flee earlier in response to multiple as opposed to single predator-like stimuli (Geist et al. 2005), and so may also flee earlier in response to the combination of a predator-like stimulus and the novel warning stimulus. From this perspective, our warning signals may have sometimes functioned more like an animal deterrent (cf. Muzzi & Bisset 1990; Babińska-Werka et al. 2015; Shimura et al. 2018) than the learning instrument we had intended (Domjan 2005; Backs et al. 2017). It could also be that the warning signals increased animal alertness in a way that encouraged their detection of the train, as the gaze of the focal animal sometimes appeared to be drawn by the warning signals towards an approaching train (e.g., Fig. 4.2).

Although our warning system increased flight initiation times for animals, the relationship between flight initiation and collision risk was not clear from our observations. Animals often moved off the track in as little as 1 s to 2 s when they chose to do so, but only infrequently did animals move directly off the track as their first response to a train. For instance, focal animals crossed the track as part of their flight response in 17% of high-confidence sequences (30% for large animals, 15% for small animals), in rare cases missing the train arrival by less than one second. These near-misses tended to occur when animals (especially deer, elk, and pigeons) were present in groups: As one animal moved off the track, its conspecifics often crossed in front of the train to follow. This grouping behaviour in both ungulates and birds may afford some protection from collisions where collective detection of trains enables earlier flight initiation (Elgar 1989; Beauchamp 2017), but any benefit of earlier responding appeared to be unimportant in cases where elk continued to cross in front of the train until the train arrived, separating the herd (cf. Altmann 1952). In one extreme event, a herd of elk appeared unable to detect an approaching train until the train operator turned off the locomotive headlight, after which the elk fled from the train between the rails. This behaviour is known to lead to collisions when the animal continues to retreat along the track until struck (e.g., Rea, Child, et al. 2010); an animal's choice of flight response has also been found to precipitate collisions with vehicles on roads (Lee et al. 2010). For both of these collision modes, earlier flight initiation caused by warning signals may plausibly reduce the risk of collisions, although determinants of an animal's choice of flight response are not yet well-understood (reviewed by Lima, Blackwell, et al. 2015). We can only speculate about changes in collision risk attributable to the warning system until collision rates are measured experimentally, although future tests of wildlife warning systems may yield more insight (Seiler & Olsson 2017).

We observed other instances where animals ran parallel to the tracks before leaving the right of way. Occasionally, animals used the same escape routes (potentially, game trails) in different retreat sequences, consistent with the idea that animals inform their flight decisions with the locations of refugia (reviewed by Stankowich & Blumstein 2005). If presence of escape routes determines an animal's escape trajectory off the right-of-way, management of vegetation and topography within the right-of-way could help to reduce collisions (I.G. Pengelly and J.D. Hamer, pers. comm.). Vegetation clearing has also been shown to reduce wildlife–train collisions (Jaren et al. 1991; Andreassen et al. 2005), its effectiveness often attributed to the reduction in attractants along the railway (cf. Pollock, Nielsen, et al. 2017). Vegetation clearing might also reduce collisions by increasing the distance to the nearest refuge, encouraging earlier flight responses (Stankowich & Blumstein 2005). However, vegetation clearing could potentially increase collision risk if uprooted vegetation is left at the edge of the right of way, blocking escape routes that may already be constrained by steep topography or adjacent bodies of water.

The potential effectiveness of vegetation clearing in reducing collisions may also be limited because other factors attract animals to the railway, including opportunities to forage on spilled grain (Gangadharan et al. 2017) or other train-killed animals (Murray et al. 2017) or to travel efficiently (Pollock, Whittington, et al. 2019). We observed that 74% of our 280 codable sequences began with the focal animal displaying foraging behaviour. In 29% of sequences that began with foraging behaviour, animals were present between the rails where vegetation was not generally found, suggesting the animals were foraging on grain. We also observed that carnivores most often appeared to be travelling (in 8 of 9 sequences; cf. Pollock, Whittington, et al. 2019) while other species groups exhibited foraging behaviour more often than any other single behaviour, including ungulates (18 of 40 sequences) and small animals (189 of 230 sequences).

Future implementations of this warning system may benefit from increased warning time. Animals in 13 treatment sequences (3 large animals, 10 small; excluded from our analysis) began to flee before the warning devices were expected to emit signals. Two other large animals (also excluded) appeared to interrupt or delay their retreat from the train to look directly towards the warning devices. An increase in warning time to 35 or 40 seconds might have allowed the activation of warning signals to precede the flight responses of all observed animals. However, the time between warning activation and train arrival must remain short enough that learning can occur (Cooper 1991; in humans, cf. Richards & Heathington 1990).

The positive effect of warning signals on flight initiation time shown in this work may encourage further development and testing. The ability of warning devices to reduce wildlife collisions could be assessed by measuring collisions directly, but the sampling effort would be substantial if a similar experiment design to ours was used. We estimated that 55 000 site-days (compared to the 520 site-days observed in this work) would be required if the present study design were used to collect a statistically useful sample of collision events (Appendix D.5). Advances in computer vision (Janzen et al. 2017) and more efficient energy management in the warning system devices (Appendix D.1) would lower the cost of such an effort. Alternative monitoring techniques such as train-mounted cameras may observe more animals per unit effort (Burley 2015), but they cannot observe the behaviours of animals around track curves. More invasive approaches (such as barrier fencing; Clevenger et al. 2001; Seiler & Olsson 2017) may be needed to reduce collisions with large groups of ungulates (e.g. elk herds) that take longer than 30 s to cross the track even when given early warning of train approach.

Wildlife warning systems could reduce the needless loss of animals to train collisions, and we suggest that the design studied here warrants a test of its ability to reduce collisions. Warning systems like this one could be implemented as a cost-effective alternative or as a complement to exclusion fencing. Reductions in wildlife collisions would allow railways to remain leaders in safety and stewardship as they serve the ever-growing transportation needs of people.

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4.8 Supporting information

1. Appendix D.1: Warning system design
2. Appendix D.2: Camera calibration
3. Appendix D.3: Parameter values obtained by bootstrapping
4. Appendix D.4: Animals observed, total and over time
5. Appendix D.5: Encounter rate extrapolation

4.9 References

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4.10 Tables

Table 4.1: Test site summary. Treatment pairs define sites that shared warning devices during the experiment: when MLS was in the treatment condition, 5MS was in the control condition and vice versa. Topography height is the difference in elevation between the track bed at the intersection of the track curve and straightaway and the elevation at the highest point inside the curve, both derived from LiDAR data. Sample sizes (n) were those used for analyses. Site locations are in Universal Transverse Mercator (UTM) coordinates for NAD83 zone 11N (EPSG:26911).

Site name (abbrev.)	Treatment pair	UTM Easting	UTM Northing	Test zone to curve direction	Topography height (m)	n large animals	n small animals
Muleshoe (MLS)	1	589728	5670054	East	2.4	7	20
Five Mile S (5MS)	1	593279	5669582	East	2.9	8	27
Five Mile C (5MC)	2	594293	5669496	West	4.7	7	97
Stables (STB)	2	602264	5673880	East	11.9	3	5

Table 4.2: Parameter estimates (est.), standard errors (SE), and Wald t statistics from two Gamma generalized linear models with identity links for which the response variable was animal flight initiation time in seconds. Reference categories (ref.) for categorical variables are indicated in parentheses. ":" indicates interactions. Boldface lines (excluding intercepts) indicate statistical significance at $\alpha = 0.05$. Train speed was centered and scaled to aid interpretation (original mean ± SD = $(60.5 \pm 4.6)\,\mathrm{km\,h^{-1}}$).

	Est.	SE	t	p
Large animals				
Intercept	8.3	1.4	5.8	<0.001
Treatment (ref. control)	10.3	2.6	4.0	<0.001
Approaching from curve (ref. straight)	4.6	2.3	2.0	0.060
Treatment:curve	-7.6	3.8	-2.0	0.060
Small animals				
Intercept	9.2	1.5	6.2	<0.001
Treatment (ref. control)	4.2	2.4	1.7	0.085
Approaching from curve (ref. straight)	-3.0	1.4	-2.2	0.030
Auditory weather present (ref. absent)	1.0	1.2	0.8	0.411
Heavy snow (ref. light)	0.5	1.2	0.5	0.638
Animal starts on track (ref. off track)	3.2	1.7	1.9	0.061
Train speed ($\mathrm{km\,h^{-1}}$; scaled)	-0.5	0.6	-0.9	0.383
Site, 5MS (ref. 5MC)	-2.1	1.5	-1.4	0.164
Site, MLS (ref. 5MC)	1.9	2.1	0.9	0.373
Site, STB (ref. 5MC)	5.1	6.0	0.9	0.391
Treatment:curve	-1.8	2.8	-0.6	0.533

4.11 Figures

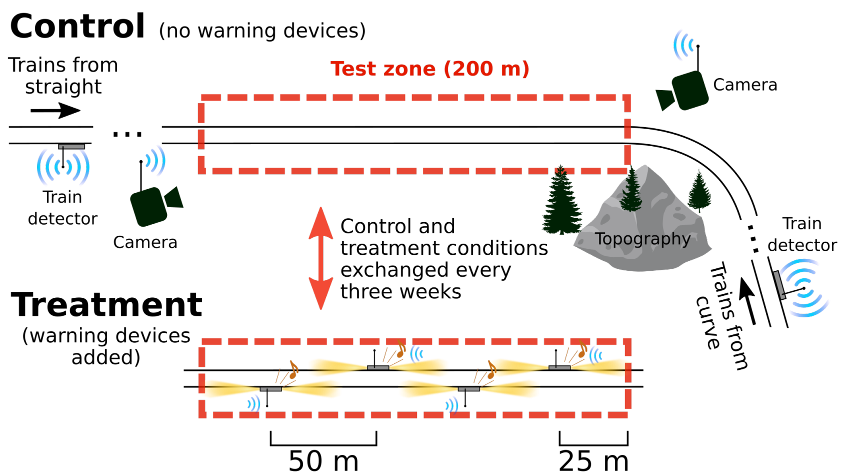

Figure 4.1: Equipment layout at test sites. Sites were chosen where a section of straight track met a section of track that curved around topography and vegetation. Cameras were placed at each end of the test zone; train detectors were placed 40 s (at mean train speed) from the center of the test zone in both directions. When a train passed a train detector, wireless signals were transmitted to activate cameras that recorded the presence and subsequent responses of wildlife. During treatment periods, warning devices activated 30 s before trains arrived. Warning devices were not present during control periods.

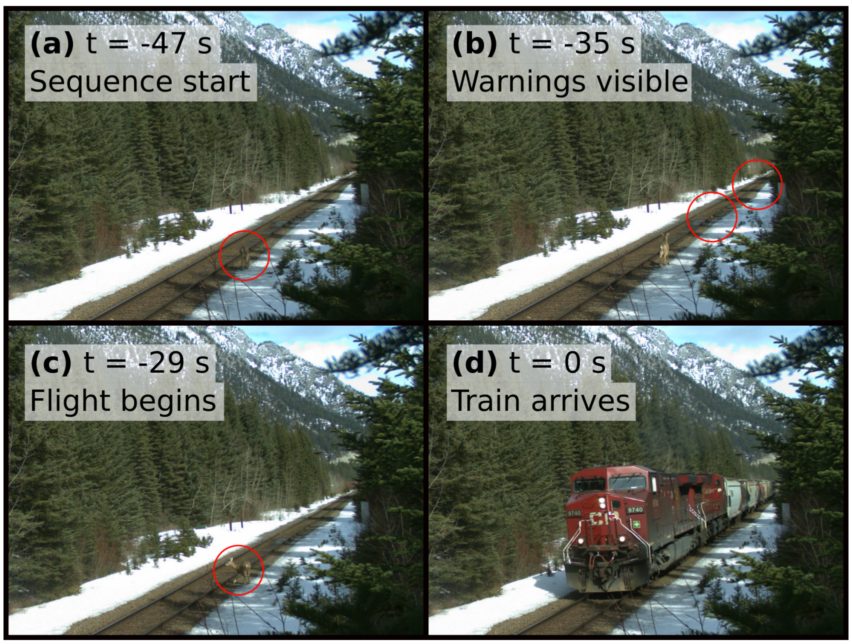

Figure 4.2: Example of key events in an animal sequence. (a) A deer (circle added) was visible foraging near the track in the first image. (b) 12 s following system activation, flashes of light from two warning devices were visible. These were not likely the first flashes, as the deer raised its head from foraging one image (1 s) earlier. (c) 6 s later, the deer turned to flee and continued to move perpendicular to the track until it was no longer visible. (d) 29 s (the flight initiation time) later, the train arrived where the deer began its retreat.

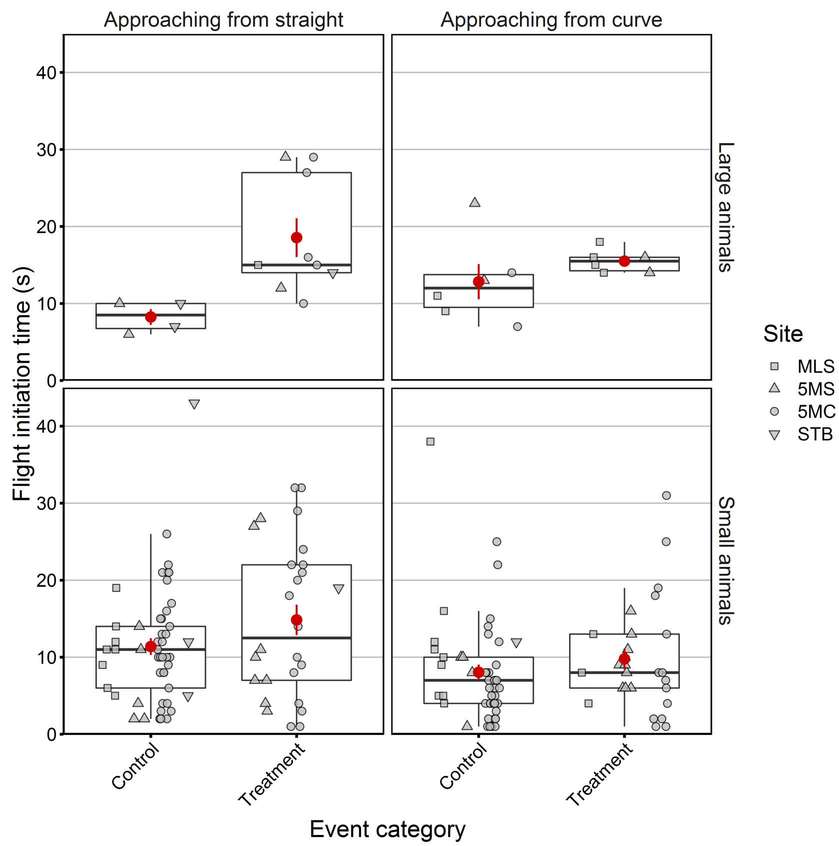

Figure 4.3: Effect of treatment on flight initiation time for four groupings of approach curvature and animal size. Box plots indicate medians, first and third quartiles, and range to 1.5 times the interquartile range. Means and standard errors are indicated by the filled circles with ranges. All data points are shown with test site indicated by shape and position grouping.

Chapter 5

General discussion

The overarching objective of this dissertation was to find a way to reduce the risk of wildlife–train collisions for grizzly bears (*Ursus arctos*) and other highly mobile species. To achieve this, I explored a rarely examined route of potential vulnerability to train collisions and designed, built, and tested a potential countermeasure to this sensory vulnerability. This chapter discusses the contributions and limitations of this thesis within the broader contexts of railway and transportation ecology.

5.1 Summary of results

In Chapter 2, I measured the audibility of approaching trains at 10 locations within Banff National Park and related these measurements to features of the track environment, features of the approaching trains, and records of past collisions. I found that raised topography within curves appeared to have a substantial effect on reducing train audibility, but this effect could not be confidently assessed with only 10 unique measurement sites. Track curvature alone had no mean effect on train audibility, but strong patterns in audibility emerged within and among sites. Pronounced variation in background noise related to roads and river may have driven differences among sites. Train speed and sound power also had significant relationships with audibility, and these appeared to be driven in part by the higher energy requirements and locomotive throttle states required to ascend the elevation gradient when moving west. I also found among the 10 locations that animal collisions historically occurred most frequently where train audibility was lowest, but when I simulated the audibility of trains across the study area, this pattern only emerged for locations with very low audibility, suggesting that train audibility is not the only factor that determines collision vulnerability in Banff.

In Chapter 3, I proposed and developed a train-triggered warning system that could help to improve the detectability of trains for animals. At locations of high collision risk, I proposed to deploy a wayside device that provides light-and-sound signals to animals in the vicinity of the track at 20 s before every train arrival. Based on learning theory, I would expect animals to learn to associate these signals with the aversive experience of train arrival and thus to leave the track when signals were provided. I designed the warning signals to be highly salient to animals but not aversive in themselves. To reduce barriers to adoption, I designed the system to require no disturbance of or integration with railway infrastructure. To meet these requirements, I devised two designs for the train detection sub-system: (1) the passing relay detected trains as they passed and wirelessly triggered warning devices placed further along the track, while (2) the approach detector detected trains as they approached and provided warning signals within a single device. I found that the passing relay design was highly reliable when detecting trains with magnetic or vibration sensors, while the approach detector design could not detect trains at reliable times using machine learning algorithms applied to in-rail vibration recordings.

In Chapter 4, I built and tested the wildlife warning system proposed in the previous chapter on wild, free-ranging animals in Banff. Using self-contained weatherproof cameras, I observed the responses of animals to trains at locations where warning signals were and were not provided, and where trains were approaching from either curved or straight track. I found that the flight initiation time of animals increased when warning signals were provided by 6.5 s for animals coyote-sized (*Canis latrans*) and larger and by 3.3 s for smaller animals. Contrary to my expectation, the increases in flight initiation time when warning signals were provided were most pronounced when trains approached from straight track, whereas for curved approaches alone the effect of the warning signals was positive but not statistically different from zero.

5.2 Implications for the reduction of wildlife collisions on railways

5.2.1 Train audibility may contribute to collision risk

A core contribution of this dissertation lies in the evidence I obtained suggesting that low train audibility could be related to an increase in collision risk for animals (Chapter 2). Although literature exists describing the behavioural responses of animals to noise generated by aircraft and watercraft (reviewed by Lima, Blackwell, et al. 2015), to the best of my knowledge no prior works have explored the effect of terrestrial vehicle audibility on collisions with wildlife. Other works may examine the effects of vehicle-mounted acoustic deterrents, but not the sound generated by the vehicles themselves (e.g., Valitzski et al. 2009; Shimura et al. 2018). I also found that train audibility appears to be affected by spatial (e.g., topography within curves, road traffic noise), temporal (e.g., noise from weather), and train-related factors (e.g., train speed and sound power; Chapter 2). While train detection with vision may be limited by analagous spatial, temporal, and vehicle-related factors, work so far has tended to examine in isolation factors that are spatial (Gunson, Mountrakis, et al. 2011), temporal (Steiner et al. 2014), and vehicle-related (Blackwell, Seamans & DeVault 2014), potentially limiting our understanding of collision processes where multiple factors interact (Rea, Child, et al. 2010; Rea, Johnson, et al. 2018). Our understanding of factors that contribute to collision vulnerability is complicated further by the idea that locations with heightened collision risk can exist independently of locations where animals are recorded to die most frequently (Ascensão et al. 2019). This complication may have been demonstrated by the inconsistent alignment of locations with low simulated audibility and locations with a high density of recorded collisions, though audibility appeared to be only one of multiple risk factors present on the railway (Chapter 2).

Further widening the scope of consideration illustrates features of the animal–train–environment system that could contribute to collision vulnerability in the ultimate, rather than proximate, sense (*sensu* Seiler & Olsson 2017). Improving train detectability in mountainous terrain without the use of active warning systems could require changes to the way railways are designed (e.g. near rock cuts, roadways, waterways, dense vegetation) and operated (e.g. speed, horn use), but organizational, policy, and historical factors have shaped the railway as it is today. As a further consequence, locations where the track curves around raised topography may also offer animals opportunities to travel efficiently among rugged topography (Pollock, Whittington, et al. 2019) and endanger animals because of limited opportunities for escape where steep topography or bodies of water abut the track. Well-intentioned interventions might also have unintended side-effects if the context of the intervention is not adequately considered (Discussion, Chapter 4). However, predictive models of collision vulnerability that integrated diverse factors may help to suggest locations where mitigation measures like warning systems might be most helpful. Such models would be independent of collision records that can obscure locations where populations are locally suppressed by collisions (Eberhardt et al. 2013) or that may simply be unavailable in many locales.

5.2.2 Non-invasive, non-aversive animal warning systems could reduce collision risk

Another core contribution of this dissertation lies in my finding that animals respond earlier to trains when warning signals are provided, even when those warning signals have no apparent biological relevance (Chapters 3 and 4; cf. Babińska-Werka et al. 2015). The warning systems may rely on simple vibration and magnetic sensors to detect trains, thereby limiting the impact on railway operations and infrastructure (Chapter 3). Based on these findings as well as the work of others (Babińska-Werka et al. 2015; Seiler & Olsson 2017; Shimura et al. 2018), active warning systems seem promising for use in the railway context.

This acknowledged, this work does not suggest that wayside active warning systems are the only or best way forward for wildlife collision mitigation on railways. Vehicle-mounted warning signals (ultrasonic whistles), though found ineffective for road vehicles, have been found useful in the railway context in at least one prior study (Muzzi & Bisset 1990). Others have investigated the mounting of airbags or other structures on the front of locomotives to reduce injuries to people even when collisions occur (Paden et al. 2016). Where wayside warning systems might cost-effectively target the locations where risk of collisions is highest, vehicle-mounted solutions could plausibly mitigate collisions risk across entire railway networks if every locomotive were thus equipped. Collision mitigation may not even require new technologies, as speed reductions have been demonstrated to reduce collision risk (Visintin et al. 2018), and more consistent use of train horns could improve the consistency of train audibility (Chapter 2). Regulatory changes promoting the dimming of headlights when a train operator spots wildlife on the tracks might under some conditions reduce the risk of collisions (Chapter 4), though this mechanism merits further study. In other contexts where lighter passenger trains are more common and wildlife collisions pose greater risk to trains (e.g., India and Asian elephants, *Elephas maximus*), animal detection and warning of the train driver to slow the train may be a viable solution (A. Gangadharan, pers. comm.).

5.2.3 Applicability of results to other contexts

Wildlife–vehicle collisions occur around the world for a wide array of species and transportation modes. Aspects of this dissertation may translate to other contexts, but I encourage caution when interpreting my results more broadly than the problem of train collisions in Banff. I have discussed elsewhere how limitations of my study designs necessarily qualify the conclusions I drew from my results (Chapters 2 and 4). Outside of the mountainous landscape of Banff, train audibility and visibility may not be so frequently limited or as widely variable; on the other hand, long-distance visibility and audibility of trains over flat terrain (J. Backs, personal observation) might encourage animal habituation to train stimuli. Different species in other parts of the world seem to respond differently to trains, exemplified by the observation that all animals observed in this work moved away from the track in response to approaching trains (Chapter 4) while this did not occur for a comparable study in Poland (Babińska-Werka et al. 2015). Of the other transportation modes, roads may be most similar to railways because road vehicles are confined to roadways where curves occur that limit visibility (Gunson, Mountrakis, et al. 2011) and could also limit audibility for animals. However, driver behaviour plays a substantial role in wildlife–vehicle collisions on roads and may be easier to alter than animal behaviour (e.g., via warning signage). Aircraft and watercraft collisions with animals may be more similar to those of trains in that the burden of collision avoidance is largely on the animals, but the vehicles are not confined to specific paths; collision mitigation research for these transportation modes has logically focused on vehicle-mounted stimuli to encourage animal avoidance (Blackwell, DeVault, Seamans, et al. 2012; E.R. Gerstein & L.A. Gerstein 2017, but see also for road vehicles Blackwell & Seamans 2009).

5.3 Limitations

In Chapter 2, I attempted to assess train audibility in a way that resembled what animals perceive. I did this by calculating full-spectrum sound levels when trains approached dividing this result by the full-spectrum background sound level when trains were not present. In fact, it is not clear that these measurements resembled what animals perceive, as many species of interest including grizzly bears, black bears (*Ursus americanus*), moose (*Alces alces*), elk (*Cervus canadensis*), and wolves (*Canis lupus*) do not have published audiograms. To support our inferences, I relied on published audiograms for deer (*Odocoileus virginianus*; H. Heffner & H.E. Heffner 2010) and dogs (*Canis lupus familiaris*; H.E. Heffner & R.S. Heffner 2007) that in fact suggest these species can detect sounds that include and exceed the range of human hearing (typically, 20 Hz to 20 kHz). The sound recorders I used often recorded sound produced by trains up to and beyond 40 kHz, with the onset of these ultrasonic sounds sometimes preceding the onset of human-audible sounds. While I chose to calculate the sound power for the full measured spectrum, trains produce sound at higher (Chapter 3) and lower frequencies, suggesting that the aural experiences of other species could differ substantially from our own.

In Chapters 3 and 4, the design of the wildlife warning system relied on the assumption that train passages were aversive to animals. This assumption appeared to be the case in my study system, as I observed that animals always moved away from the track in response to train approach (Chapter 4). Within our study system, bears familiar with the experience of train passage have been anecdotally reported to simply step aside as trains passed before resuming their activity within the right-of-way. In at least one study of wildlife responses to trains, a substantial proportion of animals showed no change in behaviour as trains passed (Babińska-Werka et al. 2015). I speculate that this difference in response could be related to the larger size of freight locomotives and trains in North America compared to Europe (Busschots 2011), and the consequently stronger auditory and visual stimuli they might produce; stronger stimuli are less prone to habituation (Blumstein 2016). It might also be the lower frequency of train traffic in our study area (19 trains per day vs. 90 trains per day in Poland, Babińska-Werka et al. 2015) that reduces opportunities for habituation to train stimuli (reviewed by Blumstein 2016).

A second assumption underlying my development of the animal warning system in Chapters 3 and 4 was that animals leaving the railway track earlier in advance of train arrival would be less likely to be struck. While earlier responses might logically reduce the proportion of animals surprised by trains (Chapters 1 and 3), I did not collect data on the internal state of animals responding to trains nor did I observe any animal responses that led to collisions (Chapter 4).

One more limitation of the study in Chapter 4 was the inability of my study design to demonstrate that associative learning was responsible for the earlier responding of animals to trains. The usable sample of large animal responses was too small to model the effect of time through the study, and a confound with season (winter vs. summer) was likely. Further, I had no means of identifying individual animals, necessary for identifying any change in behaviour over multiple trials (Domjan 2005). The measured effect of the warning system could have arisen through other mechanisms, including an enhancement of animal attention to approaching trains or an increase in perceived risk from the approaching train due to the simultaneous presence of novel warning stimuli (Chapter 4).

I also emphasize that the results of Chapter 4 allow me to make inferences only about the two species groups I used in my analysis (i.e., animals larger and smaller than coyotes). My conclusions cannot be applied to other species groupings or any single species without speculation based on limited anecdotal evidence. For instance, although the impetus for this project arose from an increase in train-caused mortality of grizzly bears, only two observed bears could be included in my analysis for large animals: one black bear in the control group, and one unidentified bear in the treatment group.

5.4 Future work

As suggested in Chapter 2, a clearer picture is needed of the importance of train audibility relative to other factors that appear to co-occur with audibility problems. These other factors included circumstances relating to animal attraction and abundance, train visibility, and right-of-way escapability. High-resolution information on animal use of the railway may be difficult to acquire, but is nonetheless critical for disentangling the contributions of animal presence and collision danger to resultant collision densities (Ascensão et al. 2019). Future work might also examine other railway contexts to determine if problems with train audibility are present more broadly than in mountainous protected areas. Manipulated experiments necessary to establish causal relationships between local topography and train audibility may be impractical in most settings, but this gap may be filled by acoustic scale models (e.g., Chambers & Berthelot 1997) and more detailed computer simulations (e.g., Karantonis et al. 2010) that may lead to the development of better approximations for the acoustic effects of hillsides than the one I developed (Chapter 2). Realistic simulations of acoustic conditions on the railway within the Bow Valley would likely require topographical data of LiDAR resolution, at least for the vicinity of the railway, and substantial computing resources (S. Bilawchuk, Acoustical Consultants Inc., pers. comm.). I also suggest separate examination of different frequency ranges of sound that may be acoustically affected by different features of the railway environment (Chapter 2). Measurement of acoustic illusions related to train sound localization or imitation (Chapter 2) may suggest alternative collision mechanisms and mitigation measures.

As suggested in Chapter 4, a larger-scale experiment (in time or in space) would be needed to determine whether warning systems can reduce train-caused mortality of wildlife. Although an experiment of this scale could be made more practical by recording only the locations and times of collisions rather than recording every animal response, such an experiment might ideally capture details of animal responses to trains as well. To reduce the intensity of data collection, alternative means of monitoring might be considered, including self-contained camera systems with computer vision capabilities that would detect animals before storing images (WildTech 2019). If such technology had been used in my experiment, the number of person-hours required for image screening might have been reduced by a factor of 100. I also speculate that advances in satellite imagery may one day allow perpetual video monitoring of the entire Bow Valley at temporal and spatial resolutions that allow interactions of large animals and trains to be viewed. One company, UrtheCast, currently offers full-colour, 30 frames-per-second video at 1 m resolution as a commercial product. Aerial video capture by drones at high enough altitudes that animals are not disturbed may also be feasible. If ground-based cameras were used as in my work, marking of individual animals (e.g., with paint, ear tags, telemetry collars) or the use of higher-resolution imagery that could identify individuals by their distinguishing features (Kühl & Burghardt 2013) could enable assessment of animal learning. Learning questions might be more easily studied with captive animals, but the intensity of visual and auditory train stimuli are difficult to simulate and results may not readily generalize to wild individuals.

To enable this larger-scale test of the train-triggered warning system from Chapter 4, improvements to the design would likely be required. The long-term reliability of technological devices in field conditions tends to limit their uptake (M. Huijser [regarding animal detection systems] and A. Gangadharan, pers. comm.). This vulnerability is soluble with the right engineering expertise and perhaps a higher overall system cost. With my present design, the longest maintenance-free time I was able to achieve on a single set of alkaline batteries was about three weeks. However, maintenance-free periods on the order of months or years would be desireable for multi-year, large-scale experiments. I predicted that refinements to the design of the electronics, wireless system, and power system (potentially including energy harvesting from rail vibrations or the rail signal voltage) could achieve maintenance-free periods of this length (see appendices for Chapter 4). A lower-profile design or movement of the devices off the track rails (e.g., to posts within the right-of-way or nearby trees) might also be required, as on multiple occasions through my nine month study period, Canadian Pacific maintenance equipment disturbed or destroyed some on-rail devices. The safety of tree-mounted devices is also not guaranteed, as some trees holding my cameras were uprooted during vegetation management by Canadian Pacific, effectively ending the experiment in July 2017. For these reasons, close collaboration with railway operators should be a prerequisite for future efforts in wayside animal warning. I also note that wayside warning systems may not be practical for protecting very long regions of track; train-based warning systems (e.g., Shimura et al. 2018) or drones that travel ahead of trains to warn animals (on track or in the air) have the potential to apply across entire railway networks. Alternative approaches that target a completely different point of failure (animal injury from collisions) might also be viable, such as air bags placed on the front of locomotives (Paden et al. 2016).

The long-term effectiveness of a warning system based on associative learning might rely on the long-term aversiveness of train stimuli, but it is not clear from existing literature whether this would be the case. I acknowledged earlier the lack of information regarding the hearing abilities of wild mammals, and data is similarly lacking on the visual system (excepting, e.g., deer; Cohen et al. 2014) that might help to determine why some visual stimuli appear useful for reducing collisions (e.g., Blackwell, Seamans & DeVault 2014) while others appear dangerous (e.g., train headlights, Chapter 4). More broadly, animals are known to habituate to some fear-inducing stimuli and not others, but the reasons for this are not conpletely understood (Blumstein 2016). For instance, African elephants (*Loxodonta africana*) have been shown to avoid the sound of African bees (*Apis mellifera africana*; Vollrath & Douglas-Hamilton 2002), but animals readily habituate to many types of frightening stimuli used to protect crops (Gilsdorf et al. 2002). These findings might suggest that the use of stimuli that are naturally meaningful to animals will produce stronger responses, though my work showed that animals appear to respond meaningfully to warning stimuli with no natural analogue (Chapter 4).

If future studies found that associative learning could be demonstrated with an animal warning system, more work should be done to define constraints on the type, timing, and spatial placement of conditioned stimuli used. Our choices of warning stimuli were largely speculative, based on limited information about animal senses (Chapter 3, Appendix C.5). It is also unclear from the literature what the optimal timing might be between the onset of the warning stimulus and the train arrival (intertrial interval, *sensu* Cooper 1991), though work on this question for humans suggests the optimal region may be between 20 s and 50 s (Richards & Heathington 1990). My choice to place the warning devices on the track rails was also guided by speculation that animals might more readily associate warning signals with trains if the signals appeared to emanate from the track. Although it is clear that only animals near enough to the track to experience the aversive train stimuli should receive the conditioned warning stimuli (Domjan 2005), it is unclear whether the process of associative learning would be affected by placement of the warning signals on the track, on posts near the track, or on trees outside the right-of-way.

The lack of data on animal–vehicle encounters, especially those that lead to collisions, remains an obstacle to their understanding and mitigation (Lima, Blackwell, et al. 2015). Yet, some data of this type have already been collected by Canadian Pacific with locomotive-mounted cameras. More data of this type could be collected and made available to researchers; to avoid analysis of countless hours of video footage (cf. Burley 2015), self-overwriting recorders in common use for surveillance cameras could allow train operators to store video only when they see or collide with wildlife on the tracks. Trackside camera installations might capture more useful data (i.e., animal behaviour before the train is visible), but at a much higher cost barring technological improvements (see discussion above, this section). Where videos are recorded, audio could be recorded as well to facilitate an integrated analysis of sensory factors that might have contributed to an animal's response. Collision events are currently recorded by train operators and reported to Parks Canada, and additional information might be reported with little additional effort, including the direction of travel for the train, local conditions like light or weather, and perhaps the approximate location of flight initiation as well as the location of the collision.

In light of the focus on animal sensory perception in this dissertation, I speculate that my own sensory perception may have limited my insight into the problem of wildlife–train collisions by restricting the set of hypotheses I chose to test. Although our knowledge of non-human perception is limited, it is clear that the limits of hearing, vision, and other senses vary widely across species and perhaps even within species (e.g., for humans with age-related hearing loss). In Chapter 2, I discussed the potential role of ultrasound and infrasound in train detection for animals with the capabilities to detect them. Colour and light intensity sensitivites different from our own (Peichl et al. 2005; Cohen et al. 2014) or the potential for ultraviolet vision in many mammals (Douglas & Jeffery 2014) could suggest mechanisms for sensitivity to train headlights (Chapter 4). If some mammals possess a magnetoreceptive sense as birds are known to (reviewed by Begall et al. 2013), disorientation might conceivably result from the magnetic properties of track rails and other steel parts (Chapter 3; C.C. St. Clair, unpublished data). The most important sense for grizzly bears is widely regarded to be olfaction, perhaps giving structure to the bears' perceptual world that few humans can conceive (von Uexküll 1934; Conover 2007, Chapter 14). Accurate simulations of animal perceptual worlds might lend new insights to our understanding of animal–vehicle interactions (Wilson 2019).

Though the most recent confirmed mortality of a grizzly bear from a train collision in Banff was in 2012 (when two cubs were killed; St. Clair et al. 2019), wildlife–train collisions continue for many species in Banff and around the world. The Western Environmental Law Center recently filed notice of intent to sue BNSF Railway Company over the deaths of eight grizzly bears in northwest Montana, USA in 2019 (Associated Press 2019), indicating continued public interest in reducing train-caused mortality and suggesting that new solutions are needed. Most pragmatically, railway companies might further aid research on this problem by recording more information on collisions that occur (from train direction to video footage; see above) and sharing more of these data with researchers. This would aid efforts towards an integrated multi-sensory understanding of wildlife vulnerability to collisions with trains and other vehicles. Meanwhile, technological improvements to the warning system proposed in this dissertation would set the stage for larger-scale tests. Work in this field may encourage further applications of behavioural theory and technology to ongoing conservation issues (Blackwell, DeVault, Fernández-Juricic, et al. 2016; Marvin et al. 2016; Proppe et al. 2017) for the benefit of both wildlife and people.

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Appendix A

Fault tree Analysis for wildlife–train collisions

A.1 How to interpret the fault tree

A fault tree is a type of failure analysis that begins by identifying the undesired event and proceeds to identifying the immediate, necessary, and sufficient causes for the event. Causes are related to each other with logical operators such as AND or OR (Vesely et al. 2002). Without easy access to fault tree software that would provide a conventional two-dimensional layout with appropriate symbols, I performed my analysis using nested, numbered lists where list items of the same level are all "under" the preceding list level and "above" the subsequent list level. I also used all-capitalized labels in place of symbols as follows (Vesely et al. 2002):

BASIC An event that is not necessarily a fault and is not developed further

NORMAL An event that is expected to occur under normal conditions

UNDEVELOPED A fault event that I have chosen not to explore further

COMMAND A fault event that involves the proper functioning of components at the wrong time or in the wrong place

OR A logical gate stating that if any events below the gate occur, the event above will occur

AND A logical gate stating that if and only if all events below below the gate occr, the event above will occur

SeqAND As for AND, but events must occur in the specified sequence

INHIBIT A gate that inhibits the event below from causing the event above unless the inhibiting condition is met

XFERFROM A symbol used to link from events in a different part of the fault tree.

XFERTO A symbol used to link to events in a different part of the fault tree.

Unnumbered (bulleted) list items are simply notes that I made regarding a given event. The alignment of list items of the same level in the tree is consistent across pages of the tree.

Please note that I performed this fault tree analysis in January of 2014, and my understanding of the problem of wildlife–train collisions have evolved since that time.

A.2 Fault tree analysis

The fault tree begins on the following page.

1 COMMAND Animal dies or is disabled by a collision with a train.

1.1 OR

1.1.1 COMMAND Locomotive strikes animal causing impact damage to animal

1. INHIBIT (Difference between locomotive velocity and animal velocity is sufficient to damage the animal)
    1. COMMAND Locomotive and animal come into contact
        1. AND
            1. NORMAL Train is present on the track and moving
            2. NORMAL Animal is present on or near the track
            3. COMMAND Distance between locomotive and animal approaches zero.
                1. OR
                    1. COMMAND Animal moves towards the locomotive
                        1. OR
                            1. UNDEVELOPED Animal detects train and responds with an aggressive charge towards the train
                                - Perception of train by the animal leads to misinterpretation of the train as an aggressor
                                - Perceptual error includes the mistaken assessment that the train is a competitor that can be beaten or at least intimidated
                                    - Potentially related to:
                                        - Appearance of train
                                        - Motion of train towards animal
                                        - Sound of train
                                        - Species of animal (e.g., common in moose, less so in grizzly bears)
                                        - Whether the animal is protecting territory, food, or offspring
                            2. COMMAND Animal detects train and otherwise errors in judgement, responding by moving towards the train
                                - What is the response of animals when they are startled?
                                    - Run away directly, or at an angle, or not at all?
                                1. OR
                                    1. UNDEVELOPED Animal detects train, tries to retreat, and mistakenly chooses to move towards the train
                                        - While this is conceivable, I think there are more likely failure modes.
                                        - On the other hand, deer tend to move in front of moving cars the moment the headlights start to pass
                                            - Is there enough information about how this process works to dig deeper?
                                    2. UNDEVELOPED Animal detects train, tries to retreat, and chooses an escape route that brings it closer to the train, implicitly misjudging train speed or direction
                    2. COMMAND Animal moves away from the locomotive, but fails to avoid it
                        1. AND
                            1. COMMAND Animal retreats down the track away from the train (instead of off the track or towards the train)
                                1. SeqAND (Top to bottom)
                                    1. COMMAND Animal percieves “down the track away from the train” as the most promising retreat path
                                        1. OR
                                            1. COMMAND Animal’s perception of other available retreat paths is obscured
                                                - We assume that perception of retreat paths is mainly visual.

   1. OR
      1. COMMAND Rain or snow obscures available retreat paths
         1. INHIBIT (Rain or snow is sufficient to obscure available retreat paths)
            1. COMMAND It is raining or snowing
               1. OR
                  1. NORMAL It is raining
                  2. NORMAL It is snowing
      2. COMMAND Train headlights illuminate mostly along the track; other retreat paths hidden by contrast between light and dark and/or loss of night vision due to headlight exposure
         1. INHIBIT (Contrast of illuminated vs. non-illuminated paths is sufficient to obscure animal's perception of non-illuminated paths)
            1. COMMAND Train headlights illuminate mostly along the track, creating contrast between the track and other available retreat paths
               1. AND
                  1. COMMAND Ambient conditions are darkened.
                     1. OR
                        1. NORMAL It is night
                        2. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.1.1.1.1.1
                        3. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.1.1.1.1.1
                  2. NORMAL Train headlights are turned on
                     - Train headlights may under some circumstances be turned off; for example, if the train operator detects an animal ahead and believes that turning off the headlights will reduce the chances of a collision
2. COMMAND Animal's assessment of other available retreat paths is prevented by interfering signals
   1. INHIBIT (Interfering signals are significant enough to prevent a sound retreat path assessment)
      1. COMMAND Animal's assessment of other available retreat paths has to compete with other stimuli
         1. OR
            1. COMMAND Animal sensory or perceptual systems are overloaded or confused by interfering signals from the train
               1. OR
                  1. COMMAND Animal's vision is saturated by train headlights
                     1. AND
                        1. NORMAL Animal's vision is sensitive to train headlights
                           - Depends on species, but many species of interest are sensitive to low-light conditions, which may exacerbate sensitivity to headlights
                           - Depends on headlight type
                           - Sensitivity to headlights may depend on natural light levels (day/night, weather)
                        2. NORMAL 1.1.1.1.1.1.3.1.2.1.1.1.1.1.1.1.1.2.1.1
                  2. COMMAND Animal's perception of the train is confused by headlight interaction with the environment
                     1. OR
                        1. COMMAND Headlights reflect off the rails in a confusing way
                           1. AND
                              1. NORMAL The rails are not snow-covered
                              2. UNDEVELOPED The headlight reflections off the rails are confusing

                2. COMMAND Headlights interact with falling precipitation in a confusing way
                    1. AND
                        1. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.1.1.1.1.1
                        2. UNDEVELOPED The headlight interactions with the rain or snow are confusing
                3. COMMAND Headlights reflect off wet or snow-covered surfaces in a confusing way
                    1. AND
                        1. NORMAL Snow is present on the ground or the ground is wet from rain or dew
                        2. UNDEVELOPED Headlights reflect off these surfaces in a confusing way
        3. COMMAND Animal's hearing is saturated by train vibrations
            1. AND
                1. NORMAL Animal's hearing can detect train vibrations
                2. BASIC Train is close enough that the vibrations are loud
        4. COMMAND Animal's hearing is saturated by train whistle
            1. AND
                1. NORMAL Animal's hearing can detect the train whistle
                2. BASIC Train is close enough that the whistle is loud
                3. NORMAL Train whistle is being blown
                    - Train operators must choose whether and how much to blow the whistle
                    - Operator choice to blow the whistle may be affected by detection of an animal in the path of the train
2. COMMAND Animal sensory or perceptual systems are overloaded or confused with interfering signals from the environment
    1. OR
        1. COMMAND Animal is disoriented by local magnetic fields
            - Note that other exotic senses, such as electroreception, are not expected to play a role in animal orientation
            - Magnetoreception is assumed to not play a significant role in train detection and localization
            1. AND
                1. UNDEVELOPED The animal passes a track location where local magnetic fields overwhelm Earth's magnetic field
                    - Preliminary experiments indicate that some track locations may have locally strong magnetic fields
                2. UNDEVELOPED Animal has magnetoreceptive ability that contributes to orientation
                    - Evidence exists that some mammals possess magnetoreceptive ability that contributes to their behaviour
        2. COMMAND Non-train noise overloads or confuses the animal's hearing
            1. OR
                1. COMMAND Animal is disoriented by anthropogenic noise
                    1. AND
                        1. COMMAND Anthropogenic noise exists at the animal's location
                            1. OR
                                1. NORMAL Road traffic is present nearby
                                    - Normal for some track locations
                                2. NORMAL Construction is occuring nearby

                                       - Less common, but happens near some track locations (e.g., Five Mile Bridge construction)
                                    3. NORMAL Aircraft are passing overhead
                                       - Happens regularly
                              2. NORMAL Animal can percieve the anthropogenic noise present
                        2. UNDEVELOPED Animal is disoriented by non-anthropogenic noise
                           - Wind, rain, thunder could be significant sources of noise, but animals may be accustomed to these noise sources
                  3. UNDEVELOPED Non-train visual stimuli overloads or confuses the animal's vision
                     - Not sure if anything could realistically cause this. Sun in one's eyes, or reflecting off snow?
3. COMMAND Animal's assessment of all available retreat paths is pre-empted by the urgency of the need to retreat
   1. COMMAND Animal is in a state of panic
      1. COMMAND Animal has been surprised by the train
         1. OR
            1. COMMAND Animal suddenly realizes that train arrival is imminent and dangerous
               1. AND
                  1. UNDEVELOPED Animal realizes the train is dangerous
                  2. COMMAND Animal suddenly perceives the train arrival is imminent
                     1. AND
                        1. NORMAL Train signals are perceived by the animal.
                           - Train is close enough that it is immediately visible and audible.
                        2. COMMAND Train signals were not previously perceived or were perceived but also ignored by the animal
                           1. OR
                              1. COMMAND Train signals were previously perceived by the animal, but animal ignored these signals
                                 1. COMMAND Train signals were previously received by the animal, but were not recognized as train signals
                                    1. UNDEVELOPED Animal has little experience with trains
                                       - Assumption is that animals who have survived train encounters before, will be more likely to survive subsequent train encounters
                                 2. COMMAND The animal is desensitized to train signals
                                    1. NORMAL The animal often perceives train signals when a train approach is not imminent
                                       - e.g. whistles can be heard throughout Bow Valley, even if a train approach is not imminent
                              2. COMMAND Train signals were not previously perceived by the animal
                                 1. OR
                                    1. COMMAND Non-train signals were saturating the animal's attention
                                       1. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.2
                                    2. COMMAND Train signals were not previously received by the animal
                                       1. AND

1. COMMAND Train signals that were produced were not receivable by the animal (out of detection range, below sensitivity threshold, or obscured by interfering signals)
    1. OR
        1. BASIC Signals transmitted to the animal were outside of the animal's sensory detection range
        2. COMMAND Signals transmitted to the animal were below the animal's sensory sensitivity threshold
            1. OR
                1. NORMAL Train was too far away to be detected
                2. COMMAND Train signals were passively obscured by environment
                    1. AND
                        1. NORMAL Acoustic signals obscured by environment
                            - e.g. by vegetation or topography, around a corner
                        2. NORMAL Visual signals obscured by environment
                            - e.g. by vegetation or topography, around a corner
        3. COMMAND Signals transmitted to the animal were obscured by interfering signals
            1. OR
                1. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.2
                2. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.2
2. COMMAND Train whistle was not produced in advance of train arrival near the animal

- Train whistle produced only once animal is visible to train operator may just cause the animal to be surprised.
- Train headlights are always on, unless train operator detects animal and chooses to turn them off
- Train vibration is always produced (if to varying degrees)
- We assume here that if a train whistle is produced, it can be received almost anywhere in the Bow Valley.

1. OR
    1. NORMAL Train operator was not required to whistle on the segment of track train was approaching from
    2. UNDEVELOPED Train operator was required to whistle by a whistle sign, but failed to do so

2. COMMAND Train suddenly appears to be coming from a different direction than it appeared a moment ago
    1. AND
        1. NORMAL Train signals are now transmitted by the environment such that localization from signals is consistent with the train location
        2. COMMAND Train signals were previously transformed by environment to appear to be coming from a different direction than the train
            1. COMMAND Train sound previously appeared to be coming from somewhere other than the train location
                1. BASIC Topography and/or vegetation causes illusory reflection of train sound in certain transmitter–receiver configurations

4. UNDEVELOPED All other retreat paths appear less available
    - Examples
        - Steep embankment down from the track may appear risky
        - Steep embankment up from the track may appear impassable
        - Nearby body of water makes retreat in that direction seem futile
    - Predict this probability using the percentage of track where one or both sides of the track have embankments that appear steep (Patrick's work?) or vegetation that appears dense

2. COMMAND Animal persists in this retreat direction until it is struck by the train
    - Not clear why this would be the case
        - Animal version of the sunk cost fallacy?
        - "Down the track" continues to be perceived as the path of least risk
        - Could model this in a simulation by re-testing the "animal percieves down the track as the most promising retreat path" for each unit of time
    1. OR
        1. COMMAND Animal's judgement is impaired and so does not choose a different retreat direction
            1. INHIBIT (Impairment is sufficient that the animal does not choose a different retreat direction)
                1. COMMAND Animal's judgement is impaired physiologically
                    1. OR
                        1. COMMAND Animal's judgement is impaired by fear / panic
                            1. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.3.1

                              2. COMMAND Animal's judgement is impaired by its consumption of fermented grain
                                 1. COMMAND Animal has consumed fermented grain recently in sufficient quantities to affect judgement
                                    1. AND
                                       1. UNDEVELOPED Fermented grain is available for consumption by the animal in sufficient quantities to affect judgement
                                       2. UNDEVELOPED Animal consumed the fermented grain in sufficient quantities to affect judgement
                              3. UNDEVELOPED Animal's judgement is impaired by other physiological conditions (hunger, fatigue)
                  2. COMMAND Animal's unimpaired judgement dictates that this retreat direction is still the best
                     1. INHIBIT ("Down the track away from the train" continues to be the best-judged direction as the retreat progresses.)
                        1. XFERFROM [1.1.1.1.1.1.3.1.2.1.1.1.1](#)
      2. COMMAND Train is moving down the track faster than the animal
         1. OR
            1. NORMAL Train is travelling at the posted speed limit, which is greater than the maximum run speed of the animal
            2. UNDEVELOPED Train speed is greater than the maximum run speed of the animal, regardless of the posted speed limit
               - Accounts for train speed greater than posted limit, as well as train speed less than posted limit but still greater than run speed of animal
3. COMMAND Animal takes no action to move
   - Deer are famously unable to retreat when confronted by bright light at night
   1. OR
      1. COMMAND Animal is transfixed, paralyzed by fear, or otherwise overwhelmed by train signals
         1. INHIBIT (Train signals received are sufficient to transfix, cause paralyzing fear, or otherwise overwhelm the animal)
            1. XFERFROM [1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.1](#)
      2. COMMAND Animal is temporarily disoriented by non-train signals
         1. INHIBIT (Disorientation from other stimuli is sufficient to prevent movement)
            1. XFERFROM [1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.2](#)
      3. COMMAND Animal is temporarily prevented from acting by train or non-train signals compounded by impaired judgement
         1. INHIBIT (This combination of factors is significant enough to prevent action)
            1. COMMAND Influence of train or non-train signals on the animal are compounded by impaired animal judgement
               1. AND
                  1. XFERFROM [1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.1](#)
                  2. XFERFROM [1.1.1.1.1.1.3.1.2.1.1.1.1.1.2.1.1.1.2](#)
                  3. XFERFROM [1.1.1.1.1.1.3.1.2.1.1.1.2.1.1.1.1](#)

1.1.2 COMMAND Locomotive runs over animal causing crushing damage to animal

1. INHIBIT (Locomotive and animal make contact such that the animal falls under the locomotive)
   1. XFERFROM [1.1.1.1.1](#)

1.1.3 COMMAND Train component other than locomotive strikes animal causing impact damage to animal

1. INHIBIT (Difference between train component velocity and animal velocity is sufficient to damage the animal)
   1. COMMAND Train component and animal come into contact
      1. AND

1. NORMAL Train is passing
2. NORMAL Animal present near the track
3. COMMAND Animal moves towards train side while train is passing
    1. AND
        1. COMMAND Animal fails to perceive or disregards the train hazard
            1. OR
                1. UNDEVELOPED Animal has a mental illness that causes erratic behaviour or sensory disabilities
                    - e.g., chronic wasting disease?
                2. UNDEVELOPED Animal has a sensory disability previous to the train encounter
                    - e.g., unable to hear and/or see normally
                    - This could be a common-cause failure mode for many other parts of the tree.
                3. COMMAND Animal does not associate available train signals with danger
                    1. AND
                        1. XFERFROM 1.1.1.1.1.1.3.1.2.1.1.1.1.1.3.1.1.1.1
                        2. UNDEVELOPED Animal's species has not evolved to associate train signals with danger
                4. COMMAND Train signals that would indicate danger to the animal are unreceivable by the animal
                    1. OR
                        1. COMMAND Visual signals of the train passage are unreceivable
                            1. OR
                                1. NORMAL Heavy precipitation is occuring (rain or snow)
                                2. NORMAL Thick fog is present
                                3. NORMAL It is a dark night
                                    - No moon or overcast.
                        2. COMMAND Audio signals of the train passage are obscured
                            1. OR
                                1. NORMAL There are high winds
                                2. NORMAL A heavy thunderstorm is occuring (near-constant thunder)
        2. COMMAND Animal compelled to cross or move towards tracks during train passage
            1. OR
                1. UNDEVELOPED Animal disoriented by sensory experience of train passage and is drawn towards it or is unable to stop previous progress towards it
                    - Visual motion is dizzying to humans
                2. UNDEVELOPED Animal can see members of its herd or family or potential mates or rivals on the other side of the train (i.e. between cars)
                3. UNDEVELOPED Animal is being pursued by predators
                4. UNDEVELOPED Animal is under distress from parasitic infection or biting insects
                5. UNDEVELOPED Animal is moving to avoid human contact or hunters

1.1.4 COMMAND Train component other than locomotive runs over animal causing crushing damage to animal

1. INHIBIT (Train component and animal make contact such that the animal falls under the train)
    1. XFERFROM 1.1.3.1.1

A.3 References

Vesely, W. et al. (2002). *Fault Tree Handbook with Aerospace Applications*. Tech. rep. Version 1.1, Office of Safety, Mission Assurance, National Aeronautics, and Space Administration, Washington, DC, USA.

Appendix B

Supporting Information for "Low audibility of trains may contribute to increased collisions with wildlife"*

B.1 Site locations, straightaway lengths, and recorder placements

We provide precise locations for each site along with the straightaway length measured from each trackside recorder (Table B.1). Coordinates indicated are for the location of the trackside recorder location with a Global Positioning System (GPS)-indicated accuracy of 3 m to 5 m. Straightaway lengths provide the approximate distances between a given trackside recorder and the start of the nearest appreciable curve along the straightaway. Recorder separations indicate the distance between trackside and forest edge microphone pairs in the plane perpendicular to the axis of the railway track.

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Table B.1: Site locations where acoustic measurements were taken for this experiment. Universal Transverse Mercator (UTM) coordinates are provided within zone 11N of the NAD83 coordinate reference system (EPSG:26911). Recorder (rec.) vertical separation (sep.) is negative when the forest edge recorder microphones were at a lower elevation than the trackside recorder microphones.

Site	Name	UTM Easting	UTM Northing	Straightaway length (km)	Rec. horizontal sep. (m)	Rec. vertical sep. (m)	Rec. total sep. (m)
A	Castle East	576017	5679520	3.4	10.80	6.35	12.50
B	Johnston Canyon	579466	5678232	1.1	6.60	-1.20	6.71
C	Hillsdale West	583183	5675495	0.4	4.88	0.80	4.95
D	Muleshoe	589728	5670054	3.1	4.28	0.41	4.30
E	Five Mile A	591301	5669279	0.3	9.77	4.95	11.00
F	Five Mile S	593279	5669582	0.6	7.73	-3.20	8.37
G	Five Mile C	594293	5669496	0.5	2.81	-0.11	2.81
H	Stables	602264	5673880	2.3	3.65	0.72	3.72
I	Anthracite	606930	5670109	0.8	4.58	-0.07	4.58
J	Carrot East	609546	5666682	1.8	3.16	-0.08	3.16

B.2 Features of cluster and measurement sites

Although we observed a correlation between low measured audibility and high collision frequency at our 10 measurement sites, *background & train & barrier* physical predictions simulated across the study area sometimes failed to predict reductions in train audibility where collisions were concentrated (Fig. 2.7). We examined our 10 measurement sites and six other locations where the highest densities of collisions were found (Fig. B.1) for other features that might explain these collision patterns. Collision clusters were identified from the data (Fig. 2.7) using a peak detection algorithm (https://github.com/stas-g/findPeaks/blob/master/find_peaks.R), removing peaks with less than 20 collisions recorded within 200 m, resulting in the identification of nine clusters. Clusters identified within 400 m of a measurement site (three locations) were assigned to the location of that measurement site.

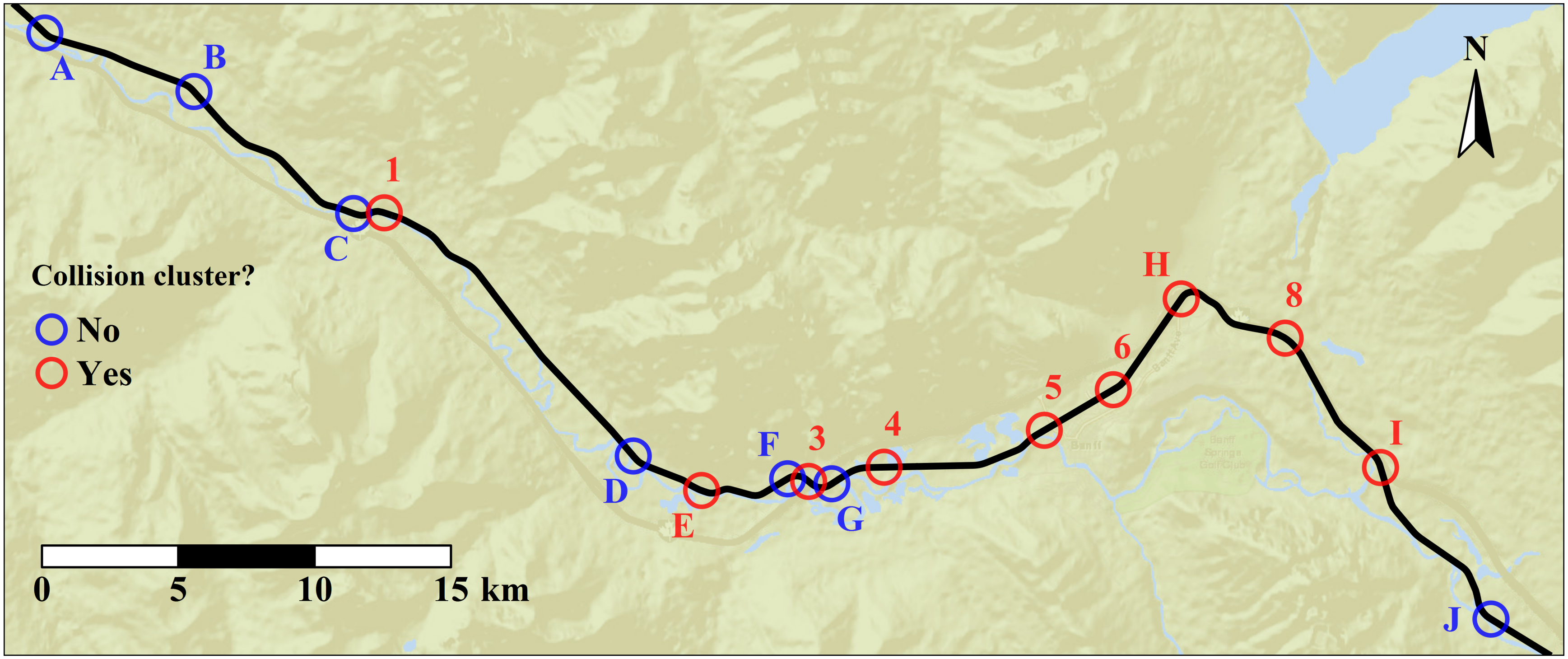

Figure B.1: Map of 10 sites (letter labels) where train audibility was measured in this study and locations of known collision hotspots or clusters (number labels). The 10 measurement sites were chosen where track curves around raised topography met straightaways greater than 300 m in length. Clusters existing within 400 m of three of the measurement sites were assumed coincident (red letter labels).

In Table B.2, we suggest features at each location affecting train detectability (excluding audibility of the train itself), animal attraction to the right-of-way, and escapability of the right-of-way for animals. These features were identified using freely available aerial imagery of the study area as well as our own measurements and experiences in the study area. Rather than providing a rigorous analysis, we offer this information as a guide to the development of future hypotheses about the relative effects of train audibility and other factors on wildlife–train collision locations. For all columns, locations where the presence of a feature was not measured are indicated with "–", while locations where a feature was not present are left blank. Columns were defined as follows:

- Name. Boldface location names identify the nine collision clusters found.
- Colls. Specifies the number of collisions recorded within 200 m of the location.
- Train detectability:
  - Horn detected. We report the percentage of eastbound (EB) and westbound (WB) train approaches recorded for which at least one horn blow could be heard at any point within the five minutes prior to train arrival.
  - Visibility low. We report locations where to the east (E) or west (W) the track curves enough to obscure visibility around vegetation or topography.
  - Noise sources. We indicate locations where noise sources (road or river) may substantially obscure the sounds of train approach, although road noise was audible to some extent at every measurement location.
- Animal attraction:
  - Apparent corridor. We report locations that could (true, T or false, F) serve as travel corridors for wildlife as suggested by the presence of

roads, water bodies, rugged topography, or human use features near the location.

  - Railway siding. We report locations with railway sidings (true, T or false, F), where trains frequently stop and where spilled agricultural products are thought to accumulate as a result (Gangadharan et al. 2017). Small quantities of spilled grain were visibly detected at all measurement sites.

- Right-of-way escapability:

  - Steep embankment. We indicate locations with steep embankments to the north (N) or south (S) sides of the right-of-way.
  - Water body. We indicate locations with water bodies present to the north (N) or south (S) sides of the right-of-way.
  - Fencing. We indicate locations with fencing (including Trans-Canada Highway wildlife exclusion fencing and other fencing) present to the north (N) or south (S) sides of the right-of-way.

Table B.2: Summary of local features that could contribute to wildlife–train collision risk, exclusive of train audibility, at the 10 measurement sites from this study and six additional collision hotspots or clusters.

Site	Name (**cluster**)	Colls.	Horn detected (%EB, %WB)	Visibility low	Noise sources	Apparent corridor	Railway siding	Steep embankment	Water body	Fencing
A	Castle East	4	(100, 88)	E	River	T	F	N,S	S	
B	Johnston Canyon	2	(27, 38)	W		F	F			
C	Hillsdale West	12	(77, 70)	E	River	T	F	N,S	S	
1	**Hillsdale Siding**	25	–		–	T	T	N	S	
D	Muleshoe	7	(9, 67)	E		T	F		N,S	
E	**Five Mile A**	16	(92, 85)	E,W		T	F	N,S	S	
F	Five Mile S	8	(19, 100)	E		T	F	N,S		
3	**Five Mile Bridge**	38	–	E,W	Road	T	F	N,S	S	N
G	Five Mile C	6	(93, 75)	W		T	F			
4	**Vermillion Wetland**	21	–	W	–	T	F		N,S	
5	**Townsite West**	42	–		–	T	T		N,S	
6	**Townsite Central**	21	–	E	–	T	T			
H	**Stables**	33	(62, 7)	E	Road	T	F			N,S
8	**Anthracite West**	42	–	E,W	–	T	F			N
I	**Anthracite**	28	(0, 7)	W	Road	T	F			N
J	Carrot East	4	(0, 73)	W		F	F		S	

We additionally examined the collision data for the species, years, and seasons for which collisions were most frequent at each location (Table B.3). Columns were defined as follows:

- Name. Boldface location names identify the nine collision clusters found.
- Colls. Specifies the number of collisions recorded within 200 m of the location.
- Top species. We list the species struck at each location (and number of collisions recorded within 200 m of the location) in descending order of collision frequency. Species abbreviations include BLAC (black bear, *Ursus americanus*), COUG (cougar, *Puma concolor*), COYO (coyote, *Canis latrans*), DEER (unidentified deer, *Odocoileus* spp.), ELK (elk, *Cervus canadensis*), GRIZ (grizzly bear, *Ursus arctos*), LYNX (lynx, *Lynx canadensis*), MOOS (moose, *Alces alces*), MULE (mule deer, *Odocoileus hemionus*), SHEE (bighorn sheep, *Ovis canadensis*), WHIT (white-tailed deer, *Odocoileus virginianus*), WOLF (wolf, *Canis lupus*).
- Top years. We list the top five years, including ties, in which collisions occurred (and number of collisions recorded within 200 m of the location) in chronological order.
- Collisions by season. We list the total numbers of collisions recorded within 200 m of the location in each of winter (W), spring (Sp), summer (Su), and fall (F). Seasons are divided according to the meteorological reckoning with winter spanning Dec.–Feb., spring Mar.–May, summer Jun.–Aug., and fall Sep.–Nov.

Table B.3: Summary of wildlife–train collision patterns at the 10 measurement sites from this study and six additional collision hotspots or clusters.

Site	Name (**cluster**)	Colls.	Top species	Top years	Collisions by season (W, Sp, Su, F)
A	Castle East	4	ELK (4)	1995 (1), 2001 (2), 2003 (1)	(0, 2, 1, 1)
B	Johnston Canyon	2	MOOS (1), MULE (1)	1985 (1), 2004 (1)	(2, 0, 0, 0)
C	Hillsdale West	12	ELK (7), MOOS (3), MULE (1), WOLF (1)	1981 (1), 1985 (1), 1986 (1), 1987 (1), 1988 (1), 1993 (2), 2004 (1), 2006 (2), 2010 (1), 2012 (1)	(4, 5, 1, 2)
1	**Hillsdale Siding**	25	ELK (18), WHIT (3), MULE (2), BLAC (1), WOLF (1)	1987 (2), 1991 (3), 1999 (3), 2007 (3), 2013 (3)	(12, 8, 3, 2)
D	Muleshoe	7	ELK (3), WHIT (3), MULE (1)	1984 (1), 1988 (1), 1991 (1), 2006 (1), 2008 (1), 2013 (1), 2015 (1)	(3, 2, 0, 2)
E	**Five Mile A**	16	ELK (12), WHIT (3), WOLF (1)	1981 (1), 1985 (1), 1986 (1), 1987 (1), 1988 (1), 1989 (3), 1995 (1), 1996 (1), 1999 (2), 2011 (2), 2015 (1), 2016 (1)	(9, 4, 1, 2)
F	Five Mile S	8	ELK (3), SHEE (3), GRIZ (1), WHIT (1)	1987 (1), 1990 (1), 1994 (1), 1999 (1), 2000 (1), 2008 (1), 2009 (1), 2016 (1)	(4, 1, 1, 2)
3	**Five Mile Bridge**	38	ELK (29), SHEE (4), WHIT (3), GRIZ (1), MULE (1)	1986 (4), 1987 (4), 1990 (3), 1992 (4), 2010 (4)	(16, 10, 6, 6)
G	Five Mile C	6	ELK (4), LYNX (1), MULE (1)	1991 (1), 1994 (1), 2002 (1), 2008 (1), 2010 (1), 2013 (1)	(3, 2, 1, 0)
4	**Vermillion Wetland**	21	ELK (15), MOOS (2), MULE (2), WHIT (2)	1998 (3), 1999 (2), 2007 (3), 2011 (2), 2012 (2), 2016 (2)	(12, 3, 4, 2)
5	**Townsite West**	42	ELK (36), MULE (2), WHIT (2), BLAC (1), DEER (1)	1997 (5), 1999 (3), 2000 (6), 2001 (4), 2011 (3), 2015 (3)	(10, 13, 17, 2)
6	**Townsite Central**	21	ELK (13), MULE (5), WHIT (2), BLAC (1)	1998 (2), 2000 (3), 2004 (2), 2009 (2), 2012 (4)	(14, 1, 2, 4)
H	**Stables**	33	ELK (27), WHIT (3), DEER (1), MULE (1), WOLF (1)	1989 (2), 1993 (2), 1995 (3), 1996 (2), 1999 (2), 2001 (2), 2009 (4), 2010 (2), 2016 (2)	(19, 5, 4, 5)
8	**Anthracite West**	42	ELK (30), WHIT (5), COYO (3), MULE (3), DEER (1)	1992 (5), 1996 (6), 2008 (4), 2015 (4), 2016 (5)	(17, 7, 3, 15)
I	**Anthracite**	28	ELK (21), WHIT (4), COUG (1), COYO (1), WOLF (1)	1985 (3), 1987 (2), 1990 (2), 1991 (2), 1993 (2), 2004 (2)	(9, 10, 4, 5)
J	Carrot East	4	WHIT (3), ELK (1)	1993 (1), 2008 (2), 2016 (1)	(3, 0, 0, 1)

B.3 References

Gangadharan, A. et al. (2017) *Grain spilled from moving trains create a substantial wildlife attractant in protected areas*. Animal Conservation, **20**(5), 391–400.

Appendix C

Supplementary material for "Warning systems triggered by trains could reduce collisions with wildlife"*

*Originally published with J.A.J. Backs, J.A. Nychka, & C.C. St. Clair (2017) *Warning systems triggered by trains could reduce collisions with wildlife*, Ecological Engineering, **106**, 563–569. Reproduced without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

C.1 Purchasing information for sensors tested

Table C.1 lists detailed information on manufacturers and suppliers for the sensors used to detect trains in this work.

Table C.1: Part numbers, manufacturers, and suppliers for sensors tested in this manuscript.

Sensor	Part Number	Manufacturer	Supplier
Digital compass	HMC5883L	Honeywell	Adafruit, with board (Product #1746)
Infrared rangefinder	GP2Y0A21YK0F	SHARP	Adafruit (Product #164)
Infrared motion detector	–	Various	Adafruit (Product #189)
Accelerometer	ADXL335	Analog Devices	Adafruit, with board (Product #163)
Vibration switch, weak	SW-18010P	Bai Ling Electronics	Adafruit (Product #1766)
Vibration switch, medium	SW-18020P	Bai Ling Electronics	Adafruit (Product #2384)
Vibration switch, strong	SW-18030P	Bai Ling Electronics	Adafruit (Product #1767)
Piezoelectric film, shielded	SDT1	Measurement Specialties	Durham Instruments

C.2 Preamplifier for the piezoelectric sensor

Figure C.1 shows a schematic of the custom preamplifier designed for the approach detector. This device performs three major functions to interface the piezoelectric film sensor (model SDT1, Measurement Specialties, USA) with the ultrasonic sound recorders (models SM2BAT and SM2BAT+, Wildlife Acoustics, USA). First, it buffers the high electrical impedance of the piezoelectric film sensor, allowing the low-impedance input of the sound recorders to receive an accurate signal (Measurement Specialties Inc. 2008). Second, it changes the average value of the signal from 0 V (at the output of the sensor) to approximately 1.2 V, the midpoint of the input range of the sound recorder (0 V to 2.5 V). Third, it protects the input of the sound recorder from electric potentials outside the range 0 V to 3.3 V, which could damage the sound recorder. This circuit is our own design, but draws from examples published by the manufacturer (Measurement Specialties Inc. 2008).

We assembled this device on a prototyping board, placed it in a die-cast aluminum enclosure, and electrically connected the enclosure to the common ground (GND) only at the sensor input to minimize the effects of electromagnetic interference on our measurements (Rich 1983). A 10 m three-conductor microphone cable (Wildlife Acoustics, USA), also shielded, was used to connect the preamplifier to the sound recorder.

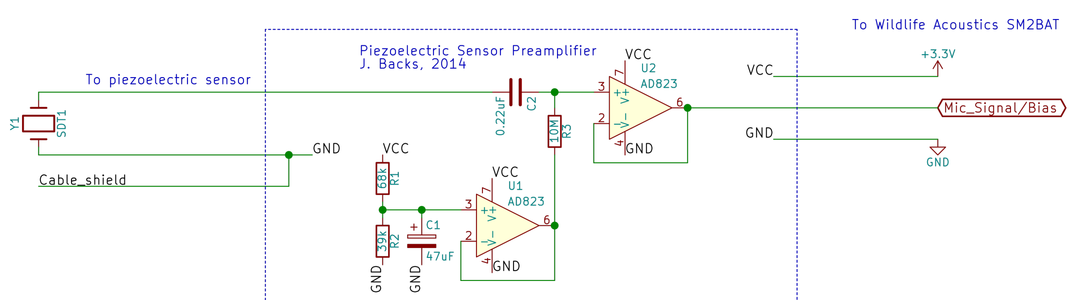

Figure C.1: Schematic of the preamplifier for the approach detector.

C.3 Details of the machine learning algorithm for the approach detector.

We converted continuous recordings from our piezoelectric sensors into a form suitable for machine learning via the following procedure.

1. Sensor recordings were converted to spectrograms and systematically inspected for patterns characteristic of train arrival. We defined train arrival as the moment the first wheel of a train passed over the sensor. The arrival times could be identified by eye in the spectrograms to within ± 0.05 s because of the distinctive acoustic patterns caused by the passage of train wheels over the sensor.

2. To extract and convert the train approach recordings into a useful form, the following operations were performed for each train approach identified.

   (a) During our inspection of the spectrograms, we noted that signals of train approach could be visually detected up to a maximum of 210 s before train arrival (though usually 30 s to 60 s). To reduce the size of the dataset for analysis, data were extracted from 0 s to 220 s before each train arrival (hereafter, approach recordings) for use in the following steps. For some train approaches, the full 220 s could not be captured because the SM2BAT recorder happened to start a new recording file within 220 s of train arrival. In these cases, approach recordings smaller than 220 s were kept only if this shorter period captured 5 s to 10 s of silence (i.e., before any signals of train approach could be seen in the spectrogram). If this condition could not be met, the train approach was not used in the model fitting. Approaches of non-train track vehicles were also not used.

   (b) Some recordings were made with 384 kHz sound recorders (SM2BAT+), while others were made with 192 kHz recorders (SM2BAT). To homogenize the data, 384 kHz recordings were down-sampled to 192 kHz (Bagwell et al. 2015).

(c) We noted that the piezoelectric film sensors recorded a great deal of power line noise (60 Hz and harmonics) as well as other unknown signals below 10 kHz. These signals did not appear to correlate with train approach and moreover tended to have a larger amplitude than signals at higher frequencies that did correlate with train approach. Recordings were thus high-pass filtered to remove all signals below 10 kHz (Bagwell et al. 2015).

(d) The signal envelope was then calculated via the Hilbert transform (Dugundji 1958; Bagwell et al. 2015). This was used as a measure of the amplitude of the signal (in total for all frequencies) over time.

3. Each train approach recording was then partitioned into smaller pieces that standard classification algorithms could operate on. For compatibility with machine learning literature, we use the following terms: the size of each piece is termed the receptive field size; the time between the starting time of one piece and the starting time of the subsequent piece is termed the stride time; a series of consecutive pieces passed to the classification algorithm as a group is called an observation.

   (a) We set the receptive field size to 1.0 s and the stride time to 0.5 s. We define an observation to be a set of 9 consecutive receptive fields to allow the classification algorithm to take into account 5.0 s of data each time it classifies an observation.

   (b) With these settings of the receptive field size and the stride time, each 220 s approach was broken down into 439 overlapping receptive fields. The values of the signal envelope within each receptive field were averaged (arithmetic mean) such that the resulting 439 numbers form a condensed representation of the original train approach recording.

   (c) From this condensed representation, a two-dimensional array was assembled. The first column of this array contained the 439 numbers from the previous step, ordered by receptive field start time from

220.0 s to 1.0 s before train arrival. The second column contained a zero in the first row, then rows from the second onwards were filled with the first 438 numbers ordered from 220.0 s to 1.5 s before train arrival. The third column contained a zero in the first and second rows, then rows from the third onwards were filled with the first 437 numbers ordered from 220.0 s to 2.0 s before train arrival. This pattern continued until nine columns were filled in total, with each row (from left to right) containing one receptive field's mean value followed by mean values from the eight previous receptive fields. Each row of this array formed one observation.

(d) A label column was added to the array. Each cell of the label column contained "true" if the value in the first column of an observation was formed from a receptive field whose start time was less than or equal to 20.0 s before train arrival; otherwise, the cell contained "false". In other words, for most approaches, only the bottom 39 values of the label column were "true".

4. The data were then partitioned into the training set (used to train or fit the classification model) and the testing set (used to test the performance of the classifier on data it had not seen). A site-stratified random sample of 80% of train approaches were designated for the training set, while the other 20% were used for the testing set. Within each of these data sets, the arrays containing labelled observations for the various train approaches were concatenated.

The data were then ready for model fitting (see Methods).

C.4 Characteristics of recorded spectrograms and the railway track

C.4.1 Observations from in-rail vibration spectrograms

We note here two observations of interest from the spectrograms of our train approach recordings that were not directly relevant to our manuscript. We also include information about the materials of the railway track.

1. Within each site and for each approach direction, train speed appeared to be inversely proportional to the time in advance of arrival at which vibration signals were visible; i.e., lower train speed resulted in earlier signal onset. This indicated that vibration transmission distance was roughly the same for each train along a given track section. We also observed that this distance was decreased wherever joints or lubrication stations (which apply thick grease to rails) were located between the approaching train and the sensor. If approach detectors are implemented in the future, they should be placed at least 20 s at maximum train speed away from these signal obstructions.

2. The in-rail acoustic train signals detectable at the greatest distances were exclusively ultrasonic, mainly 20 kHz to 40 kHz. The absence of lower frequency vibrations at long range is not an artifact of our equipment, as the piezoelectric sensor (Measurement Specialties Inc. 2009) and preamplifier (Figure C.1) both have flat frequency responses in the range recorded (10 Hz to 192 kHz). Trains generate considerable track vibration over a wide frequency range, but ultrasonic waves likely propagate the farthest as an unintended feature of the shape, construction, and materials of the track (see railway track details, below; Rose et al. 2004).

C.4.2 Railway track details

For all sites, the railway track comprised two continuously welded steel rails with a typical distance between bolted joints of 1.5 km to 2.5 km. The rails were attached via steel tie plates and straight spikes (typical on straight track) or screw-spikes and curved clips (typical on curved track) to creosote-treated wooden ties, which were lain within and underlain by ballast rock to an unknown depth. Bolted rail joints were either electrically conductive (allowing electrical continuation of the track circuit through a fishplate, which connects the rail segments) or electrically insulated (by epoxy resin placed between the rails and fishplates). Typical rails were manufactured from eutectoid steel (e.g., Nippon Steel grade DHH370S) or hyper-eutectoid steel (e.g., Nippon Steel grade HE370S) in the 136 pounds-per-yard 136RE (Railway-Engineered) American Railway Engineering and Maintenance-of-Way Association (AREMA) standard rail profile. The rails had also been subjected to vacuum hydrogen elimination and head-hardening treatments (Nippon Steel and Sumimoto Metal Corporation 2015).

C.5 Design of a passing relay prototype.

We discuss here our selection of the warning stimuli and other parts for a prototype of the passing relay. Schematics, assembly suggestions, and code follow.

C.5.1 Warning signals design

As mentioned in our paper, little data are available on auditory and visual perception ranges of many of the wild species in our study area (e.g., grizzly bears, black bears, wolves, elk, moose). However, available information for other species may guide preliminary designs for warning signals. Here we draw from the literature on animal perception as well as design guidelines for warning signals used in human contexts.

Visual stimuli

Our need for a low-cost, power-efficient visual stimulus may be met most simply by a light source. Modern light-emitting diodes (LEDs) are both inexpensive and efficient, and they are offered in a wide range of colours and luminous flux ratings. To select an LED and decide how it will be used, one must consider the suitability of various colours, flux ratings, and flash patterns (if any) for the situation of interest. The choice of LED will not affect the weather resistance of the warning device because light can be transmitted from within a weather-proof enclosure via transparent materials.

To be perceived by an animal, light must reach and stimulate photoreceptors in the eye. In mammals, the colours of light transmitted by the cornea and lens can vary among species. This may lead, for example, to variation in mammalian ability to perceive ultraviolet light (Douglas & Jeffery 2014). The colours of light most likely to stimulate photoreceptors also vary among species, with most mammals being dichromatic (Bowmaker 1998) and thus relatively insensitive to red light (wavelengths greater than approximately 620 nm; e.g., Cohen et al. 2014). A stimulus intended for perception by many species should then be chosen from within the remaining visible spectrum (from yellow through green to blue), bearing in mind that the effects of light colour within this range could still vary substantially by light level among species. For instance, green lighting has been suggested for nighttime use on offshore oil drilling platforms to allow birds to maintain their light-sensitive magnetoreceptive sense, which is disrupted by longer-wavelength light (Poot et al. 2008). Some carnivores may possess a similar cryptochrome-mediated magnetic sense (Niessner et al. 2016), and this sense could conceivably be interrupted by exposure to long-wavelength light (including white train headlights). On the other hand, a magnetic sense could be unhelpful for orientation in the railway environment due to the highly variable residual magnetization of steel track components (Colleen St. Clair, unpublished data). Additionally, we may wish to help animals maintain their dark-adapted (scotopic) vision at night by avoiding wavelengths to which rod photoreceptors (primarily responsible for low-light vision) are sensitive. For humans, red lights are often used at night for this reason (Mertens 1955). However, dichromatic animals do not have a photoreceptor specialized for long-wavelength light, and our warning signal must be highly salient both at night and during daylight hours. As a compromise, we have chosen to use amber light (near 590 nm).

To attract attention, visual stimuli must contrast highly with their surroundings. To create this contrast during daylight conditions, warning lights must have a high luminous intensity (i.e., luminous flux per unit solid angle). For instance, traffic warning lights, whether flashing or steady, must have an intensity of 200 cd to be highly salient at a viewing distance of 100 m in normal daylight (Cole & Brown 1966, 1968). The transportation literature also recommends that warning lights be dimmed at night by up to a maximum of 50% (Institute of Transportation Engineers 1998), reducing glare that could affect drivers' ability to see their surroundings. Dimming at night, along with the use of an amber colour, could help animals maintain the use of their scotopic vision while moving off the railway tracks. To meet these requirements, the LEDs chosen should have a high maximum luminous flux, and their power supply should have dimming capability.

Flashing lights are generally considered to be more attention-grabbing than steady lights for humans (Gerathewohl 1953; De Lorenzo & Eilers 1991). Based on research in the contexts of emergency vehicle and fire alarm warning lights, shorter and brighter flashes may be disproportionately attention-grabbing compared to longer, dimmer flashes of equal time-averaged ("effective") intensity (Bullough & Zhu 2012). Flash durations of 1 ms to 200 ms (depending on intensity) at frequencies of 0.5 Hz to 4 Hz are suggested by a number of studies (reviewed by Bullough & Zhu 2012). Multiple adjacent lights should also be synchronized, so as to avoid a 10 Hz to 90 Hz flash frequency that may trigger epileptic phenomena in humans in exceedingly rare cases (De Lorenzo & Eilers 1991; Bullough & Zhu 2012). Thus, for our warning lights, both flash rate and duration should be adjustable through control of the LED power supply.

Auditory stimuli

Auditory stimuli can be reproduced by small, low-cost technologies such as miniature speakers and piezoelectric buzzers. The salience of a stimulus is governed by the frequency content of the sound and the sound power level (De Lorenzo & Eilers 1991). The requirement for uniqueness of the stimulus in the experience of animals (to enable a unique learned association) leaves a wide range of possible choices. Weatherproofing may be an issue, because the sound emitted by speakers or buzzers will be reduced if no holes exist in the enclosure through which the sound can efficiently escape. As a simple alternative, a surface transducer (a specialized speaker that uses a flat surface or cavity to produce sound) can be attached to an inner wall of the warning device enclosure to produce sound external to the enclosure without the need for holes.

Though the hearing ranges of few large wild mammals have been characterized, polar bears (Owen & Bowles 2011), white-tailed deer (H. Heffner & H.E. Heffner 2010), and many smaller mammals (Fay 1988) are known to share at least part of their hearing range with humans. In particular, sensitivity in the frequency range 1 kHz to 4 kHz is common. Any warning sound with spectral components in this range should be perceptible to the large mammals that our system targets.

The sound should also be loud enough to be obvious over background noise wherever the device is placed on the railway. Although we have not quantified noise levels along the railway nor the sound power level produced by a surface transducer on our enclosure, the dependence of signal-to-noise ratio on distance from the warning device may determine the maximum spacing between warning devices. The sound should not be loud enough to damage any animal's hearing—human safety standards place a limit at, for example, 115 dB (A-weighted) for 28 s of daily exposure (NIOSH 1998). A smaller upper limit on the sound power level may be imposed by our intention to limit the audibility of the stimulus away from the railway track. In particular, the sound should not be heard by animals far from the track in a way that might encourage habituation to the stimulus. Loud sounds on the railway track may also be undesirable for people living, working, or engaging in recreation near the railway track.

Siren-like patterns and sudden noises may be more attention-grabbing at the same time-averaged sound power level than other sound patterns (De Lorenzo & Eilers 1991). However, in our study area (a national park), some areas of the railway track with a history of animal strikes are near tourist viewpoints. Pedestrians are also sometimes present on the tracks, despite the illegality of this activity. To maximize the effectiveness of the warning stimuli without being intrusive to visitors or unintentionally aversive to animals, we may choose to use the familiar sound of warning bells used at road–rail crossings in the area. Since animals and people may already associate this sound with train approach, this would likely be an advantage for our system.

C.5.2 Parts selection

Some experience with electronics design and assembly is assumed in the following subsections. All datasheets referenced are available online from manufacturer websites.

Sensing device

Sensor: We selected the digital compass (Honeywell HMC5883L; Table C.1) for our train detector prototype because of its train detection precision (discussed in our paper), low power consumption, and mechanical durability (Table C.2). We note that the guaranteed operating temperature range of the compass extends down only to −30 °C (see HMC5883L datasheet), but ambient temperatures fall below this range only infrequently in winter in our study area. Further testing would be needed to determine how cold weather affects sensor performance.

The digital interface of the compass allows the sensor to remain in an idle state until a measurement is requested. In this idle state, its current consumption is as low as 2 μA (see HMC5883L datasheet). The accelerometer (Analog Devices ADXL335) does not have this capability, and would consume more current on average (see ADXL335 datasheet). Although the vibration switch (Bai Ling Electronics SW-18010P) by our estimates would consume the least power on average, this advantage is outweighed by its poor durability.

The vibration switch uses a post-and-spring mechanism to detect vibration. The operating lifetime of this mechanism "can reach" 200 000 switchings (see SW-18010P datasheet), but our tests indicate the sensor is activated an average of 120 000 times per day in service. Although our test sensor seemed to function normally after more than 200 000 switchings, further testing would be needed to determine if the 200 000 cycle rating is realistic. Regardless, in a remote device where detection and repair of sensor problems is difficult, we cannot afford to use a sensor that could fail so quickly. The digital compass and accelerometer datasheets report no such vulnerability.

Table C.2: Comparison of three best sensor candidates for the passing relay.

Sensor	Cost (US$)	Mounting requirement	Current used (μA)	Lifespan
Digital compass	10	Away from magnets	< 100	No stated limit
Accelerometer	15	Acoustic contact with rail	350	No stated limit
Vibration switch, weak	1	Acoustic contact with rail	0.001 (estimated)	200 000 cycles

Controller: The Atmel ATmega328P functions as a miniature computer that controls our passing relay prototype. This microcontroller is the same one used in the popular Arduino Uno platform. The chip has enough memory and input/output for our needs, is inexpensive (a few dollars), and supports many power management features (see ATmega328P datasheet). The popularity of the Arduino platform also ensures the ready availability of programming libraries compatible with the other components we choose.

This microcontroller requires a few external components that are often packaged together with it in kits or on completed circuit boards. For ease of prototyping, we used a compact Ardweeny kit (CDN$10; Solarbotics, Canada). Future iterations of this prototype may consider ATmega328P kits specialized for low-power applications, such as the Arduino Pro Mini (3.3V, 8MHz version; US$10; Sparkfun Electronics, USA).

Radio: A wireless communication system is needed to relay trigger signals from the sensing device to the warning device. Based on a comparison of cost, range, legality, and power consumption (Table C.3), we selected the XBee-PRO DigiMesh 2.4 (Digi International, USA). In particular, the power management features of the DigiMesh networking protocol may significantly extend the battery life of our devices: whereas the IEEE 802.15.4 (ZigBee) protocol requires some devices on the network to remain powered on at all times, the DigiMesh protocol allows every device on the network to enter low-power "sleep" modes when not in use (see XBee-PRO DigiMesh 2.4 datasheet). Although simpler and less expensive point-to-point radio links such as the Seeed Studios WLS102B5B (Seeed Studios, China) could be adequate for our needs, we cannot legally use point-to-point radio link kits in Canada because they have not received regulatory approval from the Canadian government. Only holders of Amateur Radio Operator Certificates with Advanced Qualifications from Innovation, Science and Economic Development Canada are allowed to use unapproved radio links in Canada.

Anyone reproducing this prototype must consider the legal requirements for radio communication in their jurisdiction. While the 2.4 GHz band is designated for unlicensed use worldwide, some governments require lower transmission powers for devices that use this band. However, in many countries, other unlicensed bands are available for which higher-power transmission is allowed. Digi International produces alternate versions of their XBee-PRO DigiMesh radios to accommodate these restrictions and allowances.

Table C.3: Detailed comparison of radio candidates for the passing relay. Current use is listed for both transmission mode (TX) and receiving mode (RX).

Radio	Cost (US$)	Line-of-sight range (km)	Frequency (GHz)	Low-power support	Current used (TX/RX; mA @ V)
Basic radio link (e.g., QAM-RX2-433)	8 per pair	0.2	0.433	Via micro-controller	22/4.5 @ 5
Seeed Studios encoded link (WLS102B5B)	15 per pair	2	0.433	Via micro-controller	2.5 @ 5
XBee-PRO ZigBee (S2C hardware)	28 per unit	3.2	2.4	Some nodes sleep	205/45 @ 3.3
XBee-PRO DigiMesh 2.4 (S1 hardware)	32 per unit	1.6	2.4	All nodes sleep	250/55 @ 3.3
XBee-PRO 900HP (S3B hardware)	39 per unit	14.5	0.900	All nodes sleep	215/29 @ 3.3
Atmel ZigBit (ATZB-A24-UFLBR)	39 per unit	Not specified	2.4	Some nodes sleep	157/7.5 @ 3.3

Power:

Voltage regulation. Voltage regulation is required to provide a stable 3.3 V to every component of the sensing device. In this case, voltage regulators convert energy from a battery (where output voltage varies over the discharge cycle) into a stable voltage. To do this, regulators either reduce the voltage by dissipating power as heat (linear regulators) or switch on and off at high frequencies to maintain the desired voltage (switched regulators). Switched regulators can be far more efficient, but are somewhat more expensive and require more external components to function.

We want the sensing device to operate without intervention for months at a time. From the previous parts selections, we recognize that the XBee radios will require the most peak current of any component (up to 250 mA when transmitting; see XBee-PRO DigiMesh 2.4 datasheet). However, the sensing device will spend the vast majority of its time waiting for a train to arrive (less than 1 mA required; Table S7). Thus, an ideal regulator would be highly efficient at both of these required currents, but especially at near-zero currents. We selected the LM3671 (Texas Instruments, USA), a switched 3.3 V regulator with maximum 600 mA output. This unit is not a best fit in terms of efficiency or cost, but it provides good efficiency at both low and high currents (see LM3671 datasheet) and is available pre-assembled on a breakout board (US$5; Adafruit, USA). A more specialized regulator could be selected for later prototypes.

Power source. Batteries are a convenient, low-cost source of power for remote devices. Single-use alkaline batteries, for example, provide a high capacity at the maximum current draw of the sensing device, a low self-discharge rate, and an operating temperature range suitable for year-round operation in some climates (Table C.4). For convenience of prototyping, we chose to use rechargeable nickel metal hydride (NiMH) batteries, but the high self-discharge rate of NiMH batteries makes them unsuitable for long-term field use. The LM3671 regulator should be compatible with four "D"-size cells of either alkaline or NiMH type, based on the maximum rated input voltage of 6 V (see LM3671 datasheet). In colder climates, more costly lithium iron disulphide batteries would work with the LM3671 in four parallel battery packs of three cells each. Use of two lithium thionyl chloride cells would require a regulator with a larger input voltage range, but these batteries have a wider operating temperature range and a much higher energy density.

Power budget. To estimate the operating lifetime of the sensing device, the power required by each component is totalled under three different operating states: transmitting a detection to the warning devices, monitoring for trains, and waiting (powered-down). When a train is detected, we allow the sensing device

Table C.4: Comparison of power source candidates for the passing relay.

Power system	Cost (US$)	Capacity at 250 mA (Wh)	Self-discharge (%/month)	Operating temperature (°C)
Alkaline battery (4 D cells + holder)	10	69	<0.3	-18 to +55
Nickel metal hydride battery (4 D cells + holder)	24	48	15	0 to +50
Lithium iron disulphide (4 × 3 AA cells + holders)	42	50	<0.1	-40 to +60
Lithium thionyl chloride (2 D cells with hybrid capacitors + holder)	90	137	<0.1	-55 to +85

to use its radio for up to 5 s to contact the warning devices. If the sensing device checks for the presence of trains once per second, the remainder of the time can be spent in a powered-down state. We also allow six minutes of the powered-down state after each train detection to allow the entire length of trains to pass. All components we have selected (controller, radio, and sensor) require a 3.3 V power supply, so the power consumption in each operating state can be obtained by multiplying this voltage by the current drawn (as specified in component datasheets). The total power drawn from the battery by the voltage regulator is the amount required by device components divided by the efficiency of the voltage regulator at the provided input voltage and at the required output current. Assuming 20 trains are detected by the sensing device per day, our estimates suggest that the sensing device will consume 0.19 Wh in total per day (Tables C.5–C.7), yielding an operating lifetime of up to one year on four alkaline D cells. However, we note that more realistic networks with more than two devices may require more frequent radio communication, reducing the ability for radios to sleep between train detections and thus reducing the operating lifetime.

Enclosure: Size, material, mounting, and security requirements must be considered when selecting an enclosure.

Characteristics. The sensing device must be placed in an enclosure to protect it from water, dust, mild impact (e.g., shifting ballast rock), and ultraviolet

Table C.5: Power budget of the sensing device for a train detection event. If 20 trains are detected per day, and 5 s are spent transmitting to the warning devices per train (1.3 mWh per event), a total of 25 mWh will be expended in the transmission state per day.

Component	Power state	Power used (mW)
Sensor	Idle	0.007
Controller	Active	30
Radio	Active	830
Total	Train detection	860
Regulator	Efficiency: 93%	920

Table C.6: Power budget of the sensing device while monitoring for trains. If an estimated 0.2 s out of every second are spent in this state, excluding time within 360 s of a train detection to allow trains to pass, a total of 160 mWh will be expended in the monitoring state per day.

Component	Power state	Power used (mW)
Sensor	Active	0.330
Controller	Active	33
Radio	Sleeping	0.170
Total	Monitoring	33
Regulator	Efficiency: 89%	37

Table C.7: Power budget of the sensing device while not monitoring for trains and not transmitting. If an estimated 0.8 s out of every second are spent in this state, apart from the 360 s after train detection which is fully spent in this state, a total of 5.5 mWh will be expended in the idle state per day.

Component	Power state	Power used (mW)
Sensor	Idle	0.007
Controller	Power-save	0.003
Radio	Sleeping	0.170
Total	Waiting	0.180
Regulator	Efficiency: 65%	0.280

radiation. The enclosure must also be able to accommodate the size of the components selected for the sensing device (Table C.8). For testing purposes, we desired an enclosure that could be mounted either on the outer web of the rail or in the ballast between the rails. The enclosure must also allow radio signals to pass freely through its walls, or else a separate antenna external to the enclosure will be needed (at additional cost).

We selected the Bud PN-1334-C enclosure (US$23.70; Bud Industries, USA) to meet these requirements. Additionally, this enclosure features an optional clear lid to allow viewing of the device components (used for this prototype only). The enclosure is composed of polycarbonate, offering greater impact resistance, ultraviolet resistance, and radio-frequency transparency than other plastics commonly used for electronics enclosures. The enclosure also has a NEMA (National Electrical Manufacturers Association) 4 rating which guarantees resistance to dust, sprayed or falling liquids, and ice formation.

Table C.8: Space budget for the enclosure of the passing relay sensing device. Dimensions are from component datasheets.

Component	Length (mm)	Width (mm)	Height (mm)
Battery holder	137.5	71.5	28.5
Ardweeny controller	40	14	20
XBee-PRO (wire antenna)	33	24.5	28
Compass breakout board	18	18	3
Enclosure (Bud PN-1334-C)	200 (outer)	120 (outer)	75 (outer)

Mounting and security. The selected enclosure also features through-holes at its four corners that are external to the enclosure. These could be used to attach countersunk bolts and rare earth magnets for mounting to the rail, though this option is costly if we require magnets strong enough to deter theft of the devices (e.g., four magnets at a minimum of US$15 each from K&J Magnetics, USA). Adhesives could be used as a lower-cost and more secure means of attaching the enclosure to the rail, though a permanent bond would be needed to deter theft (e.g., methacrylate two-part adhesives). Bolting the enclosure to the rail is a less-attractive option because this would require holes to be drilled in the rail, and this requirement may not be supported by railway companies. Placing the enclosure flush with the ballast rock between ties requires no means of attachment, but this strategy relies on camouflage alone to deter theft and vandalism. Additionally, radio range may be significantly reduced by the combined obstruction of the steel rails and the wooden ties.

Other theft deterrents are possible. For example, a short steel cable could be secured with a padlock between the enclosure and a permanent fixture (such as a rail spike). The enclosure itself could be modified with a locking mechanism or security screws, or the electronics could be fully potted (engulfed in epoxy) to prevent removal and tampering. To reduce detectability of sensing devices and inactive warning devices, the devices could be designed with lower-profile enclosures and then painted to match the rusty surface of the rail. Design and testing of these ideas may be pursued for later prototypes.

Warning device

Radio: The radio used in the warning device must match the one selected for the sensing device. In this case, we selected the XBee-PRO DigiMesh 2.4 (S1 hardware, wire antenna). Because these radios are two-way, power must be provided in the warning device for both transmission and reception.

Controller: As did the sensing device, the warning device used the ATmega328P microcontroller.

Warning signals:

Visual. As discussed earlier, we have chosen to provide LED light of amber colour (near 590 nm) to minimize interference with animal scotopic vision but still be easily detected by the long-wavelength cone photoreceptors of dichromatic animals. The LED power supply must be compatible with our chosen microcontroller to allow programmable dimming and flashing of the LED. The LED must also be extremely bright (50 cd to 200 cd luminous intensity).

We selected the Cree XP-E2 PC (phosphor-converted) Amber LED (US$2.60; Cree, USA), which is among the brightest amber LEDs available (100 lm to 107 lm at 350 mA). If the enclosure is mounted on the outer web of the rail, two LEDs will be used per warning device to cast light out along the track from opposite sides of the enclosure. These can be made to flash for 10 ms every 1 s, minimizing the impact of their high instantaneous power draw on battery life and avoiding the added expense of large heat sinks for each LED. The LEDs were mounted on metal-substrate printed circuit board (MSPCB) starboards to provide some heat sinking. The starboards were then attached to lenses and lens holders (Table C.9) to focus the LED light down the tracks and thereby increase the number of candelas per lumen. We also designed an LED driver based on the TI LM3405 regulator (Texas Instruments, USA; Table C.9), which is dimmable and flashable with our microcontroller but which draws its power directly from the batteries. To simplify the design, one driver was used per LED, but for later prototype versions a single driver could be used for both LEDs with power transistors switching the drive current between them.

For future prototypes, we may suggest using an amber LED without phosphor conversion, because the phosphor-converted amber has a broad emission spectrum that may interfere somewhat with animal scotopic vision at night. We also suggest that warning devices mounted flush with the ballast between ties could use a single LED and a 360-degree reflector mounted on the top of the enclosure to ensure no light is wasted.

Auditory. As discussed earlier, we chose to provide auditory stimuli with a surface transducer adhered to the inner surface of the warning device enclosure. We selected a surface transducer capable of accepting up to 1 W input power and producing a sound power level of up to 90 dB (Bone Conductor Transducer with Wires, 8 Ω 1 W, US$9; Adafruit Industries, USA). Playback of sound can be produced by the ATmega328P via its pulse-width modulation (PWM) output in combination with a power transistor acting as a basic audio amplifier (Table C.10). Sound quality could be improved in later prototypes with the addition of

Table C.9: Parts list for the visual warning system (per light-emitting diode (LED)).

Subsystem	Component	Quantity
Light	Cree XP-E2 PC Amber LED	1
	MSPCB Starboard	1
Optics	Carlco 20 mm lens	1
	Carlco universal 20 mm lens holder	1
Driver	TI LM3405 regulator	1
	SOT23 breakout board	1
	1N5817 Schottky diode	1
	BAT85S Schottky diode	1
	0.01 μF capacitor	1
	10 μF capacitor	1
	1 μF capacitor	2
	10 μH inductor	1
	0.22 Ω resistor	1

a simple low-pass RC (resistor and capacitor) filter. The memory on board the ATmega328P can be used to store approximately 2 s of audio at 8 bits per sample and 8000 samples per second, sufficient for a warning bell sound similar to that used at road–rail crossings in the area. For alternative sounds that are longer or have higher-frequency content, additional memory could be added with low-cost integrated circuits or SD (secure digital) memory cards.

Table C.10: Parts list for the auditory warning system.

Subsystem	Component	Quantity
Amplifier	FDP8896 Power NFET (transistor)	1
	SB560 Protection diode	1
Speaker	Surface transducer	1

Power:

Voltage regulation. The same LM3671 regulator selected for the sensing device can be used to power the controller, radio, and auditory warning system. The LEDs, however, require regulated currents of up to 1 A to achieve their full brightness. The LM3405 regulator described above was chosen for this purpose.

Power source. As for the sensing device, four alkaline D cells would provide a large amount of energy at a low cost for the warning device. We used nickel metal hydride batteries for prototype testing purposes only.

Power budget. To estimate the operating lifetime of the warning device, we totalled the power drawn by each component in different operating states as was done for the sensing device. The three states were for a train detection event (warning signals active), checking for messages from the sensing device (radio active), and power-down (all components sleeping). In each case, estimating the power drawn by an LED driver is more complicated because the driver draws power directly from the battery (for which the voltage varies as it drains), rather than from the 3.3 V regulator. However, we will assume an average battery voltage of 4.9 V (1.225 V per cell) over the discharge cycle (AllAboutBatteries.com 2016). Given the LM3405 is designed to provide an output voltage of 3.5 V at an output current of 1 A (see LM3405 datasheet), and since the LM3405 is near 80% efficient under these conditions, it will consume 4.4 W when turned on. Each LED is assumed to flash for 10 ms every 1 s, staggered so that the LM3405s are not turned on simultaneously. This flashing occurs for 25 s every time the warning device receives a train detection trigger so that, accounting for both LEDs, 0.6 mWh will be consumed each time the visual warning system is activated. When the visual warning system is inactive, the two LM3405 systems together will consume approximately 3 μW. We also assume that the audio amplifier will be providing current to the transducer half of the time (on average) over the 25 s warning period, consuming an average of 205 mA or 0.7 W during this time. The amplifier should consume 6 μA or 20 μW when inactive. We also assume the radio is set to check for messages once per second and only requires 100 ms to do so. The time required for message checking may increase with the size of the radio network, so 100 ms may not be feasible for realistic networks with more than two devices. Increased time spent checking for messages will decrease the estimated operating lifetime. All components are powered down for six minutes following the completion of a train detection event.

Assuming 20 trains are detected by the sensing device per day, our estimates suggest that the warning device will consume 0.16 Wh per day (Tables C.11–C.13), yielding an operating lifetime of up to 1.2 years on four alkaline D cells.

We note that driving the LEDs alone requires in excess of 1 A of current directly from the batteries, and driving the audio warning system at the same time the radio is active may require up to 1.5 A. Drawing this much current would reduce the effective capacity of alkaline batteries if the draw were constant over time. Testing should be done on the built prototype to determine the likelihood of the device lasting for the estimated 1.2 years. Incorporation of a small supercapacitor as a secondary power source or the use of more specialized LED flash drivers with inductive or capacitive energy storage could reduce the maximum current demand on the batteries.

Table C.11: Power budget of the warning device during a train detection event. If 20 trains are detected per day, if 5 s are spent communicating with the sensing device per train, and if this time plus 20 s is spent activating the warning signals (7.5 mWh per event), a total of 150 mWh will be expended per day in the warning state.

Component	Power state	Power used (W)
Radio	Active (first 5 s only)	0.825
Controller	Active	0.33
Auditory warning	Active	0.700 (time average)
Subtotal	Reception and audio warning	1.6 for first 5 s; 0.7 thereafter
LM3671 regulator	Efficiency: 93%	1.7 for first 5 s; 0.8 thereafter
Visual warning	Active	0.88 (time average, 2 LEDs)
Total	Reception and warning	1.8 for first 5 s; 0.9 thereafter

Enclosure: The addition of the LEDs, LED drivers, an audio amplifier, and a surface transducer did not significantly increase the space required for the warning device electronics over that needed for the sensing device electronics. The same enclosure (Bud PN-1334-C) was thus used as for the sensing device prototype.

Table C.12: Power budget of the warning device while checking for messages from the sensing device. If 900 ms of every 1 s (apart from train detection events and the subsequent power-down) is spent in this state, a total of 2.8 mWh will be expended per day in the checking state.

Component	Power state	Power used (mW)
Radio	Active	0.825
Controller	Active	0.33
Auditory warning	Inactive	0.020
Subtotal	Checking	1.2
LM3671 regulator	Efficiency: 94%	1.3
Visual warning	Inactive	0.003
Total	Checking	1.3

Table C.13: Power budget of the warning device while inactive (not checking for messages and not providing warning signals). If all time except time during warning events and message checks is spent in this state, a total of 6.5 mWh will be expended per day in the sleeping state.

Component	Power state	Power used (mW)
Radio	Sleeping	0.170
Controller	Power-save	0.003
Auditory warning	Inactive	0.020
Subtotal	Sleeping	0.193
LM3671 regulator	Efficiency: 65%	0.296
Visual warning	Inactive	0.003
Total	Sleeping	0.3

C.5.3 Bills of materials

Tables C.14–C.16 list the parts (with costs) used to build the prototype devices. We list the parts used in each device (Tables C.14 and C.15) as well as materials that were needed for assembly but not entirely used (Table C.16).

Table C.14: Bill of materials for the passing relay sensing device.

Part	Part Number	Supplier	Cost (US$ @ qty. 1)
Digital compass with breakout board	1528-1030-ND	Digi-Key	9.95
Solarbotics Ardweeny controller	KARDW	Solarbotics	(CDN$)13.43
XBee-PRO DigiMesh 2.4 (S1, wire antenna)	602-1482-ND	Digi-Key	32.00
XBee breakout board	1568-1099-ND	Digi-Key	2.95
4 × D-cell	N105-ND	Digi-Key	4 × 1.60
Battery holder	BH4DW-ND	Digi-Key	3.89
LM3671 regulator breakout	1528-1430-ND	Digi-Key	4.95
Bud PN-1334-C enclosure	377-1257-ND	Digi-Key	23.70
Consumables (protoboard, solder, glue)		(Estimated)	5.00
Total			98.84

C.5.4 Schematics

Schematics are provided for the sensing device (Figure C.2) and the warning device (Figure C.3).

Table C.15: Bill of materials for the passing relay warning device.

Part	Part Number	Supplier	Cost (US$ @ qty. 1)
XBee-PRO DigiMesh 2.4 (S1, wire antenna)	602-1482-ND	Digi-Key	32.00
XBee breakout board	1568-1099-ND	Digi-Key	2.95
Solarbotics Ardweeny controller	KARDW	Solarbotics	(CDN$)13.43
4 × D-cells	N105-ND	Digi-Key	4 × 1.60
Battery holder	BH4DW-ND	Digi-Key	3.89
LM3671 regulator breakout	1528-1430-ND	Digi-Key	4.95
Bud PN-1334-C enclosure	377-1257-ND	Digi-Key	23.70
2 × TI LM3405 regulator	LM3405XMK/NOPBCT-ND	Digi-Key	2 × 1.38
2 × 1N5817 Schottky diode	1N5817FSCT-ND	Digi-Key	2 × 0.43
2 × BAT85S Schottky diode	BAT85S-TAPCT-ND	Digi-Key	2 × 0.56
2 × 0.01 µF ceramic capacitor	BC2662CT-ND	Digi-Key	2 × 0.22
2 × 10 µH inductor	RLB0912-100KL-ND	Digi-Key	2 × 0.50
2 × 10 µF ceramic capacitor	445-8549-ND	Digi-Key	2 × 0.45
4 × 1 µF ceramic capacitor	445-8417-ND	Digi-Key	4 × 0.32
2 × 0.22 Ω 5% resistor	A105965CT-ND	Digi-Key	2 × 0.30
2 × Cree XP-E2 PC Amber LED, starboard-mounted	CREEXPE2-PCA-1	LEDSupply	2 × 4.99
2 × Carlco TIR 20mm ripple wide optic	1066-1026-ND	Digi-Key	2 × 2.28
2 × Carlco 20mm universal optic holder	1066-1068-ND	Digi-Key	2 × 0.65
3 × 10 kΩ 5% resistor	CF14JT10K0	Digi-Key	3 × 0.10
Acoustic surface transducer	1674	Adafruit	8.95
Power MOSFET	FDP8896-ND	Digi-Key	1.29
SB560 protection diode	SB560FSCT-ND	Digi-Key	0.52
Consumables (protoboard, solder, glue)		(Estimated)	5.00
Total			121.99

Table C.16: List of consumables, prototyping products, and programming accessories.

Part	Part Number	Supplier	Cost (US$ @ qty. 1)
Header pins (male)	392	Adafruit	4.95
Header sockets (female)	598	Adafruit	2.95
Adafruit SMT breakout set (includes 5 × SOT23)	1528-1072-ND	Digi-Key	4.95
Prototyping board, FR-4	V2012-ND	Digi-Key	10.59
IC sockets (28-pin 0.1“ mating pitch, 0.3” row pitch DIP for ATmega328P)	2205	Adafruit	1.25
3.5mm headphone jack (for audio system tests)	1699	Adafruit	0.95
FTDI-compatible XBee Adafruit breadboard adapter	1528-1119-ND	Digi-Key	10.00
FTDI-to-USB adapter	39240	Solarbotics	(CDN$)20.18
Micro USB to USB male cable	14085	Solarbotics	(CDN$)6.68
Lead-free solder paste (for LED mounting)	MG Chemicals 4900P-25G	Amazon.com	15.02
Acrylic lacquer conformal coating (protects electronics)	MG Chemicals 419C	Amazon.com	15.79
Silicone RTV adhesive sealant	Permatex 80050	Amazon.com	5.72
Heat sink for LED testing	345-1105-ND	Digi-Key	2.34
Thermal tape for bonding LED to heat sink	1168-1853-ND	Digi-Key	0.37

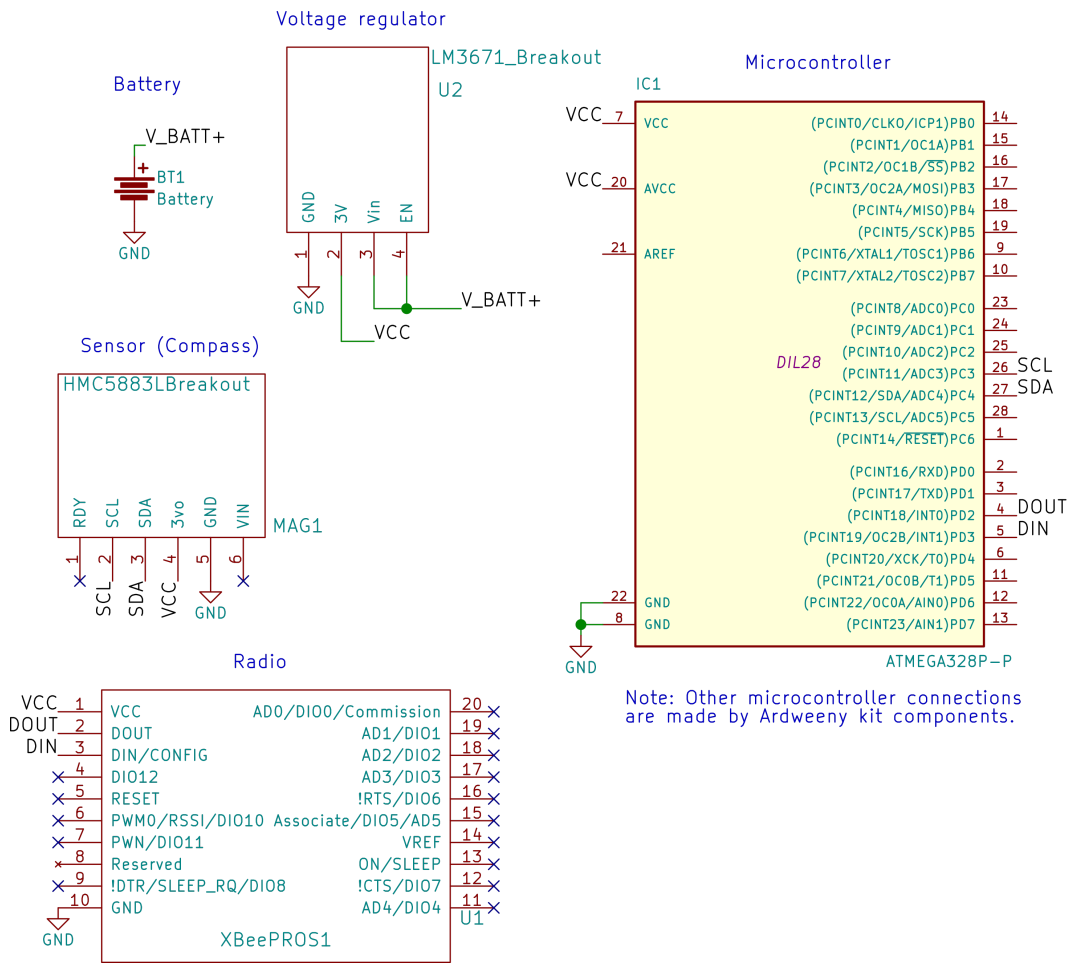

Figure C.2: Sensing device schematic for the passing relay.

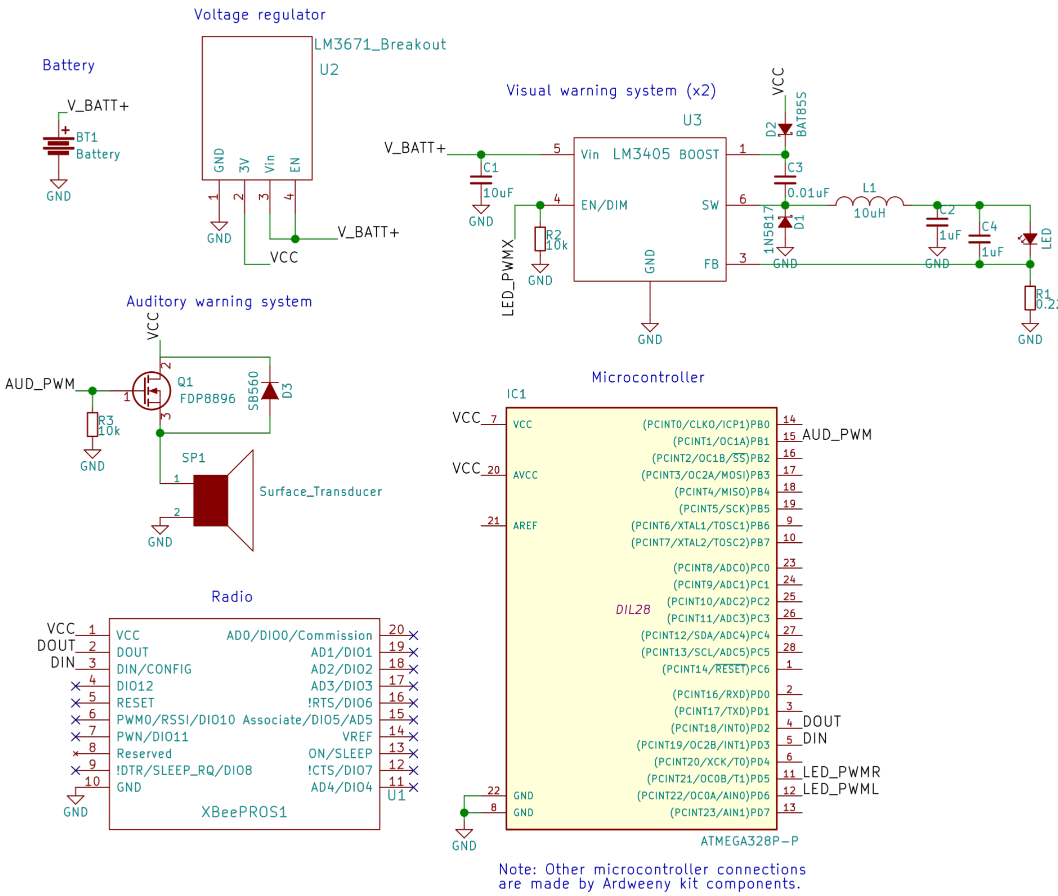

Figure C.3: Warning device schematic for the passing relay.

C.5.5 Code

The code used to program the sensing and warning devices is included in the online supporting information for the published manuscript (Backs et al. 2017). The file `sensing.ino` programs the sensing device and requires the included library `Adafruit_HMC5883_Unified_Mod`. The file `warning.ino` programs the warning device and requires the included header file `oneRing.h`. License information and references are included in the body of the code. Code was compiled and uploaded to the microcontrollers using version 1.6.9 of the Arduino integrated development environment and the TTLyFTDI USB-to-TTL Cable Adapter (Solarbotics Ltd., Canada; Table C.16).

C.5.6 Completed prototype photographs

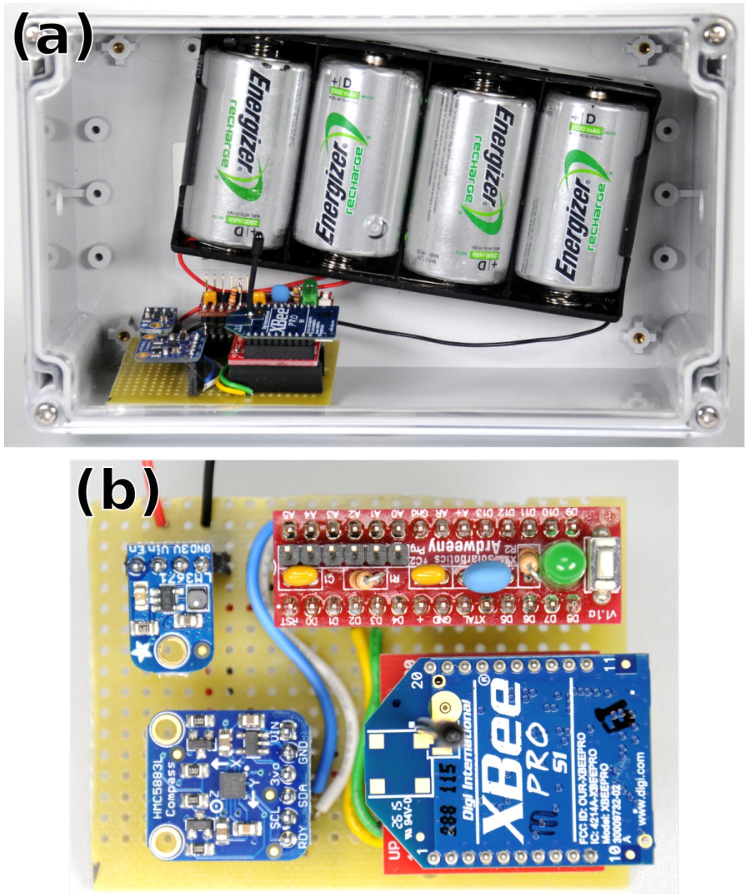

Figure C.4: Photographs of the completed sensing device. (a) Top-down view of the whole device. (b) Close-up view of the circuit board.

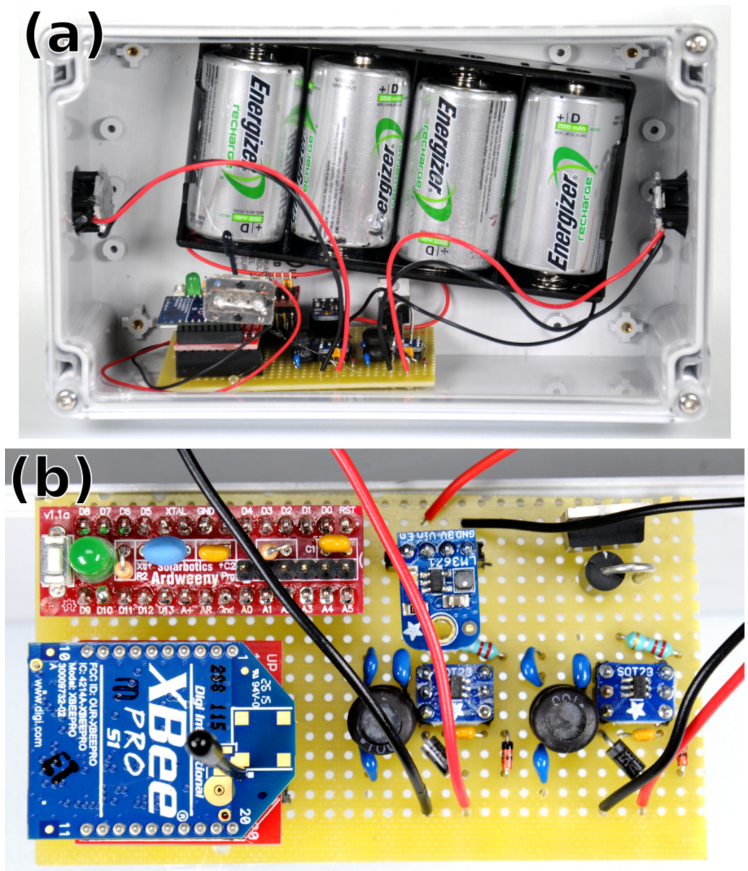

Figure C.5: Photographs of the completed warning device. (a) Top-down view of the whole device. (b) Close-up view of the circuit board.

C.6 References

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Appendix D

Supporting information for "Warning systems triggered by trains increase flight-initiation times of wildlife"*

D.1 Warning system design

This appendix provides the information needed to reproduce the warning systems used in our experiment. Familiarity with the fundamentals of electrical engineering is assumed. Datasheets for specific components are available from the component manufacturers, and will not be listed in the References. The warning system prototypes were designed by Jonathan Backs, including electronic and mechanical components except where noted. Printed circuit board layouts were designed in collaboration with G2V Optics Inc. (Edmonton, Alberta, Canada), but the authors of this manuscript retain ownership of the layouts.

D.1.1 System concept and requirements

In previous work, we designed a prototype warning system capable of providing light and sound stimuli to animals at a consistent time before train arrival (Backs et al. 2017). We improved upon and modified that prototype in these ways:

1. Trains will be detected 40 s before they arrive at the center of the test zone. This will allow cameras on both sides of the test zone to be triggered 10 s

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before the warning devices activate at 30 s before train arrival. The warning devices will provide stimuli for 35 s, allowing trains to pass before the stimuli cease.

2. To reduce equipment costs, only four warning devices will be used per 200 m test zone. The warning stimuli are then required to be visible and audible at a distance of at least 25 m.
3. The system must function in the presence of moisture and dust, and throughout the temperature range −40 °C to 80 °C, based on the expected climatic variation (plus solar heating) on the railway track in Banff National Park, Alberta, Canada.
4. The system must function for at least two weeks on a single set of batteries.
5. Train detectors and warning devices mounted on the outer web of the railway track must be
   (a) low enough in profile that they are not struck by passing trains or other track vehicles, and
   (b) resistant to vibration.
6. All devices should be visually inconspicuous to minimize theft and vandalism, and also to reduce the presence of visual cues that could influence the behaviour of animals within the test zone.

Our new prototypes were developed iteratively based on these revised requirements. In the following sections, we offer detailed instructions for the reproduction of our most recent prototypes. We also document some of the lessons learned through this process. In the last section, we propose some improvements we envision for this system.

D.1.2 Enclosures

Our enclosures for the devices composing the warning system were designed to protect the electronics within each device at a low cost and with a low physical profile. We first used an enclosure system where the devices were fitted inside an acrylonitrile butadiene styrene (ABS) tubing with an inner diameter of 1.5 inches (schedule 40 tubing; Figure D.1). ABS material was selected due to its modest transparency to wireless radio-frequency signals, its durability under a wide temperature range, and its acceptable resistance to chemical degradation from both aliphatic hydrocarbons and fresh water present in the railway environment (Campo 2008; Wiłkomirski et al. 2011; MatWeb 2020a). While polycarbonate, another common enclosure material, performs better on all of these metrics and additionally has high resistance to ultraviolet degradation, ABS was lower in cost and could be painted to provide some protection against sunlight (MatWeb 2020a,b). For mechanical stability and to transmit vibrations directly to the train detector's circuit board, we designed half-round aluminum mounts that fit snugly within the tubes and screwed directly through the tube body to external magnets that attached to the railway track (Figure D.2). This design constrained our circuit boards to be long-and-narrow in shape (e.g., Figure D.7). The tubes were made long enough to accommodate the circuit board mount as well as a set of three D-cells in series for power. While the resulting devices were indeed low in profile, they proved difficult to maintain.

Figure D.1: Photograph of the tube enclosure (a train detector) attached to the railway track.

Part-way through the present study, we retrofitted the warning system with box-shaped enclosures (Figure D.3). We selected a hinged box with a gasket seal (Table D.1) that was large enough to accommodate our existing circuit boards and

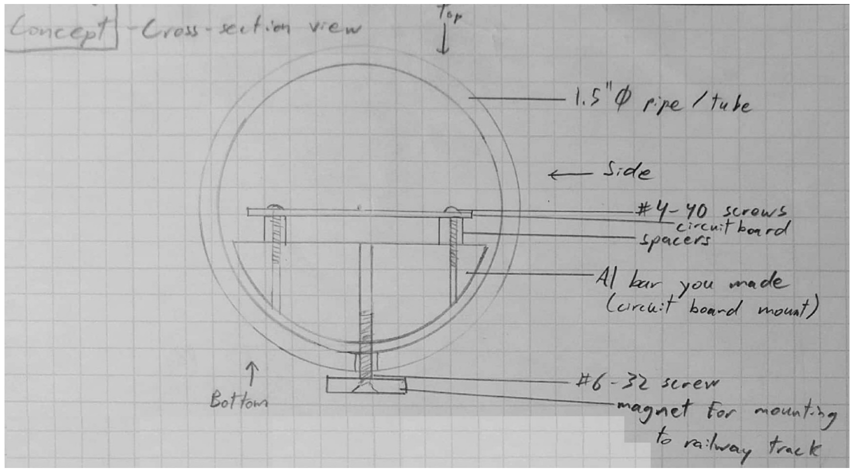

Figure D.2: Cross-sectional concept drawing for the tube enclosure. Detailed drawings for each of the tubes and the aluminum circuit board mounts are not shown.

batteries, yet small enough to be mounted within the outer web of the railway track. Whereas the tube enclosures had to be near-completely disassembled to check for damage and replace batteries, the box enclosures allowed quick access to all components of each device. Circuit boards and battery holders were attached to the interior of the enclosure using a sandwiched combination of foam mounting tape and nylon hook-and-loop, where foam tape was attached to the underside of the circuit board, followed by a layer of hook and loop, then another layer of foam mounting tape that attached to the interior of the enclosure. This mechanism was designed to reduce vibrational coupling between the circuit board and the track, reducing damage to the electronics caused by train vibrations while not appreciably hindering our ability to detect trains via vibrations. Holes were drilled in the enclosures for the speakers and lights of the warning devices as well as the camera cable on the camera controller. The components were mounted in these holes with hot-melt adhesive, and the remaining space was then sealed with silicone.

Common features

Each enclosure was provided with a dessicant packet (Table D.1) as a precautionary measure to reduce the potential for moisture to interfere with the electronics.

Figure D.3: Photograph of the box enclosure (a train detector) attached to the railway track.

Table D.1: Bill of materials for one box enclosure. Consumables are indicated with unspecified quantities. Components specific to track-mounted and tree-mounted devices are separated.

Part	Qty.	Supplier/Mfr.	Part number
All enclosures			
Hinged box ABS gray 10.63“L X 3.93”W with mounting hardware	1	Bud Industries	NBF-32008
Paint (Ultimate Hammered Burnished Amber)		Rust-oleum	–
Device decal (printable labels, paper + clear)	1	Avery	–
Foam mounting tape, weather resistant, 3/4“x1.5”, .063“ thick		McMaster-Carr	76535A31
General purpose nylon hook-and-loop, 3/4“ width, adhesive		McMaster-Carr	9273K33
Dessicant pack, indicating, silica gel, for 36 cu in space	1	McMaster-Carr	3492T13
Hot melt adhesive, craft grade		(Unknown)	–
Silicone (3M Super Silicone, 3oz tube)		McMaster-Carr	74955A53
Track-mounted devices			
Mounting magnets, countersunk for #6 screws	2	K&J Magnetics	MMR-A-X8
#6-32 screws, countersunk, 18-8 stainless steel, 3/8“	4	McMaster-Carr	91771A146
Washer for mounting screw, #6	4	McMaster-Carr	92141A008
Nut for mounting screw, #6-32	4	McMaster-Carr	91841A007
Loctite 222 (purple, low strength)		McMaster-Carr	1810A27
Tree-mounted devices with external antennas			
Self-sealing tape (protects antenna–RP-SMA joint)		McMaster-Carr	7682A65
Electrical tape, black (3M Super 33+)		McMaster-Carr	76455A22
Wood screws, 18-8 stainless steel, #8, 1-5/8“	2	McMaster-Carr	98643A350

Although a few of the enclosures occasionally allowed water entry in quantities the dessicant packets could not absorb, we did not record any instances where the electronics were found to fail because of moisture ingress.

Every enclosure (tube and box alike) was painted with a textured spray paint selected to imitate the rusted appearance of railway tracks. This treatment was remarkably effective at making the enclosures difficult to see at a distance. We also affixed upon each enclosure a label that identified the device inside and included text intended to deter theft and vandalism: “Wildlife Protection System. DO NOT DISTURB. Area is monitored.” The text was printed onto white label paper, and each label was then affixed to the painted surface of the enclosure. Clear plastic labels of the same size were then affixed overtop of the paper labels to provide some protection against moisture and debris.

Methods of attachment

Track-mounted devices were attached to the railway track with a pair of neodymium magnets (Table D.1). We used mounting magnets that came with countersunk holes for #6 screws, which were initially screwed directly into tapped holes in the aluminum circuit board mount for the tube enclosures. Later, we mounted the same magnets on the box enclosures by connecting them to the built-in mounting brackets with #6 hardware (Figure D.4). Loctite 222 was used to keep this assembly from dismantling under the influence of train vibrations. Further, for train detectors, mounting brackets were rotated such that the magnets were held outside the footprint of the enclosure, keeping them as far away as possible from the digital compass.

Tree-mounted devices were attached to trees with wood screws (Table D.1) inserted through the mounting brackets included with the box enclosures (Figure D.5). The earlier tube enclosures were more simply tethered to tree branches using bungee cords, so that they could be easily removed for maintenance. Electrical tape wrapped overtop of self-sealing tape protected the external RP-SMA antenna connectors from moisture and dust, while a bead of silicone at the top edge of

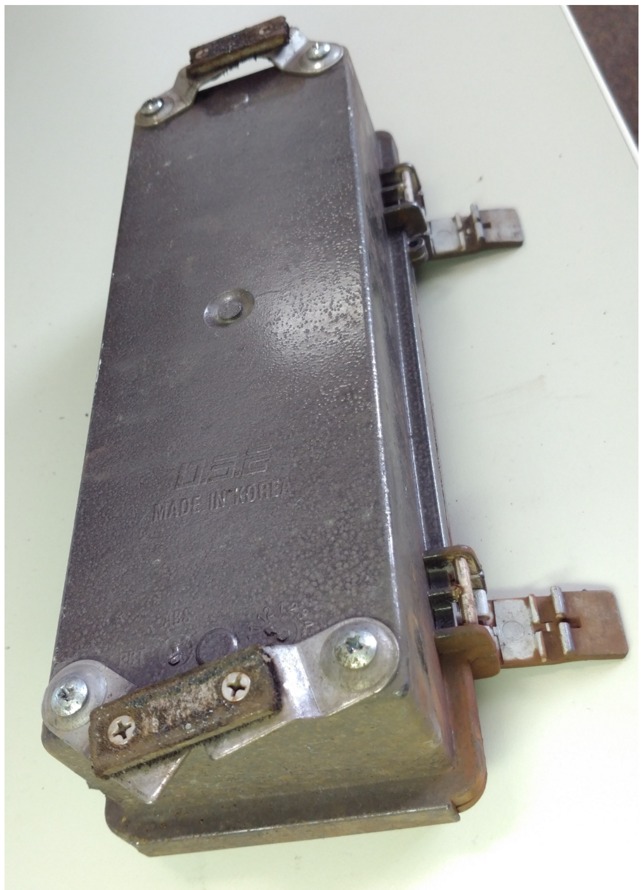

Figure D.4: Photograph of the track-facing side of a box enclosure (a train detector). This image was taken following field service, so the magnets and other surfaces are covered with iron filings and dust.

each connection (where the tape met with the enclosure body) helped to keep rainwater out of the connection.

Figure D.5: Photograph of a tree-mounted box enclosure (camera controller, upper) along with a Reconyx camera (lower). The black line between the two is the external trigger cable for the camera.

D.1.3 Train detector

Train detectors are track-mounted devices that, when passed by a train, provide a wireless activation signal to the rest of the system.

Electronic design

Our train detector was designed with two sensors together to detect trains passing over the device (Figure D.6). The two integrated sensors, an accelerometer (Analog Devices ADXL335) and a compass (Honeywell HMC5883L), were convenient to use as they were sold pre-soldered onto breakout boards with supporting components (sold by Adafruit Industries). In addition to soldering, these breakout boards were attached to the main board with non-magnetic brass hardware to reduce potential interference with the compass readings. A microcontroller (Atmel ATMega 328P) was used to read data from the sensors, determine whether a train was passing over the device, and send activation signals via the attached XBee Pro 900HP (Digi International). These radios used a mesh networking protocol that allowed all devices at a site to communicate with each other. The smaller wire antenna was chosen for the XBee, eliminating the need for an external antenna that would have made the device more fragile and vulnerable to moisture. Two pushbutton switches were integrated with the circuit board to provide quick access to "reset" and "system test" functionality. An FTDI-compatible programming header was also provided to facilitate in-field reprogramming of the microcontroller.

All components were selected to run off 3.3 V provided by a buck converter (Texas Instruments LM3671) also sold pre-soldered on a breakout board (Adafruit Industries). The buck converter was powered by a set of three D-cells in series with a total nominal rating of 4.5 V, but the design of the LM3671 allowed battery voltage begin as high as 5.5 V and to drop as low as 3.5 V as the batteries discharged. This flexibility enabled our use of higher-voltage lithium iron disulphide cells (Energizer L91 AAs; custom battery packs were made with three sets in series of four cells in parallel) when ambient temperatures dropped below −20 °C. Our design did not include any reverse-polarity protection for the LM3671, so care was always taken to insert the battery pack in the correct orientation.

This circuit schematic was converted to a circuit board layout, designed in collaboration with G2V Optics Inc. (Figure D.7). After receiving custom-manufactured boards, we hand-soldered the electronic components to the boards (Table D.2).

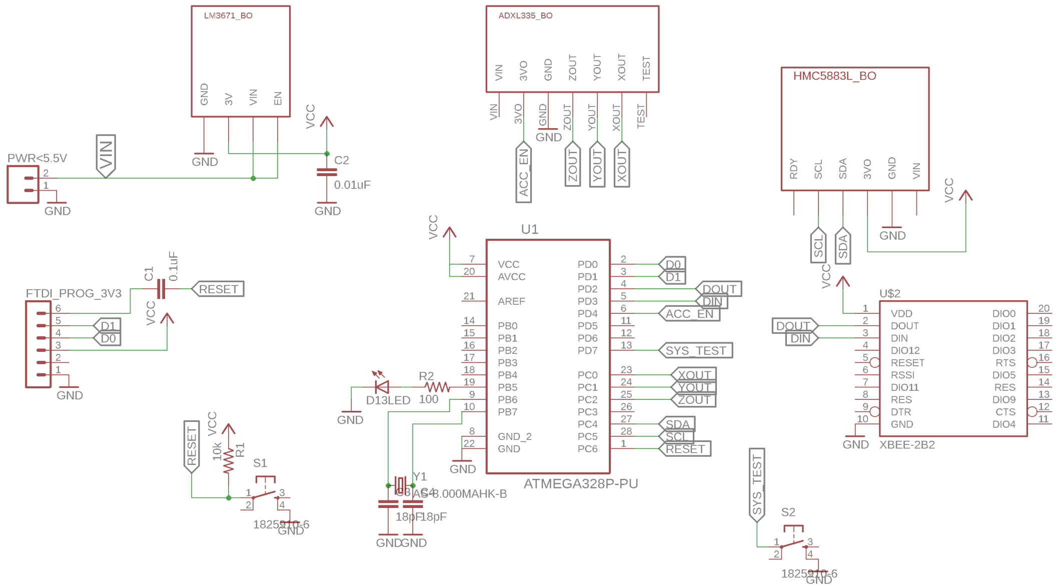

Figure D.6: Schematic of the train detector electronics.

Table D.2: Bill of materials for one train detector. The designator column indicates the label used on the printed circuit board, where applicable (Figures D.6 and D.7). Where manufacturer is unknown, the supplier is indicated in parentheses.

Part	Designator	Qty.	Manufacturer	Part number
HMC5883L compass breakout	U$1	1	Adafruit	1746
ADXL335 accelerometer breakout	U$5	1	Adafruit	163
LM3671 breakout	U$3	1	Adafruit	2745
Female header, 0.1“ pitch, by position		4	(Adafruit)	598
RESET cap 0.1 µF	C1	1	AVX	SR201C104KAR
VCC filter cap 0.01 µF	C2	1	TDK	FK18X7R1H103K
Clock cap 18 pF	C3, C4	2	TDK	FK18C0G1H180J
Pin 13 LED, 5 mm, yellow	D13LED	1	Wurth Electronics	151051YS04000
LED current limit resistor, 100 Ω	R2	1	Yageo	MFR-25FBF52-100R
Pin header, 0.1“ pitch, straight, 6 pos.	FTDI_PROG_3V3	0.17	TE Connectivity	4-103741-0
Pin header, 0.1“ pitch, positive lock, polarity enf., gold 30 microinch	PWR<5.5V	1	Molex	0705430106
2 position rectangular housing with latch, polarity enf.	PWR<5.5V	1	Molex	0050579402

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Part	Designator	Qty.	Manufacturer	Part number
Contact crimp socket 22-24 AWG gold 30 microinch, high force	PWR<5.5V	2	Molex	0016021115
Stranded core wire, black, per inch		12	(Adafruit)	2976
Stranded core wire, red, per inch		12	(Adafruit)	3068
Pull-up/down resistor, 10 kΩ	R1	1	Yageo	MFR-25FBF52-10K
Momentary pushbutton	S1, S2	2	TE Connectivity	1825910-6
Microcontroller	U1	1	Atmel	ATMEGA328P-PU
28-pin DIP socket	U1	1	3M	4828-3004-CP
Clock crystal, 8 MHz, HC49US shape	Y1	1	TXC Corp	AS-8.000MAHK-B
XBee Pro 900HP, DigiMesh non-prog, wire ant.	U$2	1	Digi International	XBP9B-DMWT-002
Female headers, 2 mm, 10 pos.	U$2	2	Sullins Connector Solutions	NPPN101BFCN-RC
Train detector printed circuit board		1	Gold Phoenix	(Custom)
Low-profile steel battery holder		1	Keystone Electronics	2199
Retaining clips for battery holder		2	Keystone Electronics	63
Breakout board hold screw, brass, pan head, #1-64, 1/4“ length		4	(McMaster-Carr)	94070A043
Breakout board hold washer, brass, #1		4	(McMaster-Carr)	95395A102
Breakout board hold nut, brass, #1-64		4	(McMaster-Carr)	92671A002

Programming

Before installation on the printed circuit board, each ATMega328P microcontroller was programmed with an Arduino bootloader. To do this, we built a chip programmer based on the Arduino Uno (http://www.arduino.cc) using an Adafruit protoshield kit (Adafruit part number 2077) and a compatible ZIF socket (3M part number 228-1371-00-0602J) according to a tutorial available on Adafruit's website (https://learn.adafruit.com/arduino-tips-tricks-and-techniques/arduinoisp). With the chip programmer connected to a computer, the Arduino IDE could be used to program the chip mounted in the programmer by selecting Board "Arduino Pro or Pro Mini," the Processor "ATmega328 (3.3V, 8 MHz)," and the Programmer "ArduinoISP," then selecting Burn Bootloader. Once a microcontroller with boot-

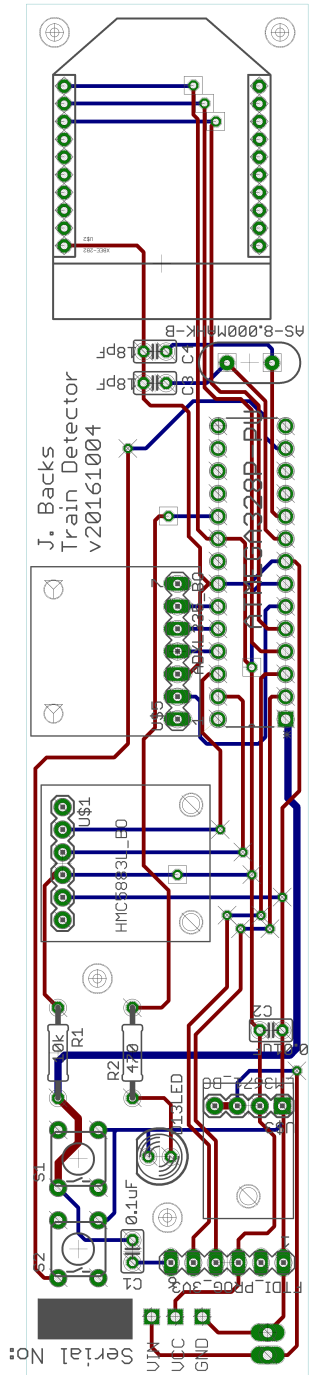

Figure D.7: Circuit board layout of the train detector electronics. Designed for manufacture as a two-layer FR4 board, >100 mil thick, 1 oz copper, white silk screen and green solder mask. Top layer traces are indicated in red, bottom layer traces in blue, and exposed copper in green. Holes and silk screen markings are indicated in grey. The SCL pin from the `HMC5883L_BO` was erroneously connected to pin 26 of the microcontroller in this layout; SCL had to be manually connected to pin 28 of the microcontroller with a jumper.

loader was installed on the board, it could be programmed via USB through the six pin FTDI interface (using a device such as the TTLyFTDI USB-to-TTL Cable Adapter, Solarbotics part number 39240, ensuring the USB voltage is stepped down to 3.3 V).

The C program `sensing.ino` was compiled and written to the microcontroller in each train detector. This code, including the required library `Adafruit_HMC5883_Unified_Mod`, will be available at https://github.com/jbacks/wildlife-warning-system upon publication of this manuscript. This program reads the values of both the compass and accelerometer once per second, and uses these readings to establish baseline readings for each sensor that is the average of the past several readings. Following the establishment of a sensor-specific baseline, each new reading is compared with the baseline for that sensor. If the difference does not exceed a pre-specified threshold value, the reading is incorporated into the running average of the baseline. If the threshold is exceeded, a flag is set until the threshold is no longer exceeded. Only if the threshold is exceeded for both sensors at once is an activation signal is transmitted to the rest of the warning system via the XBee network. In this way, only sudden and strong sources of both magnetic and vibrational changes can activate the warning system, and slow drifts in either sensor reading have no effect. This algorithm helps to reduce the number of false positives generated by the detectors. Following a trigger event, the train detector goes idle for six minutes to prevent spurious activations as the train passes.

Programming the XBees required only that we set the Preamble ID, Network ID, and encryption key to the same values as the rest of the XBees at the same site. We additionally gave each XBee a name containing the type of device and a unique number (e.g., “TD-03”; Figure D.17) via the Node Identifier parameter. We did not make use of the advanced power-saving features of the XBees in this version of the warning system.

Mechanical design

The layout of components within the enclosure was intended to maximize the performance of the train detectors (Figure D.8). The sensors were placed towards the upper end of the circuit board, which was affixed to the rear wall of the enclosure (with foam tape and hook-and-loop; Table D.1), so that each sensor would have relatively unobstructed access to their respective signals. Because train detectors were mounted on the track, battery holders (heavy when full) were attached to the bottom face of the enclosure's interior so that the holders were not shaken loose by train vibrations. Further protection against vibration-induced damage was provided by application of hot-melt adhesive and silicone sealant that held the LM3671 and XBee headers in place. The brass hardware reinforcing the connections with the sensor breakout boards was held against disassembly with Loctite 222. The wire antenna for the XBee was extended as far as possible in the direction perpendicular to the circuit board to maximize radio transmission.

D.1.4 Warning device

Electronic design

We designed our warning device to provide light and sound stimuli with attention to the balance between stimulus intensity, battery life, and cost (Figure D.9). For visual stimuli, we selected two high-power LEDs, amber in colour (Backs et al. 2017), and supporting optics that could be mounted flush with the outer face of the enclosure and sealed with silicone. Each LED was driven by a constant-current buck regulator (Texas Instruments LM3405). For auditory stimuli, we selected a weatherproof piezoelectric buzzer that could protrude from the enclosure to emit sound directly into the environment. This buzzer was driven by a pulse-width modulation signal from the microcontroller, amplified through a piezo-specialized boost regulator (Linear Technologies LT3469), to roughly approximate bell sounds as per our original design (Backs et al. 2017). When not in use, current drawn directly from the batteries by the LT3469 was reduced using a low-quiescent-current load switch (Fairchild Semiconductor FPF2701) that could

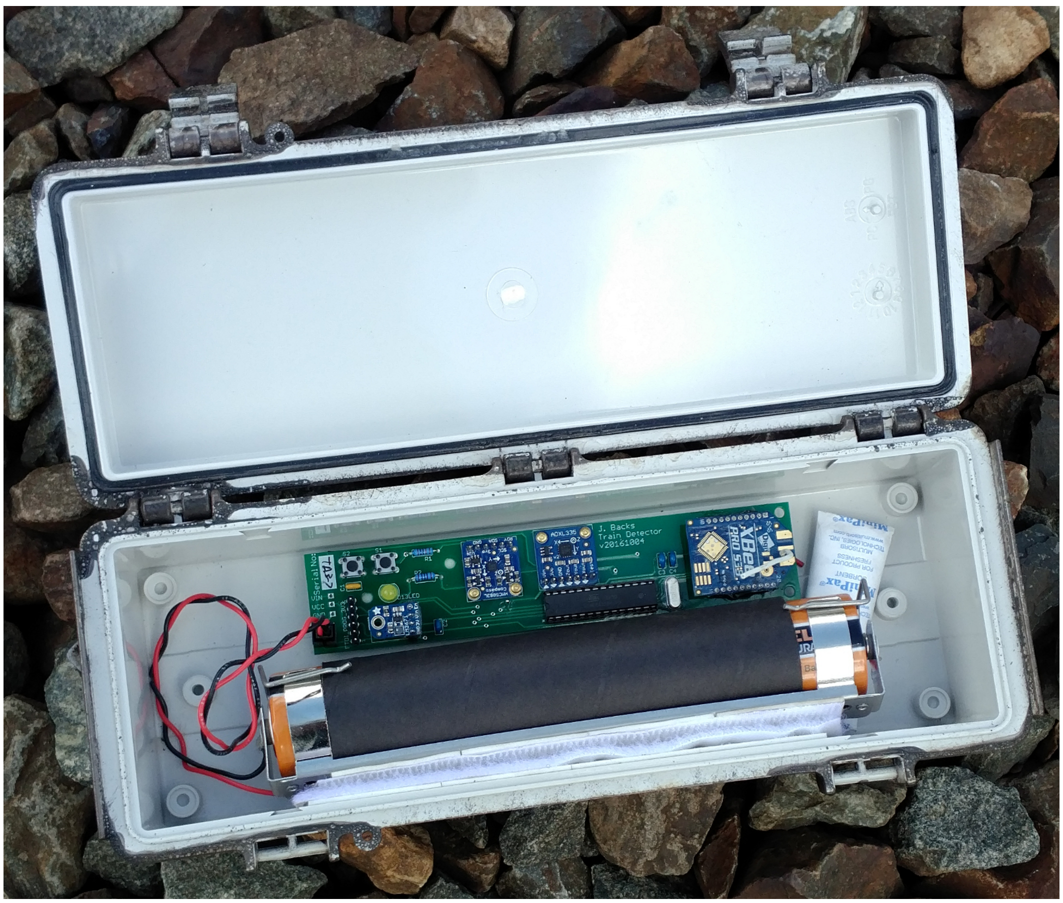

Figure D.8: Photograph of the interior of a train detector.

be turned on by the microcontroller only when warning signals were active. Power, microcontroller, programming, and radio subsystems were re-used from the train detector design.

This circuit schematic was converted to a circuit board layout, designed in collaboration with G2V Optics Inc. (Figure D.10). After receiving custom-manufactured boards, we hand-soldered the electronic components to the boards (Table D.3).

Earlier versions of this design included optional space for a more powerful piezo driver (Texas Instruments DRV2700), but after multiple attempts we were unable to get this part to work with our design. With our imprecise tools for reflow soldering, it is possible that we damaged the delicate VQFN package every time we attempted to attach it to the circuit board.

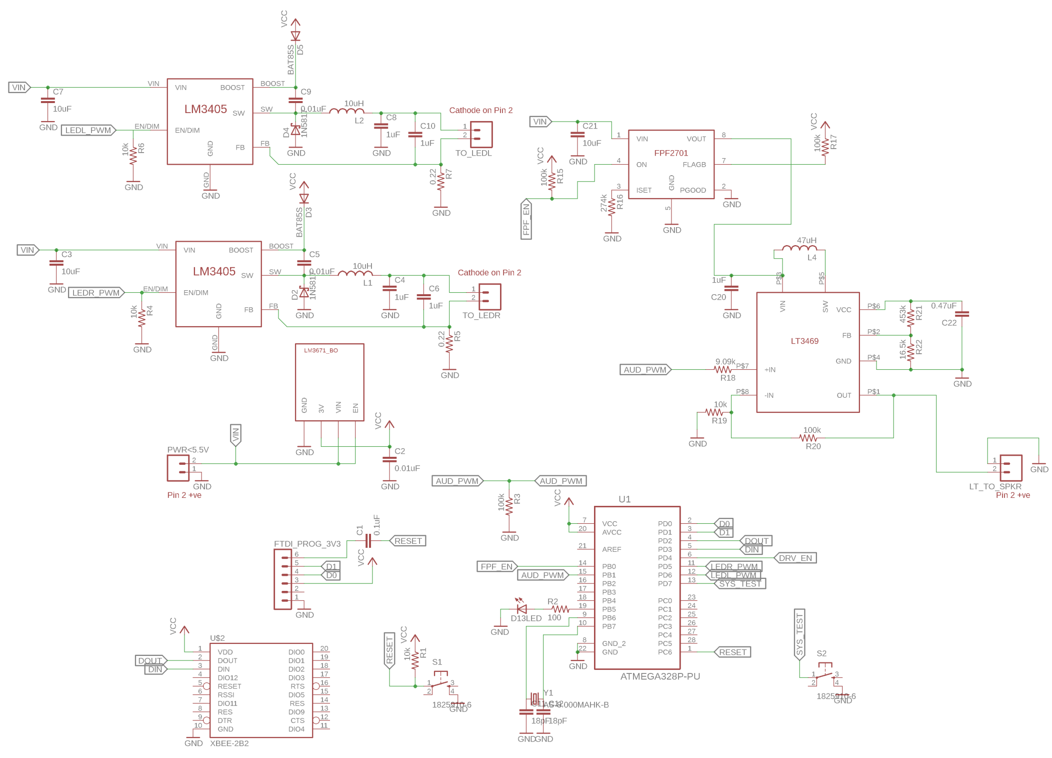

Figure D.9: Schematic of the warning device electronics.

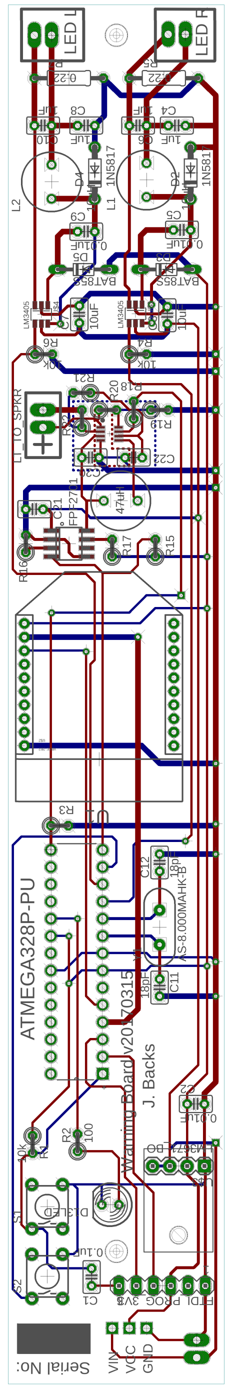

Figure D.10: Circuit board layout for the warning device electronics. Designed for manufacture as a two-layer FR4 board, >100 mil thick, 1 oz copper, white silk screen and green solder mask. Top layer traces are indicated in red, bottom layer traces in blue, and exposed copper in green. Holes and silk screen markings are indicated in grey.

Table D.3: Bill of materials for one warning device. The designator column indicates the label used on the printed circuit board, where applicable (Figures D.9 and D.10). Where manufacturer is unknown, the supplier is indicated in parentheses.

Part	Designator	Qty.	Manufacturer	Part number
LM3671 breakout	U$3	1	Adafruit	2745
Female header, 0.1“ pitch, by position		4	(Adafruit)	598
RESET cap 0.1 µF	C1	1	AVX	SR201C104KAR
VCC filter cap 0.01 µF	C2, C5, C9	3	TDK	FK18X7R1H103K
Clock cap 18 pF	C11, C12	2	TDK	FK18C0G1H180J
Pin 13 LED, 5 mm, yellow	D13LED	1	Wurth Electronics	151051YS04000
LED current limit resistor, 100 Ω	R2	1	Yageo	MFR-25FBF52-100R
Pin header, 0.1“ pitch, straight, 6 pos.	`FTDI_PROG_3V3`	0.17	TE Connectivity	4-103741-0
Pin header, 0.1“ pitch, positive lock, polarity enf., gold 30 microinch	PWR<5.5V	4	Molex	0705430106
2 position rectangular housing with latch, polarity enf.	PWR<5.5V	4	Molex	0050579402
Contact crimp socket 22-24 AWG gold 30 microinch, high force	PWR<5.5V	8	Molex	0016021115
Stranded core wire, black, per inch		42	(Adafruit)	2976
Stranded core wire, red, per inch		42	(Adafruit)	3068
Pull-up/down resistor, 10 kΩ	R1, R4, R6, R19	4	Yageo	MFR-25FBF52-10K
Momentary pushbutton	S1, S2	2	TE Connectivity	1825910-6
Microcontroller	U1	1	Atmel	ATMEGA328P-PU
28-pin DIP socket	U1	1	3M	4828-3004-CP
Clock crystal, 8 MHz, HC49US shape	Y1	1	TXC Corp	AS-8.000MAHK-B
XBee Pro 900HP, DigiMesh non-prog, wire ant.	U$2	1	Digi International	XBP9B-DMWT-002
Female headers, 2 mm, 10 pos.	U$2	2	Sullins Connector Solutions	NPPN101BFCN-RC
VIN filter cap 10 µF	C3, C7, C21	3	TDK	FK16X7R1C106K
LM3405 L–LED caps, LT3469 input filter, 1 µF	C4, C6, C8, C10, C20	5	TDK	FK18X7R1C105K
LT3469 storage cap, 0.47 µF 50 V	C22	1	TDK	FK14X7R1H474K
Schottky diode 1N5817	D2, D4	2	Fairchild	1N5817
Small signnal diode BAT85S	D3, D5	2	Vishay	BAT85S-TAP
LM3405 inductors 10 µH, 5 mm lead spacing	L1, L2	2	Bourns	RLB0912-100KL

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Part	Designator	Qty.	Manufacturer	Part number
LM3405 sense resistor, 0.22 Ω	R5, R7	2	TE Connectivity	LR1LJR22
LT3469 inductor, 47 µH, 5 mm lead spacing	L4	1	Bourns	RLB0914-470KL
Pull-up/down resistors, 100 kΩ	R3, R14, R15, R17, R20	5	Yageo	MFR-25FBF52-100K
FPF2701 ISET resistor, 274 kΩ	R16	1	Yageo	MFR-25FBF52-274K
LT3469 input resistor, 9.09 kΩ	R18	1	Yageo	MFR-25FBF52-9K09
LT3469 FB resistor, 453 kΩ	R21	1	Yageo	MFR-25FBF52-453K
LT3469 FB resistor, 16.5 kΩ	R22	1	Yageo	MFR-25FBF52-16K5
LM3405, SOT23	U$1, U$4	1	Texas Instruments	LM3405XMK/NOPB
FPF2701, 8SOIC	U$7	1	Fairchild	FPF2701MX
LT3469, TSOT23-8	U$8	2	Linear Technologies	LT3469ETS8#TRMPBF
IP68 piezo buzzer, 50 V max		1	CUI Inc.	CPT-2521C-500
Cree XP-E2 PC-Amber, mounted, 107 lm	LED-L, LED-R	2	Opulent North America	XPEBPA-L1-0000-00D01-SB01
Optic holder, 20 mm		2	Carlco Technical Plastics	10734
Optic, 20 mm ripple wide		2	Carlco Technical Plastics	10209
Warning device printed circuit board		1	Gold Phoenix	(Custom)
Low-profile steel battery holder		1	Keystone Electronics	2199
Retaining clips for battery holder		2	Keystone Electronics	63

Programming

ATMega328P microcontrollers were loaded with Arduino bootloaders and programmed with the same procedure as was used for the train detectors.

The C program `warning.ino` was compiled and written to the microcontroller in each warning device. This code, including the required header file `oneRing.h`, will be available at https://github.com/jbacks/wildlife-warning-system upon publication of this manuscript. The warning device remains idle until an activation signal is received through the XBee network (i.e., from a remote train detector). The device then waits for 10 s before activating its warning signals for 35 s. The microcontroller then alternatingly turns on and off the left and right LEDs while playing the bell sound via one of its pulse-width modulation (PWM) pins. A low-sample-rate version of the bell sound is stored as a sequence of numbers in `oneRing.h`. These numbers are used sequentially (at a rate of 8 kHz) to vary the duty cycle of a square-wave signal present at the PWM pin of the microcontroller. That signal is then amplified by the LT3469 and converted to sound energy by the piezo buzzer. The code is adapted from the PCMAudio example provided by Michael Smith on the Arduino website (http://playground.arduino.cc/Code/PCMAudio), but uses a different interrupt mechanism and one instead of two internal timers for the PWM output, allowing the microcontroller to manage the LED flashes concurrently. The timers and registers used are described in the ATmega328P datasheet.

XBees were programmed as for the train detectors.

Mechanical design

The interior of the warning devices is laid out similarly to the train detectors (Figure D.11), with the circuit board mounted on the rear interior wall and the battery holder on the floor of the enclosure. The warning light optics sit flush with the side panels of the enclosure, while the speaker protrudes through the central floor of the enclosure. When the warning device is mounted on the track, the flashes from these warning lights are visible from hundreds of meters away. We designed the speaker to point downwards with the intention that sound would be reflected by the rocky ballast, travelling more horizontally along the track than vertically into the air. The warning bell sounds are generally audible at a distance of 50 m or more, depending on ambient noise conditions. Protection against vibration damage is provided by hot-melt adhesive and silicone sealant on the LM3671 header, the XBee header, and around the three heavy inductors (black cylinders) on the right hand side of the circuit board.

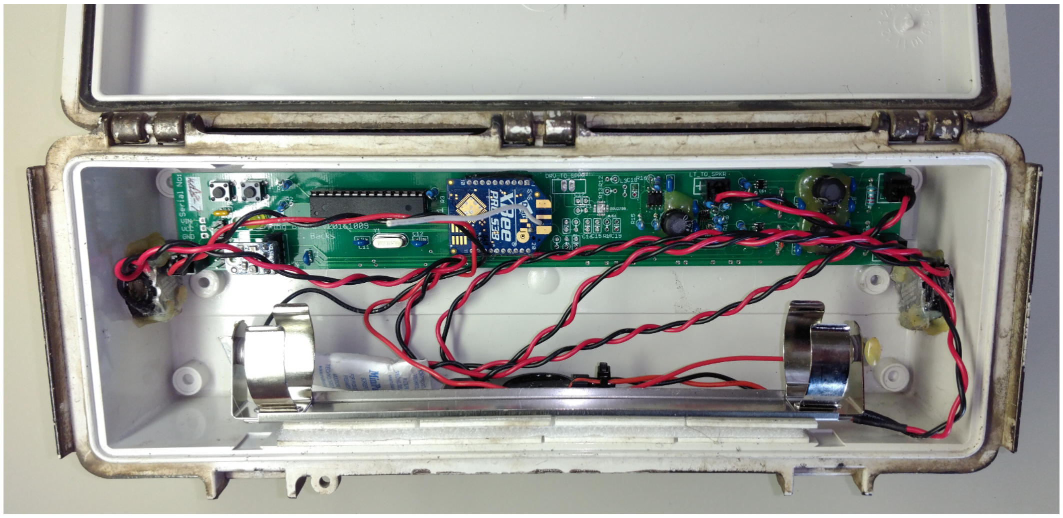

Figure D.11: Photograph of the interior of a warning device. D-cells were removed for this image.

D.1.5 Camera controller

Electronic design

Our camera controller functions as a wireless interface to the Reconyx PC900 cameras, which we used to observe wildlife in our experiment (Figure D.12). To trigger the external trigger on these cameras, Reconyx requires a pulse of 6 V to 12 V with 0.1 s to 0.5 s duration across the trigger terminal. We designed the camera controller to provide a 9 V pulse via a boost regulator (Texas Instruments LM2733) which is turned on for the required duration by the microcontroller. As for the warning device, a load switch (FPF2701) is placed between the battery output and the boost regulator input to reduce current consumption when the LM2733 is not in use. Power, microcontroller, and programming subsystems were re-used from the train detector design. An XBee radio was selected that used a u.FL connector, facilitating a flexible connection to a large external antenna that extended the radio range of the device.

This circuit schematic was converted to a circuit board layout, designed in collaboration with G2V Optics Inc. (Figure D.13). After receiving custom-manufactured boards, we hand-soldered the electronic components to the boards (Table D.4).

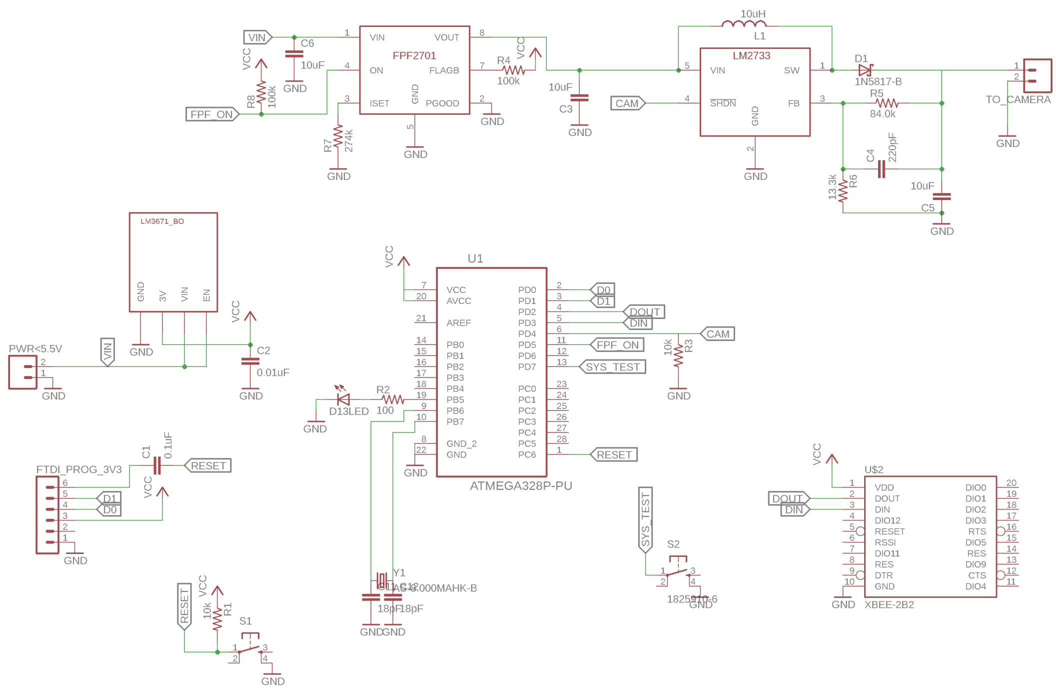

Figure D.12: Schematic of the camera controller electronics.

Table D.4: Bill of materials for one camera controller. The designator column indicates the label used on the printed circuit board, where applicable (Figures D.12 and D.13). Where manufacturer is unknown, the supplier is indicated in parentheses.

Part	Designator	Qty.	Manufacturer	Part number
LM3671 breakout	U$3	1	Adafruit	2745
Female header, 0.1“ pitch, by position		4	(Adafruit)	598
RESET cap 0.1 µF	C1	1	AVX	SR201C104KAR
VCC filter cap 0.01 µF	C2	1	TDK	FK18X7R1H103K
Clock cap 18 pF	C11, C12	2	TDK	FK18C0G1H180J
Pin 13 LED, 5 mm, yellow	D13LED	1	Wurth Electronics	151051YS04000
LED current limit resistor, 100 Ω	R2	1	Yageo	MFR-25FBF52-100R
Pin header, 0.1“ pitch, straight, 6 pos.	`FTDI_PROG_3V3`	0.17	TE Connectivity	4-103741-0
Pin header, 0.1“ pitch, positive lock, polarity enf., gold 30 microinch	PWR<5.5V	2	Molex	0705430106
2 position rectangular housing with latch, polarity enf.	PWR<5.5V	2	Molex	0050579402
Contact crimp socket 22-24 AWG gold 30 microinch, high force	PWR<5.5V	4	Molex	0016021115

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Part	Designator	Qty.	Manufacturer	Part number
Stranded core wire, black, per inch		12	(Adafruit)	2976
Stranded core wire, red, per inch		12	(Adafruit)	3068
Pull-up/down resistor, 10 kΩ	R1, R3	2	Yageo	MFR-25FBF52-10K
Momentary pushbutton	S1, S2	2	TE Connectivity	1825910-6
Microcontroller	U1	1	Atmel	ATMEGA328P-PU
28-pin DIP socket	U1	1	3M	4828-3004-CP
Clock crystal, 8 MHz, HC49US shape	Y1	1	TXC Corp	AS-8.000MAHK-B
XBee Pro 900HP, DigiMesh non-prog, u.FL	U$2	1	Digi International	XBP9B-DMUT-002
U.FL to RP-SMA, 6“		1	Digi International	JF1R6-CR3-6I
900 MHz antenna		1	Digi International	A09-HASM-7
Female headers, 2 mm, 10 pos.	U$2	2	Sullins Connector Solutions	NPPN101BFCN-RC
VIN filter cap 10 µF, 16 V	C3, C5, C6	3	TDK	FK16X7R1C106K
LM2733 feed-forward cap 220 pF 50 V	C4	1	Murata Electronics	RDER71H221K0P1H03B
Schottky diode 1N5817	D1	1	Fairchild	1N5817
LM2733 inductor, 10 µH, 5 mm lead spacing	L1	1	Bourns	RLB0912-100KL
Pull-up/down resistor, 100 kΩ	R4, R8	2	Yageo	MFR-25FBF52-100K
LM2733 FB network, 84.5 kΩ	R5	1	Yageo	MFR-25FBF52-84K5
LM2733 FB network, 13.3 kΩ	R6	1	Yageo	MFR-25FBF52-13K3
FPF2701 ISET resistor, 274 kΩ	R7	1	Yageo	MFR-25FBF52-274K
LM2733 SOT23-5	U$4	1	Texas Instruments	LM2733YMF/NOPB
FPF2701, 8SOIC	U$5	1	Fairchild	FPF2701MX
Warning device printed circuit board		1	Gold Phoenix	(Custom)
Reconyx external trigger cable		1	Reconyx	
Low-profile steel battery holder		1	Keystone Electronics	2199
Retaining clips for battery holder		2	Keystone Electronics	63

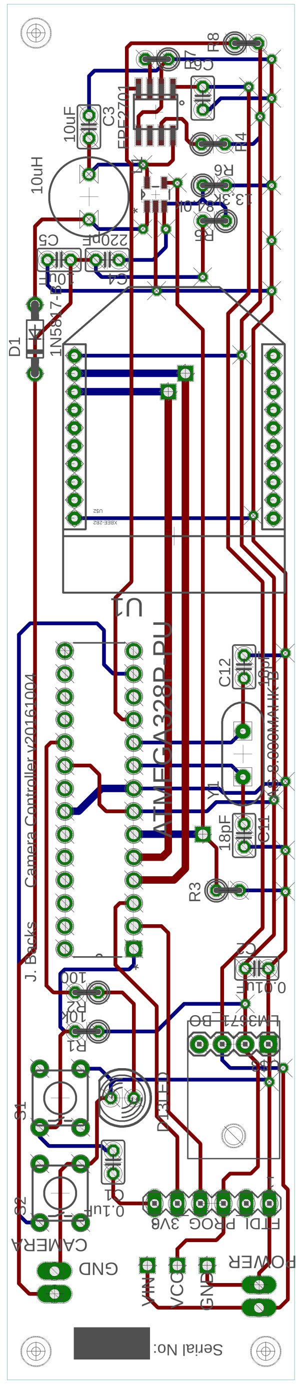

Figure D.13: Circuit board layout for the camera controller electronics. Designed for manufacture as a two-layer FR4 board, >100 mil thick, 1 oz copper, white silk screen and green solder mask. Top layer traces are indicated in red, bottom layer traces in blue, and exposed copper in green. Holes and silk screen markings are indicated in grey.

Programming

ATMega328P microcontrollers were loaded with Arduino bootloaders and programmed with the same procedure as was used for the train detectors.

The C program `camera.ino` was compiled and written to the microcontroller in each camera controller. This code will be available at https://github.com/jbacks/wildlife-warning-system upon publication of this manuscript. The camera controller remains inactive until an activation signal is received through the XBee network. Upon activation, the attached camera is activated by turning on the LM2733 for 300 ms. The device is then inactive for six minutes to preclude any spurious activations as the train is passing.

XBees were programmed as for the train detectors.

Mechanical design

The interior of the camera controllers is laid out with both the circuit board and the battery holder against the rear wall of the enclosure (Figure D.14). The circuit board is placed to minimize stress on the fragile u.FL connector, where the adapter is connected that links the XBee radio to the external antenna.

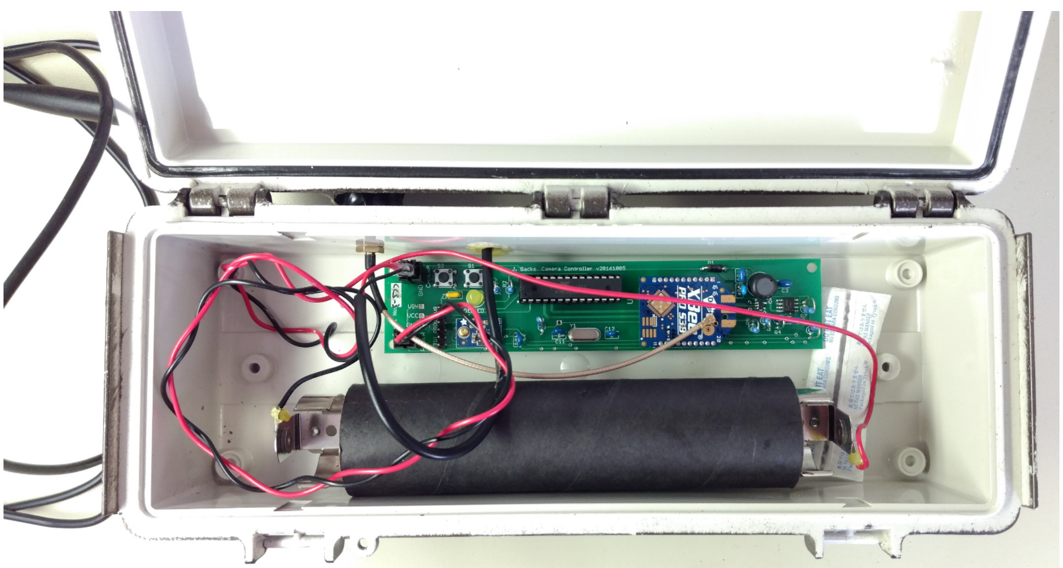

Figure D.14: Photograph of the interior of a camera controller. D-cells were removed for this image.

D.1.6 Signal repeater

Electronic design

Signal repeaters functioned as additional nodes in the XBee DigiMesh network to bridge the distance between train detectors and camera controllers. We used an LM3671 buck regulator (as for the train detector) to bring the battery output down to 3.3 V. The outputs of the regulator were connected directly to the power inputs of the XBee. As for the camera controller, an XBee radio was selected that used a u.FL connector and connected to an external antenna, increasing the radio range of the device.

The simplicity of this design allowed us to reduce costs by hand-assembling the components on prototyping board (Table D.5). For future deployments, however, the time for assembly would be significantly reduced with a printed circuit board.

Table D.5: Bill of materials for one signal repeater. Where manufacturer is unknown, the supplier is indicated in parentheses.

Part	Qty.	Manufacturer	Part number
LM3671 breakout	1	Adafruit	2745
Female header, 0.1“ pitch, by position	4	(Adafruit)	598
Pin header, 0.1“ pitch, positive lock, polarity enf., gold 30 microinch	1	Molex	0705430106
2 position rectangular housing with latch, polarity enf.	1	Molex	0050579402
Contact crimp socket 22-24 AWG gold 30 microinch, high force	2	Molex	0016021115
Stranded core wire, black, per inch	12	(Adafruit)	2976
Stranded core wire, red, per inch	12	(Adafruit)	3068
XBee Pro 900HP, DigiMesh non-prog, u.FL	1	Digi International	XBP9B-DMUT-002
U.FL to RP-SMA, 6“	1	Digi International	JF1R6-CR3-6I
900 MHz antenna	1	Digi International	A09-HASM-7
Female headers, 2 mm, 10 pos.	2	Sullins Connector Solutions	NPPN101BFCN-RC
FR4 prototyping board, pad per hole, cut to size	1	Vector Electronics	8016-1
Low-profile steel battery holder	1	Keystone Electronics	2199
Retaining clips for battery holder	2	Keystone Electronics	63

Programming

No microcontrollers were used in the signal repeaters. XBees were programmed as for the train detectors.

Mechanical design

The layout of the signal repeaters was similar to that of the camera controllers, with both the circuit board and the battery holder attached to the rear interior wall of the enclosure (Figure D.15). The circuit board was placed to minimize stress on the u.FL connector.

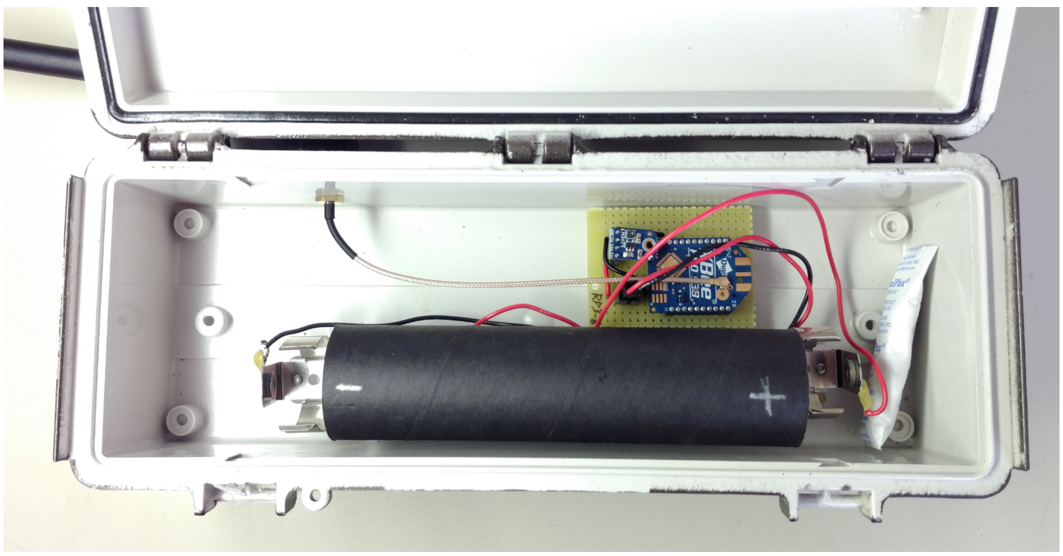

Figure D.15: Photograph of the interior of a signal repeater. D-cells were removed for this image.

D.1.7 System installation and commissioning

At a typical warning system test site, we installed four warning devices (under the treatment condition only), two train detectors, two camera controllers, and two signal repeaters. Warning devices were placed every 50 m within the 200 m test zone starting at 25 m from the test zone edge (as described in the present manuscript for the treatment condition). Camera controllers were installed in trees alongside Reconyx trail cameras, one on either side of the test zone, which observed animals within the test zone. Train detectors were placed 40 s at mean train speed from the center of the test zone. Signal repeaters were placed in trees near the train detectors where they could connect with both their train detector and the nearest camera controller.

Finding good locations for the signal repeaters was a trial-and-error process. For sites with dense vegetation or long distances between the train detectors and the test zone, up to four signal repeaters were used to maintain reliable connections among devices. As spring arrived and foliage began to appear on the trees, radio connectivity became less reliable as we had anticipated. Rather than deploying additional repeaters, Yagi-Uda antennas with gains of 10–17 dBi were used to strengthen problematic links (Figure D.16).

With every device in the network assembled, programmed, and powered as described, and the Reconyx cameras also powered and programmed, we used an additional XBee radio to test network connectivity among the devices. This XBee was programmed identically to those deployed in the devices, and connected to a laptop computer using an XBee adapter (Adafruit part number 126) and a USB FTDI interface (such as the TTLyFTDI USB-to-TTL Cable Adapter, Solarbotics part number 39240). Proprietary XCTU software (Digi International) was used to interact with the XBee radio and command it to build a map of its network. Use of a mesh networking protocol on these radios allowed this test radio to receive information about all radios in a given site's network, even if they were out of range of the test radio, because it could receive information about the furthest radios from the intermediate radios. If the network map showed that all nodes were reachable with bi-directional links (e.g., Figure D.17), the site was deemed functional.

D.1.8 Potential improvements to the design

We offer here a collection of potential improvements to the warning system that would make its design more practical and effective. We use "warning zone" instead of "test zone" in this section to refer to the length of track along which warning signals are provided.

Figure D.16: Photograph of a signal repeater connected by a cable to a high-gain Yagi–Uda antenna. These antennas were used at some sites to increase the reliability of connections between tree-mounted devices.

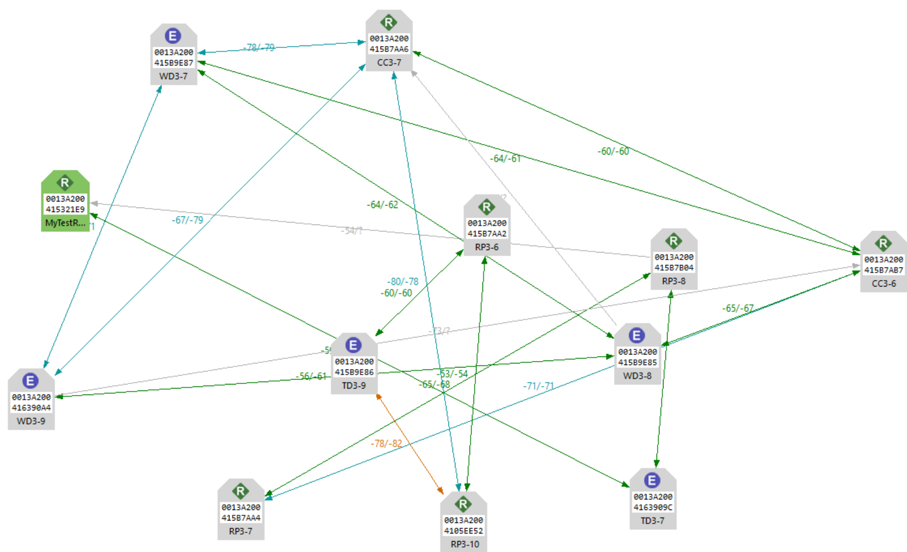

Figure D.17: Network map of the Five Mile Cluster site generated by XCTU software (Digi International). Each arrow represents a bi-directional link between network nodes. Each radio is represented by a grey (networked radio) or green (test radio) polygon. Serial numbers and node identifiers of each radio are displayed, aiding in their identification (TD = train detector, WD = warning device, CC = camera controller, RP = signal repeater). The strength of each link in dBm is indicated with a pair of numbers (one for each direction) beside each arrow; less negative values indicate stronger links.

Train speed measurement

Warning times provided to animals could be made more precise if train speed was measured for each train as it approached. For instance, suppose that the single train detectors in Figure 4.1 were replaced with pairs of train detectors with a known spacing l (Figure D.18). The speed of a train that passed this pair of detectors would then be $v = \frac{l}{\Delta t}$, where Δt is the difference of the train arrival times at each train detector. This speed can then be used to calculate the time to arrival at any point further down the track, assuming that the train speed remains approximately constant. Because freight trains rarely accelerate or decelerate quickly, we suggest this is often a safe assumption where distances between the train detectors and the warning zone are less than 1 km.

Compared with the most recent prototype of the warning system, where train detectors are placed according to the average speed of trains, the speed measurement approach has four main advantages:

1. Precision. If the train speed is known, the target warning time (e.g., 30 s) can be provided to animals in the test zone regardless of the variation in train speeds. Whereas speed distributions like those seen from westbound trains at the Stables site ($20\,\mathrm{km\,h^{-1}}$ to $55\,\mathrm{km\,h^{-1}}$) can create wide distributions in warning time (51.3 s to 19 s, respectively), speed measurement would have kept warning times close to 30 s. This could be important for enabling animals to learn an association between the warning signals and train arrival, a mechanism for early warning that is especially important where animals may have more difficulty detecting trains on their own (e.g., around curves in the track).

2. Redundancy. If one in a pair of train detectors were to fail, the other would still be able to detect the train and activate the warning signals, though not with the same precise timing.

3. Direction detection. The pair of train detectors could determine the direction of a passing train, reducing the need for communication between

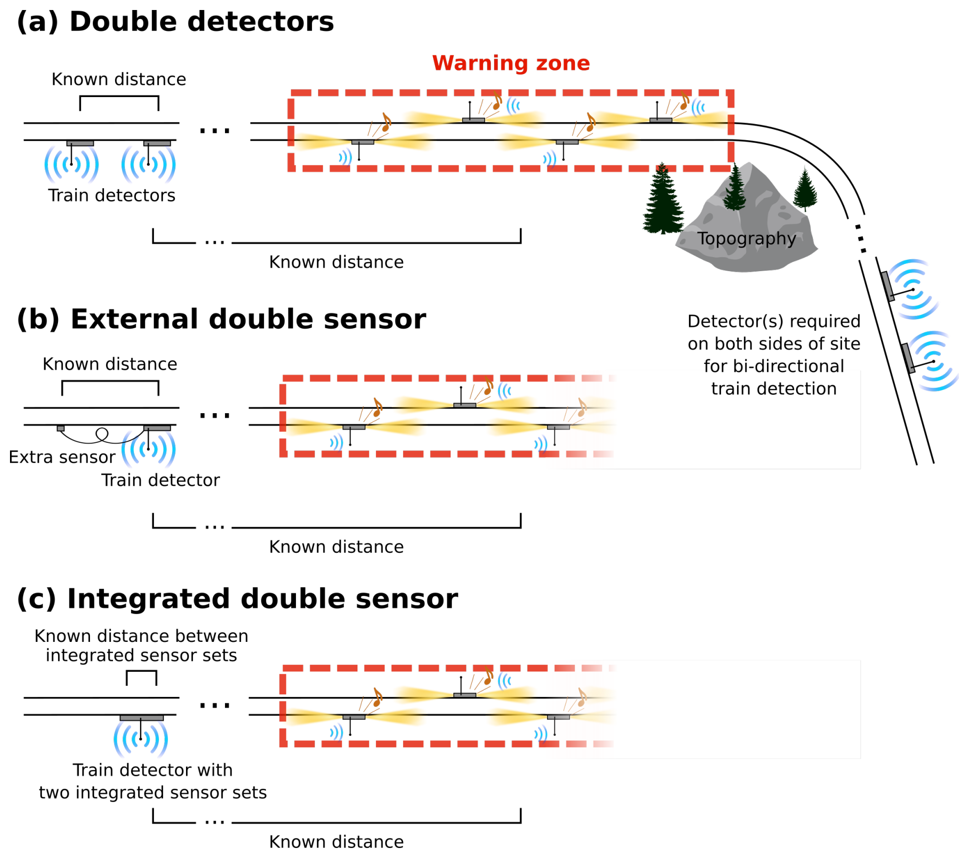

Figure D.18: Example configurations for train speed measurement with train detectors, in a situation analagous to that of Figure 4.1. (a) Two detectors placed a known distance apart can calculate the speed of a passing train by comparing the times of arrival that each records. (b) We can achieve the same end while avoiding redundancy of the power and communication systems by building a detector with an extra sensor attached externally via a cable. (c) If the sensors can detect the arrival of a train with high spatial and temporal precision, the distance between them can be reduced without sacrificing the precision of the speed measurement. In this case, it makes sense to include both sensors in the same enclosure for increased simplicity and ruggedness.

train detectors on either side of the warning zone. (This communication would normally be required to prevent spurious activations of the warning signals.) Additionally, where multiple warning zones are placed adjacent to each other (e.g., to protect a long region of track where animals are vulnerable to collisions), one pair of train detectors could detect trains for both warning zones adjacent to it, and sending activation signals to the appropriate warning devices depending on the train direction.

4. Placement flexibility. Whereas the single train detectors in the latest protoype of our warning system had to be placed at specific locations according to the mean speed of the passing trains, a pair of train detectors could be placed anywhere within a large region: at least 30 s at maximum train speed from the warning zone, and at most 1 km or so, depending on how likely trains in the area are to change their speed. The system would only require that the distance between the train detectors and the warning zone is known, so that the warning devices could be activated after an appropriate delay. This flexibility of placement would allow warning system deployments to avoid track infrastructure like switches, frogs, or bridges where it would be dangerous or impossible to place train detectors.

Speed measurement with train detectors could be implemented in different ways. As already described, two independent train detectors separated by a known distance could accomplish this task (Figure D.18(a)), but system costs could be reduced by avoiding complete redundancy of the power and communications systems for devices that are not separated by more than a few metres. For example, instead of two train detectors, the same purpose could be accomplished by one train detector with two sensors. One sensor could be integrated with the device's main enclosure while a second sensor could be placed nearby in a second smaller enclosure, connected to the other with a cable for power and data transfer (Figure D.18(b)). If alternative sensors were chosen that had a higher precision in space and time (e.g., contact microphones or treadles), the pair of sensors could be placed on opposite sides of the same enclosure (e.g., less than 50 cm apart; Figure

D.18(c)), improving the mechanical robustness and ease of installation for the device.

Technologies also exist that can both detect trains and measure speed at a distance. Examples include grade crossing predictors that measure train speed and direction through the track rails (e.g., Richards, Heathington & Fambro 1990), or the acoustic predictors proposed in our previous work (Backs et al. 2017). This approach has a number of benefits, including the ability to integrate the warning device(s) with the train detection system. Combined with longer-range warning stimuli (e.g., brighter lights and louder bell sounds), this approach could eliminate the cost and complexity of providing power to and communication among multiple devices. Alternatively, one predictor unit (for example, at the center of a warning zone) could control the activation of a series of nearby warning devices similar to the ones tested in the present manuscript.

Further, with a known train speed, warning devices could be activated individually or in sub-groups to precisely maintain the target warning time throughout warning zones longer than 200 m. To achieve this, each warning device could be programmed with its location relative to the train detectors, and could calculate independently for how much time it should wait before activating based on the speed measured by the train detectors. Alternatively, the train detectors could be given the same position information, and could command each warning device to activate individually. With a slight increase in device cost, the acquisition of this position information could be performed automatically via GPS.

Communication alternatives

Alternative means of communication could also enhance the practicality of the warning system. Low-power, long-range, low-data-rate communications technologies such as LoRa (Sanchez-Iborra et al. 2018), have become widely available only in recent years. Our warning system transfers only small amounts of data with each communication, and given that the XBee radios were among the largest consumers of power in our present prototypes, the system may increase significantly in battery life using this alternative technology. The longer range of LoRa radios may also reduce or eliminate the need for signal repeaters, further reducing the cost for protecting a given length of railway.

It may also be possible for the devices to communicate through the railway track itself. Railway signaling systems already use the electrical properties of the track rails to detect train presence (i.e., the track circuit). Warning systems could be designed to communicate via the same medium without interfering with railway signals (for example, via high-frequency alternating current signals). The benefits of this approach could be many, including increased power efficiency (signal energy is bound to the track, and not radiated to the surroundings) and more reliable communications (track signals may not be as vulnerable to weather, vegetation, and interference). The need for signal repeaters beside the track would be eliminated; repeaters would only be needed to cross insulated joints in the track. However, such a system would require close cooperation with railway companies to ensure the system did not interfere with existing railway signals. Different railways may use different signalling systems, potentially requiring adaptation of the system for different railways.

To minimize interference with railway operations and risk of damage from railway maintenance, warning system devices could be mounted on posts or trees beside the track. Such a system could use wireless communications (XBee or LoRa, for example) but with reduced need for signal repeaters, as radio antennas mounted above ground level and away from other objects tend to have greater range. Sensor systems for the train detectors could still be placed on or near the track and attached to their parent devices with buried cables. This scheme would have other advantages, including reduced need for a low-profile enclosure (reducing cost and complexity), potentially higher visibility and audibility of warning signals for wildlife on the track, and greater potential to power the devices with solar energy because warning light optics and solar panels alike would be less prone to covering by dirt or snow if they were off the ground.

Energy supply

Alternatives to reliance on battery power may drastically increase the operational lifetime of a warning system. Solar cells, for instance, are commonly used to power unattended right-of-way equipment for both railways and roads—even for other wildlife warning systems (Mulka 2009). Although the seasonal availability of sunlight at northern altitudes and in mountainous terrain decreases the practicality of this solution, solar panels can be increased in size to compensate. However, such increases in size would require the panels to be mounted on posts or in trees adjacent to the track—the panels would be too large, too fragile, or would become covered in dust too quickly to be mounted on the track at ground level. Other complications include the need for energy storage—often lead acid batteries—that require heating when ambient temperatures fall below $-20\,°C$. The solar panel itself may also require heating to keep snow from building up and preventing further energy capture.

Mechanical energy harvesting is another potential alternative, given the great quantity of vibration that moving trains emit. Energy harvesters with a variety of designs have been demonstrated for powering remote devices in railway applications (e.g. Cahill et al. 2018; Lin et al. 2018). A key advantage of this approach is that, unlike solar cells, vibration harvesters will still provide energy regardless of how dirty or snow-covered they become. Moreover, for this application, energy is provided by a passing train following every activation of the warning system, requiring only that enough energy is captured from the passing train to provide warning signals upon the arrival of the next train. Energy storage with supercapacitors may be ideal for this scenario, as these have a greater energy efficiency and longer operational life than most batteries and are often compatible with a wide range of temperatures.

One further alternative power source would be the electrical energy already supplied to the track rails by the railway signalling system. In many track circuit designs, a constant and small voltage is applied across the rails that is shunted by trains as they enter a signalling block, allowing detection of the train's presence within the block. Between train passages, warning system devices connected to both rails could siphon off small amounts of this electrical energy for storage in a battery or supercapacitor. As long as the siphoning circuits have a sufficiently high electrical impedence, they should have a negligible effect on the operation of the track circuit. However, this scheme only makes sense if the track circuit itself is powered with mains or solar electricity and not batteries.

Regardless of the energy source, refinement of the electrical design of each warning system device would minimize its energy needs. Using the power-saving features of the ATmega328P and the XBee radios alone, the lifetime of each device could be increased from three weeks to several months on three alkaline D-cells (assuming the ambient temperatures were appropriate for these batteries).

D.2 Camera calibration

D.2.1 Camera distance calibration

Cameras were manually triggered while researchers were standing along the railway track at both ends of the test zone (0 m and 200 m from the end of the track curve). These images were examined for the coordinates (in pixels) of the tops of both rails that were nearest to the photographed researchers at each distance. For one camera where these images were unavailable, the coordinates of the rail tops were recorded that were nearest to the two warning devices visible from that camera (25 m and 125 m from the nearest test zone edge). A 200 m ruler was drawn and perspective-projected using these four points for each camera, then composited onto a copy of every image belonging to sequences where animals had been recorded. Calibration references also gave an impression of the distance to the far edge of the test zone, assisting with judgements about whether a visible animal was within the test zone.

D.2.2 Camera timing and train speed

For image sequences where speed was measured, the image number was recorded in which the train was visually closest to the near edge of the test zone. Assuming that the cameras in each pair were triggered by each passing train at nearly the same time, the within-pair differences between trigger timestamps were modelled as a linear function of time since the camera pair was deployed. This function estimated the true within-pair difference in timestamps for any train passage, allowing comparison of the clock times of the images from each camera where the train was observed to enter or leave the test zone. This procedure allowed train speeds to be estimated to within $\pm 4\,\mathrm{km\,h^{-1}}$ to $\pm 10\,\mathrm{km\,h^{-1}}$.

D.3 Parameter values obtained by bootstrapping

In the Methods section of the manuscript, we asserted that our Wald statistics were accurate despite violation of the small dispersion assumption (Dunn & Smyth 2018, pg. 277). We illustrate this claim with the fact that estimates and standard errors obtained by bootstrapping with R package `car` (Fox & Weisberg 2011) were similar to the estimates and standard errors obtained by our presented models (Table D.6), suggesting that inferences made from the data would be similar in either case.

Table D.6: Comparison of original vs. bootstrapped parameter estimates (Orig. Est. vs. Boot Median) and standard errors (Orig. SE vs. Boot SE) from two Gamma generalized linear models with identity links for which the response variable was animal flight initiation time in seconds. For the *small animals* model, bootstrapped models would not converge with the Site variable so we present results here excluding the Site variable; estimates are nevertheless similar to those presented in the manuscript (Table 4.2). As before, reference categories (ref.) for boolean variables are indicated in parentheses. ":" indicates interactions. Train speed was centered and scaled to aid interpretation (original mean ± SD = $(60.5 \pm 4.6)\,\mathrm{km\,h^{-1}}$).

	Orig. Est.	Orig. SE	Boot Median	Boot SE
Large animals				
Intercept	8.3	1.4	8.2	1.0
Treatment (ref. control)	10.3	2.6	10.5	2.7
Approaching from curve (ref. straight)	4.6	2.3	4.7	2.5
Treatment:curve	-7.6	3.8	-7.8	3.7
Small animals				
Intercept	9.7	1.5	9.6	1.7
Treatment (ref. control)	3.1	2.4	3.0	2.6
Approaching from curve (ref. straight)	-3.1	1.4	-3.2	1.5
Auditory weather present (ref. absent)	1.0	1.2	1.1	1.5
Heavy snow (ref. light)	0.1	1.2	0.0	1.5
Animal starts on track (ref. off track)	3.7	1.7	3.7	1.9
Train speed ($\mathrm{km\,h^{-1}}$; scaled)	-0.7	0.7	-0.8	0.7
Site, 5MS (ref. 5MC)	–	–	–	–
Site, MLS (ref. 5MC)	–	–	–	–
Site, STB (ref. 5MC)	–	–	–	–
Treatment:curve	-1.4	2.9	-1.1	3.2

D.4 Animals observed, total and over time

We provide a list of species observed and number of indiduals per species at all four sites, including control events, treatment events, and unused events (Table D.7). Numbers per species are approximate as some species were difficult to identify or count in the photos. Size categories were chosen for convenience of observation: “Unidentified large bird” includes birds appearing to be approximately the size of an American robin and larger; “Unidentified large animal” includes animals appearing to be approximately the size of a coyote and larger.

We also summarize the number of individuals observed by month, site, and species group (Figure D.19) but offer no further interpretation. Species groups are as in Table D.7, except that “Carnivores” refers to ursids and canids together, “Small Mammals” refers to lagomorphs and rodents together, and “Unknown” refers to unidentified animals of all sizes. Counts for each species group within each month and site were divided by the number of unique train events captured in each month at each site. Thus, the mean numbers of individuals observed per event (vertical axis) allow approximate comparisons of animal use of the railway across months, sites, and species groups. See Table 4.1 for site names and locations.

Table D.7: List of animals observed.

Species	Number observed
Ursids	
Grizzly bear (*Ursus arctos*)	1
Black bear (*Ursus americanus*)	2
Unidentified bear (*Ursus* spp.)	3
Canids	
Wolf (*Canis lupus*)	2
Coyote (*Canis latrans*)	5
Unidentified canid (family Canidae)	2
Ungulates	
Elk (*Cervus canadensis*)	126
Whitetail deer (*Odocoileus virginianus*)	10
Unidentified deer (*Odocoileus* spp.)	80
Unidentified ungulate (family Cervidae)	20
Lagomorphs	
Rabbit (family Leporidae)	1
Rodents	
Beaver (*Castor canadensis*)	1
Red squirrel (*Tamiasciurus hudsonicus*)	243
Unidentified rodent (order Rodentia)	1
Birds	
Raven (*Corvus corax*)	14
Crow (*Corvus brachyrhynchos*)	36
Magpie (*Pica hudsonia*)	28
Unidentified corvid (family Corvidae)	2
Osprey (*Pandion haliaetus*)	4
Chickadee (*Poecile* spp.)	5
Pigeon (family Columbidae)	115
Unidentified large bird	280
Unidentified small bird	387
Unidentified bird	564
Unidentified animals	
Unknown large animal	21
Unknown small animal	16
Unknown animal	3
Total, all species	1972

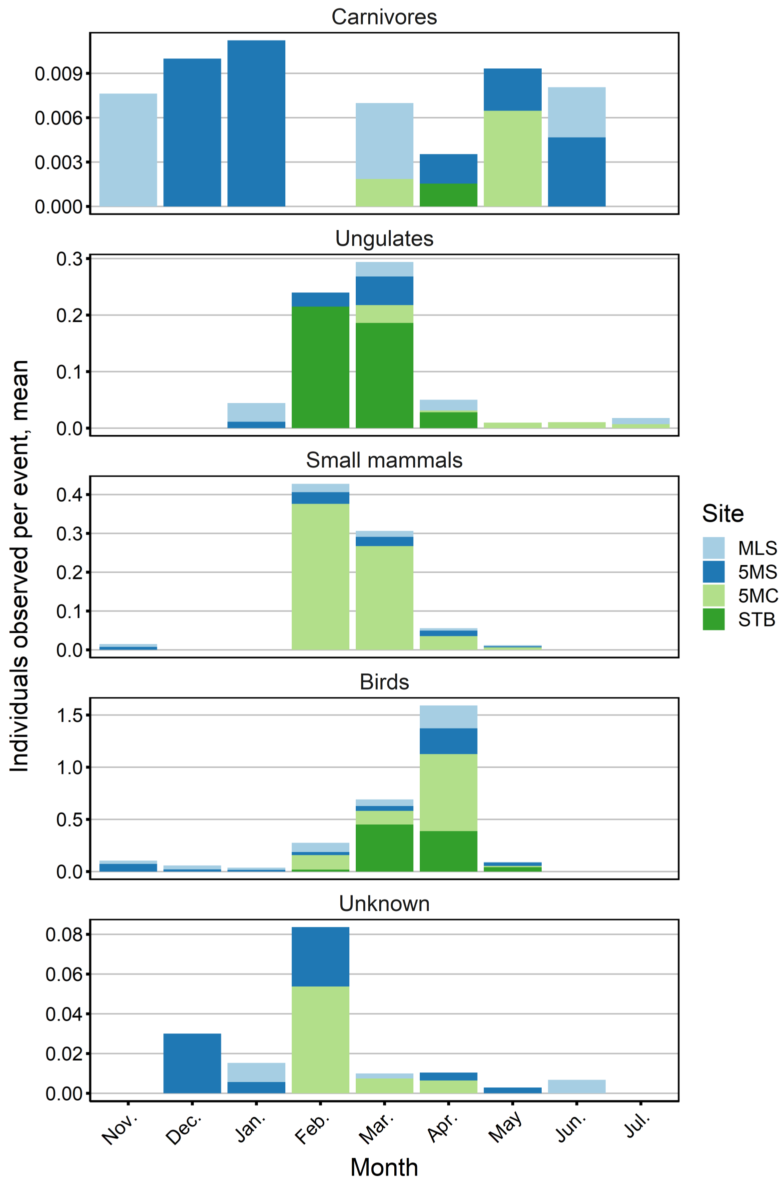

Figure D.19: Summary of unique animals observed by month, site, and species grouping in our study. Note that vertical axes differ in scale. Sequences with small animals (Birds, Small Mammals, Unknown) were recorded only opportunistically after April 20, 2017 and were not included in the analyses of this manuscript.

D.5 Encounter rate extrapolation

Averaging (weighted by sampling time) across our sites, 7.3% of unique events showed animals (1.0% large species, 6.3% small species). This could be interpreted as the probability that any given train passing through one of our sites would have encountered one or more animals. We then extrapolate over the total length of track in the study area (east half of Banff, 45.6 km), assuming that the length of track observed at each site was 300 m on average and that the distance a train travels before encountering an animal is exponentially distributed with a constant rate parameter across the study area (Chamaillé-Jammes & Blumstein 2012). We would then expect any given train passing through the study area to encounter at least one animal with near-certainty (probability > 0.99999 for all species; 0.79 for large species, >0.9999 for small species). Trains would encounter animals once every 4 km on average (every 29 km for large species, every 5 km for small species), or 12 animal encounters (2 large, 10 small) for every transit through the study area. We thus expect trains to have on the order of ten thousand encounters with large animals every year, 0.3% of which will result in a collision (1141 collisions recorded over 34 years; Gilhooly 2016). This estimate is consistent with our observation of zero collision events, as at this collision rate we could have expected to observe 0.3 collisions in the 90 large animal sequences obtained. These figures likely underestimate the encounter rate, as our cameras only captured animals at night that were illuminated by train headlights.

Our extrapolation of animal encounter rates should be taken as an order-of-magnitude estimate only. The calculation assumes our set of four test sites (total observed length near 1.2 km) is representative of the animal encounter rate for the entire study area (track length of 45.6 km). It further assumes that the rate parameter is constant along this length of track, which is clearly not the case given the variability among sites in the ratios of animal sequences to train sequences captured (11% at 5 Mile Cluster, 5% at Stables). Sites also did not represent a spatially random sample of possible sites, as they were chosen using prior knowledge to maximize the likelihood of animal–train encounters.

Nevertheless, if our choice of an exponential distribution is reasonable—that is, if trains encounter animals as a Poisson point process (Chamaillé-Jammes & Blumstein 2012)—the probability of any given train encountering animals would be high (>0.95) even for average animal-to-train ratios as low as 2%. The predicted encounter rate of 29 km per large animal is only three times greater than the rate reported for wildlife sightings on train trips in a different location in Canada (Muzzi & Bisset 1990), suggesting our estimate is of the correct order of magnitude. We might predict from these figures that 1800 site-days of sampling (compared to 520 site-days for this study) would be necessary to expect observation of a single collision event involving a large animal. Follow-up studies may note that a statistically useful sample of 30 collision events with large animals may require on the order of 55 000 site-days of sampling (38 years with the four sites used in this study).

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