Detection of Predator-Free New Zealand 2050 mammalian pest species with thermal AI cameras using a range of audio lures

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Limitations identified in current best-practice pest monitoring tools have directed research to seek alternatives capable of overcoming key management concerns. Some promising options identified include – thermal cameras, a more sensitive alternative to trail cameras; audio lures to increase the conspicuousness of monitoring devices and invoke interactions; and automatic classification AI to identify target species from in-field camera footage, reducing time and costs associated with manually analysing camera data.

This research aimed to further assess these three novel approaches through trialling the Project Cacophony AI thermal camera and sound lure device on free-ranging animals in regenerating native forest. Three categories of animal sound lure, containing three different noises were trialled – including possum (*Trichosurus vulpecula)*, rat (*Rattus spp.*), and calls from three species of common avian prey present in the area (chicken chicks (*Gallus gallus domesticus*), bellbird (*Anthornis melanura*), and fantail (*Rhipidura fuliginosa*).

The results showed a highly significant interaction between the pest species detected and the sound category of the audio lure played ($P<0.0001$). Possums were the most detected pest in the area (n = 104, 59, 76 for each monitoring trial). They responded predominantly to possum and prey noises – within those respectively, the shrill possum call and fantail call were the most favoured. Possums generally showed inquisitive and exploratory behaviour, with

some investigating the equipment closely and staying by the monitoring stations for multiple playbacks of the audio lure.

Rodents were the second most detected pest (n = 102, 20, 80 for each monitoring trial). However, individuals passed by the monitoring equipment at a distance and did not interact with it. This is consistent with behaviour observed in wild and captive rats and mice, which tend to be very sensitive and even show neophobia to novel stimuli, such as unnatural noises. Rodents favoured possum and prey noises overall; however, they preferred the slow and quiet possum noise and the bellbird call.

Rabbits and hedgehogs were detected in far fewer numbers in all three trials (n = 5, 6, 12 and n = 3, 12, 14, respectively) and were observed to survey the area around the monitoring station but not interact directly with the equipment. Cats were only detected in the possum and rat audio trials (n = 1, 12) from a distance and showed no interest in the monitoring stations. These species responded sparingly across the trials and showed no significant difference in response levels between the sound categories, making it difficult to estimate their audio lure preferences.

Although limitations with time and sample size were faced in this study, the results provide a basis for improving the methodology of assessing free-ranging pest behaviour using thermal AI cameras and animal audio lures. There is still much to explore using these technologies, as limited research has been conducted in a pest management context globally. However, preliminary research in New Zealand shows that these novel approaches are worthwhile avenues to investigate for developing an extensive range of control options to achieve a predator-free status.

Keywords: Predator free 2050, audio lure, thermal camera, pest control, conservation, New Zealand

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Chapter 1

Introduction

1.1 Pest management in New Zealand

Due to the absence of native terrestrial mammals, much of New Zealand's fauna evolved without the need to develop defence mechanisms against mammalian predators. The combination of a resource-rich environment and many predator-vulnerable species consequently provided the perfect conditions for introduced mammalian pests to thrive – including possums (*Trichosurus vulpecula*), rats (*Rattus spp.*), mice (*Mus musculus*), feral cats (*Felis cattus*), and mustelids (*Mustela erminea*) (Parkes and Murphy 2003). These introduced mammals have had a detrimental impact on native biodiversity, particularly avifauna, with numerous extinctions and 80% of the remaining avian taxa currently threatened or at risk of extinction (Murphy et al., 2019). The pressure of rapidly declining populations of native species has triggered a surge in pest management research and policy development, with the government announcing in 2016 that it has adopted the goal for New Zealand to become predator-free by 2050 (New Zealand Government, 2016). With this came an increase in funding from the government, NGOs, and charity foundations to explore technological advancements and new approaches to control pests effectively (Sage & Tabuteau, 2020).

Research on mammalian pest attractants has dramatically progressed in recent years, from studying alternative baits (Jackson et al., 2015) to long-life lures (Murphy et al., 2014), to even social/sensory lures using olfactory (Garvey et al., 2016) or auditory (Kavermann, 2013) stimuli. Current research explores new species-specific toxins, testing novel bait and toxin delivery mechanisms, improving trap designs, and assessing responses to lures and repellents. However, in the research and development of new tools, there will inevitably be obstacles and opposition. Public perception and political climate influence the scope of where we can direct research efforts, a key hurdle being the restrictions for genetic technology in pest management (MacDonald et al., 2020). Furthermore, implementing effective strategies to achieve a predator-free status by 2050 will require community collaboration which is heavily dependent on how the community views the pest control methods being used (Estévez et al., 2015). So, whilst there is a great need to explore the possibility of new tools, with no monumental breakthroughs on the horizon to achieve a predator-free status, we need to enhance existing technology to maximise the effectiveness of our current devices and management practices.

1.2 Current management challenges

To protect New Zealand's remaining native biodiversity, control methods are necessary to remove introduced pests from the environment. However, before undertaking a control operation, detection tools must first identify the pest species present in the target area. While detection rates are not an absolute indicator of the total pest population present, we can use them to infer a general species index and relative population abundance. This information is crucial in selecting which type and intensity of control method would be suitable to manage the population, to meet the desired project outcomes (Department of Conservation, 2015). One of the main challenges facing mammalian pest management is the lack of sensitivity of monitoring and control devices used to detect and eradicate pest species. The effectiveness of these devices is often determined by how attractive the bait or lure component is to the target species (Sweetapple & Nugent, 2011). To increase encounters and interactions with devices, various attractants can be utilised to make them more conspicuous in the landscape and appealing enough to provoke interaction (Morgan et al. 1995; Carey et al. 1997).

Attractants aim to stimulate an animal's visual, olfactory, gustatory, or auditory senses, thus encouraging investigation of monitoring devices or interaction with control devices. Doing so can increase the efficacy of the management operation through greater detections, more captures, or higher kill rates (Carey et al. 1997; Warburton & Yockney 2009). However, current best practice techniques for baits and lures are not always 100% effective. With issues like bait-shyness (Warburton & Drew, 1994; Devine & Cook, 1998; Allsop et al., 2017), neophobia (Sunnucks, 1998; Modlinska & Stryjek, 2016) and baits losing palatability over time (Jackson et al., 2015; Garvey et al., 2016; Sam et al., 2018), animals can easily avoid equipment, rendering trapping and monitoring devices ineffective.

Low encounter and interaction rates have been observed in many field studies of free-ranging pests. For example, Ball et al. (2005) estimated that in mixed farmland and beech forest habitat in the Canterbury foothills, there was only a 5% chance of trapping a possum with a leg-hold trap, located in the centre of its home range, each night. This probability rapidly decreased as a function of distance, with less than 1% chance of capture, each night, at 120 m from the centre of the home range. The authors also noted that field camera footage showed many possum-trap encounters did not result in capture; instead, the radio-collared possum passed within close range but did not interact with the device. It is important to note that the lure used in this study was the standard best-practice flour and icing sugar mixture, blazed up from the tree base to the trap. While this is visually alluring to possums and has a sweet smell, it is understandable that traps at further distances were encountered and interacted with less. Olfactory lures work over short distances, with visual lures working slightly greater. However, both lure types' effectiveness depends on the surrounding environment and conditions, for example, vegetation density and weather conditions (Morgan et al., 1995; Morgan 2004; Warburton & Yockney, 2009). Additionally, these types of lures require more field labour to regularly refresh them to maintain their palatability and attractive scent (Clapperton et al., 1994).

The limitations with current best-practice bait, scent, and visual lures have directed research to seek out longer-lasting, more attractive, and cost-effective alternatives. Various long-life and self-dispensing baits have since been developed, seeking to remedy these limitations; however, there is room for improvement if we are to reach the eradication goals of Predator Free 2050. Audio lures appear to be a promising alternative and have shown success in increasing the conspicuousness of monitoring and control devices in a New Zealand context (Kavermann, 2013). They address many of the limitations faced with current best-practice lures, as they are much longer-lasting and do not deteriorate over time, provided the device batteries are refreshed. Additionally, they are more conspicuous, attracting pests over larger distances and in dense vegetation (Carey et al., 1997). By increasing the conspicuousness of device stations, fewer may need to be established for adequate lure coverage of a control site. This will decrease operational costs greatly and potentially allow stations to attract pests from inaccessible areas (Kavermann, 2013). There is still much to explore using audio lures and responses from pest and non-target species, as limited research has been conducted in a pest management context globally. However, preliminary research results in New Zealand show promise and that this may be a worthwhile avenue to investigate for future pest management research.

1.3 Project Cacophony

This research was carried out in conjunction with Project Cacophony, an independent research collaborative comprising experts from a range of disciplines across New Zealand. Cacophony seeks to link the fields of technology and pest management to pursue the goal of "Predator Free 2050" with an innovative approach. The key device used in this study was the Thermal Predator Camera with Machine Vision, developed by Project Cacophony. This camera automatically captures the movement of animals and uploads video recordings to the cloud database, where they are analysed using machine vision algorithms (Project Cacophony, 2019). Additionally, Project Cacophony provided the field site for this research through their research partnership with Living Springs.

1.4 Dissertation aims and objectives

This research aims to investigate the behaviour and responsiveness of the three key Predator-Free 2050 mammalian predators, being possums and rats and stoats, towards a range of audio lures. We will also observe the responses of other pest species potentially in the area, such as cats (*Felis cattus*), hedgehogs (*Erinaceus europaeus*), and European rabbits (*Oryctolagus cuniculus*). Three key objectives will be addressed during this research:

- Observe through thermal camera footage pest behaviour and interaction rates to a range of audio lures (competitor, prey, and conspecific calls).
- Identify the most attractive audio lures for different pest species to increase the interaction rate of monitoring and trapping devices.
- Assess the accuracy of the current detection and identification AI developed by Project Cacophony in a field context with free-ranging animals.

Three field trials were conducted to compare the three categories of audio lures – possum, rat, and prey sounds. Each category had three distinct sounds, e.g. three types of possum calls, to assess animal responses to a wider range of audio recordings.

1.5 Dissertation structure

Chapter 2: Literature Review

Literature on the use of audio lures, thermal imaging, and Artificial Intelligence (AI) in pest management is reviewed to provide context to the key aspects of this research – sound lures, thermal cameras, and identification AI. Additionally, the review will identify gaps in knowledge and future recommendations from the literature and how these may be addressed through this research project.

Chapter 3: Materials and Methods

Chapter three describes the location and experimental design of the research undertaken and the special equipment that was used. It also gives a brief description of how the equipment works and how it will obtain the data needed to meet the research objectives. An outline of the statistical analysis is included to show how the results were obtained.

Chapter 4: Results

The results from the field trials are presented according to the key objectives of this research – Thermal camera detection rates of pest species, sound lure preferences across the pest species detected, and an assessment of the performance of the automatic classification AI.

Chapter 5: Discussion

This chapter will integrate the purpose of the research with the results obtained and discuss whether they fulfil the key research objectives. The limitations faced in this research will also be discussed, including how these may be addressed in subsequent research. This chapter will then conclude with recommendations for future research in the field of applied technology in conservation.

Chapter 2

Literature Review

2.1 Introduction

Literature on the use of audio lures, thermal imaging, and Artificial Intelligence (AI) in pest management was reviewed to identify what methods have been tested, analyse why the results occurred, and discuss how they may apply to the context of pest management in New Zealand. Additionally, this review will report gaps in knowledge or future recommendations identified through these studies and how they may be addressed through this research.

2.2 Thermal cameras

Device sensitivity is paramount for gathering accurate pest population data. The saturation of monitoring devices such as chew cards or PCR WaxTags® can make it difficult to distinguish between species or analyse the abundance of species in an area (Burge et al., 2017). At the other end of the spectrum, animal avoidance or insensitivity of the device mechanism can also create issues, particularly in detecting threats against vulnerable species. Trail cameras were a significant development in wildlife management and were able to remedy many of the limitations of other monitoring devices. In the context of pest management, it was important to have a multi-species detection tool that was able to identify species and even individual animals. Cameras are also a passive monitoring device that does not require the animal to do a certain behaviour to get a detection, for example, entering a tracking tunnel, chewing a chew card, sticking their head in a hole, climbing up to a leg-hold trap.

Anton et al. (2018) compared the detection rates of trail cameras and tracking tunnels, two commonly used monitoring devices in New Zealand wildlife management, to determine their effectiveness in detecting various pest species. The results showed that cameras detected significantly more hedgehogs (*Erinaceus europaeus*), possums (*Trichosurus vulpecula*) and rats (*Rattus spp.*) and were able to identify the species of rat in 50% of detections. Occasionally, the cameras missed recording mice (*Mus musculus)*; however, tracking tunnels were able to detect them. Conversely, where tracking tunnels missed detecting possums, cameras were able to record them. While trail cameras recorded substantially more animals than tracking tunnels, they are designed for detecting larger, slower animals; hence mice sometimes went undetected.

Thermal infra-red cameras programmed with detection AI sought to remedy this issue with much faster heat and motion-triggered detection. To test this, eight pen trials were conducted by James Ross and Grant Ryan at the Zero Invasive Predators research facility in Lincoln, New Zealand (Bugler & Ross, 2020). They compared the possum detection rates of passive infra-red (PIR) trail cameras and the AI infra-red camera developed by Project Cacophony. Each trial consisted of an individual possum being placed in a 2-hectare enclosure for three nights, with three detection stations including an AI thermal infra-red camera, a trail camera, and a chew card. Results showed that the AI infra-red cameras were 3.5 times more sensitive at detecting possums than PIR trail cameras. Trail cameras can miss detections due to a lack of sensitivity in the motion sensor and the delay in this triggering the start of recording, missing fast-moving animals or not capturing the full interaction of the animal. AI infra-red cameras are considerably more sensitive than trail cameras, utilising advanced and far more expensive technology, with the capacity for a much faster computational speed. This increased sensitivity and scope of the detection device also means that fewer cameras are required to monitor the same amount of area, reducing labour and operation costs. Another key difference noted from these trials was that the PIR trail cameras had a higher rate of false-positive recordings that did not contain animals triggered by bad weather such as wind and rain. Consequently, a sizeable number of videos were created that had to be manually analysed, taking far longer to work through than the automatic classification software programmed into the AI infra-red cameras.

These preliminary trials show promise for using Project Cacophony's AI infra-red cameras to monitor free-roaming pests in the wild. Field trials are the next step in substantiating the cameras' effectiveness against current monitoring devices and enhancing the cameras attractiveness using lures to increase detections.

2.3 Audio lures

Audio lures are any sound, whether natural or novel, that can attract a target species. The objective for using audio lures to attract pest species primarily focuses on increasing both encounter and interaction rates with monitoring and control devices –to overcome common management concerns, such as trap avoidance, eradicating low-density populations, and identifying and removing reinvaders. Usually, device attractants focus on visual, olfactory, and gustatory stimuli; however, there are limitations to these mechanisms. An issue with bait and olfactory lures is that they are only detected by the animal in relatively close proximity, especially in densely forested areas. Additionally, these types of lures can lose their attractiveness as the smell or palatability degrades into the surrounding environment (Clapperton et al., 1994). Conversely, audio lures are much longer-lasting and do not deteriorate over time, provided the device batteries are refreshed. Additionally, they are more conspicuous than visual or olfactory lures, attracting pests over larger distances and in dense vegetation (Carey et al., 1997).

Unfortunately, there is limited literature on audio use in pest management, with most research directed at the species being conserved – for example deterring non-targets from control devices (Shivik & Gruver, 2002), mapping or expanding territories (Reid et al., 1999; Anich & Ward, 2017), and anchoring a species post-translocation (Molles et al., 2008). Research using audio lures for pest management in New Zealand began in the 1990s, with Spur and O'Conner (1999) initially trialling a range of bird, mouse, and stoat calls to test if they were more attractive to captive wild-caught stoats (*Mustela erminea*) than the standard chicken egg bait. The results showed that silvereye (*Zosterops lateralis*), common starling (*Sturnus vulgaris*), and house sparrow (*Passer domesticus*) distress calls did not attract stoats, but that chicken chick (*Gallus gallus domesticus*), mouse (*Mus musculus*), and stoat calls did attract stoats within 5 minutes of playing. Further research was advised to determine the effects of the sound quality, duration, frequency, and type of recording (i.e. analogue versus digital). Additionally, it was recommended to further test the audio lures in field trials with free-ranging animals. Field trials on free-ranging pests were conducted by Moseby et al. (2004) in South Australia. Feline and bird audio lures and a pongo olfactory lure (feline urine and scat) were trialled to attract feral cats *(Felis cattus*) and foxes (*Vulpes vulpes*) in an arid sand dune habitat. The researchers found that only 7% of olfactory lure sites attracted cats, compared to 41% and 44% for feline and bird audio lures, respectively. Foxes showed a significant difference in the number of site visits between olfactory and audio lures versus the control sites with no lure. However, there was not enough count data to detect a statistically significant difference in their preference for audio or olfactory lures.

Field trials conducted by Kavermann (2013) indicated that audio lures appear to increase the conspicuousness of bait stations and trap sites, with Australian brushtail possums (*Trichosurus vulpecula*) finding audio-lured sites faster and more frequently than sites without. Given these results, it was hypothesised that audio-lured devices might promote greater encounter and subsequent interaction rates in situations that non-audio lured devices would otherwise be less successful. For instance, in heavily vegetated landscapes where devices are difficult to locate, or even encouraging pests to forage beyond their normal home range in search of the audio stimulus. If these results and subsequent hypotheses remain consistent, it may be possible to establish fewer, more conspicuous bait stations spaced at greater distances. This will decrease operational costs significantly and potentially allow bait stations to attract pests from inaccessible areas.

These studies highlight the gap in New Zealand pest management of assessing an array of natural or non-natural audio lures for pest species – including conspecific social calls, competitor, predator, prey noises, and even ultrasonic or novel sounds. Whilst the concept of using audio lures to attract pest species is not new, field testing of these types of audio lures (ultrasonic, competitor species, prey, and conspecific calls) to attract mammalian pests has not been undertaken in New Zealand before.

2.4 Identification AI

Utilising computer vision for neural network-based species recognition is a relatively recent addition to passive monitoring methods used in wildlife management (Chen et al., 2014). For auto-identification software to work accurately, the neural network must be trained with a labelled dataset of images – in this context, the target animals being monitored. This allows the machine to extract features and learn pixel patterns that make up the distinguishable characteristics of an animal, then recognise those patterns when presented with new images from in-field camera footage (Willi et al., 2019). However, this process is reliant on the quality of image data that the camera provides. Issues faced with manually identifying animals through trail camera footage may also translate to neural network-based identification, including the animal's size, distance from camera, and the speed it is moving (Marcus Rowcliffe et al., 2011; Gomez Villa et al., 2017).

Previous solutions to overcome difficult image datasets mainly focussed on larger animals or those with distinguishable features, such as horns or wings. Yu et al. (2013) classified 18 animal species at 82% accuracy by manually cropping 7196 images for their training dataset that contained the whole animal body. Chen et al. (2014) made the first attempt at fully automated computer vision-based species recognition. They used an automatic segmentation algorithm to crop 20 species of animals from the training images and a convolutional neural network (CNN) of six layers to analyse them further. With this approach, they achieved only 38.31% accuracy in correctly classifying the 20 species. Both Gomez Villa et al. (2017) and Willi et al. (2019) used CNNs combined with some manual identification to classify a dataset of images obtained in the Serengeti region of Tanzania – achieving similar accuracies of 88.9% and 88.7-92.7%, respectively. The combination of using a trained neural network supported by occasional manual identification appears to produce the most accurate results whilst substantially lessening the human efforts usually needed to analyse field-camera images and footage.

Another method to improve classification accuracies, particularly for small animal monitoring, is using infra-red cameras. The infra-red thermal radiation produced through the animal’s body heat helps the camera distinguish it from the surrounding environment; thus, it is less likely to be falsely triggered, and the AI can extract more accurate and distinguishable features for analysis. This was evident in Ross and Ryan’s 2018 pen trials (Bugler & Ross, 2020), where the AI was able to tag 297 thermal video recordings as “not containing 'animals’, leaving 49 recordings to analyse, compared to 5264 recordings captured by the standard PIR trail cameras over the same time period.

Chapter 3

Materials and Methods

3.1 Study site

Trials were undertaken from September 18th to October 7th, in the regenerating native forest at Living Springs (43°39’11.55 “S, 172°38’2.78 “E) south-west of Allandale, in Banks Peninsula, Canterbury, New Zealand. Banks Peninsula/Horomaka is approximately 1000 sq km in area, halfway down the South Island’s east coast (Fig. 1). This area was formed from a volcanic shield complex, that was active between 5 and 12 million years ago. Volcanic cones from the two dominant eruptive centres eroded over time, with the sea entering the calderas and forming what is now known as the Lyttleton and Akaroa harbours. Erosion, loess deposits, and build up from coalescing shingle fans eventually joined the volcanic remains to the mainland (Stipp & McDougall, 1968). The peninsula has two dominant soil types – loess, a fine wind-blown sediment, forming deep soils on the lower slopes and flat ridge tops, and volcanic soil derived from basalt, forming stony, shallow soils on the steeper slopes where loess did not accumulate (Griffiths, 1973).

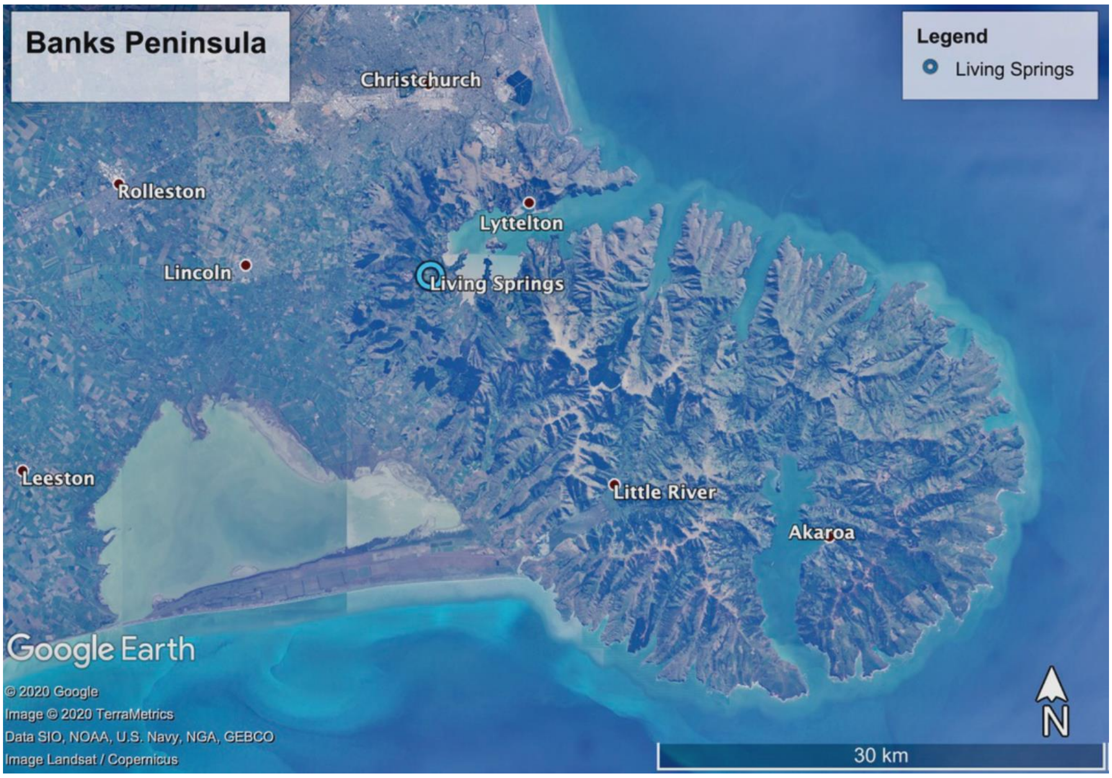

Figure 3.1. Satellite image of Banks Peninsula showing the location of the Living Springs study site (blue circle) (Google Earth Pro Version 7.3.3, 2020).

Banks Peninsula's pre-human landscape was a mosaic of successional vegetation – predominantly old-growth podocarp forests with a lush understory, in the lowlands, and exposed areas of scrub and tussocklands at higher altitudes (Wilson, 1994; Department of Conservation, 2015). Years of deforestation, land conversion to agriculture and increased housing development has left only a small percentage of remnant native forest. The current landscape is moderately hilly terrain, mainly consisting of introduced semi-arid grasslands, pasture, invasive weeds such as gorse (*Ulex europaeus*) and broom (*Cytisus scoparius*), and wild and plantation pine (*Pinus radiata*). Sparse pockets of native forest are generally confined to the valleys, where soil water content is higher, and slopes are too steep for farmland. This area received an annual rainfall of 637 mm from November 2019 to November 2020 (Environment Canterbury, 2020). The dry, windy climate aids in the propagation of the invasive species that dominate the peninsula - gorse, broom, and pine. Despite the seemingly unfavourable climate conditions and land-use practices, when facilitated, the native forest has been able to self-regenerate, examples being Hinewai Reserve (Wilson, 1994) and Living Springs, where this research was conducted.

Living Springs' landscape is variable given the range of land uses on the property – predominantly low density, dryland farming, regenerating mixed native forest, popular for recreational activities, and old pine plantations that are gradually being harvested to expand the area available for forest regeneration. For this study, nine sites were selected along various walking tracks on the 420 ha property, accessible from the Living Springs Camp and Conference Centre (fig. 2). Sites ranged from 136 m – 232 m above sea level through a range of vegetation types. Sites 1 and 2 were set in regenerating mānuka scrub (*Leptospermum scoparium*), adjacent to low-density, dry farmland. Sites 3 – 9 were set in mixed regenerating podocarp forest, with fern and broadleaf understories.

Figure 3.2. Locations of the nine trial sites at Living Springs (Google Earth Pro Version 7.3.3, 2020)

3.2 Equipment

3.2.1 Thermal cameras

This study used thermal cameras developed by Project Cacophony to automatically detect movement and capture the infra-red radiation emitted from an animal via body heat. This allows the camera to distinguish the animal from its surrounding environment without the need for illumination, producing a thermal video recording (Fig 3).

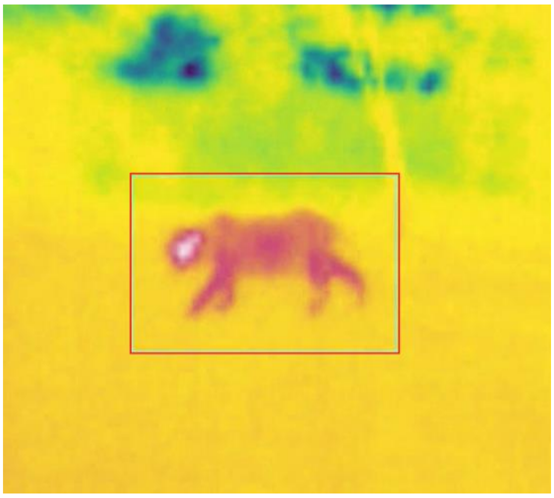

Figure 3.3. Still picture taken from a thermal video recording of a cat, with movement tracking by identification AI (red box).

The FLIR (Forward-Looking Infra-Red) Lepton 3 thermal camera is powered by a Raspberry Pi 3, a small but powerful single-board computer with customisable hardware and software to perform various functions. Cacophony developed a custom board consisting of:

- a modem that can connect with Wi-Fi or a device hotspot, allowing wireless transfer of recording data to the Cacophony servers,
- connection for mains or battery power supply,
- connection for external speaker to play audio lures,
- Device storage to save video and audio recordings until they can be uploaded to the cloud.

The thermal cameras and external batteries are secured in waterproof boxes to reduce the risk of damage, and the speakers are marine-grade waterproof. Cameras with battery supply can be left in the field to record at night-time for up to a week. Video and audio recordings are stored on the device until they can be uploaded via Wi-Fi hotspot to Project Cacophony's in-field Sidekick app. From there, the recordings can be uploaded to the API server for processing and storage on a cloud database (Project Cacophony, 2019).

Figure 3.4. Thermal camera interior (left) connected to a lithium battery (centre) and an external speaker (right) (Finlay-Smits, 2018).

3.2.2 Audio lures

Each camera can be programmed to play an audio lure at defined intervals, e.g. every 10 minutes, from 7 pm until 7 am. The Cacophony Sidekick app allows the user to adjust the volume and test the external speaker in-field to ensure it is working. The audio lures chosen for this study were selected from a range of animal noises recorded by Zero Invasive Predators. Sound categories were selected based on the current species that are commonly found in the study area. Possum and *rattus spp.* calls were chosen as they can be competitors or conspecifics to the target pest species present in this area. Bellbird, fantail, and chicken chick calls were selected for the prey sound category as these are already present in the mixed rural and native bush landscape.

3.2.3 Identification AI

Project Cacophony has developed a machine learning pipeline (fig 5.) that uses computer-vision to automatically detect and identify pest species and non-targets such as birds, insects, livestock (*Finlay-Smits*, 2018). The thermal camera input data is initially processed through two streams, analysing optical flow and thermal sensation. Optical flow is the estimation of the motion pattern of individual pixels on an image plane, which can be ascribed to the motion of objects that the camera is capturing. Optical flow algorithms delineate the region of the moving image and the velocity of the movement, which is important for detecting the size and movement patterns of target species (Turaga et al., 2010). Thermal sensation is the camera's detection of infra-red radiation to identify heat sources, helping to distinguish an animal from the surrounding environment (Havens & Sharp, 2016).

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture used in deep learning. It uses feedback connections to learn new inputs that require memory of events that happened many discrete steps earlier (Bayer et al., 2009). LSTM units do this by preventing backpropagated errors from vanishing or exploding (Vanishing Gradient Problem), a common problem with the standard feedforward neural networks (FNN). Error values are sent through a "forget gate", which allows the error to remain in the unit's cell but not have direct impact on the output, developing the cell's internal memory. The error is then continuously fed back through the unit until it learns that the value either needs to be incorporated or cut off from the network (Gers at el., 2003).

The next step in the pipeline is using a convolutional neural network (CNN) to break up each image into features using a pooling mechanism. This mechanism allows the network to analyse deeper with fewer, more specific parameters, as it can significantly reduce the amount of free or irrelevant parameters from the input. The fully connected layer then takes the output of many convolution/pooled layers and predicts the best classification to describe the image (Agdam & Haravi, 2017). Finally, the softmax function transforms the logits (raw prediction values) output from the final layer of the neural network into values between 0 and 1 so that they can be interpreted as probabilities of the image being a particular classification, e.g. species of animal.

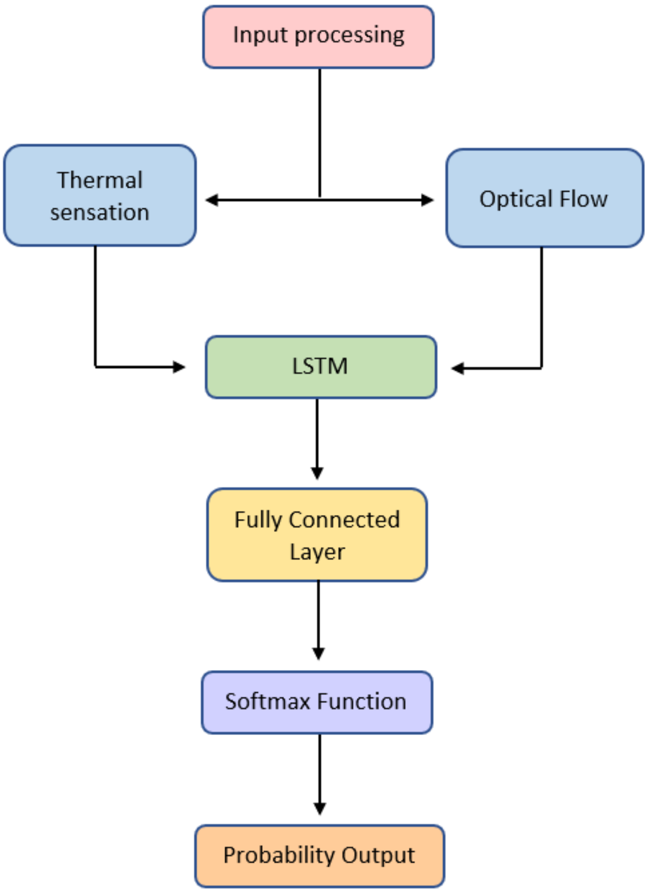

Figure 3.5. The architecture of the machine learning pipeline developed by Project Cacophony. Diagram adapted from Grant Ryan's presentation for the AI-Day conference (Ryan, 2018).

3.3 Experimental design

Each of the nine sites were set up with one thermal camera on a tripod, a battery pack, and a speaker to play the audio lures (fig. 6). The cameras were set to record from 7 pm to 7 am, each night, for one week, with an audio lure playing at 10 min intervals between these times. Battery packs were replaced with fully charged ones after each trial. Trial 1 was conducted from the 18th – 25th of September 2020, testing three possum sounds as audio lures – a long and slow call, possibly in alarm, a slow and quiet call, and a shrill call. Trial 2 ran from 7 pm on September 25th – October 2nd, and tested three rat noises, a distress call and two neutral calls. Trial 3 ran from 7 pm 2nd – 7th of October, testing the sounds of three prey species present in the area, chicken chicks (*Gallus gallus domesticus*), bellbird (*Anthornis melanura*), and fantail (*Rhipidura fuliginosa*).

Figure 3.6. Example of experimental set up at Living Springs (left). Thermal camera on tripod with battery pack and speaker attached (right) – from trials conducted by Bugler & Ross (2020)

3.4 Data analysis

The video recordings from each trial were stored on Project Cacophony's cloud database, from which they could be viewed and identified using the classification tool, as shown in figure 3.7. Classification categories included pest species (possum, rodents, cat etc.), non-targets (insects, birds, livestock, humans etc.), false-positive camera triggers due to vegetation movement, and unidentifiable/unknown. Due to the small size of rodents and their distance from the cameras, it was usually impossible to distinguish with the naked eye the species of rat, or if it was a mouse – thus, all species of rats and mice were grouped into one category as "rodents" in the classification. Data from the video recordings for each trial – including date, time, camera, AI and human identification tags, type of audio lure played etc. – was then exported to a Microsoft Excel spreadsheet for analysis.

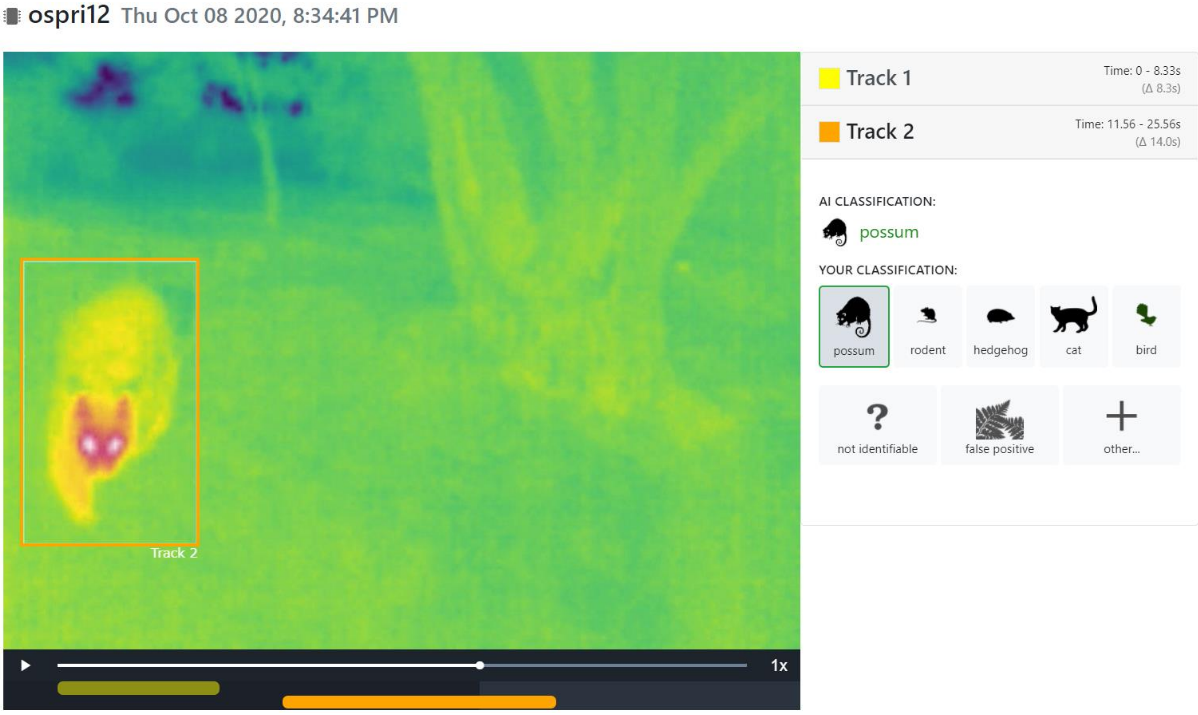

Figure 3.7. A possum correctly identified by the classification AI during the prey audio lure trial, at site 2.

R Studio v. 1.2.5033 and R version 4.0.2 (using package lme4 version 1.1-23) were used to create a Generalised Linear Mixed-Effects Model (GLMM) to compare the sound category preferences of each pest species detected. The number of each type of pest species detected per site, each trial night, was included in the model as the dependent variable and fitted with a Poisson error distribution. Fixed effects included the species of pest (possum, rat, cat, hedgehog or rabbit, audio lure sound category (possum, rat, or prey noise) and second-order interaction between these terms. The site location number was included as a random effect to account for the non-independence of any errors related to variations in measures of each site.

The significance of the fixed effects were assessed using backwards selection with function drop1. Checks for overdispersion (for the Minimum Adequate Model) were done using package blmeco (version 1.4). Where fixed effects were found to be significant, pairwise comparisons between categorical levels were made using package emmeans (1.5.1).

Chapter 4

Results

4.1 Thermal camera detections

Five pest species groups were detected during the trials at Living Springs – possum, rodent (includes rat and mouse species), cat, rabbit, and hedgehog.

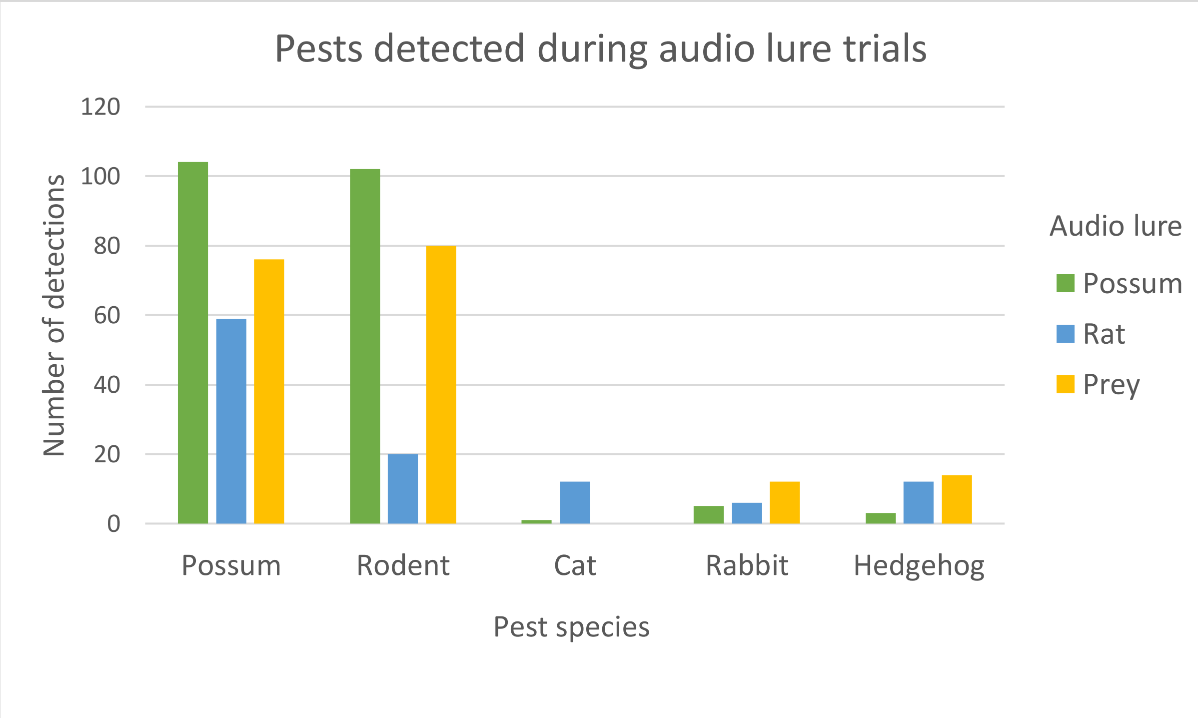

Figure 4.1. Counts of each pest species detected on thermal camera footage from nine monitoring sites at Living Springs for each audio lure trial week.

Overall, possums were the most detected pest species in the area (n = 104, 59, 76). Due to their large size and slower movement than other pest species, the thermal cameras are more likely to detect them even at a distance. However, the cameras still detected many small rodents in the area (n = 102, 20, 80). Rabbits and hedgehogs were detected in far fewer numbers in all three trials (n = 5, 6, 12 and n = 3, 12, 14 respectively), and cats were only detected in the possum and rat audio trials (n = 1, 12).

4.2 Audio lure response

The GLMM showed a highly significant interaction between species detected and the sound category of the audio lure (P < 0.001).

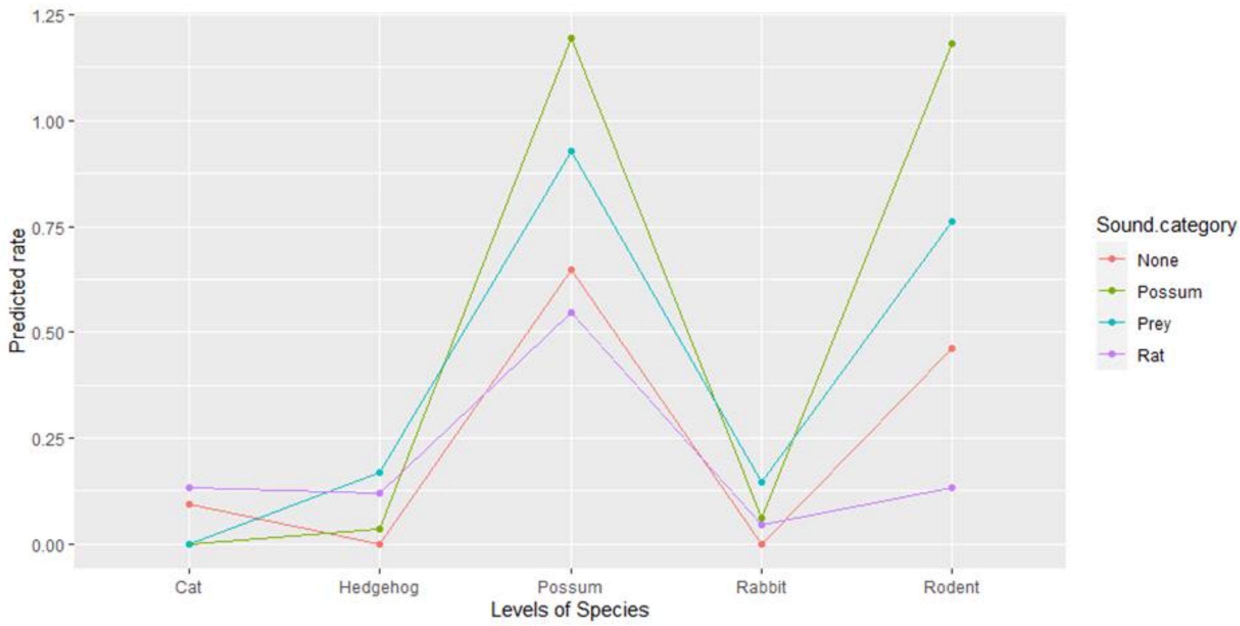

Figure 4.2. The average number of individual pests responding to each category of audio lure per night. Note: "None" category is the result of a single camera not playing the audio lure during the rat trial.

Cats only responded to the possum and rat audio trial, and at a low rate. Thus there were no significant differences in response between sound categories. Hedgehogs and rabbits both responded sparingly across the three trials and showed no significant difference in their response levels between the sound categories. Conversely, possums responded to lures at higher rates and showed a significant difference in response rates in a pairwise comparison of possum/rat audio (P < 0.001) and prey/rat audio (P = 0.02). Likewise, rodents responded at higher rates and showed significant difference in response between possum/prey audio (P = 0.0306), possum/rat audio (P < 0.001), and prey/rat audio (P < 0.001).

Table 4.1 shows the total numbers of pests that responded to each type of lure within the three sound categories in more depth.

Table 4.1. Total number of pest species detected responding to each type of lure (with the highest response number highlighted in green).

	Pest species detected				
Possum audio type	**Possum**	**Rodent**	**Cat**	**Rabbit**	**Hedgehog**
Long, slow, alarmed	32	33	0	2	3
Shrill call	47	18	0	1	0
Slow and quiet noise	20	47	0	2	0
Rat audio type					
Distress noise	22	2	0	0	0
Rat noise 1	22	7	5	2	11
Rat noise 2	6	3	7	2	0
Prey audio type					
Bellbird	9	45	0	11	12
Chicken chick	25	5	0	1	0
Fantail	43	13	0	0	2

Possums responded the most to possum and prey noises – within those respectively, the shrill possum call and fantail call were the most favoured. Rat noises were generally less attractive to possums, but they did respond to the rat distress and rat noise 1 calls at equal rates. Rats also favoured possum and prey noises overall; however, they preferred the slow and quiet possum noise and the bellbird call. It is difficult to estimate the audio lure preferences of the other pest species detected due to low numbers detected sporadically across the three trials.

4.3 Identification AI

The performance of the identification AI varied significantly for each trial. This is likely because the AI is still training to detect pests at different distances, illumination levels and environments. The identification AI fluctuated from being oversensitive and trying to classify every movement in the environment to under sensitive and missing some identifications. This is shown in the substantial difference between the numbers of video and AI tags in each trial (Table 4.2).

Table 4.2. Summary of the AI performance in each trial.

AI summary	Possum audio	Rat audio	Prey audio
Number of videos (n^v)	764	212	1197
Number of tracks (n^t)	1639	226	3013
Correct ID/n^v	101 (13.22%)	52 (24.53%)	64 (5.35%)
AI tracks, wrong ID/ n^v	234 (30.63%)	26 (12.26%)	560 (46.78%)
AI tracks, unknown ID/ n^v	489 (64.01%)	118 (55.66%)	793 (66.25%)
AI misses tracking pest/n^v	68 (8.90%)	23 (10.85%)	42 (3.51%)
false positive/n^v	301 (39.40%)	13 (6.13%)	679 (56.73%)

Both the possum and prey audio trials had a higher number of videos, AI tracks, misidentification, and proportion of false-positives, due to the AI tracking and attempting to identify moving vegetation as well as animals. Despite this oversensitivity, the AI correctly identified 101 videos in the possum audio trial and 64 videos in the prey audio trial. The rat audio trial had the highest proportion of correct identification, with 52 videos correctly identified. Additionally, the appeared decrease in sensitivity of the AI in the rat audio trial meant that only 6.13% of videos were false-positives from surrounding vegetation – as opposed to 39.40% and 56.73% in the possum and prey audio trials, respectively. All three trials had relatively low missed tracking rates (range of 3.51% - 10.85%), where the AI did not detect that a pest animal was present. Missed trackings often occurred due to the cameras inability to track animals at far distances. This is possibly due to the animals very small size on the footage not being adequate to identify changes in pixels as an animal shape or movement. Additionally, the increased distance of the heat source to the IR detector makes the animal less distinguishable against the surrounding environment.

Chapter 5

Discussion

5.1 Research Summary

Effective monitoring tools are a crucial component in planning, undertaking, and assessing the success of pest control operations. Limitations identified in current best practice devices have directed research to seek alternatives capable of overcoming key management concerns – including device sensitivity, animal encounter and interaction rates with the device, the longevity of the device in-field, and operational costs. Thermal cameras have been identified as a more sensitive alternative to trail cameras, particularly for monitoring small, cryptic, or fast-moving animals (Anton et al., 2018; Bugler and Ross, 2020). To increase the conspicuousness of monitoring devices and invoke interactions, audio lures appear to be a promising option for attracting mammalian pests in New Zealand (Carey et al., 1997; Kavermann, 2013). Additionally, automatic classification AI to identify target species from in-field camera footage has proven effective in reducing labour time and costs associated with manually analysing and recording camera data (Bugler & Ross, 2020). This research aimed to further assess these three novel approaches to pest management through trialling the Project Cacophony AI thermal camera and sound lure device in regenerating native forest.

The results of this research addressed three key objectives – to observe through thermal camera footage, pest behaviour and interaction rates with a range of audio lures, to then identify the most attractive audio lures for different pest species, and lastly assess the precision of the current identification AI developed by Project Cacophony, in a field context with free-ranging animals.

5.2 Discussion of results

5.2.1 Thermal camera detections

Possums were the most detected pest in the area (*n* = 104, 59, 76 for each monitoring trial). Due to their large size and slower movement than other pest species, such as rodents or mustelids, thermal cameras are more likely to detect them, even at a distance. Possums are known to have a curious nature, investigating novel stimuli in their environment (Carey et al., 1997; Ogilvie et al., 2006; Kavermann, 2012; Sjoberg, 2013). The audio lure likely increased the conspicuousness of the monitoring station, attracting possums from further distances to investigate the equipment. It was observed that some individuals stayed by the monitoring stations for multiple playbacks of the audio lures – around 20 to 30 minutes. Additionally, multiple possums were very interested in the thermal camera, staring straight into the lens. Like most nocturnal mammals, possums can sense infra-red light and hear sounds emitted from cameras (Meek et al., 2014; Meek et al., 2015). This may contribute to their interaction with the device; however, it did not appear to deter them in these trials but rather invoke further investigation of the monitoring equipment.

Rodents were the second most detected pest (n = 102, 20, 80 for each monitoring trial). However, individuals tended to pass the monitoring equipment at a distance and did not interact with it. This is consistent with behaviour observed in wild and captive rats and mice, which tend to show neophobia to novel stimuli, keeping distance from the monitoring station (Witmer et al., 2014; Stryjek & Modlinska, 2016). Rabbits and hedgehogs were detected in far fewer numbers in all three trials (n = 5, 6, 12 and n = 3, 12, 14, respectively) and were observed to survey the area around the monitoring station but not interact directly with the equipment. Cats were only detected in the possum and rat audio trials (n = 1, 12) from a distance and did not appear to be interested in the monitoring stations at all.

5.2.2 Audio lure response

The GLMM showed a highly significant interaction between the pest species detected, and the sound category of the audio lure played ($P < 0.0001$). Possums responded the most to possum and prey noises – within those respectively, the shrill possum call and fantail call were the most favoured. Surprisingly, they responded significantly less to rat noises – further research would help substantiate if this is a consistent behavioural feature of possums or a reflection on the rat sounds chosen for these trials.

Rodents also favoured possum and prey noises overall; however, they preferred the slow and quiet possum noise and the bellbird call. Likewise, they responded significantly less to the rat audio – subsequent research would need to explore why the rat noises chosen appeared to be either unattractive or potentially deterring for both possums and rodents. Preliminary research conducted by Zero Invasive Predators (ZIP) found that ship rats (*Rattus rattus*) are very sensitive to audio lures and could easily detect unnatural social sounds. Consequently, if the sound was too loud, the range of noises played were unnatural, more than one type of noise was played, or the audio quality was low, the lures actually may have had a repellent effect. They also found that cheap microphone and cell phone recordings were inadequate for playing back natural rat noises. Recordings require ultrasonic components to sound like wild rat calls, which prompted the team to design an ultrasonic audio box to play their sound lures. Additionally, they noted that if these audio lures were to be tested in the field, the monitoring equipment would need a passive infra-red (PIR) or similar sensor to know when animals were close by. This would ideally make the speakers play the audio lure loud enough to draw in animals when they are far away, but then turn the volume down when they came in close range to the equipment to avoid playing it unnaturally loud and becoming a deterrent. ZIP concluded that it would take extensive research to identify what sounds or combinations of sounds were attractive and what were potential repellents, particularly in developing a social audio lure for neophobic species such as ship rats. Ship rats are less social than other rat species, such as Norway or Pacific, and are more neophobic to novel stimuli in their environment (T. Agnew, personal communication, June 2, 2021). This could explain the repellent effect observed in both ZIP's trials and this research.

Cats were only detected in the possum and rat audio trials at a low rate and did not show interest in the source of the audio lure, instead passing by the monitoring stations at a distance. Thus, there were no significant differences in response between sound categories. Hedgehogs and rabbits both responded sparingly across the three trials. They showed no significant difference in their response levels between the sound categories, making it difficult to estimate their audio lure preferences.

5.3.3 Identification AI

The performance of the identification AI varied significantly for each trial. This is likely because the AI is still training to detect pests at varying distances, illumination levels and environments. The identification AI fluctuated from being oversensitive and trying to classify every movement in the environment to under sensitive and missing animal identifications. This is shown in the substantial difference between the numbers of video and AI tags in each trial. Both the possum and prey audio trials had a higher number of videos, AI tracks, misidentification, and proportion of false-positives, due to the AI identifying moving vegetation as animals. The background composition dramatically affects the accuracy and precision of the AI, with certain vegetation backgrounds markedly fluctuating in temperature and movement compared to others. The weather was a strong contributing factor, as the temperature difference in the vegetation combined with movement from wind made the AI focus on vegetation and detected hundreds of false-positives. However, it is uncertain if the varying sensitivity of Cacophony's AI will reach an equilibrium with increasing the training dataset or if the algorithm needs to be altered to have less weighting on the temperature factors and more on the movement factors in the classification process.

All three trials had relatively low missed tracking rates (range of 3.51% - 10.85%), where the AI did not detect that a pest animal was present. Missed trackings often occurred due to the cameras inability to track animals at far distances (> 10m which is beyond the effective range of trail cameras). This is possibly due to the animals very small size on the footage when they are far away from the camera and the AI not being able to adequately identify changes in pixels as an animal shape or movement. Additionally, the increased distance of the heat source to the IR detector makes the animal less distinguishable against the surrounding environment. When reviewing the species groups that the AI missed, there was no apparent difference in the number of missed trackings between animals of different sizes, such as possums and rodents. Thus, it is uncertain if the size is a factor in the AI not recognising and tracking animals.

5.3 Limitations

Behavioural and observational studies require consistency and are best conducted over longer time periods to determine patterns in behaviour and variations within species. Unfortunately, time constraints combined with technical issues creating unusable field data meant only three trials could be completed. More extended trial periods are better for observing free-ranging animals. Further trials would likely give more information on the less detected pests (i.e., hedgehogs, rabbits, and cats)

Another consideration when making inferences about audio lure response is that no behavioural descriptions were given with the animal sound recordings that Zero Invasive Predators provided. A description of what the sound was conveying (e.g. distress, social bonding, territorial behaviour) and the life stage/age of the animal (e.g. juvenile, mating, parental calls) would help explain unexpected results, like the fact that rat sounds used were significantly less attractive or potentially deterring to rats and possums.

A factor to consider when using audio lures to enhance monitoring equipment, is do some sound lures work better at certain times of the year or at sites with high animal abundance in areas with high pest density, where social interactions are numerous, and there is higher competition for resources, social lures may not be as attractive as food lures – unless the volume or type of audio lure is so novel that it evokes interaction. Audio-lures may work better in low pest density environments where an animal's interest in social interaction or investigation outweighs its interest in food resources.

An issue faced with the identification AI was the high rate of false positives triggered from moving vegetation detected as having a slight difference in temperature to the surrounding environment. It is recommended by Meek and Fleming (2012) that in the southern hemisphere, field cameras should face between the south-east, south, or south-west to minimise the camera's exposure to sunlight. Additionally, vegetation facing the sun as it rises can be more easily detected as a false-positive as it is at a higher temperature than its surroundings. Unfortunately, placing the monitoring stations away from sunlight in cleared areas without vegetation obscuring the field of view did little to help prevent false-triggers in this study. This greatly increased the time and effort it took to manually confirm classifications to train the AI to distinguish animal movement and false-positive vegetation movement.

5.4 Implications and future research

With the Predator-free 2050 milestone rapidly approaching and no technological breakthroughs on the horizon to achieve 100% eradication, we need to enhance existing technology to maximise the effectiveness of our current devices and management practices. This relies on increasing pest encounters and interactions with control devices, particularly in inhabited areas where large-scale poison operations are impossible. Audio lures appear to be a promising option as they address many of the limitations with current best-practice lures. They are much longer-lasting than any food-based lure currently on the market and do not deteriorate in quality over time, provided the device batteries are refreshed. Additionally, they are more conspicuous and can attract pests over larger distances – thus, fewer are needed for adequate lure coverage of a control site, decreasing operational costs greatly and potentially allowing stations to attract pests from inaccessible areas (Carey et al., 1997; Kavermann, 2013). With future trials, sound profiles of pest and non-target species could be compared to determine if certain sounds, such as a juvenile call, would deter or attract different species. Additionally, ultrasonic sounds and novel animal/non-animal noises could be trialled to assess if the novelty or familiarity of a noise affects its attractiveness to pest species.

Thermal cameras with identification AI are also a great development in the pest management technology available in New Zealand. While there is room for improvement in the sensitivity of the AI, the automation of monitoring and identification is a huge advancement, drastically decreasing the manual work time taken to analyse huge image or video datasets. This will help reduce the and operational costs and time taken to monitor and analyse large-scale control operations.

5.5 Overall Conclusions

Although limitations with time and sample size were faced in this study, the results provide a basis for improving the methodology of assessing free-ranging pest behaviour using thermal cameras and animal audio lures. There is still much to explore using audio lures, thermal cameras and artificial intelligence, as limited research has been conducted in a pest management context globally. However, preliminary research in New Zealand shows that these novel approaches are worthwhile avenues to investigate for developing an extensive range of control options to achieve a predator-free status.

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