Pika-boo: Acoustic signatures reveal collared pika (*Ochotona collaris*) activity across heterogenous alpine habitats

By

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Abstract

The collared pika (*Ochotona collaris*) has been listed as a species of Special Concern in Canada's *Species at Risk Act* due to its sensitivity to rapidly warming northern alpine ecosystems. Monitoring pika populations is challenging because of their remote, high-elevation habitats and potential behavioural changes induced by human presence, and yet their frequent and loud vocalizations provide an opportunity to capture population change over time. Here, I collected over 4000 hours of audio recordings from five valleys spanning the southern and central Yukon, and developed a machine learning recognizer to analyze pika vocalization activity trends and distinct acoustic signatures among and within populations. I found that a clustering algorithm can distinguish among pika calls from different populations with 83% accuracy and between juveniles and adults with 100% accuracy, but with only 60% accuracy among individual adults of a population. Across sites, pikas vocalized on average 157 calls per hour during the day and 62 calls per hour between dusk and dawn, although pikas were more active during the night at some sites. The number of vocalizations per day did not vary with temperature, wind speed or rainfall, nor did the number of vocalizations within the day vary with the presence of humans. My findings demonstrate that acoustic technology provides an effective and urgently-needed approach to monitor the at-risk collared pika in alpine habitats experiencing rapid climate change.

A linocut print of a collared pika with a foraged bouquet. Print by Charlotte Mittelstaedt.

A collared pika sits atop a talus rock. Photo by Cameron Eckert

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I would first like to thank the Tr’ondëk Hwëch’in, the Kluane First Nation and the Champagne and Aishihik First Nations for the opportunity to conduct this research in such beautiful and special alpine valleys on their lands. Where possible in this thesis, I have referred to locations by their Hän and Southern Tutchone place names.

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Park Permit: 24-RE-TP-09 (Ddhäl Ch'èl Cha Nän)

Scientist and Explorers Act Licence: 24-77S&E (Ddhäl Ch'èl Cha Nän) and 24-60S&E (Ä sì Keyi/Kluane Region)

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Glossary

Bioacoustics - A field of study that bridges biology with acoustics, usually pertaining to sounds produced by animals.

Autonomous recording unit (ARU) - Passive audio recorders that can be deployed in the field for extended periods of time.

Machine learning - The field of developing algorithms that can learn by finding patterns in data to perform new data analysis tasks.

Recognizer - A machine learning algorithm that can automatically detect the presence of vocalizations from a species of interest in audio recordings.

Vocalization - Any sound produced by an animal, including a call or a song.

Acoustic signature or **vocal fingerprint** - Distinct species, population or individual-level features of a vocalization that allow for identification at one or more of the aforementioned levels through recordings.

Call - A very short animal vocalization that is simple in structure. I refer to the collared pika's adult and juvenile vocalizations as calls.

Harmonics - Integer multiples of the fundamental frequency, which is the lowest frequency produced. Harmonics in a pika call appear as a vertical stack of lines on a spectrogram.

Acoustic individual identification - The identification of individual animals from recordings using variations in call structure.

Spectrogram - A visual representation of the frequency of a sound over time.

Fundamental frequency - The lowest frequency harmonic.

YG - Government of Yukon

PC - Pika Camp

PP - Printer's Pass

NG - Nàday Gän (Mount Decoeli)

MB - Mount Boyle

BC - Blackcap Mountain

Convolutional neural network - A type of machine learning model specializing in image classification. In an acoustics context, these networks view visual representations of audio, such as spectrograms.

Prediction score - A numerical value output by a recognizer that describes how confident the recognizer is that a clip contains a species of interest. Scores can theoretically range from -infinity to infinity. Higher scores indicate a higher confidence.

Threshold - A prediction score value set by the user, above which all predictions are considered positive identifications of the species of interest.

Precision - A metric used in machine learning that describes the proportion of predicted positives that are actually positives at a certain score threshold.

Recall - A metric used in machine learning that describes the proportion of actual positives that are predicted as positives above a certain score threshold.

F1 score - A metric used in machine learning that combines precision and recall at a score threshold.

Mel-frequency cepstral coefficients (MFCCs) - Numerical descriptors of the spectral appearance of a sound. MFCCs are common in speech recognition and are gaining popularity in bioacoustic classification tasks.

Delta-cepstral coefficients - Numerical descriptors of how a sound signal changes over time. These coefficients complement MFCCs in acoustic analyses.

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1. Introduction

1.1. Pikas as climate change sentinels

The collared pika (*Ochotona collaris*) is at the forefront of climate change, serving as an early indicator of rapid warming in northern alpine ecosystems (ECCC, 2023; Morrison & Hik, 2007). Population abundance trends of these small, cold-adapted lagomorphs, found only in alpine boulderfields (hereafter talus; Figure A1a) across northwestern Canada and Alaska (Broadbooks, 1965; Chapman & Flux, 1990), could guide conservation efforts and offer a broad and early warning of the impact of climate change on their mountainous habitats (ECCC, 2023). Threatened by extreme weather events and climate-driven shifts in the abundance of forage plants (ECCC, 2023; Morrison & Hik, 2008), the collared pika was designated as a species of Special Concern by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC) in 2011 and subsequently listed as Special Concern in Canada's *Species at Risk Act* in 2017 (ECCC, 2023).

To date, accurate pika abundance estimates have been limited by the challenges of assembling population data through traditional fieldwork (ECCC, 2023). In the Yukon, which contains 48% of global collared pika habitat (ECCC, 2023), the territorial government and community scientists have surveyed pika presence and absence in talus patches since 2009 (Cannings et al., 2019; Jung et al., 2020; Kukka et al., 2014, 2020). Since pikas' grey fur makes them inconspicuous in talus, surveys rely heavily on acoustic detections of their "eep"-sounding calls and observations of food caches and latrines (Cannings et al., 2019; Jung et al., 2020; Kukka et al., 2020). The nature of these detections and the dangers of traversing steep patches of talus restrict surveys to days with low wind and rainfall (Kukka et al., 2020). Estimating population sizes across the species' range through surveys is unfeasible because of the large number of monitoring sites and limited helicopter time to access remote alpine valleys that are far from roads or trails (Cannings et al., 2019; Jung et al., 2020; Kukka et al., 2020). Acoustic monitoring has the potential to overcome these challenges and act as a time-efficient and reliable method for studying pika population change.

1.2. Acoustic technology presents opportunities for monitoring

Previous attempts to estimate collared pika abundance have involved capturing and marking all individuals in a population (Morrison & Hik, 2008), which is laborious, expensive and intrusive. An emerging alternative method to study wildlife population dynamics is bioacoustic monitoring using autonomous recording units (ARUs) (Darras et al., 2019; Knight et al., 2024; Pérez-Granados & Traba, 2021; Shonfield & Bayne, 2017). ARUs are audio recorders that can function unattended in ecosystems of interest on a user-specified schedule, reducing time, effort and environmental limitations associated with human-conducted surveys (Knight et al., 2024; Shonfield & Bayne, 2017; Vallee, 2023). The ease of deploying ARUs allows for scientists to monitor a wider range of sites across more diverse seasonal and weather conditions (Shonfield & Bayne, 2017). ARU technology has most commonly been used to study birds, bats, marine mammals, insects and frogs (Knight et al., 2017). For many species, publicly available machine learning classifiers called “recognizers” can detect the presence of a species in a recording, which eliminates the need for manual processing of audio data (Kahl et al., 2021; Knight et al., 2017; Knight & Bayne, 2019). While the loud and frequent vocalizations of various pika species have been well-documented (e.g., Conner, 1982; Ivins & Smith, 1983; Sakiyama & García Molinos, 2023; Trefry & Hik, 2009, 2010; Volodin et al., 2021), pikas have not yet been the subject of an acoustic monitoring study using ARUs.

1.3. Pikas have individually and regionally distinct vocal fingerprints

Individuals within most vocal taxa carry unique acoustic signatures, or vocal fingerprints, just as humans have unique voices (Knight et al., 2024; Linhart et al., 2022). Studies of acoustic identification of individual animals from recordings are relatively uncommon, but the ability to differentiate individuals could allow for estimates of population size and demographic rates from year-to-year (Knight et al., 2024; Linhart et al., 2022). Although the calls of individual pikas are indistinguishable to the human ear, Trefry & Hik (2010) found that the harmonic frequencies (see Glossary; Figure 1) of collared pika calls varied more among individuals than within an individual's vocal repertoire. Collared pikas also display a heightened response to unfamiliar conspecific calls compared to familiar calls, indicating that they can discriminate between individuals (Trefry & Hik, 2009). At a coarser scale, calls from different pika populations and broader geographic regions have been distinguished through a discriminant analysis with high levels of success (Trefry & Hik, 2010). Taken together, these results reveal that collared pikas possess regional dialects and that they demonstrate potential for individual identification from recordings.

Unfortunately, acoustic identification of individuals is often labour-intensive (Knight et al., 2024). In most cases, vocalizations for individuality analyses are manually recorded at close range using a directional microphone (e.g., Cheng et al., 2010; Clink et al., 2018; Volodin et al., 2018, 2021). Passively obtained ARU recordings present challenges for individual identification because of background noise and degradation of acoustic signals at greater distances (Knight et al., 2024; Tseng et al., 2024; Yip et al., 2017). However, individual identification has been successful with high-quality calls from ARU recordings (Ehnes & Foote, 2015; Tseng et al., 2024; Wearn et al., 2024). The potential for acoustic identification of individuals has been demonstrated for multiple species of pika, but has involved manually or semi-manually extracting call features for a dataset to be used in a discrimination analysis (Conner, 1985; Trefry & Hik, 2010; Volodin et al., 2018, 2021). Recent research on individuality in Northern gray gibbon (*Hylobates funereus*) calls suggests that feature extraction can be mostly automated (Clink et al., 2018; Clink & Klinck, 2021; Wearn et al., 2024) and that discrimination can be unsupervised, with no prior information about the individuals provided by the user (Clink & Klinck, 2021; Wearn et al., 2024). These advances could transform the way wildlife managers monitor vocal species, such as pika.

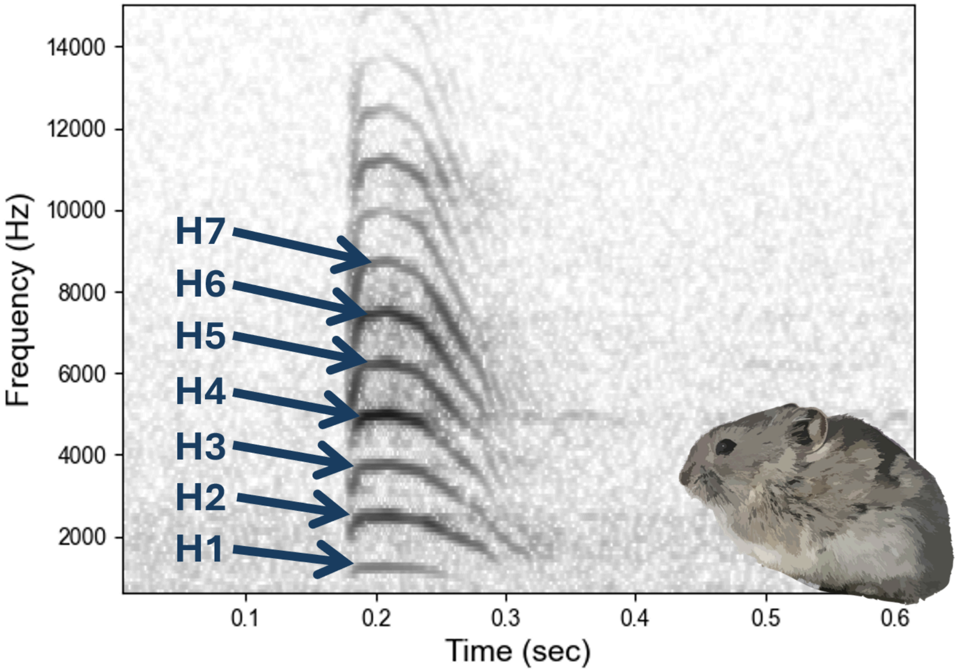


Figure 1. A sound spectrogram of a pika call, showing the call frequency over time. H1 labels the first harmonic, known as the fundamental frequency, which is the lowest frequency of the call. H2-H6 represent the second through sixth harmonic.

1.4. Daily pika activity is complex and poorly understood

Pika activity, including calling, food caching and moving, has been found to vary seasonally and diurnally (Smith, 1974). Pikas are most active during late summer and early fall (Bruggeman, 2010), when they collect and stash “haypiles” of plants in the talus, which sustain them throughout the winter (Bhattacharyya & Ray, 2015; Dearing, 1997; Morrison et al., 2004; Figure A1b). Haying is associated with an increase in vocalization activity, perhaps to defend food from conspecifics (Smith & Ivins, 1984). In early summer, a crepuscular pattern of high morning and evening haying activity has been observed in a population of collared pikas (Morrison et al., 2009). However, in late summer during peak haying season, haying trips have been observed as more constant through daylight hours, with lower but still present nighttime activity (Broadbooks, 1965; Morrison et al., 2009). In contrast, another late summer study of the collared pika observed the highest daylight haying activity levels in the morning, when temperatures were coolest (Harrison, 2023). Nocturnal activity has been more extensively documented for the closely-related but lower-latitude American pika (*Ochotona princeps*), with nighttime activity ranging from low to high levels (Camp et al., 2020; Hall & Chalfoun, 2019; Millar & Hickman, 2021; Smith, 1974; Smith et al., 2016; Smith, 2020). There is conflicting evidence to suggest that widespread observations of nocturnal activity and crepuscular morning and evening activity in the American pika may be behavioural adaptations to compensate for a heat stress-induced reduction in midday activity at warm sites (e.g., Camp et al., 2020; Smith, 1974; but see Hall & Chalfoun, 2019; Millar & Hickman, 2021). Since there are contrasting but only local scale reports of collared pika diurnal activity patterns (Broadbooks, 1965; Harrison, 2023; Morrison et al., 2009), it is not known whether pikas exhibit similar patterns across their range.

1.5. Pikas calls serve a territorial purpose

In contrast to the American pika's nine call types (Conner, 1985), only one main call has been observed in collared pikas, which sounds similar to the American pika's short call (Trefry & Hik, 2010). The short call is thought to act as an alarm call in response to predators, such as weasels and martens, and to defend territory and haypiles from conspecifics (Conner, 1985; Ivins & Smith, 1983). Calls may also facilitate contact between breeding pairs as they come together to mate under the snow in the spring (Conner, 1985). The predator-induced alarm call is thought to warn other pikas of danger, not to deter the predator itself (Ivins & Smith, 1983). Other species of pika have been observed exhibiting anti-predator responses to human presence, including reduced foraging (Stafl & O'Connor, 2015), increased alarm calling and fleeing humans (Chaudhary et al., 2025; Zhu et al., 2023). Although Government of Yukon (YG) pika surveys operate on the assumption that collared pikas vocalize after detecting humans (Cannings et al., 2019; Kukka et al., 2020), this behaviour has not been directly quantified in the species.

1.6. Weather is thought to drive pika activity

Pika foraging and vocalization activity levels vary based on weather conditions. Pikas are cold-adapted and lack physiological mechanisms needed for thermoregulation in the warm summer months (Hall & Chalfoun, 2019; Moyer-Horner et al., 2015; Smith, 1974). Instead, they shelter from the heat in the cool spaces between talus rocks (Hall & Chalfoun, 2019; Millar & Hickman, 2021; Moyer-Horner et al., 2015; Smith, 1974). Several studies of American pika have found a negative correlation between temperature and pika foraging activity, particularly at warm, low-elevation sites (Camp et al., 2020; Hall & Chalfoun, 2019; Smith, 1974; Stafl & O'Connor, 2015). Likewise, time spent haying and grazing by the less-studied collared pika has been observed to decrease with daily minimum temperature (Harrison, 2023). However, another study found relatively consistent collared pika activity throughout daylight hours during late summer (Morrison et al., 2009), regardless of temperature. Reduced haying activity has been noted in collared pika (Harrison, 2023) and American pika (Benedict et al., 2020; Hayes & Huntly, 2005) during times of high wind, which could be a risk mitigation strategy given a potentially lower detectability of conspecific or heterospecific calls (Hayes & Huntly, 2005). Precipitation has been found to have a negative effect on Plateau pika (*Ochotona curzoniae*) activity in China (Zhou et al., 2023). Additionally, call detectability in ARU recordings can decrease during unfavourable weather conditions, such as wind (Thomas et al., 2020) or rain (Kalan et al., 2015). Responses of pikas to weather combined with varying levels of noise in recordings could have implications on the number of pikas detected in ARU recordings.

1.7. Research goals, questions and hypotheses

Here, I aimed to explore the potential of ARUs as a novel tool for studying pika activity and identifying unique vocal signatures. In the summer of 2024, I collected ARU recordings of pikas from five sites across the Yukon and developed a pika recognizer to identify calls for use in my analyses. My objectives were to i) evaluate the accuracy of automated clustering in distinguishing among the calls of individuals and populations; ii) use the recognizer to monitor pika activity throughout 24-hour periods; iii) assess whether pikas vocalize more frequently in the presence of humans and iv) examine how daily weather conditions influence vocalization activity. The first objective will provide insights into the feasibility of producing population estimates from individual identification. The remaining three objectives aim to uncover details about pika behaviour that could help guide the timing and conditions of human-conducted pika surveys. Overall, my goal was to assess whether ARUs offer a valuable and effective tool for incorporation into pika monitoring programs.

Question 1: How accurately can ARU recordings distinguish between calls from different pika populations and among individuals within the same population?

Hypothesis 1: ARU recordings can be used to distinguish among populations and individuals with a high degree of accuracy because collared pikas have unique acoustic signatures and regional dialects.

Null/alternative hypothesis 1: ARUs do not provide pika call recordings of sufficient quality for acoustic identification of individuals or populations.

Question 2: How does pika calling activity vary over a 24-hour period?

Hypothesis 2: Pikas call more during daylight hours than nighttime hours because daylight provides optimal conditions for finding forage and detecting potential predators.

Null hypothesis 2: Pika calling activity does not vary over a 24-hour period because pikas capitalize on abundant summer forage availability by maintaining constant levels of activity.

Alternate hypothesis 2: Pikas call most during the nighttime and during early morning and late evening to avoid possible midday heat stress.

Question 3: How does human presence in collared pika habitat influence their calling rate?

Hypothesis 3: Pikas call more frequently in the presence of humans, using alarm calls to alert neighbouring individuals of a potential threat.

Null hypothesis 3: The presence of humans has no effect on pika calling rates because they do not perceive humans as potential predators.

Alternative hypothesis 3: Pikas call less frequently in the presence of humans because they seek refuge in the talus to avoid perceived predatory interactions.

Question 4: How do daily temperature, wind speed and rainfall impact the number of daily pika calls detected in recordings?

Hypothesis 4: Daily temperature, wind speed and rainfall will have a negative effect on the number of pika calls detected by the recognizer because pika activity is constrained by heat and inclement weather, and wind and rain cause interference noise in recordings.

Null hypothesis 4: Daily temperature, wind speed and rainfall will have no effect on the number of daily pika call detections because pika calling behaviour is only related to predator risk.

Alternative hypothesis 4: Daily temperature, wind speed and rainfall will have a positive effect on the number of pika calls detected by the recognizer because warm days provide optimal forage conditions and rain and wind may reduce the presence of predators.

2. Methods

2.1. Study sites

Audio data were collected at five alpine valleys across the Yukon, Canada, where pikas had been historically observed. I selected valleys in both the southern and central Yukon (Figure 2) to capture a range of habitat types, population sizes and potential pika dialects. Three valleys, Pika Camp (PC), Printer’s Pass (PP) and Nàday Gän (NG; also known as Mt. Decoeli) were located in Ä sì Keyi (the Kluane Region) in the southern Yukon on the lands of the Kluane First Nation and the Champagne and Aishihik First Nations (Table 1). Pika Camp and Printer’s Pass have been the site of pika research since 1995 (ECCC, 2023). Two valleys, Mt. Boyle (MB) and Blackcap Mountain (BC), were located on the lands of the Tr’ondëk Hwëch’in, in Ddhäl Ch'èl Cha Nän (Tombstone Territorial Park; Table 1). Valleys in Ddhäl Ch'èl Cha Nän have been surveyed by YG (Yukon Parks and Fish & Wildlife Branch) and Friends of Dempster County since 2009 (ECCC, 2023). Valleys varied in habitat characteristics, including the number and size of talus patches, vegetation cover, elevation, aspect and slope (Figure 3).

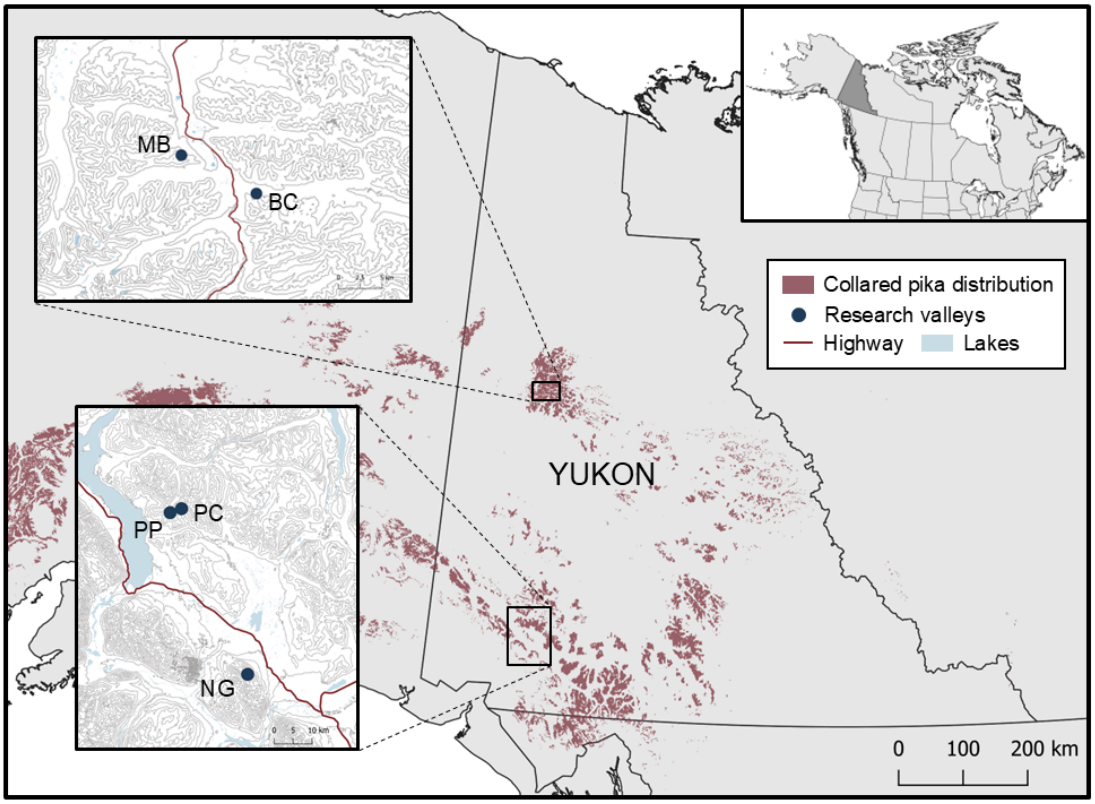


Figure 2. Map of the southern and central Yukon study areas, within the predicted species distribution of the collared pika. PC=Pika Camp, PP=Printer's Pass, NG=Nàday Gän, MB=Mt. Boyle, BC=Blackcap Mountain. The species distribution was modelled based on Global Biodiversity Information Facility observations of collared pika (GBIF.org, 2025) and WorldClim v2.1 environmental data (Fick & Hijmans, 2017) and may not reflect the entire species range. The model was made using R code adapted from Jordan Seider.

Table 1. Location, elevation and deployment dates of ARUs in study valleys. Elevation is given in metres above sea level (MASL). The “outer ARU distance” refers to the distance between adjacent ARUs forming a square array. Distances marked with an asterisk (*) indicate arrays where spacing was adjusted to accommodate habitat features.

Region	Valley	Latitude, longitude	Elevation (MASL)	Recording schedule	Outer ARU distance (m)
Ä sì Keyi (Kluane Region)	Pika Camp (PC)	N61° 12.336', W138° 16.513'	1745	18-27 July 2024	200
	Printer’s Pass (PP)	N61° 11.607', W138° 19.723'	1600	18-27 July 2024	125
	Nàday Gän (NG)	N60° 49.525', W137° 52.853'	1686	26 July - 1 Aug 2024	125*
Ddhäl Ch'èl Cha Nän (Tombstone Territorial Park)	Blackcap Mountain (BC)	N64° 33.085', W138° 11.183'	1375	6-13 Aug 2024	125*
	Mt. Boyle (MB)	N64° 35.173', W138° 22.267'	1408	8-13 Aug 2024	100

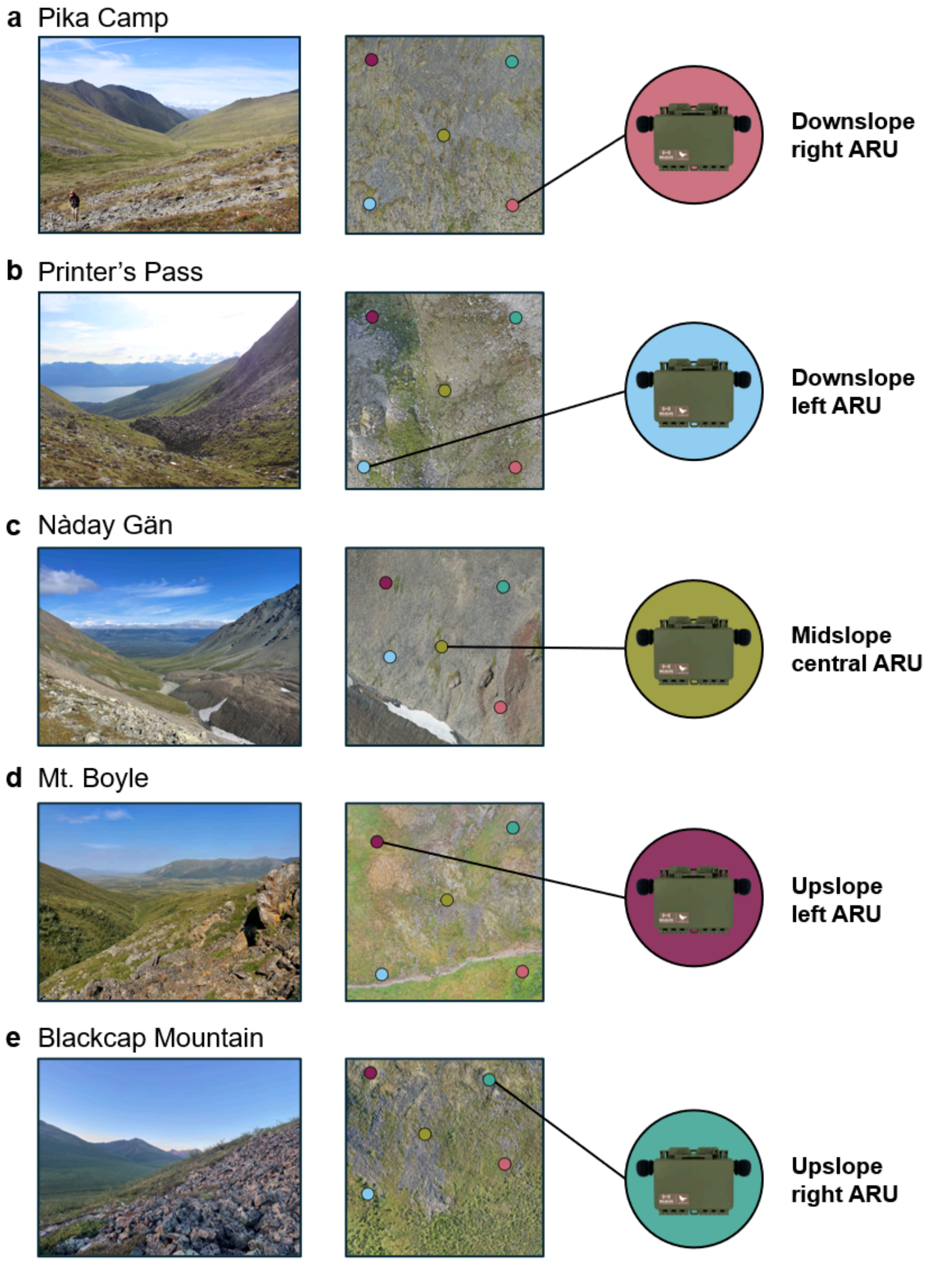


Figure 3. a-e Valley features and ARU configurations varied among study sites. Drone imagery shows the arrangement of ARUs at each of the five research valleys. Drone flights were conducted using a DJI Mavic 2. Pink, blue, green, purple and turquoise dots represent the downslope right, downslope left, central, upslope left and upslope right ARUs, respectively. Printer’s Pass and Pika Camp photos by Lauren Moody and Printer’s Pass drone flight by Ciara Norton. Remaining photos and drone flights by Charlotte Mittelstaedt.

2.2 Audio data collection

My field team deployed five Wildlife Acoustics Song Meter Mini 2 ARUs per valley, set to record within July 18-August 13, 2024 (Table 1), when pika activity is considered highest due to optimal haying conditions (Bruggeman, 2010). I programmed ARUs to continuously record in stereo at the highest quality setting, using a sample rate of 48,000 Hz and the default gain of 18 dB. I selected the sample rate in accordance with Nyquist theorem, which specifies that sampling should be done at twice the maximum frequency of a signal (Por et al., 2019).

At each valley, we deployed ARUs in a dice-face configuration, with outer units spaced 100-200 m apart depending on talus patch size (Figure 3; Table 1). ARUs were positioned 20 to 35 cm off the ground by metal stands (Figure 4). At some sites, an outer ARU was repositioned closer to the central unit to avoid environmental features such as streams (Figure 3; Table 1). ARU placement was standardized across sites with two uphill and two downhill units positioned perpendicular to the slope of a valley wall (Figure 3). Deployment length ranged from five to ten days (Table 1). Continuous recording was used, as the short deployment periods avoided exceeding the storage capacity of the devices. Constant recording also enabled 24-hour monitoring of pika activity for subsequent analysis. Audio data were saved as 16-bit, ten-minute .wav files. In total, 26,245 recordings were collected, amounting to 4,300 hours of audio data.

Figure 4. An ARU elevated off the ground by a metal stand at Mt. Boyle, Ddhäl Ch'èl Cha Nän. Photo by Charlotte Mittelstaedt.

2.3. *In situ* pika population surveys

At each valley, the field team completed a pika survey following protocols similar to those used by YG. YG surveys target a distinct talus patch, where two surveyors record pika observations without communicating (Cannings et al., 2019; Jung et al., 2020; Kukka et al., 2014, 2020). YG collects presence and absence data to calculate detection probabilities in different habitats (Kukka et al., 2014, 2020). However, the purpose of our surveys was to estimate pika population size at each site, providing a reference for identifying individual pikas through their vocalizations. Because the number and size of talus patches varied among sites, survey duration was scaled according to patch extent, ranging from 15 to 25 minutes per site.

Two observers or two groups of observers slowly walked an area delineated by the intended locations of the outer ARUs, listening and looking for pikas, and looking for fresh haypiles. Observers recorded the time, GPS coordinates and type (visual, auditory, fresh haypile) of each pika observation. Communication between observers was permitted to prevent double-counting. Where possible, observers recorded pika calls with a shotgun microphone (RØDE NTG5 microphone and Zoom H4N recorder) or iPhone in an attempt to capture high quality pika calls at close range. Throughout the duration of the site visits, additional pika observations were recorded. We detected no pikas at Blackcap Mountain but deployed ARUs nonetheless. I excluded Blackcap recordings from my analyses investigating call rates.

2.4. Developing a pika recognizer

All code for model building and statistical analyses are publicly available at https://github.com/ctmittelstaedt/Mittelstaedt_Undergrad_Thesis.

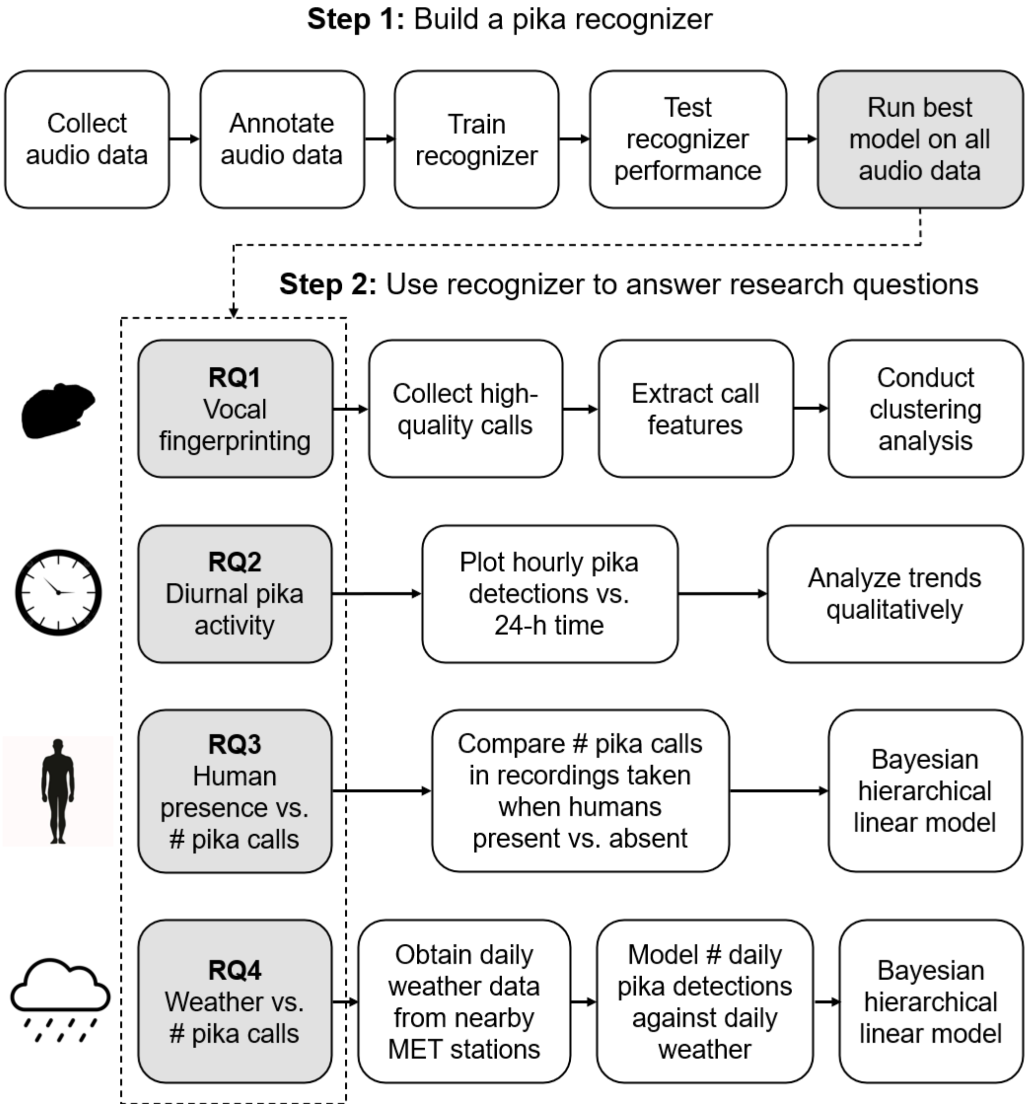


Figure 5. A workflow diagram outlining the steps of creating a pika recognizer and answering my four research questions. RQ = research question.

2.4.1. Recognizer datasets

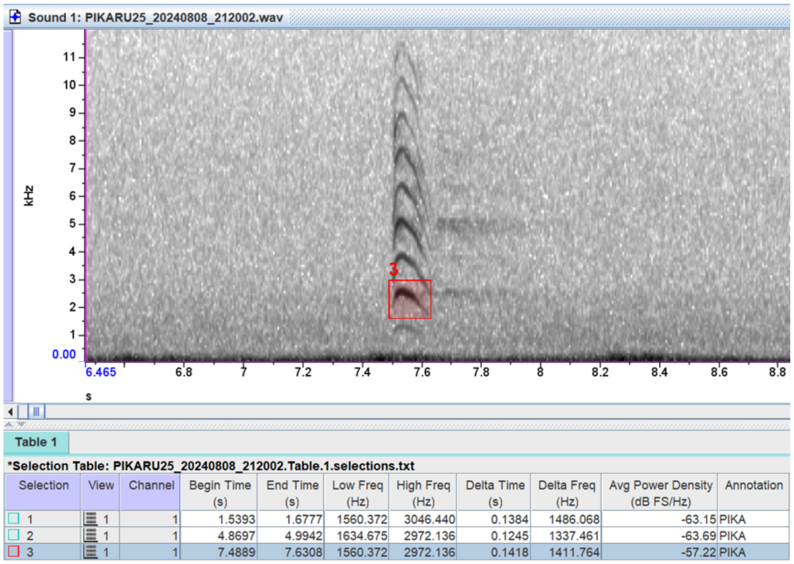
To automatically detect pika calls from my recordings, I created a convolutional neural network recognizer using OpenSoundscape v0.11.0, an open source Python utility library that provides tools for analyzing bioacoustic data (Lapp et al., 2023). Generally regarded as the “gold standard” for audio classification (Knight et al., 2017; Lapp et al., 2023; Stowell, 2022), convolutional neural networks are machine learning models specializing in image classification (Knight et al., 2017; Ruff et al., 2020).

In machine learning, three datasets are typically used to evaluate model learning and performance: a training dataset, a validation dataset and a testing dataset (Ho et al., 2024). A training dataset consists of recordings that include both the target sound and recordings that do not, allowing the program to learn how to identify the target sound. Throughout the training process, the model is evaluated using recordings in a validation dataset. A test dataset, often composed of recordings from locations not used in training, is used externally to evaluate recognizer performance. I sourced most audio data from my field recordings, which were predominantly ARU data, but included several shotgun microphone and iPhone recordings. I also obtained ARU recordings collected by the Canadian Wildlife Service at a sample rate of 44,100 Hz as part of their High Elevation Monitoring Program (Yip et al., 2021), which were publicly available through WildTrax, an online platform for sharing wildlife data (https://wildtrax.ca/).

2.4.2. Annotating pika calls in recordings

To identify pika calls for the three datasets, I visually scanned spectrograms (Figure 1) of recordings in Raven Lite v2.0.5 (K. Lisa Yang Center for Conservation Bioacoustics, 2024), a free software for viewing and editing audio data. I created annotations by manually boxing and labelling each pika call using Raven’s “Create Selection” tool. Raven automatically produces a table of annotations for each recording that includes a row for each box with features such as start time, end time, upper and lower frequency bounds and species identification (Figure 6). Although recognizers typically perform better when trained exclusively on high-quality vocalizations (Knight et al., 2017), I included a wide range of call qualities in the training data to improve detection of distant pikas (Figure 6). I only boxed the second harmonic of each call because it is the loudest harmonic (Trefry, 2008) and tends to appear in spectrograms of distant and close pika calls. In total, I annotated 20 hours of ARU recordings, which contained 1,050 calls.

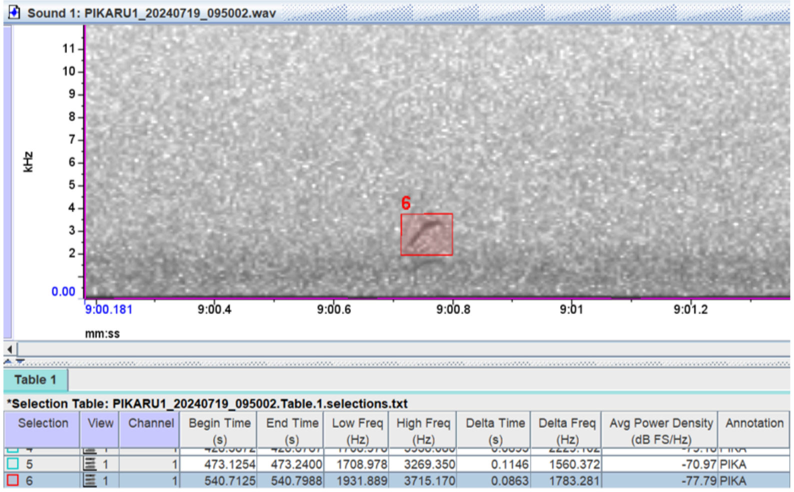
a



*Selection Table: PIKARU25_20240808_212002.Table.1.selections.txt

Selection	View	Channel	Begin Time (s)	End Time (s)	Low Freq (Hz)	High Freq (Hz)	Delta Time (s)	Delta Freq (Hz)	Avg Power Density (dB FS/Hz)	Annotation
☐ 1	1	1	1.5393	1.6777	1560.372	3046.440	0.1384	1486.068	-63.15	PIKA
☐ 2	1	1	4.8697	4.9942	1634.675	2972.136	0.1245	1337.461	-63.69	PIKA
☐ 3	1	1	7.4889	7.6308	1560.372	2972.136	0.1418	1411.764	-57.22	PIKA

b



*Selection Table: PIKARU1_20240719_095002.Table.1.selections.txt

Selection	View	Channel	Begin Time (s)	End Time (s)	Low Freq (Hz)	High Freq (Hz)	Delta Time (s)	Delta Freq (Hz)	Avg Power Density (dB FS/Hz)	Annotation
☐ 5	1	1	473.1254	473.2400	1708.978	3269.350	0.1146	1560.372	-70.97	PIKA
☐ 6	1	1	540.7125	540.7988	1931.889	3715.170	0.0863	1783.281	-77.79	PIKA

Figure 6. Pika call annotation examples in Raven Lite 2. Calls are visualized as spectrograms, with frequency (kHz) on the y-axis and time on the x-axis. Each red annotation box surrounds the second harmonic and corresponds to one row in the selection table below the spectrogram. **a** An example of a high-quality call. **b** An example of a medium-low-quality call.

2.4.3. Training and validation

OpenSoundscape views recordings as spectrograms and uses Raven tables to determine whether a pika is present in a given audio clip (Lapp et al., 2023). In Python v3.12.7 (Python Software Foundation, 2024), I divided recordings into 0.3-second clips and converted Raven annotations into clip-level labels. I considered clip labels to be "positive" when they contained a pika annotation or "negative" when the clip did not contain a pika annotation. I separated a group of clips and their clip labels for the test set, consisting of 16 five-minute files from three Canadian Wildlife Service monitoring sites, which I did not include in training, and six ten-minute ARU recordings from my sites. I used the scikit-learn v1.5.2 Python library (Pedregosa et al., 2011) train_test_split function to randomly split the remaining data into a training set containing 80% of the clips and a validation dataset containing the other 20% of clips.

I trained the recognizer using a single-class, multi-target model with ResNet34 architecture for 100 epochs (see model parameters in Table A1), meaning that the model was fully trained and validated 100 times. The recognizer viewed 64 clips at a time, and saved models every two epochs. I used OpenSoundscape's default learning parameters. I validated the model at each epoch by generating predictions on the validation dataset using a sigmoid activation layer, which outputs probabilities of pika presence ranging from 0-1. Average precision values were calculated and used to identify the epoch that produced the best model. Training took approximately 20 hours. During validation, the "best model" appeared at epoch 14 with an average precision score of 0.994. I later tested the performance of the "best model" against other epoch models external to training.

2.4.4. Evaluating recognizer performance

Outside of training, the recognizer can be used on recordings to generate prediction scores for each clip that can theoretically range from negative to positive infinity. Ideally, the recognizer will assign higher scores to clips with pikas present. Using identical clip parameters to those defined in training (Table A1), I assigned prediction scores to a small subset of the test set using four iterations of the recognizer generated at the following epochs: i) epoch 14 (the “best model”); ii) epoch 20; iii) epoch 50 and iv) epoch 100. I plotted prediction score histograms for each model run, which showed the distribution of prediction scores for positives and negatives. I selected the epoch 100 model for the remainder of my analyses because it best distinguished between positives and negatives (Figure A2). All subsequent model evaluation was done with the scikit-learn metrics module (Pedregosa et al., 2011).

Generating binary predictions of pika presence or absence in clips requires the user to specify a score threshold, above which clips are considered positives. To select a threshold, I followed recognizer evaluation recommendations outlined by Knight et al. (2017). I divided the test set into two smaller datasets, one containing recordings from my valleys and the other containing Canadian Wildlife Service recordings. I tested recognizer performance on each test set by creating a score histogram, a precision-recall curve and a threshold vs. precision-recall graph (Figure A3, A4). Precision describes the proportion of predicted positives that are positives in reality at a certain threshold, while recall refers to the proportion of true positives that are identified as such (Knight et al., 2017). I also calculated the area under the precision-recall curve, which is a commonly-used metric for classifier evaluation (Knight et al., 2017).

Additionally, I ran the recognizer on one day’s worth of ARU recordings from Blackcap Mountain, a site where no pikas were observed, to investigate potential sources of false positives. Across all ARUs, the recognizer falsely identified 20 clips as medium-scoring, with scores ranging from 10-13. For reference, clips containing true positives scored as high as 22. The medium-scoring clips from Blackcap Mountain were the result of bird vocalizations that share similar spectrogram features to pika calls. In this case, the confusion species was likely a Redpoll (*Acanthis flammea*; pers. com. Cameron Eckert).

For my analyses, I focused on minimizing false positives by prioritizing precision over recall. As a result, I set the score threshold to 10. In the test set containing recordings from my valleys, no negatives scored above 10. However, I acknowledge that a small number of false positives may arise from species such as Redpoll at this threshold, and that some pika calls will be identified as negatives.

I generated a confusion matrix and calculated precision, recall and F1 scores, which combine precision and recall, for both test sets at a threshold of 10 (Figure A3b, A4b; Table A2). The recognizer performed better on my test set than the Canadian Wildlife Service dataset (Figure A3, A4; Table A2).

2.4.5. Predicting with the recognizer

In addition to the one day of audio data from Blackcap Mountain, I ran the recognizer on four days of recordings for each ARU at each site where pikas were observed, totalling 1920 hours. I chose not to preprocess the input audio, as preprocessing the test set did not impact performance during testing. I used the same clip parameters as in training but I retroactively removed overlapping clips to avoid double-counting calls because the recognizer performed very well on partial calls during testing. The processing time was approximately 1 minute for every ten-minute audio file.

I conducted the remaining statistical analyses in R v4.4.2 (R Core Team, 2024).

2.5. Vocal variation within and among populations

2.5.1. Assembling high quality calls

Using recognizer predictions, I identified high quality pika calls (prediction score > 19, number of harmonics >= five and no noise interference) from recordings. I created three datasets: i) Ten assumed-adult calls from each of the four sites where pikas were observed to test whether clustering can detect population-level dialects; ii) Five calls from both individuals at Mt. Boyle, where only one adult and one juvenile were observed and iii) Two-four recordings per individual at Pika Camp, where the highest number of pikas was observed.

I extracted a short clip of each call using the selection tool in Raven Lite 2, with just a sliver of silence surrounding each call. Clip length varied among and within individuals and populations. At Mt. Boyle, I obtained targeted shotgun microphone recordings of the two observed individuals, and noticed that the juvenile displayed a distinctive call on a spectrogram (Figure 7). I used this information to distinguish between the two individuals when creating a dataset. I did not obtain sufficiently high-quality targeted recordings at Pika Camp to distinguish among individuals. Instead, I identified the highest quality calls and analyzed the strength of each call's signal on recordings from all other ARUs in an attempt to roughly localize the origin of the calls. I identified five potential pika territories and assumed calls originating from each territory belonged to a different individual.

2.5.2. Call feature extraction

To describe the spectral appearance of each call, I automatically extracted Mel-frequency cepstral coefficients (MFCCs) using the R package TuneR v1.4.7 (Ligges et al., 2023), following methods outlined by Clink & Klinck (2021). To standardize the MFCCs for calls of different durations, I split calls into five clips of equal length and computed 12 MFCCs for each clip. I bandpassed the frequency of calls to 700 to 9,000 Hz to remove low-frequency background noise and faint, high-frequency harmonics. I excluded the first MFCC from each clip because it represents the loudness of the sound, which does not contribute to vocal fingerprints. I also calculated 11 delta-cepstral coefficients per clip, which represent the temporal change of spectral features (Clink & Klinck, 2021). Previous research suggests that call duration can contribute to pikas' regional dialects (Trefry & Hik, 2010), so I included duration as a feature of interest in the analysis. In total, 111 features were extracted for each call.

2.5.3. Clustering analysis

As described in Clink & Klinck (2021), I conducted an unsupervised clustering analysis of pika vocalizations using affinity propagation (Frey & Dueck, 2007) through the R package APCluster v1.4.13 (Bodenhofer et al., 2011). I refer to affinity propagation as unsupervised because it does not require any training or for the user to specify a number of clusters (Clink & Klinck, 2021). However, the degree of clustering can be manipulated indirectly through parameters such as *q*, which specifies how similar data should be to be grouped together. The algorithm returned low levels of clustering for my datasets with the default settings, so I increased *q* from 0.5 to 0.7 for differentiating populations as well as the juvenile from the adult at Mt. Boyle, and 0.9 for the Pika Camp individuals.

I visualized each analysis as a dendrogram. To evaluate the accuracy of affinity propagation, I pooled the lowest-level clusters together until I reached the desired number of groups. Then, I assigned each group to a population or individual based on the highest number of calls from a population or individual within the group. I computed an F1 score for each cluster using the formula:

$$F1 = \frac{true\ positives}{true\ positives + \frac{1}{2}(false\ positive + false\ negatives)}$$

To generate overall dendrogram accuracy scores, I averaged F1 scores across all clusters.

2.6. Diurnal pika activity

To examine 24-hour pika calling activity, I extracted hourly pika call counts from recognizer prediction outputs for each ARU in each valley over three days. For Blackcap Mountain, I only used data for one day. I created a separate plot for each day at each valley, showing the number of hourly pika calls from 00:00 to 24:00. I overlaid civil twilight times accessed from the National Research Council of Canada's sunrise/sunset calculator (www.nrc-cnrc.gc.ca; Table A3). I computed the average daily number of pika calls per site and per ARU, as well as the approximate mean number of hourly pika calls during daylight and dark hours (between civil twilight times), calculated to the nearest ten minutes.

2.7. Bayesian models

I fit four Bayesian generalized linear models using the brms R package v2.22.0 (Bürkner, 2017). I ran each model for three chains with 5000 iterations and 2000 warmups. I assessed model fit and convergence by inspecting Rhat values and trace plots. I deemed a variable "significant" when the 95% credible interval for the effect size did not overlap zero.

2.7.1. Recognizer call quality model

To test whether recognizer scores correlated to call recording quality, I arbitrarily selected 37 pika calls from the recognizer prediction output for my entire test set, ensuring a wide range of prediction scores was represented. I inspected each call in Raven Lite 2 to determine the number of harmonics visible and the average power density (dB FS/Hz), which is a measure of the strength of the signal. However, I excluded average power density from the analysis because it displayed a strong correlation (c=0.83) with the number of harmonics. Therefore, I assume that the number of harmonics correlates with the loudness of a call.

I used a Bayesian model with a Gaussian family to model recognizer prediction score as a function of the number of harmonics in a call. I log-transformed the number of harmonics to reflect the variable's finite nature. Priors were normally distributed with a standard deviation of six and centred around four, zero and -13 for the harmonics coefficient, log(harmonics) coefficient and the intercept, respectively (Figure A5; Table A4).

predict_score ~ harmonics + log(harmonics)

2.7.2. Human presence model

For each pika-inhabited valley, I ran the recognizer on four ten-minute recordings per ARU, taken while the field team was present in pika habitat. As a control, I ran the recognizer on four recordings taken the next day at the same time, when the field team was not present. I then extracted the number of calls per recording.

I used a hierarchical Bayesian model with a Poisson distribution to model the number of pika calls per recording as a function of human presence, with humans present and absent as the two levels of the variable. I included site, date and ARU device as random intercepts. Priors were normally distributed with a standard deviation of three, with the effect of humans being present centred around zero and the intercept centred around one.

calls_per_recording ~ humans_present + (1 | site) + (1 | date) + (1 | ARU)

2.7.3. Weather model

To examine the relationship between daily weather conditions and the number of pika calls detected by the recognizer, I first extracted daily call counts for the four days of recordings processed by the recognizer for each ARU.

I obtained the following weather data from the nearest available weather station: i) maximum daily ambient air temperature (°C) from hourly averages; ii) daily rainfall (mm) and iii) average daily wind speed (km/h) from hourly averages. For Pika Camp and Printer’s Pass, I sourced temperature data from Polar Knowledge Canada’s East Peak weather station (approx. 2 and 5 km away and 300 and 400 m above the valleys, respectively; Scott Williamson, unpublished data) and rainfall and wind speed data from the Nav Canada Burwash Airport station (43 km away and 800-900 m below the sites; accessed from https://climate.weather.gc.ca/). For Nàday Gän, temperature and wind speed data were accessed from the Environment and Climate Change Canada Haines Junction station (17 km away and 1000m below site; accessed from https://climate.weather.gc.ca/) and precipitation data were accessed from the Yukon Wildland Fire Management Haines Junction station (18 km away and 1000m below site; accessed from https://weather.service.yukon.ca/weather/). For Mt. Boyle, all data were obtained from the Yukon Parks North Fork Pass station (6 km away and roughly equal elevation; Yukon Parks, unpublished data).

I used a hierarchical Bayesian model with a Poisson distribution to model daily pika call counts as a function of maximum daily temperature, daily rainfall and average daily wind speed. I included site, date and ARU device as random intercepts. Priors were normally distributed, with the intercept prior centred around 5.6 with a standard deviation of two. The temperature prior was centred around 0.12 with a standard deviation of one. Rainfall and wind speed priors were centred around -0.15 with a standard deviation of 0.5. To help with the estimation of priors, I centred data for each weather variable around the variable’s mean value, then uncentred data for plotting.

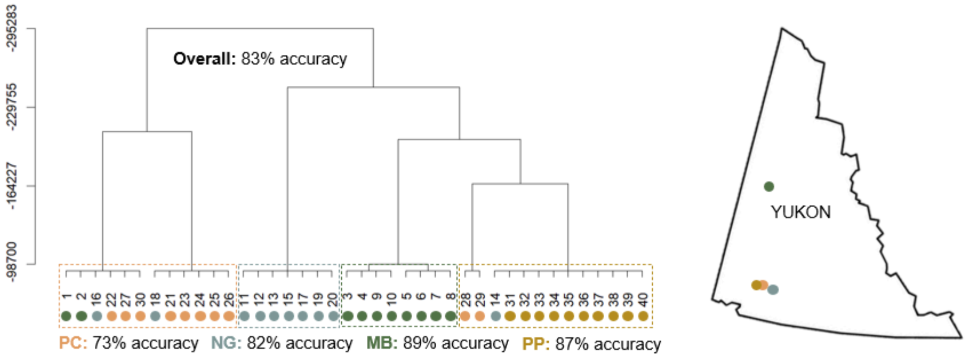
daily_call_count ~ daily_rainfall + average_windspeed + max_temp + (1 | site) + (1 | date) + (1 | ARU)

3. Results

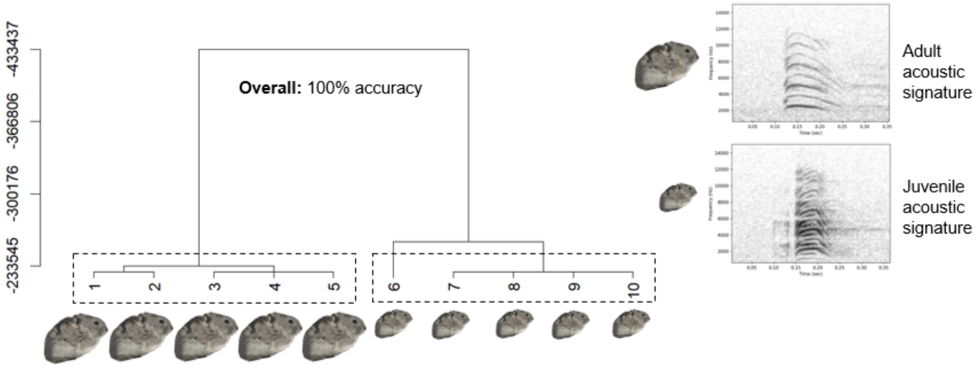
3.1. Vocal variation within and among populations

The performance of affinity propagation clustering varied across different scenarios. Pika calls were assigned to the correct population with 83% accuracy, with cluster-level accuracy ranging from 73% to 89% (Figure 7a). Pika Camp and Printer’s Pass, the two sites that were closest in proximity, produced clusters that were most distant in the dendrogram. Mt. Boyle, located hundreds of kilometres north of the other sites, produced a cluster that was nestled between Printer’s Pass and Nàday Gän. Within Mt. Boyle, where only one adult and one juvenile were observed, the clustering algorithm distinguished calls with 100% accuracy (Figure 7b). The clustering algorithm had the lowest performance on individuals at Pika Camp, with an overall accuracy score of 60% and with cluster-level accuracy ranging from 33% to 67% (Figure 7c). Therefore, affinity propagation clustering had the highest performance when distinguishing juvenile calls from adult calls, and the lowest performance when distinguishing individual adults.

a Populations



b Mt. Boyle juvenile vs. adult



c Pika Camp individual adults

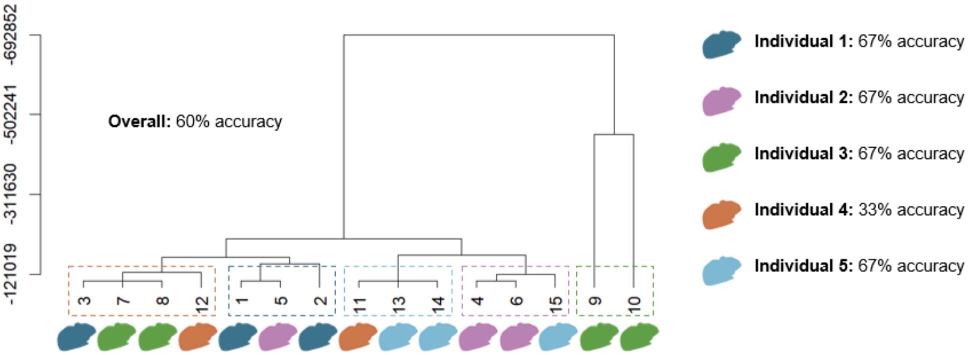


Figure 7. Dendrograms display varying accuracy of clusters of pika calls produced by affinity propagation. The y-axes represent distance between clusters, with longer vertical lines indicating greater dissimilarity. Accuracy scores for clusters are F1 scores. Overall accuracy scores are averaged F1 scores. Dashed boxes delineate clusters. **a** Calls are assigned to the correct population with 83% accuracy. PC=Pika Camp (salmon), NG=Nàday Gän (blue), MB=Mt. Boyle (green), PP=Printer's Pass (yellow). **b** Within Mt. Boyle, the juvenile and adult pika are distinguished with 100% accuracy. Small pikas represent juvenile calls and large pikas represent adults. Example calls are shown as spectrograms. **c** Within Pika Camp, individual adults are distinguished with 60% accuracy. Coloured pikas represent different individuals.

3.2. Diurnal pika activity

Calling activity quantity varied greatly among sites and across days within each site (Figure 8). Considerably more pika calls were detected at Printer's Pass than any other site, with an average of 1,953 daily calls identified per ARU (Figure 8b, Table 2). An average of 466 daily calls per ARU were detected at Pika Camp, followed by Mt. Boyle with 221 calls and finally Nàday Gän with 143 calls (Table 2). This order of call quantity did not align with the pika population size estimates from *in situ* surveys (Table 2). For example, more pikas were detected at Mt. Boyle, where the lowest number of pikas was observed, than Nàday Gän (Table 2). For Blackcap Mountain, where no pikas were observed, 20 false detections were made across ARUs (Figure 8e).

On the days studied, pikas vocalized throughout the entire 24-hour period, though with varying hourly call rates. Across all ARUs, a mean of 3,480 calls was detected per site each day, with an hourly call detection rate of 157 calls/hour during daylight hours and 62 calls/hour during darkness hours (Table 2). Interestingly, the hourly call rate was higher at night than during the day at Nàday Gän and Mt. Boyle, but lower during the night at Pika Camp and Printer's Pass (Table 2).

Calling activity patterns were complex and varied across sites and days. At Pika Camp, calling activity peaked between 21:00-24:00 on two days, but showed no obvious peaks on the other days. (Figure 8a). At Printer's Pass, strong peaks of activity were observed on some days at either or both 07:00 and 22:00 (Figure 8b). At Nàday Gän, high vocalization activity was detected around 00:00 on two days, but activity remained consistently low otherwise (Figure 8c). At Mt. Boyle, activity peaked on one day around 05:00 but remained relatively constant on other days (Figure 8d). Several ARUs within each site showed synchronized peaks and dips of vocalization activity, indicating that some pika calls may have been detected by multiple ARUs.

This was the case for every ARU at Printer’s Pass.

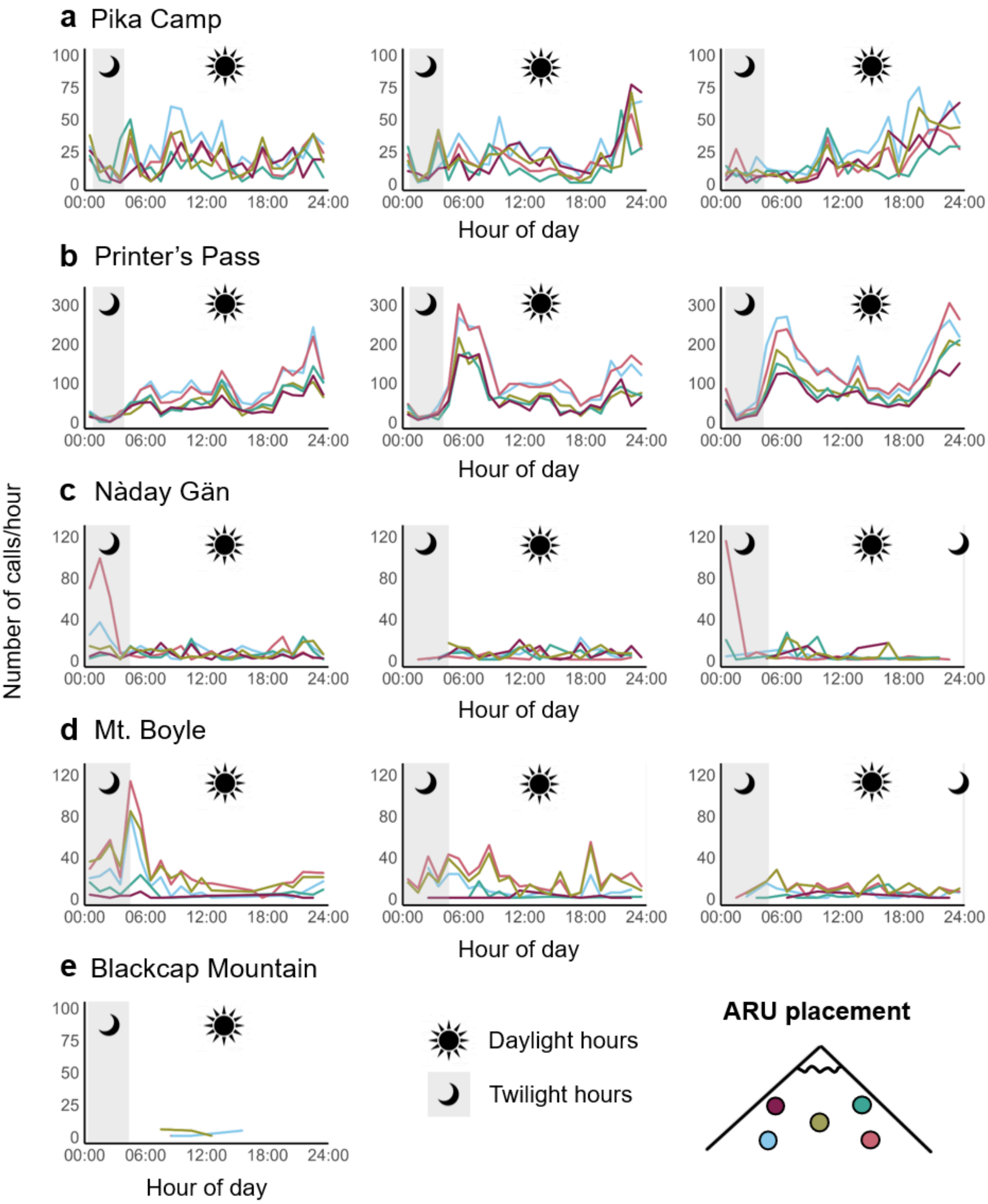


Figure 8. Pika calling activity varies across sites and days. The y-axis represents the number of pika calls detected by each ARU per hour and the x-axis represents the hour of day in 24-hour time. Within each plot, purple represents the left upslope ARU, turquoise the right upslope ARU, green the central ARU, blue the left downslope ARU and pink the right downslope ARU. Gray shading and moon icons represent dark hours (between civil twilight times), while sun icons represent daylight hours. Three days of ARU detections are shown for **a** Pika Camp, **b** Printer's Pass, **c** Nàday Gän and **d** Mt. Boyle. **e** One day with a few false positive detections is shown for Blackcap, where no pika were observed.

Table 2. Mean number of calls detected by ARUs per site and estimated number of pikas from *in situ* surveys. Calls were considered daylight calls when they occurred between pre-sunrise twilight and post-sunset twilight times, to the nearest ten minutes. Darkness calls were between post-sunset twilight and pre-sunrise twilight. PC=Pika Camp, PP=Printer's Pass, NG=Nàday Gän, MB=Mt. Boyle.

Site	Estimated number of pikas	Mean number of daily calls per site	Mean number of daily calls per ARU	Mean number of hourly daylight calls per site	Mean number of hourly darkness calls per site
PC	7	2330	466	105	48
PP	6	9767	1953	460	80
NG	4	716	143	26	46
MB	2	1106	221	40	77
	Average	3480	696	157	62

3.3. Human presence model

I found a negative but not significant effect of human presence on pika calling activity, with a predicted mean of 3.2 calls detected per recording when humans were absent and 1.3 calls when humans were present (Figure 9, Table A5). Within sites, consistently fewer calls were detected when humans were present (Figure 9). At the site-level, the predicted mean number of calls detected per recording ranged from 0.1 to 3.4 when humans were present, and 0.3 to 8.0 when humans were absent (Figure 9). The quantity of calling activity was positively related to the number of pikas observed *in situ* per site (Table 2), except at Printer's Pass. At Printer's Pass, more calls were detected than at Pika Camp, despite observing more pikas at Pika Camp.

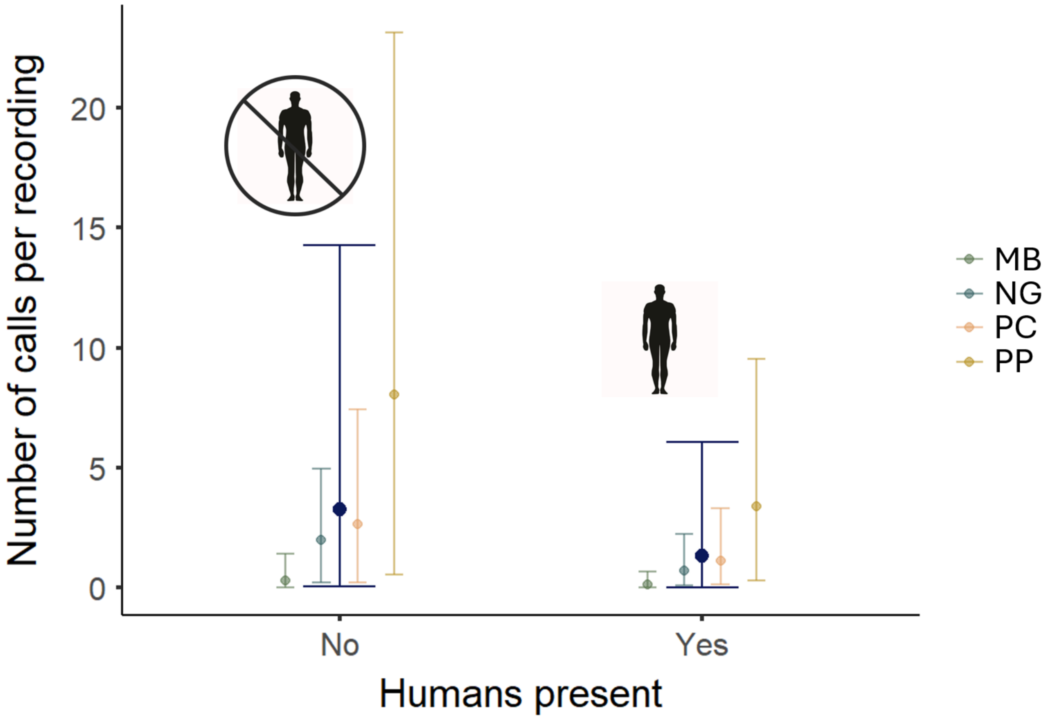


Figure 9. Across ARUs, more pika calls per ten-minute recording were detected when humans were absent. Dots represent the mean predicted number of calls per recording and whiskers represent 95% credible intervals. The effect of human presence is not significant. The larger dark blue dots and whiskers represent the overall effect across sites. The smaller, fainter dots and whiskers represent varying site-level effects, where MB=Mt. Boyle (green), NG=Nàday Gän (blue), PC=Pika Camp (salmon), PP=Printer's Pass (yellow).

3.4. Weather model

While none of the weather variables investigated were significant predictors of the daily number of pika calls (Table A5), both temperature and wind speed showed slight positive effects on call activity (Figure 10a,e). The number of daily pika calls per ARU increased by an average of 21 calls for each °C rise in maximum daily temperature (Figure 10a; Table A5). The number of daily pika vocalizations detected showed only a negligible decrease with increasing daily rainfall (Figure 10c; Table A5). The number of calls increased by 32 calls for every km/h rise in average daily wind speed (Figure 10e; Table A5). The range in temperatures, rainfall and wind speed, and the baseline number of daily pika calls detected, varied across sites (Figure 10b,d,f). Taken together, each weather variable had only a slight but not significant impact on daily call rates.

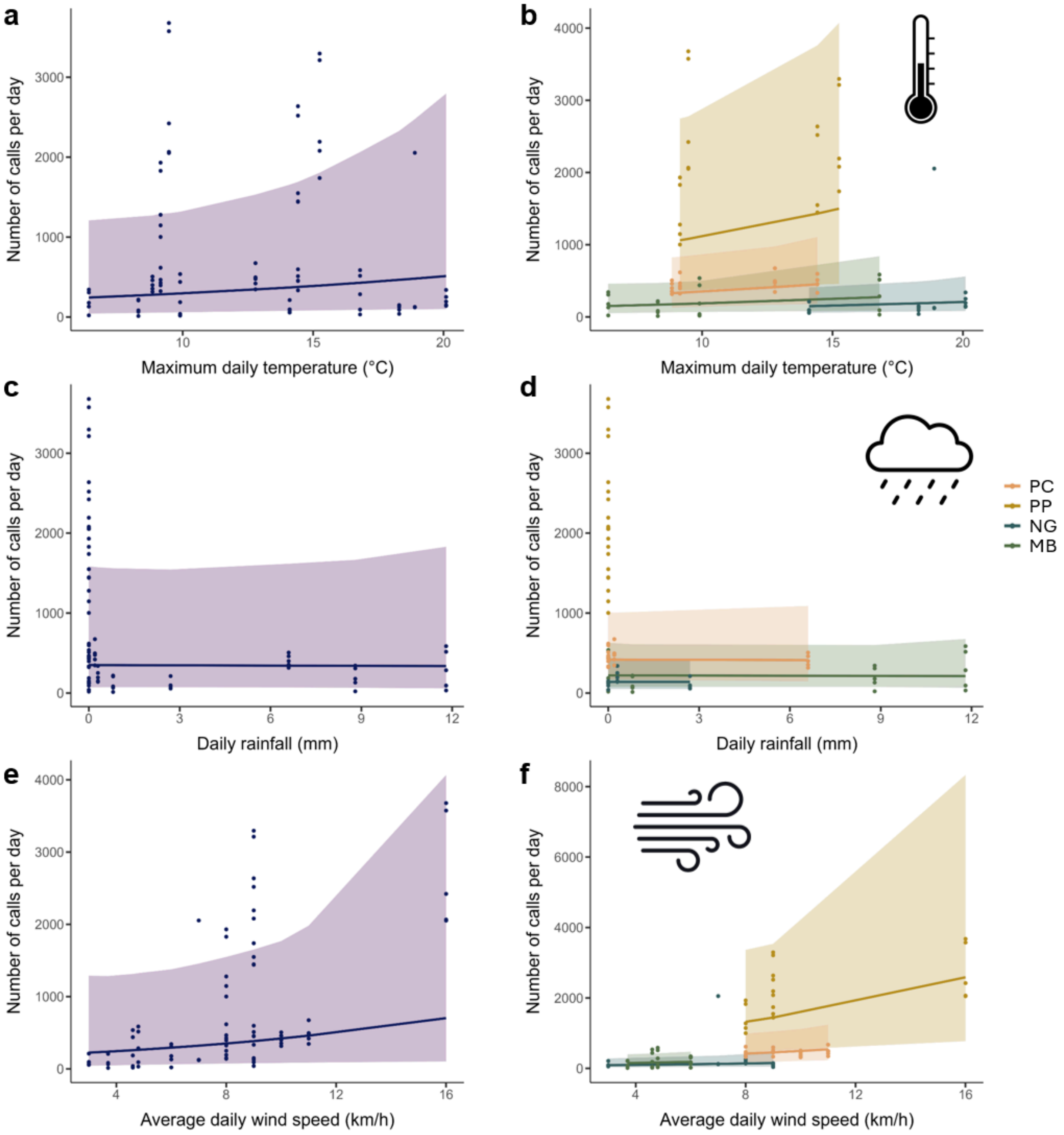


Figure 10. Weather conditions had no significant effect on the number of daily pika calls detected by each ARU. Lines represent the mean predicted number of calls per day across weather variable values. Shading represents the 95% credible intervals for predictions. Overall effects of **a** maximum daily temperature (°C) from hourly averages, **c** daily rainfall (mm) and **e** average daily wind speed (km/h) from hourly averages on daily pika call detections are shown in purple. Site-level effects of **b** maximum daily temperature (°C), **d** daily rainfall (mm) and **f** average daily wind speed (km/h) are coloured by site, with MB=Mt. Boyle (green), NG=Nàday Gän (blue), PC=Pika Camp (salmon), PP=Printer’s Pass (yellow).

4. Discussion

I found that acoustic signatures provided insights into pika calling activity, but the ability to distinguish among different calls varied across scales. Pika calls from different populations were distinguished with 83% accuracy and between a juvenile and an adult with 100% accuracy. My findings align with previous research suggesting that pikas exhibit population-level dialects (Conner, 1982; Trefry & Hik, 2010), but contrast with vocal fingerprinting studies using higher user-effort discriminant analyses that achieved over 90% accuracy in distinguishing among individuals (Conner, 1985; Volodin et al., 2018, 2021). Consistent with previous observations of late-summer collared pika activity (Morrison et al., 2009), I found that pikas called throughout a 24-hour period, but calling patterns were complex and variable. More pika calls were detected in recordings when humans were absent than present, although the difference was not statistically significant. This adds uncertainty to the degree of anti-predator alarm calling exhibited by pikas in response to human presence (Chaudhary et al., 2025; Zhu et al., 2023). Temperature, rainfall and wind speed had no significant effect on the number of daily pika calls detected, which contrasts with previous observations of decreased activity in pikas during periods of high temperatures (Camp et al., 2020; Hall & Chalfoun, 2019; Harrison, 2023; Smith, 1974; Stafl & O'Connor, 2015), rain (Zhou et al., 2023) and winds (Benedict et al., 2020; Harrison, 2023; Hayes & Huntly, 2005). My results on pika calling activity suggest that human-conducted pika surveys need not be limited to the warmest and brightest parts of the day, and that additional survey techniques could be employed to increase the auditory detectability of pikas in the presence of humans. Beyond presence and absence surveys, my findings indicate that ARUs can dramatically improve monitoring of this species at risk by offering information that can be used to infer population-level proportions of adults and juveniles and potentially population sizes.

4.1. Unique acoustic signatures could enable demographic rate estimates

Pika calls were assigned to their correct populations with 83% accuracy using affinity propagation clustering, supporting my first hypothesis that ARUs can be used to distinguish populations as collared pikas have unique regional dialects. Similarly, Trefry & Hik (2010) found that pika calls could be correctly classified by population with 75% accuracy based on call structure. In that study, classification accuracy increased by almost 20% when calls were grouped to broader geographic regions (Trefry & Hik, 2010). Surprisingly, my clustering analysis suggests that the call structure of Pika Camp and Printer's Pass, the two sites that were geographically closest, diverged more from each other than from Mt. Boyle, which is located hundreds of kilometres to the north. Previous research has theorized that regional call differences in pikas have arisen due to differing evolutionary histories of geographically distinct populations (Conner, 1982; Somers, 1973; Trefry & Hik, 2010). Given pikas' low dispersal abilities, such divergence is facilitated by the lack of interbreeding between isolated populations (Conner, 1982, 1983). Pika Camp and Printer's Pass are separated by 3 km of mountainous terrain, making dispersal highly unlikely and potentially explaining the dissimilarity of calls from these populations. One caveat to this analysis is that the calls from Mt. Boyle came from only one pika, which may not reflect the call structure of all northern pika populations. Nevertheless, the ability to distinguish calls at the population level demonstrates that ARUs produce recordings of sufficiently high quality for discrimination analysis.

In line with my first hypothesis predicting accurate acoustic identification of individuals, pika calls from an adult and a juvenile at Mt. Boyle were discriminated with 100% accuracy. With a broader vocal repertoire than collared pikas (Conner, 1985), newborn American pikas are thought to produce three types of vocalizations, two of which develop into adult vocalizations within six weeks of birth (Conner & Whitworth, 1985). Other researchers observing juvenile pikas have noted that these vocalizations are higher-pitched than those of adults during the first three weeks following their emergence from the talus (Barash, 1973). The juvenile observed at Mt. Boyle produced softer, lower-pitched calls than the adult, corresponding to a visibly distinct signature in the spectrogram (Figure 7b). Distinct differences in call structure could explain why the clustering algorithm was so effective in this scenario. Although potentially limited to the first few weeks after juveniles emerge, the ability to automatically distinguish between recordings of young pikas and adults could enable monitoring of reproductive success in populations from year-to-year. Having this marker of reproductive success would allow conservation efforts to be directed towards populations with low or decreasing levels of reproduction.

The clustering algorithm distinguished among individual adults from Pika Camp with only 60% accuracy, failing to support my first hypothesis. It is possible that the differences in the vocal fingerprints of adults are more miniscule and thus more difficult to detect than differences among populations or between juveniles and adults. This theory is supported by my description of the lowest initial levels of clustering for Pika Camp individuals in Section 2.5.3. Additionally, previous acoustic studies that have successfully identified individual pikas or demonstrated the potential for individual coding have employed manual or semi-manual feature extraction to obtain specific measurements of calls recorded at close range (Conner, 1985; Trefry & Hik, 2010; Volodin et al., 2018, 2021). Although I analyzed only high quality calls, acoustic signals can degrade with distance from an ARU, potentially impacting the features of the call (Knight et al., 2024; Tseng et al., 2024; Yip et al., 2017). Furthermore, the automatically-extracted MFCCs and delta coefficients capture the shape of a call's spectral signal, but their effectiveness at acoustic identification is reduced in the presence of background noise, which is inherent to ARU technology (Kumar et al., 2011; Zhao & Wang, 2013). Automatic individual identification of pikas would provide the most powerful acoustic tool for monitoring populations, but alternate approaches may be needed to achieve this potential with ARUs.

4.2. Diurnal pika calling activity may be linked to local conditions

In accordance with my second hypothesis predicting highest activity during the day, I found that pikas called throughout the day and night across sites with no consistent peaks in activity, but with activity levels being highest during the day at Printer's Pass and Pika Camp. These results reflect previous late-summer research on the collared pika that found lower but still present foraging activity between 24:00 and 04:00 (Morrison et al., 2009). Collared pikas' high latitude habitats presumably allow them to capitalize on long day lengths to maximize daytime foraging amidst a short growing season (Hall & Chalfoun, 2019; Harrison, 2023; Morrison et al., 2009). In contrast to my hypothesis, however, calling activity was higher during nighttime hours than daylight hours at Nàday Gän and Mt. Boyle. Such nocturnal activity has been observed for other pika species (Camp et al., 2020; Hall & Chalfoun, 2019; Millar & Hickman, 2021; Smith, 1974, 2020; Smith et al., 2016). Population-level differences in nocturnal activity of pikas could be driven in part by the daily activity patterns of nearby predators (Hall & Chalfoun, 2019). Other evidence suggests that nighttime foraging compensates for a temperature-induced midday lull in activity, which is typically more pronounced at warmer, low-elevation sites (Bhattacharyya et al., 2014; Camp et al., 2020; Smith, 1974). However, no consistent midday lulls or elevated morning or evening activity previously seen in the collared pika (Harrison, 2023; Morrison et al., 2009) were observed. Therefore, lower daylight activity at the two sites could be attributed to Nàday Gän experiencing the highest temperatures of all sites during the study period (Figure 10b) and Mt. Boyle being 200 m in elevation below the other sites (Table 1). Day length was also shortest at these sites and decreasing rapidly from night-to-night (Table A3), which could put pressure on pikas to forage throughout the night to collect enough food before winter. Taken together, the complex and potentially climate-linked nature of daily pika vocalizations could provide insights into how pikas will modulate behaviour in response to habitat warming.

At the site-level, all ARUs detected similar levels of pika calls at the same times at Printer's Pass, whereas synchronized detections were only observed between some ARUs at other sites. This indicates that multiple ARUs either detected the same calls or that pikas around the site were calling simultaneously in response to one another's calls. ARUs at Printer's Pass were spaced apart with similar distances to Mt. Boyle and Nàday Gän, but were placed on opposing walls of a valley instead of on the same steep slope, potentially increasing detectability of calls from the opposite slope. Thus, either scenario (ARUs double counting or simultaneous calling) suggests that terrain may play more of a limiting role in pika call attenuation in talus than distance. Steep and rugged terrain at Nàday Gän could explain why more pika calls were detected at Mt. Boyle despite Mt. Boyle likely having fewer pikas. Similarly, ideal terrain at Printer's Pass could explain why more pika calls were detected there than at Pika Camp. However, this does not preclude the possibility that our *in situ* population size estimates are unreliable, or that pikas at some sites may call more than at others. Overall, these findings suggest that ARU placement should be adapted to habitat characteristics.

4.3. Pika surveys should consider the effect of human presence on pika calling behaviour

I found that pika calling activity exhibited a negative but not significant response to human presence. This result challenges my third hypothesis that pikas produce alarm calls in response to humans and the general literature suggesting that pikas perceive humans as predators (Chaudhary et al., 2025; Stafl & O'Connor, 2015; Wei et al., 2022; Zhu et al., 2023). However, several studies have found that pikas accustomed to human presence produce fewer alarm calls when a human enters their habitat than pikas that are unfamiliar with humans (Chaudhary et al., 2025; Zhu et al., 2023). Pikas have also been found to call at a reduced rate after repeated encounters with humans (Chaudhary et al., 2025; Zhu et al., 2023). Despite my research sites experiencing very low annual levels of human activity, the low number of pika calls detected in recordings when my field team was present could be due to pikas being habituated to our presence after several hours of us conducting research activities. Another possibility is that pikas chose to seek refuge within the talus rather than vocalizing in response to our activities, a behaviour that has been previously observed in response to some nonhuman predators (Holmes, 1991; Morrison et al., 2004). A flight response of this nature has been documented in other species of pika due to human presence, but it is typically accompanied by alarm calling (Chaudhary et al., 2025; Zhu et al., 2023). It is also possible that elevated call rates in recordings with humans absent were induced by the presence of nonhuman predators. My findings suggest that pikas may not always exhibit high levels of vocalization activity in the presence of humans. Given that human-conducted pika surveys rely heavily on acoustic signs (Cannings et al., 2019; Kukka et al., 2020), these results have implications on the detectability of pika and subsequent occupancy modelling. Surveyors should therefore consider alternate means of inducing pika calling, such as broadcasting playbacks of predator vocalizations during surveys (Ma et al., 2023; Trefry & Hik, 2009), which has previously been found to be more time-efficient than auditory surveys (Sakiyama & García Molinos, 2023).

4.4. Weather may not strongly impact pika detectability

In contrast to my fourth hypothesis, I found that maximum daily temperature, daily rainfall and average daily wind speed did not influence the number of daily pika calls detected. The impacts of high temperatures on the cold-adapted American pika have been well-studied, with effects ranging from reduced foraging activity (Camp et al., 2020; Hall & Chalfoun, 2019; Stafl & O'Connor, 2015) to death (Smith, 1974). The relationship between collared pika activity and temperature remains relatively understudied. The lack of an observed effect of temperature in this study contrasts with low haying levels recorded for collared pikas during high temperatures (Harrison, 2023), but mirrors previously-documented summer activity, which showed a lack of daytime patterns despite temperature fluctuations (Morrison et al., 2009). Since temperature effects on American pikas seem to be most pronounced in warm, low-elevation habitats

(Bhattacharyya et al., 2014; Camp et al., 2020; Smith, 1974), the absence of an effect at my sites could be due to the relatively low temperatures experienced at my high-latitude and elevation research sites (mostly <20°C during the days studied, Figure 10a,b). Therefore, temperature may not constrain collared pika activity to the extent of American pika, although temperature thresholds for activity could become more evident in the coming years due to rapid alpine warming at high latitudes (Pepin et al., 2015; Williamson et al., 2020).

Impacts of precipitation and wind on pikas are less studied, but pikas are thought to vocalize less in windy (Benedict et al., 2020; Harrison, 2023; Hayes & Huntly, 2005) and rainy conditions (Zhou et al., 2023). YG collared pika surveys aim to maximize detectability by targeting warm periods during the day with no precipitation and low winds (Kukka et al., 2020). I expected acoustic detectability in ARU recordings to decrease further under windy and rainy conditions due to excess noise (Kalan et al., 2015; Thomas et al., 2020). However, the lack of effect detected in my recordings and analyses could be due to the period of study consisting of relatively low rainfall levels across sites (<12mm, Figure 10c,d) and low wind speeds (mostly <12 km/h, Figure 10e,f). Nevertheless, my results suggest that moderate changes in temperature, rainfall and wind speed may not strongly affect collared pika detectability, indicating that audio recording is a robust detection method in a variety of weather conditions. Wind and rain could impede surveyors' ability to visually and auditorily detect pika (Kukka et al., 2020) while traversing talus safely, but ARUs could be effective in exposed habitats across multiple seasons, filling knowledge gaps about activity and survival in colder months (ECCC, 2023).

4.5. Pika monitoring with ARUs is dependent on bioacoustic advancements

This study highlights the wide-ranging applications of ARUs in monitoring pika populations, yet a wide-scale adoption of acoustic monitoring technology is limited by the availability and quality of acoustic analysis tools. Despite previous research suggesting that collared pika calls carry sufficient information for vocal fingerprinting of individuals (Trefry & Hik, 2010), affinity propagation clustering did not accurately distinguish between individual adults. Since the application of identifying individuals could allow for population estimates, future research should test other low-effort techniques that could be capable of detecting minute differences in call structure. The analysis could also potentially produce better results with an increased sample size of calls (Trefry, 2008). While my recognizer was useful in identifying pika activity levels, it incorrectly identified 20 Redpoll vocalizations as pika calls at Blackcap Mountain. The recognizer could be improved and made more robust by i) training the model to distinguish between collared pika and Redpoll vocalizations and potential confounding vocalizations from other species; ii) obtaining recordings from more pika-inhabited valleys and iii) collecting and overlaying high quality, targeted recordings with ARU recordings during training. My results suggest that weather conditions do not influence the number of daily pika call detections. However, the weather on days used in the analysis was generally warm (mostly <20°C, Figure 10a,b), with relatively low rainfall (<12mm, Figure 10c,d) and wind speeds (mostly <12 km/h, Figure 10e,f), which limits the scope of this part of my analysis. Additionally, there is evidence to suggest that microclimates influence pika activity (Benedict et al., 2020; Bhattacharyya et al., 2014; Harrison, 2023), but data used in the weather analysis may not accurately reflect finer-scale conditions as weather data were sourced from MET stations located up to 43 km away and with up to 1000 m elevation difference. The work presented in this study, while exploratory, could serve as a foundation for acoustic tool development for pika monitoring in the future.

5. Conclusion

Climate change poses a threat to the persistence of the at-risk collared pika due to its sensitivity to heat, extreme weather events and shifts in forage abundance (ECCC, 2023). However, human-conducted monitoring is challenged by the remote and rugged nature of pika habitat, unpredictable weather and potential behavioural changes in pikas due to human presence. In this study, I demonstrated that passive acoustic monitoring can address several of the challenges typically encountered with human-conducted surveys. The use of ARUs allows for rapid deployment and consistent data collection across a variety of weather conditions, offering a more efficient and potentially less intrusive method for monitoring wildlife (Shonfield & Bayne, 2017; Vallee, 2023). My success in distinguishing between the unique acoustic signatures of adult and juvenile pikas lays the groundwork for tracking population-level reproduction rates over time. This approach could offer valuable insights into the dynamics of pika populations and the impacts of climate change on both pika populations and alpine ecosystems from year-to-year. The field of acoustic identification of individuals is progressing rapidly (Knight et al., 2024). The development of tools for this purpose holds promise for population size estimates, which are needed to inform conservation efforts at a local scale and status assessments at a species scale. My analysis revealed that daily pika activity is complex across heterogeneous habitats, and it is unclear how pikas will adjust or are already adjusting their behaviour in response to the changing climate. Given these uncertainties and the demonstrated capabilities of ARUs, I propose that pika monitoring programs adopt a two-pronged approach that leverages the strengths of both human-conducted surveys and bioacoustic monitoring. Bioacoustic monitoring provides an efficient and scalable approach to tracking the status of pika populations amidst rapid alpine warming and could contribute to broader conservation efforts by extending to other vocal species at risk.

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7. Appendix

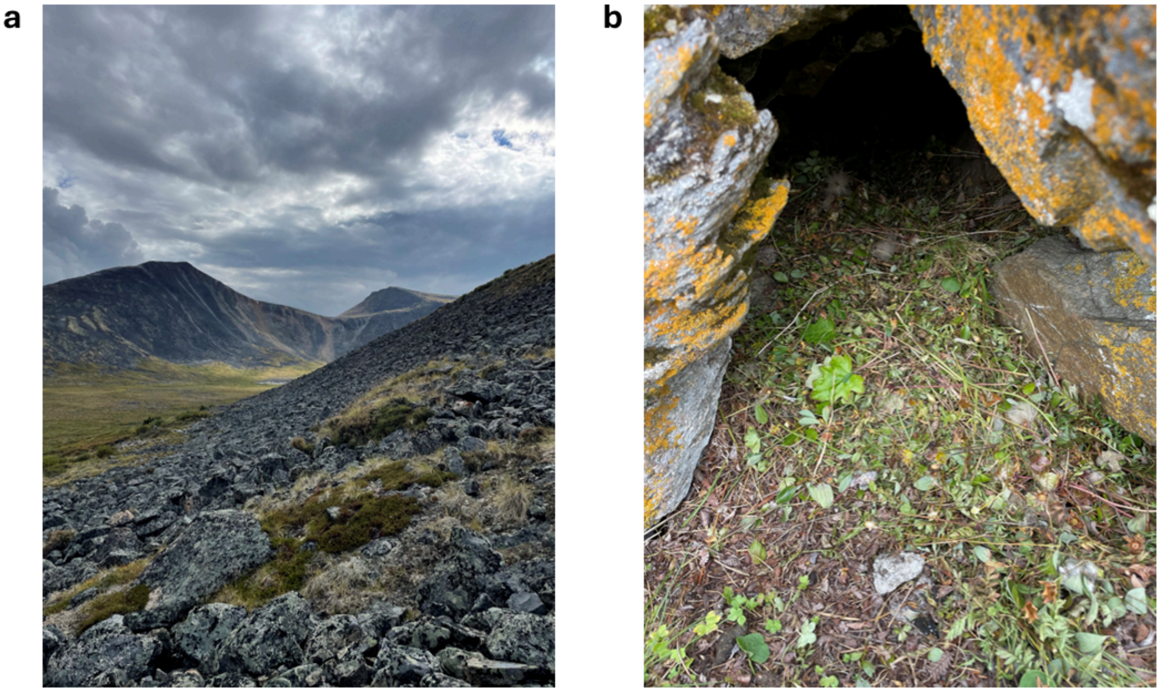
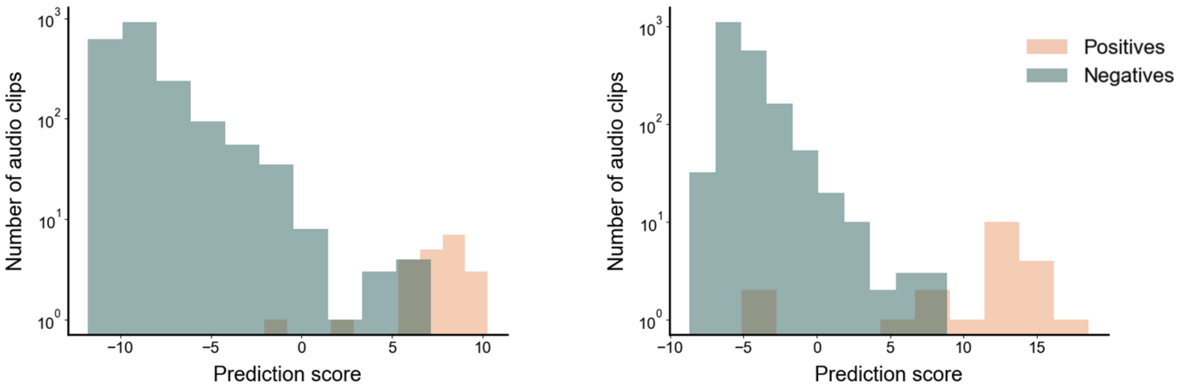


Figure A1. a A talus slope inhabited by collared pikas in Kusawa Territorial Park, Yukon. **b** A haypile made of herbaceous plants, cached between talus rocks by a collared pika.

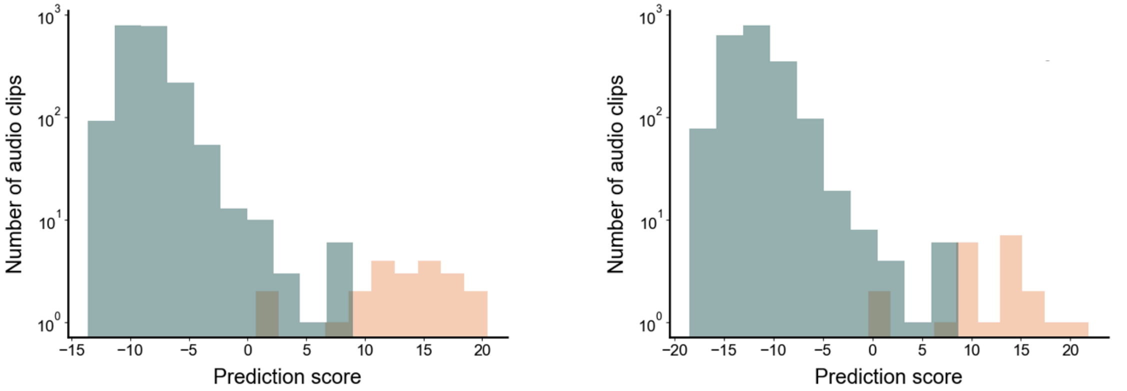
Table A1. Recognizer model training parameters.

Parameter name	Parameter value	Explanation of parameter
clip_duration	0.3 s	The recognizer viewed spectrograms as 0.3 s clips because this duration is 3x the length of a typical pika call and OpenSoundscape recommends using clips of 2-5x call length.
clip_overlap	0.15 s	Each 0.3-second clip overlapped 0.15 seconds with the previous clip to ensure that pika calls that had been split into different clips were also included in their entirety in an additional clip during training.
min_label_overlap	0.07 s	Either 0.07 seconds or 80% of a call had to be included in a clip to be considered positive, given that average pika call length is 0.11 s and rarely falls below 0.07 s.
min_label_fraction	0.8	
negatives_downsampled	2*positives	I produced a balanced dataset with a 2:1 ratio of negative to positive clips to ensure the recognizer was not biased towards assigning clips as negative.
test_size	0.2	I used the scikit-learn v1.5.2 Python library (Pedregosa et al., 2011) train_test_split function to randomly split the dataset into a training set containing 80% of the clips and a validation dataset containing the remaining 20% of clips.
min_f	700 Hz	Using the OpenSoundscape Preproccessor classes, I bandpassed the frequency range of the training spectrograms to 700-6500 Hz to remove excess noise.
max_f	6500 Hz	
overlap_fraction	0.9	Adjacent columns of pixels in each spectrogram overlap by 90%, which produced the best resolution image, as visualized with OpenSoundscape's Audio and Spectrogram classes.



a Epoch 14 (“best” model)

b Epoch 20



c Epoch 50

d Epoch 100

Figure A2. Recognizer prediction score histograms for recognizer models produced at epoch **a** 14 (the “best model”); **b** 20; **c** 50 and **d** 100. Histograms show the number of positive clips (containing pika calls) in pink and the number of negative clips (not containing pika calls) in blue across the full range of prediction scores. Higher prediction scores mean the recognizer is more confident that a pika call is present in a given clip. The epoch 100 model has the highest performance because it separates negatives from positives best and assigns the highest scores to positives and the lowest scores to negatives.

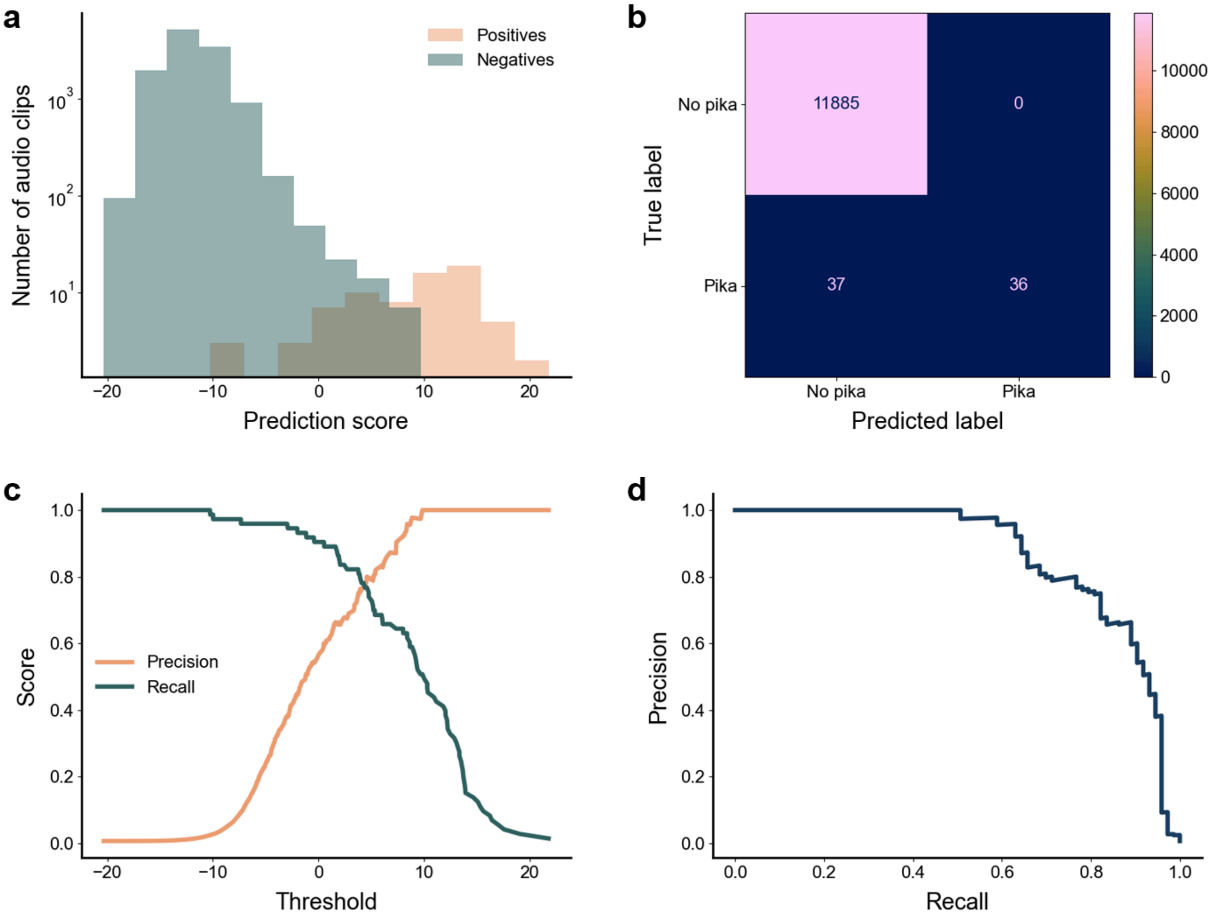


Figure A3. Recognizer performance evaluation plots for a test set composed of recordings from my research sites. **a** A prediction score histogram showing the distribution of prediction scores for positives (clips containing pika calls) in pink and negatives (clips containing no pika calls) in blue. A high degree of separation of positives and negatives indicates good performance. **b** A confusion matrix showing the number of true and false positives and negatives at a score threshold of 10. The colour scale with numbers represents the number of calls correctly or incorrectly identified by the recognizer. **c** Precision and recall scores at prediction score thresholds over the full range of test set prediction score values. **d** A curve showing the trade-off between precision and recall scores. Note that a few high-scoring negatives are actually clips that contain partial pika calls that did not meet length threshold requirements I set.

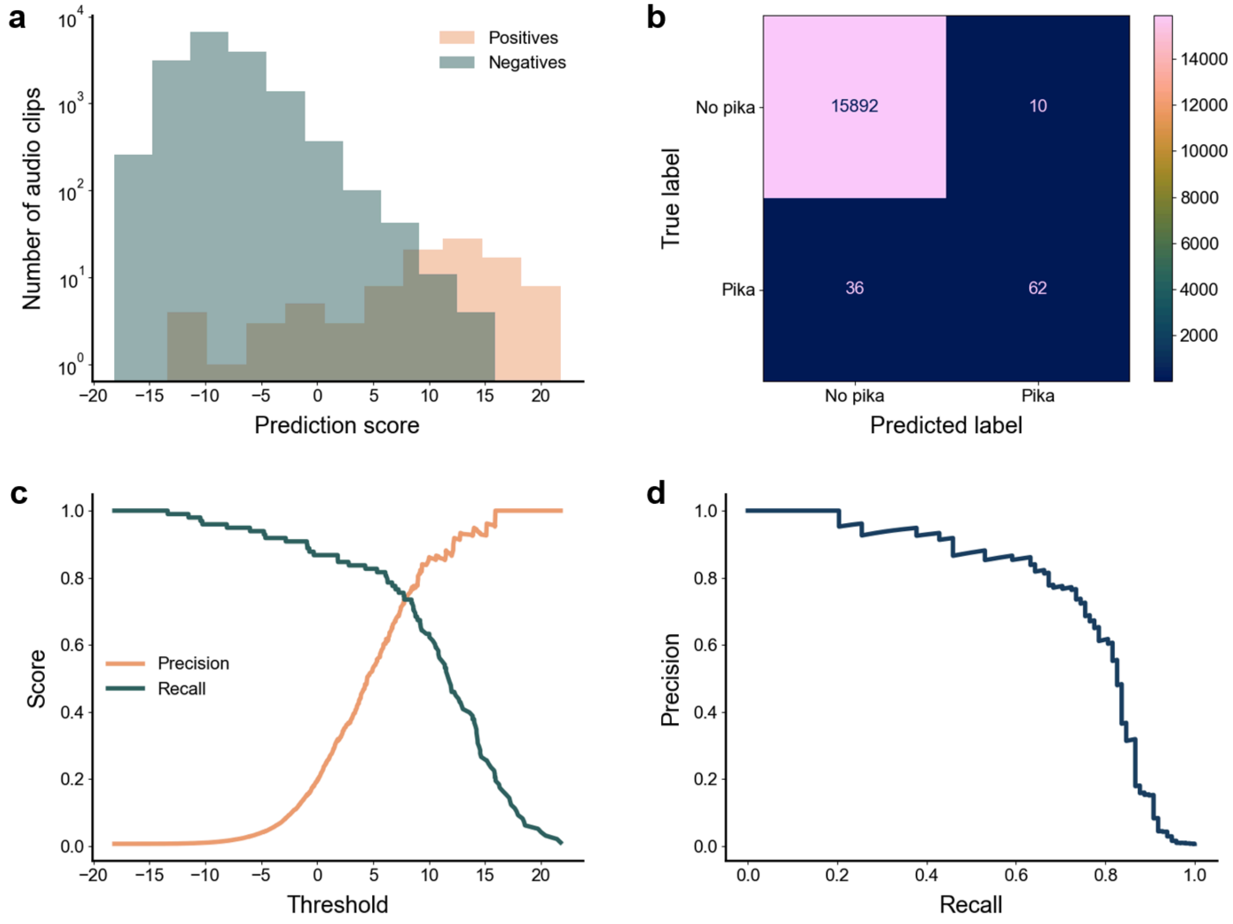


Figure A4. Recognizer performance evaluation plots for a test set composed of Canadian Wildlife Service recordings. **a** A prediction score histogram showing the distribution of prediction scores for positives (clips containing pika calls) in pink and negatives (clips containing no pika calls) in blue. A high degree of separation of positives and negatives indicates good performance. **b** A confusion matrix showing the number of true and false positives and negatives at a score threshold of 10. The colour scale with numbers represents the number of calls correctly or incorrectly identified by the recognizer. **c** Precision and recall scores at prediction score thresholds over the full range of test set prediction score values. **d** A curve showing the trade-off between precision and recall scores. Note that a few high-scoring negatives are actually clips that contain partial pika calls that did not meet length threshold requirements I set.

Table A2. Recognizer performance metrics for a dataset composed of field recordings from my sites and a dataset composed of CWS recordings at a score threshold of 10. Scores range from 0-1, with 1 being a perfect score. AUC is the best indication of performance here because the high score threshold prioritizes precision over recall, resulting in low recall and F1 scores. CWS = Canadian Wildlife Service. AUC = area under the curve.

Test set	Precision	Recall	F1 score	Precision-Recall AUC
My data	1.0	0.49	0.66	0.86
CWS data	0.86	0.63	0.73	0.76

Table A3. Daylight hours and darkness hours for the days analyzed in the diurnal activity analysis in Figure 8. I define daylight and darkness hours based on site-level civil twilight times accessed from the National Research Council of Canada's sunrise/sunset calculator.

Site	Date	Civil twilight start	Civil twilight end	Daylight length (h)	Twilight length (h)
PC	19 July 2024	00:48	03:52	20.93	3.07
	21 July 2024	00:40	04:00	20.67	3.33
	25 July 2024	00:24	04:16	20.13	3.87
PP	19 July 2024	00:48	03:52	20.93	3.07
	21 July 2024	00:40	04:00	20.67	3.33
	24 July 2024	00:28	04:12	20.27	3.73
NG	27 July 2024	00:09	04:28	19.68	4.32
	28 July 2024	00:06	04:31	19.58	4.42
	31 July 2024	23:51	04:42	19.15	4.85
MB	9 August 2024	00:09	04:30	19.65	4.35
	10 August 2024	23:59	04:35	19.40	4.60
	12 August 2024	23:49	04:44	19.08	4.92

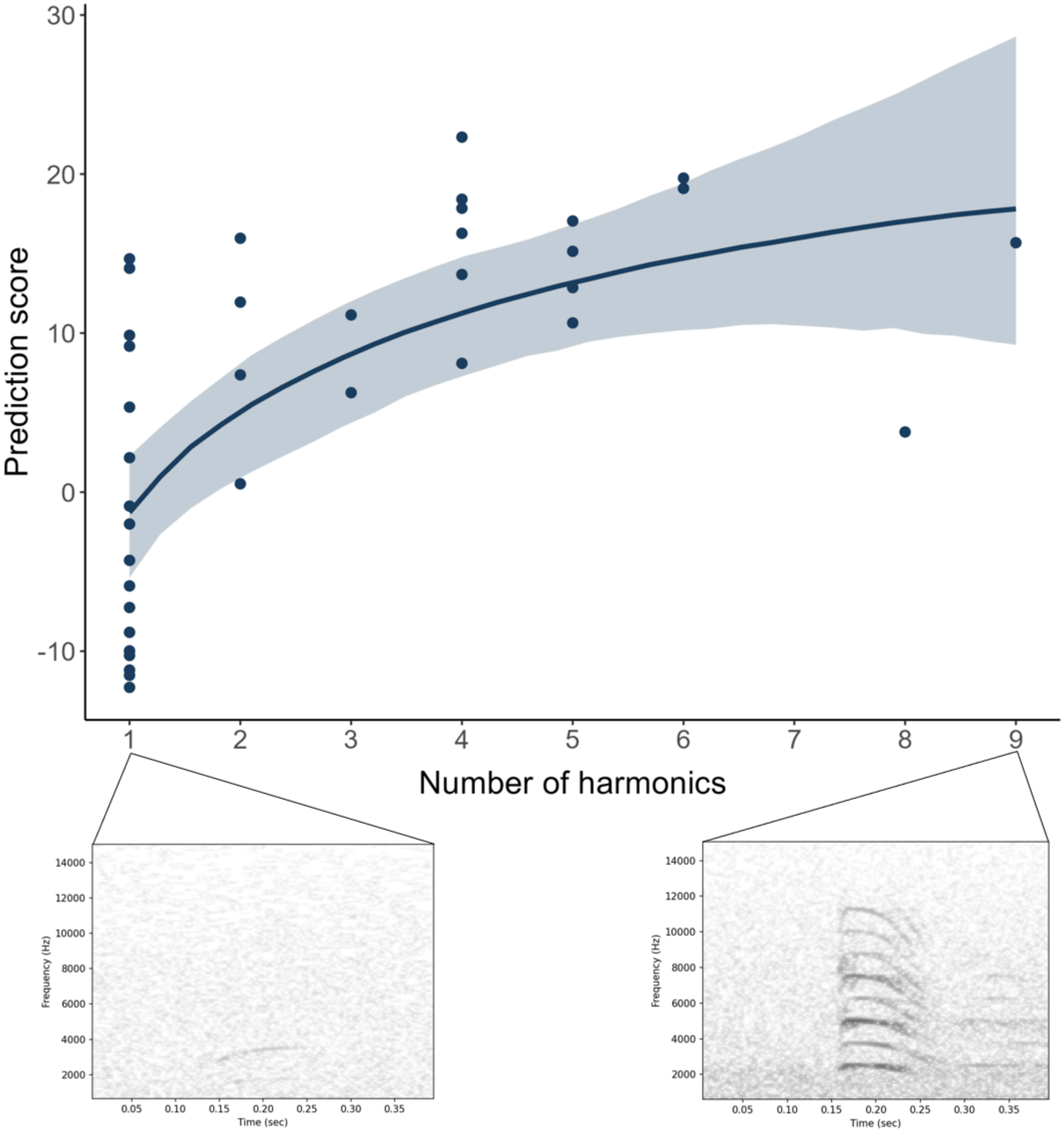


Figure A5. The log-transformed number of harmonics visible in a pika call spectrogram had a significant positive effect on the prediction score generated by the recognizer. Effect size decreased as the number of harmonics increased. Spectrograms show examples of how the recognizer views a call with one harmonic and nine harmonics, respectively.

Table A4. Bayesian model results of the recognizer call quality model show that log(harmonics) is a significant predictor of prediction score, but the untransformed number of harmonics is not. Variables are deemed significant when their credible interval does not overlap zero.

Response variable	Fixed effect	Effect size	95% credible interval
Prediction score	Number of harmonics	-0.170	-3.192 - 3.032
	log(number of harmonics)	9.337	0.646 - 17.859

Table A5. Bayesian model results of fixed effects support no hypotheses for the human presence and weather models. Effect sizes and credible intervals are expressed as raw model outputs and are log-transformed due to the use of a Poisson distribution. To meaningfully interpret effect sizes, I back-transformed the values and isolated the effects of individual variables.

Hypothesis	Response variable	Fixed effect	Effect size	95% credible interval	Supports hypothesis?
3	Number of calls detected by each ARU per recording	Humans present	-0.866	-2.376 - 0.985	No
4	Number of calls detected by each ARU per day	Daily maximum temperature (°C)	0.056	-0.050 - 0.152	No
		Daily rainfall (mm)	-0.003	-0.099 - 0.090	No
		Daily average wind speed (km/h)	0.086	-0.047 - 0.236	No