SOUNDSCAPES AND SANCTUARIES: MAPPING WOLF SANCTUARY ENVIRONMENTS USING SOUNDSCAPE ANALYSIS

by

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ABSTRACT

Soundscapes And Sanctuaries: Mapping Wolf Sanctuary Environments Using Soundscape Analysis

Robin Vance

This thesis investigates the acoustic environment of Wolf Haven International, an animal sanctuary dedicated to the care of rescued and displaced wolves and coyotes as well as the conservation of wild wolf populations. By deploying AudioMoth devices across five strategic locations within the sanctuary and continuously recording the soundscape over the course of several days, a comprehensive sound profile was derived. Extracting both decibel and frequency levels from the audio and analyzing differences by location and time of day, the research provides insight into the spatial and temporal distribution of sound at Wolf Haven. Key findings reveal significant differences in sound levels across sites, influenced by factors such as proximity to service paths or public areas, vegetation density, and built structures. The research highlights the critical role of natural sound buffers, like foliage, in mitigating noise pollution, and the importance of intentional placement of animals, including individuals sensitive to noise and wolves who can be released into the wild. The results provide a baseline for future soundscape monitoring and contribute valuable data for the ongoing development of Wolf Haven's Sanctuary Master Plan, with implications for improving animal welfare, recovery husbandry, and habitat management.

Table of Contents

List of Figures

List of Tables

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Chapter 1 - Introduction

In an era marked by significant human alterations to natural soundscapes, the inevitable impacts of anthropogenic noise have been observed and noted throughout the scientific literature from reduction in foraging efficiency in wild owls and bats to reduced pairing success in birds (Francis et al. 2017). The field of soundscape ecology, which delves into the complex interplay between soundscapes and ecological systems, has risen to prominence as researchers increasingly recognize the profound influence of auditory environments on animal behavior and ecosystem dynamics (Pijanowski et al. 2011a). Originating from the broader discipline of landscape ecology, soundscape ecology integrates the study of biophonic (relating to non-human organisms), geophonic (relating to non-biological ambiance), and anthrophonic (relating to humans) sound to explore how these components collectively shape living environments (Pijanowski et al. 2011c). This evolving discipline is crucial for comprehending how various sound sources affect wildlife, as well as for devising strategies to mitigate the adverse effects of noise pollution and enhance habitat quality for organisms influenced by sound. Habitat enhancements are of interest not only to those managing lands for wildlife habitat suitability but also to managers of captive wildlife; thus, soundscape ecology research in the context of zoological facilities is budding (Clark and Dunn 2022).

One such investigation conducted at the Cleveland Metroparks Zoo observed space use by two pied tamarinds in response to induced changes in sound across their exhibit (Wark et al. 2023). Soundscape shifts marked by decreased sound pressure levels across the whole frequency spectrum in response to COVID-19 closures at the Chester Zoo in Chester, UK, have also been explored (Lewis et al. 2023). Some zoological facilities have been making headway in incorporating soundscape monitoring to influence their animal management practices: Disney's

Animal Kingdom®, for example, uncovered the most effective sound-reducing barrier for their animal enclosures during parkwide construction efforts (Orban et al. 2017). The investigation of soundscapes of captive environments appears to be growing in the scientific literature; however, the existing library of such research is modest when compared to that of soundscapes of wildlife habitats (Clark and Dunn 2022). Notably, an exploration into soundscape-related studies within the context of animal sanctuaries yielded no results.

The distinction between animal sanctuaries and their conventional zoo counterparts is important due to the specialized goals and subsequent habitat curation unique to one or the other, and such distinction can be determined by the species in their care. Based on accreditation standards of organizations such as the Global Federation of Animal Sanctuaries (GFAS) and American Sanctuary Association (ASA), the main differences lie in the non-commercial pursuits of sanctuaries as well as how animals are acquired, plus a distinct ban on breeding efforts except under exceedingly strict criteria (The Oasis Sanctuary, "American Sanctuary Association"; GFAS, “Position Statements”). Due to the emphasis on maintaining environments that predominately cater to the well-being of the animal residents, accredited sanctuaries are indeed unique living laboratories for ecoacoustic investigations.

At Wolf Haven International, a wolf sanctuary nestled in Tenino, WA, the subtle interplay of sound and silence crafts a complex acoustic tapestry that is integral to the lives of its inhabitants. Wolf Haven International is a globally recognized wolf sanctuary accredited by GFAS and ASA with a conservation mission dedicated to the protection of wolves and wolf habitat. Since 1982, Wolf Haven has provided rescue services and permanent sanctuary to over 300 displaced, captive-born wolves, wolfdogs, and coyotes (Wolf Haven International, “About”). Wolf Haven is a lead participant in two federally managed SAFE (Saving Animals from

Extinction) programs designed to ensure the continued survival of two endangered species: the American Red wolf and the Mexican wolf. As the sanctuary embarks on the journey of developing a comprehensive Sanctuary Master Plan (SMP), a pivotal aspect of this endeavor is the investigation of the sanctuary's soundscape.

As the effects of noise within captive settings such as sanctuaries remain underexplored, a soundscape investigation at Wolf Haven International will contribute valuable information. It will shed light on how sound affects wolves in captivity, offering guidance on strategies to mitigate these impacts and thereby improve animal welfare, as well as manage potential habituation in recovery wolves from SAFE programs. Integrating principles of acoustic ecology with animal welfare practices in the context of sanctuary management presents a unique challenge. By providing baseline data for the Wolf Haven Sanctuary site, this research enables future studies to assess changes in the soundscape and their ecological implications over time. Importantly, this research aims to fill a gap in reproducible examples of soundscape investigation in a sanctuary context.

The purpose of this thesis is to explore how decibel and frequency readings of audio recorded across the landscape of Wolf Haven International can inform a soundscape map for the appropriate placement of sanctuary animals. This premise requires a working knowledge of acoustics in ecology and the methodology behind capturing sound for analysis. Additionally, it requires understanding the role that sound plays in animals' lives—wolves, in particular—and how it impacts their welfare and behavior, which helps to illuminate the related goals of Wolf Haven's soundscape investigation. For the scope of the research at Wolf Haven, the captured soundscape defined a brief moment in the sanctuary's acoustic timeline; however, as management decisions shape the environment based on this initial soundscape investigation, future investigations to discover potential changes may be considered.

Chapter 2 - Literature Review

The influence of sound on animal welfare is the focus of this review, as underpinned by the field of ecoacoustics—a subset of acoustic ecology that provides the theoretical and methodological framework for analyzing soundscapes. Key methodologies include recording and analyzing environmental sounds, along with spatial–temporal mapping to visualize sound variations over time and space. Focus is given to understanding the auditory sensitivity of wolves and coyotes, aligning the sanctuary's acoustic characteristics with these animals' hearing capabilities. Wolf Haven International's ecological and acoustic environment is then introduced, setting the stage for discussing the SMP and its role in wildlife conservation and welfare. Although the review primarily centers on Wolf Haven, it draws from a wide range of ecoacoustic literature and acknowledges potential variability in findings across different species and conservation settings. Despite limitations like its focus on a specific location and gaps in research on auditory sensitivity and soundscape mapping in similar environments, this review aims to establish a base for sound management practices that enhance wolf welfare and inform the SMP.

The Role of Sound

Sound encompasses various aspects of an animal's daily life, including communication, navigation, predator detection, and mating (Francis and Barber 2013; Blickley and Patricelli 2010; Shannon et al. 2016). It plays a crucial role in the survival and reproductive success of many species, influencing their behavior, ecology, and evolution. Sound is a primary mode of communication for much of the animal kingdom, including the canids of Wolf Haven International. Vocalizations can convey information about an individual's identity, location, reproductive status, and emotional state. This is particularly evident in social species where communication maintains group cohesion and coordinates activities. Cetaceans, such as whales and dolphins, use complex vocalizations to communicate over vast ocean distances (Tyack 2000), while birds use songs and calls for mate attraction, for territory defense, and to maintain social bonds (Catchpole and Slater 2008).

Wolves and Sound

For wolves, sound, particularly howling, is an important means of long-range communication that serves several key functions. Howling helps to maintain pack cohesion, allowing members to locate each other over large distances—a crucial means of communication in the expansive territories that wolves inhabit—ensuring that pack members can regroup after hunting or when separated (Harrington and Mech 1979). The acoustic properties of gray wolf (*Canis lupus*) howls, including a fundamental frequency range from 150 to 780 Hz and purposefully long duration, are adapted to travel long distances, cutting through dense forests and across tundra landscapes, making them an effective tool for long-range communication in various habitats (Tooze, Harrington, and Fentress 1990; Harrington and Mech 1979). Additionally, howling serves a territorial function, signaling the occupancy of an area to other wolves and potentially avoiding direct confrontations (Peterson and Ciucci 2003). Gray wolf howls often exhibit modulation in both frequency and amplitude: The howl may start at a higher frequency, descend, and then rise again, creating a characteristic "swoop" in pitch (Theberge and Falls 1967). The structure of wolf howling during choruses is characterized by parts with and without frequency modulations—the unmodulated parts concentrate sound energy around 400 Hz, while the modulated parts have maximum frequencies between 800 Hz and 1,200 Hz (Frommolt 1999). This modulation may help in individual recognition or enhance the howl's propagation properties by varying the frequencies used, thus reducing the likelihood of obstruction by other sounds in the environment.

Wolf vocalizations appear to differ across species. One study characterizing the vocalizations of red wolves (*Canis rufus*) identified several types of sounds: flat howls, barking howls, combination howls, yip howls, whimpers, growls, barks, and choruses. It was found that the flat howls of red wolves are longer and lower frequency than those of coyotes and range from 250 Hz to 1,500 Hz, with an emphasis around 800 Hz (McCarley 1978). The howl variations across different wolf clades within *Canis lupus*, including Himalayan, North African, and Indian wolves, exhibit distinct acoustic profiles. Compared to other wolf clades, Himalayan wolves have lower mean fundamental frequencies and the frequencies within their howls are not modulated, while North African and Indian wolves show higher mean frequencies and shorter-duration howls (Hennelly et al. 2017).

Coyotes (*Canis latrans*) use sound for similar purposes but have a more varied vocal repertoire, including howls, yips, barks, and bark-howls (Hennessy, Dubach, and Gehrt 2012). These vocalizations facilitate social interactions within coyote families, such as maintaining social bonds, coordinating group hunting efforts, and communicating distress or alarm. Coyote vocalizations also play a significant role in territorial defense and advertisement. The "group yip-howl" can convey the size of a coyote group to potential intruders, serving as a deterrent and reducing the likelihood of territorial disputes (Sillero-Zubiri et al. 2004).

A foundational study on coyote vocalizations identified two primary long-distance vocalizations: the bark and the flat howl. These sounds are utilized both individually and in groups. The study found that coyote vocalizations are highly variable in terms of sound type, duration, hertz (Hz), and amplitude. For instance, flat howls typically range from 300 to 800 Hz, with some variations extending beyond this range depending on the context and individual coyote (McCarley 1975). Spectrographic analysis revealed that howls generally have a fundamental frequency range between 300 Hz and 1,000 Hz, while barks are shorter and can range from 400 Hz to 600 Hz. Yips, often used in group settings, exhibit higher frequencies, typically ranging from 800 Hz to 1,200 Hz (Lehner 1978). Howls, with fundamental frequencies ranging from 300 Hz to 800 Hz, contain stable individual-specific characteristics that can be used for long-distance communication. Barks, however, show less stability and are not as effective for individual recognition over long distances. This suggests that howls are optimized for conveying information over greater distances, while barks serve more immediate, attention-attracting purposes (Mitchell et al. 2006).

The auditory capabilities of wolves are not well-understood, and, despite claims repeated on various online websites regarding wolf hearing range (Misfit Animals, "Wolf Hearing: Just How Good Is It & How Do They Use It?"; BioExplorer, "Top 16 Animals with the Best Hearing"; Wild, "A Wolf's Ears"), there is a distinct absence of primary literature or research data on the matter. It can be presumed that the frequencies at which wolves are known to communicate amongst each other must be perceptible to the average pack mate; thus, the information we have regarding wolf communication, such as their howls' fundamental frequency range of 150 to 780 Hz, may provide some insight into sound profiles that are important to their senses (Tooze, Harrington, and Fentress 1990).

We can, perhaps, derive a general sense of wolf hearing abilities by observing the known hearing abilities of other canids. Domestic dogs are known to perceive a wide range of frequencies, detecting those as low as 67 Hz and as high as 45,000 Hz at 60 dB sound pressure level (SPL), which is significantly broader than the human auditory spectrum of approximately

31 Hz to 17,600 Hz (Heffner 1983; Heffner 1998). The sensitivity of dogs to these frequencies highlights their evolutionary adaptations for more acute hearing, which is essential for various breeds, especially those engaged in hunting or working roles where sound detection is crucial (Heffner 1998; Heffner 1983; West 1985).

Additionally, one may consider the influence of size and skull morphology on auditory perception. Dogs' ability to hear such a broad spectrum can be linked to their varied physical conformation, particularly the size of the pinna and auditory canal, which facilitate sound wave capture and amplification across these wide ranges (Fay and Popper 1994; Heffner 1983; Heffner 1998). Dogs demonstrate superior sensitivity, particularly in the higher frequency ranges: Their hearing can be up to 20 dB more sensitive at 10,000 Hz and 16,000 Hz compared to humans (Dworkin et al. 1940). Given the similar ecological niches and the evolutionary lineage shared with domestic dogs, wolves might exhibit comparable, if not more acute, auditory ranges. However, without definitive measurements, such comparisons can only be inferred at present.

Anthrophonic Disturbance

Human-generated sound (anthrophony) is of concern in soundscape ecology as it pertains to the disruption of natural processes. Studies in wild environments demonstrate that noise pollution disrupts animal communication, affects predator–prey dynamics, and can lead to behavioral and physiological stress (Francis and Barber 2013; Blickley and Patricelli 2010). Exposure to chronic noise pollution has been shown to increase stress levels in wildlife, indicated by elevated cortisol levels, which can have cascading effects on health and reproductive success for both terrestrial and aquatic species (Shannon et al. 2016; Francis and Barber 2013). Increased stress can lead to changes in behavior, such as altered hunting patterns or avoidance of certain areas, which can impact their ability to find food and decrease their overall fitness (Shannon et al. 2016). If communication is impaired by noise, it may affect the ability of wolves to find and successfully mate with partners as has been observed in other species, further impacting population dynamics (Bee and Swanson 2007).

Wolves and coyotes rely heavily on acoustic communication for social cohesion, territory defense, and hunting. Anthrophony can interfere with these vocalizations, “masking” them and reducing their effective range. Auditory masking is a phenomenon that occurs when the presence of a loud sound (the masker) makes it difficult or impossible to hear another, softer sound that is present at the same time (Anet 2021). This effect can significantly impact an animal’s ability to detect, recognize, and respond to important acoustic signals in their environment. Auditory masking of canid vocalizations has the potential to decrease pack cohesion and effectiveness in territory defense, as well as increase conflicts with neighboring packs due to misunderstandings of territorial boundaries (Barber, Crooks, and Fristrup 2010).

Implications in Captivity

Captive wolves have been observed to howl more frequently than their wild counterparts (Feuerbacher and Wynne 2012). This increased vocalization rate may be due to the closer proximity of individuals within enclosures, leading to more frequent social interactions and, consequently, more vocal communication. In contrast, wild wolves may howl less frequently but with more strategic purposes, such as coordinating hunting activities or defending territory from rival packs (Feuerbacher and Wynne 2012). Captive wolves often howl in response to external stimuli, such as human-made noises or the howls of other captive wolf packs. This behavior suggests a level of habituation to human presence and activities not typically seen in wild wolves. Wild wolves, on the other hand, may use howling more selectively, responding primarily to natural cues within their environment or the vocalizations of neighboring packs (Nowak et al. 2006).

The social structure of wolf packs can influence howling behavior. For example, captive wolf packs may exhibit different social dynamics compared to wild packs due to the constraints of captivity. Differences such as limited space and predetermined group compositions can affect the context and consistency of howling. For example, captive wolves might howl more as a form of social cohesion within the artificially assembled pack (Kershenbaum, Sayigh, and Janik 2016).

Research has indicated that there may be subtle differences in the acoustic characteristics of howls between captive and wild wolves, such as variations in frequency ranges, durations, and modulation patterns (Root-Gutteridge et al. 2014). These differences could be attributed to the distinct environments and social contexts in which captive and wild wolves live. However, more research is needed to conclusively identify and understand these acoustic variations.

Noise Consideration in Habitat Management

At Wolf Haven International, care staff attempt to mimic wild conditions as much as possible, which includes the sanctuary's sound profile. The noted differences in acoustic expression between captive and wild wolves may be a consideration in habitat management following a soundscape investigation. As with wild wolves, attempts to mitigate exposure to anthrophony would serve to reduce potential habituation, and unnecessary stress response in the sanctuary's residents, especially as it pertains to wolves involved in conservation breeding efforts. Communication variations between captive and wild wolves may be an effect of the physical constraints of captivity; thus, focusing on small-scale habitat changes for soundscape management, such as those undertaken by zoological facilities, may be the most appropriate approach in optimizing naturalistic habitat. Additionally, in relation to breeding efforts, observing soundscape variations at a micro scale may prove beneficial versus assuming more homogeneity exists across the captive landscape. Such suggestions are based on conjecture in lieu of more targeted case studies that deal with noise impacts on sanctuary facilities like Wolf Haven.

The importance of integrating sound management with animal welfare practices is explored by Orban et al. (2017), who demonstrate how continuous monitoring of animal welfare in conjunction with environmental conditions like sound levels can inform better management decisions in zoological settings. By tracking daily assessments of animal health and behavior against environmental sound data, management at Disney's Animal Kingdom® was able to identify and mitigate construction-related sound stressors, enhancing the welfare of animals such as a female giant anteater. The implementation of sound-reducing barriers and other noise mitigation strategies based on this integrated approach emphasizes the potential for science-based management practices to improve the quality of life for captive animals.

Poor sound conditions can compromise the conservation goals of captive breeding programs by affecting the animals' reproductive success and survival rates. The acoustic environment needs to be carefully managed in curated animal habitats to ensure optimal animal welfare. Effective habitat management for captive wildlife involves strategies to minimize harmful noise while potentially incorporating beneficial sounds. Providing environmental enrichments, such as naturalistic soundscapes, can enhance the sensory environment for captive animals, promoting natural behaviors and reducing stress (Swaisgood and Shepherdson 2005). Hosey, Melfi, and Pankhurst (2009) discuss the use of environmental enrichment, including auditory enrichment, to improve the quality of life for captive animals. These enrichments are postulated to simulate aspects of the animals' natural habitats, supporting cognitive function and encouraging species-typical behaviors.

Investigating the variations of sound levels, frequencies, and sources throughout the sanctuary for the sake of sanctuary management planning is a unique though merited undertaking given the impact that we know sound to have on us all. Similarly to the sound mitigation strategies implemented by Disney's Animal Kingdom®, Wolf Haven International may use the findings of a soundscape investigation to alter the sanctuary's habitat for improved reduction of anthropogenic noise.

Acoustic Ecology

Acoustic ecology is a highly interdisciplinary field combining principles from psychology, ecology, behavioral sciences, and humanities to inform through sound the relationship between organisms and their environment (fig. 1; Pijanowski et al. 2011a). Acoustic ecology encompasses scientific investigation of and ecological concern with the acoustic environment, particularly within the realms of ecology and environmental science, and has emerged as a pivotal tool for understanding complex biological and ecological processes. The field's significance is underscored by its ability to non-invasively monitor and interpret the acoustic signals of wildlife, offering invaluable insights into behavior, biodiversity, and ecosystem health without disrupting the natural landscape with too much human presence during research efforts (Krause 1987).

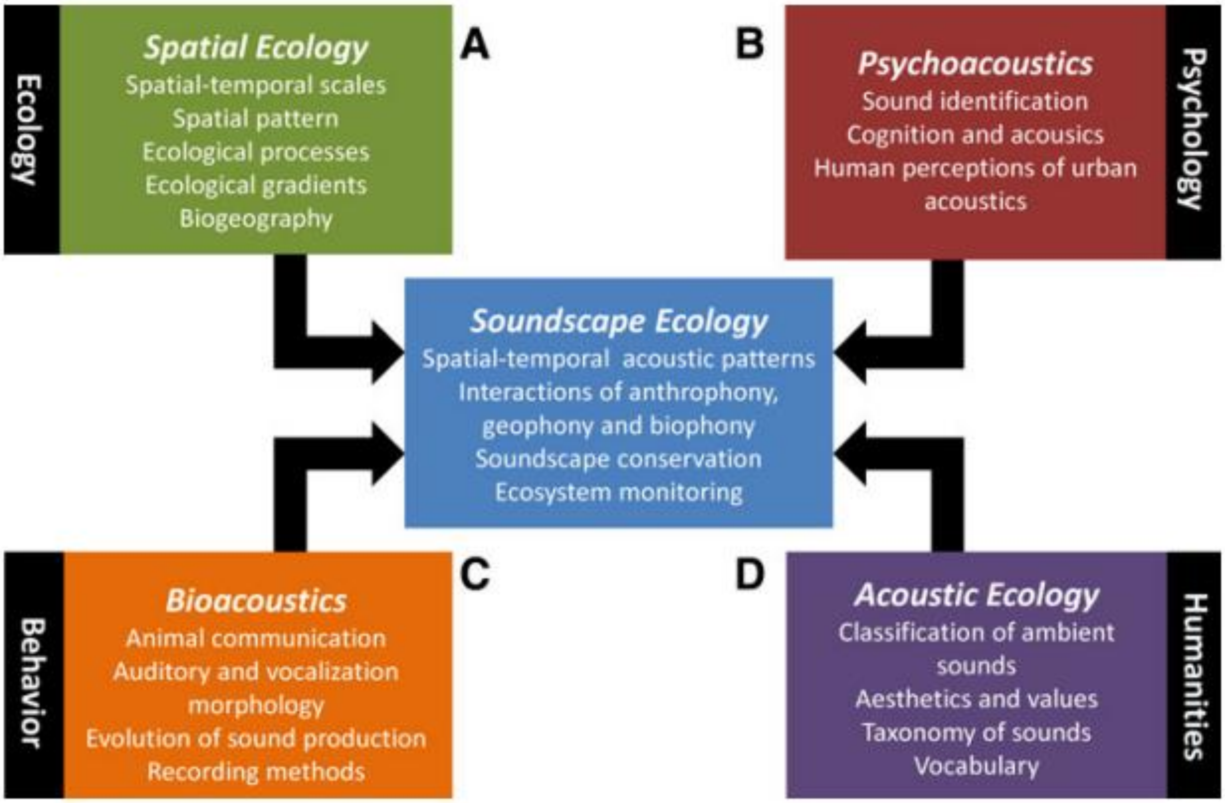


Figure 1. The multidisciplinary framework of soundscape ecology, integrating spatial ecology (A), psychoacoustics (B), bioacoustics (C), and acoustic ecology (D) to understand the ecological and psychological aspects of sounds (Adapted from Pijanowski et al. 2011a).

In the context of ecological studies, understanding the basic principles of acoustics is important for accurately interpreting sound data and its impact on wildlife. Acoustics, the branch of physics dealing with sound and its properties, involves the study of sound waves, their propagation, and their interaction with the environment. Sound waves are longitudinal waves that travel through a medium, such as air, water, or solid substrates, and are characterized by their frequency, amplitude, wavelength, and speed of propagation (Rossing 2007).

Frequency refers to the number of oscillations per second of a sound wave, measured in hertz (Hz). It determines the pitch of the sound, with higher frequencies corresponding to higher pitches. In ecological studies, the range of frequencies of interest often extends beyond the human audible range of ~20 to 20,000 Hz (20 kHz) to include infrasonic (below 20 Hz) and ultrasonic (above 20 kHz) sounds, which are perceptible to various animal species (Fay and

Popper 1994). For instance, elephants use infrasonic calls for long-distance communication, while bats use ultrasonic echolocation to navigate and hunt insects (Garstang 2004; Schnitzler and Kalko 2001). Amplitude, measured in decibels (dB), indicates the loudness of a sound. It is a measure of the sound wave's pressure and is crucial for determining the intensity of sound and its potential impact on wildlife. Higher amplitude sounds are louder and can travel greater distances, which is significant in the context of communication and territorial signals among animals (Slabbekoorn and Ripmeester 2008).

Wavelength is the distance between successive peaks of a sound wave and is inversely related to frequency. It affects how sound interacts with objects and the environment. For instance, lower frequency sounds have longer wavelengths and can travel farther and through denser vegetation or obstacles, while higher frequency sounds have shorter wavelengths and are more easily absorbed or scattered by the environment (Wiley and Richards 1982).

Speed of propagation depends on the medium through which the sound travels. In air, the speed of sound is approximately 343 meters per second at room temperature, but it can vary with changes in temperature, humidity, and atmospheric pressure (Rossing 2007). Understanding these variations is essential for accurately measuring and interpreting sound data in different ecological contexts.

Environmental factors significantly influence sound propagation. Attenuation refers to the reduction of sound intensity as it travels through a medium, which can be caused by absorption, scattering, and diffraction. Dense vegetation, for example, can absorb and scatter sound waves, reducing their intensity and altering the frequency spectrum that reaches the receiver (Morton 1975). Reflection occurs when sound waves bounce off surfaces such as the ground, water, or foliage, creating echoes that can complicate the interpretation of acoustic signals. Refraction, the bending of sound waves due to changes in medium properties, can also impact sound transmission, especially in landscapes with varying temperature gradients which are subject to change by time of day or season (Bradbury and Vehrencamp 2011). By grasping the fundamental principles of sound, researchers can better interpret acoustic data, assess the impact of environmental variables on sound propagation, and develop effective conservation strategies that consider the acoustic landscape of wildlife habitats.

Technology in Acoustic Analysis

The historical context of acoustic research reveals a gradual evolution from rudimentary sound recording techniques to sophisticated, automated systems. Acoustic monitoring of natural environments is a crucial methodology in ecoacoustics for assessing biodiversity, ecosystem health, and the impacts of anthropogenic noise. Field recordings are integral to acoustic monitoring, whereby sounds are collected from the environment to analyze the acoustic landscape and monitor changes over time. Early studies in bioacoustics primarily relied on direct human observation and basic recording devices, which were often limited by their range and fidelity (Blumstein et al. 2011). The advent of digital technology in the late twentieth century marked a significant turning point, facilitating more accurate and extensive acoustic data collection. Modern approaches to field recordings use “acoustic monitoring systems,” technologies that continuously record environmental sounds, providing data for long-term analysis of trends and patterns (Pijanowski et al. 2011b). Over the past few decades, advancements in technology and analytical methodologies have revolutionized acoustic research, enabling scientists to capture and analyze vast amounts of acoustic data with unprecedented precision.

Machine Learning and Automation

Machine learning algorithms have become integral to sound classification due to their ability to learn from data and improve over time. Machine learning and advanced signal processing techniques now play crucial roles in sound identification and classification, enabling the automatic detection and analysis of specific sounds or calls amidst background noise (Stowell and Plumbley 2014). These tools have been particularly transformative in studies of biodiversity, where acoustic data can reveal the presence and activity patterns of elusive or cryptic species that might otherwise go undetected (Sugai et al. 2019).

Techniques such as supervised learning, unsupervised learning, and deep learning are commonly used in machine learning. In supervised learning, models are trained on labeled datasets, where each sound is associated with a specific category (Vermeulen 2020). Common algorithms include random forests, support vector machines, and convolutional neural networks (CNNs). These models can achieve high accuracy in classifying sounds, especially when trained on large and diverse datasets (Stowell and Plumbley 2014). Unsupervised learning algorithms, such as clustering and principal component analysis, are used to identify patterns in unlabeled data---these techniques are useful for exploratory analysis and for identifying novel or unexpected sound patterns within recordings (Jolliffe 2002; Veen et al 2012).

Recent advances in deep learning have led to the development of neural-network–based detectors that can automatically learn features from raw audio data. CNNs are particularly effective for this purpose, as they can identify complex patterns in spectrograms. These models require large amounts of labeled training data but offer high accuracy and the ability to generalize across different environments (Stowell and Plumbley 2014). Automated detection algorithms in bioacoustics enable continuous monitoring and rapid analysis of large datasets, thus enhancing the efficiency and effectiveness of ecological research.

Utility of Coding in Bioacoustics

In the context of bioacoustic and soundscape analyses, computer “scripts” (files with a series of commands in a specific programming language that can be executed sequentially) are utilized to process large volumes of audio data efficiently. These scripts can automate the extraction of acoustic features, such as frequency and amplitude, and perform statistical analyses to identify patterns or anomalies within the audio recordings (McKinney 2010). Using coding to automate repetitive, demanding tasks as well as compute advanced analysis is an important part of modern workflows involved in processing large datasets, offering a promising means of processing audio for bioacoustic or soundscape analyses. Traditional manual methods of analyzing audio data are time-consuming, and potentially prone to human error, especially when dealing with massive amounts of data. Python is one computer programming language often used for soundscape analyses, and its powerful libraries like “librosa” for audio processing and “pandas” for data manipulation allow researchers to automate and standardize the analysis process. This automation enables the extraction of meaningful information from audio recordings, such as identifying species-specific calls in bioacoustics or analyzing environmental soundscapes (Bittner et al. 2018). By leveraging coding, researchers can handle more extensive datasets, enhance the accuracy of their analyses, and uncover insights that may not be apparent through manual analysis. Thus, the integration of coding into audio processing workflows is crucial for advancing research in bioacoustics and soundscape ecology (Gibb et al. 2019).

Soundscape Ecology

The term "soundscape," popularized by Canadian composer and environmentalist R. Murray Schafer, traditionally refers to the acoustic environment as perceived by humans. It encompasses the interplay of natural sounds (biophony), human-made sounds (anthrophony), and sounds of the physical environment (geophony), such as wind and water (Pijanowski et al. 2011b). The field of soundscape ecology, a combination of multiple disciplines within acoustic research, emerged in the late 1960s and early 1970s primarily through the work of Schafer and the World Soundscape Project, which aimed to explore and document the changing soundscapes of the world and emphasize the importance of the impact of sound on human well-being and environmental health (Simon Fraser University, "World Soundscape Project"; Schafer 1993).

Biophony refers to the collective sound produced by living organisms within a habitat, including the vocalizations of animals. These biological sounds are critical for communication, mating, navigation, and territorial defense. Biophony is a key indicator of biodiversity and can reflect the health and dynamics of an ecosystem, as changes in biophony can signal alterations in species composition, population densities, and behavioral patterns due to environmental changes or disturbances (Krause 1987).

Geophony encompasses the non-biological natural sounds generated by the physical environment. This includes sounds produced by weather phenomena (e.g., wind, rain, thunder), geological processes (e.g., earthquakes, volcanic activity), and water movement (e.g., rivers, ocean waves) (Pijanowski et al. 2011b). Geophony plays a significant role in shaping the acoustic environment and can influence the behavior and communication of animals. For instance, the sound of flowing water can mask predator–prey interactions or territorial calls, affecting species interactions and habitat use (Dumyahn and Pijanowski 2011).

Anthrophony consists of sounds generated by human activities, such as transportation (e.g., cars, airplanes), industrial operations, urbanization, and recreational activities. Anthropogenic noise can have profound effects on wildlife, often leading to habitat degradation, behavioral changes, and physiological stress (Radle 2007). The study of anthrophony within soundscape ecology aims to understand and mitigate the negative impacts of human noise on natural environments, promoting conservation and management strategies that enhance acoustic habitat quality (Barber, Crooks, and Fristrup 2010).

Methods in Soundscape Analysis

Soundscape analysis involves a range of methodologies to capture, quantify, and interpret the acoustic environment. The primary step in soundscape analysis involves deploying recording devices such as autonomous recording units to capture continuous sound data over extended periods. The placement of these devices is strategic, ensuring coverage of different habitats and environmental conditions (Gasc et al. 2015). Various acoustic metrics and indices are used to quantify soundscape components. Commonly used metrics include the Acoustic Complexity Index (ACI), which measures the complexity of biophonic sounds, and the Normalized Difference Soundscape Index (NDSI), which compares biophonic and anthrophonic sound levels. These indices help in assessing biodiversity, habitat quality, and the extent of human impact (Kasten et al. 2012).

Analyzing the frequency and temporal patterns of soundscapes is essential for identifying the sources and characteristics of different sounds. Spectrograms provide a visual representation of the frequency content over time, enabling researchers to distinguish between biophony, geophony, and anthrophony. Temporal analysis examines how soundscapes change over daily, seasonal, or annual cycles, revealing patterns related to species behavior and environmental processes (Farina 2014).

Statistical methods are employed to analyze soundscape data, identify significant patterns, and test hypotheses about the relationships between acoustic metrics and ecological variables. Modeling techniques, such as generalized linear models and machine learning algorithms, can predict the impact of environmental factors on soundscapes and simulate potential changes in different scenarios (Depraetere et al. 2012).

Integrating soundscape data with geographic information systems allows for the spatial visualization and analysis of acoustic environments. This approach helps in understanding the spatial distribution of sound sources and their relationship with landscape features and habitat types. Spatial analysis can identify areas of high biodiversity, noise pollution hotspots, and the effects of landscape changes on soundscapes (Liu et al. 2014). By employing these methodologies, soundscape ecology provides a comprehensive framework for understanding the acoustic dimension of ecosystems. We will further explore the methodologies of sound recording and monitoring, spectral and temporal analysis, spatial analysis and mapping, statistical analysis and modeling, and additional concepts in soundscape analysis in the following sections.

Acoustic Monitoring and Sound Recording

Contemporary acoustic monitoring employs autonomous recording units (ARUs), which can operate continuously in diverse and often remote environments, capturing high-quality audio data over extended periods (Darras et al. 2019). This method is particularly useful for studying inaccessible or remote areas, nocturnal species, and the impacts of human activities on natural soundscapes. In the field of signal processing, researchers Damm et al. (2012) introduce an ARU system designed for the acoustic monitoring of often-challenging, realistic outdoor recording environments. The study details the key components of the audio monitoring system, which includes an array of acoustic sensors that provide bearing information crucial for robust, unsupervised detection and localization of audio events. This approach to acoustic monitoring illustrates the potential of ARUs in capturing and analyzing complex soundscapes in natural settings, offering valuable insights for ecological studies and conservation efforts.

Site selection is of pivotal importance for the integrity of the investigation. Researchers should choose appropriate locations for deploying ARUs based on the study objectives, habitat types, and the distribution of the target species or hypothesized sound sources (Darras et al. 2019). ARUs that are suitable for the environmental conditions and the acoustic frequencies of interest should be selected. Factors to consider include battery life, storage capacity, weather resistance, microphone sensitivity, the microphone’s effective range, file output format (such as .WAV or .MP3), and fidelity of the recording files (Gibb et al. 2019). ARUs should be placed at predetermined locations, and it should be ensured that they are securely mounted and protected from weather and tampering. The height and orientation of the microphone should be optimized for the target sounds (Sugai et al. 2019). ARUs should be configured to record at appropriate intervals, which could range from continuous recording to scheduled recordings during specific times of day or night, depending on the research objectives and battery/storage limitations. Testing of the equipment—checking for issues with recording quality, battery life, and data storage—is essential to ensure the ARUs are functioning correctly.

AudioMoth as an ARU

The AudioMoth is a low-cost, compact acoustic ARU used primarily for environmental and wildlife monitoring to record natural sounds and human-made noises (Open Acoustic Devices, “AudioMoth”). The AudioMoth device, due to its versatility and cost effectiveness, has garnered substantial attention for use in biodiversity monitoring across various habitats. However, its effective range and the quality of data collected are contingent upon several environmental and technical factors (Hill et al. 2017; Hill et al. 2019).

The AudioMoth's effective range is significantly influenced by the environment in which it is deployed. Under optimal conditions, such as open landscapes devoid of substantial ambient noise, the device is capable of capturing sounds from distances up to 100 meters and potentially up to 150 meters (Hill et al. 2019). Conversely, in dense forested areas or locations with complex topography, the effective range is reduced to between 30 and 50 meters due to sound attenuation factors such as vegetation and terrain, which impede sound propagation (Wolek 2023).

In deploying the AudioMoth device for ecological monitoring, several considerations must be addressed to ensure optimal data collection. The physiology of the landscape poses an influence on the device's functionality, necessitating careful evaluation of physical and ambient noise barriers in the deployment area (Wolek 2023). The frequency of the sounds being recorded also impacts the AudioMoth's effectiveness, with higher frequency sounds, typical of many bird and bat species, having a shorter effective range and being more susceptible to environmental absorption or deflection (Prince et al. 2019).

Adjusting the device settings is essential to tailor the device for specific field conditions, balancing the need for detailed data capture against limitations in storage and battery life (Lapp, Stahlman, and Kitzes 2023). The strategic placement of devices, whether at elevated positions or within specific spatial arrangements, can potentially mitigate ground-level noise interference and ensure more comprehensive acoustic coverage of the monitored area (Prince et al. 2019). The variability in recording range and environmental interference necessitates the use of advanced data analysis methods to accurately interpret the acoustic data of a research project, especially in studies aiming to estimate species abundance or activity patterns (Hill et al. 2019).

Sound Identification and Classification

Identifying and classifying acoustic signals is a fundamental aspect of ecological research, enabling scientists to monitor biodiversity, study animal behavior, and assess environmental health. The source of a sound is called, simply, a "sound source," or "source," depending on the context. Recognizing sound sources helps in observing temporal patterns within an ecosystem. Sound source identification in ecoacoustics is pivotal for mapping soundscapes, with significant implications for, among other things, monitoring biodiversity, understanding temporal dynamics, and assessing the impact of anthropogenic noise.

Listening and identifying by ear is the most accessible, no-frills approach. This traditional method involves experts listening to recordings and visually inspecting spectrograms to identify species-specific calls or other relevant sounds, a method validated through studies that show a high correlation between field observations and simultaneous recordings (Haselmayer and Quinn 2000; Joo 2009). Although time-consuming and subject to observer bias, this method remains essential for validating automated techniques and for identifying species with well-documented vocalizations (Kogan and Margoliash 1998). Adding visual monitoring to the identification process is another well-used technique in long-term sound source identification efforts. An example of this process is monitoring birds by eyesight through their morning chorus and identifying species based on their signals at listening posts (Gage and Miller 1978). Similar methods are used in identifying nocturnal amphibians as well as for monitoring marine mammal populations, where visual observations are paired with acoustic monitoring to identify species and study behavior (Karns 1986; Buckland et al. 2012).

Visual representations of the frequencies of an audible signal over time, known as spectrograms, are often employed in detecting the origins of a sound (Vande Kamp, n.d.). Recognizing and classifying spectrogram signatures is one of the preferred methods of modern sound source identification, possibly due to the reliability with which bird vocalizations follow distinguished patterns that are readily detected by trained pattern-matching technology.

Automated Monitoring and Detection

Automated detection algorithms are designed to identify specific sound patterns within large datasets, significantly reducing the time and effort required for manual analysis. These algorithms are particularly useful in ecological studies where continuous monitoring and large-scale data collection are common. Several types of automated detection algorithms are commonly used, including threshold-based detectors, energy-based detectors, and pattern recognition systems.

Threshold-based detectors are the simplest form of automated detectors that trigger an alert when the amplitude of a sound exceeds a predefined threshold. While easy to implement, threshold-based detectors can produce a high number of false positives, especially in environments with varying background noise levels (Swiston and Mennill 2009). Energy-based detectors monitor the energy levels of incoming sound waves and identify events based on sudden increases in energy. This method is more robust than simple thresholding, as it can adapt to different noise conditions by analyzing the background energy levels (Bardeli et al. 2010). Pattern recognition systems are more sophisticated than energy-based detectors, using statistical and machine learning techniques to identify complex sound patterns. These systems can be trained on known examples of target sounds to recognize similar patterns in new data. Examples include hidden Markov models and support vector machines (Chen and Maher 2006). Time-frequency analysis techniques, such as short-time Fourier transform and wavelet transforms, are used to decompose signals into their constituent frequencies over time. These methods provide a detailed representation of the sound, allowing for the detection of specific frequency patterns that are characteristic of species or events (Mellinger and Clark 2000).

In automated spectrogram signature matching, distinct signatures from spectrograms are identified, a library of spectrograms is searched for matching signatures, and the probability of a match is calculated (Butler et al. 2007). Simpler signatures (e.g., insects and amphibians) have probabilities closer to 1, while complex signatures (e.g., bird songs) are less straightforward. Kasten, McKinley, and Gage (2010) use classification and detection experiments for automating acoustic species surveys in order to identify bird species. The detection and extraction of audio signatures, which the researchers term “ensembles,” from acoustic data streams is automated using the MESO perceptual memory system, a web-based machine-learning pattern classifier for cataloging species heard in recordings (Kasten, n.d.). The methods of automating spectrogram signature identification and matching are as endless as there are programmers able to code for such automation, thus the provided examples of sound source identification automation are not an exhaustive summary.

Feature Extraction

Feature extraction and statistical classification, as components of sound identification and classification in bioacoustic studies, allow researchers to systematically quantify and analyze the acoustic properties of sounds, facilitating the categorization of these sounds into predefined classes with high accuracy and efficiency (Mellinger and Clark 2000; Stowell and Plumbley 2014). Feature extraction is the process of converting raw audio signals into a set of measurable characteristics that can be analyzed quantitatively. This step is crucial for reducing the complexity of the data and highlighting the relevant aspects of the sounds under study (Tchorz and Kollmeier 2003). Key features extracted from audio signals often include frequency, temporal, amplitude, and time–frequency features.

Frequency features describe the spectral content of the sound and include measurements such as the fundamental frequency, spectral centroid, spectral bandwidth, and formants. The spectral centroid, for example, indicates the "center of mass" of the spectrum and is associated with the perceived brightness of a sound (Tchorz and Kollmeier 2003). Temporal features include the duration of the sound, the timing of various events within the sound, and the temporal envelope, which describes how the amplitude of the sound changes over time. Temporal features are crucial for distinguishing between different types of calls or songs that may have similar spectral characteristics but differ in their temporal structure (Janik 2009). Amplitude features involve measurements of the sound's loudness, such as root mean square amplitude and peak amplitude. Amplitude features can provide information about the energy of the sound and are useful for distinguishing between sounds that are loud and those that are soft (Mellinger et al. 2007). Time–frequency features capture both temporal and spectral information and include spectrogram-based representations, wavelet transforms, and Mel-frequency cepstral coefficients. Time–frequency features are particularly effective for analyzing sounds with complex and dynamic spectral content, such as bird songs and mammal vocalizations (Ganchev et al. 2005).

The selection of appropriate features depends on the specific requirements of the study and the nature of the sounds being analyzed. Effective feature extraction simplifies the subsequent classification process and improves the overall accuracy of the analysis. Once the features are extracted, statistical classification techniques are employed to categorize the sounds into predefined classes. These classifiers use the extracted features to make predictions about the class to which a particular sound belongs.

Decision trees are simple yet powerful classifiers that use a tree-like model of decisions and their possible consequences. They work by recursively partitioning the feature space and assigning class labels based on the feature values. Decision trees are easy to interpret and can handle both numerical and categorical data (Breiman et al. 1984). Support vector machines are a type of supervised learning algorithm that finds the optimal hyperplane that maximizes the margin between different classes in the feature space. They are effective for high-dimensional data and can handle nonlinear classification by using kernel functions to map the features into a higher-dimensional space (Vapnik 1995).

Neural networks, particularly deep learning models such as CNNs, have become increasingly popular for sound classification tasks. These models can automatically learn hierarchical representations of the data from raw input features, making them highly effective for complex and large-scale bioacoustic datasets (Stowell and Plumbley 2014). Random forest is an ensemble learning technique that enhances classification accuracy and robustness by combining multiple decision trees. During training, the algorithm constructs many decision trees, and for classification tasks, it determines the final output by taking the statistical mode of the predicted classes from all the trees in the ensemble, effectively choosing the class that is most frequently predicted (Breiman 2001).

The combination of feature extraction and statistical classification has proven to be a powerful approach in bioacoustic research. It allows for the automated identification and classification of a wide range of sounds, from bird songs and insect calls to marine mammal vocalizations and bat echolocation signals. For example, Obrist et al. (2010) demonstrated the effectiveness of using automated classifiers for identifying bat species based on their echolocation calls, achieving high accuracy rates and reducing the need for manual annotation. Moreover, these techniques are scalable, enabling researchers to handle large volumes of audio data collected from extensive monitoring programs.

Sound Mapping

Sound mapping is the visual representation of sound data over a space in time to analyze and communicate information about soundscapes. Sound maps can highlight areas of high noise pollution or, in primarily ecological investigations, identify regions with rich biodiversity. The mapping portion of the topical soundscape investigation can more clearly illustrate Wolf Haven's environmental sound profile for ease of formulating management decisions.

Mapping Sound Data with Modern Software

Mapping sound data involves translating complex acoustic information into visual formats that are easy to interpret and analyze. Modern mapping software provides powerful tools for integrating, visualizing, and analyzing sound data spatially. Geographic information systems (GISs), along with specialized sound mapping software, enable researchers to create detailed sound maps that can inform ecological and environmental management.

GIS platforms like ArcGIS Pro and QGIS allow researchers to layer sound data over geographical maps, providing a spatial context to acoustic information. These systems can handle large datasets, offering tools for data manipulation, spatial analysis, and visualization. By integrating sound data with geographic information, researchers can create maps that highlight spatial patterns in soundscapes (Goodchild and Janelle 2010). Advanced spatial tools in GIS software enable the creation of heat maps, contour maps, and other visual representations that convey the intensity and distribution of sound levels across the landscape (Esri, "ArcGIS Pro").

With time-enabled layer properties, spatial-temporal tools in GIS software can convey acoustic information through a space–time media, showcasing how acoustic characteristics change over time across a landscape.

In addition to traditional GIS tools, specialized sound mapping software offers advanced features tailored for acoustic analysis. Software such as NoiseCapture and SoundPLAN provide functionalities for creating detailed noise maps, assessing environmental noise impacts, and modeling sound propagation. These tools often include algorithms for predicting noise levels based on various environmental parameters, such as topography, vegetation, and weather conditions (Murphy and King 2014).

Integrating Sound Data with Ecological Variables

By combining sound data with information on land use, vegetation cover, and wildlife habitats, researchers can gain comprehensive insights into the factors influencing soundscapes. For example, areas with dense vegetation may exhibit lower noise levels due to sound attenuation by plant matter, while open areas may have higher noise levels due to wind and human activities (Barber, Crooks, and Fristrup 2010). In practice, integrating these variables involves collecting spatially referenced sound data and corresponding ecological data, then using GIS tools to perform spatial analyses. Techniques such as spatial autocorrelation and hotspot analysis can identify regions with significant acoustic activity, which can then be correlated with ecological features (Fortin and Dale, 2005). This integrated approach enhances the understanding of how environmental and anthropogenic factors shape soundscapes, providing valuable information for conservation and management efforts (Krause and Farina 2016).

Applications in Soundscape Management

The ability to map sound data effectively is essential for informed soundscape management. At Wolf Haven International, sound maps can guide the development of management strategies aimed at minimizing noise pollution and preserving the welfare of inhabitants. By visualizing areas and time periods marked by high noise levels, sanctuary managers can implement measures such as creating buffer zones, adjusting human activities, and enhancing vegetation cover to mitigate noise impacts (Francis et al. 2011). Additionally, sound maps can be used to monitor the effectiveness of these interventions over time, ensuring adaptive management practices (Barber, Crooks, and Fristrup 2010).

Wolf Haven International

Wolf Haven International is actively involved in two Saving Animals from Extinction (SAFE) programs under federal management, focusing on the conservation of the red wolf and the Mexican wolf (*Canis lupus baileyi*), both of which are endangered (Wolf Haven International, "SAFE"; U.S. Fish and Wildlife Service (USFWS), "Red Wolf Recovery Program"; USFWS, "Conserving the Mexican Wolf"). The SAFE initiative represents a collaborative effort involving USFWS, the Association of Zoos and Aquariums, and other partners such as Wolf Haven. This program, which evolved from what was previously known as the Species Survival Plan program established in 1981, aims to manage populations of endangered species within controlled environments and bolster their numbers in natural habitats. Serving as a breeding center for these initiatives, Wolf Haven's isolated setting makes it an ideal location for rearing wolves that are strong candidates for reintroduction into their natural habitats. To this end, Wolf Haven has seen the birth of ten litters of Mexican wolf pups and five litters of red wolf pups, as well as the successful release of three packs, totaling 22 Mexican wolves and two individual red wolves, back into the wild.

Given its commitment to the well-being of its resident wolves, conservation efforts, and the broader ecological system, Wolf Haven International presents an ideal study site for soundscape investigation. Understanding the acoustic environment of the sanctuary, from the natural sounds of the ecosystem to the potential impact of anthropogenic noise, is crucial for ensuring the SMP aligns with the best practices in animal welfare, conservation breeding, wildlife reintroduction, and sanctuary habitat management.

Climate

The sanctuary experiences a temperate maritime climate typical of the area, characterized by mild, wet winters and warm, dry summers (Kral, Putnam, and Rupp 2020). These seasonal variations have a profound impact on the sanctuary's landscape and its inhabitants. During the winter months, the area receives a significant amount of rainfall, leading to saturated wetlands and lush undergrowth in the woodlands (Abatzoglou, Rupp, and Mote 2014). This period is marked by a quieter ambiance, as the dense foliage and wet conditions can dampen sound travel, potentially affecting the wolves' vocalizations and overall activity levels (McCool, Williams, and Morse 2009).

Conversely, the summer season brings drier conditions, reducing the underbrush moisture and increasing the audibility of sounds across the sanctuary (Jannuzzi 1993). This change not only affects acoustic data collection but also influences wolf behavior, as the animals may range more widely and interact differently due to the less restrictive movement through their enclosures (Mote et al. 2003). The transitional periods of spring and fall see fluctuating conditions, which can rapidly alter from wet to dry, affecting both the ecological characteristics of the terrain and the daily routines of the sanctuary's wildlife (Hodge et al. 1998).

These seasonal dynamics provide essential insights into how environmental factors influence the acoustic landscape. Understanding these seasonal patterns will aid in the scheduling of future sound collection sessions to maximize the effectiveness of data gathering and to ensure a comprehensive understanding of the sanctuary's acoustic environment throughout the year (Kosaka et al. 2013).

Sanctuary Master Plan

Master planning for sanctuaries, zoological facilities, or managed wildlife areas is a comprehensive process that outlines the long-term vision, goals, and development strategy for the facility (The Ridges Sanctuary, "Master Plan"; Toronto Zoo, *Toronto Zoo Master Plan Booklet*; Fiby and Worstell 2003). It serves as a roadmap for future growth and improvements, ensuring that the facility can fulfill its mission, meet the needs of its inhabitants, and provide an engaging experience for visitors, all while maintaining financial sustainability and environmental responsibility. The master plan is a critical document that guides decision-making and investments, ideally for years into the future. The front-loading of research efforts—such as the completed soundscape investigation—to optimally inform these master plans is likely.

Part of the impetus for a soundscape investigation at Wolf Haven is to plan the placement of its particularly sensitive wolves. These may include wolves that are more detrimentally affected by elevated noise levels than others for various reasons (e.g., wolves with anxiety or mood disorders or wild-bound wolves rearing pups for conservation breeding). Wolf Haven International is actively involved in various conservation efforts, including species recovery programs and advocacy for wolf conservation policies. A common characteristic of conservation recovery programs involved in breeding efforts is the goal of keeping the involved animals—especially ones intended for reintroduction to their natural habitat—as "wild" as possible (ARC Trust, "Bringing back species: Reintroductions, translocations and captive breeding"). Minimizing anthropogenic noise in their environment is a key component of maintaining this goal.

Conclusion

This literature review has highlighted the significant role of sound in animal welfare, particularly within the context of ecoacoustics and soundscape ecology. By exploring the acoustic repertoire of wolves and coyotes, as well as the practical significance of sound in their communication and behavior, the review establishes the importance of managing acoustic environments to enhance animal welfare. The integration of sound data with ecological variables through GIS and specialized sound mapping software provides a robust framework for analyzing and visualizing soundscapes. This approach is beneficial for informed decision-making in managing animal environments, particularly in settings like Wolf Haven International.

Effective sound mapping and management can mitigate the impacts of anthropogenic noise, support conservation breeding programs, and improve the overall welfare of captive and wild animals. By leveraging modern mapping technologies and integrating soundscape data with ecological insights, researchers and sanctuary managers can develop strategies to preserve natural acoustic environments and enhance the quality of life for wildlife in conservation settings.

Chapter 3 - Methods

The overarching investigation into the acoustic environment of Wolf Haven International through sound-based spatial analysis was a response to the need for comprehensive sound profiles of sanctuary locations prior to future sanctuary management planning. The approach integrated both technological and analytical methods tailored to capture and interpret the complex soundscape dynamics within this unique setting. The study leveraged audio recording technology coupled with advanced spatial analysis techniques to derive actionable insights that inform the strategic placement of sanctuary animals, particularly regarding individuals easily affected by sound disturbances. Due to the sensitive nature of sanctuary operations, especially during breeding and whelping seasons when wolves experience hormonal changes, the methodology of this research was designed to be minimally invasive. This study not only quantified sound levels across various sanctuary locations but also integrated these findings with GIS to visualize sound distribution and its impact on wolf habitat suitability.

The investigation was guided by the following research questions: 1) How do average decibel and frequency levels compare across the five recording locations within the sanctuary? 2) Are there notable patterns in frequency and decibel levels throughout the day? To address these questions, AudioMoth devices were deployed at five strategic locations across the sanctuary to continuously record the acoustic environment. Decibel and frequency measurements were extracted from the audio data and analyzed across sites to uncover the spatial distribution of sound levels across the sanctuary. Measurements were segmented into hourly time bins and assessed for diurnal variation. All data was extensively visualized, using standard plotting strategies and advanced spatial–temporal mapping.

Study Site

Located in the Pacific Northwest, Wolf Haven International spans over 80 acres of native prairie, woodlands, and wetlands. This diverse ecological setting provides an ideal backdrop for the sanctuary's mission, offering a semblance of natural habitat for the wolves and serving as a living laboratory for ecological restoration and education. The sanctuary side of these grounds makes up roughly 20 acres and is designed to mimic natural wolf habitats as closely as possible, with large, fenced enclosures that allow the wolf, wolfdog, and coyote residents to roam and engage in social behaviors characteristic of their species. These enclosures are strategically placed with the individual animals' needs in mind to ensure minimal stress from human activity. Animals that are less sensitive to human presence (such as coyotes, as well as wolves and wolfdogs that were once kept as pets) are positioned closer to public routes (Shannon Wells, personal communication, April 27, 2024). Wolves and wolfdogs that are less accustomed to human presence, as well as those involved in special conservation efforts, are positioned farther from public access.

Recording Locations

Five locations for deploying recording devices were chosen with the guidance of the sanctuary's animal care specialist, Dan Monn, and sanctuary director, Pamela Maciel Cabañas, to represent a diverse spread of the sanctuary's environment. This selection ensured as much coverage of the area as feasible with the limited number of recorders available for the research: Figure 2 showcases the estimated range of the recording devices positioned across the sanctuary landscape, together capturing a representative sample of the sanctuary's acoustic environment. Due to the density of vegetation and variation in terrain characteristics of the naturally preserved landscape of the sanctuary grounds, the effective range of the recording devices was conservatively estimated at a radius of 50 m (see section *AudioMoth as an ARU*; Wolek 2023).

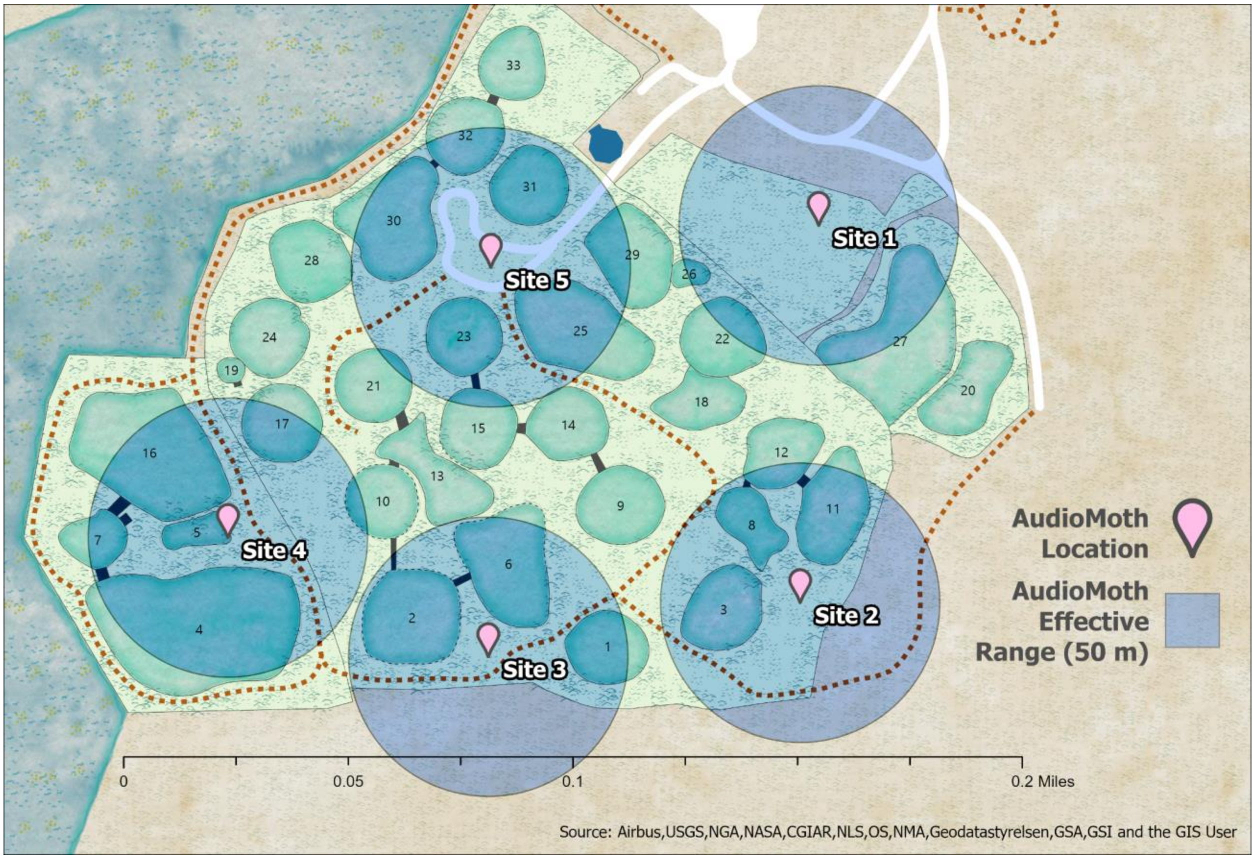


Figure 2. Depiction of the recording locations at Wolf Haven and acoustic ranges of the recording devices, "AudioMoth," used in the soundscape research for this thesis. Map by author.

Among the chosen locations was the "public" area (Site 5), unique in that guided tours are hosted in this area during certain times of the year. It was expected that this area would exhibit higher noise levels during these time periods compared to the more secluded areas of the sanctuary, serving as a comparative baseline to evaluate the relative quietness of other monitored locations.

Audio Recording

In this study, we utilized the AudioMoth device as our recorder of choice. The individual devices were configured to balance energy consumption with comprehensive coverage, and the recording locations were selected in coordination with Wolf Haven staff.

AudioMoth Device Overview

The AudioMoth device employed in this study is a versatile, low-cost acoustic logger designed to capture a broad range of sound frequencies from 10 Hz to 192 kHz (Open Acoustic Devices, “AudioMoth”; Open Acoustic Devices, *AudioMoth 1.2.0 Datasheet*). Its compact size (58 × 48 × 15 mm) ensures minimal disturbance to the natural environment during deployment. The device records uncompressed audio at sample rates from 8,000 to 384,000 samples per second onto a 128 GB microSD card, which allows for extensive data collection without frequent maintenance. SanDisk 128GB Extreme microSDXC UHS-I memory cards were utilized per Open Acoustic Devices’s recommendation regarding storage cards appropriate for use in AudioMoth devices (Open Acoustic Devices, *AudioMoth Operation Manual*). AudioMoth recordings are stored in WAV format, facilitating easy data retrieval and analysis.

The device has two color LEDs visible on the side of the device, and various combinations of these two LEDs flashing represent different modes of operation or tasks it is carrying out (Open Acoustic Devices, “AudioMoth LED Guide”). This feature proved to be a convenient design, as it facilitated quick and accessible monitoring of the devices’ battery and recording status. The hardiness of the devices was enhanced by deployment with weather-proof protective cases—ideal for data collection in the humid, rainy conditions typical of springtime in western Washington. Semi-scheduled maintenance involved replacing microSD cards and batteries; spent batteries were recharged using an Energizer Recharge™ Pro battery charger and charged Energizer Recharge™ Power Plus batteries were installed.

The AudioMoth's characterized features, along with the tactical decision to deploy the devices with Energizer Recharge™ Power Plus rechargeable AA batteries, extended the operational capacity of the devices. This significantly reduced the need for human interaction with the field site, minimizing the impact on the resident canids.

Setup and Orientation of AudioMoth Devices

Each device was secured to the mounting platform of a corresponding tripod using the hook and loop straps integrated into the devices' protective cases. Devices were physically oriented to approximate an omnidirectional pickup pattern, maximizing the acoustic data capture from all directions. A citizen science project with University College London and the Bat Conservation Trust demonstrated that AudioMoth devices have varied call capture rates at different angles (fig. 3), with successful capture of sound by a housed AudioMoth device more likely to occur at a 0° angle from the sound source (Rogers, "Microphone Directionality," January 8, 2019.). Based on the project's findings, directionality is introduced to the recording by the device's housing, complicating the achievement of an omnidirectional pickup pattern.

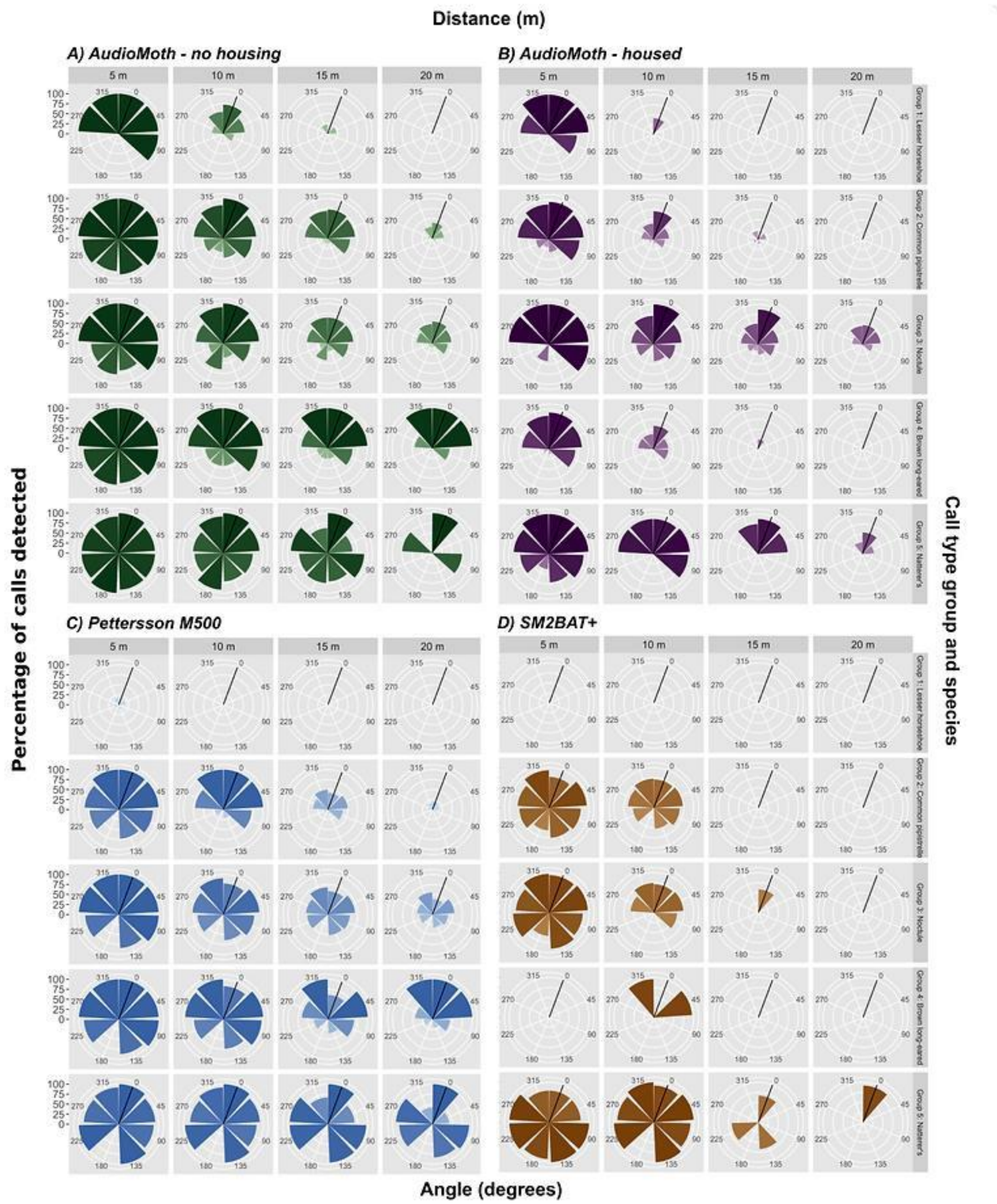


Figure 3. Call detection percentage by distance and angle for various acoustic monitoring devices. Panels show data for (A) AudioMoth without housing, (B) AudioMoth with housing, (C) Pettersson M500, and (D) SM2BAT+. Rows represent different species call sequences, and columns represent distances (5 m, 10 m, 15 m, 20 m) from the sound source. Numbers indicate the angle relative to the sensors, with the black line marking the sensors at 0°. Higher segment heights denote a higher percentage of call detections. (Figure adapted from Rogers, Alex. “Re: Microphone Directionality." Comment on "Microphone Directionality.” Device Support, January 8, 2019).

With no single, locatable sound source, the AudioMoth microphones were positioned to point directly upwards in the hope of capturing the ambient soundscape from a 360-degree perspective. By directing the microphones skyward, we anticipated that the devices would uniformly capture environmental sounds, ensuring an accurate and comprehensive auditory sample of the sanctuary's soundscape.

The tripods were installed on flat, open terrain to avoid audio distortions from environmental features such as dense foliage or heavy canopy cover, ensuring the recordings accurately reflected the ambient sound levels. Each tripod was set to a standardized height of 30" (76.2 cm), falling within the range of a gray wolf's shoulder height (National Park Service, "Wolves"; Washington Department of Fish and Wildlife, "Gray Wolf Identification"). Traffic cones were placed adjacent to the tripods to increase their visibility in the field, preventing accidental disturbances and promoting easy identification by staff during routine operations.

Each AudioMoth's operational status was checked daily following the end of the workday using the LED indicators on the device. Every three days, the microSD cards and batteries were replaced as previously described.

AudioMoth Configuration and Deployment

The AudioMoths were programmed to record continuously with a sample rate set at 96 kHz. This rate was selected to capture the broadest range of frequencies audible to wolves (see section *Wolves and Sound*) while balancing the devices' energy consumption. This setting was vital for maintaining long recording periods while ensuring a comprehensive acoustic profile of the sanctuary. The AudioMoths were configured to record in segments—10 minutes of recording followed by 10 seconds of sleep—to balance between continuous data capture and energy conservation. This continuous recording method was selected to ensure a comprehensive capture of the acoustic environment of the sanctuary throughout the entire day. Additionally, this recording method helped capture variations in sound profiles over a 24-hour cycle. This extensive coverage was deemed critical by the Wolf Haven staff to accurately reflect the natural dynamics within the sanctuary, and I supported this determination. A concise breakdown of configuration settings indicated for this research can be seen in table 1.

Table 1. AudioMoth Settings Used During Study

Configuration	Setting
Sample Rate	96 kHz
Recording Duration	10 minutes
Sleep Duration	10 seconds
Battery Type	Energizer Recharge™ Power Plus (NiMH)
Voltage Range	Use NiMH/LiPo voltage range for battery level indication
Start/End Time	00:00 to 24:00, daily
Advanced Settings	Energy-saver mode enabled

Battery management was a critical component of the recording strategy. Per the AudioMoth 1.2.0 Datasheet's electrical specifications, the required energy threshold for AudioMoth devices to write audio recording files to the device's memory card is 3.3 V; thus, if the voltage dips below 3.3 V, recording is effectively halted until battery power is restored (Open Acoustic Devices, *AudioMoth 1.2.0 Datasheet*; Knowles Acoustics, *SPU0410LR5H-QB*). Each AudioMoth was powered by a series of three Energizer Recharge™ Power Plus batteries, estimated to sustain adequate voltage for approximately 4.35 days of continuous recording. This estimation was calculated based on a daily consumption of 370 mAh, derived from the chosen configuration settings for the AudioMoth devices for this research (table 1) and a conservative estimate that Energizer Recharge™ Power Plus batteries, being nickel–metal hydride (NiMH) batteries, maintain voltage above 3.3 V for 70% of their battery life (Hill, Prince, and Brookes, 2019; Energizer, *NH15-2300 NiMH Battery Technical Data Sheet*). Voltage was assumed to measure 4.0 V at full charge. See the formula below (2300 mAh derived from a rated capacity of 2300 mAh at 21°C [70°F]; Energizer, *NH15-2300 NiMH Battery Technical Data Sheet*):

$$Usable\ Capacity = 2300\,mAh \times 0.70 = 1610\,mAh$$
$$Days\ until\ voltage\ drops\ to\ 3.3\,V = \frac{1610\,mAh}{370\,mAh/day} = 4.35\ days$$

Initial expectations were for battery replacements on the fourth and eighth days of the study. However, an unexpected early depletion occurred when batteries discharged faster than anticipated, leading to nearly 48 hours of data loss beginning late into the night on April 20th. This incident prompted a reassessment of battery life estimations and more rigorous monitoring by the staff. Subsequent battery replacements adhered closely to the recalculated schedule, with full charges confirmed before deployment to avoid premature depletion.

The deployment and recording schedules for the AudioMoth devices were closely tied to the operational hours of Wolf Haven staff, as Wolf Haven staff were directly involved in all aspects of the data collection throughout the research. Initial deployment was scheduled for the afternoon of April 18, 2024, a time chosen based on the availability of staff following their regular duties at the sanctuary. This timing ensured that staff could be thoroughly trained in the AudioMoth configuration, deployment, and handling processes. The recording ended on April 29, 2024, also in the afternoon, aligning with staff schedules for efficient retrieval and data backup.

A test run was conducted over the first 24 hours post-deployment and confirmed the functionality of the devices and the stability of the battery life under the configured settings. This preliminary test was crucial in validating the recording setup, ensuring that the AudioMoths were operating as expected and data was being collected correctly. No adjustments to the device settings were made following this test, as the collected data aligned with the study's requirements.

Data Transfer and Storage

Each audio file was saved using a year-month-day-hour-minute-second standardized filename format: "yyyymmdd_hhmmss.wav". This format marks both the date and the exact time down to the second of the initiation of recording for the file, facilitating accurate temporal alignment during subsequent data analysis.

Audio files were organized into location-specific directories to streamline the data processing workflow—for instance, audio files were stored in separate directories based on both recording location and recording period, resulting in a total of five recording location folders and four recording period subfolders within each recording location folder. For data analysis, output directories were designated for storing processed data, with each site–period combination having a unique output directory within which to store its respective descriptive statistical analysis results.

Pre-Processing for Audio Analysis

The audio data required some pre-processing steps to be useful for analysis; specifically, downsampling, feature extraction, and filtering methods were employed. Audio files that were originally recorded at a higher sample rate to capture a wider frequency range were downsampled to ensure consistency. The extraction of key audio features used to track acoustic patterns over time is also detailed. Through careful inspection and filtering, extraneous noise, including handling disturbances and rain-induced anomalies, were identified and excluded to maintain the integrity of the core dataset.

Downsampling

The original research design called for configuring the AudioMoths to record at a sample rate of 96 kHz—a rate chosen to encompass as broad a range of frequencies within the suspected wolf hearing range as possible (see section *Wolves and Sound*). The recording sample rate determines the highest frequency that can be accurately captured, with a 96 kHz sample rate capable of capturing frequencies up to 48 kHz, covering a broad range of both human-audible and ultrasonic sounds (Smith 2007).

During the audio preprocessing phase, it was discovered that most of the audio recordings were captured at a 48 kHz sample rate, rather than the intended 96 kHz target sample rate. When recording at a 48 kHz sample rate, a recording device can capture frequencies up to 24 kHz, which encompasses the full range of human hearing and extends into the ultrasonic range (Smith 2007). To ensure consistency across all recordings for analysis, the audio data at each location from recording periods 1 and 2, the periods during which the devices were correctly configured to record at 96 kHz, were downsampled from 96 kHz to 48 kHz.

The downsampling involved using Python scripting for Python version 3.12.3 to run the processes, including the libraries and associated functions outlined in table 2. Each original audio file was loaded into the chosen integrated development environment (IDE) for this research, PyCharm, where the audio data was then passed through an anti-aliasing filter, which is essential for preventing the introduction of unwanted artifacts during the downsampling process. This filter was created using a finite impulse response filter design, tailored to the Nyquist rate of the target sample rate (48 kHz). The filtered audio data was subsequently downsampled, reducing the sample rate while preserving the audio signal's integrity.

Table 2. Libraries And Functions Used in The Python Script for Audio Downsampling

Library	**Function(s)**	**Purpose**
librosa	load, feature.rms, amplitude_to_db, feature.spectral_centroid	Load audio files, extract RMS amplitude and spectral centroid, convert amplitudes to dB
scipy.signal	scipy.signal.firwin, scipy.signal.lfilter	Designing and applying the anti-aliasing filter

Feature Extraction

Deriving audio characteristics from the dataset was carried out using Python scripting, which coordinated feature extraction, determined recording times, and organized the data into hourly intervals. For each audio file, average decibel (dB) levels ("avg_db") were calculated by first loading the files into PyCharm and extracting the root mean square (RMS) amplitude. This amplitude was then converted to decibels, providing a measure of the sound intensity. Similarly, average frequency (Hz) levels ("avg_freq") were determined by calculating the spectral centroid, which represents the center of mass of the sound's frequency spectrum. The extracted decibel and frequency data were then compiled into a core dataset for subsequent statistical analysis and storage. The specific Python libraries and functions employed for audio processing, data manipulation, file pattern matching, and timestamp handling are detailed in table 3.

Table 3. Libraries And Functions Used in The Python Script for Audio Feature Extraction

Library	**Function(s)**	**Purpose**
librosa	load, feature.rms, amplitude_to_db, feature.spectral_centroid	Load audio files, extract RMS amplitude and spectral centroid, convert amplitudes to dB
numpy	mean	Calculate mean values of extracted features
pandas	DataFrame, concat, to_csv	Manage data manipulation and storage
glob	glob	Pattern matching to locate specific audio files
datetime	strptime, timedelta	Extract and manage timestamps from filenames

Within the core dataset, audio files and their associated statistics were assigned a datetime variable with hourly intervals based on timestamp overlap. To do this, overlap duration relative to the total file duration was calculated, and an audio file was placed into a date-hour category (such as 04/26/2024 09:00 vs. 04/26/2024 10:00) based on the date and hour within which most of its audio was recorded. This was employed for observing audio characteristics over time, allowing for tracking of acoustic changes and patterns within defined periods.

Extracted Feature Considerations

The data extracted from the Python script, which calculated avg_db using librosa, carries inherent limitations due to the lack of calibration against a standard sound pressure level (SPL) reference. The script operated within the digital domain, where decibel values were computed relative to an arbitrary amplitude reference of 1.0. This reference does not correspond to real-world SPL levels, which are essential for interpreting sound intensity in terms familiar to human perception. As a result, the avg_db outputs and their statistical manipulations cannot be directly compared to common SPL levels, such as those experienced in everyday environments.

Filtering Data

To ensure the accuracy and reliability of statistics derived from the acoustic data, screening steps were necessary to remove noise and anomalies that could skew the results and to provide a clearer understanding of the soundscape at Wolf Haven. Manually inspecting the first and last few temporally organized audio files from each recording period was done to identify and remove files containing handling noise, which typically occurred at the beginning and end of recordings due to the physical manipulation of equipment upon deployment and routine data collection. This inspection involved importing these files into the bioacoustic analysis software Raven Pro (version 1.6), where the files' spectrograms were scrutinized, and audio listened to for presence of extraneous handling noise. These identified files were segregated into a distinct directory to maintain the integrity of the core dataset that would be used for further analysis.

Avg_db and avg_freq were plotted by datetime with hourly intervals to visually inspect acoustic trends over the entire timeframe of the dataset (fig. 4). A significant spike in avg_db accompanied by a notable drop in avg_freq was observed across all sites around noon on 4/24/2024. The following are the reported avg_db across sites from 12 PM to 2 PM for that day; 12:00 PM: -31.85 dB; 1:00 PM: -26.05 dB; and 2:00 PM: -21.59 dB.

Figure 4. Temporal changes in average decibel levels (top panel) and average frequency levels (bottom panel) across five different sites over a period from April 19 to April 27, 2024. The lines represent the average levels recorded at each site by hourly intervals, with shading indicating the variability within each site's data.

A similar pattern of notably high avg_db and low avg_freq was observed throughout the day of the 25th. The spectrograms of the audio files associated with these timeframes were inspected in Raven Pro and the audio files themselves were listened to. The notable increase in decibel levels and decrease in frequency levels from around noon to 2 PM on the 24th corresponded with the handling of equipment by Wolf Haven staff. Rain was detected by sound and spectrogram on the 25th; thus, the rain was considered the most likely culprit of the change in audio patterns. Historical precipitation reports for Tenino, WA, during recording periods for this research were derived from World Weather Online® and plotted against the audio data (World Weather Online®, "World Weather API and Weather Forecast"). The 25th saw copious amounts of rainfall throughout the day, and the spectrograms of the associated audio files indeed indicate that the falling of raindrops hitting the devices produced spikes in decibel levels with concurrent drops in frequency levels. The findings for this day are particularly interesting, as around 10 AM, animal specialist Dan Monn reoriented the AudioMoth devices into a vertical position so that the microphone and the weatherproof case's microphone opening faced outward rather than upward toward the sky. A marked drop in decibel levels and increase in frequency levels following this reorientation suggest that raindrops hitting the microphone opening head-on produced a great deal of obstructive sound.

Audio files were removed from analysis for the period of noon to 2 PM on April 24th to account for the handling noise throughout the recordings. To account for rain-induced audio disturbance, all audio recorded during a time associated with an instance of greater than 0.5 mm of rainfall in this historical precipitation record was removed for further analysis (fig. 5). This corresponded to the time from 6 AM to 11 PM on April 25th.

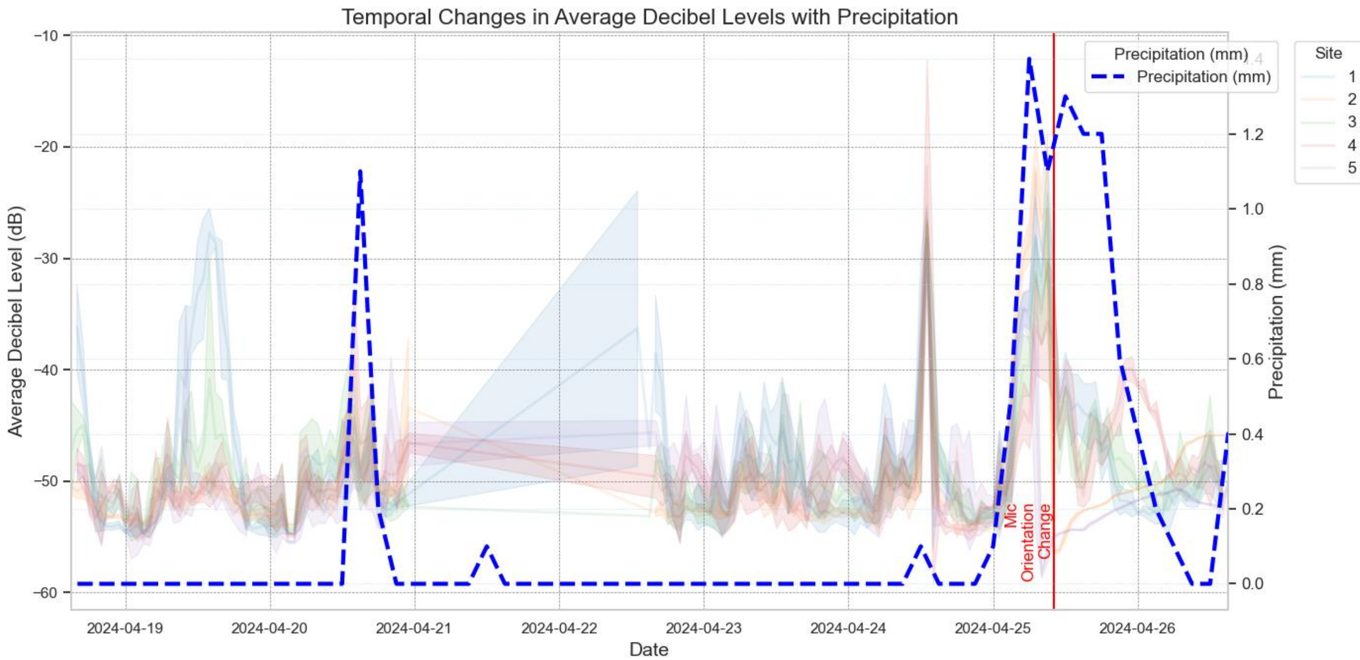


Figure 5. Average decibel levels (avg_db) plotted by site overlain by a dashed line representing plotted precipitation that occurred during the same time frame. A red line marks the date and time when recording devices had their orientations changed, resulting in a notable drop shift in avg_db across sites.

To quickly detect potential sound anomalies for the remaining audio data, z-score outlier detection analysis was performed to identify and highlight outliers in mean decibel levels within the dataset. The results were visualized as the line plot in figure 6, displaying the decibel levels over time with outliers highlighted in red to make them easily distinguishable from the general data points.

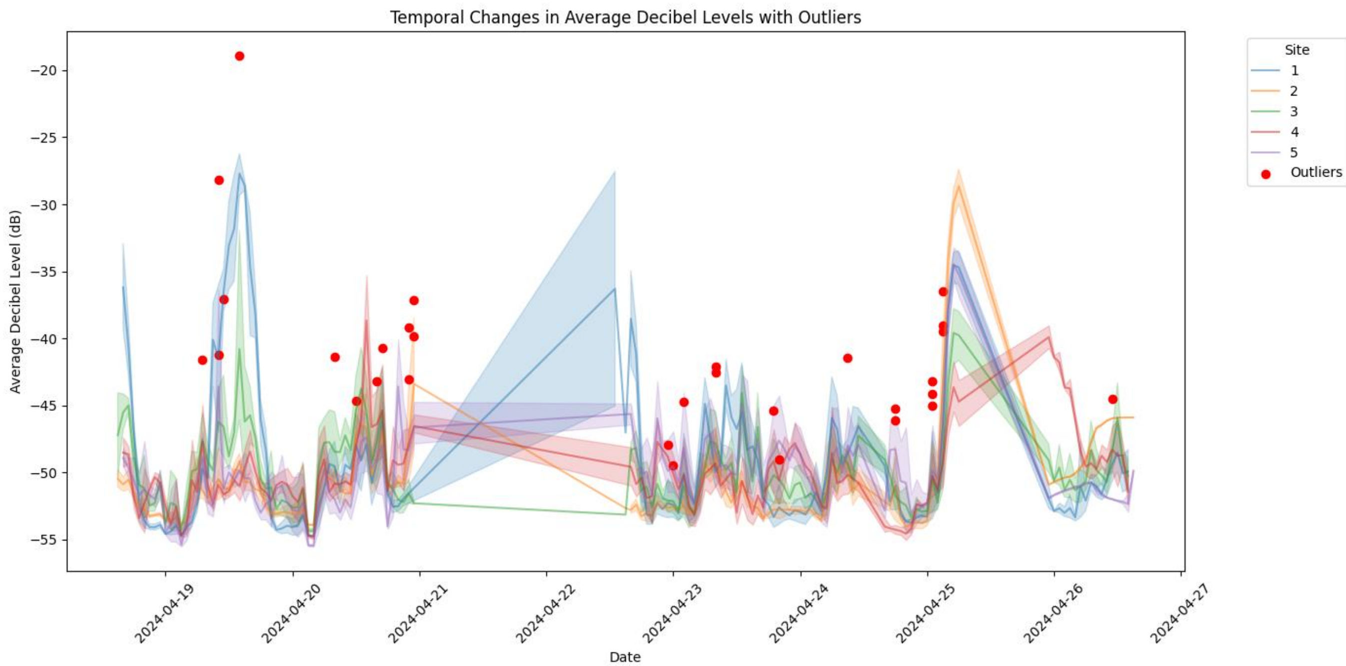


Figure 6. Average decibel levels (avg_db) across sites with outlying instances of increased decibel values dotted in red in alignment with the time and date of their occurrence.

Outliers with a z-score of 3 or greater were calculated and manually inspected for notable sound events that would contribute to elevated decibel levels. Upon inspection of the outliers within the audio files, it was observed that some outlying sound events were extraneous to the research, such as more recording device handling at site 3 on April 19th and unaccounted-for instances of light rainfall. Audio files with handling noise were eliminated from future analysis. Furthermore, audio recorded during time periods when additional rain occurred from 4 PM on April 20th to the end of the recording period around midnight and again during 6 PM on April 24th would be filtered out of future analysis. It was observed that rain began to significantly influence the audio on April 25th beginning at 1 AM as opposed to the 6 AM screening cutoff that was established for the outlier analysis. Given that the historical weather data indicates overall rainfall of somewhere between 0.1 and 0.5 mm at 1 AM on the 25th, it was decided that audio recorded during all time periods experiencing any measurable amounts of rain would be excluded from future analysis. Other outlying sound events, such as the sounds of chainsaws at work and wolf choruses, were left alone as part of the soundscape typical for the sanctuary grounds.

Exploratory Data Analysis

Conducting a soundscape analysis for the Wolf Haven sanctuary grounds required the establishment of a comprehensive acoustic profile for each recording site based on the audio data's acoustic characteristics. The research question "How do decibel and frequency levels compare across the five recording locations?" was addressed to inform these acoustic profiles by deriving descriptive statistics from all viable audio data and comparing these metrics across different locations.

Summary Statistics

Deriving summary statistics from avg_db and avg_freq and comparing these measurements across sites provided initial insight into the central tendency and variability in decibel and frequency levels at each site. The mean, median, standard deviation, and range of the averaged decibel and frequency levels from each audio file segment were calculated (table 4).

Table 4. Libraries And Functions Used in The Python Script for Summary Statistics and Plotting

Library	**Function(s)**	**Purpose**
pandas	read_csv, DataFrame, groupby, describe, to_csv	Load data, manage data manipulation and storage, calculate descriptive statistics
numpy	quantile	Calculate quartiles for identifying outliers
seaborn	boxplot	Generate visualizations for descriptive statistics
matplotlib	savefig	Save the generated plots

Outliers were identified using the Interquartile Range (IQR) method, with lower and upper bounds set at $Q1 - 1.5 \times IQR$ and $Q3 + 1.5 \times IQR$. Data points outside these bounds were flagged as outliers, and their counts were appended to the summary statistics for each site.

The audio data was then grouped by site to compute the mean, median, and standard deviation of the averaged decibel and frequency levels, providing an initial overview of the spatial distribution of acoustic characteristics within the sanctuary. Violin plots were generated from the results using the Seaborn library to visualize site-based acoustic measurements, highlighting central tendency, variability, and outliers, thus providing a comprehensive view of each site's acoustic characteristics.

To understand the daily patterns in the soundscape, summary statistics were derived for each hour of the day across all recording sites and all days. A variable for distinguishing hour of the day with no date affiliation was derived from the dataset's datetime variable by extracting only its hour component. For example, the "hourly_bin" variable for 1 PM includes data from all sites and all days, representing all data for the time between 1 PM and 2 PM. To derive summary statistics for hourly_bin, the hourly mean and standard deviation of avg_db and avg_freq were calculated using the audio files falling into each hour.

Outlier Analysis

The possibility that anomalous measures for average frequency and decibel levels might have occurred simultaneously across different sites, or across measurements at the same site and different times, was important to consider for the research. Outliers occurring across different sites during shared hourly bins could indicate the presence of widespread environmental factors affecting the recordings, such as the sudden initiation of wolf chorus, a high wind event, or planned construction at the sanctuary.

Outliers were categorized into three outlier types: “both,” indicating anomalies in both frequency and decibel levels; “decibel,” indicating anomalies only in decibel levels; and “frequency,” indicating anomalies only in frequency levels. The occurrence of outliers during the same date-hour hourly bin across more than one site constituted an “event,” and a value for events was given for the date-hour hourly bin within which the event occurred.

The percentage of outliers for each site and event was calculated by first normalizing the outlier counts of events by the entire outlier dataset, and then further segmenting events into distributions by site. This was done to facilitate a qualitative comparative analysis of the relative occurrence of anomalies. Conversely, the distribution of each site’s outliers by event and outlier type was also calculated. Stacked bar graphs were created using Matplotlib and Seaborn to visually represent the distribution calculations (table 5).

Table 5. Libraries And Functions Used in The Python Script for Outlier Analysis and Plotting

Library	**Function(s)**	**Purpose**
pandas	read_csv, DataFrame, groupby, size, unstack, to_csv	Load data, manage data manipulation and storage, group data, count occurrences, export data
numpy	nan, to_numeric	Handle missing values, convert data types
matplotlib	figure, subplots, gca, savefig	Create figures and subplots, manage plot axes, save the generated plots
seaborn	barplot, set_style	Generate visualizations for outlier analysis, set the aesthetic style of the plots

Significance Testing

To build on the findings of from the summary statistics and analyze the observed differences across sites and hours of the day, R (version 4.4.1; R Core Team 2024) was utilized to conduct tests for homogeneity of variance, normality, residuals, and significance of the data within the RStudio IDE. These analyses were later recreated with Python in PyCharm for cross-validation of results and enhanced plotting graphics. Table 6 details the respective libraries and functions utilized for these processes. Before running analyses, the Shapiro-Wilk test, Q-Q plots, and Levene's test were implemented to assess the assumptions of normality and homogeneity of variance to determine the most appropriate tests for further analysis. For the sake of uncomplicated Levene's and Shapiro-Wilks testing, the variable hourly_bin was treated as categorical, but later trend analysis treats the variable as continuous. The "site" variable, treated as categorical, represents different recording locations, while hourly_bin aggregates audio data into hourly bins based on the time of recording. For all significance analysis, the variables for average decibel ("avg_db") and frequency levels ("avg_freq") were treated as continuous.

Table 6. Statistical Tests Conducted for Significance Analysis Along with Their Corresponding Functions in R And Python

Test	**Platform**	**Library**	**Function**	**Purpose**
Kruskal-Wallis Test	RStudio	stats	kruskal.test()	Performs Kruskal-Wallis test for non-parametric comparison
Kruskal-Wallis Test	Python	scipy.stats	kruskal()	Performs Kruskal-Wallis test for non-parametric comparison
Dunn's Test	RStudio	dunn.test	dunn.test()	Performs Dunn's test for post-hoc analysis
Dunn's Test	Python	scikit_posthocs	posthoc_dunn()	Performs Dunn's test for post-hoc analysis
Shapiro-Wilk Test	RStudio	stats	shapiro.test()	Performs Shapiro-Wilk test for normality
Shapiro-Wilk Test	Python	scipy.stats	shapiro()	Performs Shapiro-Wilk test for normality
Q-Q Plot	RStudio	ggplot2	stat_qq(), stat_qq_line()	Creates Q-Q plots for checking normality
Q-Q Plot	Python	scipy.stats, matplotlib	stats.probplot(), plt.plot()	Creates Q-Q plots for checking normality
Levene's Test	RStudio	car	leveneTest()	Performs Levene's test for homogeneity of variances

The Shapiro-Wilk test was employed to evaluate the distributions of avg_db and avg_freq values for each site and each hourly bin. The test was performed using the shapiro.test function in R, applied to subsets of grouped data. The results indicated significant deviations from normality for both avg_db and avg_freq across all sites except for Site 4, as represented in the p-values with an alpha of 0.05 observed in tables 7 and 8. Normality results were similar for measurements across all hourly bins, and the few reports of non-significant normality deviations are represented in table 9 for avg_db and table 10 for avg_freq. Levene's test was an appropriate choice for testing the equality of variances in the data given its robustness with non-normal distributions, and it was conducted with a significance level of 0.05. Table 11 features Levene's test results for avg_db and avg_freq when grouped by site and hourly_bin. In addition to the statistical tests, Q-Q plots were generated for the overall distributions of avg_db and avg_freq across all sites and times to provide a high-level view of the data's normality (fig. 7).

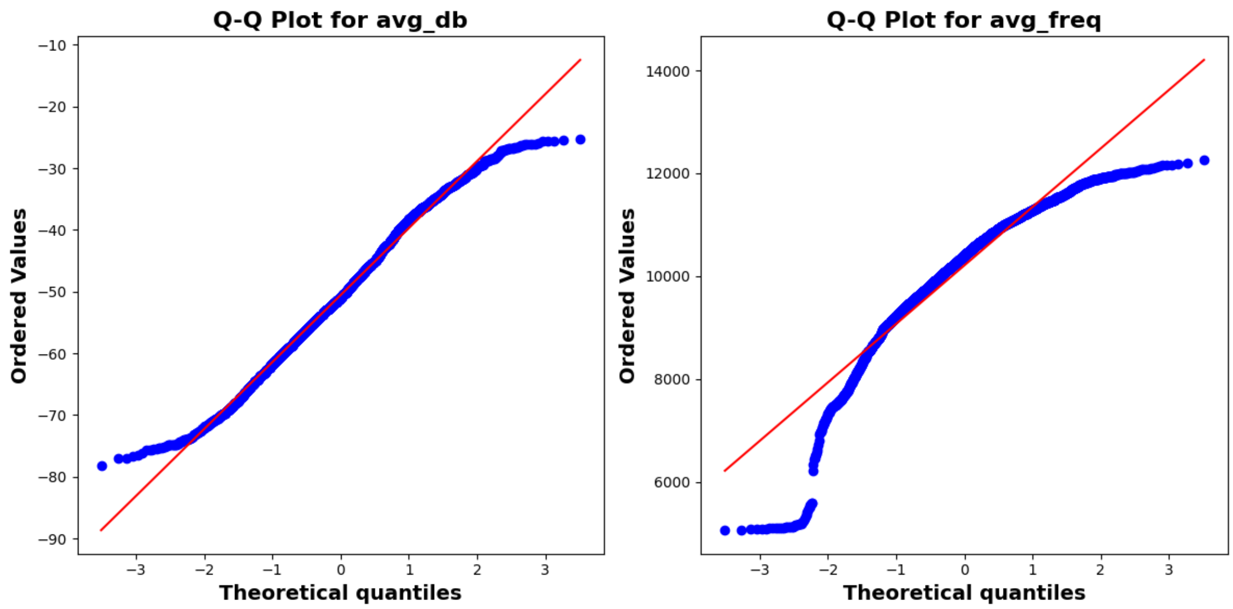


Figure 7.Q-Q Plots for avg_db (left) and avg_freq (right) derived from the dataset. Both plots compare the ordered values of the data against a theoretical normal distribution. Deviations from the red line indicate departures from normality.

Table 7. Shapiro-Wilk Test for Average Decibel Levels (avg_db) Across Sites

Site	p-value	Interpretation
Site 1	0.001	Not normally distributed
Site 2	0.023	Not normally distributed
Site 3	0.002	Not normally distributed
Site 4	0.076	Normally distributed
Site 5	0.007	Not normally distributed

Table 8. Shapiro-Wilk Test for Average Frequency Levels (avg_freq) Across Sites

Site	p-value	Interpretation
Site 1	0.007	Not normally distributed
Site 2	0.010	Not normally distributed
Site 3	0.007	Not normally distributed
Site 4	0.164	Normally distributed
Site 5	0.026	Not normally distributed

Table 9. Non-Significant Results of Shapiro-Wilk Test for Average Decibel Levels (avg_db) Across Hourly Bins (hourly_bin)

Hourly Bin	p-value	Interpretation
18	0.05108453	Normally distributed
22	0.114055819	Normally distributed

Table 10. Non-Significant Results of Shapiro-Wilk Test for Average Frequency Levels (avg_freq) Across Hourly Bins (hourly_bin)

Hourly Bin	p-value	Interpretation
5	0.195407152	Normally distributed
6	0.131787613	Normally distributed
8	0.10293597	Normally distributed
11	0.289762748	Normally distributed
12	0.675445911	Normally distributed
13	0.050102895	Normally distributed
14	0.148500975	Normally distributed
20	0.203054676	Normally distributed

Table 11. Levene's Test Results

Test	F Statistic	p-value	Interpretation
Levene avg_db Sites	65.94206831	< 0.001	Variances are not equal
Levene avg_freq Sites	7.344435309	< 0.001	Variances are not equal
Levene avg_db Hourly	11.98852057	< 0.001	Variances are not equal
Levene avg_freq Hourly	9.336512914	< 0.001	Variances are not equal

The results of the Shapiro-Wilk tests indicate that the majority of the avg_db and avg_freq values do not follow a normal distribution across hourly_bin, with only 2 of 24 hourly bins exhibiting normal distribution for avg_db and 8 of 24 exhibiting normal distribution for avg_freq. Values for avg_db and avg_freq exhibit non-normal distribution across all sites. Additionally, Levene's test yielded variances in both avg_db and avg_freq levels that differed significantly across site and hourly_bin.

Given the non-normality and unequal variances observed for most of the data, non-parametric tests were chosen as the appropriate tools for analyzing significance in differences of acoustic measurements across site. The Kruskal-Wallis test, a non-parametric alternative to one-way ANOVA, was used to determine if there were statistically significant differences in avg_db and avg_freq across the different sites. Dunn's post hoc tests conducted pairwise comparisons (adjusted for multiple comparisons using the Bonferroni method) between sites to identify which pairs yielded significant differences in avg_db and avg_freq. The analysis of temporal patterns in acoustic measurements was conducted separately using trend analysis.

Generalized Additive Model (GAM)

To uncover diurnal patterns in avg_db and avg_freq levels at Wolf Haven—answering the research question "Are there notable patterns in frequency and decibel levels throughout the day?"—a generalized additive model (GAM) analysis was conducted in R with the libraries and functions detailed in table 12. GAMs are flexible regression models that can capture nonlinear relationships between the predictor variables and the response variable by applying smooth functions to the predictors. This flexibility allows them to model complex trends and patterns in data that may not be easily captured by linear models. The models were formatted with hourly_bin as a numeric variable and site as a categorical factor. The hourly_bin variable represents sequential hourly time bins, making it a variable with inherent serial autocorrelation, where values at one time point are likely influenced by those at previous or subsequent time points. This autocorrelation can complicate the analysis by inflating the significance of trends or patterns that may not be truly independent. To account for serial autocorrelation, an autoregressive component was introduced by creating lagged variables (lag_avg_db and lag_avg_freq), representing the previous hour's values. Values missing from lagging were removed to maintain dataset integrity.

Table 12. Libraries And Functions Used in The R Script for GAM Analysis

Library	Function(s)	Purpose
mgcv	gam, summary, plot	Fit the GAM models to the data, summarize the model results, and visualize the models.
dplyr	group_by, arrange, mutate, ungroup, drop_na	Group and arrange data, create lagged variables, and handle missing values.
tidyr	drop_na	Handle missing values by removing rows with NA values.
base R	read.csv, as.numeric, as.factor	Load the dataset, convert data types to numeric and factor.

GAMs were then fitted for both avg_db and avg_freq, using the cubic spline basis function s(hourly_bin, bs = "cs") to model nonlinear trends, including the lagged variables to address autocorrelation. The data was grouped by site to account for site-specific differences that could affect the analysis of avg_db and avg_freq, which was important when creating lagged variables to handle autocorrelation within each site's data to ensure that temporal patterns were accurately captured without being influenced by variations between sites. The models were then summarized to extract key coefficients and significance levels. Visualizations were generated to display the predicted trends over a 24-hour period, and the results, including predicted values, were exported for further analysis.

Data Collection for Sanctuary Mapping

One of the two main goals of this study was to produce a detailed and accurate cartographic representation of the sanctuary, which would serve as a foundational tool for the SMP and as a spatial analysis and data visualization tool. To achieve this goal, an integrated data collection approach was implemented, combining advanced aerial drone imagery with precise in-situ ground-level surveys.

Drone Imagery

The aerial imagery used in sanctuary mapping, collected during an April 2024 drone flight, was graciously provided by drone pilot and fellow Master of Environmental Studies student Matthew Einhorn. The imagery was captured using a DJI Mavic 2 Pro drone, equipped with superior imaging capabilities courtesy of the Hasselblad L1D-20c camera. A flight mission was planned and executed using the DroneDeploy flight application on an iOS device. This setup provided a total of 303 high-resolution images with a ground resolution of 0.028 meters, facilitating the identification of fine-scale features within the sanctuary. These images were ultimately stitched together in Esri's Drone2Map (version 2023.2) software to produce an orthomosaic product.

Ground-Truthing

Aerial imagery of important sanctuary features, such as fence boundaries and enclosure shelters, was limited by the area's dense canopy cover, necessitating additional collection of location data on the ground. In-situ data collection was carried out using a combination of the Esri Field Maps mobile application on a Samsung Galaxy Note 9 cellular phone, the Juniper Systems Geode™ GNS3, and orientation from sanctuary staff. Dan Monn, an animal care specialist at Wolf Haven, played an integral role in guiding and supervising the data collection, ensuring that the intricacies of the sanctuary's layout were accurately captured and that the sanctuary residents were disturbed as little as possible during this leg of data collection (Dan Monn, personal communication, April 2024). Using his intimate knowledge of the sanctuary's terrain and layout, the drone-derived orthomosaic was marked and notated with the estimated locations of features obscured by the dense canopy cover. With this notated imagery, Dan Monn and I navigated to those specific areas to enhance the location data.

Collection efforts consisted of the recording of walked paths as line features using the Esri Field Maps application. This step was carried out by initiating and concluding data recording at the start and endpoints of various lengths of perimeter fencing. These lines were important in defining the canopy-obscured extents of both individual wolf enclosures and the sanctuary's overall boundaries. This method of data collection faced challenges posed by the sanctuary's dense vegetation, which sometimes limited physical access to certain areas. When areas were impassable, we collected standalone points of location data along the perimeters that could be reached. These points were subsequently utilized to estimate the locations of obscured fencing segments by visually interpreting the distances and angles between accessible sections. For the shelters positioned adjacent to the wolf enclosures to which they were attached, the data was initially marked as discrete points in the Field Maps app. These were later used to generate polygons in the mapping software, thus transforming point data into a tangible representation of the sanctuary's infrastructure.

All location data collected on the ground was captured by accuracy-enhanced cellular GPS. Alone, the cellular phone's accuracy margin was approximately 30 feet. The accuracy was significantly enhanced through the integration of a Juniper Systems Geode™, which reduced the margin of error to an approximate range of 2–5 feet. This heightened accuracy was a cornerstone of crafting a map that depicted the sanctuary's layout with precision.

Creating The Map

Combining advanced mapping software and precise data collection tools, a comprehensive map was produced for Wolf Haven International to enhance sanctuary staff's understanding of the sanctuary's spatial features to support informed decision-making.

Orthomosaic Assembly

Using Drone2Map, an orthomosaic was constructed by stitching together 303 aerial images captured by the DJI Mavic 2 Pro drone. The software's algorithms accounted for varying image perspectives and distortions to produce a seamless composite image. The calibrated images, with a ground resolution of 0.028 meters, provided a detailed visual base for the sanctuary. The project area spanned 0.302 km². With 911,550 tie points, common features that are identified in overlapping images and used to align and stitch images together, the project produced a robust dataset with a consistent overlap between images.

Ground-Level Data Synchronization

The Esri Field Maps application, supplemented by the Juniper Systems Geode™ GNS3, captured precise geospatial data points. This ground-level data, recorded as walking paths and individual location points in the Field Maps app, was synchronized with the aerial imagery within ArcGIS Pro. Given the margin of error for the mobile phone GPS (approximately 30 feet) and the substantial improvement provided by the Geode (reducing the error to approximately 2–5 feet), the combined dataset offered a representation of the sanctuary features with an accuracy sufficient for the purposes of this study.

Map Drawing and Feature Representation

In Esri's ArcGIS Pro software, the orthomosaic product and the synchronized ground-level data served as a foundation for the manual tracing of sanctuary features. Walked paths were converted into digital lines representing the sanctuary's pathways and boundaries, while point data marked the positions of key structural elements like wolf shelters. Where dense canopy or brush obscured features, points collected along accessible fencing segments were used to guide the interpolation of hidden sections to ensure continuous and accurate perimeter delineations.

Cartographic differentiation was applied to the various sanctuary features to enhance visual interpretation. Using public styles created by Esri ArcGIS Living Atlas team member John Nelson, distinctive visual elements were assigned to land types, paths, and structural features (Nelson, Esri ArcGIS Blog Author Page, n.d.). Aesthetic elements such as custom-designed wolf and tree vector graphics were integrated as point symbology, visual markers placed on a map using underlying geolocation information, within the map (Esri, "Point Symbols"). These elements served no direct scientific purpose but enriched the visual appeal of the map—producing an attractive end-product remained a primary goal throughout the construction of the map in ArcGIS Pro.

The final map's resolution was determined by the drone imagery's ground resolution, while the scale was implicitly established by the extent of the mapped area and the dimensions of the map (48" × 36"). For the purposes of master planning and spatial analysis, the resolution and scale were deemed sufficient. The accuracy of both the aerial and ground-level datasets, validated by the processing report statistics and the refined GPS measurements, underpinned the reliability of the map as a tool for sanctuary management and future development (fig. 8).

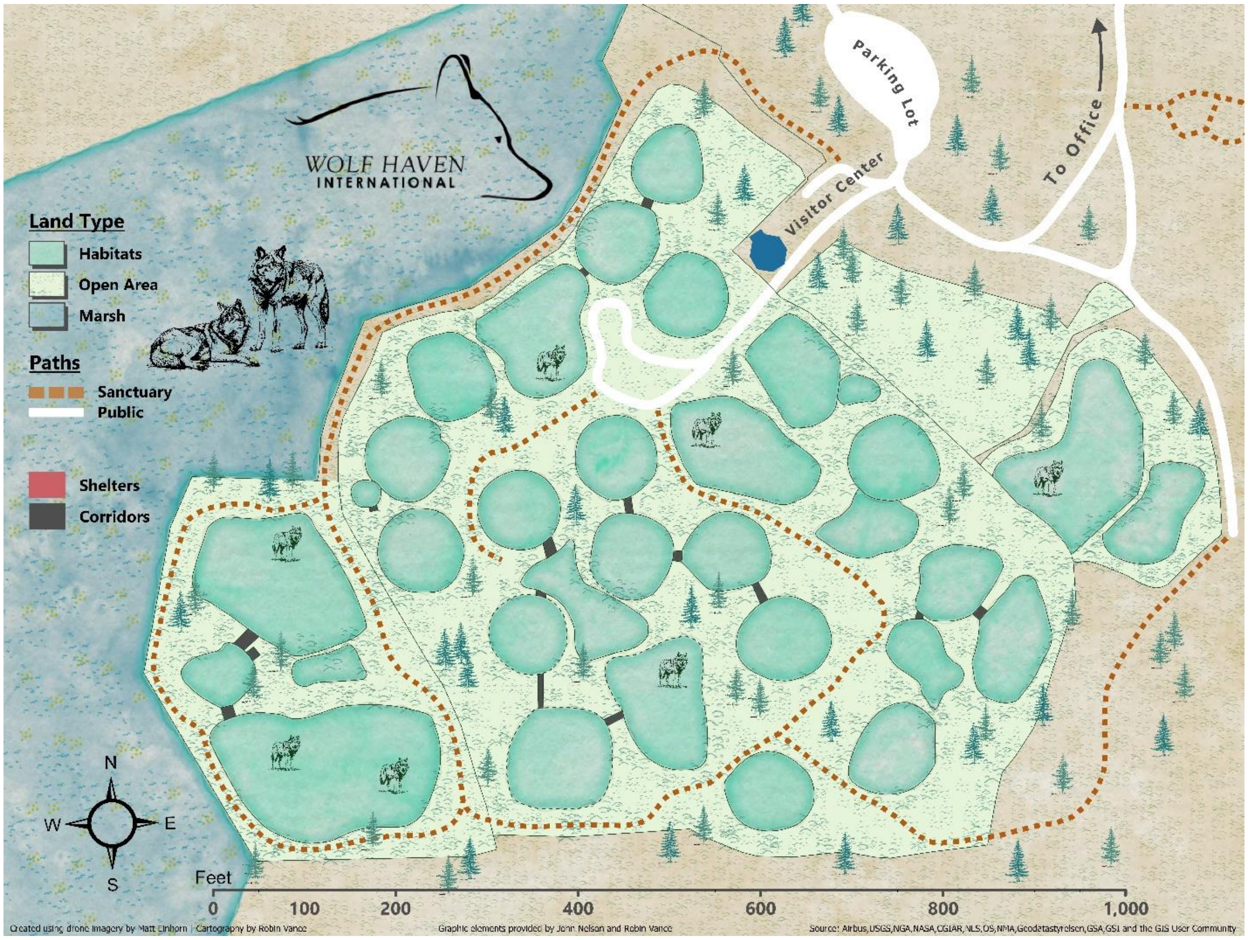


Figure 8. Graphic map of Wolf Haven International's sanctuary grounds. Map by author.

Mapping Summary Statistics

The underlying ArcGIS Pro project map served as a base for overlaying the findings of the research within both spatial and spatial–temporal contexts. Bivariate color symbology, implemented in ArcGIS Pro, was used to visualize the spatial relationship between mean and median decibel levels as well as mean and median frequency levels across all sites. The mean and median for the respective acoustic measurement were classified using the quantile method, dividing the data into equal-sized groups, ensuring that each class contained an equal number of data points. Each variable was split into three quantiles, creating a 3×3 grid of color combinations that represent different pairings of mean and median decibel or frequency levels. This approach allowed for a clear and balanced visual representation of the data, with specific colors highlighting areas where both variables were consistently low or high or where they diverged.

To visualize the diurnal changes in median frequency and decibel levels across different locations, animated time series were created in ArcGIS Pro. The data was organized into separate time-enabled feature layers based on acoustic measurement, and graduated colors were applied to represent decibel or frequency levels along a defined color spectrum. The animations were configured to display the data sequentially over a 24-hour time frame, allowing for a clear visualization of how frequency and decibel levels fluctuated across locations and over time. The output of both the static visualization of the data's summary statistics and its animated temporal trends are considered in the *Discussion*, including links to the animated videos and images of the summary statistics maps.

Chapter 4 – Results

This section delves into the temporal patterns of sound intensity and frequency across different recording sites. The summary statistics of the exploratory data analysis, as well as the visualizations of those summary statistics, help to identify daily fluctuations and site-specific variations. The analysis also examines the influence of sound events, the presence of outliers, and diurnal patterns, using advanced statistical techniques to understand the dynamics of the sanctuary's soundscape.

Initial Visualization

Visualizations of the viable audio files' extracted features, namely average decibel (dB) and frequency (Hz) levels, illuminated initial patterns across time and location. The data was resampled into hourly bins to compute the hourly mean and standard deviation of the audio files' average dB (fig. 9) and Hz (fig. 10) levels at each site, smoothing out short-term fluctuations and highlighting broader trends. The time periods excluded from this, and all following analysis, correspond with the periods characterized by compromised audio recordings: April 20, 2024, 15:00 to April 22, 2024, 13:00; April 24, 2024, 12:00 to 15:00; April 24, 2024, 18:00 to 19:00; and April 25, 2024, 00:00 to April 26, 2024, 09:00.

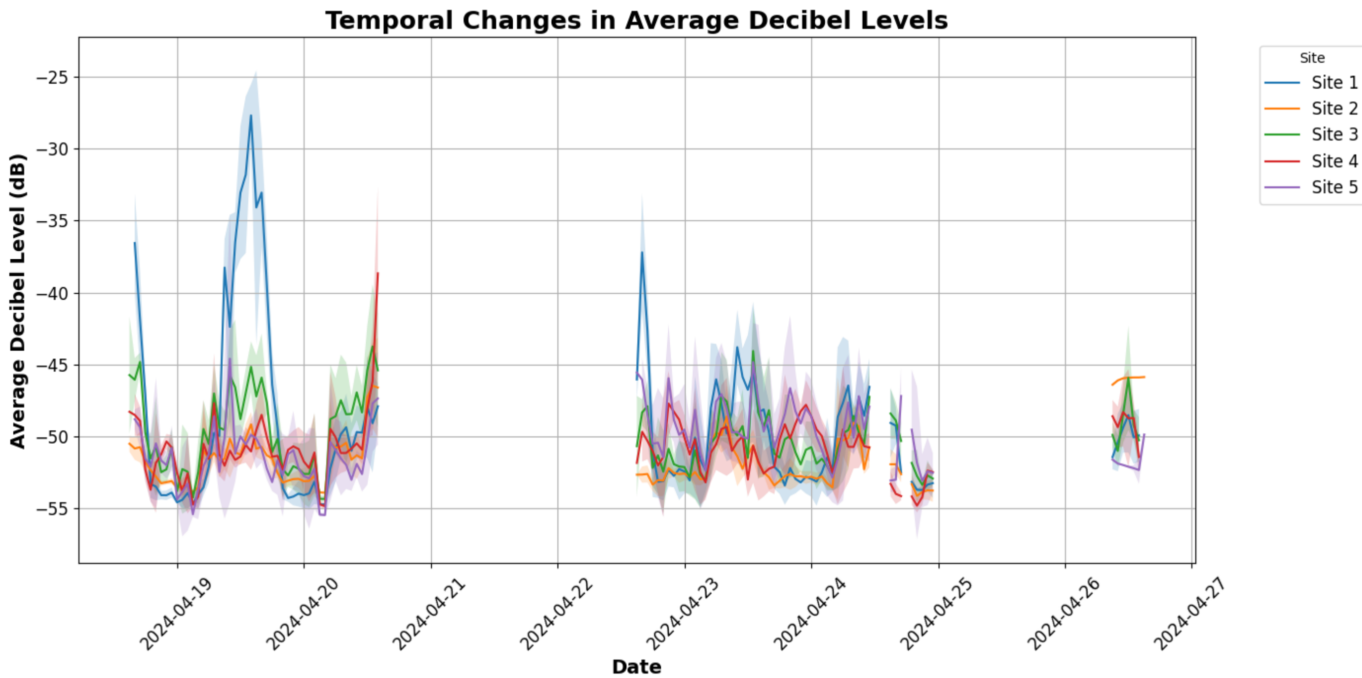


Figure 9. Average decibel levels (dB) by hourly bin over time for five recording sites. Colored bands around the lines indicate standard deviation, reflecting variability in the measurements. Temporal gaps in the dataset are represented by breaks in the graphed lines.

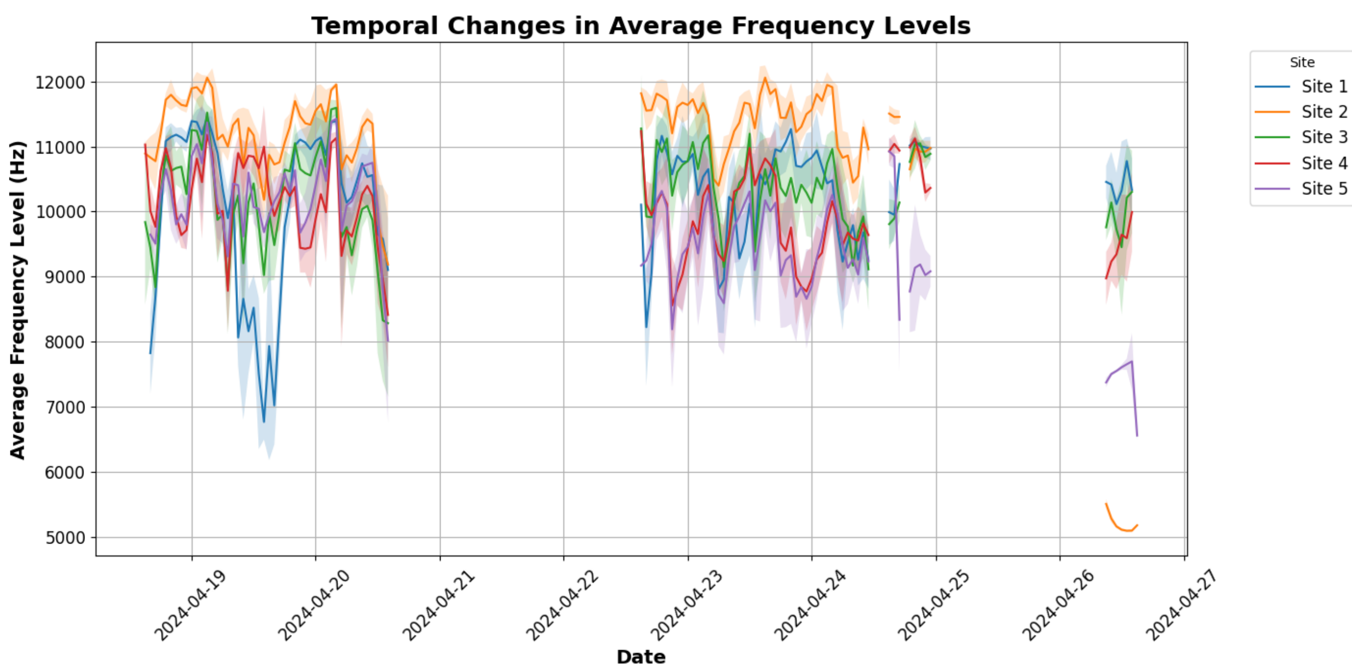


Figure 10. Average frequency levels (Hz) by hourly bin over time for five recording sites. Colored bands indicate standard deviation.

Summary Statistics by Site

The results presented here are derived from analysis of descriptive statistics of each audio file, including average decibel and frequency levels. Thus, the central tendency and variability reported for each site reflect the averaged sound characteristics of these individual files, rather than raw, continuous measurements.

The interpretation of averaged decibel levels in the context of soundscape analysis is derived based on the statistics' general qualities: The mean and median values of the averaged decibel levels indicate the central tendency of sound intensity at each site; therefore, locations with higher mean and median values have generally louder environments. The standard deviation shows the variation in decibel levels within each site, with higher standard deviations indicating more variability in sound intensity. and the range provides the difference between the maximum and minimum (averaged) decibel levels, highlighting the spread of sound intensity at each site. Similarly, the interpretation of averaged frequency levels within the context of soundscape analysis is derived based on much the same principles, keeping in mind the inherent properties of frequency levels as opposed to decibel levels. The median frequency was used as the basis for informing the violin plots for figure 11 and figure 12 to provide a more representative measure of central tendency, given the presence of outliers, skewed distributions, and non-normality of the avg_db and avg_freq data.

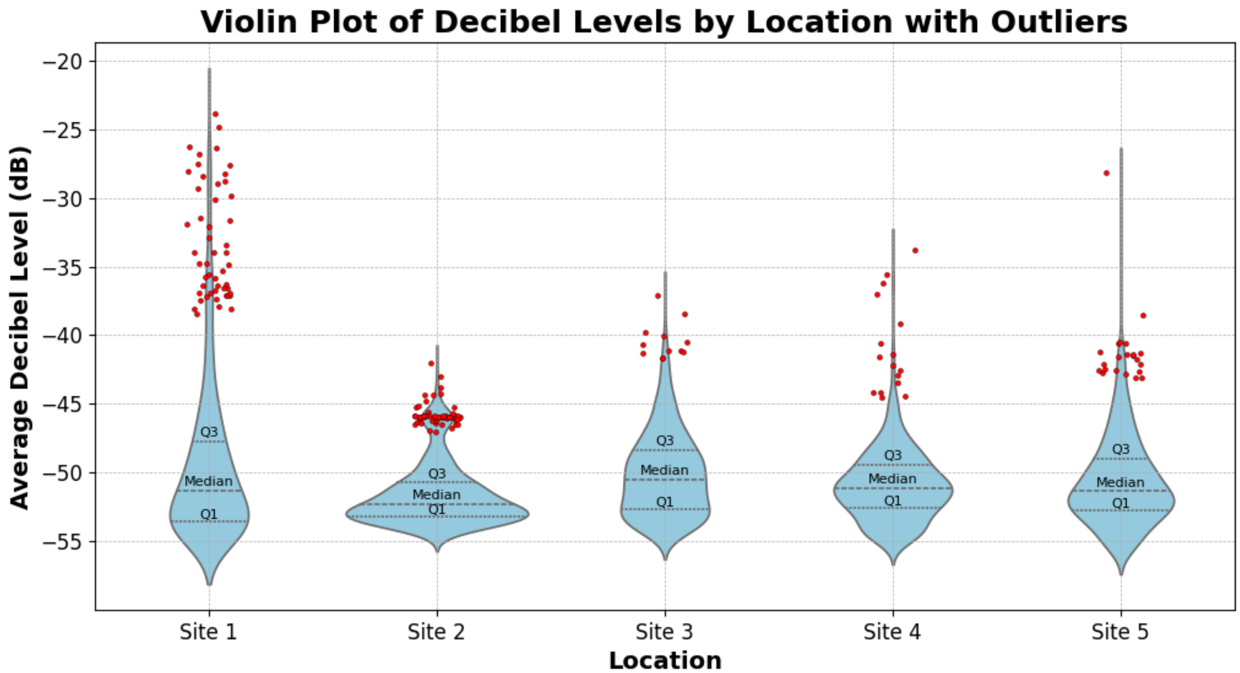


Figure 11. Violin plot of decibel levels by site using median. The plot shows the median, interquartile range (IQR), and outliers (red dots) for each site. Outliers are defined as data points outside 1.5 × IQR above the third quartile (Q3) or below the first quartile (Q1), indicating occasional deviations from the central tendency. Sites with wider IQRs indicate greater variability in sound intensity.

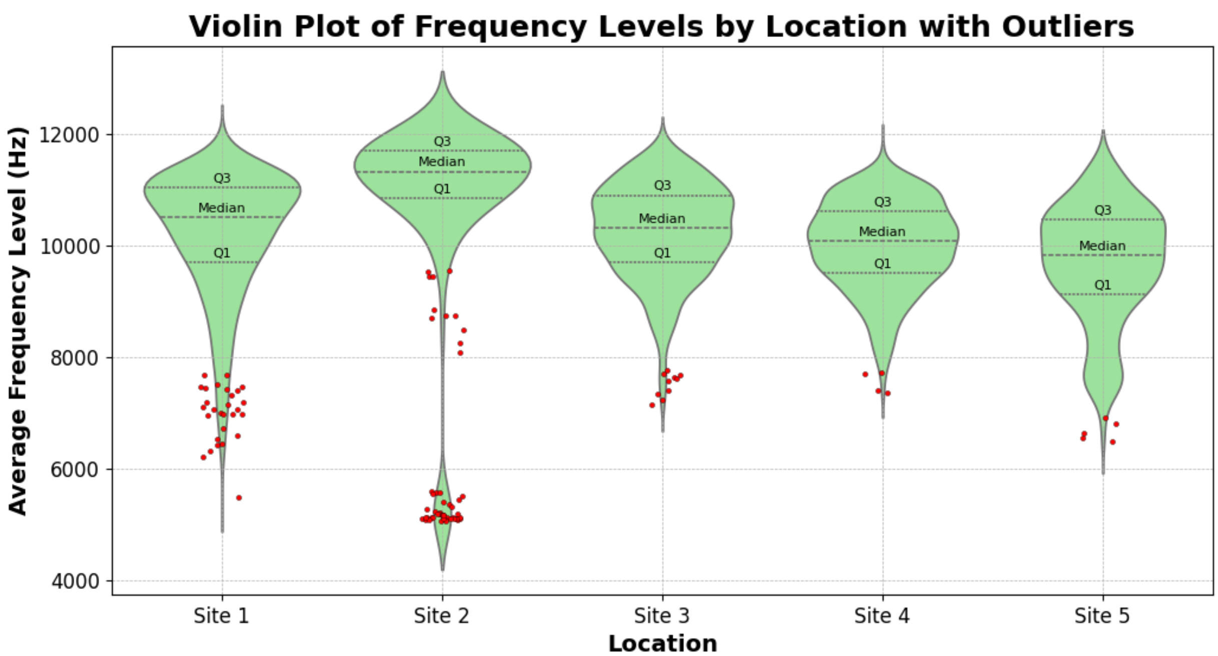


Figure 12. Violin plot of frequency levels by site using median. The plot shows the median, interquartile range (IQR), and outliers (red dots) for each site. Outliers are defined as data points outside 1.5 × IQR above the third quartile (Q3) or below the first quartile (Q1), indicating occasional deviations from the central tendency. Sites with wider IQRs indicate greater variability in sound intensity.

Based on the summary statistics for averaged decibel levels at each site (table 13), each location exhibited distinct trends that reflect the variability in sound intensity across locations. At Site 1, the median of the averaged decibel levels is approximately -51.32 dB, with an interquartile range (IQR) spanning from -53.52 dB (25th percentile) to -47.71 dB (75th percentile). The decibel levels at Site 1 show several outliers as represented in figure 11, particularly on the higher end, with values rising above -23 dB. These outliers suggest several periods of unusually high sound levels at this site, with a total of 50 outliers identified. When compared to all other sites, Site 1 exhibits both the widest spread in sound intensity, with a difference between the 25th and 75th percentiles of 5.8 dB, and the greatest variability in sound intensity, with a standard deviation of 6.01 dB. Additionally, Site 1 hosts the greatest average dB level.

Table 13. Summary Statistics for Average Decibel Levels (avg_db) by Site.

Site	Count	Mean	STD	Min	25%	Median	75%	Max	Outliers
Site 1	620	-49.31	6.01	-54.79	-53.52	-51.32	-47.71	-23.87	50
Site 2	628	-51.53	2.33	-54.44	-53.16	-52.28	-50.73	-41.99	57
Site 3	620	-50.04	3.14	-54.58	-52.64	-50.49	-48.33	-37.09	12
Site 4	618	-50.81	2.81	-55.13	-52.57	-51.11	-49.40	-33.79	16
Site 5	621	-50.59	3.30	-55.57	-52.77	-51.34	-48.97	-28.15	22

Site 2 exhibited a median decibel level of approximately -52.28 dB, with an IQR ranging from -53.16 dB to -50.73 dB and a standard deviation of 2.33 dB. This narrower IQR and lower standard deviation compared to Site 1 indicate more consistent sound intensity. A total of 57 outliers are present, with values rising above -41 dB. The clustering of Site 2 outliers nearer to the 75th percentile than other sites' outliers suggests that these outliers represent a secondary spread of slightly higher sound levels within the dataset that are not common but occur with some regularity (fig. 11). When compared to all other sites, Site 2 exhibits both the smallest spread in sound intensity at 2.43 dB and the least amount of variability in sound intensity with a standard deviation of 2.33 dB. Additionally, Site 2 boasts the lowest maximum value of average dB level at -41.99.

At Site 3, the median decibel level was -50.49 dB, with an interquartile range (IQR) spanning from -52.64 dB to -48.33 dB and a standard deviation of 3.14 dB. Its spread of 4.3 dB and standard deviation suggest a moderate spread and variability in sound intensity at this site; however, compared to other sites, it sports the fewest outliers at 12 with the second lowest maximum value of average dB level at -37.09 dB. The violin plot of figure 11 displays Site 3's moderate sound profile, with the second greatest spread in sound intensity but moderate stability in dB levels with few deviations.

Site 4 experienced a median decibel level of -51.11 dB, with an IQR ranging from -52.57 dB to -49.40 dB and a standard deviation of 2.81 dB. The relatively low spread of 3.17 dB and small standard deviation suggest stability in the range and variability of Site 4's average dB levels. It's characterized by the second lowest number of outliers at 16, with values rising slightly above -33 dB, indicating occasional but few deviations in sound intensity.

Site 5 had a median decibel level of -51.34 dB, with an IQR spanning from -52.77 dB to -48.97 dB and a standard deviation of 3.30 dB. The spread of the IQR is 3.80 dB. Similarly to Site 2, Site 5's 22 outliers appear to cluster with some regularity around a secondary spread of average dB levels somewhat greater than the IQR, with the site's maximum value deviating from this secondary cluster at -28 dB. Site 5 exhibits the second highest variability in sound intensity across all sites with a moderate spread.

Overall, the average dB levels across all sites display unique variability and spread in sound intensity, with Site 2 being the most consistent and Site 1 being the least consistent. The presence of outliers at all sites suggests periods of atypical sound intensity, with varying degrees of deviation from the median.

Table 14 details the summary statistics for averaged frequency levels across the different locations, which, like with averaged decibel levels, are rather distinguished at each site. At Site 1, the median frequency level was 10,511 Hz, with an IQR spanning from 9,706 Hz to 11,047 Hz. The frequency levels at Site 1 show 28 outliers with values as low as 5,489 Hz. Site 1 boasts the greatest spread in frequency levels between the 25th and 75th percentiles at 1,340 Hz, the second greatest standard deviation at 1,133 Hz, and the second greatest instance of outliers among all sites. As with its decibel levels, Site 1's frequency statistics indicate relatively unstable and variable frequency levels at this location.

Table 14. Summary Statistics for Average Frequency Levels (avg_freq) by Site

Site	Count	Mean	STD	Min	25%	Median	75%	Max	Outliers
Site 1	620	10,200	1,133	5,489	9,706	10,511	11,047	11,911	28
Site 2	628	10,896	1,583	5,059	10,858	11,332	11,711	12,267	50
Site 3	620	10,259	858	7,141	9,709	10,325	10,907	11,847	10
Site 4	618	10,003	796	7,355	9,511	10,081	10,621	11,746	4
Site 5	621	9,681	1,053	6,494	9,129	9,831	10,465	11,506	5

Site 2 was characterized by both a higher median frequency level than all other sites at 11,332 Hz and the greatest standard deviation at 1,583 Hz. Interestingly, with an IQR ranging from 10,858 Hz to 11,711 Hz, Site 2 also experienced the narrowest IQR spread of 853 Hz among all sites. As with its average dB levels, the majority of the 50 outliers at Site 2 suggest a cluster representative of a secondary spread of uncommon but somewhat regularly occurring frequency levels at notably lower Hz (fig. 12). This site also experienced the single lowest minimum average Hz level of 5,059 Hz and single greatest average Hz level of 12,267 Hz.

Sites 3 and 4 maintained rather similar sound profiles. At Site 3, the median frequency level was 10,325 Hz, with an IQR spanning from about 9,709 Hz to 10,907 Hz and spread of 1,198 Hz. Site 4 displayed a median frequency level of 10,081 Hz, with an IQR ranging from 9,511 Hz to 10,621 Hz and spread of 1,111 Hz. Both sites experienced the lowest standard deviations in average Hz levels at 858 Hz and 796 Hz, respectively, and rather few outliers, with Site 4 boasting the fewest.

Site 5 experienced the lowest median averaged frequency level of all sites at 9,831 Hz and second highest IQR spread at 1,336 Hz spanning from 9,129 Hz to 11,506 Hz. Its 5 outliers cluster with some regularity around a secondary spread of average Hz levels somewhat lower than the IQR, very similarly to the cluster of outlying average dB levels noted in figure 11.

Site 1 and Site 2 exhibit high variability and numerous outliers in their frequency levels, which would typically suggest unstable acoustic environments. However, Site 2's secondary spread of clustered outliers requires further scrutiny, especially given the similar clustering observed in its average dB levels. Sites 3 and 4 have more consistent frequency levels with fewer outliers, while Site 5, despite having the lowest median frequency, shows moderate variability and a distinct clustering of outliers.

Outlier Analysis Results

Outlier properties were investigated by type and by event association, with summary statistics for outliers by site and event association calculated and plotted on the bar graphs exhibited in figure 13. Each data outlier is categorized as outlier_type "both," "decibel," or "frequency," indicating whether it is an outlier in both decibel and frequency levels, just in decibel levels, or just in frequency levels. Outliers occurring across different sites during the same time frame are marked with the same "event" value, with a total of 12 observed events across all outlier data. Event 1 occurred on 4/19 during the hour 07:00, Event 2 on 4/19 during the hours 09:00-11:00, Event 3 on 4/19 during hour 16:00, Event 4 on 4/20 during hour 05:00, Event 5 on 4/20 during hours 12:00-14:00, Event 6 on 4/22 during hour 21:00, Event 7 on 4/23 during hours 07:00-08:00, Event 8 on 4/23 during hour 13:00, Event 9 on 4/24 during hour 06:00, Event 10 on 4/24 during hour 09:00, Event 11 on 4/26 during hours 11:00-12:00, and Event 12 on 4/26 during hours 14:00-15:00. As represented by the data in table 15, a large proportion of data points were marked as outliers for both decibel and frequency types, suggesting that instances with unusual frequency measurements also tend to have unusual decibel measurements.

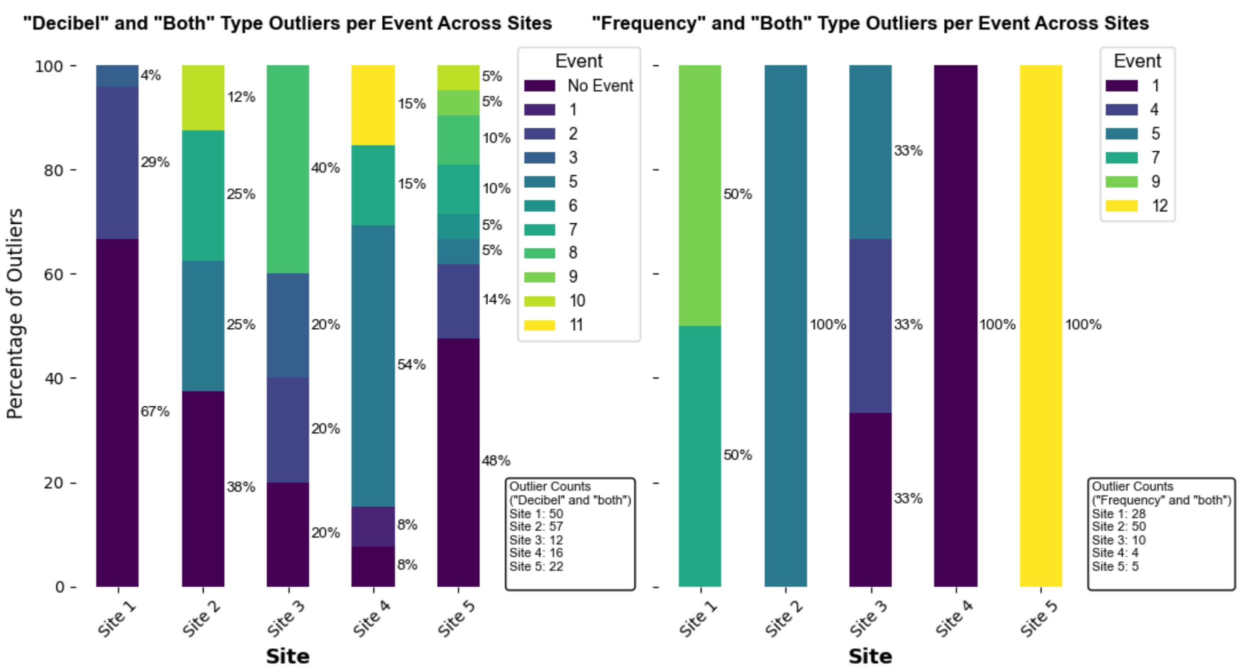


Figure 13. Summary of outliers across avg_db (left) and avg_freq (right) at various sites during notable sound events where more than one site experienced outlying audio measurements. The count amounts detail the total count of outliers being represented per site in the respective bar graph of the counts' keys. Outlier types "decibel" and "both" are represented in the avg_db graph, while outlier types "frequency" and "both" are represented in the avg_freq graph.

Table 15. Counts And Percentages of Outliers by Outlier Type (outlier_type) Across Sites

Site	Both	Decibel	Frequency	Total	Decibel (%)	Frequency (%)	Both (%)
Site 1	26	24	2	52	46.15	3.85	50.00
Site 2	49	8	1	58	13.79	1.72	84.48
Site 3	7	5	3	15	33.33	20.00	46.67
Site 4	3	13	1	17	76.47	5.88	17.65
Site 5	1	21	4	26	80.77	15.38	3.85

Site 1 experienced a balanced distribution of outliers, with both-type anomalies accounting for 50% of the total outliers, suggesting a consistent presence of simultaneous anomalies in both frequency and decibel levels at this site. The remaining outliers were primarily decibel-type anomalies (46.2%), with a small fraction being frequency type (3.85%). Site 2 had a distinct skew towards both-type outliers, which made up 84.5% of the total, possibly signaling simultaneous irregularities in both frequency and decibel levels during anomalous sound events. Site 3 showed a more diverse distribution of outliers, with 46.7% classified as both type, indicating that simultaneous frequency and decibel anomalies were somewhat common but not overwhelmingly dominant. Decibel-only outliers accounted for 33.3%, while frequency-only outliers represented 20% of the total, suggesting that this site experienced a range of different anomalous events. Site 4 was dominated by decibel-only outliers (76.5%), suggesting that most anomalies at this site were related to variations in decibel levels. Both-type anomalies were less common (17.7%), and frequency-only anomalies were rare (5.88%). Site 5 exhibited a high percentage of decibel-only outliers (80.8%), indicating that anomalies at this site were primarily driven by changes in decibel levels. The frequency-only anomalies were more prominent here (15.4%) compared to other sites, while both-type anomalies were least common (3.85%).

Each site's experience of sound events is better represented in figure 14, with the outlier profile of each site segmented by event designation. It is evident that a significant proportion of outliers across all sites have no event designation, meaning they were unique to an individual site. This is particularly pronounced in Sites 1, 2, and 5, where "No Event" outliers constitute 61.5%, 36.2%, and 38.5% of the total outliers, respectively. This suggests that a large portion of the outliers are not linked to any specific event.

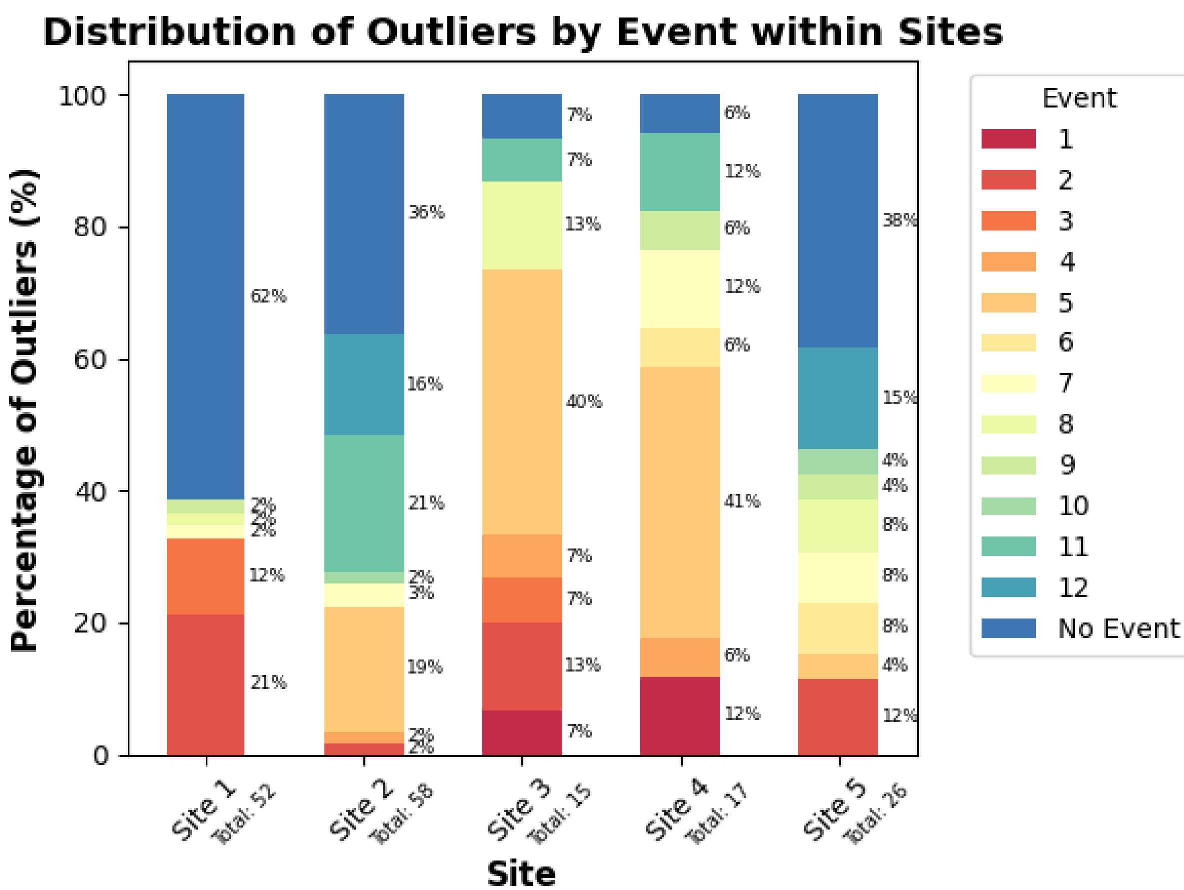


Figure 14. Stacked bar chart illustrating the distribution of outliers by event within each site. The data is segmented by event, with each bar divided by the percentage contribution of each event to the total number of outliers for the site. Total outlier count is listed under each site along the x-axis.

Variability in event distribution does appear unique across sites. For Site 1, the plurality of outliers with event designation are associated with Event 2 (21.2%), followed by Event 3

(11.54%), with the other events contributing less than 2% each. In Site 2, Events 11 and 5 are particularly prominent, accounting for 20.7% and 19.0% of the total outliers, respectively, with Event 12 also showing a substantial share at 15.5%. Site 3 stands out with Event 5 comprising 40% of the total outliers, while other events contribute between 6.67% and 13.3%. Event 5 dominates the distribution of Site 4, accounting for 41.2% of its total outliers, though its outliers' other event designations are more evenly distributed, each contributing 5.88% to 11.8%. Finally, Site 5 displays a relatively balanced distribution of outliers across various events, with Event 12 having the highest contribution at 15.4%, followed by Event 2 at 11.5%.

The distribution of outliers by sound event provides a new perspective from which to assess the data's sound anomalies, highlighting outlier event composition. The plurality of outliers, 38.69%, did not belong to any event, as showcased in the distinguished subplot of figure 15. This fact indicates that a large portion of the outliers were isolated to specific sites, reflecting localized disturbances rather than widespread environmental factors.

Events 2, 5, and 7 are the most diverse events, constituted by outliers over 4 different sites, suggesting that these events are possibly linked to a substantial anomaly affecting multiple sites simultaneously. Event 5 had 25 outliers, the most of any event and accounting for 14.9% of total outliers. Event 2 also displayed a high outlier count with 17 outliers (10.12%). Event 7 (with 7 outliers) constitutes around 4% of total outliers, which may indicate it was the result of a short-lived sound disturbance with a far-reaching impact. Event 11, with 15 outliers (8.93%) across 3 different sites, marks another notable event, albeit potentially more localized than Events 5 and 2. Event 12 has 13 outliers, representing 7.74% of the total outlier count. Unlike Events 2, 5, and 11, however, Event 12 includes outliers from only two distinct sites.

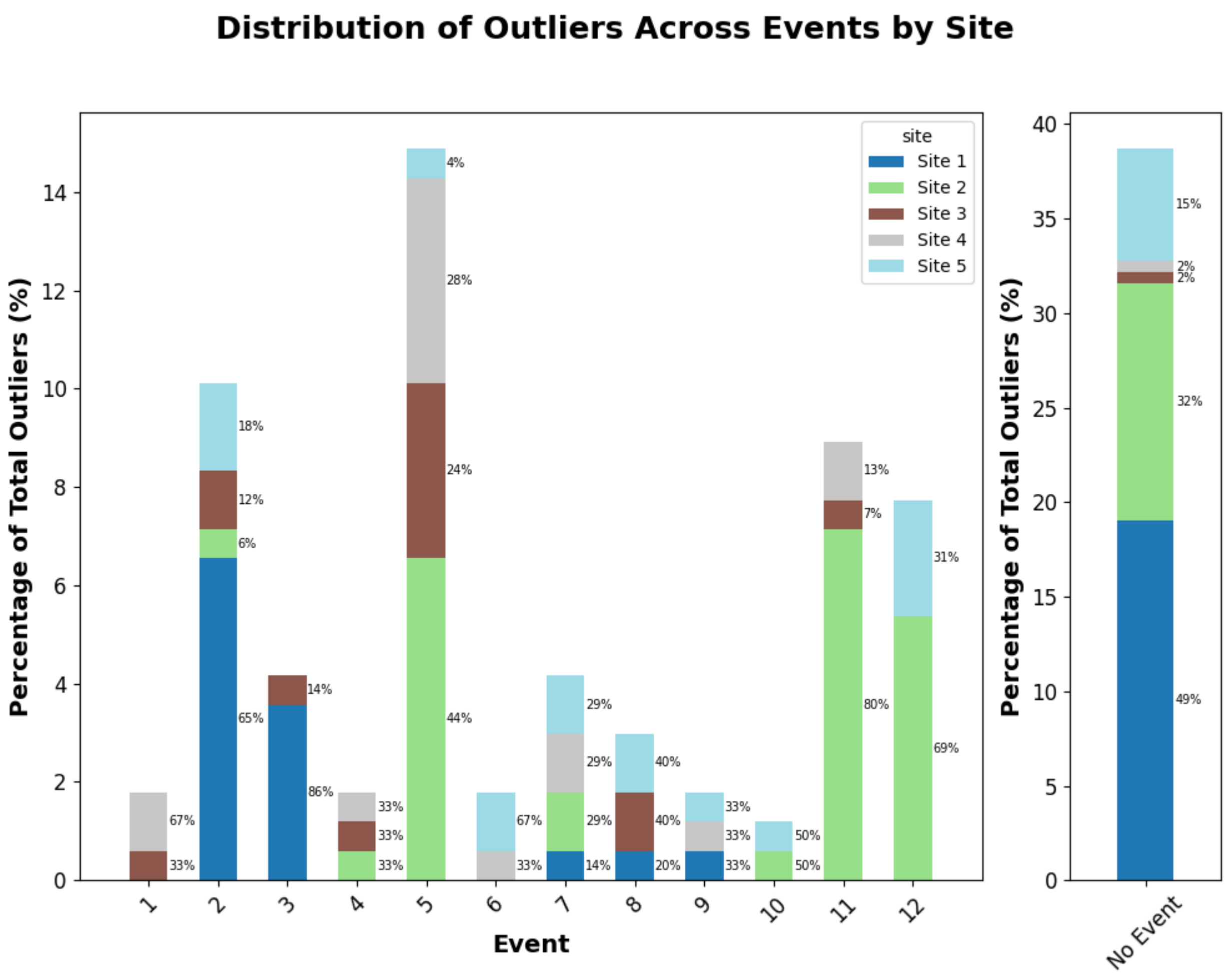


Figure 15. Stacked bar chart representing distribution of outliers by event and site. The left plot shows the percentage of outliers across events (1-12) for all outliers in the dataset, segmented by site. Each bar reflects how outliers are distributed among sites for a given event, with segments labeled by the percentage of outliers contributed by each site to the total for the event. The right plot isolates the "No Event" category, displaying the percentage distribution of outliers not associated with any specific event, also segmented by site.

Summary Statistics by Hour

The summary statistics for daily acoustic patterns, including median decibel (table 16) and frequency levels (table 17), were derived from avg_db and avg_freq aggregated by hour of day for the total dataset. As with the violin plots for summary statistics by site, the median was used as the basis for informing the line plots in figure 16 and figure 17 when analyzing avg_db and avg_freq by hourly_bin. These plots illustrate a visually pronounced pattern throughout the diurnal soundscape, with standard deviations shown by the colored bands around the lines, providing a measure of variability.

Table 16. Aggregated Hourly Median Decibel Levels (avg_db_median) by Hourly Bin (hourly_bin)

Hourly Bin	Site 1	Site 2	Site 3	Site 4	Site 5
0	-53.70	-53.05	-52.92	-50.57	-51.23
1	-53.84	-53.08	-53.03	-51.79	-51.90
2	-53.28	-53.07	-52.30	-50.78	-52.13
3	-54.33	-53.70	-54.06	-54.25	-54.69
4	-53.70	-53.64	-53.53	-54.11	-53.95
5	-52.09	-51.79	-50.11	-51.73	-52.14
6	-50.26	-50.12	-49.03	-50.44	-50.41
7	-48.85	-50.74	-49.42	-51.14	-49.46
8	-50.35	-50.11	-49.21	-50.91	-50.76
9	-49.25	-50.33	-49.56	-51.08	-51.71
10	-47.96	-51.47	-49.23	-50.89	-51.05
11	-47.13	-51.14	-48.42	-50.71	-51.77
12	-46.21	-49.92	-49.06	-51.05	-51.14
13	-47.18	-48.80	-46.88	-49.11	-50.08
14	-47.01	-48.58	-47.02	-50.43	-50.37
15	-47.63	-51.63	-49.42	-52.56	-50.96
16	-45.07	-52.05	-47.59	-49.92	-49.29
17	-43.32	-52.03	-48.92	-51.03	-50.12
18	-47.85	-52.40	-50.47	-50.82	-51.58
19	-53.13	-52.95	-51.50	-52.69	-52.17
20	-53.65	-53.42	-53.22	-53.47	-52.87
21	-53.76	-53.10	-52.68	-50.99	-51.19
22	-53.47	-53.05	-52.38	-49.73	-50.26
23	-53.62	-53.07	-52.52	-50.19	-50.83

Table 17. Aggregated Hourly Median Frequency Levels (avg_freq_median) by Hourly Bin (hourly_bin)

Hourly Bin	Site 1	Site 2	Site 3	Site 4	Site 5
0	11,129.64	11,741.70	10,974.08	9,536.33	9,752.38
1	11,187.68	11,837.91	11,160.70	9,977.22	10,221.73
2	10,888.37	11,728.84	10,613.61	9,694.31	10,089.96
3	11,298.10	11,907.56	11,503.51	10,795.41	11,027.71
4	11,027.43	11,918.34	11,210.56	10,700.71	10,681.25
5	10,409.13	11,032.60	10,214.98	9,953.30	10,166.89
6	9,702.17	10,708.77	9,713.46	9,686.46	9,702.39
7	9,653.91	10,774.09	9,531.75	9,571.76	9,473.08
8	10,354.58	10,997.37	9,516.68	9,708.19	9,889.19
9	10,079.62	10,970.68	9,945.82	10,084.14	9,682.12
10	9,941.50	11,254.12	10,087.73	10,156.23	9,649.65
11	9,541.04	11,297.65	9,960.35	10,169.84	10,028.07
12	9,891.12	10,803.96	10,186.45	10,431.97	9,913.26
13	9,878.35	9,963.85	9,674.83	10,025.88	9,103.25
14	9,132.65	9,904.24	9,395.52	10,134.54	8,011.62
15	10,120.59	11,381.25	10,159.50	10,775.48	10,218.90
16	9,524.03	11,369.96	9,837.63	10,319.68	9,778.15
17	9,091.94	11,361.35	10,081.74	10,332.55	9,846.10
18	9,905.19	11,278.81	10,442.07	10,263.27	10,209.95
19	11,003.61	11,455.47	10,721.67	10,473.96	10,264.84
20	11,114.05	11,637.47	11,106.10	10,584.67	10,140.80
21	11,019.52	11,362.49	10,732.14	9,594.45	9,185.60
22	11,007.11	11,445.02	10,747.73	9,405.93	9,232.71
23	11,002.10	11,547.44	10,794.86	9,531.53	9,326.55

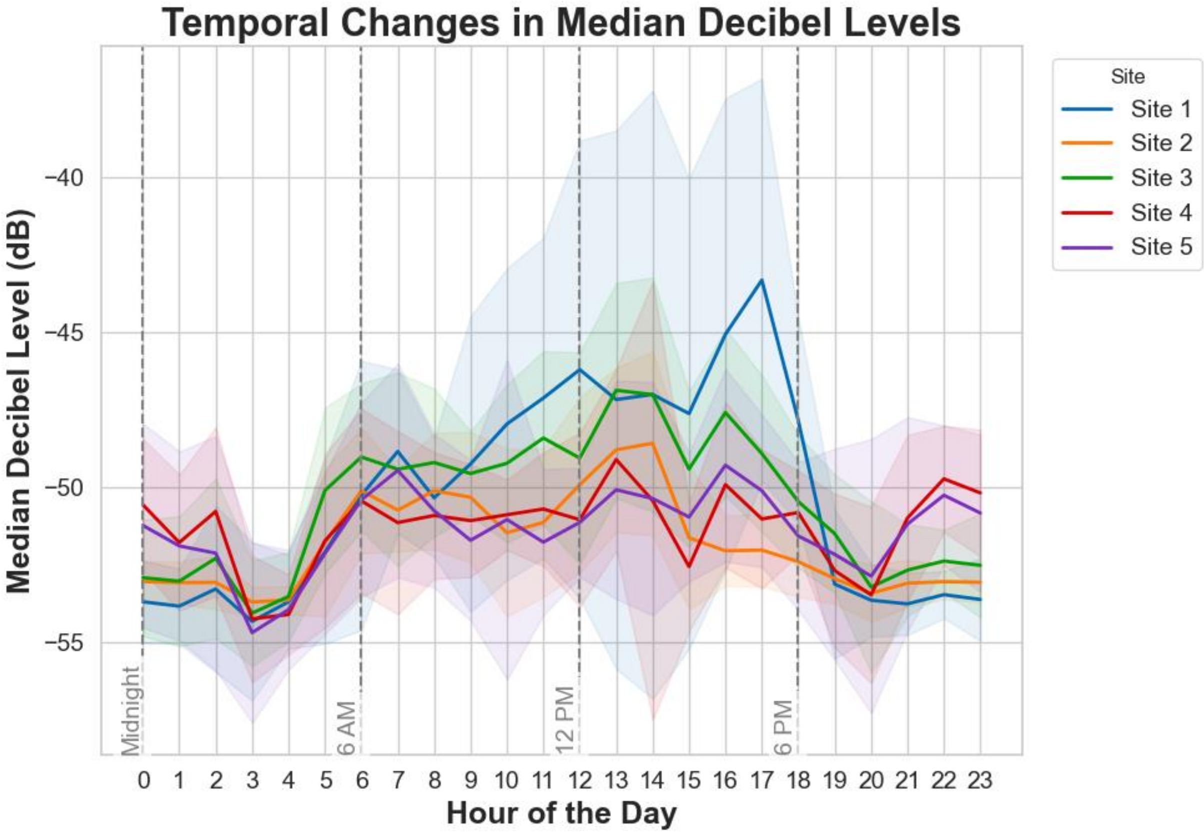


Figure 16. Line graph of median decibel levels derived from aggregated average decibel levels by hour of day for the total dataset. Standard deviation indicated by colored bands around the lines.

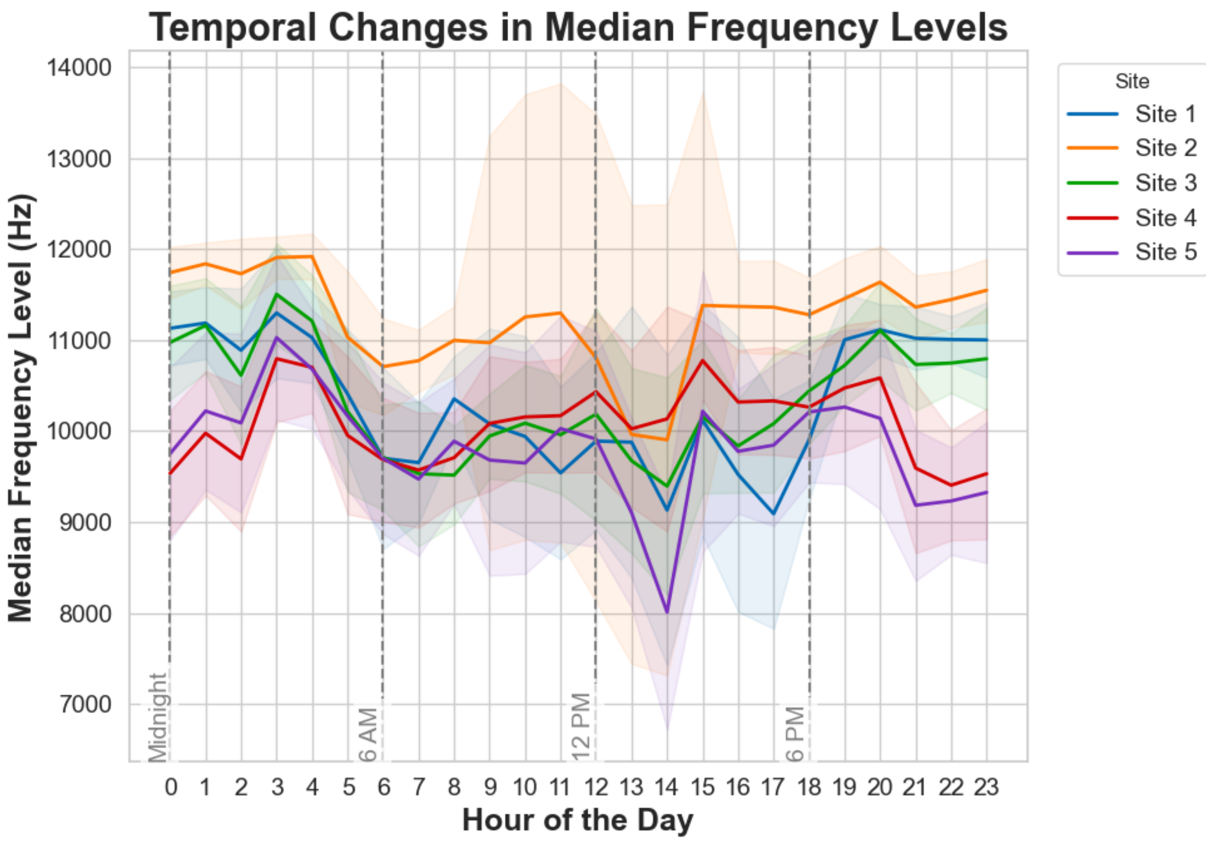


Figure 17. Line graph of median frequency levels derived from aggregated average frequency levels by hour of day for the total dataset. Standard deviation indicated by colored bands around the lines.

Figure 16 displays how aggregated hourly median decibel levels ("avg_db_median") exhibit noticeable fluctuations throughout the day across all sites. Generally, sites demonstrate lower avg_db_median during early morning hours, with the approximate lowest values just above -55 dB recorded around hourly_bin 3 and 4, suggesting quieter conditions between 3 and 4 AM. Following this dip in avg_db_median, all sites appear to experience a gradual increase in noise as the day progresses. A peak in diurnal noise levels is observed during the time between hourly_bin 12-16, particularly at Site 1, which experiences avg_db_median greater than -45 dB during this time, Site 2, and Site 3. A secondary dip in avg_db_median occurs at hourly_bin 20, which saw decibel values only slightly above those of the early morning dip at around -53 dB. In the time between the two lowest dips in noise levels, starting after hourly_bin 20, avg_db_median at Site 4 and Site 5 notably increase and decrease in an arching pattern until hourly_bin 1, though all sites appear to experience this trend to varying degrees.

Interestingly, site noise levels exhibit a wide range of variability throughout a 24-hour period, as evidenced by the clear separation of all lines at most hourly bins observed in figure 16, except at the two dips during hourly_bin 3-4 and hourly_bin 20. At these points, all site lines converge such that there are relatively miniscule discrepancies apparent across site noise levels. The avg_db_std (standard deviation of avg_db), visualized by the colored bands surrounding the plotlines in figure 16, indicates variability in noise levels. When taking the range of avg_db_std across sites into account, the hours between 3 and 4 AM clearly exhibit the least amount of variability in noise levels. However, all noise following 6 PM—until 8 AM the next day—appears to exhibit roughly half the amount of variability observed during the opposing 10-hour timeframe of 8 AM - 6 PM.

Figure 17 showcases variation in avg_freq_median values across site and time that is rather similar in its temporal trends to the avg_db_median values displayed in figure 16. Early morning hours (e.g., hourly_bin 0-4) see higher avg_freq for all sites relative to each site's overall frequency trends. A sharp decrease in avg_freq begins at hourly_bin 4 for all sites, with levels dipping to a low point around 9,500 Hz at hourly_bin 6-7 for all locations except Site 2 which experiences a congruent decrease but with a much higher low point around 10,900 Hz. Beginning at hourly_bin 8, variability in avg_freq_median greatly increases across all sites, particularly at Site 2 where variability increases approximately threefold. Despite variability increasing significantly across all sites at this time, a general pattern in avg_freq_median continues to be shared closely until hourly_bin 12 as depicted by the similarity in line behavior for Site 2, 3, and 4 especially. Lines for Site 1 and 5, while deviating slightly from the shared rhythm of the other three, maintain similar avg_freq_median with Site 3 and 4.

An extreme drop in avg_freq_median takes place from hourly_bin 12 to 14, with the lowest values for all sites recorded at hourly_bin 14. Site 5 is particularly impacted here, claiming the lowest recorded avg_freq_median of all sites at around 8,000 Hz, over 1,000 Hz less than the next lowest avg_freq_median occurring at Site 1. All frequency levels increase at hourly_bin 15, and avg_freq_median lingers around the same Hz value ranges experienced prior to the decrease between hourly_bin 12 and 15 at all sites but Site 1, which experiences quite a notable decrease at hourly_bin 17 when compared to its pre-12 PM levels. Gradually, avg_freq_median increases or generally stabilizes across all sites by hourly_bin 20. To varying degrees, all sites experience a lowering and rising in avg_freq_median between hourly_bin 20 and hourly_bin 1, like a reverse of the arching of avg_db_median observed over the same timeframe in figure 16. All sites' frequency levels peak between 3 and 4 AM.

Statistical Significance Testing

The Kruskal-Wallis test results indicated significant differences in both avg_db ($H = 77.43$, $p < 0.0001$) and avg_freq ($H = 744.00$, $p < 0.0001$) when grouped by site, suggesting that both average decibel levels and average frequency levels vary significantly depending on the site (table 18). Significant differences in both avg_db ($H = 972.78$, $p < 0.0001$) and avg_freq ($H = 520.15$, $p < 0.0001$) were also observed when grouped by hourly_bin, suggesting that both average decibel levels and average frequency levels vary significantly depending on the time of day.

Table 18. Kruskal-Wallis Test Results

Test	Variable	Group	Statistic	Adjusted p-Value	Significant
Kruskal-Wallis Test	avg_db	site	77.43	< 0.001	Yes
Kruskal-Wallis Test	avg_freq	site	744	< 0.001	Yes
Kruskal-Wallis Test	avg_db	hourly_bin	972.8	< 0.001	Yes
Kruskal-Wallis Test	avg_freq	hourly_bin	520.2	< 0.001	Yes

Dunn's post hoc test results for avg_db by site, which are detailed in table 19, revealed that 7 out of 10 pairwise comparisons were significant, specifically, the comparisons between Site 1 and Site 2, Site 1 and Site 3, Site 2 and Site 3, Site 2 and Site 4, Site 2 and Site 5, Site 3 and Site 5, and Site 4 and Site 5 showed significant differences (adjusted p-values ranging from <0.001 to 0.003). In contrast, the comparisons between Site 1 and Site 4, Site 1 and Site 5, and Site 3 and Site 4 were non-significant (adjusted p-values of ~1).

Table 19. Dunn's Post Hoc Test Results for Average Decibel Levels (avg_db) by Site

Group 1	Group 2	Variable	Z	Adjusted p-value	Significant
Site 1	Site 2	avg_db	5.244	< 0.001	Yes
Site 1	Site 3	avg_db	-3.444	0.003	Yes
Site 1	Site 4	avg_db	0.248	1.00	No
Site 1	Site 5	avg_db	0.001	1.00	No
Site 2	Site 3	avg_db	-8.698	< 0.001	Yes
Site 2	Site 4	avg_db	-4.991	< 0.001	Yes
Site 2	Site 5	avg_db	-5.245	< 0.001	Yes
Site 3	Site 4	avg_db	3.688	0.001	Yes
Site 3	Site 5	avg_db	3.446	0.003	Yes
Site 4	Site 5	avg_db	-0.247	< 0.001	No

Dunn's post hoc test results for avg_freq by site, which are detailed in table 20, revealed that 9 out of 10 pairwise comparisons were significant, with the only non-significant comparison being between Site 1 and Site 3 (adjusted p-value of ~1). All other pairwise comparisons showed significant differences (adjusted p-values ranging from <0.001 to 0.002).

Table 20. Dunn’s Post Hoc Test Results for Average Frequency Levels (avg_freq) by Site

Group 1	Group 2	Variable	Z	Adjusted p-value	Significant
Site 1	Site 2	avg_freq	-15.51	< 0.001	Yes
Site 1	Site 3	avg_freq	1.004	1.00	No
Site 1	Site 4	avg_freq	6.027	< 0.001	Yes
Site 1	Site 5	avg_freq	9.634	< 0.001	Yes
Site 2	Site 3	avg_freq	16.52	< 0.001	Yes
Site 2	Site 4	avg_freq	21.54	< 0.001	Yes
Site 2	Site 5	avg_freq	25.18	< 0.001	Yes
Site 3	Site 4	avg_freq	5.024	< 0.001	Yes
Site 3	Site 5	avg_freq	8.629	< 0.001	Yes
Site 4	Site 5	avg_freq	3.596	0.002	Yes

GAM Analysis

To truly account for the temporal nature of hourly bins in determining the significance of any observable patterns in avg_db or avg_freq over time, generalized additive models (GAMs) were used to examine diurnal patterns in acoustic measurements aimed to elucidate the relationship between the response variables—avg_db and avg_freq—and the time of day, represented by the hourly_bin variable. For both avg_db and avg_freq, the model included a 1-hour lagged variable to account for the influence of the previous hour's measurements.

The avg_db model’s intercept estimate was -22.74, with a standard error of 0.758 and a highly significant t-value of -29.99, indicating that the baseline decibel level is robust (table 21).

The lagged variable (lag_avg_db) had a coefficient of 0.55, with a t-value of 36.65 and a p-value less than 2e-16, signifying a strong positive relationship between the current hour's avg_db and that of the previous hour. The smooth term for hourly_bin, with an effective degrees of freedom (edf) of 7.43 and a significant F-value of 19.75, highlighted a significant nonlinear effect of the time of day on avg_db. The adjusted R-squared value of 0.437 suggests that the model explains 43.8% of the variance in avg_db, with a generalized cross-validation (GCV) score of 8.231 and a scale estimate of 8.206, based on 3,102 observations.

Table 21. Average Decibel Levels (avg_db) GAM Analysis Results

Section	Parameter / Term	Estimate / Value	Standard Error	t Value / F Value	p-Value
GAM Analysis Results	Intercept	-22.7	0.758	-29.99	< 0.001
	Lag_avg_db	0.55	0.015	36.65	< 0.001
Smooth Term Results	s(hourly_bin)	7.43	9 (Ref.df)	19.75	< 0.001
Model Performance Results	Adjusted R-squared	0.437			
	Deviance Explained	43.8%			
	GCV Score	8.231			
	Scale Estimate	8.206			
	Number of Samples (n)	3102			

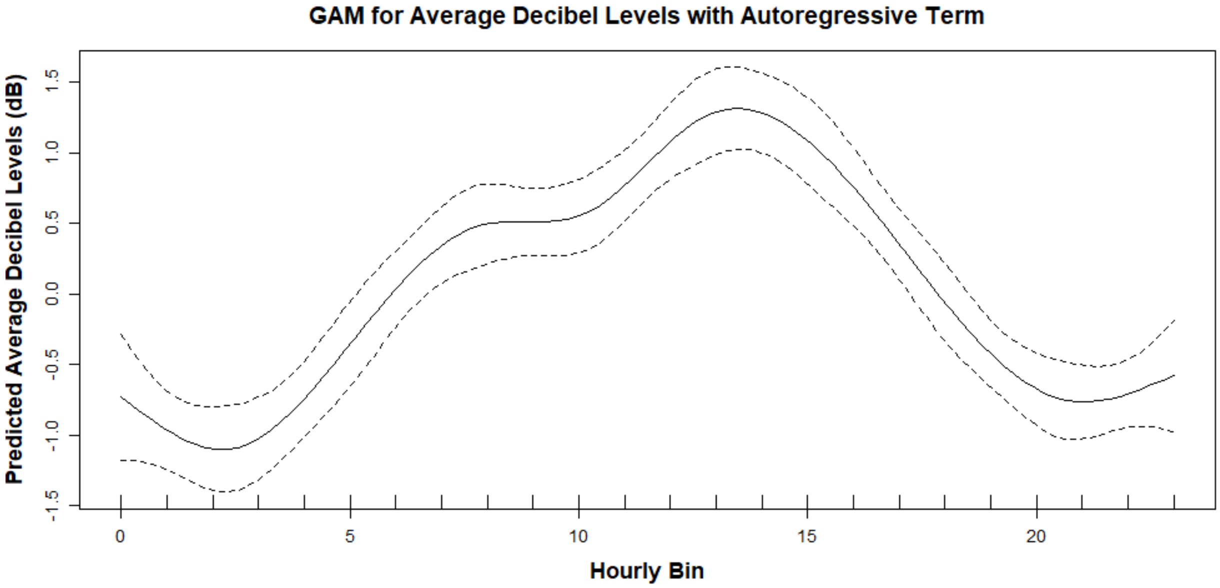
For av_freq, the model's intercept estimate was 3,182, with a standard error of 133.6 and a t-value of 23.82, demonstrating a significant baseline frequency level (table 22). The lagged variable (lag_avg_freq) had a coefficient of 0.688, with a t-value of 52.92 and a p-value less than 2e-16, indicating a strong positive correlation between the current and previous hour's avg_freq. The smooth term for hourly_bin, with an edf of 7.189 and an F-value of 8.096, showed significant nonlinear effects of time on avg_freq. The adjusted R-squared value indicates that the model explains 54% of the variance in avg_freq, with a GCV score of < 0.001 and a scale estimate of < 0.001, based on 3,102 observations.

Table 22. Average Frequency Levels (avg_freq) GAM Analysis Results

Section	Parameter / Term	Estimate / Value	Standard Error	t Value / F Value	p-Value
GAM Analysis Results	Intercept	3182	133.6	23.82	< 0.001
	Lag_avg_freq	0.688	0.013	52.92	< 0.001
Smooth Term Results	s(hourly_bin)	7.189	9 (Ref.df)	8.096	< 0.001
Model Performance Results	Adjusted R-squared	0.539			
	Deviance Explained	54%			
	GCV Score	< 0.001			
	Scale Estimate	< 0.001			
	Number of Samples (n)	3102			

The results of the GAM analysis reveal significant diurnal patterns in both avg_db and avg_freq, indicating that sound measurements are not random throughout the day but follow a recognizable pattern. The strong positive coefficients for the 1-hour lag variables suggest that avg_db and avg_freq are significantly influenced by the previous hour's values, indicating a notable degree of autocorrelation in the soundscape data. For avg_db, the model explains 43.8% of the variance, reflecting the considerable, though not exhaustive, explanatory power of the time-of-day effect. The smooth term for hourly_bin further underscores the nonlinear diurnal patterns in sound levels, with specific times of the day showing peaks or troughs (fig. 18). In contrast, the avg_freq model explains a somewhat greater proportion of variance (54%), suggesting that frequency levels are more stable and consistent over time, with clear diurnal patterns.

In figure 18, the smooth line, which represents the predicted avg_db, shows two significant peaks. The first peak occurs between hourly_bin 7 and 8, and the second, more pronounced peak appears around hourly_bin 13. These peaks suggest that noise levels are higher during the times 7-8 AM and 1 PM, which might correspond to increased activity in the sanctuary or environmental factors influencing sound levels. The 95% confidence intervals, represented by the dashed lines, indicate the uncertainty around the predictions. The relatively narrow intervals, hovering around an uncertainty range of 1 dB across all hours, suggests that the model's predictions are consistently reliable, reflecting relatively consistent diurnal patterns in the data. Fluctuations in avg_freq throughout the day are observed in contrast to avg_db, exhibiting a notable dip in the plotted smooth line between hourly_bin 7 and 8, followed by a more pronounced dip around hourly_bin 13. The confidence intervals are similarly consistent to avg_db for avg_freq across all hours, with an approximate uncertainty range of 250 Hz.



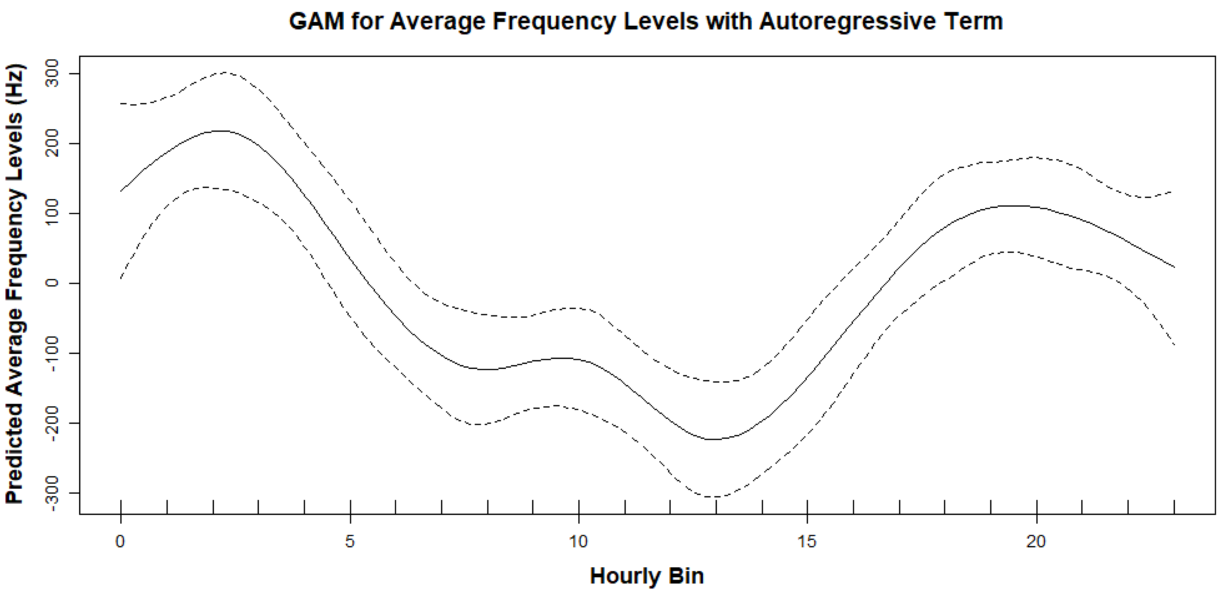


Figure 18. Plots generated from the generalized additive models (GAMs) with an autoregressive term. GAM plots provide insights into the diurnal patterns of average decibel levels (dB) and average frequency levels (Hz) at Wolf Haven across a 24-hour period. The models' "smoothed terms" appear as solid black lines while the 95% confidence intervals appear as dashed lines.

Chapter 5 - Discussion

The foundational soundscape analysis presented here, supported in no small part by the Wolf Haven team, has produced insights into the once-cryptic sound experiences of the sanctuary's resident canids. The initial research questions have been answered: 1) Average decibel and frequency levels are different across the five recording locations within the sanctuary, and 2) There are in fact notable patterns in frequency and decibel levels throughout the day. The following sections will include research results realized in spatial–temporal formats and supported by qualitative synthesis of acoustic measurements for each of the study's five recording locations across time. This research was not without its unique troubles, and the challenges and limitations faced in pursuit of answering all manner of sound-related queries are discussed in *Challenges and Limitations*. Should research continue in a similar manner at the sanctuary, improvements in methodology were considered in response to the tribulations endured and documented here. In response to the more promising avenues that this scientific investigation has opened but not explored to their full potential, future research suggestions will be detailed in the hopes of achieving an even greater understanding of the sound environment at Wolf Haven.

Sound Measurements Across Time

The animated maps created from the study data showcase clear sanctuary-wide trends in the diurnal patterns of both sound intensity and frequency, with additional insight into nuanced site-specific fluctuations (see appendix D, video D1 and video D2). Routine inspection of audio files that was conducted throughout multiple aspects of data analysis resulted in consistent observations of acoustic phenomena that align with the analytical results produced for the research.

The early morning hours, particularly between 3 and 4 AM, are distinguished in Video D1 by the cool hues with the lightest shades, representing the lowest decibel levels, suggesting a period of relative quietude. Unsurprisingly, this time frame corresponds with minimal human activity; however, reduced geophony and biophony also contribute to the relative silence (fig. 19). Throughout the night, no wind noise of substance was observed via manual inspection. The frequencies that visually dominated nighttime spectrograms typically came from the sound sources of insects and frogs. Outlying sound events for night hours were often the result of wolf and coyote chorus, though distant train sound and helicopter blade chop were also observed, especially during periods of deep silence from biophonic sources such as between 3 and 4 AM.

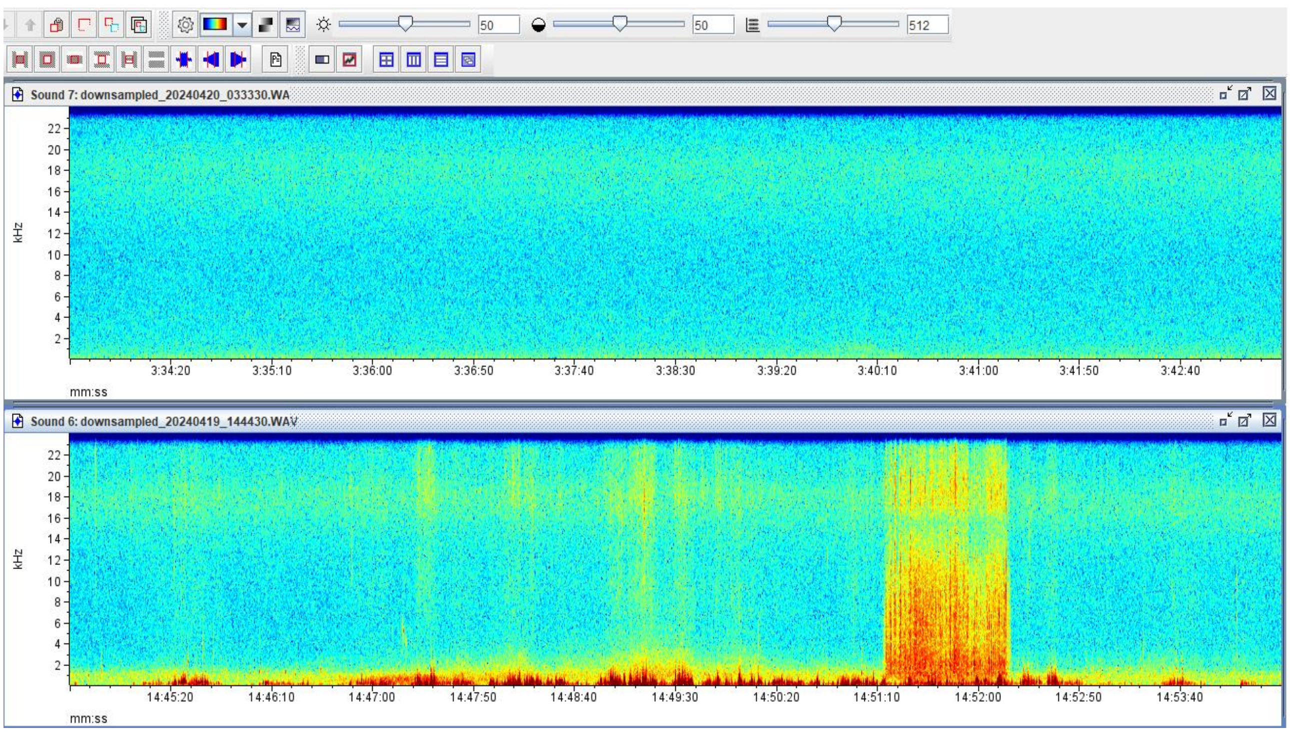


Figure 19. A comparison of two spectrograms in a Raven Pro 1.6.5 workspace for audio files associated with Site 1: one recorded beginning 03:33:33 on 4/20/24 (top), and one recorded beginning 14:44:30 on 4/20/24 (bottom). The intensity of sound is visualized along a color spectrum with cooler hues representing more subdued audio and warmer hues representing more intense sound, and frequency (kHz) is displayed along the y-axis, with variation in sound intensity displayed across different frequency ranges. The bottom spectrogram is visualizing wind noise around 0-2 kHz range as spikes of deep red, and chainsaw activity from around 14:51:15 to 14:52:15. The top spectrogram is characterized by a distinct absence of variation in the sound profile.

As the day progresses, a steady increase in sound intensity is visualized by warmer colors in video D1, peaking between noon and 2 PM across most sites (shown in orange and deep red hues), though Site 1 appears to experience continuously high decibel levels until peaking at the 4-5 PM time frame with a deep purple hue—the color representing the highest decibel levels in the defined spectrum. Per manual observation, this peak in noise levels corresponds with increased human activity characteristic of sanctuary operations. Manual inspection of anomalous noise disturbances around this time were predominately from motorized equipment and vehicles, such as chainsaws and off-road vehicles; however, instances of heavy wind were consistently present throughout the midday hours of some sites, namely Site 1, and would occasionally be the cause of decibel level outliers (fig. 19).

When looking at the sanctuary's landscape holistically, there is a remarkably strong inverse relationship between decibel levels and frequency throughout the day, illustrated most clearly in the plotted GAM results of figure 18 (see section *GAM Analysis*). A peculiar secondary peak in noise levels occurs between 7 and 8 AM, though much less pronounced than the larger midday peak (fig. 18). What is most intriguing about this time frame is that it is coupled with a dip in frequency levels of matching proportion. Because both the decibel and frequency levels shift slightly and simultaneously in the few hours following 8 AM, indicating a "lull" in activity, with a decrease in decibel levels and increase in frequency levels, it stands to reason that the secondary peak in noise levels observed between 7 and 8 AM aligns with the beginning of the workday for Wolf Haven staff. A scheduled event that results in temporary increased human activity throughout the sanctuary but that does not introduce an exceptional amount of noise to the environment, unlike chainsaws at work, is the likely culprit of this disturbance in the soundscape. Routine caring of the animals directly, which involves caretakers traversing across the whole of the sanctuary and which begins and ends at approximately the same time every day, is highly suspected.

Video D2 visualizes site-specific declines in frequency to levels below 10,000 Hz as early as 5 AM, highlighting impacted locations over time using warm hues. This decrease is possibly an effect of the reduction of mass insect noise manually observed during night hours, as well the beginnings of the slightly higher pitched birdsong manually observed during early morning hours. This assumption is based on manual observations only; thus, targeted data analysis would be required to confirm or reject this hypothesis.

During periods of highest sound intensity, the dominant frequencies tend to shift lower, a phenomenon characteristic of sound sources involving large, powerful forces that generate significant energy, such as the heavy wind noise depicted in figure 20 (Broner, 1978; Sullivan, 2005). Heavy machinery noise, such as that of the chainsaw event on 4/20/2024 (fig. 19), carries sound intensity across a broad frequency range; however, the greatest recorded intensity is concentrated in the sound's lower frequency ranges. Heavy wind experienced at some sites and the machinery associated with the midday hours at the sanctuary are contributors to the loud, low-pitch sound profile of this time frame.

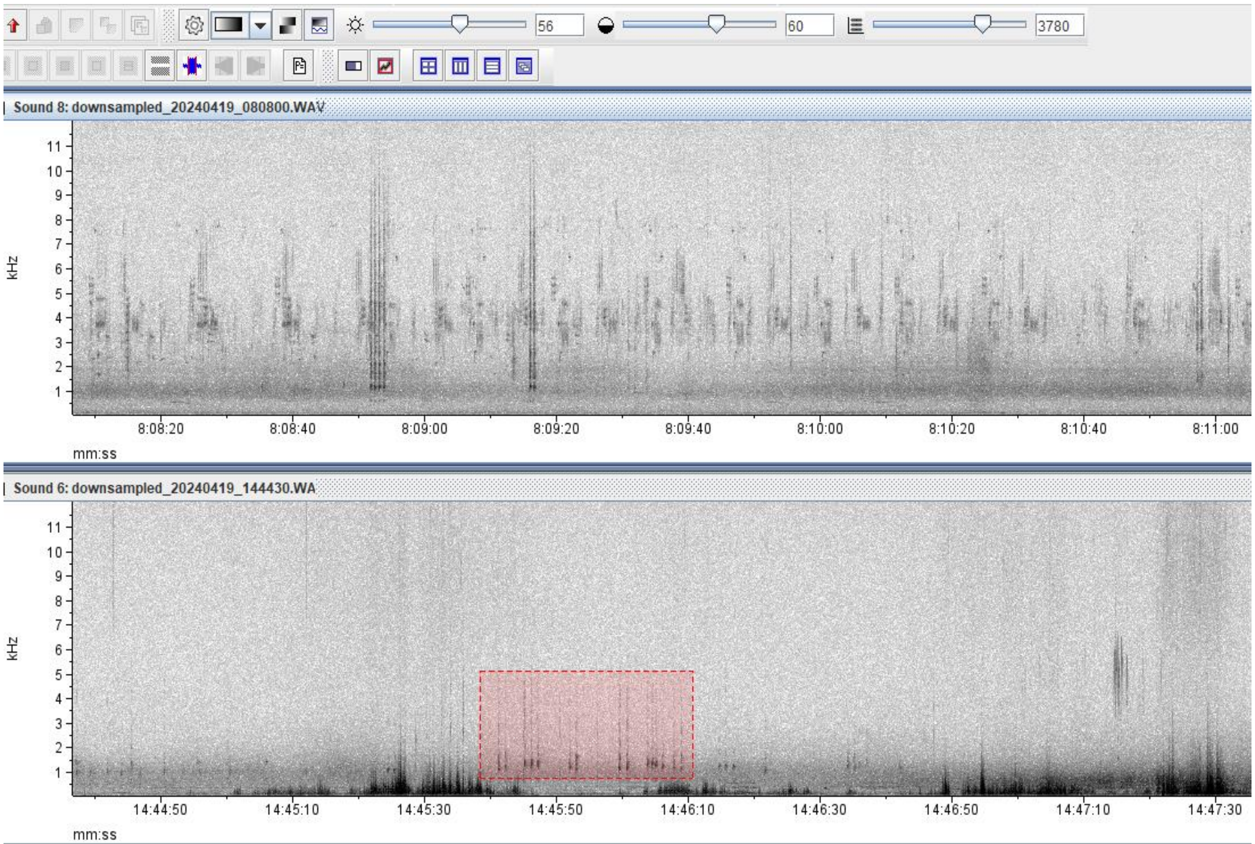


Figure 20. A comparison of two spectrograms in Raven Pro of Site 1 audio files, one recorded beginning 08:08:00 on 4/19/24 (top), and one recorded beginning 14:44:30 on 4/19/24 (bottom). Sound intensity is visualized by shading, with darker shades indicating greater sound intensity. Frequency (kHz) is displayed along the y-axis. The top spectrogram is of songbird vocalization, characterized by energetic bursts of sound across a wide range of mid to high frequency. The bottom spectrogram captures wind noise, characterized by intense, consistent sound of lower frequency. Raven vocalizations are highlighted in red.

Conversely, higher frequency sounds, characteristic of small, delicate, or refined sound sources, such as those of passerine birdsong (fig. 20), are more closely associated with the sanctuary's quieter periods (Bradbury and Vehrencamp 2011). This dynamic suggests that the sanctuary's soundscape is heavily influenced by both the temporal distribution of natural sounds and the periodic intrusion of anthropogenic noise.

Sound Measurements Across the Sanctuary

Originally, it was hypothesized that Site 5 would serve as a particularly noisy baseline for all other sites to "measure up to" to determine their relative noisiness. This was likely due to the mental association both Wolf Haven staff and I had between Site 5, a.k.a. “The Public Route,” and human activity. Of course, audio recordings were conducted during the off-season when regularly scheduled guided tours that utilize this route are not in operation; thus, Site 5 did not experience the same acoustic inputs that it would when tours are conducted. No site in particular was assumed to be especially quiet prior to this investigation.

In order to garner the clearest picture of decibel level variation across the sanctuary, a comparative analysis incorporating both mean and median averaged decibel levels by site was performed and visualized (fig. 21). The same sort of comparative analysis was conducted for the mean and median averaged frequency levels for all sites (fig. 22). When interpreted together with consideration of outlier analysis results, these analyses combine the study’s resulting summary statistics in a broadly holistic manner. From this multilayered perspective, it was observed that Site 5, while boasting a moderate mean value, ranked low in terms of its median value compared to all but Site 2. Additionally, comparative analysis of frequency levels resulted in both low mean and low median values, defining a peculiar low-intensity, high-pitch sound profile for Site 5. The bulk of Site 5’s average decibel values are concentrated on the lower end of decibel levels, but there were enough high values to increase the mean beyond the median. The outlier analysis results for Site 5, showcasing a relatively balanced distribution of outlier by sound event across a total of eight events for “decibel” and “both” type outliers, compliment the results of the comparative analyses by suggesting that Site 5 is receptive to sound inputs from across the landscape (see section *Outlier Analysis Results*, fig. 13). This is a sensible discovery, given its rather central location relative to all other sites.

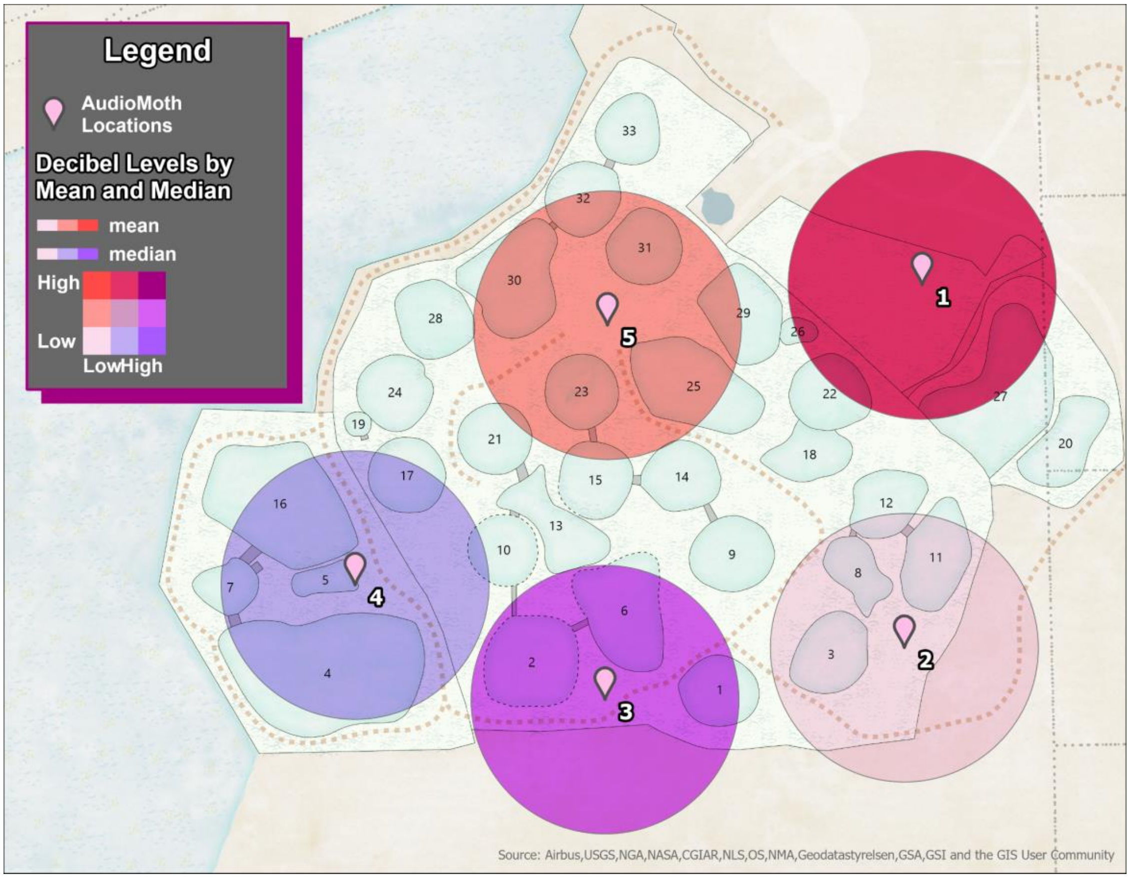


Figure 21. Depiction of the recording sites within the context of the sanctuary landscape. The acoustic ranges (50 m radius) of the AudioMoth devices, represented by surrounding circles, are colored according to the bivariate color scheme indicating differences in mean and median avg_db levels within and across sites.

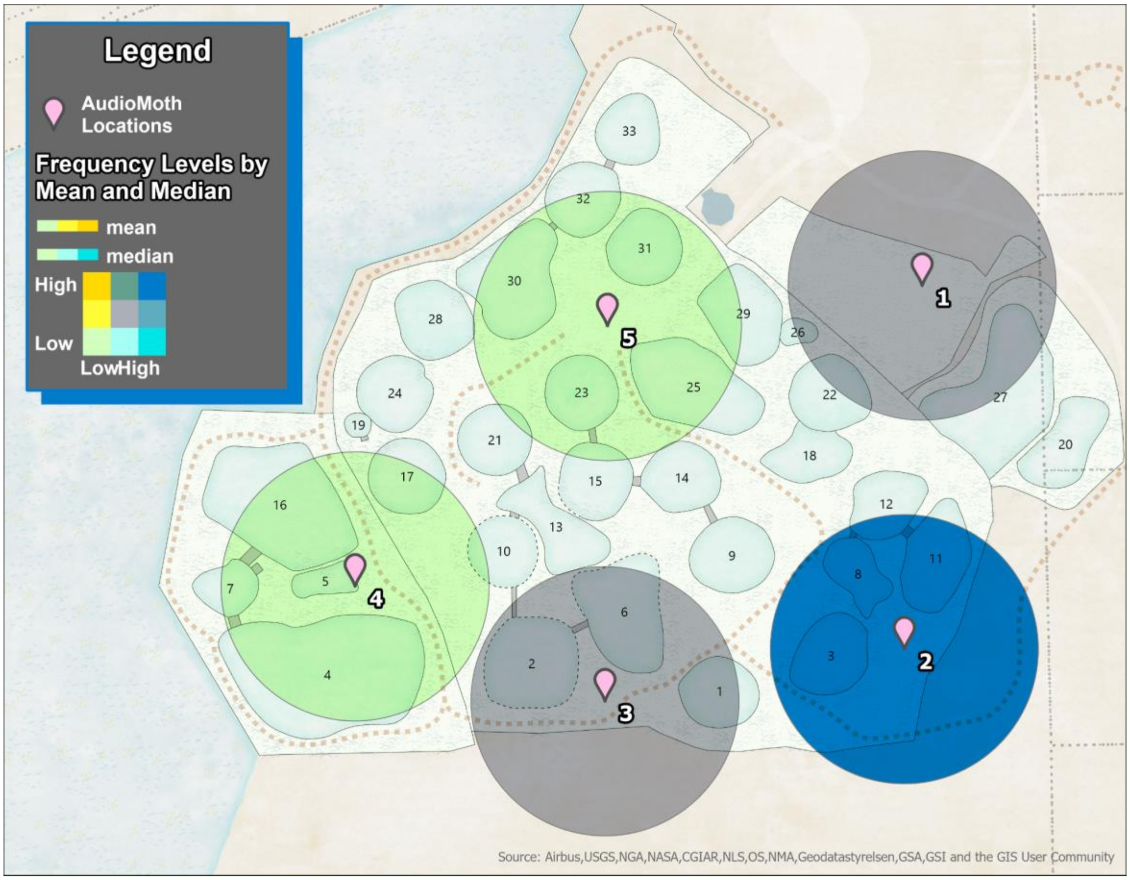


Figure 22. Depiction of the recording sites within the context of the sanctuary landscape. The acoustic ranges (50 m radius) of the AudioMoth devices, represented by surrounding circles, are colored according to the bivariate color scheme indicating differences in mean and median avg_freq levels within and across sites.

Conversely, Site 4's experience was characterized by moderate median and low mean decibel levels—in this respect, sites 4 and 5 experienced mid-range sound intensity. A higher median than mean in terms of decibel levels indicates that the site's data is mostly composed of higher values, but a concentration of lower values sizeable enough to shift the mean is present—the "bottom-heaviness" of Site 4's violin in figure 11 is a testament to this notion (see section *Outlier Analysis Results*). Site 4 shares additional similarity with Site 5 in its low median frequency level and its low mean frequency level, though, though it differs from Site 5 in that it experienced the second lowest outlier count, with sound events appearing rather specific to its southwestern location within the sanctuary (i.e. sharing very similar event designation distributions with the neighboring Site 3; see section *Outlier Analysis* Results, fig. 14).

Sites 1 and 3 stand out as possessing sound profiles characterized by the greatest sound intensity across sites, with high mean and moderate median decibel levels for Site 1 and moderate mean and high median decibel levels for Site 3. These sites also experience both moderate mean and median frequency levels, though a glance at their respective outlier analysis results highlights a stark contrast in the acoustic experience between the two. Across all sites, Site 1 boasts the second largest total outlier collection at 52 outliers, with 62% of its total outliers belonging to no event designation, the greatest no-event-designation distribution by twenty-four percentage points. The remaining outliers with event designations are distributed across the lowest number of event designations, at five events. Such results are tentatively suggestive of a few things, one being that Site 1 is not particularly receptive to sound inputs from other regions within the sanctuary, and another being that this site experiences several localized, outlying sound events. Given its high mean and moderate median decibel levels, it is possible that the suggested outlying sound events resulted in the skew that shifted the mean higher than the median of Site 1's data. The sound inputs that make up Site 1's overall sound profile are likely quite varied in terms of sound source, given the mid-range frequency levels it experienced.

Site 3, with its moderate mean and high median decibel levels, may be more likely to experience greater sound intensity at any given time when compared to Site 1, but a large portion of its decibel level data is composed of rather low values. The violin plot in figure 11 supports the concept that while Site 1 indeed displays a range of many low values that exceed the lowest values observed at Site 3, it also displays an exceptional number of high decibel values well beyond the range of Site 3's greatest decibel values. As previously alluded to, the outlier analysis results for Site 3 are quite comparable to those for Site 4, with multiple similar outlier distributions in terms of event designation as well as a small outlier count of 15—the smallest, in fact. Site 3's moderate mean and median frequency levels could be an effect of sound source diversity.

The sound profile of Site 2, with its low mean and median decibel levels and high mean and median frequency levels, suggests that this site experiences a distinctly quiet sound environment dominated by high frequency sounds. A sizable portion (36%) of Site 2's acoustic outliers have no event designation, indicating a more localized sound profile, which is further supported by the interesting lack of balance among its outliers' event distribution (fig. 14). An incredible 58 outliers, the largest outlier count among sites, is at first peculiar given the consistency in decibel and frequency level data for this site. However, comparison against this consistency further distinguishes Site 2's acoustic characteristics from the other locations. A detailed observation of the clustering of its outliers in figure 11 suggests that Site 2's decibel level outliers, while many, congregate entirely within a relatively small range of decibel values that are only slightly higher than most of its data range. An interesting observation of outlier clustering of very low frequency level values is also observed in figure 12 (see section *Outlier Analysis Results*), separated by multiple kHz from the majority of the data. These unique qualities suggest that Site 2 hosts a very isolated sound environment, sheltered in some way from the same decibel level and frequency level variability experienced to greater degrees in all other sites. The ranges in these levels within Site 2's acoustic profile are very narrow, and its high outlier count is perhaps due to an oversensitivity to outliers as an effect of these small ranges. It would be very interesting indeed to investigate what could be contributing to its outliers of very low pitch and low intensity. Some possible sounds sources of very low pitch and low intensity include distant thunder, wind, animal footsteps, distant machinery, and environmental hums (Few 1964; van den Berg 2004; Garstang et al. 2005; Broner 1978; Humphreys 2003).

At any given time, Site 5 is likely a moderately quiet locale, at least during seasons where guided tours do not take place. By many accounts, it is sensitive to the acoustic goings-on of sanctuary life and appears especially sensitive to sound sources of low frequency and moderate-to-high intensity, which are typically anthropogenic in nature (Broner 1978; Sullivan 2005; Stansfeld and Matheson 2003). Thus, while somewhat quiet, it is one of the more unpredictable locations surveyed. Many components of Site 4's acoustic profile are not much different from Site 5, though some practical distinctions set Site 4 aside as being more acoustically segregated and notably more predictable. It experiences moderate sound intensity and low frequency levels; thus, human activity is likely a major contribution to the overall sound environment. Site 3 is among the louder locations, though possibly more diverse in the sound sources that contribute to its overall sound profile. It is quite similar to Site 4, owing to their being neighbors in a shared, relatively secluded southwestern region of the sanctuary. Site 2 is somewhat of a golden child among the surveyed locations, with its markedly predictable, quiet sound environment with seemingly little human influence. While not completely unaffected by sound events in other sanctuary locations, noise that is not especially localized is buffered to a much greater extent than observed at any other site. Site 1 stands out as having the most unpredictable acoustic profile, very sensitive to all manner of sound across a broad decibel and frequency spectrum. It is acoustically quite segregated from all other sites, with an environment that is uniquely perforated by multiple extreme, anomalous sounds.

Applications for Sanctuary Master Planning

In sum, Site 1 is the poorest choice for maintaining a calm, naturalistic environment, while Site 2 excels in these regards. Site 5's acoustic environment is decently quiet, though relatively unpredictable at the time of the recordings, with a propensity to change during tour seasons. Sites 3 and 4 are similarly predictable, with Site 3 proving to be slightly louder and more varied in sound source. At face value, these results and their implications for sanctuary management are straightforward; however, some nuances should be discussed that would explain some of the reasoning behind these findings.

The locations of the AudioMoth recording devices for Site 1 and Site 2 are rather different from the others. The devices for Sites 3, 4, and 5 were placed adjacent to one or more service paths, which are frequented by Wolf Haven staff and their motorized transportation. The recorder for Site 1 was positioned upon a hill within an open field, absent of trees and barren of much foliage due in part to the season when recordings took place. The field sits outside of the main sanctuary grounds, separated by at least one wall of solid wooden fencing. The recorder for Site 2 was placed in a grove of trees and ferns nestled behind a few wolf habitats, away from service paths. Given this context, it is no surprise that the results position Site 1 as separate, loud, and unpredictable and Site 2 as protected and naturalistic.

Given these considerations, the results of the research provide valuable information beyond the isolated sound bubbles of this paper's maps. Site 2 is not a fair representation of the general soundscape of the southeastern region of the sanctuary when compared to other sites, to be sure, but its acoustic measurements are a testament to the powerful efficacy of foliage and perhaps also uneven terrain as natural sound buffers. Site 1, while loud and unruly in its sound profile, provides insight into the efficacy of artificial sound buffers with its uniquely segregated acoustic environment, which likely resulted from the surrounding built environment. By virtue of the barren field it encompasses, it, too, bolsters the importance of foliage in noise reduction, and the elevated plane upon which its recorder was set is another variable in the overall soundscape discussion. These considerations provide a shift in the perspective of the sanctuary's soundscape beyond the impact of regionality within the landscape toward the immediate tangible characteristics within its regions, such as proximity to service paths, vegetation density, built structures, and terrain.

Sites 3, 4, and 5 and the comparisons drawn between them are still fully viable components of the soundscape summary. When considered apart from Sites 1 and 2, acknowledging the similarities in service road proximity and the differences in regionality, it is deduced that Site 4 encompasses a relatively quiet section of the sanctuary with a localized sound environment. It is possible that certain unaccounted-for variables, such as exact proximity to service paths compared to other sites, or the consistency and duration of human activities occurring within the site compared to others, have resulted in the domination of lower-pitched sounds at Sites 3, 4, and 5. Thus, it is difficult to gauge an accurate representation of the types of sounds being experienced at these sites based on the frequency level comparisons drawn. Focusing on the decibel levels and spread as depicted in figure 11, it is at least clear that the sound intensity of Site 4, and to a similar extent Site 3, is rather consistent. Site 3, however, does experience somewhat elevated decibel levels of greater variability. Site 5, though not especially loud on most occasions, has a sound environment that is subject to more influences from surrounding locations. It would be premature to draw conclusions about Site 5 before additional audio data is collected during tour seasons.

For the purposes of sanctuary management, it is reasonable to posit Site 4 as belonging to a region within the landscape that is promising in terms of a relatively isolated acoustic experience for resident wolves. Site 3, with its comparable consistency in sound levels, may be worth considering for improvements in sound reduction should increased sound buffering and isolation be a concern. Site 5 is the location for wolves and coyotes presumed to be more acclimated to human presence and ineligible for conservation breeding or release. As such, Site 5's variable and influenced sound profile may not be of great concern to the objectives of Wolf Haven management. If it is ever intended as housing for more sensitive animals, however, it should be noted that it is not currently the most optimal sound environment for wolves who require a more isolated acoustic experience, and extra care would need to be taken to improve sound reduction at this site due to its centrality. As it stands, Site 5 is not especially loud during times without tours. It is yet unknown exactly how the region that Site 2 encompasses compares to Sites 3, 4, and 5 given the incongruence in recording device placement; however, the recording location provides an example of what an environment with optimal acoustic conditions consists of, which could inform the future implementation of naturalistic sound buffers in the sanctuary. Site 1 is currently incompatible with a naturalistic acoustic experience—if developments are considered for Site 1 that would call for such an experience, significant remediation of the site for sound mitigation would be required.

Challenges and Limitations

Roadblocks were met both during both the data collection phase and the data analysis phase of the research concerned with processing acoustic characteristics. Upon final recovery of the recording devices, it was discovered that the device for site 2 had been incorrectly placed in a backward position within the weatherproof casing, causing the microphone to be misaligned and unable to capture sound through the designated permeable film.

To evaluate the extent of this issue, average decibel and frequency levels were calculated for each site across all recording periods. The analysis revealed that site 2 experienced the most substantial differences when comparing the final recording period (4) to earlier ones (1-3), with an average increase of 4.48 dB in decibel levels and a decrease of 5,322.61 Hz in frequency levels, the greatest changes among all sites. Additionally, manual audio and visual inspections confirmed these discrepancies for site 2 during period 4. The inspection also identified chronic recording anomalies at site 5, lasting several days and affecting the recording timeline during period 4, which spanned from the afternoon of April 26th to the afternoon of April 29th. Because of this, audio recorded during period 4 was eliminated from all comparative analysis.

It was discovered that the sampling rate for all recordings had been inadvertently set to the AudioMoth device's default sampling rate of 48 kHz instead of the intended 96 kHz. As a result, all recordings from recording periods 1 and 2 had to be downsampled to 48 kHz to ensure consistency across the dataset. Despite this, inspection of the audio files' metadata and spectrograms as well as manual listenings of the audio revealed that potential quality discrepancies between audio files recorded at a 48 kHz sampling rate and those that were downsampled were imperceptible.

Due to heavy rainfall, the orientation of the AudioMoth devices was changed from the microphone pointing skyward to a vertical orientation with the microphone pointing outward at 10 AM on April 25th. It is possible that this change in orientation introduced variability in the data in yet unknown ways. However, the ultimate elimination of much of the data from 10 AM April 25th to the end of recording period 3 due to rain presence renders this a minor issue, potentially impacting only the audio recorded during subsequent periods of no rainfall from 9 AM to 12 PM and the hour of 9 PM on April 26th.

While performing analysis on the audio data, the hard drive where the audio files and analysis-related documentation were being stored corrupted, resulting in a delay in the analysis while files were recovered.

The utmost care was taken to ensure that all data undergoing analysis was of reliable quality, despite the setbacks discussed. The original sampling rate of 96 kHz would have provided a greater range for analyzing acoustic characteristics and enhanced overall audio quality; however, the resulting audio used for analysis was fully sufficient for the purposes of this research. Regarding the elimination of recording period 4, the loss of 3 days' worth of audio was a sizeable reduction in the sample size from which descriptive statistics could be derived. This was further exacerbated by previously discussed elimination of audio files for analysis relating to rain-induced noise disturbance, and the 48-hour period where recording unknowingly stopped on the night of the 20th. Roughly four days' worth of quality audio recordings were retained for analysis.

Another source of frustration in this study is the limitation imposed by the decibel level calculations, which were derived using a Python script without calibration to a standard sound pressure level (SPL) reference. The decibel values produced by the librosa function are based on a digital amplitude reference of 1.0, which does not correspond to real-world SPL values that are intuitive and widely recognized in acoustic research. As a result, these values lack the context needed to relate them to typical sound levels experienced by humans, such as conversational speech or ambient environmental noise.

This inability to map the calculated decibel values to an SPL introduced a key limitation: The results cannot be easily interpreted in terms of human auditory perception, which relies on an SPL as a standard metric. While this did not impede the overall analysis that aimed to distinguish general sound patterns and comparisons across time and location, without this calibration, there is a risk of misinterpretation, as the decibel levels may be mistakenly assumed to represent specific SPL values. Additionally, the lack of a direct SPL reference complicates comparisons with other studies, which typically report sound levels in terms of an SPL.

One of the greatest pitfalls that was personally faced while performing data analysis for this research was dedicating an inordinate amount of time to configuring automated sound detection and sound classification models before accepting that both greater skill in such tasks and more time than was feasible for the scope of the thesis would be required to achieve satisfactory models. Thus, there remains an incredible opportunity to perform granular analysis on the sound profiles of the sanctuary sites, which is further discussed in *Future Research Directions*.

Improvements in Methodology

Several methodological improvements can be recommended for future soundscape studies. Ensuring the correct placement and orientation of recording devices should be a top priority. A marked drop in decibel levels and increase in frequency levels following the reorientation of AudioMoths at 10 AM on 4/25/2024 suggest that rain hitting the microphones while in a “skyward” orientation is a great contributor to obstructive sound (see section *Filtering Data*, fig. 5). Based on the significant disruption that rain posed to the recordings, if devices are to be positioned with microphones facing skyward, weather patterns should be monitored closely, as such positioning is incompatible with rain events. This study’s focus was not on optimal orientation of AudioMoth devices nor on the influence of rain on recordings based on such orientation; thus, it is yet unknown whether vertical alignment of the AudioMoth, with the microphone facing outward, is fully compatible with rain events in terms of the resultant audio recordings. However, should recordings need to occur during rain events, a vertical alignment is suggested based on current observations.

AudioMoth devices can be synchronized using GPS Sync firmware, which ensures precise time alignment by connecting to an AudioMoth GPS Board (Open Acoustic Devices, *Using AudioMoth GPS Sync to Make Synchronised Recordings*). This setup allows each device to record audio aligned with GPS time within one microsecond. The synchronization involves generating standard WAV files and corresponding CSV files with time data, which are processed using the AudioMoth GPS Sync desktop app to produce synchronized audio files. For research requiring continuous 24-hour recordings in 10-minute segments with 10-second breaks, deploying GPS-synchronized AudioMoth devices can mitigate issues of temporal misalignment caused by staggered deployment times, thus eliminating the need for post-processing alignment and enhancing data analysis accuracy.

There are many steps associated with both configuring and deploying AudioMoth devices, and it is unsurprising that small inconsistencies occurred with them during the research. Standard operating procedures (SOPs) written for device deployment should be addressed in a step-by-step manner when deploying AudioMoths to avoid misalignment of the AudioMoth device within the weatherproof casing, as encountered with the device at site 2. Similarly, SOPs written for configuring the recording settings should be addressed in the same methodological, step-by-step manner when adjusting recording settings within the dedicated AudioMoth configuration app. If treated as a checklist of sorts, and perhaps formatted to that standard, these SOPs could mitigate accidental misconfigurations that are otherwise very easy to make.

Additionally, while making routine transfer of data and battery checks, checking the metadata of an audio file to ensure that it complies with the expected configuration settings provides a chance to recognize any discrepancy in important recording settings. This can be done on the fly by inspecting the properties of an audio file: If using a PC, right-click and navigate to “Properties” to open the properties window. The file size and file length properties under the “General” tab and the bit rate property under the “Details” tab can provide a lot of insight in a short amount of time.

The formula used to estimate battery life proved to be too generous in its calculations for this research. In the future, time and care permitting, a separate formula should be calculated based on field tests, or the field tests themselves can be used to give a general sense of battery depletion over time. If possible, checking the battery life and memory card storage of the devices on a schedule can catch a low battery or technical error before too much recording opportunity is missed.

The original audio recordings for this research were uploaded to cloud storage immediately upon retrieving the data from the field, which is additionally recommended for all future soundscape research at Wolf Haven. Had files stored in the external hard drive not been recoverable, the files backed up to the cloud would have been accessed. Integrating more sophisticated data management systems that combine local and cloud storage solutions can safeguard against data loss due to hardware failures. For instance, the external hard drive corruption experienced during this research likely would not have occurred had processing not been run on files stored within the external hard drive, and consequent recovery of output files from the external hard drive would have been mitigated as well. A 2 TB Google Drive storage account was connected by the Google Drive application on a PC, with file navigation made possible through the Windows Explorer interface. Despite the PC's relatively small available local disk space, data stored on Google Drive could be made local and processed in batches with minor inconvenience.

Future Research Directions

Given the exploratory nature of the foundational research conducted, there is much untapped potential for the collected data to be further analyzed depending on research goals. Certainly, collecting more data of the same nature and performing the same or similar analyses as presented in this thesis would significantly improve understanding regarding the temporal and site-specific trends of Wolf Haven's soundscape, either by supporting the findings of the foundational research or by providing contradicting findings. Repetition of this same research is something that I would suggest, especially given the data loss experienced in the preliminary research.

Identifying which sound sources dominate the sound profile of each site or hour of the day would contribute immensely to the sanctuary's soundscape analysis, qualifying the geophonic, anthrophonic, and biophonic experience of the sanctuary's resident wolves based on time and location. Automated sound detection and sound classification would be a powerful means of achieving this sort of analysis because, due to the sheer amount of data that comes with continuous audio recording, manual inspection and annotation of sound sources in audio files is exceedingly laborious. Regardless of the sound source identification method chosen, categorizing sound sources and measuring the prevalence of sound categories by site or hour would provide valuable information to Wolf Haven staff; while understanding general sound levels throughout the sanctuary is certainly helpful in understanding the wolves' experience of sound, the nuanced insight provided by analysis by sound category would shed light on the true nature of these levels. For instance, while preliminary findings suggest that Site 5 may not experience as great of sound intensity as originally expected, perhaps the sound profile of Site 5 is composed of more anthrophonic sound than other sites, which is an important consideration given Wolf Haven's goals of preserving naturalistic conditions for wolves.

For the purposes of this research, the outlier analysis performed only delves into an initial investigation of when and where outliers occurred simultaneously; however, it is clear that the potential of such analysis to provide uncomplicated sound event identification is far-reaching for Wolf Haven's audio data. The recognition of simultaneously occurring outliers allows for targeted inspection of audio files to distinguish between genuine data points and noise or artifacts requiring filtering, such as with the outlier investigation demonstrated during summary statistics analysis. Notable patterns in outliers could provide the impetus for many future research endeavors, such as a review of wolf-sound-related events for behavioral observations, a targeted assessment of construction project sound levels, or a comparative spatial-temporal analysis between outlying sound events and baseline acoustic levels.

Even the simple matter of manually investigating each outlier's associated audio file to contribute to the dataset of this study could be a worthwhile look into the most "disruptive" sound events that occur at the sanctuary, in terms of anomalously distinct decibel or frequency levels. With the use of any software that provides spectrograms of decent resolution for audio files, this process would be straightforward and only as time consuming as necessary to sift through all 168 outliers, a much more accessible way to approach outlier analysis than building automated models.

Finally, the limitation of data that is not calibrated to a standard SPL is potentially worth remedying if there is a need to compare that data to other data that is calibrated in such a way, or if Wolf Haven staff deem it particularly useful for educating the public about soundscape metrics in an accessible way. To address this, implementing a calibration process to align the decibel calculations with a known SPL reference would be required; however, this known SPL reference can be retroactive applied to the existing audio data for calibration.

Conclusion

From the conception of this research idea by Wolf Haven International sanctuary director Pamela Maciel Cabañas through fashioning the study results into words, the sound characteristics across the sanctuary remained little understood by all but the wolves and coyotes, the ravens and the chickadees, and the very many bird and bat species living as part of the acoustic experience of the landscape. To paraphrase the artist and author Tony Angell (quoted in Reaume 2021), the sounds of Wolf Haven as experienced by its non-human residents contain answers to questions we may never learn to ask.

Slowly meandering the length of the winding path that borders the public-facing enclosures, I listened as Pam acknowledged the sanctuary's potential for a more suitable infrastructure, one that could foster all manner of studies to provide answers to her unending curiosities. I had already suspected from the onset of our meeting that morning that Wolf Haven was different from the facilities I knew as a seasoned volunteer in the animal husbandry world. The wolves looked silently over us from a vantage point just uphill enough that it was easy to spot them once I knew what to look for, which surely came several minutes after they'd figured out the same. They watched until I could no longer see them past the looming entrance gate to sanctuary grounds, though perhaps even after that. The air was quiet, save the hushed conversation between Pam and me. The wolves, in their beautifully natural homes, paced with anticipation along fence lines or stood at a distance with restless stares while we walked, and, as I took in all that was around me, I knew that my suspicions were right. It was so clear: the cautious playfulness of the animals, the silence of unstressed caregivers, the warm welcoming of eager strangers and ideas—it was a place that prioritized all of the right things. It was a place of science.

It has been a great pleasure and honor to contribute to the scientific advancement of Wolf Haven International, which, in turn, will add to humanity's collective understanding of the lived experiences of all animals that we endeavor to care for in human-controlled environments. By understanding the acoustic environment of these animals, we grow an intelligence that is intimate to the animal's being, something that man's hubris typically stifles. Even more exceptional is that this method of gaining such insight is unobstructive to the lives of the study subjects. Beyond what was accomplished with this research, there lies a great potential to uncover the specifics of animal behavior, dissect the composition of an environment's sound sources, and learn all manner of truths that would be impossible using more intrusive methods. While preserving the sanctity of the animals' habitats, we discovered the temporal trends of the soundscape at Wolf Haven and determined significant differences in regional acoustic measurements, and it is with great hope that this information provides the blueprint for enhancing the lives of the canids that call this sanctuary home.

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Appendix A: Technical Datasheets

A.1 AudioMoth 1.2.0 Datasheet

AudioMoth 1.2.0 Specifications

- Microcontroller: Silicon Labs Wonder Gecko
- Sample Rates: 8 kHz to 384 kHz
- Power Supply: 2.4 to 5.5 V
- Microphone: MEMS, omnidirectional
- Storage: Supports up to 128 GB microSD cards
- Dimensions: 58 x 48 x 15 mm

Source: Open Acoustic Devices. *AudioMoth 1.2.0 Datasheet*. Accessed April 30, 2024. https://github.com/OpenAcousticDevices/Datasheets/blob/main/AudioMoth_1_2_0_Datasheet/AudioMoth_1_2_0_Datasheet.pdf.

For the full datasheet, please refer to the AudioMoth 1.2.0 Datasheet PDF.

A.2 SPU0410LR5H-QB Datasheet

SPU0410LR5H-QB Zero-Height SiSonic Microphone

- Manufacturer: Knowles Acoustics
- Microphone Type: Silicon MEMS, omnidirectional
- Frequency Response: 100 Hz to 10 kHz
- Sensitivity: -38 dBV/Pa at 1 kHz
- Signal to Noise Ratio: 63 dB(A)
- Total Harmonic Distortion: 0.2% at 94 dB SPL
- Dimensions: 3.76 x 3.00 x 1.10 mm

Source: Knowles Acoustics. *SPU0410LR5H-QB: Surface Mount, Omni-directional, Bottom Port Silicon Microphone*. March 27, 2013. Accessed April 30, 2024. https://mm.digikey.com/Volume0/opasdata/d220001/medias/docus/384/SPU0410LR5H-QB_RevH_3-27-13.pdf.

For the full datasheet, please refer to the SPU0410LR5H-QB Datasheet PDF.

A.3 Energizer NH15-2300 Datasheet

Energizer NH15-2300 (HR6)

- Classification: Rechargeable
- Chemical System: Nickel-Metal Hydride (NiMH)
- Designation: ANSI-1.2H2 IEC-HR6
- Nominal Voltage: 1.2 Volts
- Rated Capacity: 2300 mAh at 21°C (70°F) based on a 460 mA (0.2C) discharge rate

- Typical Weight: 27 grams (0.95 oz.)
- Typical Volume: 8.3 cubic centimeters
- Operating Temperature Range: 0ºC to 40ºC (discharge), 0ºC to 50ºC (charge)
- Storage Temperature Range: -20ºC to 30ºC
- Humidity: 65±20%

Source: Energizer. *NH15-2300 Nickel-Metal Hydride (NiMH) Battery Technical Data Sheet*. Accessed April 30, 2024. https://data.energizer.com/pdfs/nh15-2300.pdf.

For the full datasheet, please refer to the Energizer NH15-2300 Datasheet PDF.

Appendix B: Technical Reports

B.1 Report on AudioMoth Performance Testing | A quantitative report of audio recording quality

Authors: Lapp, Sam, Nickolus Stahlman, and Justin Kitzes.
March 2022

This report provides a quantitative analysis of the audio recording quality of two autonomous recording units (ARUs): the AudioMoth by Open Acoustic Devices and the Song Meter Micro by Wildlife Acoustics. The report includes detailed on- and off-axis frequency response curves and polar sensitivity charts, with tests conducted in both open grassland and mixed second-growth forest environments. It examines the performance of the AudioMoth both in free space and in various protective housings, as well as the effects of mounting AudioMoths on trees of different sizes.

Source: Lapp, Sam, Nickolus Stahlman, and Justin Kitzes. 2023. "A Quantitative Evaluation of the Performance of the Low-Cost AudioMoth Acoustic Recording Unit." *Sensors* 23 (11): 5254. https://doi.org/10.3390/s23115254.

For the full report, please refer to the full report.

Appendix C: Operation Manuals

C.1 AudioMoth Operation Manual

Open Acoustic Devices
April 12, 2024

This manual provides comprehensive guidance for configuring, deploying, and updating AudioMoth devices. It includes detailed instructions on choosing the appropriate settings, handling various operational modes, and utilizing the AudioMoth Configuration App for optimal device performance. Additionally, the manual offers insights into protective housing, battery recommendations, and SD card usage to ensure accurate and reliable audio recording in diverse environmental conditions.

Source: Open Acoustic Devices. *AudioMoth Operation Manual*. June 6, 2024. Accessed August 24, 2024. https://github.com/OpenAcousticDevices/Application-Notes/blob/master/AudioMoth_Operation_Manual.pdf.

For full access to the AudioMoth Operation Manual, please refer to the AudioMoth Operation Manual PDF.

C.2 Using AudioMoth GPS Sync to Make Synchronized Recordings

Open Acoustic Devices
June 23, 2024

This manual explains how to synchronize recordings across multiple AudioMoth devices using the AudioMoth GPS Sync system. It details the setup process to ensure that recordings are temporally aligned, addressing issues of non-aligned audio recordings. The synchronization process involves using a GPS receiver to update the device's real-time clock and measure the sample rate accurately before each recording, ensuring precise timestamps to within a few milliseconds.

Source: Open Acoustic Devices. Using AudioMoth GPS Sync to Make Synchronised Recordings. June 23, 2024. Accessed August 24, 2024. https://github.com/OpenAcousticDevices/Application-Notes/blob/master/Using_AudioMoth_GPS_Sync_to_Make_Synchronised_Recordings/Using_AudioMoth_GPS_Sync_to_Make_Synchronised_Recordings.pdf

For the full manual, please refer to the AudioMoth GPS Sync Manual PDF.

Appendix D: Animated Timelapses of Research Data

D.1: Video of the Animated Comparative Analysis of Decibel Levels Across All Sites

Description: This video compares hourly decibel levels across all research sites over a 24-hour time frame.
Duration: 28 seconds.
For access to the animation, please refer to the Link to Video D1
URL: https://drive.google.com/file/d/1Hn7HNBQ5XjRkV-xiqMt-2Tg-wulm4L9S/view

D.2: Video of the Animated Comparative Analysis of Frequency Levels Across All Sites

Description: This video compares hourly frequency levels across all research sites over a 24-hour time frame.
Duration: 28 seconds.
For access to the animation, please refer to the Link to Video D2
URL: https://drive.google.com/file/d/1-N0VyUzsMScOV9fcX4UQgkQ5QEKweXZf/view