MEASUREMENT, QUANTIFICATION AND INTERPRETATION OF ACOUSTIC SIGNALS WITHIN AN ECOLOGICAL CONTEXT

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ABSTRACT

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Increasing awareness of the degree to which human activities are altering the state of the Earth's Biosphere has fostered an interest in ecological variables that clarify complex relationships and represent the dynamic nature of living systems. The study of a location's acoustic signals (its soundscape) integrates an array of biophysical factors and changes with the location's characters. This study begins with the formation of an analytical framework to quantify and interpret acoustic signals from the environment. This framework classifies three primary constituent regions of the soundscape, the anthrophony (0.4 to 2 kilohertz), the biophony (2.5 to 11 kHz) and the geophony (diffuse signal, full spectrum). Based on this framework, the structure of the biophony is examined through a spectral analysis of a series of avian, insect, and amphibian vocalizations. This analysis confirms the hypothesis that the strongest concentration of biological activity is between 2 and 5 kHz. The analytical tools are then applied to a series of acoustic observations gathered in the Muskegon River Watershed, where the acoustic signatures of three different land cover types (urban, forested/outdoor recreation, agriculture/grassland) are examined in two sets. Analyses of Variance indicate significant differences between the sites. Finally, indices of biological and anthropogenic activity are compared to population density values. The results of these correlations indicate that an accurate assessment of a region's soundscape and corresponding biophysical attributes requires an observation system of a sufficient spatiotemporal scale, thereby limiting the value of acoustics as an ecological indicator. However, such an observation system would enable the measurement and integration of an array of ecological variables.

Dedicated to Champ

I'll miss you, furball

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General Perspective

Presently, the human population is expanding development throughout the globe. In terms of both overall population and land use intensity, we are rapidly altering the structure of Earth's ecosystems. From changes in species composition to habitat structure and type, we are altering the operation of ecosystems on multiple scales. Fortunately, we are also working to understand our impacts on these ecosystems that we occupy. By enhancing our understanding of the ways in which we affect ecological functions, we may be able to mitigate or minimize the severity of the negative consequences of our continued development. For instance, the National Academies' National Research Council outlined eight critical research topics for the next generation of environmental studies (National Research Council 2001):

- Biogeochemical Cycles
- Biodiversity and Ecosystem Functioning
- Climate Variability
- Hydrologic Forecasting
- Infectious Disease and the Environment
- Institutions and Resource Use
- Land-Use Dynamics
- Reinventing the Use of Materials

Inherent in the study of Biodiversity and Ecosystem Functioning and their relationship to land use and land cover patterns is the need for ecological variables that reflect the dynamic nature of ecosystems. We are beginning to realize that ecosystems function in dynamic equilibrium, with constant variations and changes, rather than as steady-state systems (Odum 1963; Laszlo 1996). This understanding has led to the need for a measurable variable that reflects these spatiotemporal dynamics of patterns in ecological activity.

Sound as a dynamic variable

Sound, being one of the five basic senses, has historically been an overlooked variable in ecological studies. In the past, this is likely due to the complexity of an acoustic signal and the equipment necessary to capture and analyze the signal. However, the present availability of relatively inexpensive computer technology has made the digitization and quantification of acoustic signals more feasible. In terms of key criteria for ecological indicators and biocomplexity assessment (Dale and Beyler 2001), sound is an optimal variable as it meets the following requirements:

- The analysis of sound simplifies the interpretation of complex biological measurements by integrating several factors into a single variable.
- Analysis of acoustic features integrates different biocomplexity measures because the signals are tied to multiple other variables.
- Continuous stationary acoustic monitoring reveals spatiotemporal patterns that cannot be captured in single-point site-by-site observations.

- Ecological acoustics can be measured automatically with minimal human interference.

Therefore, I have decided to examine the role of sound as an indicator of ecological quality and examine derived analytical relationships to other features using data from the Muskegon River Watershed.

Muskegon River Watershed

The Muskegon River Watershed is the second largest watersheds in the state of Michigan, draining a total surface area of 2,723 square miles. It was formerly part of the vast timber operations in Michigan, and much of the forests present now are secondary or early successional. Partially due to its size (219 miles in length), it is a diverse watershed that encompasses many of Michigan's different habitat types. This region has also been the subject of several recent intensive ecological studies as part of a proposed model watershed assessment for the state. The data for my thesis is derived from one such study that is examining multiple variables in an attempt to assess the quality of the watershed and outline necessary steps for restoration (Stevenson *et al.* 2001). Given the topic of this study, it has generated a significant volume of data on the Muskegon River Watershed, including multiple acoustic samples throughout the watershed. These factors make the Muskegon River Watershed an ideal test bed for the establishment and implementation of a large-scale study of ecological acoustics.

Goals and Objectives

The overarching objective of this thesis is to develop and verify an analytical approach to the quantification and interpretation of ecological acoustics. To accomplish this, I focused on the following three objectives:

- Design and implement an analytical framework to assess the ecological features of acoustic signals and to handle large-scale acoustic data for comparison and statistical analysis.
- Verify the apparent spectral distribution of biological signals and enhance our understanding of biophony.
- Integrate the theoretical and analytical tools to a real-world scenario by relating acoustic signals to other ecological variables in the Muskegon River Watershed.

Methods and Outline

To accomplish the above objectives, I have divided this work into five sections, which comprise the five chapters of this thesis. They begin with the general principles and framework for the interpretation of ecological acoustic signals, and develop into an analysis of the acoustic properties and correlated variables in the Muskegon River Watershed. The chapters are organized as outlined below:

Chapter One: Introduction to Ecological Acoustics

This chapter comprises a general overview of the current status of acoustics research, and reviews the background information necessary for the development of an interpretive framework.

Chapter Two: Development of an interpretive framework

This chapter reviews the fundamental principles of the standardized framework for interpretation of ecological acoustics developed by Gage (Gage *et al.* 2003). This includes the justification of acoustic measurements and the process involved in quantifying the signals

Chapter Three: Automation System to Facilitate Analysis of Acoustic Signals at the Landscape Level

This chapter describes the necessity of automation when working with large-scale acoustic data and reviews the automation system I developed to handle large-scale analysis.

Chapter Four: Spectral analysis of the acoustic signals of three groups of organisms in the Northeastern United States

This is a spectral analysis of the vocalizations of three groups of organisms and their spectral frequency distributions. This study is an attempt to enhance our understanding of the biophony and its constituent members, as well as to verify the spectral frequency distribution of acoustic signals in the environment.

Chapter Five: Acoustic Signatures of Different Locations

The temporal properties of different land cover types are compared to discern differences in the acoustic signatures of land cover types.

Chapter Six: Establishment of baseline relationships between acoustic signals and population density in the Muskegon River Watershed

After establishing an operational analytical and interpretive system, I applied the principles to several sets of acoustic observations from the Muskegon River Watershed and correlated the results to census block data from the 2000 census.

Chapter Seven: Summary and Conclusions

The research described in this thesis uncovers the fundamental principles of the analysis of acoustic signals from an ecological perspective. Specifically, it describes the analytical processes involved in quantifying large-scale samples from the soundscape.

Chapter One:
Introduction to Ecological Acoustics

Introduction

Acoustic information plays a significant role in the life history and behavior of many animals, including humans. While we receive constant auditory input, most of this information goes unnoticed unless it becomes a nuisance or ceases suddenly. Unconsciously, however, sound has a dramatic impact on an individual's emotional state and decision-making. The increasing prevalence of personal music devices such as MP3 players and portable CD players reflect our desire to optimize our acoustic environment. In addition to the psychological element in humans, sound functions in ecology in a dual role as both an indicator of ecosystem activity, particularly when related to human disturbance and biological diversity, and a stressor on ecosystem function and services. As an indicator, the array of acoustic signals in a location represents features such as the biological composition, the intensity of anthropogenic activity and the diversity of vocal organisms. An examination of a location's acoustics from the perspective of stressors implies that certain acoustic signals may inhibit or degrade certain ecological services deemed critical or relevant to human health. A thorough understanding of the properties of ecological acoustics from both perspectives will allow for the quantification and characterization of ecological features that may otherwise be too difficult or costly to measure. To accomplish this, these properties must be studied within the context of a comprehensive framework that accurately standardizes the interpretation, quantification and synthesis of acoustic signals.

Physical Characters of Sound

In physical terms, a sound wave is a flow of energy in the form of lateral vibrations through a medium capable of oscillation. A sound wave may be defined by these physical components of oscillation, including the frequency (measured in Hertz), the amplitude, which translates into the intensity (often in dB SPL, or Decibels Sound Pressure Level), and the temporal attributes of signals length, periodicity and change. Sound waves also exhibit more complicated physical properties, such as harmonics, which are essentially integer multiples of a pure tone's fundamental frequency (Hartmann 1998), and the patterns of reflection and deterioration of signals in a three-dimensional setting. As a sound wave is a pressure wave, many of these physical properties are largely contingent upon the characteristics of the medium as well as the origin. Its status as a pressure wave also implies that a sound signal will not propagate in a vacuum, as there is no vibrational medium. When a medium is present, the energy of a sound wave decays at the same rate as other pressure waves, one over the square of the spherical distance proportional to the propagation properties of the medium ($decay \propto k\,(1/d^2)$). These physical characteristics of sound waves have been an intensive field of study and research, including analyses of the speed of sound waves in an array of media at various temperatures (Lide 2004). These basic physical attributes of acoustic signals should be key components of any interpretive framework.

Human Perception of Sound

In addition to its physical elements, an entire field of physics, referred to as Psychoacoustics, has arisen that examines the human perception of sound. This field of study examines sound as it relates to human physiology and psychology. Psychoacoustics does incorporate the physical components of sounds and tones, but focuses on different features and utilizes a broader terminology than that applied to the basic physical analysis. For instance, human perception of pitch is related to frequency, but not in a one-to-one ratio. Therefore, an understanding of the ways in which humans perceive changes in the pitch of a signal requires knowledge of both the signals actual change in frequency and knowledge of the abilities of the human ear and brain to discriminate and interpret such changes in signal frequency. The musical scale is structured around a combination of both of these elements of signal structure and perception (Hartmann 1998).

While the ideal human range of frequency perception ranges from 20 Hz to 20,000 Hz, the average human can typically discern frequencies ranging from 30 to 17,000 Hz. Given the broad array of sounds in this range, the hearing of many vocal organisms (particularly birds) also falls in this range, albeit with a significant degree of variation (Heffner and Masterton 1980; Bailey 1991; Dooling *et al.* 2002). Although the audible spectrum extends to 20 kHz, information carried in human speech usually only requires the lower portion up to 4 kHz (which is, incidentally, the maximum frequency detectable by most telephone transducers). The dynamic range of the human voice, however, extends across the audible spectrum. Music also fills the audible spectrum, but the majority of information-carrying energy is still concentrated at the lower end. Human perception of sound tends to be compressive, where slight changes in frequency are significant at low pitches, and become increasingly difficult to perceive as the frequency rises (Masterton *et al.* 1969). Other vocal organisms tend to utilize different portions of the spectrum, such as birds, which tend to concentrate their signals at a range between 3 and 7 kHz.

Sound in Ecology

Traditionally, sound studies have held a somewhat limited application in ecological analyses. A significant obstacle here has been the difficulty involved in gathering a sufficient volume of usable acoustic information from a given environment. Prior to the advent of digital technology, the only medium available for sound storage was a spool of magnetic tape run along a steel head (Hopp *et al.* 1998). These cassettes generally have a less than optimal signal to noise ratio and their fidelity deteriorates with each successive playback. Moreover, a single cassette can typically hold no more than 80 minutes of reasonable quality audio information. While these technological limitations have limited the feasibility of large-scale ecological studies of acoustics, they have allowed researchers to examine the acoustic behavior of vocal organisms in depth. Commonly, sound is used to track populations of vocal organisms, or studied as a means of organism communication (Heffner and Masterton 1980; Shackleton *et al.* 1991; Bukhvalova and Zhantiyev 1994; Greenwood 1996; Kroodsma and Miller 1996; Buskirk 1997; Hopp *et al.* 1998; Bailey *et al.* 2001; Slabbekoorn and Smith 2002). This has yielded a large amount of information about the vocalizations of specific organisms and their physiology, but relatively little information about sound in the environment itself. One significant exception to this trend is, of course, the Navies of various nations. Submarine warfare in particular, which relies largely on the ability of the submarine to remain concealed and passively collect information, has made significant progress in the analysis and interpretation of acoustic signals. These techniques have been applied successfully to the detection and identification of aquatic mammals such as whales and dolphins. While these techniques are theoretically applicable to terrestrial acoustics, the transition is by no means straightforward. To begin with, the propagational properties of water and the atmosphere differ significantly, and water is a much more conducive medium (the speed of sound in seawater at 25°C is 1,535 m/s as opposed to dry air at the same temperature, 346.3 m/s (Lide 2004)). This implies that acoustic signals must be sampled at a higher spatial resolution in terrestrial studies to compensate for the faster signal decay and obtain an equitable volume of information. Partially due to differences in the conductivity of these media, as well as the intended application, the transducers utilized in marine and terrestrial acoustic sampling differ. Finally, naval applications focus primarily on the detection and identification of specific signals. While such a system is applicable to automated species identification for species richness assays, it still lacks the broader scope of an ecological observation system designed to measure acoustics at the landscape scale.

In both marine and terrestrial acoustics, the advent of digital technology has resolved several of the fidelity and storage limitations incurred by traditional analog recordings. Digital devices such as MiniDisc and flash memory recorders allow researchers to deploy large-scale observation systems that collect data at a sufficiently higher fidelity and larger concentration to allow an accurate analysis and interpretation of the information. As technology has improved the availability of acoustic information, ecologists have developed new applications for acoustic studies. For instance, the larger volume of available information allows researchers to examine assemblages of vocal organisms at the community rather than individual level (Bailey *et al.* 2001; Nischk and Riede 2001; Schwartz *et al.* 2001). Additionally, researchers have begun to examine novel applications of sound studies beyond the observation and tracking of individuals or species complexes. Several initial and proposed studies indicate that acoustic signals may be used to derive species richness estimates for the extrapolation of biodiversity indices (Horne 2000). For instance, Reide ([Riede, 1993 #96]) used the frequency modulation across species of Amazonian rainforest crickets to estimate richness of cricket species in various portions of the forest. Of course, acoustic identification of species has traditionally been used in bird surveys, particularly in forested habitats where visual identification ranges from difficult to impossible (Gill 1995). Another potential significant contribution of acoustic studies is in systematics. Several researchers have suggested and begun to apply analyses of the variations of acoustic signals to the identification and recognition of individual species (Sandborn and Phillips 2001; Helbig *et al.* 2002; Freeberg *et al.* 2003). Finally, another important aspect of ecological acoustics is the relationship between the physical environment and the acoustic signals. Features such as vegetation, topography and meteorology will all affect the propagation and assemblage of acoustic signals in a landscape (Roffler and Butler 1967; Aylor 1971; Morton 1975; Wollerman 1999; Benoit-Bird and Au 2001; Nischk and Riede 2001).

Another branch of acoustic studies, focused primarily on the examination of human sound as a stressor, has begun to examine the increasingly significant anthropogenic mechanical contributions to the assemblages of signals in a region. This increasing presence of mechanical signals and its effect on human health and behavior is a large focus of the field of acoustic ecology. The implications of mechanical noise extend, of course, beyond the realm of human health and influence anthropogenic degradation of ecological services and conditions (Schafer 1977, 1994; Krause 1999; Truax 1999; Wollerman 1999; Krause 2001). The Federal Aviation Administration, for instance, conducted a large-scale survey of the effects of sonic booms on humans and wildlife (Federal Aviation Administration 1985). Taken together, the examination of acoustic signals as indicators and stressors enables the development of an interpretive framework that yields information about both elements of the assemblage of signals present within a region.

While this array of research has provided a great deal of useful information about the various ecological elements of acoustics, a large-scale interpretation requires a standardized framework for a universal interpretation of ecological acoustics. This research was the foundation upon which the interpretative framework described in the next chapter was constructed.

Chapter Two: Development of an Interpretive Framework to Assess Ecological Features of Acoustic Signals[1]

Introduction

A large-scale interpretation of a region's acoustic features (or its soundscape) requires standardized implementation of observation techniques and interpretative analyses. Given the wide array of acoustic studies that have already been conducted, an ideal interpretive approach would integrate these studies as well as future studies into its framework. The framework described here attempts to do this by building upon some of the initial work in acoustic studies. While the interpretation described in this framework does attempt to unify standing concepts in acoustics, the quantification and statistical approaches described in detail in the next chapter represent a novel application of existing techniques.

Definition of the Soundscape

The term "soundscape" occurs frequently in the field of acoustic ecology. The working definition of soundscape in this field is any collection of sounds specified as an area of study (Schafer 1977, 1994; Truax 1999). This implies that the term soundscape may apply to anything from a musical composition to the entire planet. In the study of the ecological aspects of acoustics, I have defined the area of study as the set of sounds

[1] An article similar to this chapter was originally written with me as the second author. Because I was not the first author, I have attempted to revise the original paper to reflect my own input. I did include segments of the original paper where I was largely responsible for the text (primarily the segment on the analysis of signals). For the sake of clarity and honesty, I have included the original paper as it was initially submitted in Appendix I.

generated by the biophysical and social interactions and activities within a landscape, where the landscape is a heterogeneous land area composed of a cluster of interacting ecosystem patches (Turner *et al.* 2001). The working definition of the soundscape, then, is the acoustic signals associated with the landscape and its constituent habitats.

Classification of Signals in the Soundscape

A useful characterization of an ecosystem's soundscape involves a classification system that describes the signals in terms of their biophysical components. Generally, various signals in the acoustic spectrum are thought of as originating from either natural processes or human activity. This analytical framework distinguishes three main categories of sounds that occur in the soundscape: *biophony*, *anthrophony*, and *geophony*. The term *biophony* describes the complex chorus of ambient and prominent biological sounds encountered in a region. In the analytical framework, this category encompasses only the natural sounds produced by organisms

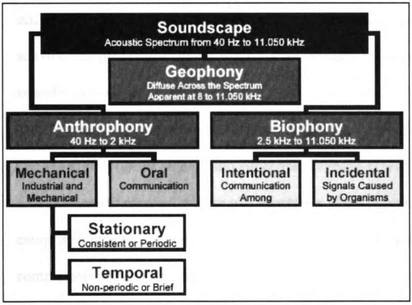

Figure 1. Conceptual classification schematic of the soundscape and the three principal components. Several hypothetical subclasses are also depicted below these components. While the Anthrophony and Biophony tend to have discrete spectral ranges, the Geophony tends to occur across all spectral bands, but is more diffuse.

other than humans, including birds, amphibians, insects and bats. This is the class of sounds most extensively studied in ecological acoustics (Bosch *et al.* 2000; Bailey *et al.* 2001). While human oral signals would technically be considered a component of the biophony, I have decided to classify them separately for two reasons. The first is that one of the primary objectives of this research is to isolate and quantify the degree of anthropogenic disturbance within an ecosystem. To do so, the assemblage of anthropogenic signals, including oral, must be treated separately from other biological organisms. Similarly, if my objective were to quantify the impact of ducks' acoustic activity in the soundscape, I would group anthropogenic activity with other organic activity, and place duck signals in a separate category (perhaps Anserophony?). However, as anthropogenic activity is my current focus, *anthrophony* refers to the collection of anthropogenic signals in the soundscape. The simplest classification of the anthrophony divides anthropogenic signals into either vocalizations or signals produced by mechanical or technological means. Of these two subclasses, the mechanically induced signals comprise a majority of anthropogenic signals in most samples, with negligible oral components. This is the second reason I have opted to place anthropogenic vocalizations in a separate category. While the theoretical basis may be debatable, the practical implications are merely an increased conceptual convenience. Finally, the third category, *geophony*, refers to the pattern of signals present within the soundscape generated by physical (primarily geological) processes occurring in the region. Examples of these classes of signals are those emanating from waterfalls, river flow, wind or rain.

This classification system represents a very simplistic and rudimentary approach to signal categorization. As understanding of the characteristics of sounds in these categories increases, this classification system may be refined. For instance, subdivisions in the classification can be made based on the persistence of the signal (stationary versus temporal), the function of the signal (intentional versus incidental) or the periodicity of the signal (periodic versus random). However, for the purpose of this research, I focus my analysis and discussion on the three major classes mentioned above, while still outlining some of the more complicated subunits in Figure 1 for illustrative purposes. Moreover, the simplicity of the approach has expedited the interpretation and enabled the development of the quantitative framework built on a minimal number of assumptions that may be corrected or modified without necessitating the redevelopment of the entire framework.

Quantification of Acoustic Signals

The analytical system I have helped to develop is designed to analyze acoustic samples with strictly standardized parameters. While a more flexible system would be preferable, the volume of information and my extremely limited programming skills necessitated the establishment of a relatively inflexible system. The analytical parameters can be adjusted, but such an undertaking would require substantial modification of the software system. Therefore, the initial analysis utilized slightly broader parameters that were narrowed as the necessary minimal standards were determined. After examining the amount of information distributed across the audible spectrum (20 – 20,000 Hz), it was determined that the majority of information is concentrated below 11 kHz. This results in a sampling rate of 22.050 kHz, twice the maximum frequency to be analyzed[2]. To optimize signal fidelity while minimizing file size, single-channel (monaural) 16-bit samples are used. These sampling parameters are relatively high quality, although not quite on par with standard CD quality (CD standards are 44.1 kHz 16-bit stereo samples).

Visual Representation of Acoustic Samples

To maximize the amount of information available while simultaneously minimizing the size of the data files, the acoustic samples were converted into visual spectrograms. These spectrograms are essentially 3-dimensional representations of the original acoustic signals. The frequency of the signal is plotted on the y-axis, time is plotted on the x-axis and the z-axis represents the amplitude (Figure 2). The generation of a spectrogram utilizes a series of Fast Fourier Transforms (FFT), which calculate the amplitudes of the integrated frequencies over time. The spectrograms utilized in this analysis were generated by a program called Spectrogram® (Horne 2001) with a FFT size of 4,096 and a frequency resolution of 5.4 Hz. The theoretical minimum frequency was 0 kHz (although the minimum frequency of most microphones used was 20 Hz), and

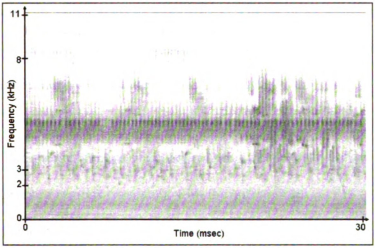

Figure 2. A spectrogram with a maximum frequency of 11.025 kHz and a 90 dB black and white palette. This spectrogram also illustrates the division of biological and anthropogenic signals into discrete frequency bands.

[2] This sampling rate is dictated by the Nyquist Sampling Theorem, which states that the minimum sampling rate must be twice the maximum frequency.

the maximum was 11.025 kHz. The amplitude was scaled across 90 dB with a blue color palette. Spectrogram® also generated all of the spectrograms with identical dimensions (500 pixels high x 1,000 pixels wide).

Quantification of the Spectrogram

The functionality of IDRISI® (Clark Labs 2000) allowed me to analyze the spectrograms in terms of topological and x, y spatial features within the signal, i.e. the spectrogram was treated as a multiphase map of the acoustic signal. Sound intensity values were converted to an 8-bit series with a range of 0-255 possible values related to the initial dB values of the signal. The maximum dB value that the microphone could relay to the computer had a corresponding analysis value of 255. On the other hand, an acoustically silent (i.e. no energy above 10^{-12} watts/metre^2 was captured by a microphone) recording would receive a corollary value of zero.

The spectral ranges of acoustic signals in the environment tend to aggregate within two primary regions consistent with the anthrophony and biophony. The first region occurs at the lower frequencies of the sound spectrum (Schafer 1977, 1994). This band typically extends from 0.4 to 2 kHz and consists primarily of mechanical signals (i.e. trains, cars, air conditioners, etc.), and is therefore aptly referred to as the anthrophonic region. The second band of concentration begins in the range of 3 kHz and is prevalent up to 8 kHz, though it may extend to the top of the spectral range of the recorded signal (11 kHz). This realm of acoustic activity consists primarily of signals generated by biological organisms, and is therefore referred to as the biophonic region. This frequency band is classified as the biological band based on observations of the data collected and the frequency ranges referred to in the literature (Shackleton *et al.* 1991; Naguib 1996; Ping *et al.* 1996; Bennet-Clark 1997, 1998; Bennet-Clark 1999; Bosch *et al.* 2000; Bailey *et al.* 2001; Rundus and Hart 2002; Freeberg *et al.* 2003). These two bands correspond to two of the three taxonomic categories of the soundscape described above, but do not cover acoustics emanating from the physical (i.e. wind, rain, etc.) or geophonic component. This is because the geophony, when present, occurs as a signal that is diffuse throughout the entire spectrum. Generally, when a geophonic signal is present, the frequency bands above 8 kHz will exhibit greater signal intensity than in signals without geophony. When geophony is present, it may be detected, therefore, by its tendency to generate stronger signals at the higher frequencies above the predominant range of the biophonic spectrum (that is, strong signals above 8 kHz). Using this partitioning of the acoustic spectrum, I helped to develop a methodology to quantify the three primary acoustic elements, the anthrophony (α), biophony (β), and geophony (γ), by calculating the mean value of acoustic intensity in the spectral frequency range allocated to each of these regions. In some cases, the mean value of these spectral ranges was divided by the mean activity of the entire signal (σ) in an attempt to "normalize" the intensity of the signals so that same bands of signals with different overall intensities could be compared. We calculated the mean values of the α, β, γ and σ bands by assigning a numeric value to each pixel (0 – 255, mentioned above) in the specified range and calculating the mean value of the z-axis. The α, β and γ activity ratios were calculated using the equations in Table 1. A value > 1 for any of the indices indicated that the mean concentration of acoustic activity in the analyzed region was greater than the average value for the entire signal. Therefore, the region with the highest value was the predominant source of acoustic activity in the signal. For example, if the β_r had the highest value, then biological activity was predominant, while a larger α_r value indicated dominant anthropogenic activity. As Table 1 indicates, the range of the geophony actually falls within the biophony range. This is because the geophony is typically a diffuse signal without a particular spectral range. When a significant geophonic component is present in the signal, however, there is a high concentration of activity from 8 to 11 kHz.

Index	Ratio	Percentage
Anthrophony	$\alpha_r = \left(\frac{\alpha}{\sigma}\right)$ α= Mean from 0 to 2 kHz α_r = Ratio of anthropogenic activity mean to grand mean	$\alpha_p = \left(\frac{(L1 + L2)}{\sum 11 Levels}\right) \times 100$ α_p = Percentage of activity in the anthrophony band
Biophony	$\beta_r = \left(\frac{\beta}{\sigma}\right)$ β= Mean from 2 to 11 kHz β_r = Ratio of biological activity mean to grand mean	$\beta_p = \left(\frac{\sum L3 to L11}{\sum 11 Levels}\right) \times 100$ β_p = Percentage of activity in the biophony band
Geophony	$\gamma_r = \left(\frac{\gamma}{\sigma}\right)$ γ= Mean from 8 to 11 kHz γ_r = Ratio of geological activity mean to grand mean	$\gamma_p = \left(\frac{\sum L8 to L11}{\sum 11 Levels}\right) \times 100$ γ_p = Percentage of activity in the geophony band
Activity	$\rho = \left(\frac{\beta}{\alpha}\right)$ ρ= Ratio of biological to anthropogenic activity	**Global Variables** L = 1 kHz level σ= Mean value of entire signal (Grand Mean)

Table 1. Formulae for the calculation of activity concentration values for the three primary regions of the soundscape. The column on the left depicts the formulae for the calculation of ratio values in

terms of the entire spectrum, while the column on the right lists the formulae for the calculation of values in terms of percentage of the entire spectrum (from Gage et.al. 2003).

In some cases, we divided the β value by the α value to calculate ρ, the ratio of biological to anthropogenic activity, or the Index Value to emphasize the comparison of biological and anthropogenic activity. In addition to computing the ratios of activity from our classification system, we also determined the percentage of total activity a single band contributes to the total signal (Left-hand column of Table 1). A γ_p value near 100% coincident with a β_p value of approximately the same value indicated that the primary signal source in the sound sample was geophony (geo-physical) activity. When the α_p value was greater than 50%, it indicated that the primary signal source was anthrophony (anthropogenic) activity, whereas a value of β_p greater than 50% indicated that biophony (biological) activity was the dominant source.

Index Value Assumptions

The implicit assumption underlying the interpretation of the anthrophony and biophony index values is that regions with higher biophony values and lower anthrophony values represent systems with less anthropogenic stressors than systems exhibiting the opposite features. This rests on the twofold assumption that regions with fewer disturbances will retain a larger concentration of vocal organisms and will exhibit lower concentrations of anthropogenic activity. These two assumptions generally hold true in environments that are not in geophysical extremes (i.e. desert or arctic systems), and less disturbed systems do generally exhibit more biological activity (Krause 1998, 2002). These derived index values then represent an indirect method to quantify the degree of anthropogenic stress in a system. Therefore, a large-scale assessment and analysis of ecological acoustic signals should provide information about the condition of and stress on various habitats. While it may require some refinement to handle regions outside the implicit assumptions, this analysis presents a basic methodology to enable the analysis of acoustic signals in terms of anthropogenic stressors and valued ecological attributes.

Chapter Three:
Application of the interpretive framework to landscape-level acoustic data

Introduction

The interpretive framework described in chapter two establishes the fundamental principles of the analysis of acoustic signals from the environment. While this framework is an accurate method of analysis for individual samples, the labor and processing required prevents the application of this analysis to landscape-level or large-scale acoustic surveys without the implementation of a system capable of tracking and organizing multiple samples. Unfortunately, the software to process multiple image files through a GIS program, extract, and organize the statistical results was not readily available. Therefore, I aided in the development of an interface layer that handles the file processing and automation component. This automation system is referred to as the Ecological Soundscape Analysis System (EAS), and represents the first step in the automation of ecological soundscape assessment.

The Need for Automation

The analytical processes described in chapter two apply to a single file. However, an accurate assessment of a region's acoustic properties requires multiple samples over both space and time. As Gage et al. (submitted, see Appendix A) demonstrate, the infrastructure to acquire acoustic samples of a sufficient spatial-temporal scale is feasible, but requires a significant data-management component. A series of sensors deployed in the Muskegon River Watershed have been gathering high temporal resolution samples for the past three years. The acoustic data analyzed from the Muskegon River Watershed (see Chapters 5 and 6) was obtained from some of these sensors, as well as from several manual and volunteer recording networks in the watershed. Each of the recording instruments that were part of the cyber infrastructure recorded signals at half-hour intervals throughout the day. This resulted in 48 files from each instrument every day, or 17,520 files per year. Samples from manual or volunteer recordings were generally from 80-minute Minidisk recordings. While the analysis of an 80-minute sample is feasible, the time and processing required by a computer to perform such an analysis would rapidly swamp the resources available to this project. Therefore, these samples were broken into twelve 30-second subsamples. This process both alleviates the processing requirements and adjusts the Minidisk recordings to the 30-second standard utilized by the rest of the computational infrastructure. This also implies, however, that each Minidisk sample translates into 12 actual samples to be processed and analyzed. In addition to these initial files, several steps in the analytical process generate multiple new files based on these originals. Table 2 below lists the various numbers of files generated by the analysis described in the previous chapter.

	Recording Instrument Stations			**Manual Recordings**
	Day	**Month**	**Year**	**Sample**
# of Files	48	1,440	17,520	12
12 Bands	576	17280	210,240	144
Index Bands	144	4,320	52,560	36
Totals	720	21,600	262,800	180

Table 2. Numbers of files generated by a single automated and manual recording system and the subsequent analysis.

As the values in this table indicate, the analysis of acoustic signals at a landscape level requires a significant volume of file processing, if each file is to be included in the analysis. This need for an automation system led to the development of EAS.

EAS as an interface layer

EAS is essentially an interface layer between the acoustic spectrograms and the programs required to analyze and quantify their values. It incorporates both a file management and a file processing component. The file management aspect tracks the file names and locations and ensures they are associated with the proper metadata. The file processing component reads the numerical values output by the statistical analyses and organizes them with the metadata to allow for further interpretation and analysis of the quantitative information from the acoustic signals. As the analytical and processing demands became more complicated, these two aspects of EAS, initially two separate programs, were integrated into the single program that became EAS.

To understand how EAS operates as this interface layer, however, a bit more explanation of the two separate processes it links is needed. To generate a quantitatively accurate representation of the sound file to be analyzed, a program called Spectrogram® reads the wave file graphs the intensity of the signal against its frequency and temporal span. This process is described in detail in Chapter 1. In the end, Spectrogram produces a spectrograph for each sound file. The spectrographs used for this research were all standardized with the following parameters:

- Time Span: 30,000 milliseconds, corresponding to a thirty second sample
- The input files, as mentioned in Chapter 1, were 16-bit monaural signals.
- Decibel Scale: 90 dB with a bluescale color palette
- Time Scale: 30 milliseconds (each pixel represented a 30-millisecond sample)
- A linear frequency scale was used (as opposed to logarithmic, which expands the lower frequencies and compresses the higher).
- Fast Fourier Transform Size: 512 points
- Frequency Resolution: 43.1 Hz
- Low Band Limit: 0 Hz (i.e. lowest possible)
- High Band Limit: 11,025 Hz (Highest possible while adhering to the Nyquist Sampling Theorem)

The sizes of the spectrographs were standardized at 500 pixels high by 1,000 pixels wide. Finally, the sonogram images needed to be resampled to an 8-bit scale in order to be read by IDRISI®. To keep track of the large numbers of files this research generates, important metadata was coded in the image file names. Each file name had a specific template, based on the type of file. Table 3 below describes the different file name templates and the code EAS assigns to them.

Site Class	Permanent Site	Sampling Site	Manual Recording
Desc.	Site with recording instrumentation	Part of the large-scale sampling of the MRW	Recording made with an MD or other recorder
Template	AAYYYYMMDD_hhmmss	CCCCCMMDD_hhmmFF	AAYYYYMMDD_hhmmssFF
Code	S	A	M

Table 3. File Name template used by the analysis system for the different site types.

IDRISI is the second half of EAS' interface level. While it is a powerful spatial analysis program, IDRISI was not designed primarily to perform repeated analyses on large numbers of images.

To interface between the spectrograms and IDRISI, the GIS program, EAS utilizes both Microsoft Windows and IDRISI API protocols. Based on the variables selected by a user, EAS reads the list of input files and generates the proper macro command lines for IDRISI to run to perform the spatial analysis. EAS then calls IDRISI and instructs it to run the macro file at the command line level, and then waits for IDRISI to complete the analysis. After IDRISI has finished, EAS reads each histogram generated by IDRISI and copies the pertinent values into a single comma-delimited text file. This text file may then be imported into a database or statistics program for further visualization and interpretation of the data.

Stepwise Operation of EAS

To generate the statistical information from the spectrograms, EAS uses stepwise logic that divides into nine sequential operations. This stepwise orientation of the program arises both for the sake of programming simplicity, and because each step has been integrated into the program as demand has necessitated, often resulting in a new version of the original program. The section below describes the purpose and function of each processing step in turn.

Steps 1 and 2: Input and Output Paths

In step 1, the user selects the directory path to the spectrograms from the directory list in frame one. EAS then creates an internal file list of all the files in that directory. In step two, the user tells EAS where to place the output from the analysis, and the desired name of the macro file. Separating the input and output specifications allows greater organization of the statistics, and is useful when one wishes to compare the statistics of multiple sites. The output includes both the raster files and the histograms, so EAS creates two subdirectories in the output directory. The 'rasters' folder contains all the raster and histogram files, and the 'results' folder contains the final text file and any orthographs created.

Step 3: Specification of Data Source

The samples used in these studies of acoustic characteristics are gathered in four predominant manners: Scalable Modular Instruments (SMIs), Manual Recordings, Volunteer Recordings, and samples gathered in conjunction with aquatic and other measurements (Aquatic Samples). SMI sites are permanent, and record thirty seconds of sound at every half-hour. Manual, Volunteer, and sampling recordings all use the Sony Minidisk recorders to obtain a single 80-minute sample, which is then subdivided into 12 thirty-second subsets at five-minute intervals. The filename format is different for each of these data types, so EAS must know which data type it is dealing with. With the exception of the aquatic samples, all the recordings have a standard two-letter abbreviation assigned to them. The aquatic samples use an 11-character site code, and so the user inputs this code in step three if the data set is from an aquatic sample.

Step 4: Specification of Metadata

Files transferred from a minidisk or DAT (Digital Audio Tape) medium do not generally transfer with a standard file name format. EAS reads the file metadata from the file name string, however, so a correction is needed for these non-standard file names (See the section regarding file names below). To correct this, a series of text boxes in step four allow the user to enter the date and start time of these recordings, which will then replace the metadata EAS finds in the file name. If the user checks the option box to use the metadata, EAS will store the variables in the text boxes as strings, and insert them into the file name parameters of the macro file at the appropriate position, so that IDRISI® converts the file names for its rasters and histograms into the proper format. This entire procedure does not apply to files from the SMIs, however, for two reasons. Foremost, the SMIs do name the sound files with the standard format specified below, so EAS will not need to change the metadata values. Second, files captured via SMIs are temporal data sets, meaning they have multiple start times. EAS is capable of specifying only one start time, so the SMI metadata would be distorted if EAS were to attempt to specify the same time to all the data files.

Step 5: Two-Letter Site Abbreviation

Initially, EAS maintained an internal record of the entire list of site abbreviations that it displayed in a drop down menu. However, the volume of sites established soon began to increase faster then EAS could be updated. Therefore, the user now may either select an abbreviation from the list or specify a new one in the text box below the list. In either case, the program stores the two characters as a text string and enters them into the macro file.

Step 6: Windowing Options

The ability to "window" the spectrographs into different frequency bands was the feature of IDRISI that enabled bandwidth analyses of the acoustic signals. IDRISI will window a spectrogram into rectangles based on the positions of the pixels in the top left and bottom right corners of the rectangle. To work properly, however, all the input spectrograms must have the same dimensions. After discussing this with Richard Horne, the creator of Spectrogram, he agreed to build a batch processor into Spectrogram that outputs spectrographs of a predetermined size (1,000 pixels wide by 500 pixels high). Because the frequency scale used in these spectrographs is linear, each pixel represents the same range in the y-axis. Therefore, the dimensions of a given window need only be entered once into EAS, and it can replicate this window across multiple spectrographs. To maximize both legibility and computing resources, EAS instructs IDRISI to divide the spectrograms into 11 bands with bandwidths of approximately 1 kHz each. IDRISI requires that the x, y coordinates of its windows be in terms of pixels, so the number of pixels in any given band may be calculated by dividing the number of pixels in the y-axis (500 pixels) by the signal bandwidth (11 kHz). This yields a value of approximately 45 pixels for each 1 kHz band. EAS then instructs IDRISI to generate a histogram and calculate the mean amplitude value for each 45-pixel band, which enables the comparison of the distribution of acoustic activity across frequency bands.

A second windowing option, Temporal Windowing, offers the user the opportunity to window the spectrogram horizontally, across the time domain. This option allows the user to examine changes in the acoustic activity at a greater temporal resolution (300 msec per division). While this option is not as informative as the bandwidth analysis, it does provide a basic indication of the variation in activity over time within the sample.

Step 7: Landscape and Other Analyses

The macro parameters in IDRISI to initiate its landscape analysis tools operate in a manner similar to the basic IDRISI commands, so EAS may instruct IDRISI to apply various landscape analysis algorithms to the spectrograms. The landscape analyses offered in EAS are:

- Diversity
- Dominance
- Fragmentation
- Relative Richness

For a description of these analyses and the mathematics behind them, consult Turner et al.'s Landscape Ecology (2001). If the user selects any of these analyses, EAS simply writes the proper parameters into the macro file for IDRISI to perform upon execution of the macro commands. While the interface to these analyses is relatively straightforward, their translation to the different spatial parameters of the spectrogram is not, and these analyses are not implemented frequently. Further examination of the results of various landscape analysis algorithms and correlation between multiple variables may help to elucidate the meaning of these analyses as they apply to the acoustic spectrum.

An analysis that does apply readily to the spectrogram is the Biophony Indexing. These indices are essentially an extension of the approach used to perform the bandwidth analysis, with different window sizes specified to generate windows for the anthrophony, biophony, and geophony. EAS uses the same windowing macro and instructs IDRISI to divide the full spectrum into the three windows based on the pixel coordinates at their respective frequency positions.

Macro Generation and Implementation

Because EAS generates a list of macro commands in a separate file, the implementation phase divides into two steps. In the first step, EAS writes the series of command lines for the various processing and analyses that the user selected into the .iml (IDRISI Macro Language) file. These command lines are based on internal processes built into the IDRISI system, which IDRISI calls and performs based on the specified parameters. However, IDRISI does not access these commands until the second step, when EAS calls IDRISI and instructs it to run the macro file it created. This is done using an API command called Run_Macro, which opens IDRISI and instructs it to run the macro file designated in the command line parameters.

Step 8: Histogram Extraction Tool

Step 8 contains the entirety of EAS' second function, the reading and extraction of the pertinent statistical values from the multiple text histograms generated by the GIS processing in IDRISI. This step utilizes Microsoft's Scripting Runtime Library to open, read and copy information from a series of text files sequentially. When EAS generates the macro commands for IDRISI, it also creates a list of the histogram text files it expects IDRISI to create when it runs the macro file. When the extraction tool begins operation, it opens the first file in the list, scans it for the pertinent lines of text, copies these lines into a text file and then closes the file. It then repeats this process for every file in the list. The file name string in the macro file uses a series of alphanumeric codes to organize the files based on the various analyses and processes performed on the bitmapped spectrograms. The extraction tool also reads these strings and copies the important portions into the same comma-delimited text file that it copies the values in the histograms into to ensure the final data is organized and readable when entered into a database.

Step 9: Generate Orthographs

The Orthographic function is a recent add-on to the EAS system. The purpose of this utility is to create three-dimensional orthographic representations of the bitmap spectrograms. These three-dimensional images are particularly useful for visualization of the acoustic activity, as well as for creating slick graphics for presentations and theses.

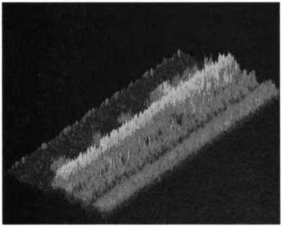

Figure 3. An example of a slick graphic generated from the orthographs.

The orthograph utility generates and runs a second macro file, similar to the first macro file that lists IDRISI's commands for the actual analysis. It uses the file names and paths listed in the same internal file list used for the first macro file, but it generates a much simpler series of commands that instruct IDRISI to generate the orthographs and export them as bitmap images.

Code Structure and Logic

The program code for EAS was written entirely in Microsoft Visual Basic 6.0® because it is one of the easiest programming interfaces to work with and because IDRISI's external command library is designed for Visual Basic. The user interface modules are all built into Microsoft Visual Studio®, and have been incorporated into the program code. Partially because of its iterative nature, the code in EAS is largely modularized into distinct components. The majority of operation takes place in the Macro Generation procedure, which is where the program incorporates all the user-selected options into the macro file. Prior to pressing the "Generate Macro" button, the user must press the "Lock Parameters" button, which locks all the options selected into the program. Then, when the user presses the "Generate Macro" button, EAS reads all the selected options and translates them into the appropriate IDRISI® commands. The decision tree in Figure 3 attempts to describe the order in which EAS processes the options entered by the user before generating the histograms.

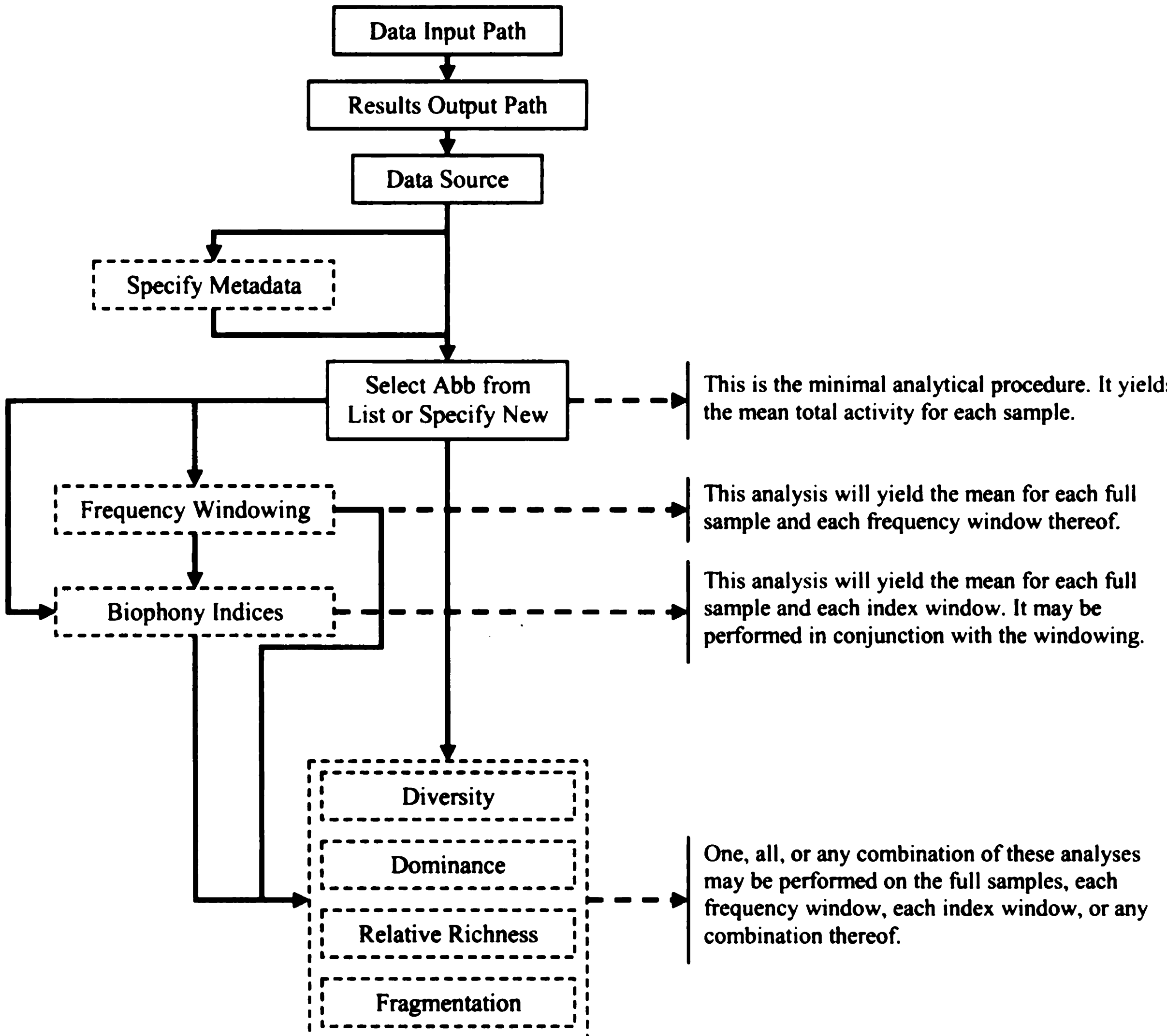

Figure 4. The order and hierarchy of operational steps programmed into the EAS code logic. Each analytical option is handled with an if...then procedure.

The output processing is slightly less complicated. The numeric codes in the file names attached to the histograms describe the frequency bands, analyses, and metadata attached to each file, so that the histogram extraction process only needs to read these codes and place the values in the appropriate columns. The decision tree in figure 4 below describes the output procedure.

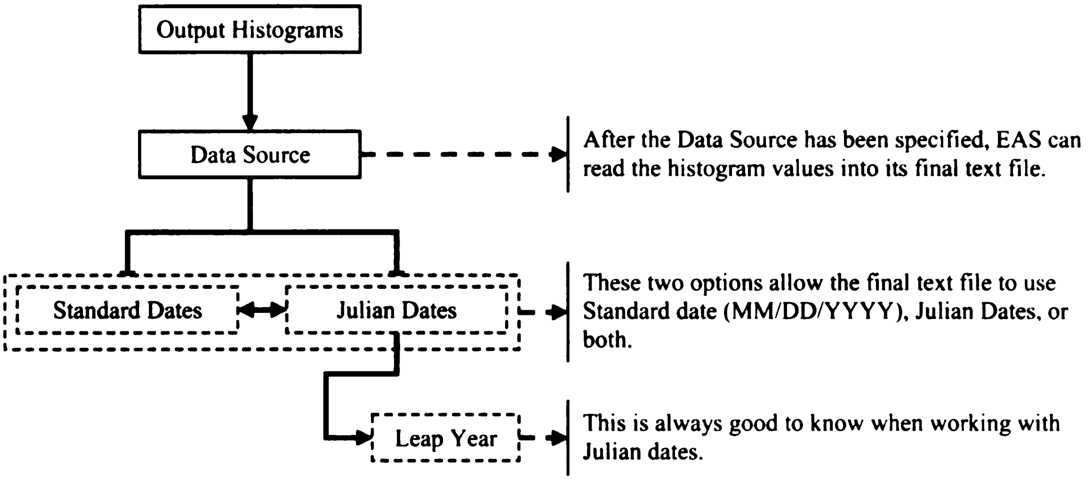

Figure 5. A hierarchical representation of the code logic within the histogram extraction utility. Again, the various options are handled with if…then operators.

EAS reads the histogram files iteratively into a single comma-delimited text file that stores both the calculated values and the associated metadata. To track the metadata through the several analytical steps, EAS uses certain characters at certain positions in the file names. This implies, of course, that each file name string is identical in length, and has the proper information at the correct positions in the string. As was mentioned in the description of Step 4 above, EAS can generate these standard file name strings if they are not already present. In either case, the histogram extraction component uses these file name strings to assign the proper calculated values to their respective sources. Figure 5 below is an illustration of how these file name strings are structured.

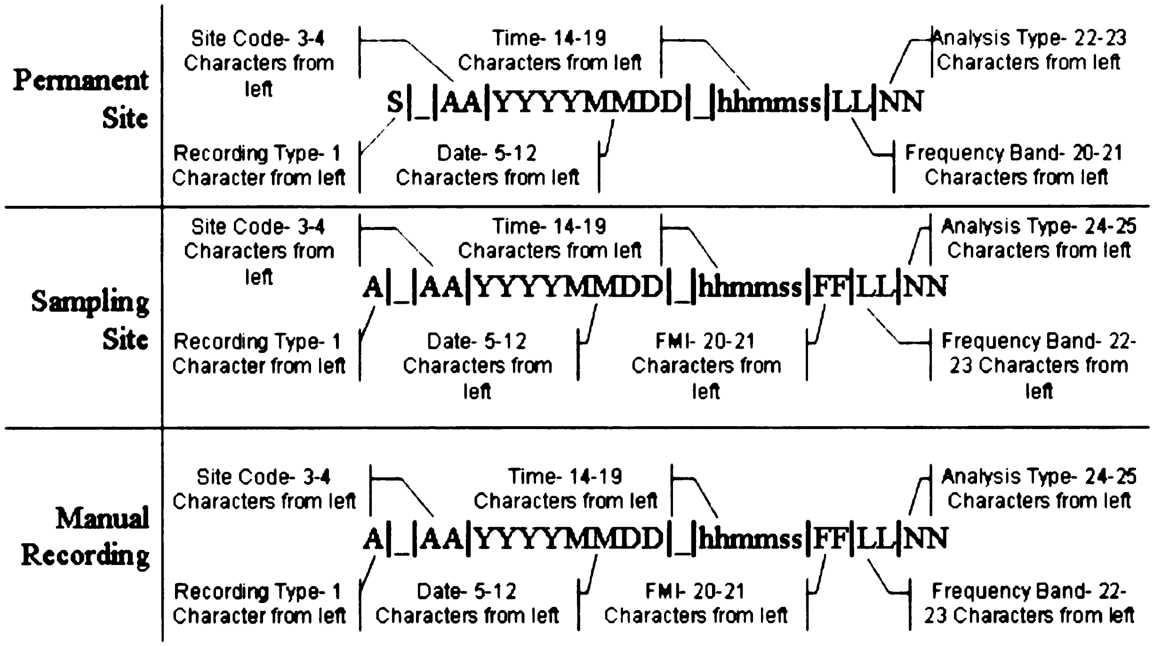

Figure 6. An explanation of the file name metadata for each of the three site types.

Conclusion

This program arose from the need for a programming layer to interface with and allow IDRISI® to handle multiple data files and automate the repetitive processing steps that would otherwise require intensive manual operation. This automation inevitably reduces the flexibility of the analysis by limiting the types of valid input data and the number of analytical options available. I have attempted to circumvent this limitation by using modular code segments that may be updated and modified with a minimal impact on the overall program operation. Moreover, the analysis of time-series or landscape-scale acoustic data sets would not be feasible without the automation that EAS introduces to the process. EAS enabled the batch processing of both the bandwidth analysis presented in the following chapter and the acoustic samples from the Muskegon River Watershed presented thereafter. The simple program that began as a batch-processing extension to

IDRISI® became a critical tool in the analysis of acoustic data on both temporal and landscape scales via the methods described in the previous chapters.

Chapter Four: Spectral Analysis of the Acoustic Signals of Three Classes of Organisms in the Northeastern United States

Introduction

Of the three spectral regions of the soundscape, the biophony typically carries the most diverse array of ecological information. This is because it is the region utilized by the majority of vocal organisms in the biosphere to relay and broadcast acoustic signals. While the anthrophony may occasionally carry intentional signals (i.e. a train whistle that signals a locomotive is indeed approaching), the majority of persistent signals in the anthrophony are incidental (i.e. fans, automobile motors and jet engines). The geophony, consisting exclusively of acoustic signals initiated by geophysical processes, may affect the composition of signals within the biophony, but does not carry a great deal of biological information itself. Therefore, given the concentration of signals in the biophony, the question arises of how, if at all, the signals are organized in a manner that allows each vocal member to communicate effectively.

Spectral bandwidth is an inherently limited resource, particularly in the biophony, where communication is the primary objective and signal reception and accurate interpretation is critical. Faced with a similar task of signal organization, the United States Federal Communication Commission regulates and assigns high-frequency spectral bandwidth to television, radio, and other operators to prevent the chaos that would ensue if signals were allowed to overlap at random. Similarly, Dr. Bernard Krause has proposed that evolution and natural selection regulates the spectral frequencies and temporal properties of vocal organisms in a manner that allows each organism to communicate with minimal signal interference. This signal regulation operates as a form of niche partitioning wherein each species adjusts the frequency and temporal structure of its signal to an unused portion of the acoustic spectrum (Krause 1987). As with most evolutionary theories regarding character displacement at the community level, the cause of this niche partitioning remains difficult to ascertain due to the existence of a variety of possible alternatives to competition (i.e. Is signal structure more dependent on physiological attributes, evolutionary history, or a combination of variables?). While an extensive study of the phylogenetic history and ecosystem structure of vocal organisms may elucidate a single explanation, this question is second to that of whether organisms actually do partition their signals into different spectral locations. This, too, is a challenging research question that has been approached in several studies of the acoustic behavior and spectral response of organisms to inter and intraspecific interference (e.g. (Bukhvalova and Zhantiyev 1994; Bosch *et al.* 2000; Schwartz *et al.* 2001)). I have attempted to approach this question from a larger-scale perspective by analyzing and comparing the spectral structure of samples from three taxonomic classes of organisms (Aves, Insecta and Amphibia). Krause proposes two primary partitioning mechanisms (frequency and time) in his acoustic niche hypothesis. While an analysis of the timing of signals remains impractical (i.e. the only way to satisfactorily measure the timing would be to examine the timing of organisms vocalizations in their habitats), an analysis of the frequency partitioning simply requires a sizable proportion of different organisms' vocalizations.

Therefore, this study in part examines the degree to which different groups of organisms utilize different spectral frequency ranges.

Birds, Bugs and Bullfrogs

I selected samples from the Classes Aves, Insecta and Amphibia for analysis because these three classes of organisms are some of the most prevalent members of the biophony. Additionally, each class represents diverse members and unique features of the biosphere. Birds comprise one of the most diverse classes of terrestrial vertebrates, with a current species estimate totaling almost 10,000 (Gill 1995). Additionally, birds exhibit a great diversity of speciation and niche partitioning amongst the vertebrates. Insects comprise one of the most diverse classes of vocal invertebrates, with a current species estimate ranging anywhere from 5- to 80-million (Romoser and John G. Stoffoloano 1998). Finally, amphibians, while perhaps not exhibiting the same degree of diversity of niches or speciation as their vocal counterparts (estimate 5,500 species), occupy an important position as an indicator of ecological change (Duellman and Trueb 1986). Their unique life history makes them particularly vulnerable to detrimental impacts of human activity and disturbance. Taken together, these three classes of organisms comprise an informative and diverse component of the biophony.

The Use of Acoustic Signals

Most vocal organisms communicate similar forms of information through their acoustic signals. The most common information communicated includes mating status, territory claims, alarms and warnings, and coordination. Commonly, organisms use a variety of signals contingent upon the type of information they are attempting to communicate. For instance, many songbirds' alarm calls have relatively higher frequencies than their mating or territorial signals because higher frequency signals are more difficult to localize. Organisms also adapt their signals to habitat features that influence the relative strength and propagation of the call. For instance, birds that live in the equatorial rainforests tend to have shorter and simpler vocalizations than those that live in open areas, as the rainforest vegetation tends to distort and absorb vocalizations that are more complex (Gill 1995). Among insects, some species of crickets will dig burrows with dimensions that resonate at the frequencies of their chirps to enhance the volume and range of their signals (Bailey *et al.* 2001).

Objectives

The primary objective of the study described in this chapter is to examine and begin to understand the complex structure of acoustic signals within the biophony. The theory of evolution through natural selection leads to the intuitive conclusion that organisms will attempt to organize their signals within the acoustic spectrum in a manner that minimizes signal interference, thereby minimizing the amount of energy expended on acoustic communication. Additionally, previous research, based on observations of a series of acoustic samples (Gage *et al.* submitted), has indicated that the majority of organisms' vocalizations lie in a frequency range of 2 to 11 kilohertz. This range was estimated by examining a series of acoustic observations and attempting to delineate where the majority of vocalizations occurred. I attempted to verify this conclusion by examining the spectral frequency range of a collection of "pure" signals (i.e. signals from commercial recordings with background noise filtered out).

Methods

I used a series of commercially available compilations of organism vocalizations to obtain an adequate data set for analysis. These compilations consisted of vocalizations of 265 species of birds (Bird Songs Eastern/Central 2002), 42 species of amphibians (Elliott 2004), and 52 species of insects (Rannels *et al.* 1998). Appendix B contains a list of the Scientific and Common Names of the organisms sampled for analysis, as well as their taxonomic classification. Each species' sample consisted of a relatively "pure" (little or no background noise in the sample) recording of the organism's primary mating and contact vocalizations. The statistical research hypothesis was that the primary frequency bandwidths of the three Classes of organisms differed significantly from one another.

Sound Signal Analysis

Each signal was downsampled from a CD-quality track to 22.050 kHz and converted into a single-channel monaural wave file prior to analysis. A spectrogram was then generated from each wave file with a 90 dB scale and a 30-millisecond pixel resolution. The frequency analysis parameters were on a linear scale with a Fast Fourier Transform size of 4,096 points and a frequency resolution of 5.4 Hz. The theoretical low band limit was 0 Hz, and the high band was 11.025 kHz[3]. These signal parameters were the standard

[3] This high band limit is constrained by the Nyquist Sampling Theorem, which states that the maximum signal frequency must be no greater than ½ the sampling rate, or $Sampling\ Rate = 2 \times f(\max)$

parameters outlined in Chapter 1. Each spectrogram was then read by a raster-based GIS program that divided the image into 11 frequency bands of 1 kHz each, and calculated the mean amplitude value in each band based on an 8-bit scale.

Statistical Analysis

Prior to statistical analysis, the mean of each frequency band of each sample was divided by the mean of the entire signal to yield a proportioned mean for the frequency bands that took into account the relative intensity of the signals, thereby allowing valid comparison across signals. These weighted means were then averaged by Class and used to generate bandwidth histograms that depict the average distribution of activity across the 11 frequency bands. The three taxonomic classes of signals were then compared in SAS based on the square roots[4] of the weighted means of their 11 frequency bands in an ANOVA using a standard linear model designed to handle fixed effects with $\alpha = 0.05$. To account for the lack of independence between the 11 frequency bands in each sample, the ANOVA was run with a repeated heterogeneous first-order autoregressive structure. To determine where the significant differences occurred, the differences of the least squares means were compared. Using the square root of the mean for each band fit the data to the AOV conditions (normal distribution, homogeneity of variance and using the repeated statement compensated for the lack of independence between bands).

[4] The square root was used to fit the data to the normal distribution of residuals assumption of the ANOVA process.

Results

Spectral Bandwidth Histograms

The spectral bandwidth histogram for the entire series of organisms indicated the strongest concentration of acoustic activity was in the 3 – 4 kHz band, with an average proportioned mean of 1.79. The 2 – 3 and 4 – 5 kHz bands were also comparatively high, with means of 1.60 and 1.61 respectively (Table 4a). In the Class Aves, the strongest band was 3 – 4 kHz with a mean of 1.90, while the 4 – 5 kHz band also had a mean of 1.81 (Table 4b). In the Class Insecta, the band with the highest concentration was 6 – 7 kHz, with a mean of 1.41 (Table 4c). The activity in the Class Amphibia was at relatively lower frequencies, with a maximum mean of 2.65 at 1 – 2 kHz (Table 4d).

a) All Samples			b) Aves		
Band	Avg Weighted_MN	SE	Band	Avg Weighted_MN	SE
1	1.05	0.09	1	1.06	0.11
2	1.15	0.07	2	1.06	0.08
3	1.60	0.07	3	1.61	0.08
4	1.80	0.07	4	1.90	0.08
5	1.61	0.07	5	1.81	0.08
6	1.18	0.05	6	1.27	0.06
7	0.95	0.05	7	0.94	0.05
8	0.73	0.05	8	0.70	0.05
9	0.49	0.04	9	0.43	0.04
10	0.31	0.03	10	0.21	0.02
11	0.22	0.02	11	0.12	0.01
c) Insecta			d) Amphibia		
Band	Avg Weighted_MN	SE	Band	Avg Weighted_MN	SE
1	0.28	0.05	1	1.99	0.22
2	0.40	0.10	2	2.65	0.24
3	0.84	0.18	3	2.39	0.20
4	1.31	0.26	4	1.68	0.17
5	1.15	0.15	5	0.90	0.10
6	1.22	0.13	6	0.51	0.07
7	1.41	0.18	7	0.45	0.13
8	1.39	0.15	8	0.20	0.05
9	1.14	0.11	9	0.12	0.03
10	0.99	0.11	10	0.12	0.03
11	0.87	0.12	11	9.42E-02	2.51E-02

Table 4. The results of the spectral analysis of the acoustic signals of a) all 354 organisms sampled; b) 264 species in the Class Aves; c) 49 species in the Class Insecta; and d) 41 species in the Class Amphibia. The value in the column "Band" is the high end of that frequency band (i.e. Band 1 = 0 – 1 kHz), and SE refers to the standard error of the means.

Based solely on the histograms, the distribution of activity across the spectrum already appears to differ between the three Classes of organisms. The spectral plots depicted below provide a visual representation of the distribution of activity across the spectral band.

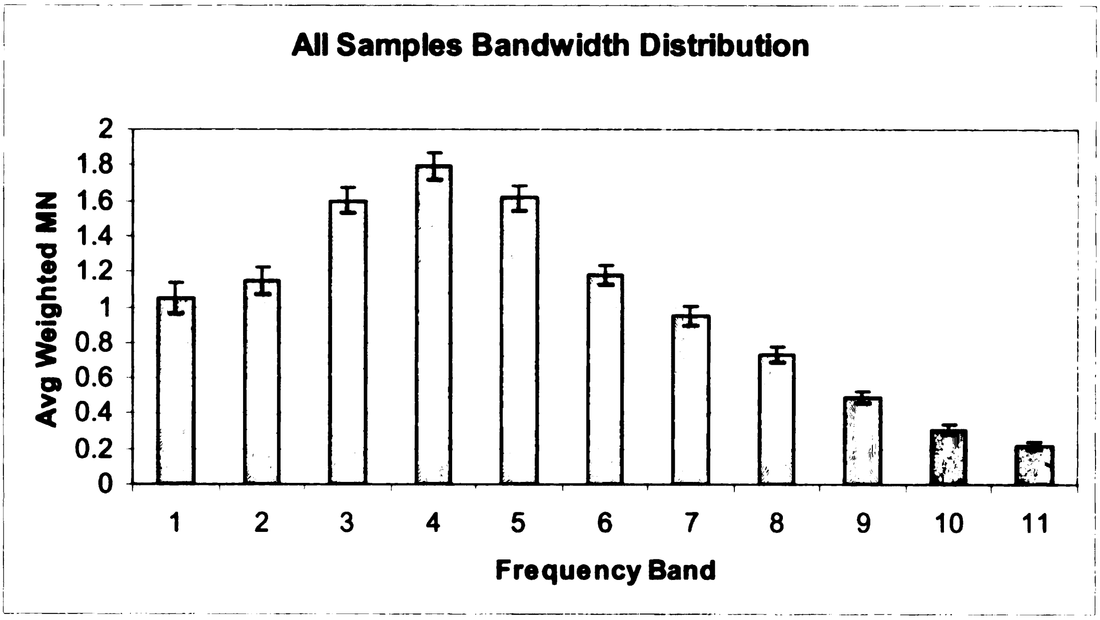

Figure 7. Spectral bandwidth distribution of all three Classes (354 samples). Avg Weighted MN represents the mean concentration of activity for each frequency band, which is the respective 1 kHz spectral band.

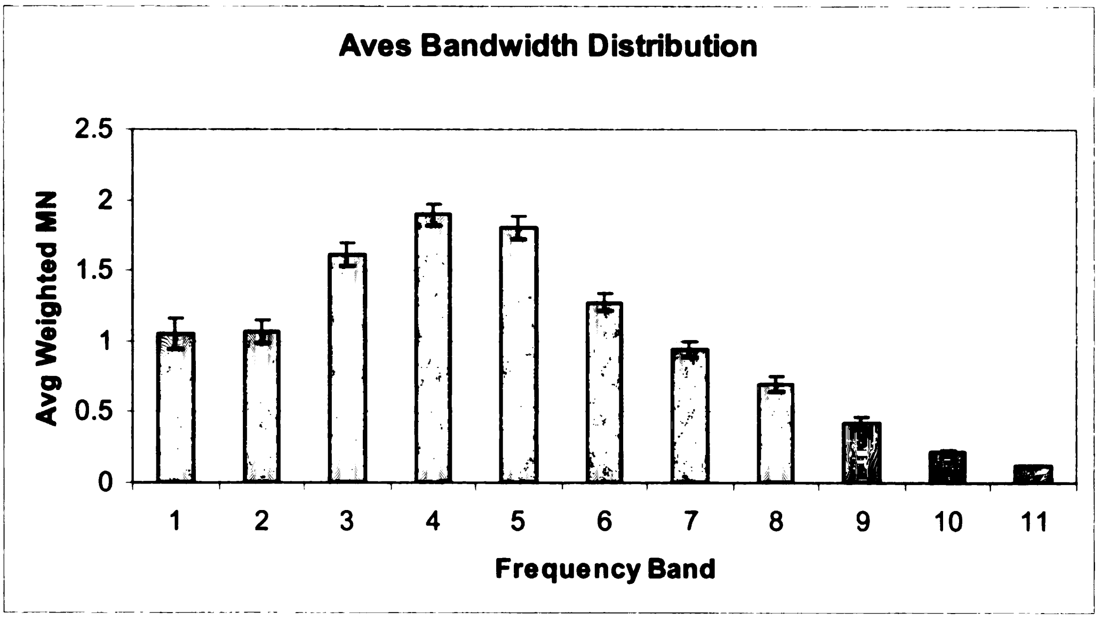

Figure 8. Spectral bandwidth distribution of acoustic samples from 264 avian species (150 Passerines, 114 Non-passerines), with maximum activity from 2 – 5 kHz.

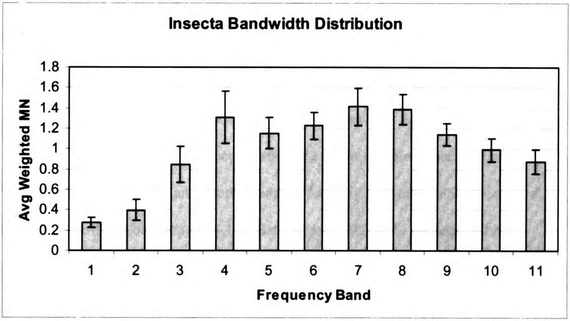

Figure 9. Spectral bandwidth distribution of acoustic samples from 49 species of insects, with two activity peaks. The highest activity concentration in a single band is at 6 – 7 kHz.

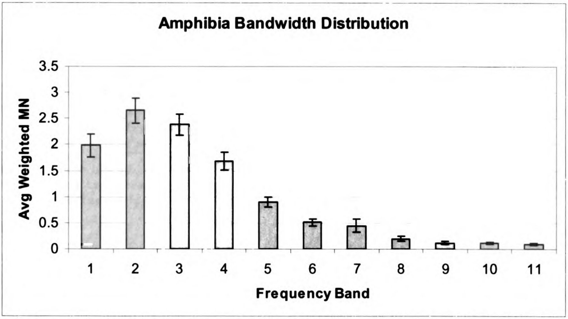

Figure 10. Spectral bandwidth distribution of acoustic samples from 41 species of amphibians. The highest concentration of activity is at 1 – 2 kHz.

Analysis of Variance

The ANOVA results of the Class-level analysis indicated a statistically significant difference between the spectral bandwidth distributions of the samples based on their taxonomic Classes with a 0.05 probability of a Type I error (*p-value* < 0.0001, $\alpha = 0.05$; Table 5). This indicated that the spectral structure of three primary members of the biophony (Avians, Insects, and Amphibians) differed significantly within the general spectral range of the biophony (2 – 11 kHz, Figure 6). Based on the bandwidth histograms, amphibians tended to utilize the lower segment of the spectrum (1 – 3 kHz, Figure 7), birds tended to utilize slightly higher frequencies (3 – 5 kHz, Figure 8) and insects tended to utilize even higher frequencies (6 – 8 kHz, Figure 9). Insects also appeared to have the most varied signals in terms of spectral structure (relatively high concentrations of activity from 3 to 9 kHz).

Type 3 Tests of Fixed Effects				
Effect	Num df	Den df	F Value	Pr > F
Class	2	352	0.23	0.7945
Band	10	3520	30.05	< 0.0001
Class*Band	20	3520	12.58	< 0.0001

Table 5. Results of a mixed ANOVA of the spectral properties of three Classes of organisms (Insecta, Amphibia and Aves) across 11 frequency bands (0 – 11 kHz). The effect labeled Class*Band indicates the analysis of the weighted means by Class and frequency band.

The ANOVA indicated that the Class*Band effect was significant (which, in this case, was the desired outcome, as the interaction effect was the variable of interest), so I compared the mean differences of the three Classes by band using the Least Significant Differences ($\alpha = 0.05$). All but four of the bands were significantly different. The Class Amphibia was not significantly different from Insecta at band 5, nor did it differ from

Aves at bands 4 and 11. The class Aves did not differ significantly from Insecta at band 6. All other bands were significantly different (Table 6).

Class 1	Class 2	Band	Estimate	SE	t Value	Pr > |t|	Significant Difference?
Amphibia	Insecta	1	0.90	0.90	6.48	<.0001	Yes
Amphibia	Insecta	2	1.12	0.15	7.59	<.0001	Yes
Amphibia	Insecta	3	0.81	0.15	5.58	<.0001	Yes
Amphibia	Insecta	4	0.33	0.14	2.38	0.0172	Yes
Amphibia	Insecta	5	-0.07	0.12	-0.62	0.5384	No
Amphibia	Insecta	6	-0.39	0.10	-4.00	<.0001	Yes
Amphibia	Insecta	7	-0.56	0.09	-6.24	<.0001	Yes
Amphibia	Insecta	8	-0.72	0.08	-8.99	<.0001	Yes
Amphibia	Insecta	9	-0.70	0.07	-10.25	<.0001	Yes
Amphibia	Insecta	10	-0.64	0.05	-11.81	<.0001	Yes
Amphibia	Insecta	11	-0.58	0.05	-11.51	<.0001	Yes
Aves	Insecta	1	0.38	0.10	3.70	0.0002	Yes
Aves	Insecta	2	0.38	0.11	3.44	0.0006	Yes
Aves	Insecta	3	0.46	0.11	4.24	<.0001	Yes
Aves	Insecta	4	0.38	0.10	3.65	0.0003	Yes
Aves	Insecta	5	0.28	0.09	3.23	0.0012	Yes
Aves	Insecta	6	0.00	0.07	0.06	0.9503	No
Aves	Insecta	7	-0.23	0.07	-3.38	0.0007	Yes
Aves	Insecta	8	-0.36	0.06	-6.10	<.0001	Yes
Aves	Insecta	9	-0.44	0.05	-8.66	<.0001	Yes
Aves	Insecta	10	-0.53	0.04	-13.13	<.0001	Yes
Aves	Insecta	11	-0.53	0.04	-14.44	<.0001	Yes
Amphibia	Aves	1	0.52	0.11	4.74	<.0001	Yes
Amphibia	Aves	2	0.75	0.75	6.39	<.0001	Yes
Amphibia	Aves	3	0.36	0.11	3.09	0.002	Yes
Amphibia	Aves	4	-0.04	0.11	-0.40	0.6896	No
Amphibia	Aves	5	-0.37	0.09	-3.81	0.0001	Yes
Amphibia	Aves	6	-0.39	0.08	-5.12	<.0001	Yes
Amphibia	Aves	7	-0.34	0.07	-4.73	<.0001	Yes
Amphibia	Aves	8	-0.36	0.06	-5.66	<.0001	Yes
Amphibia	Aves	9	-0.26	0.05	-4.87	<.0001	Yes
Amphibia	Aves	10	-0.11	0.04	-2.65	0.008	Yes
Amphibia	Aves	11	-0.04	0.04	-1.05	0.2948	No

Table 6. Comparisons of Least Squares Means by Class at the 11 frequency bands. $p < \alpha$ indicates a significant difference (LSD, $\alpha = 0.05$).

Discussion

The ANOVA results and the means comparisons indicated a significant differentiation of frequency structures of the samples. The overlap between Aves and Amphibia at band 11 is probably due to the low concentration of activity in that band for both orders. The other three overlapping bands (4, 5 and 6) are likely regions where signals may coincide spectrally. An analysis of the temporal features of these three bands from field recordings where the three Classes of organisms occur would enable researchers to determine whether temporal modulation occurs in regions of spectral competition. While these results do not conclusively prove Krause's Niche Hypothesis (Krause 1987), they do indicate a significant degree of signal variation between groups of vocal organisms. The bandwidth distribution of the samples also indicates that the majority of organic vocalizations, at least in the Northeastern United States, are concentrated in a frequency range between 2 and 5 kHz. This, of course, is a generalization, and several organisms utilize spectral bands outside this approximate region of concentration. Of particular significance is the relatively low frequency class of signals generated by amphibians. The spectral bandwidth utilized by these organisms appears to overlap with the variety of mechanical "noises" generated by human activity. This may place amphibians at a relatively higher risk of acoustic interference from human activity than other organisms. Human mechanical signals tend to be stronger and more continuous than organic vocalizations, thereby "masking" organic signals when they overlap at the critical band (Hopp *et al.* 1998). This region of overlap merits further investigation, as it may help, in part, to explain recent observations of declines in amphibian populations (Alford and

Richards 1999). Further investigation of the manner in which organic vocalizations are partitioned in the biophony would also reinforce the concept of frequency modulation within the biophony. Specifically, analyses of the frequency structure of vocalizations within the same habitats would indicate whether the signals were modulated to avoid acoustic interference, or whether the modulation was more a byproduct of physiological constraints. Additionally, an analysis of the temporal features of acoustic signals would indicate whether temporal modulation occurs in conjunction with frequency modulation in organisms with limited capacities to modulate the critical frequency bands of their signals. The results of this investigation do indicate at the least a rough degree of signal modulation within the biophony based on the taxonomic Classes of vocal organisms.

Chapter Five: Acoustic Signatures of Different Locations

Introduction

An interesting question that arises in the examination of acoustic signals is whether different locations and consequent land use/ land cover types exhibit unique acoustic "signatures," or defining characteristics. Intuitively, the differences in biophysical elements between a wetland and a city, for instance, could lead one to conclude that the acoustic signatures would also differ significantly. In addition to this spatial element of variation, the acoustic activity within a region should exhibit temporal variation on both a seasonal and diurnal scale. For instance, the Dawn Chorus is a documented event in bird communities, and several species engage in song in the evening (Gill 1995). This vibrant chorus of song in the morning will significantly influence the overall diurnal pattern of acoustic activity at a location. Moreover, in the mid to late summer of most temperate regions, the daily biophony transitions from birds throughout the day to amphibians and crickets throughout the night. Similarly, the intensity and composition of biophonic vocalizations varies across seasons. In the temperate regions, the winter generally exhibits a significantly lesser degree of organic activity than does the spring, summer or fall. The second major component of the soundscape, the anthrophony, also exhibits some predictable spatiotemporal variations. Sounds of traffic and other human activity are generally less intense at night, particularly as one travels farther from major urban centers. The typical times of the highest concentration of traffic noise correlate to the traditional morning 'Rush Hour', the afternoon 'Lunch Break' and the evening 'Rush

Hour'. While the qualitative features of a landscape's soundscape may differ dramatically, a quantitative measure is needed to determine the degree to which anthropogenic activity is the causal agent for the observed differences between two given land cover types.

The derived ratio (ρ) between biophonic and anthrophonic activity described in chapters two and three should be a useful quantification that retains the expected spatiotemporal patterns. Additionally, a single-region analysis of both the anthrophony and the biophony may elucidate spatiotemporal patterns in these two features. A visual interpretation of the temporal patterns of the ratio value may help to demonstrate any potential exchange between anthropogenic and biophonic activity within or between various land cover types.

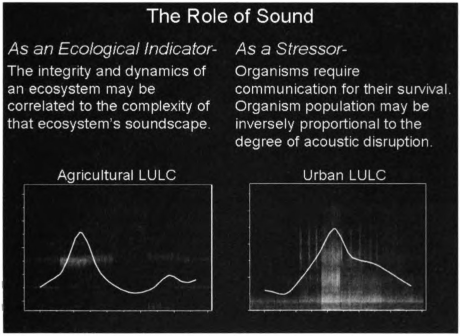

Figure 11. An overview of the dual role of sound in ecological research. The two graphs on the bottom depict a summary of the total activity within two different locations over 24 hours.

Objectives

This chapter summarizes two separate analyses conducted at different times over the past three years in attempts to determine whether α, β and the derived ρ value could be used to detect spatiotemporal differences in the data. General observations indicate that the biophysical and human constituents within a given location tend to affect the temporal patterns of the soundscape on a diurnal scale (Sound as an Ecological Indicator and Stressor Slide, Figure 10). However, these initial observations are both rudimentary and based on overall acoustic activity, rather than focused on the differential contributions by biological and anthropogenic sources. Therefore, the two separate analyses described here represent somewhat more comprehensive examinations of this phenomenon. By using ρ in addition to α and β, the analysis focuses on the differential contribution of one of the two signal classes, in addition to the overall activity.

Study One: 14 Days, 2 Locations

This study utilized data gathered at half-hour intervals over 14 days (2001-06-11 to 2001-06-24) at two different locations with permanent recording stations in the summer of 2001. One location, Meadows (MS), was a small private ranch located a few miles outside of Big Rapids, MI. The second location, Paris Park (PP), was a county park located in Paris, MI. Meadows was situated in the midst of a low-intensity agricultural complex, while Paris Park was a fish hatchery, public campground, and the headquarters for the Mecosta County Parks Commission. In the 14-day analysis, the signals from 07:30 and 19:30 were analyzed using the standard spectrograph analysis with the automation system described in Chapter 3, and then the ratio of biophony to anthrophony was plotted against time for both locations (Figure 11), followed by the average values for anthrophony (Figure 12) and biophony (Figure 13).

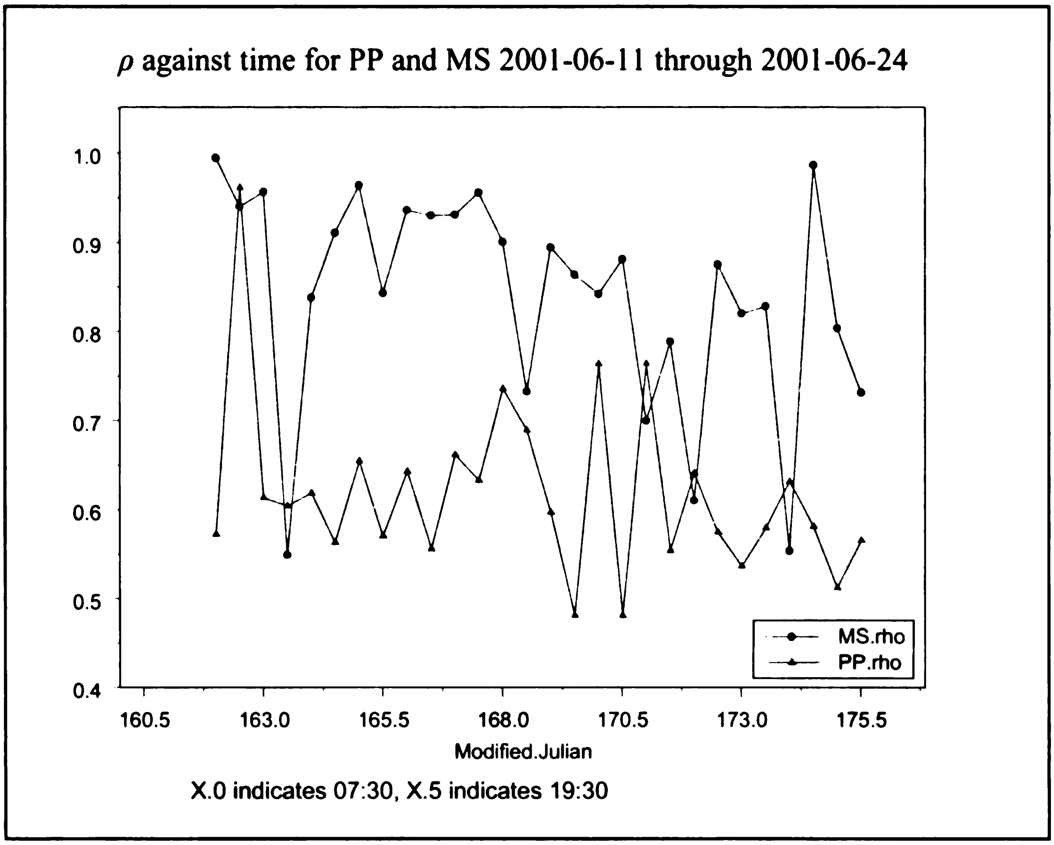

Figure 12. ρ **plotted against time for PP and MS 2001-06-11 through 2001-06-24. Overall, MS has a higher value, indicating a stronger biophonic contribution.**

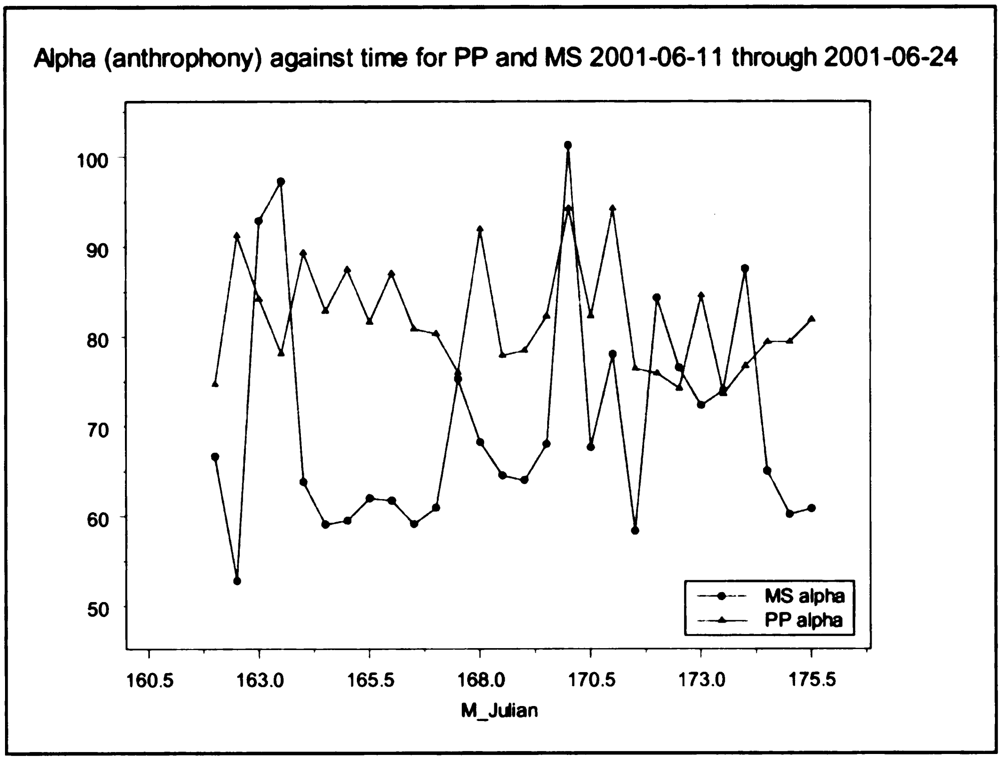

Figure 13. ***α*** **plotted against time for PP and MS 2001-06-11 through 2001-06-24. With a few exceptions, PP has a higher alpha value on each day.**

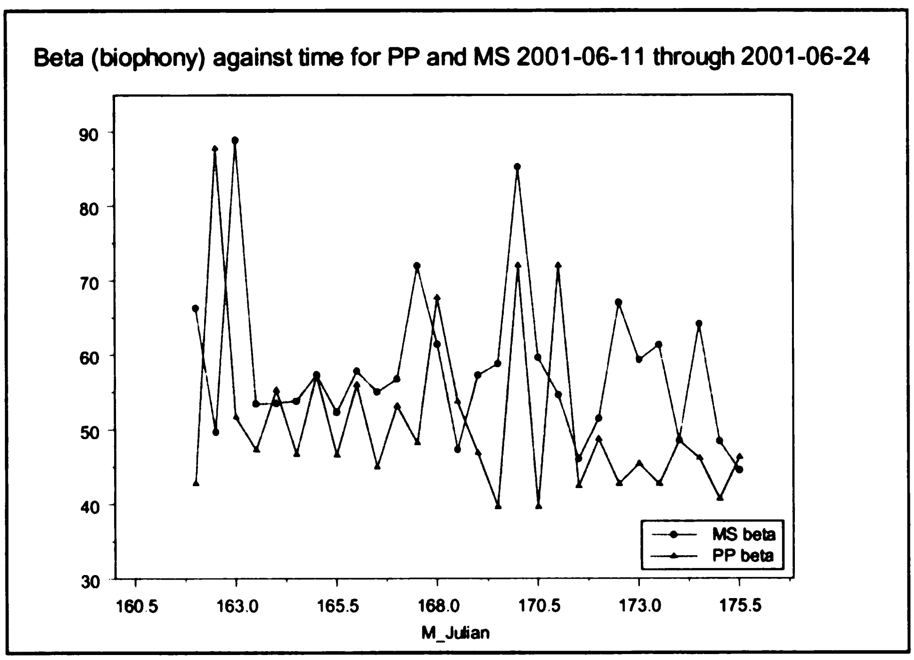

Figure 14. ***β*** **plotted against time for PP and MS 2001-06-11 through 2001-06-24. The beta values are closer than the alpha.**

In addition to the temporal plot, an Analysis of Variance was performed to determine whether the two sites differed significantly. Because replication was not feasible, the separate sampling days served as pseudoreplicates. The lack of a clear linear progression of ρ over time at both locations allowed this approximation to fulfill the random sample requirement, and the ANOVA was performed with a first-order autoregressive matrix to account for the lack of independence between samples. The ANOVA is still not entirely statistically valid, but it does provide a rough indication of whether the two sites differ significantly.

Effect	*Num df*	*Den df*	*F-Value*	*Pr > F*
Location	1	26	68.54	<.0001
Time	1	26	0.27	0.6068
Location*Time	1	26	0.46	0.5046

Table 7. ANOVA results for the test of Location effects over 14 days at two locations (α=0.05). The main effect Location is significant, while the interaction effect, Location*Time, is not.

As the ANOVA results indicate, neither the Time nor the Location * Time Interaction is significant. Therefore, the data appears to indicate that the Location main effect yields a significant difference between the two data sets (Table 7).

Study Two: 3 Months, 2 Locations

This study represents a more comprehensive and long-term analysis. In this case, the full set of acoustic data was analyzed over three months at two locations. Paris Park was at the same location described above. Ferris State was a recording site situated on the Ferris State University Campus in downtown Big Rapids, MI. The administration at Ferris State

University had agreed to host the site and provide housing for me while I conducted research in the Big Rapids area. Unfortunately, logistical difficulties with the campus water supply shut down the delivery system in the summer housing, and we relocated midway through the summer. As the second location consisted of a slightly different acoustic structure, I have analyzed the data from the two Ferris State locations separately. Set one extends from (2002-05-20) May 20 to (2002-06-20) June 20, and set two runs from June 25 (2002-06-25) to July 17 (2002-07-17). All 48 samples from each day were analyzed and incorporated into the time series for both locations. Again, the ρ value was calculated as the ratio of biophony to anthrophony, and was plotted over time (Figure 13). The Friedman Supersmooth (a smoothing function that uses an iterative process to determine basic trends) was plotted to highlight any clear temporal variations in signal strength.

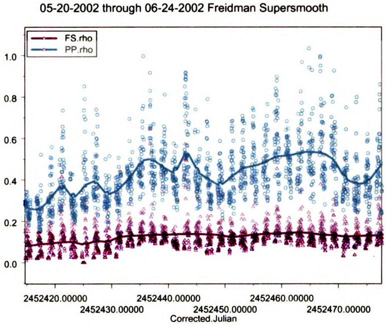

Figure 15. *ρ* plotted over time for PP (Paris Park) and FS (Ferris State) from 2002-05-20 to 2002-06-20 (dates are in Julian format). Overall, PP has a relatively stronger biophony component than FS.

For both temporal sets, Paris Park exhibits a higher degree of biophony than Ferris State. The first set shows a greater degree of variation and oscillation over time in Paris Park than Ferris State while both sites oscillate more frequently in the second set. Interestingly, both sites follow similar patterns of oscillation in the second set.

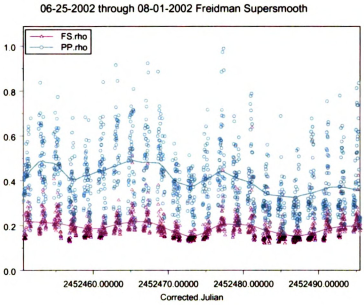

Figure 16. ρ plotted over time for PP (Paris Park) and FS (Ferris State) from 2002-06-25 to 2002-08-01. Again, PP has a relatively stronger biophony component than FS.

An ANOVA was performed using the days as pseudoreplicates, and the results indicated a significant interaction effect (Table 3). However, the temporal plots indicate a difference between the biophonic intensity of the two locations.

Effect	Num df	Den df	F-Value	Pr > F
Set One				
Location	1	62.1	318.26	<.0001
Time	47	2771	5.33	<.0001
Location*Time	47	2771	2.28	<.0001
Set Two				
Location	1	44	212.4	<.0001
Time	47	1947	9.47	<.0001
Location*Time	47	1947	4.32	<.0001

Table 8. ANOVA results for the two data sets from PP and FS ($\alpha = 0.05$).

Discussion

The two studies described above represent similar approaches to the determination of a location's acoustic signature. The underlying assumption that the biophony and anthrophony values represent biological and anthropogenic activity remains untested, however. Overall, Meadow's low-intensity agricultural cover type could conceivably represent a lower degree of anthropogenic activity than the Paris Park outdoor recreational facility. This conceptual difference does correlate to the acoustic signatures insofar as the biophony is higher in the Meadow site than Paris Park. However, there are no grounds to attribute the land cover type as the causal mechanism behind the observed differences. Alternate explanations, such as relative distances of the microphones from signal sources or the positions of the microphones, cannot be eliminated based on the information available. Similarly, Paris Park appears to represent a significantly lower concentration of anthropogenic acoustic activity than Ferris State, an urban cover type. While the number of humans in the landscape appears to be the causal factor for the degree of anthrophony in the analysis, I did not include this in the study.

Chapter Six: Correlation Analysis of Acoustic Signals and Ecological Features in the Muskegon River Watershed

Introduction

As our capacity to measure and interpret ecological acoustics increases, so too does our desire to understand how these signals influence and represent dynamic and continuous elements of the Earth's biosphere. In order to be a useful measure of ecological activity, the relationships between acoustic analyses and other ecological indicators and measurements must be examined. To this end, I have begun to research correlations between the derived acoustic indices (anthrophony and biophony) and population density in the Muskegon River Watershed.

The Muskegon River Watershed has been a region of intensive ecological study within the past five years. Various research projects and assessments, including a large-scale collaborative assessment (Stevenson *et al.* 2001), have been conducted in an attempt to ascertain and preserve the ecological integrity of the watershed. This watershed encompasses a significant portion of Michigan's natural resources, including freshwater supplies, agricultural production and fisheries (Stevenson *et al.* 2001). These research projects have yielded a large array of data on multiple ecological features of the Muskegon River Watershed. The datasets include a significant archive of acoustic samples gathered from a variety of habitats (Gage 2004). Several of these acoustic samples were gathered in conjunction with other variables including water chemistry and land cover information. As the map below illustrates, these samples were gathered throughout the watershed.

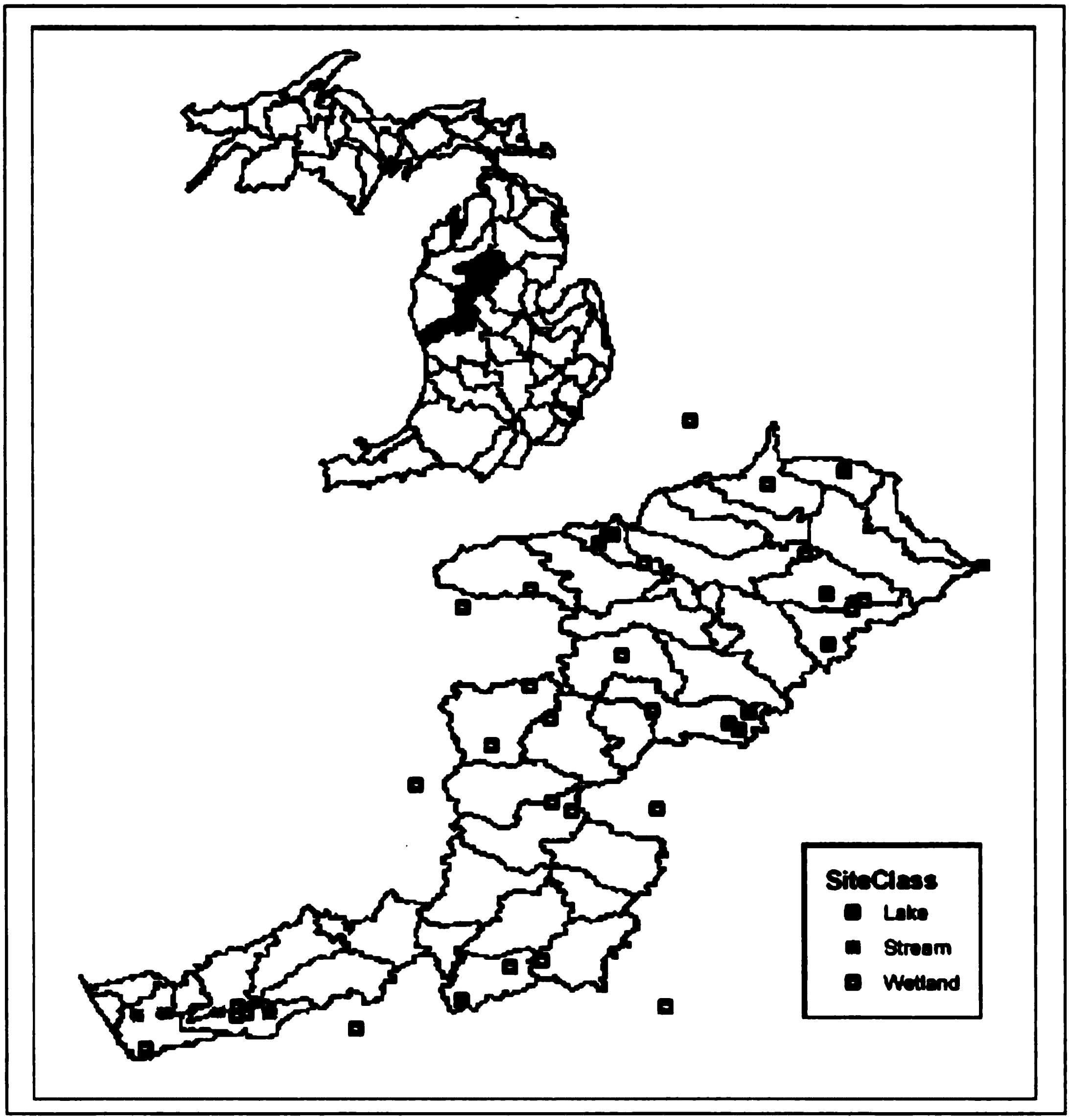

Figure 17. Map of three different classes of sampling locations (Lakes, Streams, and Wetlands) in the Muskegon River Watershed sampled in the summers of 2001 and 2002. 80-minute recordings were made at each sample site during the time of sampling (also appears in Appendix A).

I used the analytical framework described in Chapter 1 in conjunction with the automation system described in Chapter 3 to quantify the acoustic samples in terms of the biological and human mechanical activity, and compared these values to population density information derived from the 2000 national census (U.S. Census Bureau). These acoustic index values were based on the spectral distribution of anthropogenic and biological activity described in the first two chapters and investigated in Chapter 3.

Objectives

The objective of the analysis described in this chapter was to examine whether relationships exists between acoustic samples, as quantified by the index values, and corresponding ecological variables. This assessment arose from the need to understand and quantify a baseline relationship among variables to guide the use of acoustic sampling in ecological assessment. Previous research had indicated that physical constituents of the ecosystem will affect acoustic properties, but a framework to integrate these variables into the acoustic features in a manner that also yields information about anthropogenic impacts on ecological processes was not available until our proposed investigation. While many studies have reported on how physical properties such as vegetation and land cover would affect the transmission and propagation of acoustic signals (e.g. Aylor 1971; Rundus and Hart 2002), the links in the causal chain that connected the resultant acoustic features to anthropogenic activity did not appear to be thoroughly documented. This thesis, as a component of the study proposed by Stevenson *et al.* (2001), attempted to fill some of these gaps in our knowledge of acoustics by examining the relationship between the composition of the acoustic spectrum as represented by the sampling regime and the degree of human activity within the system, as represented by the population density.

Methods

The three steps in this study encompassed the data gathering techniques, the analysis of the signals, and the correlation techniques. These are described as Data Gathering, Index Derivation and Regression Analysis.

Data Gathering

As part of the collaborative assessment of the MRW, teams from Stevenson's laboratory sampled a series of lakes, streams and wetlands in the watershed. In addition to gathering water quality samples, each team was equipped with a Sony MZ-R700 Recording Minidisk Walkman and several 80-minute minidisks. At each site, the researchers used the MD Recorder with a Sony ECM-MS907 Stereo Microphone set to a 120° pickup range, and recorded for 80 minutes. In addition to these recordings, they recorded water temperature, pH, DO, and other variables. The acoustic samples were stored on the minidisks in a Sony proprietary format. The MD recorders stored 44.100 kHz 16-bit Stereo samples. The minidisks were then recorded to 80-minute audio CDs in the same format as Compact Disk Audio (CDA) files via a Philips CDR 775/17 Compact Disk Recorder. These CDs were then 'ripped' into a computer via Roxio's Soundstream program. Soundstream converted the CDA files to Windows Waveform (wav) files (the standard file format used in the analytical framework), but retained the 44.100 kHz 16-bit Stereo format. Therefore, I split the files into 12 30-second sub-samples, and output them sequentially as separate files. The program then resampled each file at 22.050 kHz, and spliced the two channels into a monaural sample. This process generated the 12 30-

second 22.050 kHz 16-bit wav files, which were the standard parameters for spectral analysis. Prior to statistical analysis, recordings in which the sampling crews were audible were excluded.

Index Derivation

The wav files from the data set were then used to generate standard series' of spectrograms with FFT (Fast Fourier Transform) sizes of 4,096 points, a frequency resolution of 5.4 Hz and a linear frequency scale. A GIS program was used to examine the three-dimensional spectrograms and divided each one into its anthropogenic (α) and biological (β) region, based on the spectral delineation of these two regions as described in Chapters 1 and 2. The mean amplitude of these two regions was then calculated and used as a measure of anthropogenic acoustic activity (anthrophony) and biological acoustic activity (biophony).

Regression Analysis

The data was analyzed in SAS® to test the correlation between the derived anthrophony and biophony values and the population density (based on census blocks) of the sampling regions with predictive linear regression models. These models followed the basic formula $y = mx + b$, where y = the mean of the variable of interest, x = the derived index value, m = the slope of the best-fit line, and b = the y-intercept. The value for anthrophony or biophony was used as the dependent variable, as the hypothetical relationship proposes that population density affects the intensity of anthropogenic or biological activity within a system. The natural log (ln) of the anthrophony, biophony and density values was used to minimize error in the distribution of points and bring the values closer to a Gaussian distribution.

Results

In terms of both the strength and direction of correlation, neither the anthrophony value nor the biophony value appeared to exhibit a significantly strong correlation to population density (Table 9). The anthrophony had an r^2 value of 0.02 and a slope of 0.39. The biophony had a slightly higher r2 value of 0.04, and a slope of 0.24. Overall, the graphs appeared to have a large degree of scatter among the data points (Figures 18 and 19).

Variable	y-Intercept	Slope	r^2
Anthrophony	4.79	0.39	0.02
Biophony	0.02	0.24	0.04

Table 9. Summary information on correlation analysis between anthrophony and biophony values and population density.

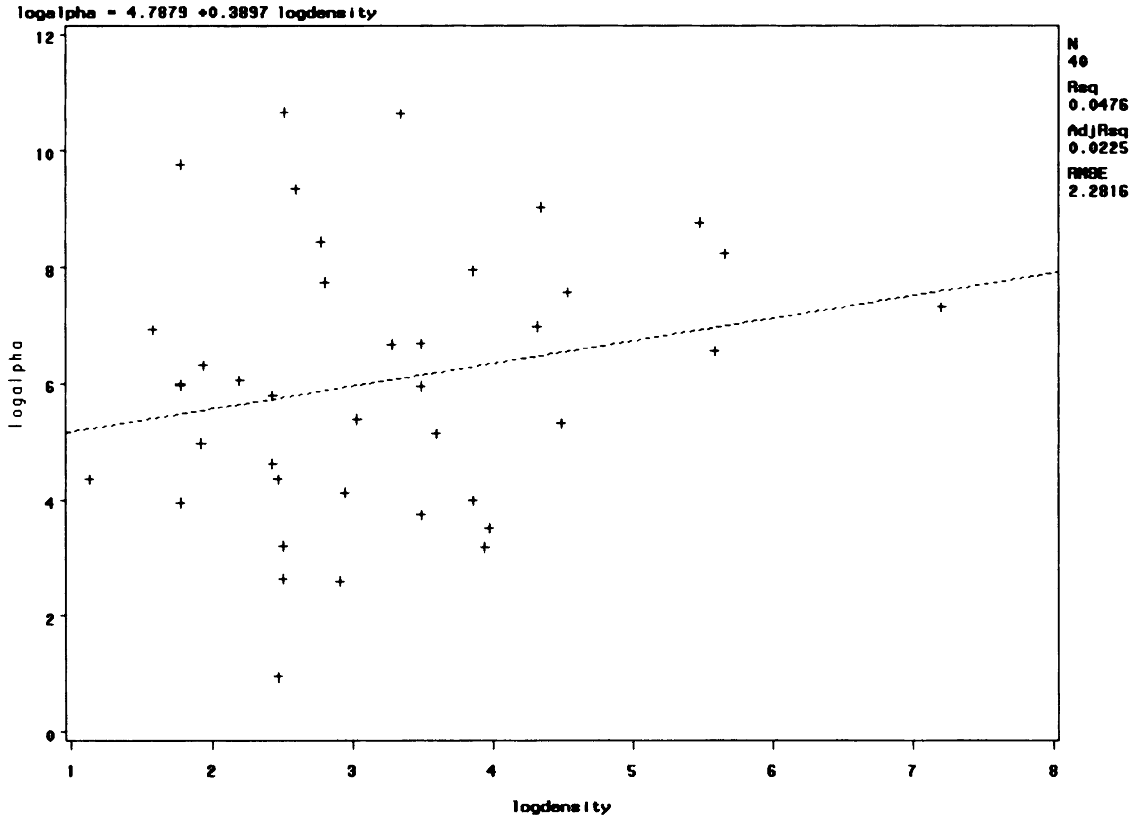

Figure 18. Graph of the linear relationship between the anthrophony (y-axis) and the population density (x-axis).

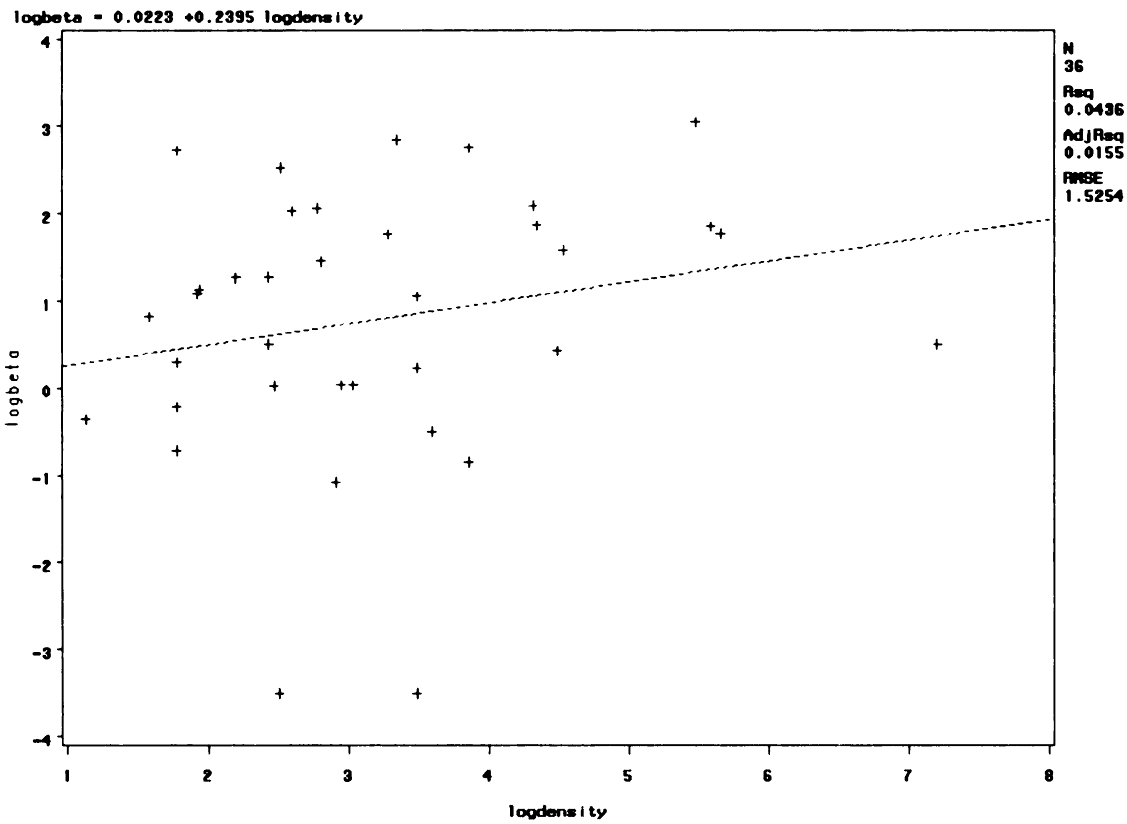

Figure 19. Graph of the linear relationship between the biophony (y-axis) and the population density (x-axis).

Discussion

Several possible explanations exist for the relatively low correlations between the anthrophony and biophony and the population density. Perhaps the most pertinent factor is that acoustic signals are much more dynamic than other variables insofar as they change with a greater frequency and reflect the immediate activity in the ecosystem. The samples analyzed represented single-point samples taken once at each site visit. Therefore, external conditions such as the time of day and season influence the acoustic signals in a manner that would distort the correlation. Of particular relevance is the fact that none of these samples incorporates the Dawn Chorus (Gill 1995). If the time of sampling is a significant factor, it would be a rationale for long-term continuous monitoring of acoustic signals. This long temporal-scale sampling requirement limits the effectiveness of acoustics as ecological indicators, however, as it implies that using them as such would require a rather extensive observation network. Examining the biophony as a valued ecological attribute may prove more fruitful, as it may reflect the concentration of vocal organisms, which may be considered a favorable ecological condition. Moreover, the anthrophony should be examined as an environmental stressor, considering the degree to which human activity is modifying the biosphere. The relationship between these acoustic samples and the other ecological attributes, however, may not be as straightforward as a simple linear correlation would elucidate. A distributed sensing network that simultaneously measures acoustic and other features over extended spatiotemporal scales may provide a richer dataset that would elucidate stronger correlations between biophysical ecological variables and their acoustic features. Additionally, the species recognition system being pursued by Gage *et al.* (2004) may help to develop and index of biodiversity that would prove to be an invaluable ecological assessment tool that utilizes acoustic analysis. The results of this research provide some insight into the possible ways acoustic samples represent (or fail to represent) ecological processes occurring within the system. The dynamic nature of these signals implies that they will continue to yield a significant quantity of information on the dynamic features of the Earth's biosphere, provided they are analyzed systematically and thoroughly.

Chapter Seven: Summary and Conclusions

Objectives

Sound is a multidimensional and complex variable that encompasses a wide array of information about the structure and composition of the habitat from which it emanates. The analytical approach applied in this research focused on the examination of the spectral features of acoustic signals and their relationship to the environment. To summarize, the objectives stated in the introduction are restated with summaries of the research findings.

Objective One: Implement an analytical framework that reflects the ecological features of acoustic signals and is capable of handling large-scale acoustic data for comparisons and statistical analysis.

The analytical framework used in this study focused on the spectral properties of acoustic signals. The natural tendency of anthropogenic and biological signals to occur at two different spectral bands enabled the development of an analytical system that quantifies the biological and anthropogenic activity in the system. This analysis simplified the interpretation of the acoustic signals and, with further refinement, may yield a meaningful interpretation of the degree of anthropogenic disturbance within an ecosystem. The automation system designed to handle acoustic spectrograms enabled the analysis of acoustic data from larger spatiotemporal scales.

Objective Two: Verify the apparent spectral distribution of biological signals and enhance our understanding of the biophony.

A spectral analysis of a representative sample of birds, insects and amphibians indicated a statistically significant degree of signal partitioning within the biophony. At the taxonomic level of Class, amphibians generally vocalize at the lower frequencies (1 – 3 kHz), birds (particularly passerines) generally vocalize at slightly higher frequencies (3 – 5 kHz) and insects tend to utilize the higher frequencies (6 – 8 kHz). Overall, the majority of organic signals were concentrated between 2 and 5 kHz, and almost all the signals were within the delineated range of 2 to 11 kHz.

Objective Three: Tie the theoretical and analytical tools to a real-world scenario by relating acoustic signals to other ecological variables in the Muskegon River Watershed.

Comparisons amongst a variety of sites and variables indicated that further research and refinement is required of the analytical framework in terms of both data collection techniques and statistical analysis. The absence of a strong correlation of both the biophony and the anthrophony to population density may be a result of the sampling approach, the correlation technique or a combination of factors.

Spectral Analysis

The acoustic analysis framework developed in this research was unique in its focus on the spectral properties of the acoustic signals. While traditional terrestrial acoustic studies (such as noise assessment) focus primarily on overall signal intensity, the focus on the spectral features yielded more information about the source and nature of the signals that were analyzed. The drawback to this analysis was the initial complexity of the analysis, and the computational resources required. However, the automation program described in Chapter 3 made the analytical process possible by improving the computational efficiency to process significant volumes of acoustic data relatively quickly. This spectral band analysis led to the development of the anthrophony and biophony measurements, which enable straightforward assessments of the proportion of biological activity and anthropogenic activity in a signal. The challenge is to relate these measures of anthropogenic and biological activity in a sound signal to the corollary system.

Future Directions

This research has initiated several interesting enquiries into the ecological aspects of acoustic signals. Future undertakings should enhance our understanding of the information about ecological processes and dynamics that acoustic signals reveal. First is an approach that is already beginning to be examined by Gage *et al.* (2004) that utilizes pattern recognition systems to identify species specific vocalizations in acoustic samples. This system may be used to perform species richness assessments of various habitats. Such a system could be used to further our understanding of the patterns of and anthropogenic impacts on the Earth's biodiversity. Potential research projects include an examination of the correlation between land use and disturbance intensity and species richness, and the ways these correlations vary with latitude, elevation and climatic conditions.

Second, the bandwidth analysis of amphibian vocalizations described in Chapter 4 indicate that amphibians vocalize at a lower frequencies that often overlap the frequencies of mechanical anthropogenic signals. The interference incurred by this signal overlap may be partially responsible for observed declines of amphibian populations, particularly where development has fragmented wetland habitats. Specifically, the interference introduced by mechanical signals may impair the mating success of amphibians, thereby reducing the overall population. Different intensities of critical band interference would be introduced to mating groups of amphibians, with a control group that is has no introduced interference. Resultant numbers of successful copulations would then be observed and compared across treatments to determine whether signal interference detrimentally affects reproductive success.

Third, it is necessary to pursue the Acoustic Niche Hypothesis further by sampling biological vocalizations across gradients of both disturbance and land cover (i.e. forest, grassland, wetland, built) and examining the spectral bandwidth compositions to determine whether the same species of organisms will use different bandwidths in different habitats. The replication of observations over several instances of the same disturbance intensity and land cover type would begin to reveal whether any frequency modulation observed is a result of competition for spectral space or adaptation of signal structure to differential propagation in different habitat types. If the former were the stronger pressure, then frequency modulation would have a stronger correlation to bandwidth availability, and lower disturbance intensities would likely yield a greater proportion of frequency modulation. If the latter were a stronger pressure, then modulation would vary more with land cover than with population sizes, and may not be as strongly correlated to disturbance intensity.

The last proposed project is to increase the spatiotemporal resolution of the sampling network to gather a larger representative sample of acoustic signals from different habitats. Simultaneous samples of acoustics with established variables that are considered ecological indicators (Chapter 6) would begin to reveal how the biophysical conditions of an area are reflected in its acoustic signature. The variables that demonstrate the highest and most consistent correlations would be targeted for initial analysis. Additional variables could also be sampled, such as energy availability (i.e. net primary production or potential evapotranspiration) to test the hypothesis that the intensity of biological acoustic activity (as well as species richness) is influenced by energy availability and habitat disturbance.

Appendix A

Gage, Stuart H., B.M. Napoletano, M. Colunga-Garcia, J. Qi. (2003) An Analytical Framework to Interpret Acoustic Observations in Heterogeneous Landscapes. <u>Ecological Applications.</u> *In Review*

Introduction

4.5 Million years of evolution has refined humans' auditory senses to the point where we can localize, interpret and react to acoustic signals virtually instantaneously (Masterton et al. 1969). However, as is often the case, the sense of familiarity imbued by these abilities has allowed us to overlook the volume and diversity of information we extract from the acoustic world. Sounds produced by the environment can be valuable but are an untapped resource to assess the health of the Earth's ecosystems. The arrays of sounds in a place depend on a complex array of circumstances including the type of habitat (e.g. wetland, desert, forest, grassland), the time of day and the season of the year. The diversity of sounds at a place depends on the heterogeneity of the landscape and on the status of its ecosystems. Many groups of animals, including birds, mammals, amphibians and insects, produce sound and use it to communicate (i.e. Schwartz et al. 2001, Hopp et al. 1998).

With the growth and expansion of human populations has come a greater need to understand the dynamics of ecosystems and their complex interactions (Michener et al 2001). As humans increasingly expand the urban infrastructure, we tend to disrupt the very ecosystem services that are critical to us (Daily 1997). In addition, the fragmentation of natural ecosystems reduces habitat available for wildlife (Krause 1998). At the onset of our quest to understand environmental acoustics, we postulated that the consideration of sound as a variable in ecosystem studies would help to increase our understanding of ecosystem change due to human disturbance as well as to indicate biological dynamics over time.

Patterns of acoustic signals reflect the dynamics of physical, biological, and social components of ecosystems (see Aylor 1971). Changes in the spatial and temporal distribution of acoustic signal patterns reflect changes in those dynamics. The exact meaning of these signals, in terms of the processes and interactions they represent between social and bio-physical systems is a challenging area of study. This "heartbeat of the ecosystem" as represented by its acoustics holds information about the dynamic processes and the changing states of the ecosystem. We have found that sound is a relatively easy variable to sample, and our increasingly extensive study of the temporal and spatial distribution of acoustic signals has produced a rich volume of information about ecosystems. Repeated discrete sampling of the sounds in a given area, however, rapidly generates a volume of data that is difficult to manage. Moreover, the multidimensional aspect of acoustic signals necessitates a complex analysis that examines multiple variables simultaneously.

We have found that the proper examination of an acoustic signal in an ecological context requires, at a minimum, information about its frequency, intensity, and temporal properties. These issues makes sound a variable complex to manage, analyze and interpret. This study began with the objective of developing quantitative approaches to assess ecological processes within a watershed through the application of environmental acoustics. During this process, we developed a framework for the study of patch-level acoustic signals in an ecosystem. This paper describes this framework, including: a) the definition of a soundscape, b) the classification of signals in the soundscape based on their physical, biological, and social origins, and c) an analytical approach to quantify the components of acoustic samples taken from the environment. The analysis of acoustical signatures within the context of this framework will enable the use of sound as a means of comparing different types of places or different times within the same place under varying environmental conditions.

Definition of a soundscape

Sound is, in physical terms, the transmission of vibrations of a certain frequency range through a medium (Hartmann 1998). Both air and water provide the media for most sound transmissions, although some sounds are also transmitted through the ground. The soundscape is a common term in the field of study known as acoustic ecology. The working definition of soundscape in this field is any group of sounds specified as an area of study (Schafer 1977, 1994, Truax 1999). This implies that the term soundscape may apply to anything from a musical composition to the entire planet. For the purposes of our study of the ecological aspects of acoustics, we define the area of study as the set of sounds generated by the biophysical and social interactions within a landscape, where the landscape is a heterogeneous land area composed of a cluster of interacting ecosystem patches (Forman and Godron 1986).

Our defined soundscape, then, is the acoustic signals associated with the landscape. Research to measure and understand soundscapes builds on three areas of ecological acoustics: a) communication and acoustic behavior of organisms, b) effects of "noise pollution" on humans and other organisms, and c) acoustic design in large-scale human systems and structural acoustics of architecture. Studies of communication of organisms in the environment focus on the behavior, social structures and evolutionary trends of organisms (Kroodsma and Miller 1996, Bailey et al. 2001, Schwartz et al. 2001, Fischer et al. 2002). These studies entail general population surveys and provide warning signals of major problems in the system (Carson 1962). Noise pollution studies (e.g. sonic booms or aircraft disturbances) have investigated how human development affects natural systems and social behavior (Federal Aviation Administration 1985, Komanoff 2000). Studies in "Acoustic Design" examine the effects of different sound types on stress in humans and other organisms and provide valuable insight into the relationships between sound and behavior (Schafer 1977, 1994). Our research on environmental acoustics has produced methods to characterize acoustics in human dominated ecosystems. Our findings are in three areas: *soundscape classification*; measurement of *diurnal patterns of acoustics*, and the development of *indices relating human and biophysical acoustics*.

Classification of sounds in the soundscape

Generally, researchers consider the various signals in the acoustic spectrum as originating from either natural processes or human activity. For the purpose of our framework we have distinguished three main categories of sounds that occur in the soundscape: biophony, anthrophony, and geophony. Krause (1987), in his studies of natural soundscapes, devised the term ***biophony*** for the complex chorus of ambient natural sounds. In our framework, this category encompasses only the natural sounds produced by organisms, including birds, amphibians, insects and bats. This is the class of sounds most extensively studied in ecological acoustics (Bosch et al. 2000, Bailey et al. 2001). The term ***anthrophony*** refers to the human-induced sounds within an ambient soundscape. Human induced sounds are primarily oral (i.e. speaking, singing, whistling or shouting) or mechanical (use of technology). Because humans are organisms, their oral signaling would technically fall into the realm of the biophony. However, we need to specify a separate class for human derived signals to measure and quantify the impact of human activity on the soundscape. Moreover, mechanical sounds are the most dominant anthrophonic sounds in the soundscape and oral activity comprises a negligible proportion of anthropogenic signals in our investigations. Finally, the third category, ***geophony***, refers to the pattern of signals present within the soundscape as a result of physical processes occurring in the region. Examples of these classes of signals are those emanating from waterfalls, river flow, wind or rain.

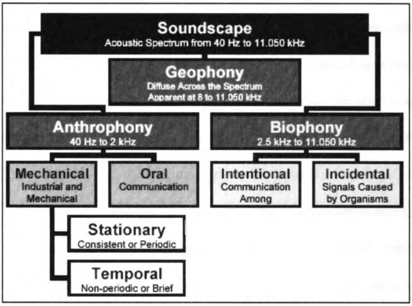

Figure 20. Conceptual classification schema of the soundscape and its three primary components and their typical frequency ranges. Several hypothetical subclasses are also depicted. While the Anthrophony and Biophony tend to have discrete ranges, the Geophony tends to occur across the spectrum.

As our understanding of the characteristics of sounds in these categories increases, we may further refine our classification. For instance, subdivisions in the classification can be made based on the persistence of the signal (stationary versus temporal), the function of the signal (intentional versus incidental) or the periodicity of the signal (periodic versus random). However, for the purpose of this paper, we focus our analysis and discussion on the three major classes mentioned above, while still outlining some of the more complicated subunits in Figure 20 for illustrative purposes.

Quantifying acoustic samples from the environment

An acoustic signal is characterized by multiple physical attributes, among which are timing, frequency, and intensity (Hartmann 1998). To process and synthesize acoustic observations gathered under field conditions we have developed the following methodology. First, we convert the time, sound frequency and sound intensity into spectrograms. Spectrograms are three-dimensional grids where the x-axis denotes time, the y-axis represents the frequency of the signal (Hz), and the z-axis represents the intensity (dB SPL as received by the microphone). We standardized the dimensions of our spectrograms in pixels as 500 x 1000 in the y and x axes respectively. In the y-axis, 46 pixels represent approximately 1,000 Hz, which we refer to in this paper as a single **Frequency Band**. In the x-axis one pixel represents 30 milliseconds of a Fast Fourier Transformation of the original signal. We used the functionality of IDRISI® (Clark Labs **2000**) to analyze the spectrograms in terms of topological and x, y spatial features within the signal, i.e. the spectrogram was treated as a multiphase map of the acoustic signal. Sound intensity values were converted to 8-bit series of values with a range of 0-255 possible values. For example, if a spectrogram represented a signal that entirely filled the spectrum with the maximum sound intensity, then the average value would be 256. On the other hand, if the signal was acoustically silent (i.e. no energy above 10^{-12} watts/metre^2 was detected by a microphone), then its average value would be 0.

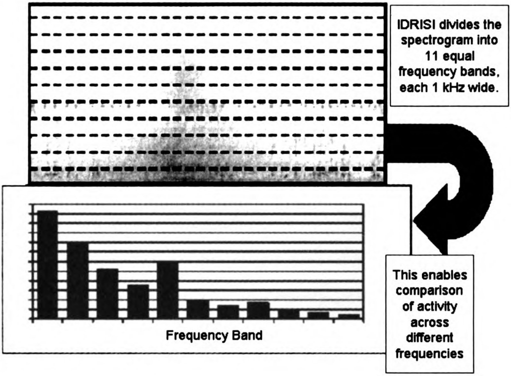

Figure 21. The frequency windowing procedure. Each spectrogram is divided into 11 frequency bands and the mean amplitude is calculated for each band. This process allows a relative comparison of the frequency bands with the highest concentration of acoustic activity.

To determine the distribution of activity over the spectral frequency range of the spectrogram, we windowed the image into multiple spectral bands based on the 1,000 Hz Frequency Bands. We averaged the intensity values in each Frequency Band to obtain what we call the Relative Sonic Amplitude (RSA). This allows us to quantify the amount of acoustic activity in the entire sample, as well as within each frequency level. The spectral properties of acoustic signals in the environment tend to aggregate within two primary regions. The first region occurs at the lower frequencies of the sound spectrum (Schafer 1977, 1994). This band typically extends from 0.2 to 1.5 kHz and consists primarily of mechanical signals (i.e. trains, cars, air conditioners, etc.), and is therefore aptly referred to as the ***anthrophonic region***. The second band of concentration begins in the range of 3 kHz and is prevalent up to 8 kHz, though it may on occasion reach the top of the spectral range of the recorded signal. This realm of acoustic activity consists primarily of signals generated by biological organisms, and is therefore referred to as the ***biophonic region***. We have delineated this frequency band as the biological band based on our observations and the frequency ranges referred to in the literature (Shackleton et al. 1991, Naguib 1996, Ping et al. 1996, Bennet-Clark 1997, 1998, Bennet-Clark 1999, Bosch et al. 2000, Bailey et al. 2001, Rundus and Hart 2002, Freeberg et al. 2003). These two bands correspond to two of the three taxonomic categories of the soundscape described above, but do not cover acoustics emanating from the physical (i.e. wind, rain, etc.) or geophonic component. This is because the geophony, when present, occurs as a signal that is diffuse throughout the entire spectrum. The geophony is a diffuse signal that is strongest at the lowest frequencies but that continues with a relatively high intensity into the higher frequencies. Generally, when a geophonic signal is present, the frequency bands above 8 kHz will exhibit greater signal intensity than in signals without geophony. (When geophony is present, it may be detected, therefore, by its tendency to generate stronger signals at the higher frequencies above the predominant range of the biophonic spectrum (that is, strong signals above 8 kHz).)

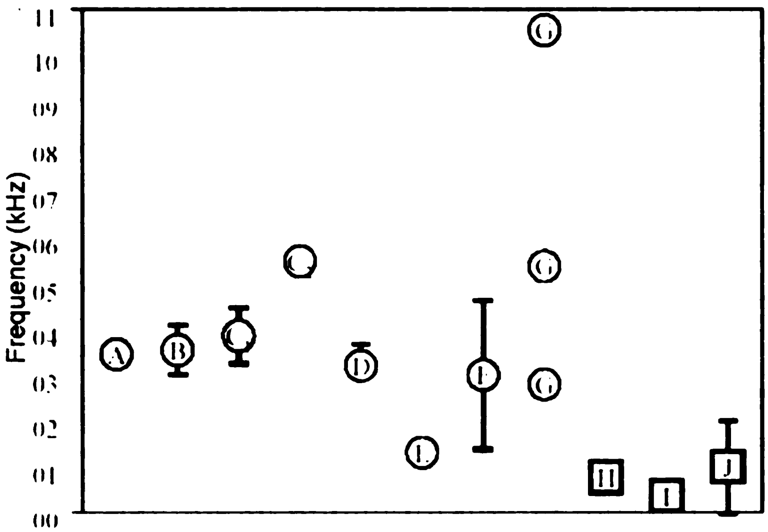

Figure 22. Frequency range comparison of multiple signals and signal types. A) Brachypterous cricket (Bailey, 2001); B) Pycnonotus sinensis (Ping, 1996); C1) Cyclochila australasiae, inward (Bennet-Clark, 1997); C2) Cyclochila australasiae, outward (Bennet-Clark, 1997); D) Poecile atricapillus (Otter, 2002); E) Zenaida macroura (Krause, 1987); F) Chaetura martinica (Krause, 1987); G) Terpsiphone paradisi (Krause, 1987); H) Locomotive; I) Motor Boat; J) Air Conditioning. As the distribution indicates, the anthropogenic signals generally tend to occur at lower frequency ranges than the biological signals.

Using this partitioning of the acoustic spectrum, we developed a methodology to quantify the three primary acoustic elements, the anthrophony (α), biophony (β), and geophony (γ), by calculating the mean value of acoustic intensity in the spectral frequency range we allocated to each of these regions, and comparing their values to the mean activity of the entire signal (σ). We calculated the mean values of the α, β, γ, and σ bands by assigning a numeric value to each pixel in the specified range and calculating the mean value of the z-axis. The α, β, and γ activity ratios were then calculated using the equations in Table 10. A value > 1 for any of the indices indicated that the concentration of acoustic activity in the analyzed region was greater than the value for the entire signal. Therefore, the region with the highest value was the predominant source of acoustic activity in the signal. For example, if the β_r had the highest value, then biological activity was predominant, while a larger α_r value indicated dominant anthropogenic activity. To emphasize the comparison of biological and anthropogenic activity, we divided the β value by the α value to calculate ρ, the ratio of biological to anthropogenic activity.

Index	Ratio	Percentage
Anthrophony	$\alpha_r = \left(\frac{\alpha}{\sigma}\right)$ α = Mean from 0 to 2 kHz α_r = Ratio of anthropogenic activity mean to grand mean	$\alpha_p = \left(\frac{(L1+L2)}{\sum 11 Levels}\right)\times 100$ α_p = Percentage of activity in the anthrophony band
Biophony	$\beta_r = \left(\frac{\beta}{\sigma}\right)$ β = Mean from 2 to 11 kHz β_r = Ratio of biological activity mean to grand mean	$\beta_p = \left(\frac{\sum L3\, to\, L11}{\sum 11 Levels}\right)\times 100$ β_p = Percentage of activity in the biophony band
Geophony	$\gamma_r = \left(\frac{\gamma}{\sigma}\right)$ γ = Mean from 8 to 11 kHz γ_r = Ratio of geological activity mean to grand mean	$\gamma_p = \left(\frac{\sum L8\, to\, L11}{\sum 11 Levels}\right)\times 100$ γ_p = Percentage of activity in the geophony band
Activity	$\rho = \left(\frac{\beta}{\alpha}\right)$ ρ = Ratio of biological to anthropogenic activity	**Global Variables** L = 1 kHz level σ = Mean value of entire signal (Grand Mean)

Table 10. Formulae for the calculation of activity concentration values for the three primary regions of the soundscape. The column on the left depicts the formulae for the calculation of ratio values in terms of the entire spectrum, while the column on the right lists the formulae for the calculation of values in terms of percentage of the entire spectrum.

In addition to computing the ratios of activity from our classification system, we also determined the percentage of total activity a single band contributes to the total signal (Left-hand column of Table 1). A γ_p value near 100% coincident with a β_p value of approximately the same value indicated that the primary signal source in the sound sample was *Biophony* (geo-physical) activity. When the α_p value was greater than 50%, it indicated that the primary signal source was *Anthrophony* (anthropogenic) activity, whereas a value of β_p greater than 50% indicated that *Biophony* (biological) activity was the dominant source.

Case Studies

We present three case studies from our research that represent characteristics of acoustic signals and the applications to which we have applied our environmental acoustic framework. In the first case we compared the diurnal soundscape patterns at four different locations. In the second case study we determined the acoustic quality of a location and compared the acoustic quality at different locations. The third case exemplifies the combination of acoustic measurements with other environmental data (e.g. temperature) to examine the complexity of environmental acoustics, particularly when measuring acoustic signals resulting from communication by organisms.

Case study 1. Diurnal Soundscape Patterns

We compared the diurnal acoustical signals from four different locations using an automated system to sample and capture acoustic signals from the same location at frequent intervals. This procedure allowed us to sample acoustics at regular times of the day and night, thus enabling the characterization of diurnal patterns of sound. To obtain high temporal resolution acoustic data, we deployed an automatic digital recording system using a Bird Bug® 100M parabolic microphone that sampled acoustic signals at a 22.050 kHz 16 bit sampling rate for thirty seconds every half-hour. We sampled the acoustic signals for three contiguous days from four locations in the Muskegon River Watershed located in mid-west Michigan. These locations included an equestrian center, a private ranch, a wetland, and a public park and campground. Tables 11 and 12 list the summary statistics and Pearson's Correlations respectively.

Abbreviation		EC		
Name		West Michigan Equestrian Center		
Land Use		Agriculture/ Outdoor Recreation		
Date		**2002-08-23**	**2002-08-24**	**2002-08-25**
	ρ	1.52 ± 0.79	1.62 ± 0.71	1.48 ± 0.51
Mean	**α**	26.26 ± 8.49	25.67 ± 8.13	22.84 ± 6.61
	β	34.61 ± 7.51	36.85 ± 6.59	31.34 ± 6.31
Abbreviation		GC		
Name		Haymarsh Wetlands		
Land Use		Wetland/ Residential		
Date		**2002-08-23**	**2002-08-24**	**2002-08-25**
	ρ	0.66 ± 0.22	0.73 ± 0.21	0.65 ± 0.18
Mean	**α**	15.16 ± 4.02	17.32 ± 5.11	14.35 ± 1.96
	β	10.13 ± 4.31	12.21 ± 3.78	9.18 ± 2.31
Abbreviation		PP		
Name		Paris County Park		
Land Use		Outdoor Recreation		
Date		**2002-08-23**	**2002-08-24**	**2002-08-25**
	ρ	0.78 ± 0.16	0.76 ± 0.14	0.71 ± 0.25
Mean	**α**	45.23 ± 9.06	42.97 ± 6.21	44.56 ± 6.96
	β	34.13 ± 5.59	32.41 ± 7.20	31.10 ± 10.40
Abbreviation		MS		
Name		Cooper Residence and Ranch		
Land Use		Agriculture/ Pasture and Livestock		
Date		**2002-08-23**	**2002-08-24**	**2002-08-25**
	ρ	1.72 ± 1.62	2.01 ± 2.28	1.61 ± 1.33
Mean	**α**	0.59 ± 0.22	0.60 ± 0.44	0.84 ± 0.71
	β	0.97 ± 0.89	1.02 ± 0.94	0.92 ± 0.55

Table 11. Summary statistics of the means and standard deviations of ρ, α, and β values calculated for three consecutive days at four different locations. ρ represents the ratio of biological to anthropogenic activity, while α and β represent the anthropogenic and biological activity respectively.

		Equestrian Center		Haymarsh		Cooper Ranch		Paris Park	
		23-Aug	**24-Aug**	**23-Aug**	**24-Aug**	**23-Aug**	**24-Aug**	**23-Aug**	**24-Aug**
ρ	**24-Aug**	0.7617		0.7703		0.8159		0.1673	
	p-value	0.0000		0.0000		0.0000		0.2558	
	25-Aug	0.5824	0.5771	0.4833	0.5242	0.7464	0.7291	0.1187	0.5027
	p-value	0.0000	0.0000	0.0005	0.0001	0.0000	0.0000	0.4217	0.0003
α	**24-Aug**	0.5204		0.1122		-0.0408		0.4620	
	p-value	0.0001		0.4476		0.7832		0.0009	
	25-Aug	0.0761	0.1746	-0.1377	0.3606	0.1950	0.0313	0.3278	0.2076
	p-value	0.6072	0.2353	0.3505	0.0118	0.1840	0.8329	0.0230	0.1568
β	**24-Aug**	0.4185		0.2712		0.8374		0.6518	
	p-value	0.0031		0.0623		0.0000		0.0000	
	25-Aug	0.5479	0.4571	0.4740	0.4524	0.7219	0.7736	0.5919	0.7624
	p-value	0.0001	0.0011	0.0007	0.0012	0.0000	0.0000	0.0000	0.0000

Table 12. Pearson's correlations of ρ, α, and β means over the three-day period. All sites except Paris Park exhibit a significant correlation of ρ values.

The private ranch (Figure 23, C) exhibited diurnal patterns of acoustic activity that remained relatively low at night and during mid-day. Acoustic activity peaked around 0600, coinciding with the well-known 'Dawn Chorus'. The anthropogenic activity was minimal during the 144 ½ hour samples from this location. The other three locations however, exhibited different patterns and none of the acoustics peaked at dawn (Figure 23). The equestrian center (Fig 23A) and the public park (Fig 23D) were outdoor recreational facilities, which explained why the peak in activity observed during the midday. The wetland site (Fig 23B) contained relatively large populations of crickets, cicadas, and other acoustically active insects, which are active in mid to late summer. Insects were responsible for the higher concentration of diurnal activity at the wetland site, as well as for the higher concentrations of nocturnal activity at the public park, the equestrian center, and the wetland site. Insect vocalization is more regular and is sustained for longer time spans than are vocalizations from birds or amphibians.

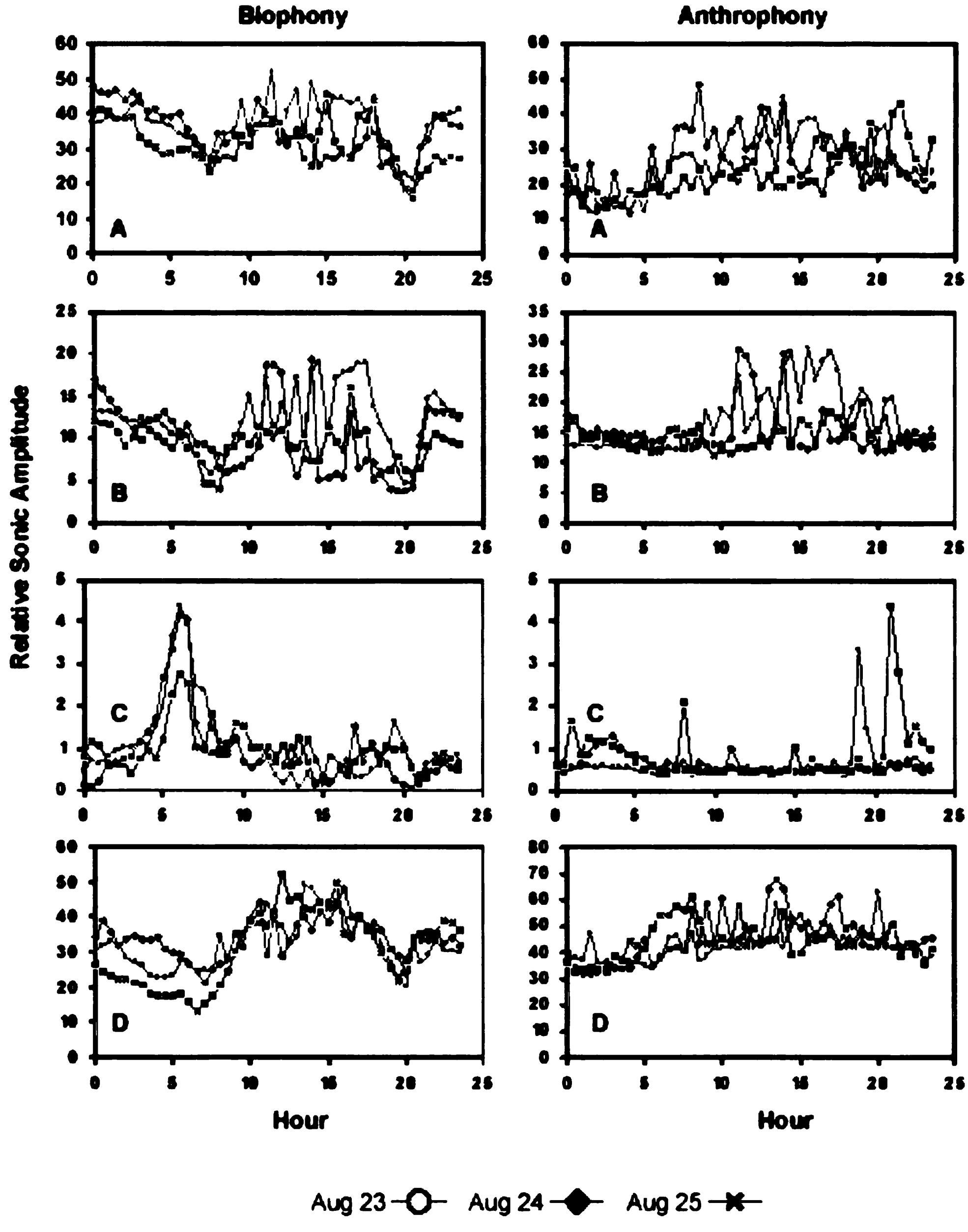

Figure 23. Biological and Anthropogenic activity curves over three 24-hour periods at four sampling sites. A) Equestrian Center; B) Haymarsh Wetlands; C) Cooper Ranch; D) Paris Park. The column of graphs on the left is the biophony curves, and the column on the right is the anthrophony curves. Sites C and D appear to show the least similarity between the temporal distribution of anthropogenic and biological activity.

After examining the differences in diurnal acoustic trends at the four locations, we examined seasonal variations in these trends by selecting a day to represent each of mid-Michigan's four seasons, and plotted the acoustic activity (mean RSA) at ½ hour intervals for each day (Figure 24). The results exhibited different acoustic activity trends in each season. The seasonal variation that occurs in Michigan has a significant impact on biological activity and species composition of the landscape, which may affect the trends of diurnal activity.

Case study 2. Activity Concentration Analysis of Multiple Locations

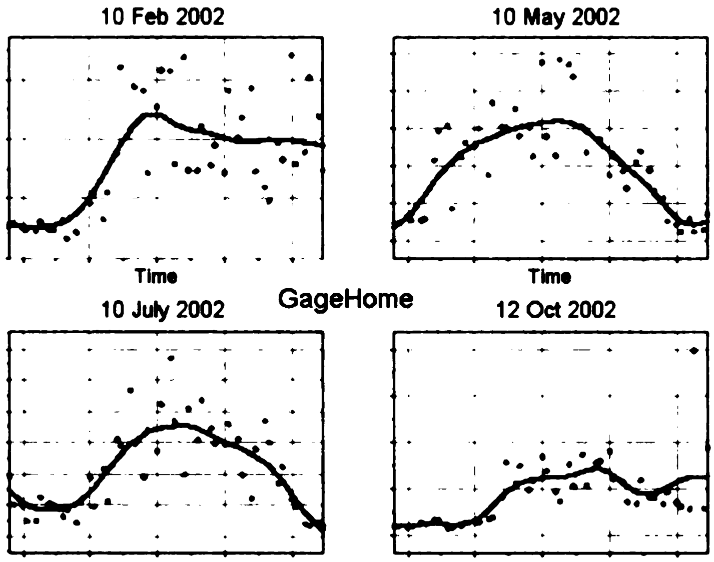

Figure 24. Diurnal activity trends of the entire analyzed spectrum at a single site (Gage Home) at four different times of year, representing four different seasons. While a single day is a rather small representation of an entire season, the figures appear to illustrate seasonal variations in activity trends.

This case illustrates our ability to detect differences in the acoustic composition of multiple locations. This allows us to establish different reference levels of disturbance based on the acoustic properties of a wide gradient of habitats. To elucidate the different acoustic character of multiple locations, we computed $\rho=\beta/\alpha$ from recordings made in a series of streams, lakes and wetlands in the Muskegon River Watershed over a three-year period as part of an ecological assessment and restoration initiative (Figure 6). Acoustic recordings from 41 different sites throughout the watershed were collected using a Sony

Minidisk® recorder and a Sony ECM-MS907® Stereo Microphone. All streams were sampled in late August, while all lakes were sampled in the late spring through early summer, a time of peak activity for many organisms. Wetlands were sampled throughout the mid-summer, from early June to late July.

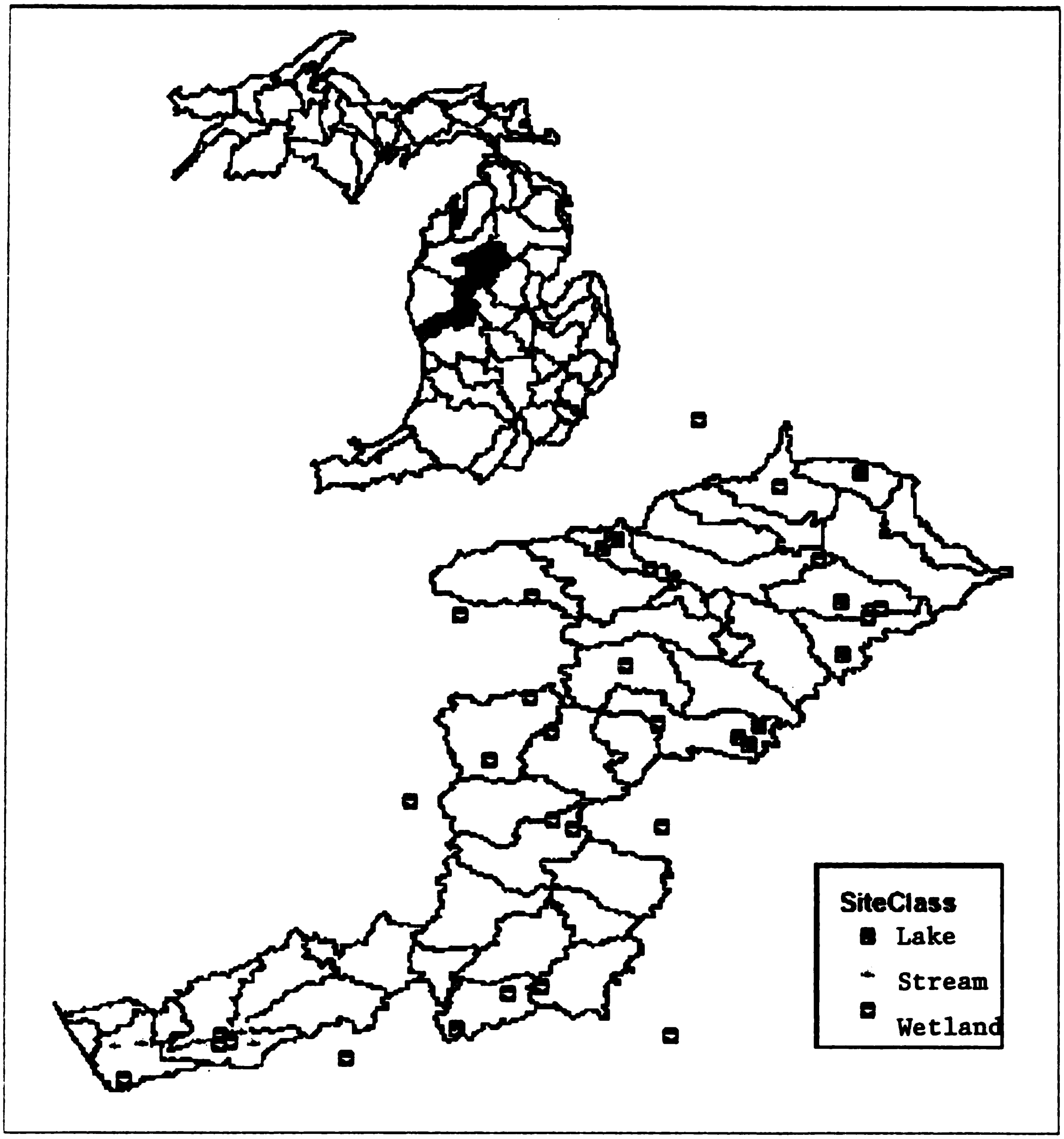

Figure 25. Map of three different classes of sampling locations (Lakes, Streams, and Wetlands) in the Muskegon River Watershed sampled in the summers of 2001 and 2002. 80-minute recordings were made at each sample site during the time of sampling.

We digitized the recordings from these samples into 12 30-second sub-samples and computed $\rho=\beta/\alpha$ for each location to calculate the ratio of biological to anthropogenic acoustic activity as described in the section on Quantifying Acoustic Signals described above. We then compared the ranges of values after sorting them into groups of streams, lakes, or wetlands. This allowed us to not only compare multiple locations, but also to compare the properties of the different location types (i.e. did lakes exhibit more anthropogenic activity than did wetlands?). In this analysis streams exhibited the highest ratio of biophony and lakes exhibited the highest ratio of anthrophony. The maximum and minimum ρ–values were from wetland sites (0.274 and 0 respectively, where 0 is the smallest possible value, indicating no detectable Biphony). Table 4 lists the statistics of the ratio values for the three classes of locations.

	Streams	Lakes	Wetlands
Mean	0.1210	0.0386	0.0824
n	5	11	25
SD	0.0802	0.0402	0.0613
Max	0.2486	0.1311	0.2739
Min	0.0505	0.0001	0.0000
Range	0.1980	0.1310	0.2739

Table 13. Summary statistics for the three sample classes (Lakes, Streams, and Wetlands) gathered in the Muskegon River Watershed. The Streams class had the highest calculated mean, the Lakes class had the lowest, and the Wetlands class had the broadest range of values.

Lakes were all sampled during a period of higher biological activity. The low ratios encountered in the lake samples indicate that lakes were the most heavily impacted landscapes in terms of anthropogenic disturbance. Additionally, all lake samples were taken at boat launches for logistical reasons. The streams yielded the highest mean ρ-value, indicating that these sites generally demonstrated the least concentration of anthropogenic activity. Finally, the wetlands exhibited the largest range of ratio values, with one location registering no biological activity (Figure 26).

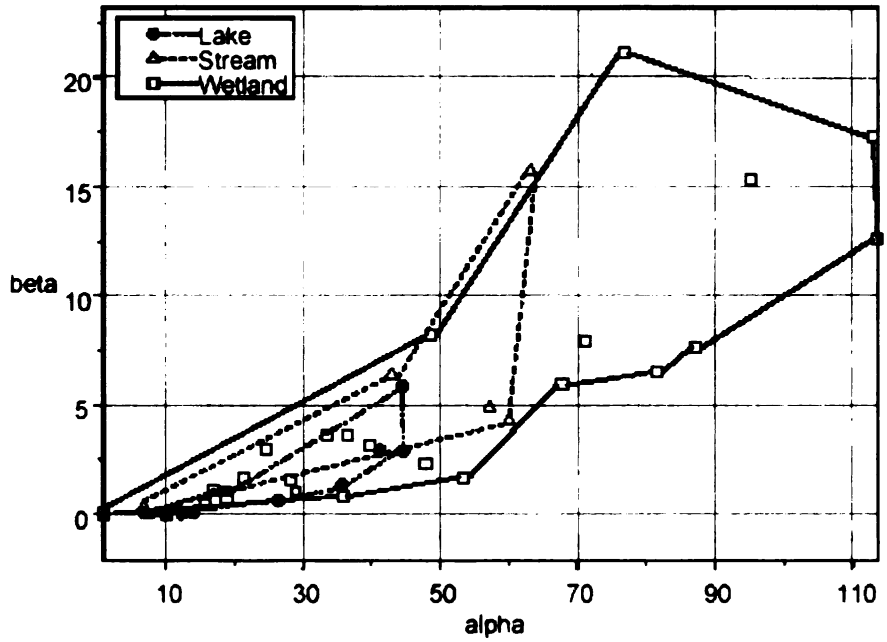

Figure 26. α (anthrophony) region plotted against β (biophony) region for the three classes of sampling sites (Lakes, Streams, and Wetlands) in the Muskegon River Watershed. The maximum range of each class of samples is indicated in by the boundary lines. The wetlands encompass the largest range of activity, while the lakes encompass the smallest.

Case study 3. Temperature – Acoustics Relationships

This study exemplifies the combination of acoustic measurements with other environmental data to examine the complexity of environmental acoustics, particularly when measuring acoustic signals that emanate from organisms that respond to physical factors such as temperature. The occurrence and intensity of sounds made by some organisms (ex. amphibians, insects) are often influenced by temperature (Bailey 1991). We investigated the interrelationship between acoustic signals and temperature, illustrating our ability to extract specific components of the acoustic signal (Biophony) and relate that component to temperature readings recorded at the same time period. The example we selected illustrates the relationship between acoustic signals and temperature recorded at ½ hourly intervals during April and September, 2002. Recordings of acoustic signals were made using the Bird-Bug microphone connected to a digitizing sound card (Creative Labs) in a microcomputer. Recordings of 30-second duration were written to disk using Total Recorder. Air temperature measurements were transmitted to the microcomputer using a RainWise wireless weather station and recorded at the same time as recordings were captured. These observations were made in Meridian Township, Michigan (N42° 43.46, W84° 22.57) in a rural-suburban habitat. April and September were selected, as they are seasonal transitions when temperature and acoustics signals vary. The time of 22:00 hrs was selected as amphibians and crickets are often signaling at this time in this landscape. A spectrogram was produced for each acoustic signal sampled at 22:00 hrs each day of each month. The mean acoustic intensity was calculated for each of 11 frequency bands at 1 KHz intervals. Band 4 (3-4 KHz) was selected to represent biological events in the signal. The acoustic intensity in band 4 was compared to temperature at the time of recording for each day in April and September, 2002. There was a significant correlation between temperature and the acoustic amplitude in Band 4 in both April and in September at 22:00 hrs. The relationship was stronger in September than in April (Figures 27 and 28). The acoustic signals in April were generated by Spring Peepers and the September signals were generated by tree crickets. Table 14 shows numerical values of acoustic intensity and recorded temperature at 22:00 hours for two consecutive days in April and September.

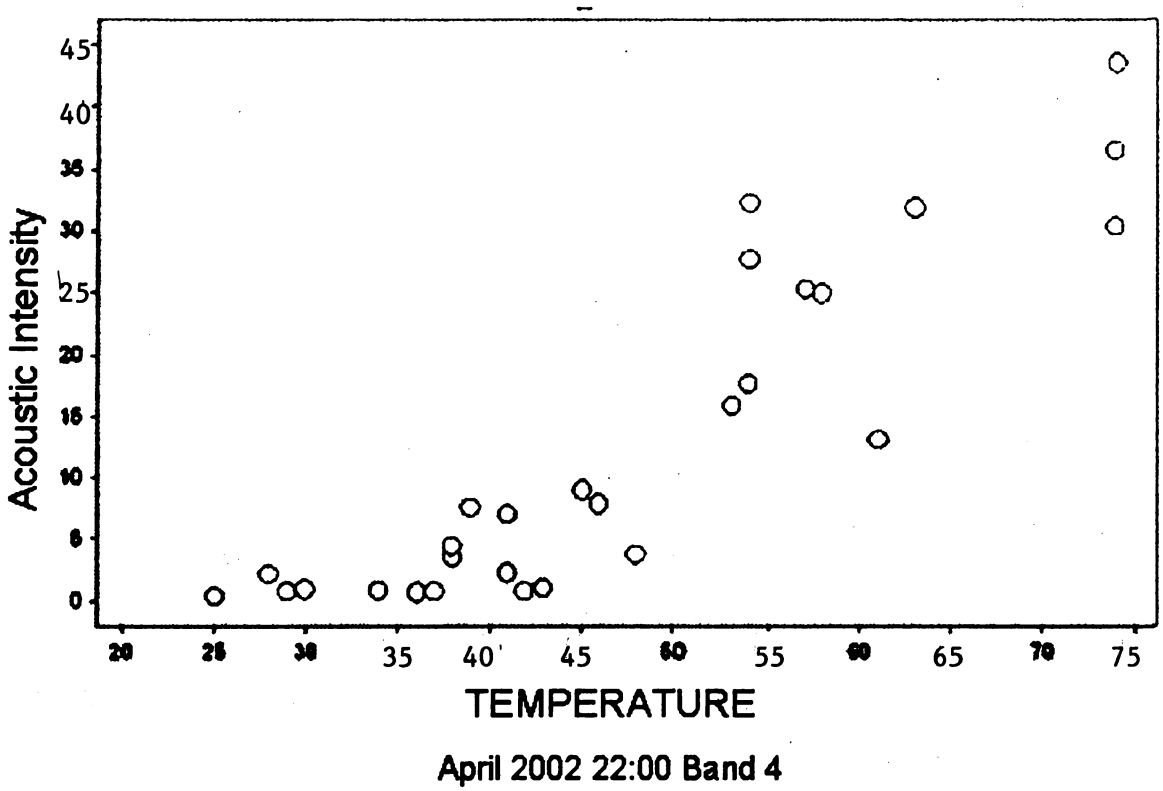

Figure 27. Acoustic Intensity of band 4 (3 – 4 kHz, a highly biological band) plotted against temperature throughout April 2002 at 22:00. These plots indicate that the intensity of activity in band 4 increases with rising temperature.

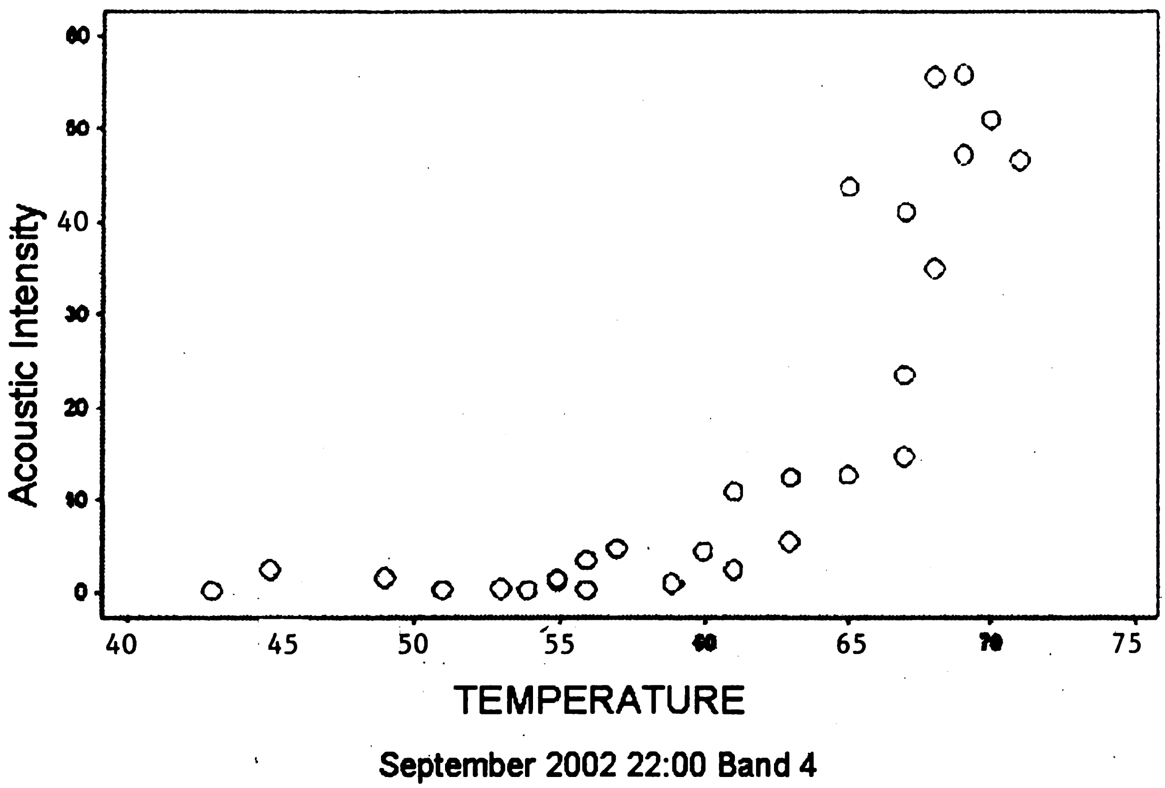

Figure 28. Acoustic Intensity of band 4 (3 – 4 kHz, a highly biological band) plotted against temperature throughout September 2002 at 22:00. These plots indicate an even sharper increase in activity once a temperature threshold of roughly 65° F is surpassed.

Date	B4 (3 - 4 kHz)	Temperature	% Change in Temp	% Change in Activity
April 7, 2002	00.91	43	25.58	2934.07
April 8, 2002	27.61	54		
Sept 14, 2002	46.67	71	-21.13	-99.66
Sept 15, 2002	00.16	56		

Table 14. Mean value of activity in band 4 (3-4 kHz) at 22:00 on four different days with four different temperatures. The lower temperatures appear to correlate with lower activity means, and higher temperatures with higher means.

Conclusions

Our investigation of ecological acoustics revealed that a framework for the collection, analysis and interpretation of environmental acoustics on a landscape scale had not been developed. This paper provides a framework to facilitate the scientific community's ability to communicate and quantitatively interpret environmental acoustics. We consider the study of acoustic signals to be a valuable resource that will allow us to interpret ecological change. We developed a simple classification system of acoustic signals that was based on the frequency domains of different components of these signals to enable a quantitative interpretation of the soundscape in terms of its human and biophysical components. Earlier work by Krause (Krause 1998) provided an excellent start by characterizing the biophony, but in order to quantify the ecological impacts of our increasingly mechanized society, we found it necessary to separate mechanized anthropogenic activity into the anthrophony. We built our interpretation on the foundation of Schaffer's initial soundscape concept (Schafer 1977, 1994), enhancing it by attempting to quantify the activity by means of the spectrogram and statistical analyses. Many studies have been conducted on acoustic signals of specific organisms and how organisms use acoustics to communicate (sea mammals, insects, birds, amphibians), as well as acoustic surveys to assess the occurrence of these organisms. We did not find, however, any examples of methods to obtain data at regular intervals over long time periods that would enable the examination of temporal patterns of soundscapes. Thus we developed new analytical methods to examine soundscapes' various temporal features. The analyses provided in the case studies represent the diversity of information our approach to ecological acoustics may yield. These cases were our first steps to demonstrate that it is possible to extract vital ecological information by examining the temporal and frequency aspects of ecosystems and examining relationships between acoustic signals and other ecological variables. We have developed a sizeable digital library of acoustic signals at regular intervals from several locations in Michigan and at a few other places in the United States (California, New Mexico, Colorado). We are developing a cyber-infrastructure to enable automated processing and analysis of incoming signals from different landscapes in the United States for near real-time display on our "Clickable Ecosystem" web site (http://envirosonic.cevl.msu.edu/). We will use this site to communicate the information we gather and analyze from acoustic signals.

Appendix B

List of species used in the Spectral Analysis

	ORDER	FAMILY	Subfamily	Genus species	English Name
AMPHIBIA	**ANURA**				
		BUFONIDAE			
				Bufo americanus	American Toad
				Bufo cognatus	Great Plains Toad
				Bufo fowleri	Fowler's Toad
				Bufo quercicus	Oak Toad
				Bufo terrestris	Southern Toad
				Bufo valliceps	Gulf Coast Toad
		HYLIDAE			
			Hylinae		
				Acris crepitans	Northern Cricket Frog
				Acris gryllus	Southern Cricket Frog
				Hyla andersonii	Pine Barrens Treefrog
				Hyla arborea	Green Treefrog
				Hyla avivoca	Bird-voiced Treefrog
				Hyla chrysoscelis	Cope's Gray Treefrog
				Hyla femoralis	Pinewoods Treefrog
				Hyla gratiosa	Barking Treefrog
				Hyla squirella	Squirrel Treefrog
				Hyla versicolor	Gray Treefrog
				Pseudacris brachyphona	Mountain Chorus Frog
				Pseudacris brimleyi	Brimley's Chorus Frog
				Pseudacris crucifer	Spring Peeper
				Pseudacris nigrita	Southern Chorus Frog
				Pseudacris ocularis	Little Grass Frog
				Pseudacris ornata	Ornate Chorus Frog
				Pseudacris streckeri	Strecker's Chorus Frog
				Pseudacris triseriata	Western Chorus Frog
		MICROHYLIDAE			
			Microhylinae		
				Gastrophryne carolinensis	Eastern Narrowmouth Toad
				Gastrophryne olivacea	Great Plains Narrowmouth Toad
		MYOBATRACHIDAE			
			Limnodynastinae		
				Limnodynastes dorsalis	Bullfrog
		PELOBATIDAE			
				Pelobates syriacus	Eastern Spadefoot
				Spea bombifrons	Plains Spadefoot
		RANIDAE			
				Rana areolata	Gopher Frog
				Rana areolata	Crawfish Frog
				Rana blairi	Plains Leopard Frog
				Rana clamitans	Green Frog
				Rana daemeli	Wood Frog
				Rana grylio	Pig Frog
				Rana heckscheri	River Frog
				Rana okaloosae	Florida Bog Frog
				Rana palustris	Pickerel Frog

	ORDER	FAMILY	Subfamily	Genus species	English Name
				Rana pipiens	Northern leopard Frog
				Rana septentrionalis	Mink Frog
				Rana sphenocephala	Southern Leopard Frog
				Rana virgatipes	Carpenter Frog
AVES	**ANSERIFORMES**				
		ANATIDAE			
			Anatinae		
				Aix sponsa	Wood Duck
				Anas acuta	Northern Pintail
				Anas americana	American Wigeon
				Anas clypeata	Northern Shoveler
				Anas crecca	Green-winged Teal
				Anas platyrhynchos	Mallard
				Anas strepera	Gadwall
				Clangula hyemalis	Long-tailed Duck
				Oxyura jamaicensis	Ruddy Duck
				Somateria mollissima	Common Eider
			Anserinae		
				Branta bernicla	Brant
				Branta canadensis	Canada Goose
				Chen caerulescens	Snow Goose
				Cygnus columbianus	Tundra Swan
	APODIFORMES				
		APODIDAE			
			Chaeturinae		
				Chaetura pelagica	Chimney Swift
		TROCHILIDAE			
			Trochilinae		
				Archilochus colubris	Ruby-throated Hummingbird
	CAPRIMULGIFORMES				
		CAPRIMULGIDAE			
			Caprimulginae		
				Caprimulgus carolinensis	Chuck-wills-widow
				Caprimulgus vociferus	Whip-poor-will
			Chordeilinae		
				Chordeiles gundlachii	Antillean Nighthawk
				Chordeiles minor	Common Nighthawk
	CHARADRIIFORMES				
		CHARADRIIDAE			
			Charadriinae		
				Charadrius alexandrinus	Snowy Plover
				Charadrius melodus	Piping Plover
				Charadrius semipalmatus	Semipalmated Plover
				Charadrius vociferus	Killdeer
				Charadrius wilsonia	Wilsons Plover
				Pluvialis dominica	American Golden-Plover
				Pluvialis squatarola	Black-bellied Plover
		LARIDAE			
			Larinae		
				Larus argentatus	Herring Gull
				Larus atricilla	Laughing Gull

ORDER	FAMILY	Subfamily	Genus species	English Name
		Sterninae		
			Chlidonias niger	Black Tern
			Sterna antillarum	Least Tern
			Sterna caspia	Caspian Tern
			Sterna dougallii	Roseate Tern
			Sterna forsteri	Forster's Tern
			Sterna hirundo	Common Tern
			Sterna maxima	Royal Tern
			Sterna nilotica	Gull-billed Tern
			Sterna paradisaea	Arctic Tern
	RECURVIROSTRIDAE			
			Himantopus mexicanus	Black-necked Stilt
	SCOLOPACIDAE			
		Phalaropodinae		
			Phalaropus tricolor	Wilsons Phalarope
		Scolopacinae		
			Actitis macularia	Spotted Sandpiper
			Arenaria interpres	Ruddy Turnstone
			Bartramia longicauda	Upland Sandpiper
			Calidris alba	Sanderling
			Calidris alpina	Dunlin
			Calidris mauri	Western Sandpiper
			Calidris minutilla	Least Sandpiper
			Calidris pusilla	Semipalmated Sandpiper
			Catoptrophorus semipalmatus	Willet
			Gallinago gallinago	Common Snipe
			Limnodromus griseus	Short-billed Dowitcher
			Limnodromus scolopaceus	Long-billed Dowitcher
			Numenius phaeopus	Whimbrel
			Scolopax minor	American Woodcock
			Tringa flavipes	Lesser Yellowlegs
			Tringa melanoleuca	Greater Yellowlegs
			Tringa solitaria	Solitary Sandpiper
CICONIIFORMES				
	ARDEIDAE			
			Ardea herodias	Great Blue Heron
			Botaurus lentiginosus	American Bittern
			Butorides virescens	Green Heron
			Ixobrychus exilis	Least Bittern
			Nyctanassa violacea	Yellow-crowned Night-Heron
			Nycticorax nycticorax	Black-crowned Night-Heron
COLUMBIFORMES				
	COLUMBIDAE			
			Columbina passerina	Common Ground-Dove
			Zenaida macroura	Mourning Dove
CORACIIFORMES				
	ALCEDINIDAE			
		Cerylinae		
			Ceryle alcyon	Belted Kingfisher
CUCULIFORMES				
	CUCULIDAE			

ORDER	FAMILY	Subfamily	Genus species	English Name
		Coccyzinae		
			Coccyzus americanus	Yellow-billed Cuckoo
			Coccyzus erythropthalmus	Black-billed Cuckoo
			Coccyzus minor	Mangrove Cuckoo
FALCONIFORMES				
	ACCIPITRIDAE			
		Accipitrinae		
			Accipiter cooperii	Coopers Hawk
			Accipiter gentilis	Northern Goshawk
			Buteo jamaicensis	Red-tailed Hawk
			Buteo lineatus	Red-shouldered Hawk
			Buteo platypterus	Broad-winged Hawk
			Haliaeetus leucocephalus	Bald Eagle
	FALCONIDAE			
		Falconinae		
			Falco peregrinus	Peregrine Falcon
			Falco sparverius	American Kestrel
GALLIFORMES				
	ODONTOPHORIDAE			
			Colinus virginianus	Northern Bobwhite
	PHASIANIDAE			
		Meleagridinae		
			Meleagris gallopavo	Wild Turkey
		Phasianinae		
			Phasianus colchicus	Ring-necked Pheasant
		Tetraoninae		
			Bonasa umbellus	Ruffed Grouse
			Falcipennis canadensis	Spruce Grouse
GAVIIFORMES				
	GAVIIDAE			
			Gavia immer	Common Loon
GRUIFORMES				
	ARAMIDAE			
			Aramus guarauna	Limpkin
	GRUIDAE			
		Gruinae		
			Grus canadensis	Sandhill Crane
	RALLIDAE			
			Coturnicops noveboracensis	Yellow Rail
			Fulica americana	American Coot
			Gallinula chloropus	Common Moorhen
			Laterallus jamaicensis	Black Rail
			Porzana carolina	Sora
			Rallus elegans	King Rail
			Rallus limicola	Virginia Rail
			Rallus longirostris	Clapper Rail
PASSERIFORMES				
	ALAUDIDAE			
			Eremophila alpestris	Horned Lark
	BOMBYCILLIDAE			
PASSERIFORMI			*Bombycilla cedrorum*	Cedar Waxwing

	ORDER	FAMILY	Subfamily	Genus species	English Name
AVES		CARDINALIDAE			
				Cardinalis cardinalis	Northern Cardinal
				Passerina caerulea	Blue Grosbeak
				Passerina ciris	Painted Bunting
				Passerina cyanea	Indigo Bunting
				Pheucticus ludovicianus	Rose-breasted Grosbeak
				Spiza americana	Dickcissel
		CERTHIIDAE			
			Certhiinae		
				Certhia americana	Brown Creeper
		CORVIDAE			
				Corvus brachyrhynchos	American Crow
				Corvus corax	Common Raven
				Corvus ossifragus	Fish Crow
				Cyanocitta cristata	Blue Jay
				Perisoreus canadensis	Gray Jay
		EMBERIZIDAE			
				Aimophila aestivalis	Bachmans Sparrow
				Ammodramus caudacutus	Saltmarsh Sharp-tailed Sparrow
				Ammodramus henslowii	Henslows Sparrow
				Ammodramus leconteii	Le Contes Sparrow
				Ammodramus maritimus	Seaside Sparrow
				Calcarius lapponicus	Lapland Longspur
				Chondestes grammacus	Lark Sparrow
				Junco hyemalis	Dark-eyed Junco
				Melospiza georgiana	Swamp Sparrow
				Melospiza lincolnii	Lincolns Sparrow
				Melospiza melodia	Song Sparrow
				Passerculus sandwichensis	Savannah Sparrow
				Passerella iliaca	Fox Sparrow
				Pipilo erythrophthalmus	Eastern Towhee
				Plectrophenax nivalis	Snow Bunting
				Pooecetes gramineus	Vesper Sparrow
				Spizella arborea	American Tree Sparrow
				Spizella pallida	Clay-colored Sparrow
				Spizella passerina	Chipping Sparrow
				Spizella pusilla	Field Sparrow
				Zonotrichia albicollis	White-throated Sparrow
				Zonotrichia leucophrys	White-crowned Sparrow
		FRINGILLIDAE			
			Carduelinae		
				Carduelis flammea	Common Redpoll
				Carduelis pinus	Pine Siskin
				Carduelis tristis	American Goldfinch
				Carpodacus mexicanus	House Finch
				Carpodacus purpureus	Purple Finch
				Coccothraustes vespertinus	Evening Grosbeak
				Loxia curvirostra	Red Crossbill
				Loxia leucoptera	White-winged Crossbill
				Pinicola enucleator	Pine Grosbeak

ORDER	FAMILY	Subfamily	Genus species	English Name
	HIRUNDINIDAE			
		Hirundininae		
			Hirundo rustica	Barn Swallow
			Petrochelidon pyrrhonota	Cliff Swallow
			Progne subis	Purple Martin
			Riparia riparia	Bank Swallow
			Stelgidopteryx serripennis	Northern Rough-winged Swallow
			Tachycineta bicolor	Tree Swallow
	ICTERIDAE			
			Agelaius phoeniceus	Red-winged Blackbird
			Dolichonyx oryzivorus	Bobolink
			Euphagus carolinus	Rusty Blackbird
			Euphagus cyanocephalus	Brewers Blackbird
			Icterus bullockii	Bullock's Oriole
			Icterus galbula	Baltimore Oriole
			Icterus spurius	Orchard Oriole
			Molothrus ater	Brown-headed Cowbird
			Quiscalus major	Boat-tailed Grackle
			Quiscalus mexicanus	Great-tailed Grackle
			Quiscalus quiscula	Common Grackle
			Sturnella magna	Eastern Meadowlark
			Sturnella neglecta	Western Meadowlark
			Xanthocephalus xanthocephalus	Yellow-headed Blackbird
	LANIIDAE			
			Lanius ludovicianus	Loggerhead Shrike
	MIMIDAE			
			Dumetella carolinensis	Gray Catbird
			Mimus polyglottos	Northern Mockingbird
			Toxostoma rufum	Brown Thrasher
	MOTACILLIDAE			
			Anthus rubescens	American Pipit
	PARIDAE			
			Baeolophus bicolor	Tufted Titmouse
			Poecile atricapillus	Black-capped Chickadee
			Poecile carolinensis	Carolina Chickadee
			Poecile hudsonica	Boreal Chickadee
	PARULIDAE			
			Dendroica caerulescens	Black-throated Blue Warbler
			Dendroica castanea	Bay-breasted Warbler
			Dendroica cerulea	Cerulean Warbler
			Dendroica coronata	Yellow-rumped Warbler
			Dendroica discolor	Prairie Warbler
			Dendroica dominica	Yellow-throated Warbler
			Dendroica fusca	Blackburnian Warbler
			Dendroica magnolia	Magnolia Warbler
			Dendroica palmarum	Palm Warbler
			Dendroica pensylvanica	Chestnut-sided Warbler
			Dendroica petechia	Yellow Warbler
			Dendroica pinus	Pine Warbler
			Dendroica striata	Blackpoll Warbler

	ORDER	FAMILY	Subfamily	Genus species	English Name
				Dendroica tigrina	Cape May Warbler
				Dendroica virens	Black-throated Green Warbler
				Geothlypis trichas	Common Yellowthroat
				Helmitheros vermivorus	Worm-eating Warbler
				Icteria virens	Yellow-breasted Chat
				Mniotilta varia	Black-and-white Warbler
				Oporornis agilis	Connecticut Warbler
				Oporornis formosus	Kentucky Warbler
				Oporornis philadelphia	Mourning Warbler
				Parula americana	Northern Parula
				Protonotaria citrea	Prothonotary Warbler
				Seiurus aurocapilla	Ovenbird
				Seiurus motacilla	Louisiana Waterthrush
				Seiurus noveboracensis	Northern Waterthrush
				Setophaga ruticilla	American Redstart
				Vermivora chrysoptera	Golden-winged Warbler
				Vermivora peregrina	Tennessee Warbler
				Vermivora pinus	Blue-winged Warbler
				Vermivora ruficapilla	Nashville Warbler
				Wilsonia canadensis	Canada Warbler
				Wilsonia citrina	Hooded Warbler
		REGULIDAE			
				Regulus calendula	Ruby-crowned Kinglet
				Regulus satrapa	Golden-crowned Kinglet
		SITTIDAE			
			Sittinae		
				Sitta canadensis	Red-breasted Nuthatch
				Sitta carolinensis	White-breasted Nuthatch
				Sitta pusilla	Brown-headed Nuthatch
		SYLVIIDAE			
			Polioptilinae		
				Polioptila caerulea	Blue-gray Gnatcatcher
		THRAUPIDAE			
				Piranga olivacea	Scarlet Tanager
				Piranga rubra	Summer Tanager
		TROGLODYTIDAE			
				Cistothorus palustris	Marsh Wren
				Cistothorus platensis	Sedge Wren
				Thryomanes bewickii	Bewicks Wren
				Thryothorus ludovicianus	Carolina Wren
				Troglodytes aedon	House Wren
				Troglodytes troglodytes	Winter Wren
		TURDIDAE			
				Catharus fuscescens	Veery
				Catharus guttatus	Hermit Thrush
				Catharus minimus	Gray-cheeked Thrush
				Catharus ustulatus	Swainsons Thrush
				Hylocichla mustelina	Wood Thrush
				Sialia sialis	Eastern Bluebird
				Turdus migratorius	American Robin

	ORDER	FAMILY	Subfamily	Genus species	English Name
		TYRANNIDAE			
			Fluvicolinae		
				Contopus cooperi	Olive-sided Flycatcher
				Contopus virens	Eastern Wood-Pewee
				Empidonax alnorum	Alder Flycatcher
				Empidonax flaviventris	Yellow-bellied Flycatcher
				Empidonax minimus	Least Flycatcher
				Empidonax traillii	Willow Flycatcher
				Empidonax virescens	Acadian Flycatcher
				Sayornis phoebe	Eastern Phoebe
			Tyranninae		
				Myiarchus crinitus	Great Crested Flycatcher
				Tyrannus dominicensis	Gray Kingbird
				Tyrannus tyrannus	Eastern Kingbird
				Tyrannus verticalis	Western Kingbird
		VIREONIDAE			
				Vireo altiloquus	Black-whiskered Vireo
				Vireo atricapilla	Black-capped Vireo
				Vireo bellii	Bells Vireo
				Vireo flavifrons	Yellow-throated Vireo
				Vireo gilvus	Warbling Vireo
				Vireo griseus	White-eyed Vireo
				Vireo olivaceus	Red-eyed Vireo
				Vireo philadelphicus	Philadelphia Vireo
				Vireo solitarius	Blue-headed Vireo
	PICIFORMES				
		PICIDAE			
			Picinae		
				Colaptes auratus	Northern Flicker
				Dryocopus pileatus	Pileated Woodpecker
				Melanerpes carolinus	Red-bellied Woodpecker
				Melanerpes erythrocephalus	Red-headed Woodpecker
				Picoides arcticus	Black-backed Woodpecker
				Picoides borealis	Red-cockaded Woodpecker
				Picoides dorsalis	American Three-toed Woodpecker
				Picoides pubescens	Downy Woodpecker
				Picoides villosus	Hairy Woodpecker
				Sphyrapicus varius	Yellow-bellied Sapsucker
	PODICIPEDIFORMES				
		PODICIPEDIDAE			
				Podilymbus podiceps	Pied-billed Grebe
	STRIGIFORMES				
		STRIGIDAE			
				Aegolius acadicus	Northern Saw-whet Owl
				Aegolius funereus	Boreal Owl
				Asio flammeus	Short-eared Owl
				Asio otus	Long-eared Owl
				Athene cunicularia	Burrowing Owl
				Bubo virginianus	Great Horned Owl
				Megascops asio	Eastern Screech-Owl

	ORDER	FAMILY	Subfamily	Genus species	English Name
AVES				***Strix nebulosa***	Great Gray Owl
				Strix varia	Barred Owl
		TYTONIDAE			
				Tyto alba	Barn Owl
INSECTA	**HOMOPTERA**				
		CICADIDAE			
				Diceroprocta vitripennis	Diceroprocta
				Magicicada septendecim	Magicicada
				Okanagana canadensis	Okanagana 1
				Okanagana rimosa	Okanagana 2
				Tibicen auletes	Tibicen 1
				Tibicen canicularis	Tibicen 2
				Tibicen chloromera	Tibicen 3
				Tibicen linnei	Tibicen 4
				Tibicen lyricen	Tibicen 5
				Tibicen pruinosa	Tibicen 6
	ORTHOPTERA				
		GRYLLIDAE			
			Eneopterinae		
				Anaxipha exigua	Say's Bush Cricket
				Orocharis saltator	Jumping Bush Cricket
				Phyllopalpus pulchellus	Red-headed Bush Cricket
			Gryllinae		
				Gryllus veletis	Northern Spring Field Cricket
			Nemobiinae		
				Allonembius tinnulus	Tinkling Ground Cricket
				Allonemobius allardi	Allard's Ground Cricket
				Allonemobius fasciatus	Striped Ground Cricket
				Eunemobius carolinus	Carolina Ground Cricket
			Oecanthinae		
				Neoxabea bipunctata	Two-spotted Tree Cricket
				Oecanthus celerinictus	Fast-calling Tree Cricket
				Oecanthus exclamationis	Davis Tree Cricket
				Oecanthus fultoni	Snowy Tree Cricket
				Oecanthus latipennis	Broad-winged Tree Cricket
				Oecanthus nigricornis	Black-horned Tree Cricket
				Oecanthus niveus	Narrow-winged Tree Cricket
				Oecanthus pini	Pine Tree Cricket
		GRYLLOTALPIDAE			
				Neocurtilla hexadactyla	Northern Mole Cricket
		TETTIGONIIDAE			
			Conocephalinae		
				Conocephalus fasciatus	Slender Meadow Katydid
				Conocephalus spartinae	Saltmarsh Meadow Katydid
				Orchelimion nigripes	Black-legged Meadow Katydid
				Orchelimion vulgare	Common Meadow Katydid
				Orchelimum nemoralis	Lesser Pine Katydid
				Orchelimum robustus	Woodland Meadow Katydid
			Copiphorinae		
				Neoconcephalus ensiger	Sword-bearer Conehead Katydid

	ORDER	FAMILY	Subfamily	Genus species	English Name
				Neoconcephalus exiliscanorus	Long-beaked Conehead Katydid
				Neoconcephalus nebrascensis	Nebraska Conehead Katydid
				Neoconcephalus retusus	Round-tipped Conehead Katydid
				Neoconcephalus robustus	Robust Conehead Katydid
			Phaneropterinae		
				Amblycorypha oblongifolia	Oblong-winged Katydid
				Amblycorypha rotundifolia	Round-winged Katydid
				Microcentrum retinerve	Lesser Angle-winged Katydid
				Microcentrum rhombifolium	Greater Angle-winged Katydid
				Scudderia curvicauda	Curve-tailed Bush Katydid
				Scudderia furcata	Fork-tailed Bush Katydid
				Scudderia septentrionalis	Northern Bush Katydid
				Scudderia texensis	Texas Bush Katydid
			Pseudophyllinae		
				Pteryphylla camellifolia	Northern True Katydid
			Tettigoniinae		
				Atlanticus testaceus	Short-legged Shield-bearer
				Metrioptera roeselii	Roesel's Decticid

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