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Acoustic Observations in Agricultural Landscapes

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Sounds emanating from various habitats and ecosystems provide a rich source of information to interpret ecological phenomena at multiple scales. Acoustic communication is a fundamental property of many animals for breeding and defending territories (Fletcher 1953, Peterson and Dorcas 1994), and acoustic signatures can be used to measure the spatial and temporal distributions of vocal organisms in ecosystems (Kroodsma and Miller 1996, Pijanowski et al. 2011a). Ecosystem sounds, in general, create a *soundscape*, made up of acoustic periodicities and frequencies emitted in aggregate from an ecosystem's biophysical entities (Schafer 1977, Truax 1984, 1999, Qi et al. 2008). Soundscapes can be partitioned into anthropogenic, biological, and physical sources (Napoletano 2004, Qi et al. 2008, Pijanowski et al. 2011a, Joo et al. 2011). They can then be further subdivided to provide valuable insights into the ecology of vocal organisms and their habitats, including their diversity and abundance, as well as phenological events such as seasonal arrivals, dates of reproduction, and breeding communication behavior.

Interpreting animal sounds has been used for many years to survey vocal organisms. For example, the U.S. North American Breeding Bird Survey—one of the largest long-term, national-scale avian observation programs—has been conducted for over 30 years by observers using both auditory and visual cues (Bystrak 1981, Robbins et al. 1986). The North American Amphibian Monitoring Program identifies amphibian species primarily by listening for their calls at night (Weir and Mossman 2005). Recent advances in sensor networks enable the large-scale, automated collection of acoustic signals in natural areas (Estrin et al. 2003, Porter et al. 2005, Pijanowski et al. 2011b, Aide et al. 2013, Ospina et al. 2013). The systematic and synchronous collection of sound recordings at multiple locations, combined with ancillary measurements such as light, temperature, and humidity, can produce an enormous volume of ecologically relevant information.

Soundscape information has the potential to increase our understanding of ecosystem change if sampled over appropriate time intervals (Truax 1984, Wrightson 2000, Sueur 2008). The analysis of entire soundscapes may also produce valuable information about the dynamics of interactions among ecological systems in heterogeneous landscapes (Carles et al. 1999). Further, rapid analysis enables the timely delivery of important environmental information to natural resource managers and can promote public involvement through public access to information about nearby and distant environments.

Automated, distributed acoustic measurements via sensor networks provide additional benefits to ecology and the environmental science community. First, analysis of observations collected through continuous monitoring at fixed sites can reveal spatiotemporal patterns that cannot be captured using site-by-site observations (Gage et al. 2004, Gage and Axel 2013). By monitoring soundscapes continuously from fixed locations, acoustic information can reveal ecosystem change over scales of days to years (Truax 1984). Second, because acoustic monitoring systems can simultaneously monitor multiple locations, acoustic variances can be compared to environmental heterogeneity (Thompson et al. 2001, Michener et al. 2001, West et al. 2001). Third, microphones can collect data from all directions simultaneously despite visual obstructions such as trees or buildings, and at all times of day including night. Finally, recording technology can operate in the field unattended, thereby allowing observations to be made without the interference generated by human presence (West et al. 2001).

Here, we illustrate the use of older recording technology (tape recorders with a clock used in 2005) and the subsequent development of wireless monitoring technology (sensor–transmitter–receiver used in 2007) to measure the soundscape, transmit the sound to a remote computer, and analyze it to understand the spatial and temporal variability of sounds emanating from ecosystems in the Kellogg Biological Station Long-Term Ecological Research site (KBS LTER). In particular, we describe the design, development, and deployment of an automated acoustic recording system and then its application to examine ecological phenomena in a complex agricultural landscape.

Soundscape Taxonomy

The sounds emanating from an ecosystem can be treated as the transmission of signals that carry information (Shannon 1948, Raisbeck 1964). The organism or force generating a sound acts as the encoder and transmitter of a signal that travels through a medium such as air or water. An organism receives the acoustic signal and then registers and decodes it into information.

Acoustic signals can be generally classified as either natural or human-induced sounds (Schafer 1977). Krause (1998) called the natural sounds *biophony*. Napoletano (2004) further classified soundscapes as biological, geophysical, or anthropogenic (Fig. 14.1). Biological sounds can be *intentional* or *incidental* signals. Intentional signals are produced by organisms that wish to communicate information such as mating or distress calls. Incidental signals may contain useful

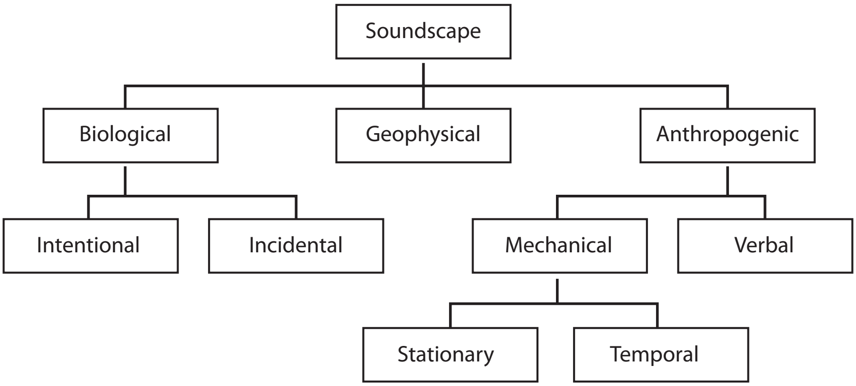

Figure 14.1. An acoustic taxonomic schema of biological, geophysical, and anthropogenic sounds. Anthropogenic verbal communication can also be considered biological, although here they have been categorized separately for clarity.

information but are not dispatched for the explicit purpose of communication. Similarly, human-induced sounds can be *verbal* or *mechanical*. Verbal signals are those produced by the human voice (e.g., talking, shouting, or singing). Conversely, mechanical signals are produced by machinery and technology. Mechanical signals can be *stationary* or *temporal*. Stationary sounds are those that impose themselves on the ambient soundscape indefinitely (e.g., turbulence from ventilation fans), while temporal sounds include noises that impinge on the soundscape for a limited period (e.g., occasional automobile or train traffic). Each of these components occurs at a range of frequencies that can be used to quantify the soundscape. Importantly, this schema differentiates between sounds produced by vocalizing animals and those produced by machines.

Soundscape Analysis

Acoustic diversity metrics attempt to measure and quantify the number and type of signal sources in the soundscape (Slabbekoorn and Peet 2003, Katti and Warren 2004, Warren et al. 2006). Organisms make selective use of acoustic frequencies when attempting to communicate information such as mating potential, territory size, and the presence of predators (Narins 1995, Catchpole and Slater 1995). Essentially, each vocalizing species can develop a dynamic niche by modulating the temporal periodicity and frequency of its respective signals to unused portions of the soundscape in order to avoid competition for spectral or temporal resources (Narins 1995). This suggests that soundscape diversity might be a sensitive index for identifying ecological change. Dale and Beyeler (2001) identified the value and characteristics of ecological indices, among which by their criteria would include environmental acoustics. Derived metrics from the soundscape are potentially valuable as ecological indices because they can provide predictable measures of ecosystem stress that can be used to interpret and measure both ecological and anthropogenic disturbances.

A soundscape consists of a complex of specific sounds (e.g., birdsong, flowing water, train whistle) of varying intensity depending on the source and the distance from the sensor. These sounds can be used as signatures since they are repeatable. A soundscape can also consist of sounds that occur at different frequencies (e.g., birdsong at higher frequencies, mechanical sounds at lower frequencies). Quantifying either type of signal is difficult since multiple organisms may sing simultaneously and their frequencies may overlap, making signature identification difficult. On the other hand, some animals have simple sounds (e.g., spring peeper frogs, *Pseudacris crucifer*) that can be readily quantified. Some organisms signal at low frequencies (e.g., American crow, *Corvus brachyrhynchos*), and thus signal at frequencies similar to those of some mechanical sounds, introducing exceptions to the idea that biological sound can be separated from mechanical sound based on frequency analysis. These problems have prompted research into pattern recognition to characterize entities in the soundscape (e.g., Reynolds and Rose 1995, Anderson et al. 1996, Acevedo et al. 2009, Ranjard and Ross 2008, Brandes 2008, Waddle et al. 2009, Kasten et al. 2010).

To date, most research on soundscapes has focused on understanding acoustic characteristics based on descriptive and qualitative analysis of sounds (Schafer 1977, Krause 1998). Quantitative methods to analyze the soundscape using frequency extraction have been developed by Napoletano (2004) and Qi et al. (2008) using spectrograms. Analysis begins with the creation of a spectrogram, which is a time-varying spectral representation of an acoustic signal that can be visualized, with frequency (in hertz or Hz) of an acoustic signal on the *y*-axis and time on the *x*-axis (Haykin 1991). To analyze a spectrogram image produced from a sound recording, one can transform the recording to an image that can then be divided into intervals (e.g., 1-kHz intervals) using image analysis software. The power level represented by the pixel values in each interval can then be summed to provide a value for each frequency interval. This enables the signal power in each frequency interval to be quantified. A more efficient method is to compute the total Power Spectral Density (PSD in watts Hz^{-1}) (Welch 1967) for each 1-kHz interval. This method requires less computational time and eliminates the need to produce spectrogram images and subsequently apply image analysis techniques to quantify the number of pixels in each frequency interval. The specifics for these latter computations are described in Kasten et al. (2012).

Soundscape Index

Napoletano (2004) found that mechanical sounds (anthrophony) mostly occur at low frequencies (1–2 kHz), whereas most biological sounds (biophony) are prevalent above 2 kHz. Geophony (e.g., wind and rain) typically occurs across the entire soundscape spectrum. We developed a Normalized Difference Soundscape Index (NDSI) to separate biophony from anthrophony:

$$\mathrm{NDSI} = \frac{(\beta - \alpha)}{(\beta + \alpha)}$$

where α and β represent the amount of acoustic energy in the biophony (2–11 kHz) and anthrophony (1–2 kHz) frequency domains, respectively. The value of NDSI can range between –1 (pure anthrophony) to 1 (pure biophony). The index has exceptions: some vocalizing organisms such as large birds and amphibians can produce sound within the anthropogenic frequency range, and geophony as well as anthrophony (loud engines) can obscure sounds across the entire spectrum. However, the overall patterns in the soundscape represented by this index can be used to characterize the soundscape both spatially and over time (Gage and Axel 2013).

An Automated Acoustic Recording System

Prior to the development of automated acoustic recording technology, acoustic observations of birds and amphibians were made by visiting a habitat, listening for signals, interpreting them, and then recording their occurrence. By 2000 emergent technologies such as web cameras connected to the Internet were being used to transmit visual observations and the capacity to make automated acoustic observations quickly followed. However, file size associated with acoustic observation can be large and the use of wireless technology to transmit large files remains challenging.

Soundscape recording at KBS LTER was initiated in 2001 using a desktop computer in a field shed at the Main Cropping System Experiment (MCSE; Table 14.1) (Robertson and Hamilton 2015, Chapter 1 in this volume). The computer was programmed to record, capture, and transmit recordings via the Internet to a remote server on the Michigan State University (MSU) campus. A microphone on the outside of the shed captured recordings at regular intervals.

Use of Tape Recorders to Assess Biodiversity and Acoustic Variability in KBS Habitats

Digitizing and quantifying sound recordings provide both a measure of the changing patterns of the soundscape in an ecosystem as well as the identification of vocal species and a characterization of changes in biodiversity of vocal species communities at various temporal and spatial scales (Qi et al. 2008, Joo et al. 2011). At KBS, we recorded sounds in five MCSE communities—Alfalfa, Poplar, Coniferous Forest, Mid-successional, and Deciduous Forest—from May 18 to July 15, 2005 (Fig. 14.2). These early observations of the soundscape were made using an analog cassette tape recording unit that contained a clock to start and stop the recording (Sangean VersaCorder®, C. Crane Co.) and an omni-directional boundary microphone (Model 330-3020, Radio Shack Corp.). These units were placed at each recording site and were set to turn on and off six times in a 24-hour period. The 6095 recordings collected using this technology were converted from analog to digital to enable quantitative analysis. These observations are available at http://lter.kbs.msu.edu/datasets/127.

Table 14.1. Description of the KBS LTER Main Cropping System Experiment (MCSE).[a]

Cropping System/ Community	Dominant Growth Form	Management
Annual Cropping Systems		
Conventional (T1)	Herbaceous annual	Prevailing norm for tilled corn–soybean–winter wheat (c–s–w) rotation; standard chemical inputs, chisel-plowed, no cover crops, no manure or compost
No-till (T2)	Herbaceous annual	Prevailing norm for no-till c–s–w rotation; standard chemical inputs, permanent no-till, no cover crops, no manure or compost
Reduced Input (T3)	Herbaceous annual	Biologically based c–s–w rotation managed to reduce synthetic chemical inputs; chisel-plowed, winter cover crop of red clover or annual rye, no manure or compost
Biologically Based (T4)	Herbaceous annual	Biologically based c–s–w rotation managed without synthetic chemical inputs; chisel-plowed, mechanical weed control, winter cover crop of red clover or annual rye, no manure or compost; certified organic
Perennial Cropping Systems		
Alfalfa (T6)	Herbaceous perennial	5- to 6-year rotation with winter wheat as a 1-year break crop
Poplar (T5)	Woody perennial	Hybrid poplar trees on a ca. 10-year harvest cycle, either replanted or coppiced after harvest
Coniferous Forest (CF)	Woody perennial	Planted conifers periodically thinned
Successional and Reference Communities		
Early Successional (T7)	Herbaceous perennial	Historically tilled cropland abandoned in 1988; unmanaged but for annual spring burn to control woody species
Mown Grassland (never tilled) (T8)	Herbaceous perennial	Cleared woodlot (late 1950s) never tilled, unmanaged but for annual fall mowing to control woody species
Mid-successional (SF)	Herbaceous annual + woody perennial	Historically tilled cropland abandoned ca. 1955; unmanaged, with regrowth in transition to forest
Deciduous Forest (DF)	Woody perennial	Late successional native forest never cleared (two sites) or logged once ca. 1900 (one site); unmanaged

[a]Site codes that have been used throughout the project's history are given in parentheses. Systems T1–T7 are replicated within the LTER main site; others are replicated in the surrounding landscape. For further details, see Robertson and Hamilton (2015, Chapter 1 in this volume).

The number of bird species present and the number of their vocalizations were measured by listening to the acoustic samples and identifying each species' songs and calls. Additionally, a bird species diversity index was calculated (Shannon and Weaver 1963, Magurran 1988, Blair 1996, Hobson et al. 2002).

We recorded 43 bird species and 881 vocal activities (songs and calls) during the 2-month recording period. Species richness and the number of vocalizations varied

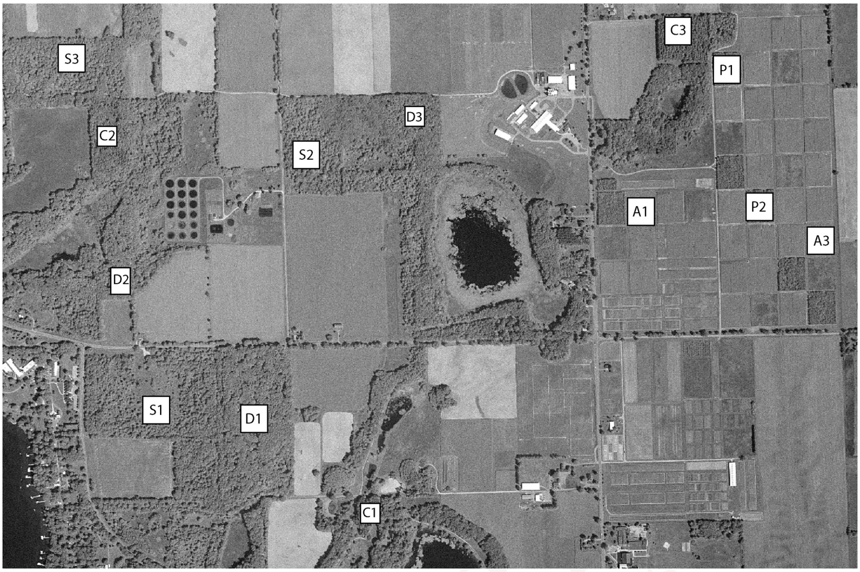

Figure 14.2. Sampling locations at the KBS LTER Main Cropping System Experiment (MCSE) where acoustic tape recorders were deployed from May 18 to July 15, 2005 and set to record six times per day. A = Alfalfa, P = Poplar, C = Coniferous Forest, S = Mid-successional, D = Deciduous Forest.

greatly among the sampling sites (Table 14.2). Fewer bird species were detected in the Alfalfa and Poplar systems than in the Coniferous Forest, Deciduous Forest, and Mid-successional communities. Bird species richness was positively correlated with the number of bird vocalizations (Fig. 14.3). A maximum frequency range of 3 kHz occurred in the Coniferous Forest and Deciduous Forest sites, whereas the maximum frequency range in the Alfalfa, Poplar, and Mid-successional community sites reached 5 kHz, showing that in these recordings, the overall acoustic frequency was lower in forests than in the agricultural (open habitat) communities (Table 14.2).

Use of Wireless and Wired Technology to Record, Transmit, and Interpret Acoustic Observations

Acoustic Sensor Technology Development

We designed and developed an Automated Acoustic Observatory System (AAOS) in 2007 utilizing a low-power sensor platform, a local server, wireless technology, and a remote server. Figure 14.4 illustrates the conceptual framework for placing automated acoustic recorders in remote locations for month-long or longer periods, making automated sound recordings at intervals of minutes to hours, with periodic transmissions to a remote server. The AAOS consists of four components (Fig. 14.4): (A) acoustic recorders in the field that record sounds at frequent

Table 14.2. Avian species identified by listening to digital recordings in KBS LTER Main Cropping System Experiment (MCSE) locations.[a]

Site[b]	Dominant Species (call density)	Species Richness	Number of Vocalizations	Shannon–Wiener Index	Frequency with Maximum Acoustic Power (kHz)
A1	Song sparrow (0.68)	9	34	1.64	5
A2	Song sparrow (0.58)	13	59	2.10	3
P1	Indigo bunting (0.65)	11	27	2.09	5
P2	Song sparrow (0.69)	11	38	1.97	3
C1	Red-winged blackbird (1.00)	16	80	2.31	3
C2	Tufted titmouse (0.42)	14	46	2.46	3
C3	Northern cardinal (0.53)	9	30	1.69	3
S1	Song sparrow (0.59)	25	146	2.64	5
S2	Brown thrasher (0.41)	17	53	2.48	5
S3	Northern cardinal (0.45)	17	77	2.47	3
D1	Scarlet tanager (0.6)	12	73	2.09	3
D2	Baltimore oriole (0.44)	21	120	2.65	3
D3	Eastern wood-pewee (0.31)	25	98	2.91	3

[a]The dominant species was determined based on call density (i.e., the number of vocalizations for that species divided by the total number of recordings). The normalized acoustic power density was generated in each frequency range by slicing every 1000 Hz from 0 to 11,000 Hz. The right column is the most powerful frequency recorded at each site.
[b]A = Alfalfa, P = Poplar, C = Coniferous Forest, S = Mid-successional, and D = Deciduous Forest systems of the MCSE; numbers refer to replicate locations.

intervals, (B) a wireless router to send acoustic recordings around tall vegetation (e.g., poplar trees), (C) a local server to receive the recordings via wireless communication and store the sound recordings locally, and (D) a regional server where the sound recordings are received via the Internet from the local server and analyzed. The recordings, results from the analysis of them (normalized soundscape power by frequency interval), and computed soundscape indices from these values are then placed in a sound library (E) that can be accessed simultaneously by users. The characteristics of this digital acoustic library are described further in Kasten et al. (2012).

Early efforts using autonomous acoustic recorders in the field identified power as the factor that limited recordings to short periods until the advent of low-power processors. Wireless technology allowed the deployment of distributed acoustic sensors, powered by a 12-V battery charged by solar panels, that collect sound recordings frequently (e.g., 30-minute intervals for 30-second durations) and transmit the recorded sounds to a local server for subsequent transfer to a remote server via the Internet. The acoustic sensor platform was designed and developed based on the Crossbow Stargate processor (Crossbow 2006). This processor operated using Linux and required relatively low power (~3 watt). The hardware components of the sensor platform (Fig. 14.5) included

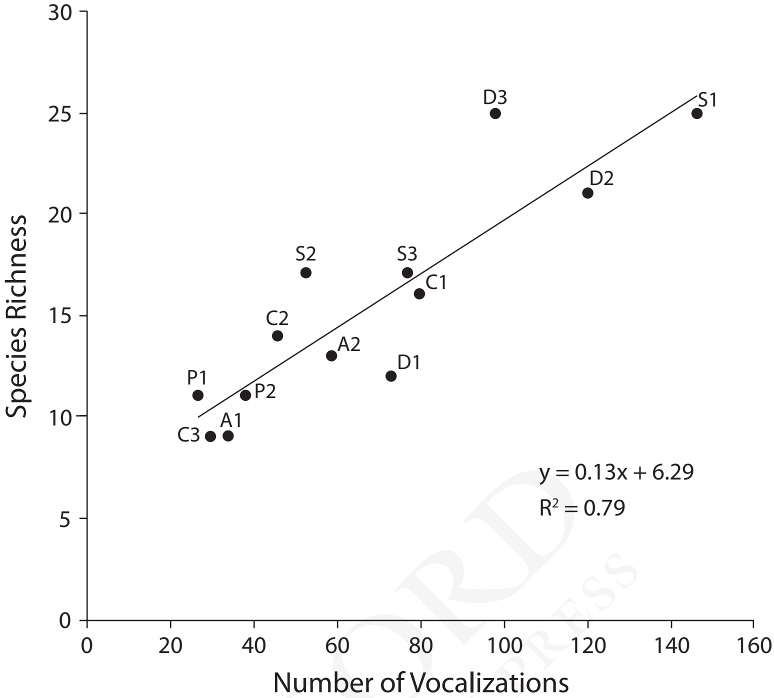

Figure 14.3. The relationship between avian species richness and the number of vocalizations identified from the acoustic samples. The letter and number near each point refers to an MCSE system/replicate number in Figure 14.2.

a processor, a power supply to convert 12-V battery input to 5-V output, an acoustic sensor (microphone), a web camera, a USB hub for additional sensors, a 2-GB flash card for local storage, a wireless communication card (802.11b), and a waterproof case. Power was supplied via a 12-V deep cycle battery charged using an 18-W solar panel.

We programmed the acoustic sensor to capture a 30-second acoustic sample at 30-minute intervals, and to transmit the recording in WAV format to a local server. The local server received approximately 100 MB of audio recordings each day from each recorder. Recordings archived on the local server were subsequently transmitted daily to the web-based digital acoustic library hosted on a laboratory-based server. These recordings are available at http://lter.kbs.msu.edu/datasets/127.

The observatory integrates acoustic sensor technology, wireless networks, and ecological applications using sound recordings from the field. This new assessment tool for ecology and environmental science provides significant opportunities to measure and interpret acoustic signals at relevant spatial and temporal scales (Kasten et al. 2012).

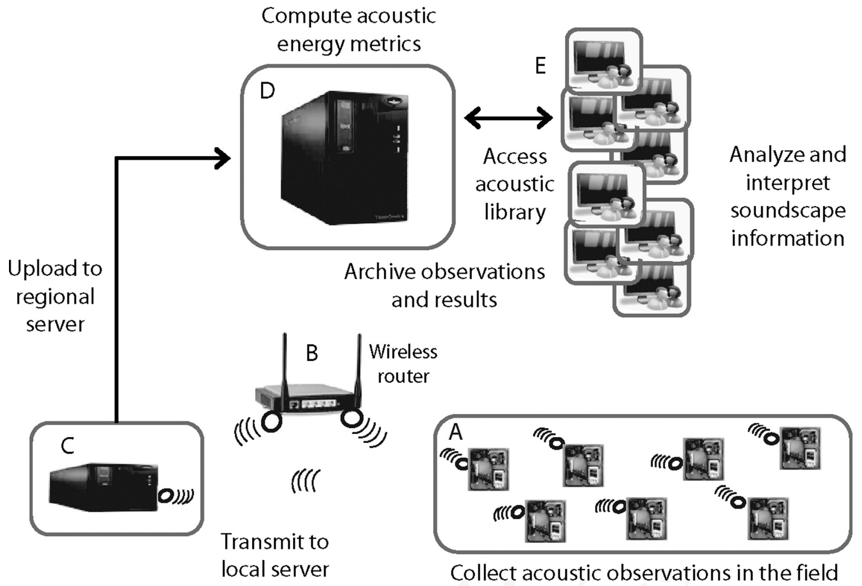

Figure 14.4. The Automated Acoustic Recording System consists of four components: A) acoustic recorders in the field that record sounds at frequent intervals and transmit them using wireless technology, B) one or more wireless routers to relay recordings around tall vegetation, C) a local server to receive the recordings via wireless communication and store them, and D) a regional server where the recordings are received via internet from the local server. The recordings are processed in the regional server and placed in a sound library (E) where they can be accessed.

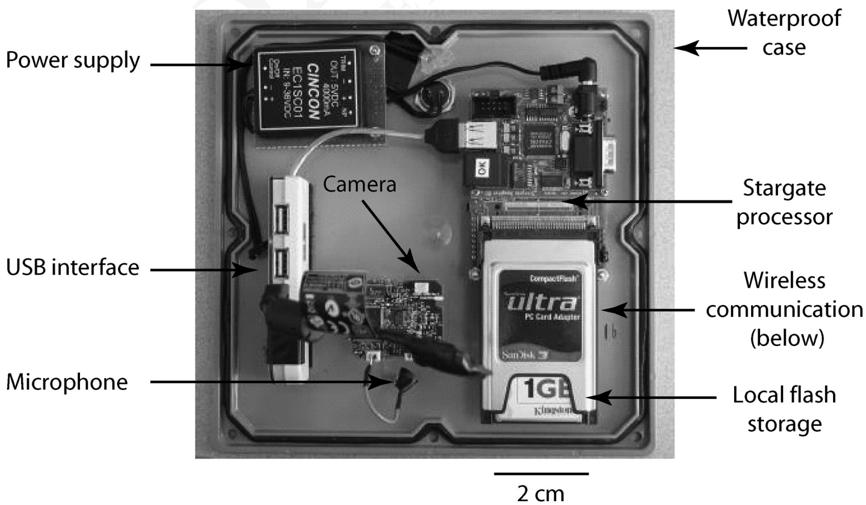

Figure 14.5. The acoustic recorder hardware configuration including a processor, wireless communication, storage, USB interface, power supply, camera, microphone, and a weatherproof enclosure.

We used the AAOS to characterize four of the MCSE communities during June 2007 to investigate the stability and efficiency of the recorders and the integrity and quality of recordings, as well as to determine differences in soundscapes among the communities. The placement of the acoustic recorders, the position of the local server (line power and internet access), and the location of wireless routers used to transmit acoustic signals around tall vegetation to the local server are given at http://lter.kbs.msu.edu/datasets/127. Automated acoustic recorders were placed in Conventional, No-till, Poplar, and Early Successional systems. Winter wheat had been planted in the Conventional and No-till systems the previous fall. A recorder was deployed in three replicates of each system for a total of 12 recorders. The automated recording system collected 11,977 sound recordings, of which 11,777 recordings were valid. Table 14.3 shows the sensor code, location where each sensor was placed, the number of recordings, statistics for total acoustic energy measured by each acoustic sensor, and the percentage of successful recordings. Two sensors malfunctioned during the month-long test (MS04, MS17), whereas others did not record for the entire time due to communication issues or battery failure. The maximum possible number of recordings was 1440 for the month (48 × 30). The Stargate-based acoustic sensors performed adequately during their first field deployment at KBS LTER, although several communication and battery

Table 14.3. Details on the deployment of acoustic sensors in the KBS LTER MCSE.[a]

Sensor Code	Location	Number of Recordings	Total Acoustic Energy (watts kHz^{-1})		Recording Success (%)
			Mean	Standard Deviation	
MS02	Poplar	930	1.50	0.25	65
MS03	Wheat[b]	1374	1.59	0.26	95
MS04	Poplar	[c]M	M	M	M
MS05	Wheat[b]	1151	1.53	0.25	80
MS06	Wheat[b]	1438	1.62	0.28	99
MS07	Early Successional	1426	1.54	0.24	99
MS09	Wheat[b]	1271	1.66	0.23	88
MS11	Early Successional	1151	1.70	0.28	80
MS12	Wheat[b]	1284	1.68	0.28	89
MS13	Wheat[b]	862	1.65	0.23	60
MS15	Early Successional	1090	1.57	0.31	76
MS17	Wheat[b]	M	M	M	M

[a]Details include sensor code, the system where each sensor was located, the number of recordings made during June 2007, statistics for total acoustic energy, and the success of each sensor to record 48 times per day for 30 days.
[b]Wheat includes both Conventional and No-till systems.
[c]M is missing observations due to faulty wireless transmission to server.

drawdown issues were identified that were later resolved. A primary issue was transmission through dense vegetation to the local server. To solve this problem, we placed two wireless routers in strategic positions to avoid tall vegetation between the sensor and local server.

Interpretation of Spatial and Temporal Change in Acoustic Observations

The analytical component of the AAOS automatically computes Power Spectral Density (PSD) values (Welsh 1967) for each of 10 frequency intervals between 1 and 11 kHz. These values were normalized (0–1 range) so that soundscape energy could be compared between locations. In addition, acoustic indices were developed from these values. One index, the Normalized Difference Soundscape Index (NDSI), was used to examine spatial and temporal variability of the KBS LTER soundscape (Kasten et al. 2012, Gage and Axel 2013). The mean NDSI was positive in all systems, indicating that biophony dominated the soundscape everywhere. The means (±standard errors) of the NDSI for the winter wheat (Conventional and No-till combined), Poplar, and Early Successional communities were 0.52 ± 0.01, 0.79 ± 0.01, 0.52 ± 0.08, respectively. Poplar had the highest mean NDSI among the three habitat types and was significantly different from the winter wheat and Early Successional systems ($F = 348.81$, $p < 0.001$), indicating that the Poplar system was more dominated by biological sounds compared to the other communities.

Although overall mean NDSI values are informative, acoustic energy patterns (expressed as watts kHz^{-1}) vary depending on the source of the sound as well as the time of day and the season. The acoustic frequencies and patterns of the frequencies may provide insight into ecological phenomena. The patterns of acoustic energy (watts kHz^{-1}) in each system are shown for four different acoustic frequency intervals (1–2 kHz; 2–3 kHz; 3–4 kHz; and 4–5 kHz) in Fig. 14.6. Both human activity (anthrophony) and some other organisms signal at lower frequencies (e.g., some amphibians, larger birds). Note the precipitous change in acoustic energy at 1–2 kHz (Fig. 14.6A) in all three systems at dawn and dusk. Also note the rise and fall in acoustic energy that can be attributable to human activity during daylight hours (08:00–20:00 h), especially in open areas (wheat and Early Successional systems) compared to Poplar where sound is buffered by vegetation. At the next highest frequency interval (2–3 kHz; Fig. 14.6B), we observe moderately high levels of soundscape energy in all systems during nighttime. At this frequency, the Early Successional community has the highest acoustic energy during the daytime compared to wheat or Poplar. In the next frequency interval (3–4 kHz; Fig. 14.6C), there is a precipitous rise in acoustic energy at dawn (0530 h) and a sharp decline at dusk (2100 h). It is within this frequency range that many species of birds signal. Relatively high levels of energy due to birdsong are sustained during the day. Although the energy in the frequency range of 4–5 kHz (Fig.14.6D) is less than that in the lower frequencies (Figs. 14.6A–C), energy is higher at night in wheat and Poplar and relatively constant in the Early Successional community.

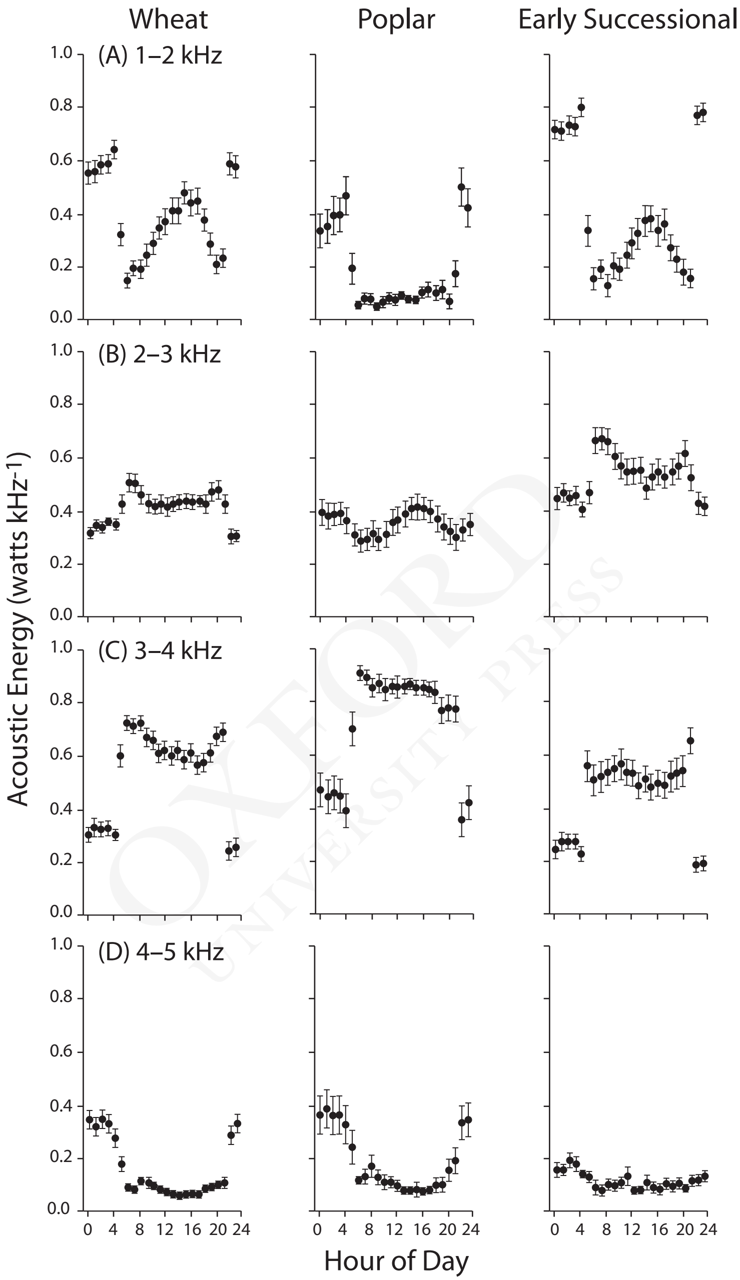

Figure 14.6. The patterns of acoustic energy (watts kHz^{-1}) in each of the examined MCSE systems (Table 14.3) are shown for four different acoustic frequency intervals: A) 1–2 kHz, B) 2–3 kHz, C) 3–4 kHz, and D) 4–5 kHz. Wheat includes both Conventional and No-till systems.

Broader Adoption of Acoustic Technology for Ecological Monitoring

The Biophony Grid Portal

Soundscape research at KBS LTER resulted in a pilot grid computing initiative, led by the National Center for Supercomputer Applications (NCSA) (Butler et al. 2006). The Biophony Grid Portal was developed to demonstrate the potential of grid computing to enhance collaboration and sharing within and external to the national LTER community, based on a large acoustic dataset and algorithms developed by KBS LTER researchers to identify entities in the soundscape. The grid utilities were developed at NCSA, the access system was developed by the LTER Network Office (LNO), and the digital data were located on a grid-enabled server at MSU.

The Biophony Grid Portal was designed to allow an investigator to identify an entity in a subset of a digital sound archive from a set of available locations. The recordings on the MSU server were linked to metadata on the LNO server. An investigator could log onto the grid and access the Biophony Grid Portal via the Internet. The investigator could then select the entity sound signature from a list of recognized entities (e.g., train whistle, chipping sparrow, etc.), together with a location and a range of dates to search. Based on location and the date range, the subset of sound recordings was retrieved from the MSU server and transmitted to the NCSA High Performance Computer (HPC). Results were provided via the Biophony Grid Portal where the investigator could listen to the entity signature, examine the soundscape spectrograms, listen to the sounds, and retrieve a table of signature match probabilities based on the recordings examined.

The grid computing infrastructure contributed to LTER Network–level synthetic science. Scalability of solutions has emerged as an increasingly significant issue, and grid technologies are an important approach to addressing and solving large-scale data and analytical requirements (Butler et al. 2006).

Current Technology

The application of automated soundscape recording, and subsequent storage, analysis, and interpretation have advanced considerably over the past decade. Today, recording technologies are available commercially (e.g., http://www.wildlifeacoustics.com) and new models and acoustic sensor innovations are under way. Digital libraries to archive, analyze, and access acoustic observations have been developed (Villanueva-Rivera and Pijanowski 2012, Kasten et al. 2012, Aide et al. 2013); sound pattern recognition applications have evolved (Kasten et al. 2010, Acevedo et al. 2009, Aide et al. 2013, Ospina et al. 2013); and acoustic indices have been further developed (e.g., Sueur et al. 2008, Joo et al. 2011). The importance of the soundscape as an ecological attribute has been acknowledged (Pijanowski et al. 2011a), and a research plan has been devised to apply the principles of soundscape ecology to monitoring ecological phenomena across landscapes (Pijanowski et al.

2011b). In addition, ecology journals have dedicated issues to soundscape ecology and ecological acoustics (e.g., see *Landscape Ecology* [2011] 26; *Ecological Informatics* [2013] 21).

Summary

There is rising interest in using sound as an ecological attribute that can be monitored and analyzed to provide information about ecological phenomena. Acoustic sensors can further advance ecological science by allowing researchers to capture observations in locations and times that are not easily accessible or feasible, and at time scales that were previously impractical to accommodate. Acoustic sensors will provide new knowledge about organisms and further our understanding of human activities that cause environmental disturbance. The commercialization of programmable acoustic sensor platforms that can be deployed for months with little maintenance will revolutionize how we listen to and interpret our environment. Although there are still constraints to developing a real-time acoustic sensor network system (e.g., power consumption and wireless communication distances), progress in sensor system development will enable biologists to measure and observe complex ecological attributes at detailed spatial and temporal scales, and potentially to forecast changes in ecosystems at regional scales (NRC 2001, Porter et al. 2005, Joo 2009, Joo et al. 2011).

The AAOS has been tested in an operations framework at KBS LTER and now has been expanded to other locations. This web-enabled system has been developed (http://www.real.msu.edu) to accommodate a large number of sensor observations (Kasten et al. 2012) and includes >1,000,000 recordings in 20 soundscape projects ranging in location from Alaska to Australia. The infrastructure developed for this soundscape application will readily fit into a scalable cyber-infrastructure schema such as cloud computing for large-scale acoustic observation networks. New applications using commercially available automated acoustic sensors coupled with digital libraries, remote access systems, and pattern recognition technologies have enabled rapid advances in the large-scale observation and interpretation of soundscapes and their attributes.

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