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Biologist's Toolbox

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Advancing ecological research through automated sensing networks: a field station perspective

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Abstract

The increasing pace of global change is driving unprecedented rates of biodiversity decline, necessitating innovative approaches to monitor and understand ecosystems. In this article, we discuss the transformational potential of automated sensing technologies and examine how field stations can play a pivotal role in the implementation and support of large-scale sensing networks. Recent advances in sensor technology, wireless communication, and machine learning algorithms have made automated, large-scale biodiversity discovery and monitoring possible. However, the implementation of these developing technologies can pose unique challenges and considerations. Field stations, as research centers representing highly diverse environmental contexts, are uniquely positioned to navigate these technological complexities and act as testing grounds for the integration of automated sensing approaches to the broader field of ecological research. Here, in outlining our experiences constructing a field station-based sensing network, we describe key considerations for establishing a robust, long-lasting automated sensing system.

Keywords **field station, sensing network, automated sensing, environmental monitoring**

Ecosystems face increasing environmental stressors, driving unprecedented rates of global biodiversity decline (IPBES 2019). Monitoring these changes depends on our ability to characterize the dynamic processes that shape ecological communities over space and time (Brown 1995, Dietze et al. 2018). To capture these complex trends, large-scale, long-term, high-resolution data collection is needed (Mihoub et al. 2017, Farley et al. 2018). Traditionally, ecological monitoring has involved field-based observations, which can be costly and time-consuming, challenging in remote habitats, and require specialized expertise (Buchanan et al. 2009). Although *in situ* monitoring remains invaluable, automating ecological data collection with sensing technology networks vastly expands the spatial, temporal, and quantitative scope of biodiversity monitoring (Besson et al. 2022). When combined with field-based methods, continuous, fine-scale automated sensing can fill current data gaps to deepen our understanding of biodiversity change and ecosystem function.

Advances in automated sensing technology have conferred a data revolution in ecology. Specifically, many trends in technological development enable large-scale, automated monitoring, such as sensor miniaturization, advances in wireless communication, edge computing, complex machine learning analytics, and real-time data delivery (Nittel 2009, Gibb et al. 2019). Systems of small, durable sensors with low power requirements can be deployed across the landscape for extended periods of time without being serviced (Porter et al. 2009). Wireless long-range and mesh network communication protocols facilitate information transmission over long distances, expanding monitoring access in remote or inaccessible environments (Hart and Martinez 2006). Machine learning algorithms can be leveraged for edge computing in the field, meaning data are processed at the collection point, reducing transmission requirements and increasing network autonomy (Sheng et al. 2019). Data processing that is streamlined with artificial intelligence techniques can produce rapidly available data and, while requiring thorough quality assurance and control, reduces overall reliance on manual evaluation. Together, these technological advances facilitate automated, real-time biological monitoring across broad spatio-temporal scales.

Sensor systems have been developed to measure an ever-expanding portfolio of biological and environmental variables of interest, leading to a data-intensive shift in ecological studies and improving scientists' ability to discover patterns in complex environmental systems (Kelling et al. 2009, Michener and Jones 2012). By joining biological sensors with environmental covariates, the drivers

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of biodiversity dynamics can be examined, elucidating the effects of climate change and other biotic and abiotic factors. For example, co-located automated sound recording systems and environmental microclimate loggers have been used to track changes in anuran calling behavior in shifting thermal environments (Llusia et al. 2013), or automated tree trunk dendrometers co-located with an *in situ* meteorological station have shown differential changes in growth rate for multiple tree species as a response to heat waves (Burri et al. 2019). Together, integrated biological and environmental sensing approaches can improve ecosystem monitoring, inform data-driven conservation strategies, and strengthen scientists' ability to test ecological hypotheses.

The rapidly expanding field of sensing technology presents a myriad of opportunities and pathways to take in constructing an automated sensing network, thus requiring key decisions to be made regarding sensor hardware, software, and infrastructure. Sensor selections can be customizable to their application, leveraging a combination of molecular, image, sound, physical, and chemical signals (Wägele et al. 2022, Zeuss et al. 2024). Beyond sensor type, decisions are needed on device customization, communication infrastructure, and data storage and management. Tailoring these aspects of a sensor network to its deployment context will play an important role in the network's longevity and effectiveness. Here, we describe key network design considerations based on our experience deploying a field station-based automated sensing network.

Acting as centers for scientific research in the natural environment, field stations provide ideal arenas to develop automated sensing networks. Often located in ecologically important, unique habitats, field stations support environmental research in protected landscapes over long time horizons, playing a valuable role in monitoring ecosystem change and threats to natural systems (Wyman et al. 2009, Eppley et al. 2024). Additionally, most field stations are affiliated with academic institutions, facilitating collaboration across disciplines and acting as a hub for scientific research and innovation (Tydecks et al. 2016). With increasing calls for adaptive, long-term ecological monitoring, field stations unite protected habitats with scientists equipped to apply cutting-edge approaches to environmental research (Lindenmayer and Likens 2009, Michener et al. 2009, Lindenmayer et al. 2022). In outlining our experience deploying a field station sensing network, we emphasize the importance of investing in infrastructure that is adaptable to changing technologies, describe examples of custom vs. commercial sensing, discuss approaches to data management for broad usability, and provide recommendations for network implementation and futureproofing.

Key considerations for assembling an automated sensing network

Each ecological sensing network will be unique based on local factors and available resources. Regardless of those individual qualities, every network requires sensors, power, and a way to transmit and manage data. When it comes to sensors, there are many commercially produced options on the market, but there are also many technological components that can be customized to specific uses desired by the scientists using them. Some field stations may be capable of hardwiring devices into their electrical grid, but at other times, decisions must be made around batteries, solar arrays, or other methods for powering the network. Finally, optimizing data communication and management will have a significant effect on the autonomy of the network. Devices that record data locally, and must be regularly serviced to download data, will be less automated than those that have connectivity to the internet or other communication methods.

In our automated sensing network development and deployment, we wanted to enable automated and continuous long-term biodiversity (box 1) and environmental (box 2) data collection, prioritize utilizing existing infrastructure, and emphasized data management security, longevity, and broad utility to future users. Here, we outline our lessons and considerations in more detail (figure 1).

Tradeoffs in sensing equipment: commercial versus custom-built

When selecting sensing equipment, the choice of commercial or custom-built presents tradeoff considerations for researchers. Commercial sensing devices are available ready for deployment, often backed by customer support systems and field-tested. Commercially produced devices are less likely to require specialized knowledge, typically designed with user-friendliness in mind. However, commercial devices may be cost prohibitive or lack adaptability to specific deployment contexts. Working with commercial products can also require reliance on proprietary data communication and processing systems, which will affect transparency and reproducibility. For example, in our field station sensing network (see box 1), we deployed a commercially made trail camera system, which greatly simplified deployment with pre-configured communications and image pipelines, but also required use of their proprietary management software, which can have negative effects on functional longevity and utility (Bradley and Barrera 2023). As an alternative, custom-building sensing equipment can drive down costs and is customizable and open to the needs of the network being constructed (Chan et al. 2021). One comparison between custom and commercially available microclimate monitoring systems found cost savings scaled with system breadth, with the custom system saving only 13% of the cost of the commercial system with a single sensor, but due to its modular design saving 80% of the cost when creating integrated arrays of eight sensors (Cannon et al. 2022).

There is a strong and growing community of custom, open-source sensor developers. Devices are designed to be low-cost, with hardware specifications and programming software openly shared for others to use or modify. Through the release of tutorials, help forums, and continuous software and hardware development, the approach of open-source platforms like Arduino and Raspberry Pi has decreased the learning curve and created an interactive community of beginners and experts (Fisher and Gould 2012, Ferdoush and Li 2014, Chan et al. 2021). The low-cost nature of these customizable platforms enables large-scale deployment, improving the spatial and temporal coverage of a sensing network (Horsburgh et al. 2019). As a tradeoff for their scalability, custom sensor systems have higher demand for in-house maintenance, troubleshooting, and node replacement, with a susceptibility to lower accuracy or drift, requiring frequent calibration (Mao et al. 2019). Therefore, time for system troubleshooting and development, as well as technical knowledge held by the research team, will serve as constraints for custom sensor system development.

Beyond its initial construction, consideration is needed for long-term sensor network maintenance, accounting for on-site personnel capacity and technological expertise. Maintaining a complex, custom designed sensing system will require personnel time and technical knowledge. If there is capacity for such maintenance on site, custom

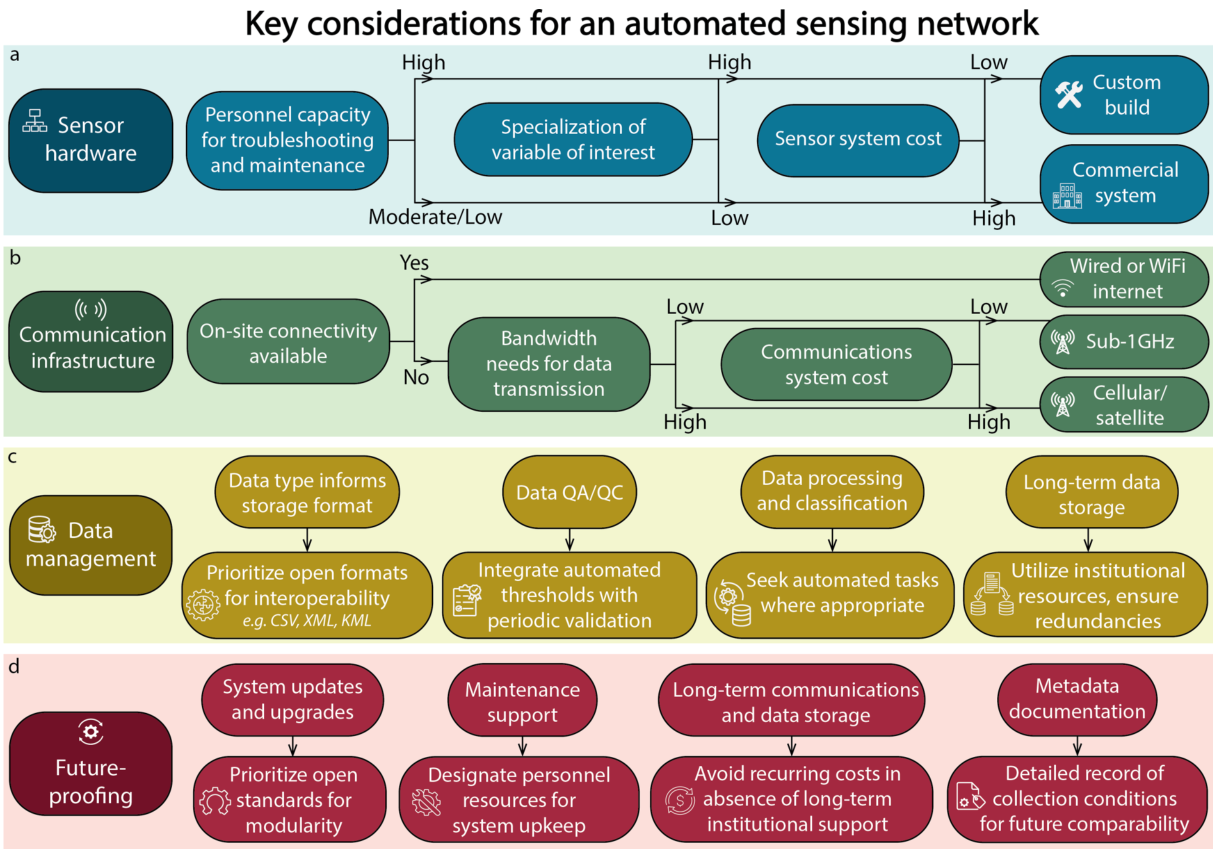

Figure 1. Key decision points for assembling an automated sensing network related to (a) custom constructing versus commercially purchasing sensor hardware, (b) selecting a communication infrastructure, (c) data management from collection to long-term endpoint, (d) future-proofing a network for long-term utility.

sensor networks should be accompanied with detailed construction and servicing documentation so that field station or research personnel can properly service network components. Where capacity for maintaining complex sensor systems is limited, a modular sensor network made up of commercially available and replaceable parts will increase its longevity, especially as commercial products are typically accompanied by detailed manuals and customer support teams (Bachér et al. 2020, Bradly and Barrera 2023). Ultimately, the decision between commercial and custom equipment will depend on the unique needs of the network—hinging on cost, personnel, and desired level of customization. For cost and personnel in particular, a custom system will have lower upfront costs with higher long-term maintenance demand, whereas a commercial system often features higher upfront costs, but typically requires less technical maintenance long term.

Sensor types and their applications

Ecological sensors can be categorized into three major modalities: physical (e.g., air temperature), chemical (e.g., atmospheric carbon dioxide), and biological (e.g., camera trap) (Rundel et al. 2009). Physical sensors assess properties of the environment that can be directly measured, such as temperature, humidity, particulate matter density, wind speed, UV light levels, and so on. Chemical sensors detect compounds, ions, or gases by converting chemical interactions into signals, such as electrochemical sensors that measure CO_2 gas through a chemical reaction on the electrode surface. These physical and chemical sensing approaches contribute environmental context and habitat quality information to ecological assessments and research, making them broadly useful to field station users across subject areas. On-the-ground environmental sensors can also provide ground-truth and fine-scale data to complement remotely sensed or coarser resolution datasets (e.g., WorldClim global climate database, Fick and Hijmans 2017). Deploying a network of abiotic sensors facilitates the collection of high-resolution environmental data, and automation capabilities increase the sustainability and potential longevity of such efforts.

Many abiotic aspects of the environment are relevant to ecological sensing and interpretation. Atmospheric and weather sensing provides high-resolution data on local climatic conditions and their temporal dynamics (e.g., Rahut et al. 2018). Water quality and condition metrics like dissolved oxygen and stream flow velocity inform what aquatic life can be supported and whether aquatic ecosystems are changing over time (e.g., Islam et al. 2023, Sindhu 2025). Metrics on soil and subsurface characteristics provide information on belowground nutrient and hydrological processes (e.g., Blume et al. 2009). Quantification of chemical and pollutant levels, such as atmospheric CO_2 and artificial light at night, resolves local environmental stressors and when paired with biodiversity data, their dynamics over time can be used to infer how local abiotic conditions are affecting ecological communities (e.g., Fröhlich et al. 2025).

Box 1. A field station sensing network deployment—biodiversity sensing.

To support new and ongoing research in the Texas Field Station Network, we deployed an automated sensing network at the Lady Bird Johnson Wildflower Center comprised of multiple biodiversity sensing systems, including camera traps and two acoustic recording approaches (figure 2, table 1). Sensors were physically distributed among long-term controlled burn and mowing treatments maintained at the station.

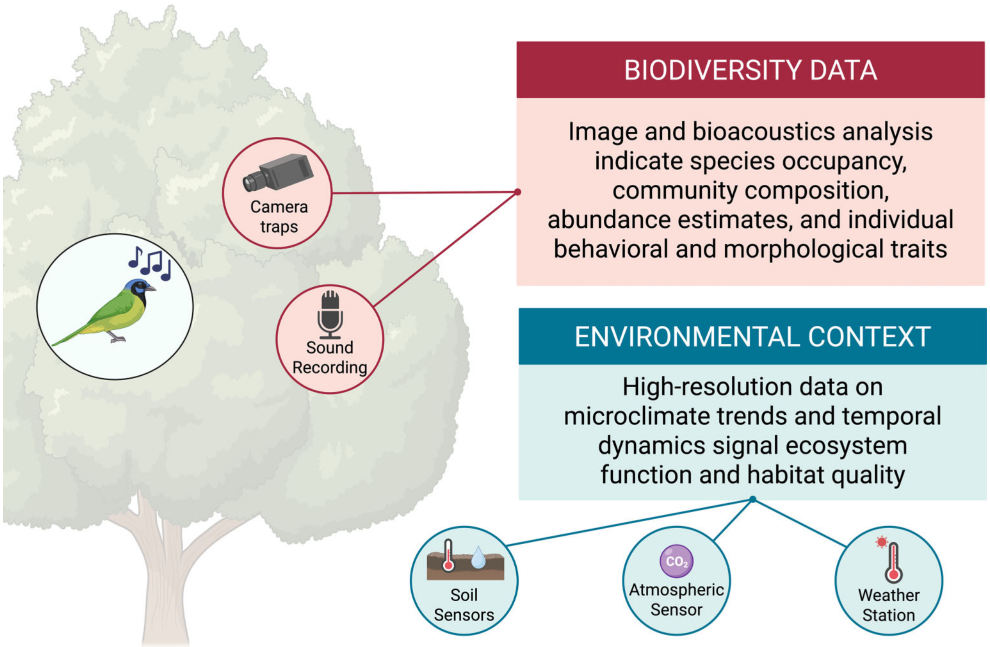

Figure 2. An overview of the automated sensing network components collecting biodiversity (camera traps, sound recording) and environmental (soil sensors, atmospheric sensor, weather station) data, with the environmental insights they provide.

Camera traps

To collect image data on local fauna, we deployed a meshed network of 17 commercially made trail cameras with passive infrared detection triggers (BuckEye Cam X80 Wireless System). Although we had initially explored custom-made image collection options, we found that designing effective triggers is challenging, that commercial options are generally more robust, and in our case, worth their cost for useability (table S1). All cameras in the system are powered with solar kits from the same company, simplifying installation and integration (Buckeye Cam 12 V, 11.25 W Solar Panel Kit).

For data management, the use of a commercially designed product with its own proprietary communication and meshing system greatly streamlined deployment. Once installed, cameras were already set up to collect images and transmit them to a wireless base receiver on-site using a 902–928 MHz frequency band (up to 3 km line of sight range). A key aspect of this mesh network is that each camera is equipped to act as a connectivity repeater, allowing some devices to be placed farther away from the base, thus extending the range of the wireless camera network. Additionally, cameras can be programed with alternative routing options if a receiver goes offline, increasing network robustness.

Once data are transmitted to the base receiver, the system has its own proprietary network management software, serving as the initial point of image reception, storage, and sorting. Although depending on proprietary software is not ideal, we felt the tradeoff for a ready-to-deploy system with simple communication and processing was worthwhile. Once obtained, images and all relevant camera metadata are uploaded to university Box cloud storage, making them remotely accessible for downstream analyses.

Acoustic recorders

To collect soundscape data, we employ two types of acoustic recording devices. On the commercial end, we deployed eight acoustic loggers (AudioMoth 1.2.0). These recorders are useable off-the-shelf, can be configured with the AudioMoth app, and run on AA batteries. The advantage of these recorders is their simplified, easy-to-use design, which requires little training or electronics knowledge. At the relatively low cost of ∼$100 per device, many recorders can be deployed over large spatial areas. However, their simplified design lacks a remote communication component, meaning that manual retrieval is required to collect sound files stored locally on an SD card. The rate at which the SD card becomes full depends on sampling frequency and can be adjusted to decrease the number of field visits required.

On the more complex, customized end, we also deployed an in-house constructed acoustic recording device (see Contina et al. 2024, which discusses an earlier iteration). These solar-powered recorders are run with small, Raspberry pi computers, which are capable of edge computing, status communication, and data transmission through cellular connectivity. Although this device requires some electrical and coding knowledge to deploy, the built-in communications capability allows the device to run remotely without regular in-field visits to collect data, increasing autonomy. To record sound, an external microphone array is attached to the central computer, allowing data collection to be controlled and transmitted in real-time.

Table 1. The build source, communication mode, and data management strategy employed for each sensing system deployed at field station test sites.

Sensor system	Build source	Communication infrastructure	Data management
Camera traps	Commercial, Buckeye Cameras	Proprietary 900 MHz mesh network (a Sub-1 GHz protocol)	Uploaded to university Box cloud storage
Sound Recording	Commercial, Audiomoth	Manual SD card retrieval	Uploaded to university Box cloud storage
	Custom	Cellular modem	SQLite database
Soil Sensors	Hybrid, Vegetronix	Cellular modem	SQLite database
Atmospheric Sensor	Custom	Low Power Wide Area Network -LoRaWAN (a Sub 1-GHz protocol)	Automatic database upload to SharedAirDFW[a]
Weather Station	Commercial, Ambient Weather	Sub-1 GHz protocol and Wi-Fi	Automatic database upload to Ambient Weather Network[b]

[a]www.sharedairdfw.com/
[b]https://ambientweather.net/

On these custom-constructed devices, sound segments are labeled with an automated classifier and stored in onboard storage for later automated transmission or manual retrieval. Labeled metadata are stored locally in an SQLite database to ensure consistency and efficient queries, which are used for onboard data management, for example, deleting redundant sound recordings when onboard storage is near capacity. These species identifications and associated metadata are transmitted to a server, where they are stored in a PostgreSQL database for visualization and analysis. By automating the path from sound recording to sound identification, bioacoustics data recorded by the custom device can be viewed in real-time, addressing some of the processing bottlenecks that can arise from large-scale bioacoustics recording schemes. For both acoustic recording approaches, once raw sound files are collected, they are uploaded to a university Box cloud storage folder, making them remotely accessible. Overall, we found the best acoustic recording set-up will depend on the application, with the simpler commercial acoustic loggers providing an affordable and easy to deploy option for broad spatial coverage, and the custom device providing a robust system equipped for long-term, automated sensing where there is technological support within the field station team.

Biological sensors use identifiable elements (e.g., image, sound, etc.) to detect specific biological components or organisms, such as acoustic recognition of a unique bird species call. These sensors can be used to describe the biological processes and communities occupying a site of interest. For example, bioacoustics monitoring provides data on species presence, community composition, and behavioral patterns of activity (e.g., Pillay et al. 2019, Wituszynski et al. 2024). The collection and analysis of images with methods like camera traps can capture phenological changes, provide estimates of organismal abundances, reveal behavioral and morphological traits, and provide insight into individual organismal health (e.g., Peltoniemi et al. 2018, Ruczyński et al. 2020, Sittinger et al. 2024, Barroso and Palencia 2025).

In deciding what type of sensor to use for collection of biological data, target organism and deployment strategy will be key considerations. Bioacoustics approaches, for example, work best for groups with well-curated acoustic datasets, primarily birds, marine mammals, bats, amphibians, insects, and primates (Oswald et al. 2022). Image or video analysis can be used for a plethora of organismal identification and species interaction applications, though resolution and target organism will affect sensor selection. Motion-activated

Box 2. A field station sensing network deployment—environmental sensing.

Our automated sensing network deployment used multiple environmental sensing approaches, including soil temperature and moisture sensors, atmospheric air quality monitors, and weather stations (figure 2, table 1).

Soil sensors

To assess variability in the soil environment, we deployed commercial soil temperature and moisture sensors (temperature: Vegetronix THERM200, moisture: Vegetronix VH400). These sensors are purchased ready to use but without their own power or control system. We opted to connect the sensors to the Raspberry pi-based, custom acoustics recording system, making them a hybrid between commercial and custom construction. By connecting them to the Raspberry pi-based system, soil data collection can be controlled remotely and transmitted in real-time with the same infrastructure as the bioacoustics recorder, simplifying data management and collection.

Atmospheric air quality monitor

The air quality monitor deployed in our sensing network is part of a larger collaborative effort called Shared Air DFW, which consolidates pollution data collected from their network of custom-constructed Multi-scale INTegrated Sensors (MINTS), which are equipped to measure particulate matter and carbon dioxide levels (Wijeratne 2021). These sensors use LoRaWAN, a sub-1 GHz radio frequency communication technology, allowing for wireless data transmission to a central endpoint.

The team that created this network has constructed their own data pipeline, which displays real-time pollution data on an online dashboard (www.sharedairdfw.com/) and stores data long-term with the Open Storage Network (OSN), an NSF funded distributed data sharing and transfer service that hosts data in the Amazon S3 “simple storage service” bucket format. Historical project data is accessible by connecting to OSN portal web tools or with third-party software tools that can interact with S3 buckets, such as Cyberduck, Rclone, or programming environments, including Python, Julia, and R. The advantages of this approach are that the external team managing this larger network hosts and curates the air quality data, and by contributing to this large-scale project, our data are interoperable with data collected across the network. The caveats of using the MINTS system are that hardware maintenance is difficult for a custom device not built in-house, and we have less data autonomy as routing data through the pipeline created by an external research group leaves our data integrity dependent on external group stewardship. Overall, we found that joining a larger data collection network was very worthwhile, and the existing infrastructure, interoperable data, and data storage support from the network are strong assets.

Weather station

To monitor local climate, we deployed a commercial weather station from Ambient Weather Network (Ambient Weather WS-5000), equipped with sensors that measure temperature, humidity, pressure, precipitation, wind, dew point, heat index, solar radiation, and sunrise and sunset. Data collected by the weather station transmits to an on-site, internet-connected central console using sub-1 GHz radio frequency, a connection that can be extended up to 1000 ft. if unobstructed. When received, the central console automatically uploads data to the Ambient Weather Network, which is visible in real-time through their online dashboard (https://ambientweather.net/). The automated transmission of data to a central hub and online dashboard greatly increases the autonomy and simplicity of using weather station data. A caveat of this approach would be applications in which users wish to place the weather station outside of the ≤1000 ft. range of the central console, which must be connected to the internet. In this case, antennas can be added to increase radio frequency transmission range, or longer-range communication methods such as LoRaWAN can be explored to maintain the autonomy of weather station data collection. Akin to our experience with the air quality monitor, we found that the cyberinfrastructure and external data management of joining a larger data collection network were strong assets. In this case, the commercial weather station and communication structure greatly simplified deployment and have remained robust.

game cameras placed at high-traffic pathways in a habitat work well for larger-bodied animals. Contrastingly, small animals may require camera placement at more confined sites, such as a narrow tunnel, and depending on proximity, may be better captured by continuous or regular interval recording schema if they are unlikely to trigger motion-activated camera sensors on their own (Wägele et al. 2022). The breadth of biological sensing approaches needed in a network will depend on the diversity of size, life history, and activity patterns exhibited by the target organisms of interest.

Taken together, each environmental and biological sensing approach can collect valuable information for ecological insight, and deciding what variables will be of most interest to field station users and personnel should be considered at the design stage when assembling an ecological sensing network. Engaging with field station stakeholders will help ensure target data streams are of maximum utility to field station users.

Communication infrastructure for long-term automated data collection

Communication infrastructure is a key determinate for the autonomy of a sensing network. In their simplest form, sensors can be deployed in a stand-alone configuration, with data recorded locally and periodically retrieved. Such a configuration requires on the ground personnel and produces lag time between data acquisition and analysis. If personnel are available and real-time data is not a priority, communication considerations will be simplified. However, field personnel can be a limited resource, and lags between data collection and processing can lead to bottlenecks. Incorporating infrastructure that transmits data and sensor health information can address these limitations, highlighting the essential role of communications in the automated sensing model. The ever-evolving considerations for optimized communications configurations depend on resource availability and site characteristics.

There are two communication modes to consider when establishing an automated sensing network. The first is the transmission of data from the sensing system to a central location. In a less remote deployment, sensing sites may have one or more internet connection options, whether wired or wireless, allowing for local communication between the sensor and the endpoint. Although potentially more resource intensive, the increasing availability of cellular and satellite internet has expanded connectivity opportunities for remote sites as well.

The available power, bandwidth, and transmission costs are important resource considerations in the design of the network as they will dictate whether data must be processed locally through edge computing or can be sent as raw streams for processing elsewhere. Sampling frequency, data classification, and communication rates will all depend on the energy budget of the system, requiring fine-tuning with power availability on site (Mainwaring et al. 2002). Often, a hybrid model may be appropriate in which data are classified and summarized locally, and raw data streams are fully or selectively stored in media on-site. The regularly transmitted summaries would require limited power and bandwidth while providing near-real-time information, as compared to the high power and bandwidth requirements for transmitting large volumes of audio or video data, for example. A major advantage of edge computing is the ability to manage data in the field. In scenarios where local storage may be exceeded before retrieval, research teams may employ a selective deletion policy for raw data that has been processed, which could, for example, be random or stratified-random sampling. In our bioacoustics sensor deployment (box 1), we employ a selective data thinning approach for audio files, which iteratively deletes processed audio files evenly across labeled groups within each recording day, maintaining representative sound recordings of each classification label to use for future ground truthing.

Supporting some form of remote communication with the sensing network facilitates network autonomy. Even if data streams will not be transmitted, having the ability to discern sensor health and recording status remotely is useful for system development, debugging, and maintenance purposes (Yang et al. 2010). Remote system status monitoring is especially helpful in distant or difficult to access deployments, where regular maintenance checks may be unfeasible. Early detection of system disruption allows for responsive maintenance, decreasing potential data collection loss during system down-time (Yang et al. 2010).

The second mode of communication to consider is inter-sensor, or “node-to-node,” communication. Establishment of a mesh network among sensors enhances data transmission, increases resilience to node failures, and allows for time synchronization (Nurlan et al. 2021). Sensor nodes might be heterogeneous or have specialized roles allowing for adaptable configurations as various nodes are added or removed. Depending on locally available resources, researchers may wish to use ordinary and widely supported Wi-Fi in the 2.4/5 GHz range or adopt Internet of Things (IoT) technologies, which have lower power requirements to connect sensor nodes. IoT systems are compatible with wireless connectivity protocols in the sub-1 GHz radio frequency range, which have greater coverage and better transmission through obstacles, though they are comparatively limited in data transfer rate as compared to traditional Wi-Fi. Examples that can operate in this mode include LoRaWAN, Zigbee, and DigiMesh (Yang et al. 2021, Malik et al. 2023). Generally, traditional Wi-Fi is robust and has greater data transfer rates, making it a preferable fit in scenarios where Wi-Fi connectivity is available, or if cost is less limited, where many Wi-Fi devices can be installed to achieve appropriate coverage. Sub-1 GHz technologies are good solutions where cost is limited or greater transmission range with low power and bandwidth requirements is desirable (Nguyen et al. 2025).

As with all information technology, security is an important consideration. Researchers should reference industry best-practices and employ them in establishing their sensing network. Commodity IoT devices, for example, are notoriously insecure, so any IoT device involved must be carefully configured. If breached, intruders could use the network to gain further access to sensitive networks downstream, as part of a distributed attack on external resources, or manipulate sensor data, impacting data collection and research efforts. Although a full consideration of network security is beyond this discussion (e.g., Yaacoub et al. 2022), best practices would be for researchers to engage with their IT staff when implementing internet-connected devices, especially for field stations, which are typically subject to institutional rules and regulations for cybersecurity. Most guides emphasize security in-depth, where each layer is secured, and an intruder must defeat multiple mechanisms. General advice is to always use encrypted communications, disable all unneeded network services, and require strong passwords.

Some sensor devices run a full operating system, typically a Linux-based distribution (Bansal and Kumar 2020). In these cases, secure shell (ssh) is a popular and recommended method to communicate across devices as it uses symmetric key encryption and can forward additional protocols through encrypted channels. However, automating regular communications with ssh presents some challenges, as it is important not to leave unencrypted private keys on remote devices where they might be retrieved by an intruder. Open-source Virtual Private Network (VPN) software and communication protocols, such as WireGuard or OpenVPN, provide a solution by allowing devices to join an encrypted virtual network. In addition to encryption, implementing default-reject firewall rules that only allow connections from trusted hosts to specified ports is advisable. We have implemented many of these practices in SensOS, an open-source sensor orchestration platform (https://github.com/Rosalia-Labs/SensOS).

In all, coordinated establishment and management of communication infrastructure centralizes efforts to maintain reliable connectivity and strong cybersecurity. Redundant or conflicting communication modalities across individual projects can be avoided (e.g., protocol mismatches, signal crosstalk, bandwidth limitations). Maintaining remote communication with and between sensor nodes increases network resiliency and protects data collection (Sumanth et al. 2024). An agreed-upon set of structured communication infrastructure guidelines should be shared with all field station users, addressing network access protocols, cybersecurity settings for individual sensor devices, and data protection and encryption policies, to maintain communications consistency and security.

Data management for broad and continued use

Automated sensing networks can produce massive collections of data. Given the volume of data created, streamlining data processing in ways that reduce dependence on personnel completing individual tasks increases autonomy. Once data are collected, they need to be assured through quality-controlled measures, described by document-ing relevant metadata, and preserved in a repository where they can be accessed later for analysis (Michener and Jones 2012). Downstream, multi-sensor data fusion approaches are needed to unite heterogeneous data from multiple incoming data streams into a comprehensive view of the system (Nandhini 2023, Priyanka et al. 2024). Therefore, careful cyberinfrastructure development is needed for each step of data processing, including determining how raw data are accessed, how and when data are processed, the type and structure of the database that data will be stored in and, importantly, how each of these processes may be automated (Yang et al. 2010).

The volume of data produced by sensing networks faces potential bottlenecks when manually extracting useful information is time-consuming, such as data from camera traps and acoustic recorders (Keitt and Abelson 2021). However, advances in artificial intelligence methods have enabled automation of many data processing steps, accelerating the collection of usable information. Deep learning models, which are a type of artificial intelligence, can be trained for semi- or fully automated identification tasks. For example, the sound classifier BirdNet identifies species from audio recordings by recognizing their unique calls, acting as a fully automated classifier from sound input to species identification (Kahl et al. 2021). By comparison, an image classifier like MegaDetector filters camera trap images to separate animal detections from images of vehicles and people, making the workflow semi-automated, as further downstream processing will be needed to identify the animals in images sorted by the classifier (Beery et al. 2019). In all cases, data processing through automated workflows will require quality control and validation. Determining the appropriate allocation of human effort to reviewing and validating AI predictions, including how many and which detections to manually review, community-wide quality assurance and control standards, or how to combine validated and unvalidated data in integrated models, all remain an active areas of research (Campbell et al. 2013, Knight et al. 2020, Rhinehart et al. 2022, Azmi et al. 2025) and review (Stowell 2022, Game et al. 2025, Kitzes et al. 2026).

As data management and classification algorithms are developed, they are also becoming more user-friendly, with simple graphical user interfaces and large online help repositories, making them accessible for use by scientists without programming or computer science backgrounds. Establishing machine-assisted pipelines for data collection and processing has the advantage of being reusable for many researchers once established, making such protocols useful in cases of long-term data collection and carrying projects beyond individual assistantship and funding cycles. In addition to their applicability to current and future research, AI-informed data pipelines can be used retroactively on previously unprocessed data, whether in digital or written form, as a step toward addressing the volumes of dark data that can accrue at research stations over time.

Although not the target of ecological sensing networks, humans can be detected by biological sensors, and a plan for ethical handling of these instances is essential, especially at field stations where multiple research and student groups can occupy overlapping spaces. Many approaches have been developed to address potential privacy concerns arising from automated recording of image and sound data (Young et al. 2022). For sound, recordings screened by autonomous classifiers can detect and zero-out sound files determined to contain human vocalizations (Cretois et al. 2022). By deleting the sound files but noting the detection of human vocalization, inferences can still be drawn on potential human disturbance at a site with no retention of sound files and no need for researchers to process the files manually. For image data, classification algorithms have been developed to automatically detect images containing humans and blur sections of images where humans are present (Beery et al. 2019, Fennell et al. 2022). Importantly, these classification approaches can be built into data processing pipelines to automate the removal or anonymization of human records before data are viewed manually by any human researchers.

With calls for increased data sharing and information flow, especially at field stations that sit at the axis of academic research, education, and public outreach, it is important to plan for how information will be disseminated (Whitlock 2011, Hampton et al. 2013, Tydecks et al. 2016). Decisions related to the form, location, and curation of data can affect its accessibility to broad user groups. To address these challenges, frameworks like the FAIR data principles outline how to improve data utility, emphasizing findability, accessibility, interoperability, and reusability (Wilkinson et al. 2016). Generally, the appropriate form for data storage will depend on the data being stored (e.g., images, audio, numerical measurements), but across types, storing data in open formats is key for maximizing accessibility and long-term utility. Open formats are those that do not require proprietary software, hardware, or purchasing commercial licenses to access data. Proprietary formats can be changed, deprecated over time, or cost limiting, making their long-term use less stable. Open data formats include comma-separated values (CSV) for tabular data, portable network graphics (PNG) for images, extensible markup language (XML) for documents, keyhole markup language (KML) for spatial data, and so on. Specific to the field of ecology, Ecological Metadata Language (EML) defines a comprehensive vocabulary, readable XML markup syntax, and modules for methodology description, all to uniformly document ecological research data, thus facilitating data sharing among ecologists and environmental scientists (Jones et al. 2019). No matter the format, the end goal for data curation should be clear documentation and linkage between data and metadata, especially in long term, collaborative field station research contexts, where data may be accessed for future use and reuse by researchers not involved in the original collection.

Beyond its form, data storage location will affect accessibility. With connections to academic infrastructure, field station networks can leverage institutional computing and storage resources. When available, using an institutional storage solution provides the benefit of enhanced security and cost savings as compared to non-institutional for-cost models. There are also associational resources, such as the Organization of Biological Field Stations Data Registry, which houses searchable datasets that comply with the EML documentation standard (Brunt and Michener 2009). Organized data repositories often offer the added benefit of data access and publishing embargo management, key considerations in data sharing. Alternatively, low-cost, cloud-based solutions can be used for long-term storage, with third-party providers managing data backup and security, though with the tradeoff of necessitating long-term payment plans. These methods allow stored data to be accessed remotely, increasing availability.

No matter the method, every storage medium can fail, risking data loss. To protect from loss, it is ideal to keep more than one on-site copy (e.g., on a computer, external hard drive) as well as an off-site copy (e.g., mirrored server, cloud storage) of data, which are backed up regularly. These redundancies also ensure data are protected against data loss related to theft or natural disasters (NRC 2014). Creating robust, accessible data archives increases their utility to science, allowing for result verification, data re-use in meta-analysis or addressing new questions, and as a tool for educational applications.

Future-proofing a sensing network

As sensing technologies are developed and improved at a rapid pace, the key considerations for assembling a harmonious, automated sensing network remain consistent. Supporting infrastructure should streamline connections between sensing nodes and central data collection, be resilient to the environmental context it is deployed in and prioritize longevity of the network. Resilient technological networks are characterized by modularity, repairability, and attentive feedback mechanisms (Anderson 2025). System upgrades will be necessary and adhering to open standards when assembling infrastructure will allow for flexibility when combining hardware and software components. Open standards, including sensor interfaces, communication protocols, and data formats, are intended to bypass reliance on a single vendor and ensure interoperability of information and communication technologies over time (Krechmer 2006).

Not to be underrated, essential aspects of network longevity are maintenance and funding. Sensor hardware will require regular upkeep, which calls for trained personnel and detailed system documentation to support cases of personnel turnover. Maintaining cyberinfrastructure systems requires IT oversight and, depending on the data storage and communication needs of the network, funds for long-term connectivity and data maintenance. Data storage costs can be particularly tricky as they inherently outlast funding cycles and typically scale with digital accessibility. Communication costs can also affect data availability, as opting for more expensive options like satellite or cellular connectivity can simplify and speed up data streams. Funding agreements at the institutional level are therefore fundamental to research data collection quality and academic integrity across a sensing network.

Beyond its storage, utilizing standardized interfaces and open-source software simplifies data access, allowing researchers to find, share, and query interoperable data sets (Nittel 2009). Efforts to standardize sensor platforms in particular have produced open standards frameworks for sensing web enablement, emphasizing the importance of machine readability and making data discoverable long term (Botts et al. 2008). A key tenet of these standardized approaches is pairing datasets with detailed sensor information, including the sensor's capabilities, location, and interface, ensuring comprehensive metadata is available for data retrieval and interpretation by future users (van Klink 2024). For optimal utility long-term, it is best to form a data structure plan at the onset of sensing network design, with periodic review and updating as best practices change over time.

Conclusions

Automated sensor networks enable the collection of large amounts of biodiversity and environmental data over space and time, with advances related to sensing devices, wireless communication, and information processing simplifying sensor network development. However, initial equipment selection and network construction require key decisions related to sensor type and customization, communication infrastructure, and data management and design for long-term use. In outlining the key considerations for deploying a field station-based automated sensing network, we conclude that sensor selection primarily hinges on funding and personnel technological expertise, with custom-built devices being scalable and low-cost, but dependent upon regular technical upkeep, whereas commercially purchased devices are higher cost, but more robust and field-ready. Communication solutions will be dependent on resource availability at sensor sites, and investment in communication infrastructure that allows remote network access where possible will increase sensor system autonomy, reducing the need for on-site manual intervention. Finally, we recommend careful planning for data management, processing, and structural standards to avoid dark data bottlenecks and maximize long-term data utility for field station users.

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Data Availability

There are no new data associated with this article.

Author contributions

Nicole Wonderlin (Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing), Timothy Keitt (Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Writing – review & editing)

Supplemental material

Supplemental data are available at *BIOSCI* online.

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