"The Devil You Know": Barriers and Opportunities for Co-Designing Microclimate Sensors, A Case Study of Manoomi

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Current environmental challenges have profound local consequences and often benefit from the collection of fine-grained microclimate data. Advances in wireless sensor networks and the Internet of Things have led to technologies nominally suited to support remote sensing; however, in practice long-running deployments of in-field environmental sensors are rare. Field conditions are often remote and culturally sensitive, with limited power, Internet, transportation, and human infrastructure; advances in device technology alone will not suffice. We ask how communities, Internet of Things researchers, government, and other interested parties can work together to co-design useful, low burden, sustainability-focused infrastructure. Toward this end, we conducted 11 semi-structured interviews with 13 experts who use or rely on environmental sensing technology. To complement our interview data, we engaged in three months of participant observation while immersed in organizations specifically working toward manoomin (wild rice) conservation. We make two primary contributions. First, we confirm and enrich a five-stage model, the microclimate sensor lifecycle, focusing on desired features and persistent challenges. Second, we outline a space for co-design of microclimate sensors with emphasis on the cost of experience, the generally unaddressed issue of technical usability in the messy field, and the opportunity for community engagement to improve technical design and outcomes. Furthermore, we discuss future design opportunities, recommendations, and challenges in the microclimate sensor design, deployment, and sustainability space.

CCS Concepts: • **Human-centered computing** → *Ubiquitous and mobile computing systems and tools*; **Empirical studies in ubiquitous and mobile computing**; • **Applied computing** → *Environmental sciences;*

Additional Key Words and Phrases: Environmental Sensors, Co-design, Community Engagement

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1 Introduction

The confluence of global environmental disasters, including climate change, biodiversity loss, and the spread of invasive species, has profound local consequences that require the collection of microclimate data. Emerging data analysis tools can help to extract more from existing datasets to a degree, but to truly tackle environmental challenges, we need to better support the scientists and technicians who are deploying sensing systems in the field to generate new dataset. Although field research locations and challenges vary, many often lack access to sufficient electricity, the Internet, transportation, and human infrastructure.

The high burden of retrieving data from these remote sensors can be partially alleviated through **Wireless Sensor Networks (WSNs)** and **Internet of Things (IoT)** devices that deploy custom embedded systems to automatically upload data to the Internet. WSNs, which have been around since the 1990s, and IoT devices, which became popular in the 2000s, have been created for a wide variety of environmental monitoring applications, such as volcanic activity [3], wildfires [29, 41], air quality [28], and agriculture [36]. These papers tend to focus on the technical design for a short-term deployment by operators who are computer science and engineering researchers rather than studying extended deployments by users with less technical literacy.

While these proof-of-concept designs are important in furthering the field, minimal literature exists that explores the long-term feasibility of such systems. Furthermore, past WSN and IoT research tends to engage with a specific community only once it is time to test a prototype, if at all. Community-driven co-design presents a valuable opportunity to ensure that sensing systems are both feasible and useful over the long term rather than serving as mere proofs-of-concept.

This research project is grounded in our work designing a sensing system specifically to aid in the conservation of manoomin, the Ojibwe word for a species of wild rice (Northern Wild Rice; *Zizania palustris*) indigenous to the Great Lakes region of North America. It has served as a pillar of both Ojibwe culture and subsistence for generations. Manoomin has faced compounding pressure in recent decades from increased temperature and precipitation variation, competition from non-native species, and land use change from mining and residential development. As part of the National Science Foundation Coastlines and People and Strengthening Resilience of Ojibwe Nations across Generations grants, we work in a multidisciplinary team of Indigenous knowledgeholders, academic researchers, and resource management institutions to co-develop environmental sensors for manoomin conservation. Being engineer-focused, our initial aim was to design and develop a modular hardware system that would generalize the sensing needs for manoonin and broader communities focused on microclimate research. However, to justify future engineering effort and ensure that this development is also relevant, translatable, and collaborative with the broader field-science community, we chose to conduct interviews with people who deploy environmental sensors, use the associated data, or coordinate between shareholders in this space for a variety of purposes in a variety of settings. These interviews and subsequent analysis are the basis of this article.

Our desire to understand and improve the development and adoption of embedded systems for microclimate monitoring resulted in the following research questions, which drove our interview questions and three months of participant observation:

(1) How are scientists interacting with technology in the field and what aspects of that technology do they like or wish they could change? These answers inform our efforts to illuminate the technical roles and requirements of microclimate sensing.

(2) How are scientists using the data from microclimate sensors, and how does the technology of these sensors limit or aid in data analysis and result generation? The benefits and limitations of current implementations can serve as a basis for our design processes, allowing us to make informed design decisions with communities concerned with the conservation of manoonmin.
(3) Under what conditions are computer science research projects translating into useful tools for scientists? To ensure technology adoption in field work settings, what constraints, assets, and workflows should computer science researchers know about? These ground our findings in the successes and failures of previous research-based projects.

Our analysis of these interviews and observations resulted in two primary contributions:

(1) An enriched analysis of valuable features and persistent challenges within the five stages of the microclimate sensor lifecycle. This is the focus of Section 4. We recognize that identification of the lifecycle itself builds on prior work and is primarily novel from the perspective of technical development.
(2) The complexities, challenges, opportunities, and recommendations for co-designed microclimate sensors grounded in three themes: *the cost of experience*, *technical requirements and tradeoffs*, and *community engagement*. This is the focus of Sections 5 and 6.

These findings led to a pivot in our approach to designing a manoomin sensor from a general-purpose device to one that is specifically tailored to the challenges and assets within the manoomin landscape and community. The custom manoomin monitoring sensors that we plan to design and deploy are beyond the scope of this work, though the relationships built and insights gained through this work have already contributed to the deployment of commercial sensors with project partners.

This article is organized as follows: The remainder of Section 1: The Introduction gives background on the naming of the article, the intended audience, and the authors' positionality statement. Section 2: Related Work engages with similar and intersecting research, and Section 3: Methods, describes our interview study, participant observation, and analysis process. In Section 4: The Microclimate Sensor Lifecycle, we build on prior understanding of the stages of microclimate research, contextualizing our interview participants' experiences and providing insight related to each part of the process. Section 5: Interview and Observation Themes draws on Section 4 to explore themes that span many stages of microclimate science and motivate the design space for microclimate technology. Section 6: Discussion provides opportunities, recommendations, and challenges that emerge from this design space, and Section 7: Conclusion and Next Steps talks about where to go from here.

1.1 “The Devil You Know”

The title of this article, “The Devil You Know,” is a quote from an interview participant that epitomizes many of the barriers to adopting new technology in conservation and environmental monitoring spaces. Its origin is an idiom that means “it is better to deal with a difficult person or situation that one knows than with a new person or situation that could be worse” [34]. As our findings will illustrate, researchers, land managers, and other people working in this space typically would rather stick with an existing solution, even if its performance is poor, than risk the transition to a promising but untested device. Field work is already complicated enough, so unexpected or unreliable behavior during a deployment can nullify a season of work and the associated funding. This follows a larger trend we witnessed throughout participant observation, where current field methods are driven by consistency with past methods, sometimes resulting in arbitrary or counterintuitive processes for the sake of year-to-year consistency. Unless a new device offers significant advantages in price or functionality and is tested by a trusted user group, conservationists will almost always stick with "the devil they know" instead of taking a risk with "the devil they do not know." We discuss the implications of this observation in Section 5.

1.2 Audience and Author Positionality

We intend that this article will be most relevant to researchers and developers of embedded systems seeking projects with value beyond a proof-of-concept or academic publication, which is directly related to our personal goals of this work. Additionally, we intend this work to be informative to the broader community of field scientists by providing insight into the roles technology can play in improving data collection and analysis, as well as to the **human–computer interaction (HCI)** community for insights into how HCI concepts translate to stand-alone hardware systems. Although community-driven research is becoming a popular topic, we are aware of no prior literature that informs how to pursue IoT projects for community-engaged environmental monitoring research.

Collectively, the authors of this article have female and male gender identities and ethnically identify as Asian, Indigenous/Native Hawaiian, and White. They have a combined 25 years of community-engaged technology research, 40 years of software and hardware development expertise, and six months of first-hand experience with field ecology.

2 Related Work

This work draws upon and aims to strengthen connections between research fields, including HCI, methods in field ecology, WSNs, and the IoT, as well as drawing from other topics related to data sovereignty and citizen science.

2.1 Conservation Technology for the Ecological Community

The ecology and conservation communities have demonstrated a clear need for more customized and networked sensing systems, both through surveys and through their own design of custom embedded systems. In 2021 WILDLABS, an organization that promotes conservation technology, published the results of surveys of 248 "conservation technology users and developers," finding that of 11 technologies with the potential to aid in conservation, "networked sensors" had the lowest "current performance" among respondents, despite having the third highest "capacity to advance conservation" [33]. In a review of conservation tools, Schulz et al. celebrate the AudioMoth acoustic monitor for its widespread adoption among the conservation community, attributing its successful translation from academia to the field to its Human-Centered Design approach and open source model [31]. The authors consider five use cases to explain and explore technology with uses toward conservation, but notably none of these use cases incorporate networked sensors or IoT, suggesting that these technologies have yet to find widespread adoption or applicability to challenges in conservation.

Indeed, through multiple attempts, the ecology community has attempted to address the dearth of affordable, accessible, and networked sensors by creating their own, often in a "Do-it-yourself" fashion. We hold these projects in high regard and celebrate their creators, while simultaneously positing that the incorporation of more advanced engineering processes would lead to richer, more reliable products. Mickley et al. published an open source environmental sensor with parts that total $20 and whose performance is comparable to commercial sensors, allowing larger deployments on a limited budget [25]. However, the design does not follow engineering best practices for reliability and maintainability, for example, using a breadboard and wires instead of soldering components to a Printed Circuit Board and relying on embedded software written in Lua. Similarly, Rebaudo et al. created a custom IoT system to collect temperature data over two years in three different environments. While this system implements wireless data transfer using LoRa, it achieves ranges of only 25 meters in dense forest environments and experienced loss of 6% of all data due to internet connectivity failure [30]. Finally, in 2023 Mühlbauer and Zavattoni et al. published a custom, low-cost sensor network that uses Arduinos to measure humidity and temperature, which they demonstrate are comparable to commercial sensors, since their loss of precision was made up for by their increased spatiotemporal resolution. The advertised usefulness of the sensor despite its 50% data loss rate and 59% moisture measurement error rate indicate that imperfect embedded systems are still quite valuable to field ecologists [26]. Overall, these efforts highlight the scientific community’s unmet need for low-cost IoT sensors. Interestingly, none of these articles discusses challenges or costs from custom hardware assembly and maintenance, a key flaw that the interviewees and the subjects identified.

A growing body of literature aims to address the disconnect between technological tools and conservation practitioners. Cole et al. distill observations from their workshop teaching computer vision to ecologists, focusing on building technical capacity among the ecology community rather than designing tools that only leverage existing skills within the community. They offer some straightforward insights, such as the importance of comfort with Python prior to the workshop and grouping participants with similar goals together, as well as some non-intuitive lessons, like avoiding Jupyter Notebooks, because it makes the transition to a command line interface challenging, and avoiding deep learning library wrappers, because they conceal complexity and are challenging to customize [12].

2.2 Embedded Systems and the Internet of Things

While the literature on WSN and IoT deployments is extensive, most papers focus on a novel technical capability rather than the more human-centered property of usefulness to a specific community. The projects mentioned in the introduction that measure volcanic activity [3], wildfires [29, 41], air quality [28], and agriculture [36] focus on technical performance metrics such as range, throughput, and battery life, rather than their ability to be sustainably deployed and maintained by a community with different technical experiences than those of academic computer scientists. When papers describe their engagement with communities, it is typically not until the field deployment stage of the project, so there is minimal literature on engaging with communities during the design phase of WSN and IoT projects. Kranenburg and Bassi assert that co-design practices could potentially address conventional challenges in IoT by discovering more privacy-centric and energy-aware solutions that align with user business models [35].

The embedded systems literature does include some practical recommendations for field deployment. We take inspiration from Barrenetxea et al., who published a reflection on common pitfalls and recommendations based on their SensorScope WSN, including for development, testing, and deployment [4]. These insights primarily relate to the technical nature of the system rather than its sustainable use by an outside organization, but do also mention designing for a specific environments. The FarmBeats team also published a similar experience paper that is in line with some community engagement principles, such as leveraging existing farm resources and ease of use for farmers [22], which we draw from. Finally, Ceriotti et al. provide clarity through their field-based wireless sensor network research that was conducted by biologists, rather than engineers, due to logistical constraints [10]. Their discussion of lessons learned from field deployments by operators with a technical background different from conventional WSN researchers offers a model for future work.

The COMPASS community has dedicated its attention to ensuring that technical systems translate into practical and sustainable solutions for specific types of users. Joyner and Till introduce an IoT-based hydroponics system for subsistence farmers in rural South Africa, but only discuss plans for a real-world deployment and do not appear to engage farmers prior to system deployment [21]. We take inspiration from NkhukuProbe, which similarly implements a low-cost sensing system to improve conditions in Malawian chicken coops, accompanied by "interviews, diary, observation and data logging" during deployment to understand user experiences [19]. LoRaX explores a design space for extended internet coverage through the LoRa protocol, but does not mention engaging with target users [37]. Abidi et al. measure particulate matter in Delhi to perform an empirical analysis of government policies intended to limit pollution, finding that find-grained data in the real world are crucial to environmental policy [1]. Despite these advances, very little literature exists for co-designing embedded sensors that will be operated by users other than the technical researchers, hence our exploration. Other publications outside of IoT within the COMPASS community commonly engage communities when designing technology, such as in applications of wildlife poaching [17] and disaster shelters [11].

2.3 Co-design and Community Engagement

The HCI community has a long history of engaging communities to understand their relationship with existing technology and to create new more useful technology. Co-design with communities, especially in the context of Information and Communication Technologies and Development, enables designers to understand users and their needs and build trust to increase the efficiency of design outcomes through dialogue and participation [14]. Technical solutions that do not center on the lived experience of community members or incorporate local knowledge limit their usefulness [32]. Through the use of interviews, focus groups, cultural probes, and ethnographies, co-design has been applied to applications of disaster shelters [11], maternal health care [27], and wearables for low-income communities [13]. These works motivate a design space and future research by directly engaging with a user community. The related approach of asset-based design "seeks to build upon what the individuals and community already have" instead of a needs- or deficit-based approach that can lead to a community's "self-view of powerlessness" [40]. Sustainable Interaction Design, later termed Sustainable HCI, aims to bring a "perspective of sustainability" when making design decisions [6] and spans many domains while broadly relating to the United Nations' Sustainable Development Goals [15, 18].

Co-design faces several barriers, especially when working with historically marginalized populations. Power and privilege imbalances originating from differences in education, language, socioeconomic status, and gender can prevent authentic collaboration, but can be ameliorated when facilitators are "aware of their own privilege, as well as the power differentials of outside stakeholders" [20]. Co-designed solutions can also deviate from their intended use and cause harm to people due to miscommunications, system complexity, and the diversity among target users [38]. Working with Indigeneous communities, as is the case with manoomin conservation projects, which presents additional considerations related to extractive colonialism and data sovereignty. The FAIR principles [39] provide standards and benchmarks for promoting data reuse, while the CARE principles [8] protect ownership and promote responsible and ethical use of Indigenous data, including traditional knowledge. Dogan and Wood explore how these principles could be integrated into environmental research and find that some Indigenous Knowledgeholders share justifiable skepticism about whether their community will see the benefits of the conservation work in which they participate [16]. Co-design also addresses challenges such as continuity, stakeholder participation, and knowledge transfer [14], shortcomings that extended embedded systems deployments can face.

The overlap of research fields in the development of embedded platforms, sustainable human-computer interaction, and co-design remains a gap in the literature that we look to bridge, in part, in this work. Our goal is to bring perspectives motivated by codesign and HCI to the design

		Area of Work/Research	Organization Type	Role	Years in Role	Community Partnership Types	Lifecycle (Discussed first hand experience within lifecycle)	Sensing Modalities	Collection Methods	Goals & Outcomes of Data Collection/Analysis
Field Researchers	P1	Ecology (Fish) & Hydrology	Federal Government	Graduate Student	1	N/A		Temperature & Depth Sensors, Cameras	Manual from sensor local storage, Device Upload (Cellular or WiFi)	Water Level & Stream Flow
	P2	Ecology (Fish) & Hydrology	Academic Research/ Non-Profit	Field Scientist	25+	N/A		Fish Tagging, Camera, Hydrological Sensing: temperature, depth, pressure, rain	Manual from sensor local storage, Device Upload (Cellular or WiFi), LoRA (new)	Public Datasets and publications for Hydrology
	P3	Ecology (Primate)	Academic Research & Community Outreach	Graduate Student, Community outreach coordinator	5	Indigenous Communities, International governments, Corporate partners		Audio Logging, environmental DNA, geospacial	Manual from sensor local storage	Species Identification, Species distribution
	P4	Water Toxicology	Academic Researh	Principal Investigator	3	Industry and local government		Water and biological samples, high-resolution mass spectrometry (in lab)	Manual collection from sensor local storage	Water contaminants - effects on the gut microbiome
	P5	Water Level and Flooding	Academic Research & Community Outreach	Principal Investigator	25	Local Government, local businesses and residents		Ultrasonic for water surface monitoring, commercially available LoRaWAN gateways	Real time streaming via LoRA to WiFi or cellular-enabled powered hubs	Water level for Emergency Monitoring (end-goal) - Low cost, low maintence, easy installation urban water sensor
	P6	Ecology (Amphibian microclimate), realized effects on climate change	Academic Researh	Graduate Student	4	Local Government (Intl.)		Temperature, humidty, soil moisture, wind speed, radiation, cameras, audio logging, satellite images	Manual collection from sensor local storage	Microclimate modeling for climate change prediction
	P7	Conservation (Birds)	Charity Organization & Academic Research	Researcher	<1	N/A		Satellite images (hyperspectral), acoustics, cameras, environmental DNA, LiDAR, manual point counts	Manual observation or collection from sensor local storage (prior role)	Regional biodiversity indicators driving legislation for consveration
	P8*	Conservation (Wildlife)	Tribal Government	Manager: Wild Rice Program	30+	Tribal Government, Acedemic		Water & air quality, wildlife health, species distrubution	Manual collection from sensor local storage	Wildlife management decisions, public health decisions
	P9*	Contaminant Response/Ecolo-gical Health	Tribal Government	Manager: Environmental Response Division	18	Tribal Government, Academic		Water & air quality, wildlife health, species distribution, distributed groundwater temperature sensing	Manual collection from sensor local storage	Wildlife management decisions, public health decisions, ecological assessments"
	P10*	Conservation (Plants)	Tribal Government	Manager of specific ecology program	30+	Tribal Government, Academic		Water & air quality, wildlife health, species distribution,	Manual collection from sensor local storage	Wildlife management decisions, public health decisions

*particpants interviewed together.

		Area of Work/Research	Organization Type	Role	Years in Role	Community Partnership Types	Research Goals
Managerial	P11	Machine Learning Application for Conservation Efforts	Academic & Industry Research (Public Company)	Researcher	~8	Various Organizations (data aggregation)	Wildlife management decisions, public health decisions
	P12	Public Data Archival	Federal Government Agency	Manager & Principal Investigator	10+	Various government funded projects	Public datasets and informatics processes
	P13	Conservation (Wildlife)	Non-Profit Charity Organization	Research Program Manager	~5	Conservation Organizations	State of Conservation Technology Survey

Lifecycle Stages	Problem Identification
Technology Selection	Deployment
Maintenance	Data Analysis

Fig. 1. Key factual information of the interview participants.

and development of embedded technology for our specific use case of manoomin conversation. Although the fact that this article does not fit neatly into one of these fields, we hope that it sparks more discussion and consideration of this intersection.

3 Methods

Motivated by the goal of designing a microclimate sensor to aid in manoomin conservation in the western Great Lakes region of North America, we sought to understand both the broad role that embedded systems play in ecological sensing and the specific role that technology could play among organizations concerned about manoomin health. For this broad understanding, we conducted 11 semi-structured interviews with a diverse group of 13 experts, described in Figure 1, who use or rely on environmental sensing technology. To understand how to design technology to specifically contribute to manoomin conservation, we engaged in participant observation with nine organizations working on manoomin conservation.

From the research questions in the Introduction section, we developed a semi-structured interview guide, included in Appendix A, to understand the state of environmental sensing for a particular individual and their organization. We designed the guide to promote open conversation while directing the general flow of the interview. We did not address every question to every participant as it was up to the interviewers' discretion to skip areas that did not pertain to the particular participant or to ask more detailed questions for areas of interest. The guide included two main sections of questions and discussion points. The first, "General Framing," aimed to capture a baseline of the participant's interest or investment in a specific field of ecology and a high-level understanding of the data they collect, what problems they encounter, and what they would change without resource constraints (e.g., *if you had a magic wand, what would you change?*). The second section, "Field Research," was less structured and contained sub-sections of questions to understand a participant's involvement and/or workflow in the field.

Figure 1 provides high-level detail of our interview participants. Most, but not all, of the participants had direct involvement in field research, i.e., going out into nature in their current role (10/13), but they all had at least indirect involvement. For participants who spent time in the field, we asked for specific details on their experiences, including equipment details, how sensors are configured and validated, how many and how frequent field excursions are, and the data cleaning and analysis process. For those with less access to the field, usually in a management or orchestration role, we ask for more high-level opinions based on experience with field sensors, their data or toolkits, and systems that aid in data collection. Specifically, participants P11, P12, and P13 serve in roles that involve data and project management rather than in roles where they conduct the field research themselves. This work is enriched by incorporating the perspectives both of participants who are engaged with field microclimate science directly and indirectly.

The research team submitted the interview guidelines, a research protocol, a recruitment email, a participant consent form, and a data security plan to the Institutional Review Board of Northwestern University and Georgia Institute of Technology, both of which deemed the research exempt with low risk. The research team consisted of three graduate students and two principal investigators, all authors of this work.

The research team conducted 11 video conference interviews in the spring of 2023 with 13 participants. We recruited participants through a combination of connections with research collaborators, cold emails from contacts found through web searches, and snowball sampling referrals from prior interview subjects. We acknowledge that this sampling method introduces bias into our findings, namely recruitment of those with similar experience, but only two of the subjects were referred from another subject. We engaged participants through an email recruitment, followed by a consent form and scheduling. All interviews except one were conducted with a single participant; interview eight included three members of the same organization. All other participants were from different organizations. Each interview consisted of a primary interviewer who led the conversation, and most had one or two remaining members of the research team present who would ask follow-up questions and ensure that the questions remained aligned with the interview guide. The interviews were approximately one hour long, beginning with verbal consent and ending with voluntary demographic questions. Each interviewer provided a brief introduction and a general overview of the research project to the participants at the beginning of the interview. To compensate the participants for their time, we offered each a $25 Visa gift card issued through a standard process managed by Northwestern University's financial department. Two participants declined the gift card due to their organization's policy on accepting payment.

The self-identified demographics of the participants are the following: five participants identified as female, seven participants identified as male, and one chose not to identify their gender.

For age, three participants were between 20 and 29, two between 30 and 39, three between 40 and 49, four between 50 and 59, and one chose not to disclose. For race, one identified as Hispanic, nine identified as White or Caucasian, one identified as being from a specific Indigenous tribe, one identified as a combination of Indigenous and European ancestry, and one chose not to identify.

All interviews were recorded, including voice, video, and Zoom chat text, and later transcribed by a research assistant who was not involved in the interview process. The research team, composed of both researchers conducting the interviews and researchers not present during the interviews, then coded the interviews in two stages. First, we performed ground-up (inductive) coding by parsing the transcripts into stand-alone ideas, iteratively grouping them by theme using a Figma board.[1] These five themes are *community building*, *economics*, *technical considerations*, *current problems*, and *wants*. Second, after identifying these themes, we performed top-down (deductive) coding by iteratively reassigning the original stand-alone quotes from the transcripts into one, multiple, or none of these five themes. We then re-analyzed the stand-alone quotes to make sure that we did not miss any major areas. We used these codes as the basis for Sections 4–6.

The second method used in this work is participant observation [23] of nine organizations that work on manoomin conservation. On the basis of our observations in the "Community Engagement" theme of this work, we realized the importance of engaging directly with the community prior to designing a manoomin sensor. One of the first authors arranged to spend three months immersed in field work with organizations focused on manoomin conservation during the summer of 2023. This includes two tribal natural resource departments, two intertribal commissions, two tribal cultural engagement departments, two federal research and conservation organizations, and one academic research organization. We had already interviewed members of one of these organizations for this work, but the rest were separate from our interview participants. To contextualize our themes as recommended by Barter and Reynold [5], we use these observations as the basis for the vignettes in Section 5.

4 The Microclimate Sensor Lifecycle

Our interviewees described a variety of recurring shortcomings, desires, and perspectives common across subdisciplines and geographic specialties. In this section, we aggregate these commonalities and present a narrative of the stages of the microclimate sensor lifecycle enriched by the perspectives of those with firsthand experience. We provide these steps as a synthesis of experiences from across disciplines, focusing on their relevance to an engineer developing *in situ* embedded systems. We do not intend the lifecycle to be absolute, but rather for providing the context for our findings in Section 5.

We define microclimate sensors as *in situ* devices that are deployed in remote locations, do not rely on wired infrastructure, and measure some aspect of their environment. These devices can collect data locally, requiring manual extraction, or transmit data over wireless communication protocols (e.g., cellular or **long-range wide-area networks (LoRaWAN)** [2]). In the interviews, we also encountered the use of remote mobile sensing devices, which travel to remote locations to make observations (e.g., satellites, drones, or planes), manual sensing (e.g., ecological point counting), and devices that were connected to the power grid. However, given the research interests of this work, we primarily focus our definition of *in situ* sensors that were most prevalent.

Based on the processes described in the interviews, we organize the lifecycle of microclimate sensors into the following areas: data need finding, technology selection, deployment, maintenance, and data analysis. In each section below, we define the lifecycle component and discuss specific experiences from our data, highlighting common problems and opportunities.

[1] https://www.figma.com/

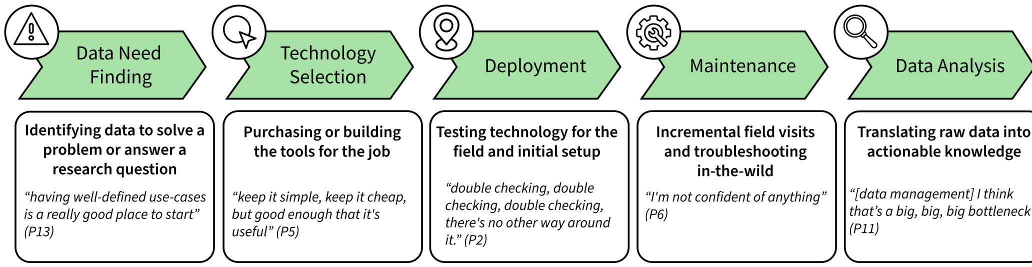

Fig. 2. The microclimate sensor lifecycle, highlighting the main high-level components of an end-to-end project including representable quotes from our interview participants.

4.1 Data Need Finding

The first step is to identify a need that justifies the collection of field data. P13, who is a project manager in a "collaborative conservation technology partnership" with the aspirations to "improve development and adoption of tools for more effective conservation," emphasizes that "having well-defined use cases is a really good place to start" and also highlights the importance of building a story around how data can make a difference. Sensing can address a specific and urgent problem where data are not currently available. Three examples of this in our interviews include P5, who detects water levels in a coastal community to warn of the immediate risk of flooding and structural damage to bridges, P1 and P2, who perform hydrological sensing of small tributaries for fish migrations, and P3, who uses audio to track the presence of a primate species in a specific geographical region. Sensing can also be exploratory in nature, arising from a research question that typically requires collecting a wider range of data points to understand emerging ecological trends. For example, P7's work involves the task of compiling "composite indices that aggregate biodiversity" of smaller regions that national scale-scale datasets often lack the resolution to accurately show. P8, P9, and P10 are concerned with recent changes in ecology, such as the collapse of a fish hatchery or disturbances in fish recruitment and the decrease in the harvest of local wild plants, which are specific problems but require wider data exploration to determine causality. Finally, sensing can be motivated by access to and expertise in a specific technology. P4 performs a very specific hydrological spectral analysis driven by specialized laboratory equipment, conducting exploratory sampling in collaboration with local governments and community groups to identify contaminants, which in turn can help identify problems that need to be addressed in the water supply.

On the surface, sensing problems may not appear technically challenging, but rather present major challenges in logistics and implementation. Limiting constraints include budget, mentioned by all interviewees actively deploying sensors, robustness to the environment, like for P3 and P6 who deploy sensors that they check as infrequently as once a year, or theft and safety. We found that in practice, even with existing well-established products, ecologists often face technical problems that lead to failures. Here, creative and novel sensing techniques can come into play, offering data to help with ecological problems within the strict constraints imposed by environment and budget. In these cases, the importance lies in the impact of a solution, rather than its pure technical achievements. Even for purely technical contributors, it is crucial to understand the problem space and a solution's potential impact to design systems capable of translating into real-world applications. The major challenge often lies in areas considered to be beyond the scope of technical research, such as the uniqueness of a particular application or goal.

4.2 Technology Selection

When choosing from a range of possible sensors and approaches, budget poses a frequent and fundamental filter. Most of our participants selected preexisting devices (P1, P2, P3, P6, P8, P9, and P10) usually from the space between hobbyist- and enterprise-grade devices, or community-supported projects (P3, P5, and P6) that have emerged from research filling a specific gap. Finally, P12, who manages data for a large government research agency, had experience with more sophisticated permanent devices that served as infrastructure for decades-long environmental collection efforts that can cost "a quarter of a million dollars" for installation. Whatever the constraints for a particular research project, we noticed that there is not much room for trial-and-error in the selection of technology. P13, who has a broad perspective on collaboration with multiple organizations, attributes this to the nature of research grant funding; projects have limited timeframes, and communities were stuck with what they had initially selected, often lacking the long-term funding required for continued success. This type of mentality leads to an early tradeoff analysis before all factors are known.

Although sometimes an off-the-shelf product did not meet the needs, most of the interview participants still preferred solutions that already existed in the marketplace. Participants P1, P2, P6, and P9 mentioned using the Onset brand HOBO Data Loggers product line.[2] P6 also mentioned Lascar,[3] Tomst,[4] and Campbell Scientific[5] products as common general-purpose environmental sensors with wide applications. The participants appreciated that the vendors thoroughly tested these devices, offered software applications to aid in deployment, and provided technical support. However, they have limited use for lower-budget microclimate monitoring due to high hardware and subscription software costs, therefore preventing scaling. P6 notes that, for a typical Ph.D. student's field budget, "if you're using HOBO Pros, you'll be able to purchase five at most, which is not really that scalable."

In some cases, users purchased and repurposed devices from their intended market use-case; *camera traps* are a strong example of this, which are chosen for general sensing needs. When paired with recent advances in **machine learning– (ML)** based image analysis, photos provide rich data and automated cameras are easier to find, deploy, and maintain compared to specialized equipment that often requires regular calibration on site. Camera traps or *trail cams*, which are designed to track and hunt wildlife, are widely available and relatively inexpensive. P1, P2, P6, P7, P8, P9, P10, and P13 mention the use of cameras in some capacity. P1 discusses the tradeoff of two popular brands of cameras Bushnell[6] and Reconyx[7] in terms of their cost, timekeeping, and ability to retrofit.

When there is no suitable off-the-shelf device, organizations must weigh whether to use existing designs, such as academic research or smaller community-supported projects, or to develop a custom solution. Through pariticpant observation, we learned about Spudnik,[8] an example of custom single-use deployment. This Arduino-powered device, built by John Coleman at the Great Lakes Indian Fish and Wildlife Commission,[9] measures air pressure, rainfall, water and air temperature, and water level. Another similar example is an ultrasonic water level sensor built with "hobbyist components" and supported by an open source project at the Coastal Ocean Applied Science & Technology Lab at the University of North Carolina Wilmington [7]. Both devices not only offer an impressive example of the technical capabilities using widely available components but also expose drawbacks in cost and scale, which we expand on in Section 5.1.

[2]https://www.onsetcomp.com/
[3]https://www.lascarelectronics.com/
[4]https://tomst.com/web/en/systems/tms/tms-4/
[5]https://www.campbellsci.com/
[6]https://www.bushnell.com/trail-cameras-2/
[7]https://www.reconyx.com/
[8]https://github.com/colemanjj/Spudnik-07
[9]http://glifwc.org/

Many organizations cannot facilitate the development of internal solutions and the effort required to deploy at scale. However, complete efforts exist to fill these gaps with new devices, as in the case of P5. P5 has led the development and deployment of a custom sensor to monitor the water level at bridges in a coastal community. These devices opted for simplicity, both in terms of cost and energy allocation, but still require the support of "real administrators, not run by students that are graduating, [...] a production environment with all the expertise on security and certificates and firewall management, etc." to scale and provide impact to the community. This type of technological robustness is crucial to selecting devices from research or nonprofit organizations, and P5's organization is a shining example of success, promoting the design methodology of "keep it simple, keep it cheap, but good enough that it's useful." We will discuss more about the tradeoffs of academic research in Section 6.2.4

A middle ground between commercial products and custom solutions is those built within smaller, cross-organizational communities focused on similar goals. These are devices built out of necessity that have achieved wide use within their communities, filling a gap that does not meet a wide consumer market need. Our participants mentioned several such projects, including AudioMoth from Open Digital Acoustic Devices (P3, P7, P11, and P13), Swift from Cornell Lab of Ornithology[10] (P3), and FieldKit[11] (P13). Community projects are a more stable option than a *in-house* solution, and provide better long-term technological resilience to consumer projects that can simply stop production and support at their discretion. We found that experienced field scientists tended to think that open source projects provided the best guarantees. We discuss this more in Section 5.2.

Finally, the choice of technology can come simply from convenience. Field researchers are burdened with learning new technologies in addition to their daily responsibilities, as alluded to in 'the devil you know" title quote. P13 explains "it's a huge pain in the butt to switch systems and learn something new, [field scientists] don't have time." Above all else, the technology selected must meet the capacity of those involved in the downstream lifecycle. Understanding the tradeoffs and hidden labor is something that comes with broad exposure to the field and is crucial to success.

4.3 Deployment

The deployment involves everything needed to initially install a microclimate sensor, including device configuration, laboratory testing, physical installation, and field validation. This step is separate from recurring visits, because unique activities take place during deployment that require additional time commitment. Generally, the participants found that the deployment was a pain point, as successful installations require extensive experience and knowledge of the technology and environment. P2 emphasizes that the only way to reduce errors in the field is repetition: "It's a lot of just double checking, double checking, double checking, there's no other other way around it."

Field researchers often conduct mock or pilot deployments to test the feasibility of a system before installing it in the wild. Such deployments are especially important when using a new or altered system, but regardless are always required to verify base functionality, like ability to power up, and statuses, like battery health. P13 states that wildlife monitoring devices are "often [used on low risk species] like cattle to deploy trackers first and then can put them on other more high-risk species." P1 notes the need for pilot studies to gauge the battery life of devices, even when such specifications are reported: "[we] see how long [a device] went a few different times and monitor what's going on with our first setups, sort of our pilot setups, and then I will usually drop back a week or so from the shortest period the batteries work." There are enough unknowns

[10] https://www.birds.cornell.edu/ccb/swift/
[11] https://www.fieldkit.org/

and inconsistencies even with off-the-shelf devices that most participants did not feel comfortable deploying without validating each one.

In actual deployments, validation of a sensor *in situ* before physically leaving the deployment site is important to reduce unscheduled visits. Unfortunately, validation often requires additional equipment to communicate with the device or collect ground-truth measurements for comparison. For example, P1 mentions running a dummy tag through a fish-tagging gate to ensure that the system is working properly and P3 brings speakers and microphones to field sites to test the quality of audio recorder deployments. Some devices require configuration to be altered on site with parameters that are only measurable at the time of deployment. Devices, such as Onset’s products, provide mobile phone applications to do this over Bluetooth, which most participants preferred, as they usually have a phone on hand. However, some products require computer software or an internet connection, which is difficult in the field, especially on multiday expeditions. The additional equipment used in sensor deployment adds cost to the overall project. Although smartphones and laptops are common, some participants purchase lower-cost devices specifically for field work to avoid risking their own devices in harsh weather and terrain. For example, P2 once dropped their phone in a river and now uses an older phone in the field, and P3 purchased a cheap laptop exclusively for exhibitions.

Another serious concern for deployment is the security of the device. The theft and damage from people, weather, or wildlife is a common experience (P1, P2, P3, P4, P5, P6, and P7). This makes the deployment method very important for the longevity of data collection. P1 details a specific theft experience in which a trail camera was installed on a bridge, “in a security box [that] we Python lock to a tree” only later to be damaged and stolen by a passerby whose actions they caught on camera. P6 mentions that they pair sensors with notes in the native language acknowledging the type of research, details on the permissions they acquired to use the land, and “effectively a plea to not steal our equipment.” P7 recounts all the ways that sensors have been damaged or lost in the wild, including theft, wildfires, flooding, and even being eaten by cattle. This damage is most detrimental to sensors without connectivity, because researchers do not know that their device has been compromised until they perform a scheduled visit, sometimes many months later, and are never really sure what happened. Collectively, participants expressed their desire for a sense of security in the devices they deploy, whether through secure mounting techniques, discrete or camouflaged casing, remote tracking capabilities, or a combination of several approaches.

4.4 Maintenance

Once a device is deployed, it often needs to be re-visited several times throughout its lifetime for repairs, data collection, battery replacement, or at the very minimum to collect the device. Most participants stuck to a set schedule based on battery life or storage limits, but some also spoke of timing site visits with events of interest, for example, a weather event, or to address a problem, such as a network-connected device not reporting. P6 and P3 both deploy in remote international locations that require significant time and planning to visit. In these cases, intermediate maintenance is practically impossible, and participants do not know the quality of the data until the end of the study when they collect their equipment. Others, like P1, P2, P8, P9, and P10, who work near their deployment sites, can make a round trip visit to a sensor in a day or, in some cases, have the convenience of live monitoring with networked devices. P5’s deployments are nearly all connected via LoRaWAN, a key design choice for live flood monitoring, which allows instant data collection. This is a feature not normally available to ecological sensing either due to cost or network coverage, but a necessity for the specific use case that takes place in an urban setting. Visiting a site is a time-consuming task, and the participants emphasize that any information about the function of the sensor between visits is extremely valuable.

At a minimum, site visits are dictated by estimates of battery life and storage: "the biggest issue we've all had since we've been using [a new sensor] would be data storage and battery." Devices without Internet connectivity rely on pilot deployment and theoretical power draw calculations to estimate lifetime, but even in the case of live streaming capabilities, batteries remain unpredictable, with P5 noting their experience with battery failures that are discussed further in Section 5. Storage is more predictable than battery life but is still subject to failures and deployment errors. P7 explains a mistake of not properly programming a memory card, resulting in another round trip to the sensor location. Even with sufficient storage, time series data must maintain an accurate time reference, which is a challenge without Internet connectivity. The prioritization between storage, connectivity, and power consumption constraints depends on the application; for users like P5 who monitor weather, real-time data are a necessity, while others studying the longer-term microclimate such as P3, P5, and P6 would prefer more data rather than lower latency.

All field visits cost time and money, so limiting them reduces the burden of conducting field research or broadens the feasible extent of data collection. At a minimum, providing researchers with more tailored sensors would reduce the stress and uncertain of field deployments embodied by P6's reflection: "I am not confident of anything, [I am] flying across the planet in hopes and prayers that the sensors you deployed last year are still there, [and] are still functioning as you intended them to do."

4.5 Data Analysis

Translating sensor data into usable knowledge is the last step in the lifecycle, which can happen in tandem with continuous data collection or after a deployment finishes. The type of analysis is specific to the use case, but usually involves validation, data cleaning, aggregation, and publication. We spoke with three participants who participate in data analysis as a primary function of their role: P4 studies water quality, P11 applies machine learning to environmental monitoring and wildlife conservation, and P12 manages a large data archive center focusing on climate-related datasets. Other participants analyze data as part of their role as a field scientist: P1 and P2 work to prepare public hydrology datasets from stream flow measurements, P3 analyzes the presence of particular species based on audio data to produce distributions, P5 automates bridge inspection due to localized flooding, P6 builds microclimate models that predict the effects of climate change on amphibians, P7 aggregates biodiversity indicators of multiple species to lobby government action as a result of climate change, and P8, P9, and P10 make decisions on wildlife management and public health for an Indigenous nation. In the analysis portion of the lifecycle, the data become actionable in a variety of ways. Even in the best-case situations with well-defined collection modalities, making sense of the data can be a significant challenge.

The participants described formatting and cleaning the data from sensor deployments as a tedious task. For deployments with a mix of sensors, P12 finds that "interoperability is a real challenge" when managing large, diverse, government-funded datasets. P11 contextualizes this challenge in machine learning applications, asserting that data management is a "big bottleneck" that is "the biggest issue consistently across [small] organizations... Machine learning models are [roughly] 10% of the problem, you have to have some way to get the data to your model." Additionally, the volume of data scales needed for machine learning models and the amount of manual labor required for data labeling present additional challenges for many of our participants. P7 explains how "on average, it took [my assistant] four times the length of the recording to correctly annotate all the birds."

Not all collected data can or should be aggregated into public datasets for publication. When government agencies collect data on public land, there is an obligation to remove personally identifiable information when consent is not given. This is a common problem when using trail cameras.

Redaction must be done before release or model training. P2 explains that "having individuals in pictures is something [the principal investigator is] concerned with right now" and explores AI methods to omit images with people from "thousands of photos," while P1 manually checks all images "just make sure, 'hey, there's no people in here, I can upload."' Furthermore, it is important to realize that public data sharing is not always appropriate. Federal rules tied to funding require P10's tribal natural resource department to publish sensitive data from their reservation. Data sovereignty agreements can combat this, but must first achieve wider compatibility with requirements from funding organizations.

This lifecycle section provides crucial context to understand the themes we extracted from the interviews and present in the subsequent section. Knowledge about our interview participants, the roles they play and their common experience through their collection and use of microclimate sensor data grounds the design space that we present in this work.

5 Interview and Observation Themes

In this section, we present the technical requirements and processes that we derive from interviews and participant observations. We explore how the insights and experiences of participants and partners alter the conventional understanding of the goals and constraints of conservation technology by IoT researchers through the lens of three themes: (1) cost of experience, (2) technical requirements and tradeoffs, and (3) community engagement. In addition to the insights distilled from interview participants, we provide specific anecdotes from participant observation. All insights and assertions are directly grounded in interviews or participant observation, while Section 6 discusses opportunities, recommendations, and challenges that connect and extend beyond these interviews and observations.

5.1 Cost of Experience

An IoT researcher should be familiar with and account for all costs imposed by their technical approach, striving to build *low-cost experiences* rather than exclusively low-cost hardware. The monetary cost of a technical sensing approach plays a large role in determining its feasibility, and, in fact, most IoT research projects advertise the costs of procuring the required hardware. However, a major takeaway from the interviews is that often the cost of hardware procurement is only a small part of the overall cost of a project, and evaluations of IoT research should account for this fact. The interviewees mentioned additional monetary and time costs such as hiring personnel, travel, training, and data management that IoT research typically does not account for. Due to the varying structures in funding sources, the relative importance of these and other costs changes from project to project. Field scientists can sometimes save money on these other expenses, for instance, by coupling travel with another project or finding volunteer sources of labor, in which case the hardware costs really are the limiting factor in project success. In other instances, hardware is a small percentage of the overall cost.

5.1.1 Vignette 1: Time is money. An example of why low-cost experiences are often more important than low-cost hardware emerged from participant observations. The participant is a project partner whom monitors the water quality and weather in areas that support manoomin by using a custom-designed sensor called Spudnik,[12] that we previously discussed in Section 4 and that we show in Figure 3. A first author joined Spudnik's designer, who also builds and deploys the system, while hiking to a field site to collect water samples manually. During a conversation about environmental sensing, the designer talked about how pleased they were with Spudnik's capabilities

[12]https://github.com/colemanjj/Spudnik-07

(a) (b)

Fig. 3. (a) Spudnik that failed from beaver chewing its wires (b) Onset HOBO datalogger after being removed from the sandy river

and data quality despite the low material cost of around $200, significantly lower than comparable commercial systems. They would have liked to deploy more, but each unit took about 40 hours to build and test, which was prohibitive for someone with a busy field schedule. For them, Spudnik's true cost was $200 plus 40 hours of time (and salary), likely much more expensive than the alternatives. Still, maintaining a few devices made sense, because their organization once had free time for its employees to dedicate to building them, while it probably did not have that money in liquid form to purchase comparable hardware. Different organizations will have different priorities, including using personnel time to assemble hardware versus spending their budget on hardware. IoT publications should evaluate and communicate not only the cost of materials, but also the time or complexity required for an average user in their application's community to build and maintain such a system.

5.1.2 Contextualizing and framing costs. Field scientists are under a wide variety of time and monetary pressures that directly affect the development of their field science. Understanding the full context of these constraints is important for the success of long-term projects. Several researchers spoke about the budgets and costs they manage in their current research paradigm. Although these vary widely, P6 offered insight into typical project funding in ecology, where, for a Ph.D. student, project funding "is on the scale of $1,000 to $5,000, which is inclusive of everything relative to data collection ... so that will probably boil down to a thousand dollars or less for practically all equipment." They continued to explain how larger funding sources, such as an advisor's $250,000 NSF grant, a "moderate sized grant for ecologists", would typically cover around $10,000 in equipment costs, or 4% of the total grant. The participants also discussed the costs of the "gold standard" equipment and related maintenance for their field. A NOAA Inland station costs $100,000 up front (P5), and a USGS stream gauge incurs $15,000 in labor costs for annual maintenance (P1). P6 also described how Campbell Scientific products are "the gold standard for ecologists, meteorologists, [and] basically anyone who wants to be measuring local weather and climate" but that "the reason that a lot of ecologists don't use them for scalability is that their products are much more expensive." An additional context relevant to cost is that many interviewees perform duties beyond their role as a researcher, with P2 explaining that they take care of "all the equipment maintenance," "all the financial aspects," and "all the animal care." Therefore reducing physical and cognitive drain is of high value.

5.1.3 Costs at each stage of the sensor lifecycle. The participants elaborated on the additional time and money costs at each stage of the project. Although many of these deployment costs are fixed regardless of the technology employed, interviews motivate a reduction in the time commitment and complexity of sensing technologies. For example, during the technology selection and acquisition phase, P1 discussed modifying trail camera sensors prior to deployment by tapping their motion detection sensor so that it did not take images outside the specified time interval. Several other participants alluded to the manual labor that went into modifying and verifying the operation of sensors prior to deployment, typically with more work required for more custom solutions. A common topic when discussing the burden during the sensor installation phase was the travel time, ranging from two hours driving each way to a watershed (P1) to two months hiking through a rainforest in Madagascar to reach remote sites (P3). Sensor deployments can also sometimes require the installation of significant additional infrastructure, such as the "significant connectivity infrastructure" needed for the Kifaru Rising Project (P13). In the cases where participants would prefer to use the existing communication infrastructure, the connectivity costs are often prohibitive. P2 described how their sensing could be dramatically improved if their trail cameras used the cellular network to upload pictures to the Internet, but they "just can't afford it yet." Similarly, P5 described a project to monitor the water level that uploads data to the cellular network, which increases both hardware requirements and costs, because "the cellular radio isn't gonna live off the battery very long" and imposes a recurring cost that amounts to "real money."

Participants explained opportunities in the sensor maintenance and data retrieval phase, such as how data retrieval can avoid travel costs if data are uploaded via a network rather than retrieved manually, the benefits of which P6 describe as "incredibly powerful." The interviewee elaborated on how their current data retrieval method required "a $1500 flight to Madagascar' or alternatively hired research assistants, each of which "requires a multi-week expedition" for which he must pay for "salary, stipend, food, housing, et cetera to go to these really remote locations." P1 feels they have to "baby [their remote sensors] a little bit" by checking the data portal every day, and they also visit their sensors more often than the battery or storage restrictions required for fear of data loss . Furthermore, discussing the personal burden imposed by sensor deployments, P5 explained how challenging it is to add more sensors, because "calibration is hard and maintenance is hard." Finally, theft presented a serious challenge with financial implications for both P1 and P4, with P4 explaining the stress inherent in the process in which "you just have to cross your fingers and nobody's going to hook it to his trailer or his truck and run away."

The final stage, data processing, also imposes a significant time burden, primarily in validating and correcting data during quality assurance and quality control. P1 was frustrated with the mental load of filtering raw camera trap files, manually checking and correcting timestamp offset, and backing them up in the meantime. P2 described the workload to verify the reasonableness of the collected data and release them to the public as akin to "doing a paper in itself."

5.1.4 Conventional cost. Despite the additional expenses discussed above, equipment costs remain an important factor referred to by many participants. P3 described cost as "the biggest constraint" for her dissertation when explaining why she uses more $99 AudioMoth acoustic sensors than $349 Swift acoustic monitors. P13 expressed a similar constraint, saying "low cost is an absolute must for any conservation application." On several occasions, participants explained how they prefer lower-quality sensors that require more manual labor if it means they can purchase more to deploy. P11 described how "in many cases, it's much cheaper for them and much more sort of ready use for them to just go check on the sensors every week." Such a strategy is the only way within to measure the "spatial variability across a landscape or region" (P6) even if it means manually "check[ing] on the sensors every week" (P9). While this may seem intuitive to a system designer, a key insight emerged: For practitioners to consider trying something new, it needs to have a strong value proposition, because the cost to try out and learn a new system is too high. PP explained: "Ecologists, they choose the common products that are more expensive, because that's what's known." P13 described a "hump you have to get over" for a product to be "enough better than anything else you're going to be having access to" in convincing scientists to switch to a new system rather than using "the devil you know." Finally, P13 also described how some conservation technologies are too expensive to even explore, even if their use would bring about a paradigm shift that would ultimately reduce costs.

5.2 Technical Requirements and Tradeoffs

New solutions should aim to reduce the burden and expand the capabilities of microclimate sensing. In this section, we synthesize common tradeoffs and design considerations in the technical space. Most importantly, we found that the integration of domain knowledge and technical expertise is key in promoting success. However, there is not always a clear right answer, but rather a compromise that needs to be struck between competing goals, often of systems capabilities, quantity and quality of data, and the system's usability in the field. In this section, we highlight how to apply technical expertise and align it with the objectives of the development of microclimate sensors.

5.2.1 Vignette 2: Field challenges with device interaction. An example of participant observation that motivates the need for community engagement comes from one of the first authors assisting in the deployment of an Exodus Render commercial trail camera[13] with an employee of a tribal natural resource department. After boating for an hour to reach a remote lake not accessible by car, the project partner selected a tree that provided a good vantage point from which to observe the manoomin. By mounting a trail camera that uploads images over the cellular network, they could monitor the manoomin plants' health without the two-hour round-trip commitment to get to that location. The trail camera setup is shown in Figure 4. Ideally, we would have turned on the camera, mounted it in a spot with a good view of the emerging manoomin, and verified while on site that the physical configuration and settings were accurate and that the cellular connectivity was strong enough. Unfortunately, the trail camera's visual interface was only accessible without the solar panel plugged in, so we could not manually verify its setup. The website for the uploaded images that we navigated to on a smartphone showed that an image had been uploaded, but the website was not configured for smartphones, so we could not verify the setup in this way either. Thinking that we had configured the trail camera correctly, we embarked on the hour-long boat ride back to the partner's office. When we logged in to the trail camera website there, we could no longer see new images or reconfigure the device's settings. Our best guess was that the camera was right on the edge of its connection range to the cellular tower or that the battery started out with just enough energy to transmit one photo and that the solar panel was not configured correctly, but we had no way to debug the system. Had the system designer been aware of this, they could have prevented this problem by designing the visual interface to be accessible while the solar panel is connected, designing the website to better operate on mobile devices, or coming up with a new way, such as a local Bluetooth connection, to verify device operation in the field. Building these community partnerships prior to design can avoid these costly pitfalls.

5.2.2 Usability in the field. No matter how strong the capabilities of a piece of technology are, its user interface must be well suited for its use case. We found that in-field validation and cross-platform support are the key to usability. If each device has a different interface and connection

[13] https://exodusoutdoorgear.com/products/the-exodus-render-4g-lte-cellular-trail-camera

(a) (b) (c)

Fig. 4. (a) Trail camera deployed with a tribal natural resource department, (b) SAGE node deployed in the western great lakes region of North America, (c) pole installation for a future SAGE node.

method for updating configurations, then validating, or retrieving data, deployments become more complex and therefore error prone. P2, who uses a variety of sensors in their field deployments, notes the different modalities. “For two of our gauging stations, we can log in with an app to get the data off the readers,” while mobile connections are also available with their Bluetooth temperature loggers and trail cameras. Others require a computer for setup, as is the case with some of the Onsets products and audio loggers. P3 notes the frustration of incorrect sensor configurations without on-site validation: “sometimes [sensors] just didn’t record, the settings didn’t get [saved], they were supposed to run from 5 am to 8 pm, but they ran continuously, sometimes when they recorded [data], they were running the wrong sample rate.” It is common for devices to offer minimal indication of functionality, for example, “a little blinking light” as a form of validation in the field.

Field scientists want simple but reliable methods to validate technology; however, deployments often require a mix of support devices to cater to different applications and systems. P3 mentions using cheaper equipment in the field to avoid damage to personal devices: “I would usually bring a phone, not my real iPhone, but I would get an Android, the rest of the world just uses Androids. [...] I bought one of those $200 PC laptops, download the desktop apps [...] ahead of time.” P6’s computer operating systems have a similar issue, as they note “LasCar products have proprietary software that is only windows compatible, so as a primarily [macOS] users for my machines, that tends to be a hurdle, but perhaps less so working in [a] developing nation where [macOS] tend to be less common.” P3 has a similar experience, commenting that “Swifts only have an app for Windows.” It is a challenge to develop cross-platform applications. Interfaces on a device are an option; however, they often increase cost, are simply not possible due to configurations, and make updates more complicated.

Usability is easily overlooked due to the effort required to develop intuitive user interfaces. However, allowing configuration and validation in the field is a crucial step in ensuring success. P13, who manages a yearly survey of deployed devices, notes field ecologists’ experiences with deployments: “they say it’s hard to deploy, I need technical help, it’s expensive, [or] it relies on connectivity that I don’t have.” This makes it difficult to design a universal interface or deployment protocols that will meet the needs in the field. P11 goes so far as to argue that consistency across devices is not possible and is a false hope of generalized design efforts: “[field sensors are] not going to have the same standard, you just have to understand that there is no way to fix the problem of different sensors having different formats,” later explaining that building skill sets to deal with such problems is a more suitable solution over attempts of interoperability. Usability therefore needs to be considered on a case-by-case basis, and instead of focusing on generalization, start with the needs of the specific need and community impact.

5.2.3 Tradeoffs in data quantity, quality, and connectivity. "Anytime [we ask] they always want more [data]," explains P2, who develops and deploys hydrological monitoring technology, describing the common challenge of feature selection. It is challenging to communicate to prospective users the downsides of improving a product by adding more features, more data, real-time data, or higher precision. The benefits that come with higher frequency, precision, or real-time access will always be interesting, but they also introduce tradeoffs in longevity, coverage, reliability, and ultimately success. Projects that distill the requirements to the needs of the specific use case tend to be the most successful. When approaching a constrained problem as a technical expert, it is key to understand these tradeoffs, effectively communicate them, and provide a well-informed recommendation that centers the goals of the conservation use case.

Data collection methods directly affect the complexity of sensing projects. Choosing the most advanced technology is not always the best decision. The most important component of success is to use reliable technology, which may mean reducing the versatility. P11 explains that "building something edge-based needs to have a very strong justification," keeping devices as simple as possible is beneficial, and if complexity needs to be added, it needs a direct goal-aligned justification. P5's flood monitoring system is a strong example of this justified complexity; flood monitoring requires real-time data and a wide distribution, and deployment within a community requires low-cost components to reduce theft and vandalism. The system is successful because the design only includes justified features, which, from a technical perspective, results in a modest device that provides great impact to the community it serves.

Regarding quality and precision, P11 notes that "temperature sensors accurate within five degrees instead of within sub degree [...] will affect any downstream analysis, no matter what the analysis is." This notion can be generalized for any sensing device: It is important to understand what level of precision is needed. P1 explains the levels of sensors used in their field monitoring "we're comparing different qualities of sensors; we have a really low quality sensor, which is the Hobo sensor, then we have a medium quality, which is the Troll, and then we have a high quality, which is the radar." Testing devices side by side allows a comparison of data, quantifying the tradeoff between accuracy, cost, and other features. Additionally, context-aware sensors can help increase quality at times of interest, although again with a cost in complexity. P2 explains that data gaps can be acceptable if they occur during uninteresting times, in this case during droughts, but if data are missing during periods of rain, then it is devastating to their research. Adapting this domain knowledge to projects can have large impacts, for example, selectively conserving or harvesting power during periods of varying sunlight, a form of adaptive sensing. Reducing the quantity of data collected at appropriate times can lengthen deployments by extending memory capacity and battery life, thus reducing project costs or increasing deployment distribution.

5.2.4 Vendor lock-in. We found a concerning problem with sensor technology in that research quality suffers from vendor lock-in. Vendor lock-in is an economic concept in which customers are dependent on a vendor for either product selection or are faced with a cost for switching vendors. P6, when we asked them if their current use of proprietary software limited their choice of future sensors, they replied "Yes, so much so that it defined my research questions themselves, as in, it's not even really in the vocabulary or toolkit of a lot of ecologists to be thinking about integrating different sensors, because we're so accustomed to using the proprietary software." instead systems should aim toward being well-documented, open source, and inexpensive to maintain, because, as P11 describes, "it's very difficult to fund sustainably a software tool that needs a lot of maintenance."

The subject went on to describe how dependence on private and proprietary tools makes her nervous because “inevitably, if that organization goes away, then they lose their work… so the more that these things can be open source, the more stable they can be for the community.”

We outline a specific observation regarding Onset HOBO products, shown in Figure 3 recovered directly from the field. Onset HOBO devices are popular among our partners, which are on the cheaper end of the microclimate monitoring sensor spectrum, to record time-series environmental data, such as temperature or pressure, at pre-set intervals. The most commonly used HOBO devices had no wireless connectivity for intermediate data monitoring, meaning that partners would simply set up their devices at the start of the field season and then return three to nine months later, hoping that their sensors were still there and the data were valid. Although its widespread use attests to its value, HOBOs were also widely praised for being rugged to harsh environments and having a common interface across most devices. However, the proprietary nature of the devices required users to send devices to the factory to replace batteries and locked users out each year if they failed to pay the roughly $150 to replace a screen cap, resulting in increased costs, complexity of deployment, and complaints. They also have no way of verifying the data until they are plugged back into a computer, leading to many cases where the settings were misconfigured or batteries died early. In addition, HOBO sensors can easily be lost; one partner mentioned only finding two or eight dissolved oxygen sensors deployed during the winter season, and another deploys twice as many sensors to combat sensor loss. In many ways, HOBO data loggers are a success story of the microclimate world, achieving goals specificity to one task, common interfaces across devices, and reduced complexity due to the use of one vendor. However, they also fail in many ways by not providing users with feedback or intermediate data in the field and tying users to Onset not just for new products, but also to continue using the products they have already purchased.

5.3 Tradeoffs between Proprietary and Open Source Solutions

Existing off-the-shelf products often have very narrow functionality and tend to lock users into a specific technological ecosystem, which we discuss in Vignette 2. Addressing this issue, P11 emphasizes reservations with the use of proprietary tools, stating concerns about “conservation organizations investing a lot into a tool that’s private, because inevitably, if that [company] goes away, they lose their work, and they don’t have the resources [to recover].” P13 continues on to position for organizations to have a “concise exit strategy” and a “sustainability plan,” which we discuss in Section 6.1.4. A solution to combat these issues is to engage in community-controlled, open source projects, but such efforts need to be considered and managed carefully.

Open source projects ensure longevity and flexibility. When targeting a specific use case in the field, P13 states “having open source options is really great,” referring to the AudioMoth acoustic monitoring project as an outstanding example. However, usability and overgeneralization should be approached with caution. P13 also warns about a problem: “it’s always a really tricky balance because having [tools] being open source makes them super customizable, and then it also means that it’s not as simple as an off-the-shelf solution. It’s just going to require more technical skills or training to use.” P11 extends this to an organization’s data needs: “it’s very difficult to think about, can we build a single tool that will work for all of these organizations? It doesn’t seem to be the case, you really do need someone to come in and build out [a] database.” P11 emphasizes that solutions cannot be over simplified and that tools should provide fine-grained customization when needed.

5.3.1 Emergent methods to reduce the deployment burden. Participants introduced several strategies and methods to reduce the burden of deploying sensors that IoT researchers should be aware of. The most common were technology and processes that save time and field effort, such as P1's "grab[bing] the [SD] card and swap[ping] it" instead of downloading data in the field and reinserting the same SD card. Co-deploying lower-quality or novel sensors with proven counterparts was a recurring strategy for both validating conventional sensors, such as a $500 water-level gauge with a $100,000 NOAA station (P5), and verifying machine learning models, such as predicting water flow from images of a river with ground truth provided by a co-located pressure transducer. P9 was also keen to point out that lower-cost sensors sometimes work better than their high-cost version, with stand-alone piezometers providing more accessible data than an expensive USGS station. The final strategy that the interviewees used was to borrow and reuse the sensing equipment from partners. P10 described creating a collaboration with a nearby university to deploy water-level sensors that their organization would have struggled to acquire quickly. Although it is unlikely to drive the primary use case of a sensor, developers could extend a device's usefulness through awareness of these strategies.

5.4 Community Engagement

The benefits of community-engaged and community-driven co-design are well understood in the HCI and COMPASS spaces, as explored in Section 2, but have yet to achieve widespread acceptance in embedded systems, WSN, and IoT literature. These fields typically opt to focus on the development of novel technology rather than to fulfill a need of a specific community, even though they often include a specific use case to motivate and test their contribution. We acknowledge that not every IoT research project needs to engage with a community. There is still a role for preliminary research and proof-of-concepts that push the technical boundaries without translating to an immediate impact. However, as the IoT research community recognizes the threats of environmental catastrophes and shifts its focus to developing systems that address specific challenges, a responsibility emerges to undertake community-engaged and community-driven work.

In this section, we explain the community and social components of our interviews and explore how they should shape IoT and environmental sensing research. Twelve of the 13 interviewees focused on the community surrounding specific technologies as critical to their usefulness. Typically, the relationship we focus on is between the developers and the community of scientists or resource managers collecting and analyzing the data, although other communities such as those of citizen scientists, funders, and supporting government agencies were also mentioned. Observations and recommendations fall into two groups: (1) analysis relevant to specific short-term research projects and (2) recommendations for long-term, systemic changes. This first portion of analysis primarily addresses how to develop technology that has a direct and positive impact on the community, while the second portion explores how community engagement can allow potential users to better leverage emerging IoT research.

5.4.1 Opportunities to align research and community priorities. IoT research has the potential to address some of the historical shortcomings of the research community by improving the agency and independence of marginalized communities. Indigenous communities and other groups that nurture longstanding ties to place often possess deep knowledge and insight into the workings of a natural environment through Traditional Ecological Knowledge and other non-scientific ways of knowing. Scientists and governments have often extracted this information from communities under the guise of helping them, ultimately taking advantage of an unbalanced power relationship. For example, P8 and P10, both employees of a Tribal Natural Resource Department, shared how, during a "collaboration" with the state Department of Natural Resources for the collection of eagle blood data, in which both parties collected samples, it took years for the state to release any data to the tribe, because "there's no reason to share with us before you share with the public, so we're viewed as the public and not a sovereign nation." As of 2023, they had still not shared the complete data collected in 2012, and what data they did share was a "table that has no lab reports and no units." Similarly, they had to borrow federally owned sensors to gather air quality data, and getting the data back took two to three years and was overall "just a mess."

Using technical system development as a conduit for community engagement, IoT researchers can align their goals with those of local communities without promoting extractive practices. See Section 6.5 for discussion on this topic.

5.4.2 Vignette 3: Collaboration breeds collaboration. Although this project has not yet produced a prototype sensor that is ready for deployment, the three months of community engagement have already contributed to impactful connections with partner organizations. The one-on-one discussions during trips to and from field sites, group workshops to establish sensing priorities, and cultural events that naturally accompany time spent within a community have built not only trust, but a genuine excitement to deploy sensors when they are ready. When interacting with partners at conferences and on video calls, they will frequently ask how the prototyping is going or tell us about a site they found that they are excited to monitor with our future sensor. We anticipate that this will be a huge boon to our community and logistical support during the deployment phase and eventually transitioning into a stable long-term sensing system that requires minimal upkeep by us, the researchers. Furthermore, our improved understanding of community sensing goals has allowed us to serve as intermediaries with other sensing projects, such as the SAGE node for edge computing-defined software sensing [9]. This has already resulted in the deployment of infrastructure for a tribal natural resource department to monitor microclimate and air quality on their reservation, a top priority with the rise in Canadian wildfires. The deployment of the SAGE nodes, shown in Figure 4(b), also fosters long-term collaborations between research laboratories to expand the scope and possibilities of microclimate sensing. We relied heavily on our understanding of community goals and technical capabilities to write the associated "Memorandum of Understanding" outlining data collection and management on the tribal reservation. Both the tribal and university attorneys endorsed the document, attesting to how powerful cross-disciplinary partner engagements can be, and have already begun the installation process by erecting physical infrastructure, shown in 4(c).

5.4.3 Engagement during a specific project. Partnering with a specific community or potential user group before embarking on a research project was a common participant recommendation, either directly advocating for it or indirectly explaining its usefulness through an example. This process of forming relationships from the outset rather than waiting for the evaluation stage or never doing it has benefits at many stages of the research project. Experiencing frustration, P7 recounted how many computer scientists he met at a workshop were developing "a tool in search of a use" rather than "actually having a target end user."

Engaging with a specific community at each phase of the project yields research that is more likely to translate into something useful. It may seem contradictory that focusing on a specific community is superior to exploring a large problem space when deciding in what direction to take a new research project. P13 relayed how the responses to the State of Conservation Technology survey indicated that what some users thought were good aspects of the technology, such as power consumption, ease of deployment, and cost, were what other users thought were the worst aspects. When deciding on the initial goal and scope of IoT research, conversations with shareholders can drive project selection and leverage community knowledge. Motivating the novelty that naturally emerges through community engagement, P10 talked about how "the data that's most useful to us oftentimes isn't the standard data collected by standard means." Researchers can also iteratively hone project ideas by communicating tradeoffs and opportunities of specific technical approaches.

P13 explains the "confusion around what level of connectivity is required" when selecting sensing systems, which early conversations would clarify.

After deciding on a problem and an approach together, the research team will likely develop a prototype that they need to evaluate. The initial investment of community engagement will pay dividends here, because it not only provides direct access to a field test site but also presents a group of people who are excited to help with the logistics and legwork of running a field test. In their ecological field work, P3 describes how their conversations with partners in the indigenous communities of Betsileo and Tanala provide information on "where existing trails were" and "logistics, like: 'Oh, where can we camp?', 'Where can we get water?"' Similarly, P5 leverages long-standing relationships with community partners in Savannah, Georgia who "want to be involved" in monitoring coastal flooding by "hosting them [LoRa gateways] on their houses."

This approach adds responsibilities for the communication and continuity portions of the project. Several participants commented on the importance of communicating the results of the research with the community. P4 described how their student synthesized bioactivity data from the Portland Harbor Superfund Site "to report back to the community." P5 described engaging with their user community in an academic setting by "presenting at the hurricane preparedness conference in the track targeting emergency first responders." Similarly, ensuring that systems have a lifetime after development and evaluation presents an additional consideration.

5.4.4 Systemic engagement. Looking past individual projects, interviewees emphasized how IoT research can engage more systematically and benefit communities. By building long-term relationships between researchers, developers and user communities, challenges can be tackled by building *communities of practice* [24], expanding the technical capacity of users, and tailoring technology for communities that have not conventionally been involved.

The technologies that interviewees held in the highest esteem, such as AudioMoth and EarthRanger,[14] a data integration and visualization platform, P13 described as successful, because they have "a community of practice around them, where people can share what's working for them, ask questions to the developers or people who are technically savvy enough to answer questions they can crowdsource. And then they feel like they're not alone in deploying these tools as well." P1 referenced a community of practice, one even describing how "if a collaborator calls and needs technical support, I help them" and how he had "become a shipper" of custom trail cameras that he would distribute to others in the community. Finally, *"group buys"*, where a set of independent groups who want to buy the same technology go in on a purchase together to achieve economies of scale, are a huge advantage of communities of practice. The interviewees P3 and P13 described how the AudioMoth group purchase model has been a "game changer" and the "holy grail of conservation tech development," because it simultaneously lowers prices, connects disparate users with each other and demonstrates the developer's commitment to accessibility. While the interview data did not offer insight into how to create these communities of practice, simply knowing about and making technology compatible with them is an important first step for researchers.

Four interviewees spoke extensively about building technical capacity, both at the individual and community levels. While IoT and data analysis solutions that require minimal technical experience from the user, such as plug-and-play hardware and no-code ML applications, are sometimes warranted, participants warned that they should not be the default goal for conservation technology. P11, who is an expert in applying artificial intelligence to conservation challenges, elaborated on how no-code graphical user interfaces for ML are "very expensive to build, very expensive to

[14] https://www.earthranger.com/

maintain" and instead recommends to "actually build the machine learning programming skill in an ecologist." P13 also commented that "there definitely is some capacity building and training and support that could go into more clearly illustrat[ing] why this [technology] would be helpful for people and how they can leverage it." This insight serves as a call for IoT researchers to communicate their research with and develop training and tutorials for potential users who are outside their domain of technical expertise.

At the level of community capacity building, citizen science presents a mature audience that the IoT research community has yet to engage with widely. Describing how "enormous numbers of people who are very knowledgeable about birds" are an untapped resource, P7 envisions a role for citizen scientists to "go out and set up camera traps or acoustic recorders." P12 spoke on how the citizen science community is "brokering things" and how he expects it to be "changing a lot… over the next five years." For P12's organization, citizen science serves as "both a way to collect data that we can't collect, but also to engage the public, more broadly speaking, in science processes and understanding the changing earth around us." As citizen science becomes more common, tools should adapt to align with a broader array of experience levels while also serving as a teaching aid. Education of individuals and participation in untapped citizen science groups present opportunities for IoT research to become more impactful and directly benefit specific communities.

6 Discussion

In this section, we discuss the opportunities, recommendations, and challenges that the interview and observation themes illuminate. These largely originate from our process and plans for a manoomin-centric sensor.

6.1 Opportunities and Recommendations

6.1.1 A middle ground to real-time monitoring. Tradeoffs between data quantity, quality, and connectivity have interdependence; Addressing one can negatively affect the others and poses a complicated tradeoff challenge. The need for real-time data came up multiple times in our interviews, but implementation can be challenging and expensive. P5 notes the complexities of building a LoRaWAN network for their sensors due to the difficult requirement of real-time monitoring. However, a middle ground may be beneficial to some use cases, especially those where deployments are extremely remote, like P3's and P6, where sending a "ping" or "health check" could greatly benefit the success of their research. Such a solution is also mentioned by P13: "do health check type things to figure out if we do need to send someone to go hike 10 kilometers." Smaller incremental data packets that provide high-level information about the sensor function could allow the field scientist to know if a sensor needs maintenance and make trips to the field more efficient. Similarly, communication in the other direction (to the sensor) could enable adaptive sensing, where the field scientist could alter configurations, such as the collection frequency, based on weather or other factors. P6 state the importance of such a feature: "I would love it if I could change ... the resolution of data recording" referring to sensors deployed for multiple years. The development of such a feature requires an analysis of the cost, but with the future development of wide-spread satellite communication, this may be possible even in extremely remote environments.

6.1.2 Application development in microclimate field science. When working in the field, sensor interaction with mobile phones seems to be the preferred method, given their ubiquity and the ability to build interfaces (apps) for multiple sensors and communication standards. Cross-platform support becomes a challenge with such applications, since the popularity of phone and computer operating systems vary. Generally, we found that the support for Android and Windows is the most desirable for cost and worldwide support. When implementing on-site wireless connectivity, **Bluetooth Low Energy (BLE)** is an optimal protocol for localized communication, which is an important requirement for onsite validation and configuration. It has minimal impact on the battery and is supported by all modern mobile phones and a wide variety of microcontrollers. However, BLE has limited bandwidth and may not be suitable for the validation of images, video, or audio data. Higher bandwidth devices might require a localized WiFi connection or on-device interface; for example, many trail cameras have screens to help with setup and validation. It is important that these methods do not affect the battery life in transit or in deployment. There exists a gap in the research on evaluating the usability of microclimate device interfaces in the field, and this is an area that we would like to explore in the future.

6.1.3 Sharing knowledge across disciplines. P13 highlights the importance of increasing technical literacy among field ecologists, especially in the application of machine learning, where expert domain knowledge and expert technical skills are required for success. We argue that knowledge sharing should be promoted and that all areas of multidisciplinary work should be promoted. However, technical skills should not be the only focus, P7 expresses concern about a dwindling knowledge in field ecology, “you need to have natural history knowledge to be able to interpret something,” in other words, having generalized technical skills is not enough and there is a need for experience with nature to work with environmental data. Therefore, knowledge sharing should not be limited to core technical foundations, but should include sharing from all sides of ecological projects. Future exploration is needed to understand how to incorporate multidisciplinary knowledge sharing in microclimate research.

6.1.4 Have an exit strategy. Research projects generally have a limited support timeline, and commercial products can become useless if the company that funds them stops supporting them or goes out of business. To build users’ trust that they will be able to leverage a product even if circumstances outside of their control change, build an exit strategy into every project. Projects should aim not only to be open source with good documentation, but also to provide links to places where users can order replacement parts or ask questions. Especially if a project is not open source, designers should have a contingency plan to release documentation and design files to the public in case they can no longer support it. With an exit strategy, potential users will be less resistant to try out a new device, opening doors to a richer sensing landscape.

6.1.5 Embedded systems research and its alignment with partner data sovereignty. While making environmental data publicly available is often a good research goal, there are cases in which doing so would violate the sovereignty of communities in and around the study sites. By focusing on creating the tools to collect these data rather than the data itself, embedded systems and IoT research incentives situate the field to protect data sovereignty rather than jeopardize it. Researchers can present evidence for the effectiveness of their system by providing technical metadata, such as power consumption, range, and throughput, as well as a user study, while allowing partner communities to decide what to do with the actual environmental data collected throughout the project. By creating tools that are easier to use, more accessible and cheaper, research can allow communities to gather their own data to answer their questions faster and more independently while aligning with academic incentives, serving as a means of empowerment rather than extraction.

6.2 Challenges

6.2.1 Not doing too much. While some research aims to push theoretical or technical boundaries, other research tries to solve a specific problem grounded in the goals of a community. When these two aims overlap, it is important to decouple these two components as much as possible. When engaging with the community, be realistic about the risks and shortcomings of new technology development, and encourage the community to narrow the project's scope. Novel technical ideas will likely emerge in the course of community engagement, but try to evaluate them in a way so that the partner community is not reliant on the success of an unproven technology. This is an important lesson from our original assumptions of designing an overly generalized modular sensing tool for manoomin.

6.2.2 Differing timelines and funding models. Computer science researchers tend to have incentives to publish quickly and often apply for funding often. Microclimate scientists tend to work on longer timelines, taking years or even decades to plan experiments and collect data. Communities, especially those based on place or culture, often operate on a decade or even a generation-long scale and may have been addressing a challenge for years before partnering with researchers. Similarly, the sources and requirements for funding can vary as much. Although there is no way around these differences, serious conversations about timelines and funding can help align goals in a way that everyone benefits. The conventional academic model for technology research is not set up to support long-term deployments and support, though emerging concepts of "novelty" create new opportunities for prolonged partnerships by valuing novel applications and community-oriented goals rather than exclusively novel technology.

6.2.3 Managing community expectations. The initial phase of community engagement is an exciting time with many possibilities and opportunities. In the midst of this excitement, it is essential that researchers are direct about the impacts that a new technology can have on the community. Technology in a vacuum cannot fix social or environmental challenges, and techno-optimism can hurt long-term partnerships by eroding community trust. It is best to be clear about the potential outcomes and limitations of technology, especially when it is over-hyped and untested.

6.2.4 Clashing of goals in academic disciplines. From an engineering perspective, it is important to understand that while there are ecological monitoring problems that require unique and novel solutions, most of the time they require established methods that are intelligently planned and work reliably at scale. In today's landscape of academic research on hardware and software, such projects may not have technical contributions; therefore, impact becomes the contributing factor to the research. P8 recalls iterating on "problems in the applied arena" in the implementation of promising academic projects in field research. P10 recounts this project as a success, but notes it "was a huge learning curve for us" and "next time we do it, would be a much different game" referring to the lessons learned in the iterations of the deployment of a novel sensing method to locate preferential flows in a lake (e.g., springs). However, academic collaboration has its benefits. P10 notes a preference for working with university research as opposed to funded research through government agencies such as the Environmental Protection Agency and USGS in the United States, which requires complicated quality assurance and regulation. In P8/P9/P10's particular organization, University help is a way to "actually get some work done" and can avoid data sovereignty problems. P5 mentions the importance of "build[ing] a system that is supported outside of an academic team," noting "it takes a real [development operations team] to run a stable system," which is reflected in their distributed water level monitoring system. The clashing of these goals can become a challenge for engineering-focused academic research, and we argue for the consideration of separating technical contributions from community-engaged research. When applying work to the field, long-term support and community impact should be the primary goal, and testing new technical solutions that distract from these goals can have detrimental effects on a community's goals.

7 Conclusion and Next Steps

This work has provided information on the use, selection and design of environmental sensors for monitoring and research of microclimates. We extract a detailed understanding of the microclimate sensor lifecycle, themes to drive community-engaged design, and directions for future exploration from 11 semi-structured interviews and participant observation. This work serves as the basis for our ongoing research into the design of specific tools and devices for manoomin conservation, but generalizes to similar community-engaged projects for microclimate research, which is a growing area of ecological concern amid the escalation of climate change.

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