

Buoy Meets World: Aquatic Sensing Insights from 169 Days of Low-cost Wetland Buoy Deployments

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Abstract—Wireless sensor networks (WSNs) provide abundant opportunities to study and steward the natural world. Inexpensive WSN hardware allows for improved accessibility, scalability, and overall sustainability of environmental monitoring. Despite decades of technological development, limited research has evaluated low-cost WSNs deployed over long time periods and at wide geographic scales, especially in rural places that often lack the power, communications, and organizational infrastructure to promote their sustained operation. To address this gap, we analyze the metadata of 21 solar-powered, LTE-connected, low-cost water-quality sensing buoys co-designed with community partners and deployed over a 6 month period in the Great Lakes region of the United States. We present findings on the accuracy of various low-cost sensing modalities, the complexities of sufficient solar power, the unpredictability of rural cellular LTE-M connectivity, and the possibility of correlated failures across interacting subsystems. We find that many low-cost sensing modalities provide comparable data to their expensive counterparts; solar panel configurations must consider more than just total energy output; cellular connectivity is unpredictable but relatively reliable within 4 km of a tower; and subsystems can interact unexpectedly and therefore care should be taken to minimize system complexity. These findings will aid future WSN and embedded systems engineers in better designing and deploying devices for sustainable and impactful long-term environmental monitoring.

Index Terms—Wireless sensor networks, Internet of Things, Sensor Systems and Applications, Environmental monitoring, Wetlands, Rural Areas

I. INTRODUCTION

Due to a confluence of global and local factors, many natural environments experience increasingly challenging conditions that impact the health and well-being of humans, non-human animals, and broader ecosystems. Similar to other Information and Communications Technologies (ICT), wireless sensor networks (WSNs) present opportunities to promote sustainability, specifically by reducing the burden of high resolution

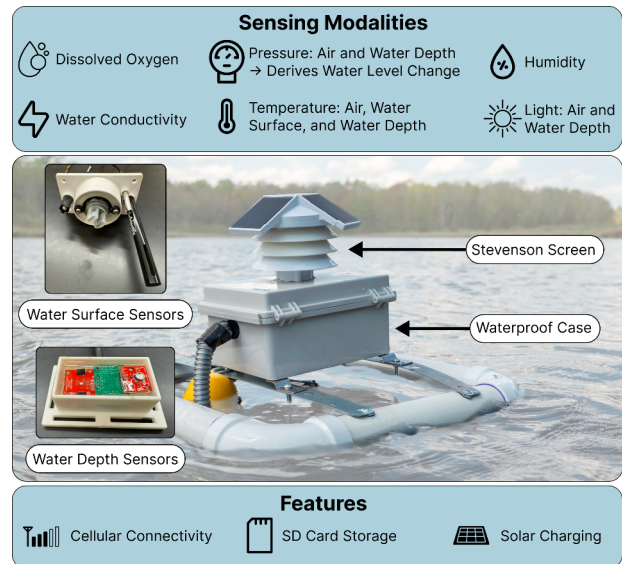


Fig. 1. Makak water quality sensing buoy. Includes a list of sensing modalities and core features. Waterproof case is approximately 28cm x 20cm x 13cm. Photo credit: David Cournoyer.

monitoring to better measure and respond to environmental degradation. From providing wildfire alerts [1] to monitoring farmland biodiversity [2] to measuring soil conditions [3], these technologies can operate in diverse settings to scalably collect relevant data and transmit them to the Internet. Yet realizing this potential requires analyzing these systems under the complex, dynamic conditions in which they operate, rather than the controlled settings often employed by computational approaches [4], [5]. Most deployments and successive evalua-

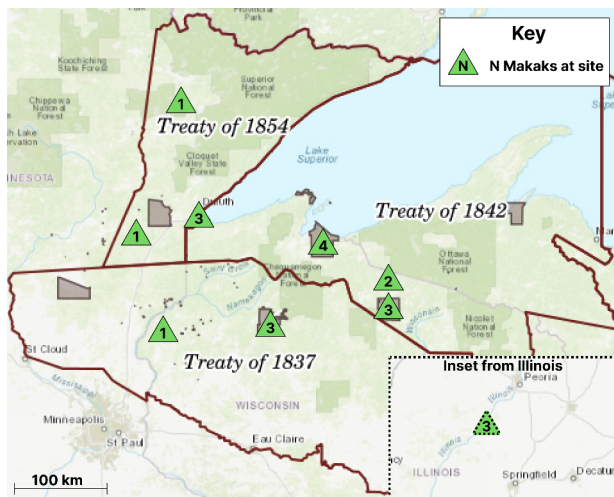


Fig. 2. Map of Makaks deployed in 2025. Triangle labels indicate the number of Makaks within a 25km radius. Primarily depicts Wisconsin, Minnesota, and Illinois, United States of America. Base map from maps.glifwc.org.

tions remain relatively limited in geographic scale and temporal duration [6], rarely spanning multiple months or hundreds of square kilometers. For WSNs to achieve their full potential, research must move beyond the lab to evaluate deployments that collect sensor data under real-world conditions and over extended timescales. In this paper, we contribute an empirical analysis of such a deployment, helping to address this gap.

We present analysis from a 21 device WSN deployed over nearly 100 sq. km during six months in 2025. These devices, named Makak after the Ojibwe word for “container”, were envisioned as a way to understand water quality data key to the health of Manoomin (wild rice), a culturally and ecologically important plant species native to the regional wetlands. System goals centered on “sensing what Manoomin experiences” were co-developed with expert Indigenous water stewards from local communities, leading to the development of a floating buoy platform. Our partners envision using Makak data for both long-term scientific inquiry, such as studying how sunlight and humidity affect wild rice abundance, and immediate management actions, including revoking permits when water quality near construction sites degrades. We build on our pilot deployment of an earlier Makak system [7], addressing many of the identified shortcomings and introducing substantial changes, highlighted in Fig. 3. Both designs emerged through an iterative, relationship-based process, described in detail in the earlier paper, aligning with calls to center Indigenous methods in sustainable ICT design [8].

Makak is a low-cost (sub-\$700) buoy that is solar- and battery-powered, uses LTE-M (Long-Term Evolution Machine Type Communication) cellular connectivity, and measures ten sensing modalities shown in Fig. 1. The buoy comprises commercial electronics and mechanical components that we modified, integrated, waterproofed, coded, tested, and assembled before deploying them in our partners’ waterways of interest

throughout the Great Lakes region of the United States, as shown in Fig. 2. As Section II-B describes, our redesign uses a different microcontroller, incorporates additional sensing modalities, adds solar power, and is housed in a new form factor. These changes, along with deploying 2.5× as many devices, lead to new and more robust insights. In the remainder of this paper, we use the term *Makak* to refer to this redesigned WSN deployed in 2025.

In this work, we describe the analysis and associated insights learned from these Makak deployments. Although we conducted diverse analyses to understand the successes, challenges, and failures of these 21 devices, we focus on the findings that generalize to other WSN instances, especially those deployed for long periods and in rural areas. Specifically, we focus on addressing four sets of questions:

- 1) **Low-cost sensing modalities:** How accurate are the low-cost sensors that Makak uses compared to more expensive standards? What changes in quality can we observe over time? What recommendations can we make on sensor selection, integration, and maintenance?
- 2) **Solar charging:** How effective was solar charging at powering the Makaks throughout their deployment, especially in shaded locations? What recommendations can we make on solar panel sizing, orientation, or charging circuitry, especially for devices like Makak that have no fixed orientation in space?
- 3) **LTE-M connectivity:** How reliably did the Makaks upload data over the LTE-M cellular network, and were there any trends in which devices successfully connected to the network? What recommendations can we make around site selection to maximize connectivity?
- 4) **Subsystem interaction:** What trends are there between the behavior of different electronic subsystems? What recommendations can we make around system architecture, testing, and overall design philosophies?

These research questions align with the challenges common to many WSNs, Internet-of-Things (IoT) devices, and ICTs around power consumption, network connectivity, and monetary cost [9]. Situating ourselves within the ICT4S field, we examine the challenges long-term WSN deployments face in addressing societal sustainability goals in addition to briefly exploring the direct footprint of the devices themselves. In contrast with research that examines the direct environmental impacts of ICTs, we focus primarily on exploring their roles in enabling sustainable outcomes that could promote structural change [5] while still contextualizing their drawbacks. Our solar-powered, low-resource design also aligns with opportunities for “computing within limits” [10], demonstrating how relatively simple systems can provide comparable value to their costly counterparts, and aligns with community calls to leverage ICTs to address data uncertainty challenges and promote sustainability decision making from a “plurality of perspectives” [8]. We contend that evaluating long-term and geographically dispersed WSNs is fundamentally different from evaluating short-term, co-located WSNs. The dynamic

nature of deployment environments, lack of nearby infrastructure, memory storage limitations, and site inaccessibility for maintenance introduce challenges to sustaining sensor data streams. WSN literature acknowledges the frequent failure of nodes when they are deployed for multiple weeks, even when they had been validated over multi-day test runs [11]. Indeed, none of our insights about long-term sensor data quality, solar power, connectivity, or subsystem interaction would have been visible had we evaluated only the first seven days.

Our devices experienced mixed success, with roughly a third collecting little to no data, a third collecting and uploading data consistently, and a third somewhere in the middle, as Fig. 4 demonstrates. 20 of 21 devices were successfully recovered, but nearly all devices had limited or no power, causing decreased or ceased data collection. Our primary contributions are the findings and design recommendations that stem from long-term Makak data:

- 1) Our **low-cost temperature, pressure, and light sensors provide quality data** comparable to expensive commercial devices, whereas **low-cost conductivity sensor data are not reliable and humidity and dissolved oxygen data have mixed results**.
- 2) Embedded devices must **consider the impact of deployment location on solar panel voltage, not just overall generated energy**, especially for devices with multiple solar panels facing different directions.
- 3) LTE-M connectivity remains hard to predict, but **deploying devices within 4 km of a tower will give a high probability of reliably connecting**.
- 4) **WSN subsystems can interact unexpectedly and cause cascading failures**, especially in wetland environments. Keeping designs simple while providing multiple layers of failsafes should be a central design principle.

II. RELATED WORK

We review the literature relevant to designing, deploying, powering, and connecting WSNs, especially water-based systems and networks deployed for longer periods of time.

A. Long-Term Sensor Network Deployments

WSN literature evaluating long-term deployments offers insight into system longevity and degradation that most studies, which typically evaluate systems over a few hours to days, cannot provide. Although we identified many research projects focused on rural WSNs, few of them included a field deployment, and even fewer deployed for multiple months. Long-term urban deployments, which are more abundant in literature, can provide relevant insights: a healthcare deployment recommends avoiding modular hardware [12], an air quality WSN identifies challenges in predicting LTE-M coverage [13], and a noise monitoring network predicts sensor faults [14]. Many networks choose LoRaWAN [15] or Sigfox [16] for their connectivity, but these protocols face clear challenges when scaling to a large number of devices [17] and thus are impractical in many real-world applications. Long-term rural deployments report that harsh environments and more frequent

hardware failures can critically reduce the amount of data recovered [18]. Recommendations for improving the success of rural WSNs include leveraging relay nodes to forward traffic [19] and creative energy harvesting paired with very low duty cycles [20]. Overall, WSN literature highlights the central challenges of energy, network coverage, and sensor quality in real-world deployments [21], and practical challenges such as the local environment and making sense of messy data [22].

Water quality monitoring WSNs tend to focus on measuring controlled environments, such as for aquaculture [23] or fish tanks [24], or deeming whether water is safe for human consumption [25]. Typical sensing modalities include water temperature, pH, turbidity, conductivity, dissolved oxygen, and oxidation reduction potential [26], [27]. Despite the abundance of proposed energy harvesting techniques, solar panels with rechargeable batteries appear to be the most common approach [27]. A unique challenge for water-based devices is biofouling from prolonged water exposure [28]. We build on prior research by emphasizing device longevity and data accuracy from low-cost sensors.

B. Solar Power and LTE Connectivity

Solar energy is very sensitive to the deployment location, which impacts the available energy on both daily and seasonal scales [29]. Solar panels can face performance degradation of up to 67% under heavy cloud cover [30] and 94% during rain [31]. Embedded systems often combine multiple solar panels at different orientations in parallel, which fails to maximize the harvested energy and may not charge the battery at all in low light [32].

Prior work has highlighted the lack of LTE coverage in rural areas [33] and inaccuracy of LTE coverage maps by network providers [34]. Hilly and forested areas attenuate signal strength due to the distant-independent “vegetation factor”, which can be partially mitigated by placing antennas at higher elevations [35]. LTE coverage has also been demonstrated to be especially poor on rural Tribal lands [36]. LTE-M leverages LTE cellular infrastructure to theoretically extend coverage ranges and save power by offering variable datarates [37]. Frequent challenges to deploying LTE-M WSNs align with challenges from deployments with other communications technologies, primarily energy consumption, coverage, supporting high volumes of devices, and security [38].

III. DESIGN PROCESS

A. Hardware Design

Makak comprises several connected subsystems: micro-controller, power, data storage, connectivity, real-time clock (RTC), 10 sensing modalities, and enclosure. As shown in Fig. 3, all subsystems except two sensing modalities are new to this version of Makak. System architecture and components were driven by a combination of lessons from our prior prototype [7], partners’ requests, and goals of low-cost, robust, and easy-to-deploy hardware. Each sensing modality reflects partner priorities around monitoring microclimate (temperature, pressure, and humidity), water quality (conductivity and

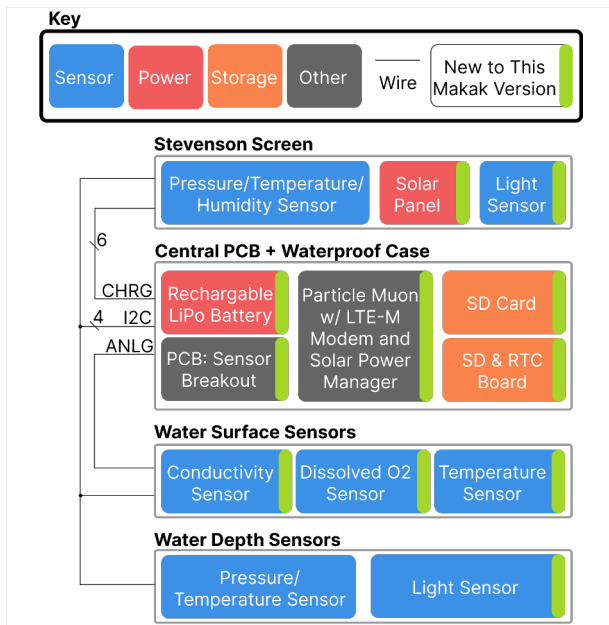


Fig. 3. Block diagram of Makak, highlighting features new to this version.

dissolved oxygen), water level (differential pressure between air and water), and photosynthetically active radiation (light).

The buoy consists of a waterproof case for the electronics, on top of which sits a custom 3D-printed Stevenson screen [39] that houses the solar panels, a light sensor (SEN-15436), and the temperature, pressure, and humidity sensor (BME280), as seen in the middle panel of Fig. 1. The case sits on top of a PVC-pipe float and contains waterproofed wire glands for wires from the two other sensor fixtures: the water surface sensors, which sit just below the water's surface and measure conductivity (Atlas Scientific EC-Kit-0.1), dissolved oxygen (Atlas Scientific ENV-20-DOX), and water temperature (DS18B20), and the water depth sensors, which are affixed to the anchor and measure light (SEN-15436), pressure and temperature (MS5803-14BA). Inside the case is a Particle M-SoM¹ with a Particle Muon Carrier Board² that integrates the microcontroller (Realtek RTL8722DM), LTE-M modem (Quectel BG95-M5 for AT&T and T-Mobile carriers in North America), and power manager. A 3250 mAh rechargeable 18650 lithium ion battery stores the energy from the three 0.6W solar panels connected through diodes. Also inside the case are a custom printed circuit board (PCB) to interface with individual sensors and an independently powered RTC and SD interface board and SD card, which acts similarly to an "SDcloud" [40] data buffer that pushes readings to the cloud during the next LTE-M connection. The other two sets of external sensors (water's surface and at the anchor) each consist of a custom 3D-printed and epoxied waterproofing

enclosure and connection points for each sensor. Solar panel design is further discussed in Section V-B1.

Prior to the full-scale deployment, we conducted multi-hour test deployments in a lab-based flume and an outdoor water body. These verified the mechanical design and individual sensing modalities but were not long enough to illuminate the shortcomings revealed by a long-term deployment. We intended to conduct more robust test deployments, but given partner goals of deploying devices early in the spring and our experience from the prior year's pilot deployment, we deemed it worthwhile to proceed with the full-scale deployment.

B. Environmental Impact

We briefly consider the environmental impact of the buoys themselves, focusing on the direct (first level) lifecycle implications of device production, operation, and disposal from the Hilty and Aebischer model [5]. A full ISO 14040-compliant assessment is outside the scope of this work.

For **production** and **disposal** CO_2eq impacts, a similar environmental-monitoring IoT device has a cradle-to-gate footprint of 3.65 kg CO_2eq [41], primarily driven by the PCB, casing, integrated circuits, and battery. We perform a lightweight differential analysis, replacing the three AA batteries (0.5 kg CO_2eq) with a single 14.7 Wh lithium ion battery with an average cradle-to-gate emissions of 90 kg CO_2eq per kWh [42], corresponding to 1.3 kg CO_2eq . Makak adds three 0.6 W solar panels at 0.8 kg CO_2eq per W [43], contributing 1.44 kg CO_2eq . At 2.8kg, the Makak case is 18 times as massive as the reference, contributing about 10.5 kg CO_2eq . This brings the manufacturing CO_2eq emissions for Makak to roughly 15.5 kg.

The impacts from **operation** are dominated by transportation. As a solar powered-device, Makak directly emitted nominal CO_2-e during deployment. The device collects 80 bytes of data 96 times per day, which for a full 169 day deployment corresponds to 1.24 MB of data transmitted over the LTE network. By aggregating data into four messages per day, the network data overhead is nominal, and at 0.8 kg CO_2eq per GB [44] the total emissions from LTE communications are roughly 1 gram CO_2eq . A typical deployment involves two 50km trips driving an 8.5 km/l truck (2026 Ford F-150)³, consuming 11.8 liters of gasoline, which corresponds to 27.6 kg of CO_2eq ⁴. Notably, manually collecting these data emits a single trip's worth of emissions- 13.8 kg CO_2eq -per measurement, meaning Makak reduces net emissions of data collection if they each replace four or more dedicated trips.

For the single unrecovered device, we must also consider the ecotoxicity of the lithium and cobalt from the lithium-ion battery, possible lead from the circuit boards, and the silver and zinc from the dissolved oxygen sensor, all of which can pose human and ecological health risks [45]. We discussed the possibility of losing devices with our partners, all of whom are conservationists whose job is to steward

¹<https://docs.particle.io/reference/datasheets/m-series/msom-datasheet/>

²<https://docs.particle.io/reference/datasheets/m-series/muon-datasheet/>

³<https://fuelconomy.gov>

⁴<https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator>

these ecological systems. They understood that devices may be lost and determined that the potential deployment benefits outweighed the costs and risks.

C. Ethical Considerations

This work aims to realize decolonial frameworks of practice within sustainable ICT design [46] by embodying partner values in the design process and deploying technologies to contribute to a more just society. From initial conceptualization in 2019 through the post-deployment analysis in 2026, Ojibwe partner goals and values have driven project priorities. We received approval for this project from each partner Tribe and organization under their specific protocols, which variably involved drafting Memoranda of Understanding (MoUs), submitting deployment permits, and seeking approval from Tribal leadership. We held regular discussions with partners about how best to minimize negative environmental impacts while providing useful data and infrastructure, debating the environmental and community impacts of each design decision. This project also received IRB exemption determination from Northwestern University as study number STU00216413.

IV. DEPLOYMENT AND ANALYSIS METHODS

A. Deployment

We deployed 21 Makaks with eight different partner organizations, including three sovereign Tribal Native American Nations, two inter-Tribal natural resource management organizations, one federal organization, one state organization, and one nonprofit. Partner goals and priorities determined each device's location, with some small adjustments at the field site to improve the likelihood of reliable sunlight and connectivity. Fig. 2 shows the deployment sites. The Western Great Lakes region experiences a humid climate with large temperature swings and frequent precipitation, and is situated in a biodiverse landscape with large forests and vast wetlands.

With partner support, we deployed Makaks in wetland streams and lakes between May 6 and June 12, 2025. Devices were not cleaned or serviced until retrieval between September 29 and October 22, 2025, with the exception of Makaks 21, 23, and 24 which we used to evaluate sensor quality. We accessed sites via canoes, powerboats, wading, and from the shoreline. We initially configured devices to capture data every 5 minutes and upload aggregated data every hour for validation, but we later remotely reduced these rates to 15 minutes and 6 hours to limit power consumption. A few partners provided reference data from co-located YSI EMM350 Pisces⁵ and YSI Global Water WL16U Depth Logger⁶ professional-grade sensors.

B. Analysis Methods

After retrieving all Makaks, we used multiple data sources to characterize the performance of each device:

- Cloud and SD card sensor data readings.
- Connectivity metadata from cell towers.

⁵<https://www.ysi.com/emm350>

⁶<https://www.ysi.com/File%20Library/Documents/Specification%20Sheets/XA00197---WL16-Pressure-Transducer-and-Datalogger---Spec-Sheet---Web.pdf>

- Post-retrieval images documenting physical degradation.
- Post-retrieval battery voltages.
- Reference data from co-deployed commercial sensors.
- Crowdsourced cell tower locations from *CellMapper.net*, manually verified with Google Maps satellite imagery.

To understand each deployed Makak's status, we synthesized the above data sources through a data inventory:

- 1) **Sensor data:** Combine cloud and SD sensor data for each Makak. Remove sensor readings and timestamps outside of physically possible ranges.
- 2) **Connectivity status:** Determine which towers each Makak connected to, when it connected, and how much data it uploaded.
- 3) **Observed status:** Combine sensor, connectivity, and battery metadata with insights from Makak pictures to generate a JSON file noting the subsystem, description, severity, and dates of status changes.
- 4) **Failure classification:** Synthesize the sensor, connectivity, and observed status information to determine cause(s) of failure: power, water damage, real time clock, microcontroller, non-water hardware issues, no failure, and indeterminate.
- 5) **Deployment-wide status:** Analyze trends from all Makaks to generate emergent findings and insights.

V. FINDINGS

The data collected over the six month deployment period highlight four findings that provide insights for other deployments of low-cost WSNs, especially those for wetlands: (1) Many individual sensing modalities can provide comparable data quality to expensive counterparts even over extended deployment periods; (2) Sizing and configuration of solar panels must account for not just panel net power but also the voltage for battery charging circuitry; (3) Cellular connectivity is difficult to predict but was generally reliable within 4km of a tower; (4) Seemingly isolated subsystems reveal correlations between the timing of failure events. The sample size of 21 deployed devices is too small to make many definitive claims about general behavior, but anecdotal findings provide directions for future deployments and research.

Aggregated across all devices, we deployed 21 Makaks for a total of 2,951 sensor-days. Of these, data were collected on 1,588 sensor-days (53.8%), and cellular connectivity was achieved on 1,152 sensor-days (39.0%). A timeline of each device's deployment window, sensor readings, and network connections is provided in Fig. 4. There was a wide range of success among the deployed devices, with five devices recording data fewer than 15% of days and seven devices recording data more than 85% of days. Similarly, 11 devices connected to a cell tower on less than 30% of days, while the other 10 devices connected on more than 50% of days. 20 Makaks were recovered; only one device, which was deployed in a rough, choppy bay, could not be found.

The primary causes of total system failure, the point after which no more data were collected, were water damage (seven

Makaks) and real-time clock corruption (four Makaks), while two Makaks ceased reporting due to lack of power, one Makak failed for an indeterminate reason, and seven Makaks operated successfully throughout their deployment period. Nearly every Makak (at least 15 of 21) missed significant numbers of data readings and network connections due to lack of power.

A. Low-Cost Sensing Modalities

We evaluated individual sensing modalities by comparing Makak readings to robust commercial sensors, ranging from thousands to hundreds of thousands of dollars, at multiple sites; while logistical and financial constraints limited co-deployment, validation at any site demonstrates that the modalities can provide accurate data.

TABLE I
MAKAK SENSOR VALIDATION AGAINST REFERENCES.
QUALITY RATING:
++ (GOOD): $r_w \geq 0.8$ AND $r_d \geq 0.8$;
+ (MOD): $r_w \geq 0.5$ AND $r_d \geq 0.5$;
o (WEAK): $r_w \geq 0.3$ AND $r_d \geq 0.3$;
- (POOR): $r_w < 0.3$ OR $r_d < 0.3$.

Makak	Metric	Quality	N	Coverage	r_w	r_d
21	Air Pressure	++	722	23%	.99	.99
21	Air Temp	++	722	23%	.98	.94
21	Conductivity	o	1035	33%	.39	.69
21	Dissolved O ₂	+	1166	37%	.67	.54
21	Light	++	572	18%	.90	.95
21	Rel Humidity	++	722	23%	.95	.95
21	Water Temp	++	1216	39%	.86	.81
24	Air Pressure	++	762	24%	.99	.99
24	Air Temp	++	762	24%	.99	.97
24	Conductivity	-	1558	50%	.24	.21
24	Dissolved O ₂	++	1609	51%	.51	.87
24	Light	++	642	20%	.92	.97
24	Rel Humidity	o	762	24%	.37	.98
24	Water Temp	++	1678	53%	.93	.86
06	Water Level	++	142 [†]	97% [†]	.85	n/a

1) *Low-Cost Sensing Modalities: Analysis:* We evaluate most modalities against a YSI EMM350 Pisces, which recorded water quality and meteorological data near two Makak devices (identifiers 21 and 24) at the Emiquon deployment site. We analyzed air pressure, air temperature, conductivity, dissolved oxygen saturation, light, relative humidity, and water temperature data from all three devices, limiting comparisons to times when the Makak and EMM350 reported valid data for that modality. Table I conveys the results of these comparisons, the number of hours over which the comparison was conducted (N), and the percent of hours the comparison was conducted over the Makaks' deployment period (Coverage). We resample all data to hourly, then derive two data streams for each modality and device: window (24-hour moving-average filter) and diurnal (average of hour-of-day grouping). We compute the Pearson correlation for each, deriving the windowed correlation r_w and the diurnal correlation r_d . The windowed correlation provides insight into

how the readings correlate over longer periods, whereas the diurnal correlation indicates how aligned their daily trends are.

We perform a similar analysis for water level at a different location, using a YSI Global Water WL16U Depth Logger to validate Makak 06. The analysis differs because our reference sensor reports at a daily frequency, so N and Coverage correspond to days, rather than hours[†]. We downsample windowed data to daily, and evaluate r_w . The windowed correlation is shown for water level in Fig. 5. We use correlation to determine a quality rating for each sensor-reference pair.

For any modality, we would not expect readings even from identical sensors to record the same values because of differences in exact deployment location and sensor positioning. This is especially true for dissolved oxygen, which is sensitive to water flow and photosynthetic activity [47], and conductivity, which is impacted by flow and water depth [48]. The low coverage percentages for Makak 21 and 24 reflect gaps in the Makak and reference EMM350 recordings.

2) *Low-Cost Sensing Modalities: Results:* High correlation alone is not sufficient to demonstrate sensor accuracy, but when paired with in-situ calibration provides evidence that the sensor captures changing conditions. Air pressure, air temperature, light, and water temperature demonstrate high ($\geq 80\%$) r_w and r_d correlation for both Makaks, and water level shows a high r_w correlation, suggesting these implemented sensors are generally trustworthy for deployments of up to 5 months and temperatures within 0 and 40 C. Of note, Makak's low-cost visible-light sensor was highly correlated with the more sophisticated photosynthetically active radiation (PAR) reference sensor, suggesting that the general-purpose light sensor can still provide insight into light availability relevant to plant growth. Makak 24's dissolved oxygen data show high diurnal correlation, with peaks in the same hour corresponding to maximum photosynthetic activity due to sunlight. We expect Makak 24 to have a higher diurnal peak dissolved oxygen reading because it is in vegetation, while the reference measurement is in open water. However, Makak 21 demonstrates only moderate diurnal correlation of dissolved oxygen, and neither device has a high windowed correlation, so overall the dissolved oxygen sensor shows promise but needs further validation at higher geospatial resolutions. Both of 21's relative humidity correlations are strong, but 24 shows a weak overall correlation but a strong diurnal correlation. We attribute this discrepancy to condensation and trapped moisture in the Stevenson screen, as demonstrated by the Makaks tending to max out (100%) more often than the EMM350. Conductivity showed weak or poor correlation for all metrics, indicating that the Makak's implementation of the conductivity sensor is insufficient for most applications.

B. Power and Solar Charging

The dearth of data and connectivity from later months is attributable to insufficient power for at least 17 of the 21 deployed Makaks, indicating a major issue in our solar energy harvesting and energy management approach. We provide

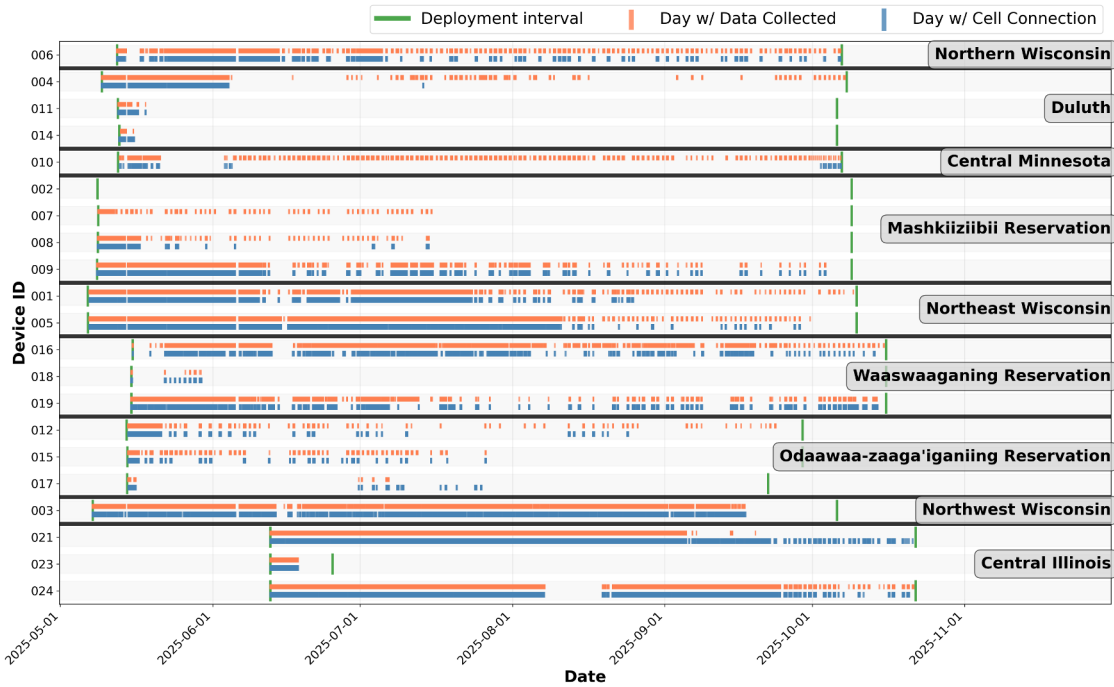


Fig. 4. Data and connectivity timeline of each Makak, grouped by region

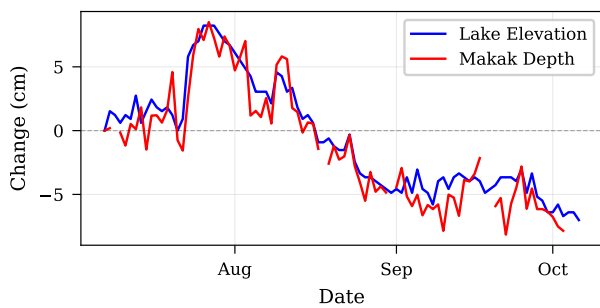


Fig. 5. Comparison of lake depth changes between Makak and HOBO sensors, showing strong positive correlation over 85 days ($r = 0.96$)

details of our design before analyzing why it was insufficient for most of the deployments.

1) *Power and Solar Charging: Design:* Designing the solar panel configuration for a small floating buoy that remains stationary but freely rotates proved complex. Our prior deployments showed that flat surfaces are highly susceptible to biofouling from birds and mammals [7], which can significantly reduce solar output. To mitigate this, we mounted solar panels atop the Stevenson screens at a 33° tilt (chosen to maximize regional energy availability⁷) and distributed panels in multiple directions so that in any orientation at least one panel would face roughly south. Because panels could receive

⁷<https://sunsolar tilt.com/pages/calculator>

unequal illumination, each was wired in series with a low-dropout diode then wired in parallel with each other, allowing currents to sum without backfeeding.

To decide the number and size of the panels, we used the U.S. National Renewable Energy Laboratory's PVWatts calculator⁸, which uses a location's weather data, solar panel size, solar panel orientation, and typical losses to compute the amount of energy it should generate on average for each month of the year. With an 11.7 Wh battery and an upper estimate of expected monthly energy consumption of 18 Wh (based on the Particle's calculator⁹), we estimated that we could rely on monthly average without worrying about daily variation. For our deployment locations, we used the calculator to compute the amount of energy a 0.6 W solar panel should produce each month at a 33° tilt, pointing due north (the worst case scenario). Within our deployment window, 11 Wh is the lowest monthly expected generation. Our solar panel datasheet specifies a 5.46 V output voltage and 100 mA output current at maximum power, which accounting for the diode's 0.4 V drop (7.3% loss) means a single 0.6 W panel should produce 10.2 Wh in the worst case month and orientation. Given space constraints, we included three such panels wired in parallel, providing 30.6 Wh. Because the panels are oriented 120° apart and thus not all pointing north, the actual lower bound of expected energy is 94.5 Wh, providing a 5.2x factor of safety to accommodate unexpected losses.

⁸<https://pvwatts.nrel.gov/>

⁹<https://docs.particle.io/tools/developer-tools/battery-calculator/>

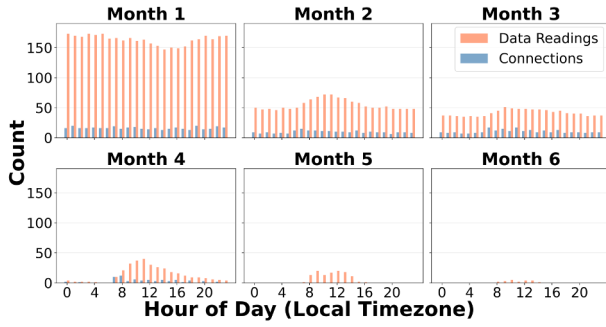


Fig. 6. Distribution of the hourly number of sensor readings for Makak 01, aggregated for each deployment month. Target: 4 readings per hour x 30 days = 120 readings. Month 1 is higher because of the initial higher sampling rate.

2) *Power and Solar Charging: Results:* Energy was an issue for nearly every device. We expected 96 sensor readings and 4 cloud uploads per day, but most devices reported far fewer especially after one month. For example, as Fig. 6 demonstrates, Makak 01 took data readings and connected to a cell tower with a relatively even hourly distribution over the first 30 days of the deployment. Days 31-60 and 61-90 show a slight skew towards sunlight hours and fewer overall readings. The remaining time periods show this trend strengthening, eventually with almost no readings outside of sunlight hours.

This clear energy imbalance indicates our incorrect understanding of the amount of sunlight available, the efficiency of converting sunlight to stored energy, the rate of device energy consumption, or some combination thereof. Unfortunately, the microcontroller manufacturer had not calibrated the battery fuel gauge¹⁰, so we did not have direct access to device battery percentage. Analysis of which devices demonstrated the earliest onset of daylight bias suggests that *tree cover is at least partially to blame*. The four devices deployed under dense tree canopy all started showing signs of daylight skew by at least week 6, significantly earlier than most of the devices that were deployed under an open canopy.

Measurements of the voltage and current generated under different sunlight conditions also suggest that *our focus on overall energy, rather than further breaking down the analysis into voltage and current, severely overestimated the amount of energy harvested*. The PVWatts tool provided an estimate of how much energy the panel would produce over a month, but did not provide insight into the distribution of voltages and currents that composed this energy calculation. We assumed that all of this energy would be generated at least at 4.4V, the minimum voltage our charging circuit needs to charge the battery. However, outdoor tests under partial cloud cover showed a generated voltage of 3.45V. The Makak could not leverage sunlight under these and similar conditions, greatly reducing the amount of energy available. There are too many factors and unknowns to further quantify these impacts, but clearly insufficient energy was harvested.

¹⁰<https://community.particle.io/t/muon-and-battery-weird-behavior/68807>

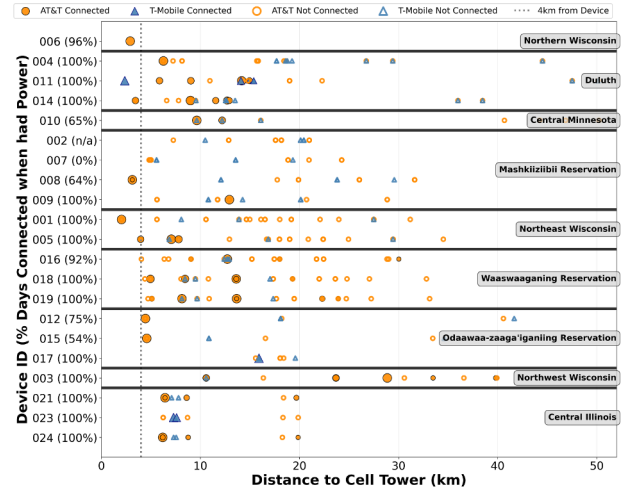


Fig. 7. Visualization of the distance from each Makak to nearby AT&T and T-Mobile towers (differentiated by shape/color), whether or not it connected (shading), and how many times it connected (size). N/a indicates there is no evidence the device powered on.

C. Cellular Connectivity

Reliable, low-latency connectivity is crucial for many WSN applications, and leveraging existing cellular networks can be a scalable and reliable option [49]. However, predicting coverage, especially in the rural United States where coverage maps are often inaccurate, presents a challenge [33].

1) *Cellular Connectivity: Analysis:* Makaks relied on the built-in modem to decide which tower to connect to, with our state machine deciding when to initiate connections based on the time and battery state. Each time a Makak connected to a cell tower, we recorded metadata with the cell identification number, signal strength, signal quality, and timestamp. We used these metadata to determine how reliably each device connected, the system state when it did not connect, and the variety of cell towers it switched between. To ensure that our analysis accounted for nearby towers that the Makaks did not connect to, we manually added the AT&T and T-Mobile cell ids within a 10km radius of each Makak. Fig. 7 shows the connection status, distance to each cell tower, and number of connections for the first 30 days of each Makak deployment.

2) *Cellular Connectivity: Results:* Connectivity varied widely across devices. During the first month of deployment on days when they had power, 15 devices connected on over 90% of days, 4 devices connected 50 to 90% of days, and 2 devices never connected. Of these 19 that connected, 10 sent a plurality of their transmissions to the closest tower, while one Makak made connections to a tower nearly 40km away. These trends indicate that predicting whether a device will connect to any tower, let alone when a device will connect to a specific tower, is very challenging. Although there are best practices that improve reliable connectivity probability, the best ways to promote connection are via accurate, fine-resolution coverage maps and connectivity surveys using the system hardware.

Most Makaks connected to the same tower for the entire deployment, yet one device connected to 13 towers. Some devices oscillated between multiple towers throughout the deployment, while others (19, 21) appeared to have handoffs between towers during different time periods. Most devices connected primarily or exclusively to AT&T towers, which appear to be more abundant in the region. Devices that connected to T-Mobile towers seemed to do so even when other towers were closer, for example in the case of Makaks 21, 23, and 24, which were all deployed within 100 meters of each other. This tendency is likely attributable to the modem. All three devices that connected primarily to T-Mobile towers lasted for a week or less and were ultimately deemed to have water damage as their most likely cause of failure. Our most generalizable finding is that **of the devices that were not able to reliably connect to a tower, none of them had a cell tower within 4 km**. Many devices still connected even if they did not have a tower within 4km.

D. Subsystem Interaction

We designed Makak with the knowledge that subsystems would fail, and we therefore tried to isolate them and have fallback modes of operation when failures occur. There are clear limitations to isolation, for example with failures in key subsystems such as battery and SD storage preventing the other subsystems from functioning. Other subsystems, like individual sensing modalities and connectivity, were designed to not impact each other if something went awry. We cannot determine how often this design goal was successful, but by analyzing the temporal relationships between different subsystem failures we can identify useful insights.

To identify correlations between subsystem errors, we first generated baseline histograms of singular subsystem error timings across all deployed Makaks. Using the qualitative status data that we synthesized for each subsystem from sensor and connectivity data, we plotted the timing distribution of partial and total failures of each subsystem in two ways: (1) the number of days since the deployment started and (2) the number of days since May 1. This dual approach was necessary because devices were deployed over the course of 37 days, so we could visualize trends based on the deployment duration as well as any synchronization that may have happened due to weather or the time of year. We then generated histograms for the timing difference between each pair of subsystem changes/error for the same Makak to identify any trends between subsystems.

The only systems that showed evidence of correlation between events were the changes in sampling rate and the failure of the water surface temperature. As Fig. 8 conveys, on 14 occasions these events occurred within 6 days of each other, suggesting a relationship between the events without providing insight into the causal chain. We can see that other water surface temperature and sampling rate change events happen independent of each other, so their relationship is not the only factor driving their changes.

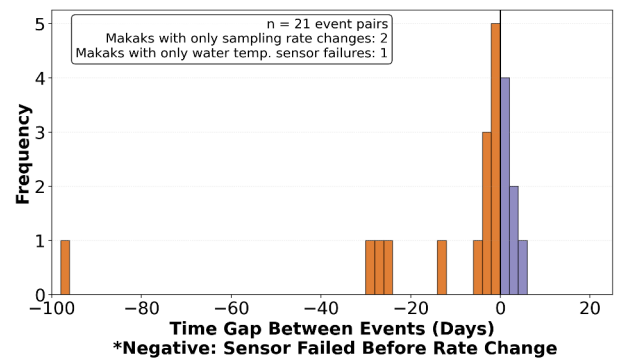


Fig. 8. Histogram of the timing difference between sampling rate changes and water surface temperature sensor failures on the same Makak. Note that the histogram has a point for every pair of events, so if one Makak experienced three sample rate changes and one sensor failure over the course of the deployment, three data points would be added.

Sampling rate changes most likely stemmed from a change in the amount of available energy, causing the Makak to go in or out of low power mode, or an error with the real time clock (RTC) that determined how long to sleep between data readings. The water surface temperature sensor demonstrated high fragility, likely caused by water damage, providing nulls or erroneous zeroes on at least 67% of the Makaks. Although we cannot determine the causal relationship between subsystems, we speculate that RTC malfunctions could cause the sampling rate to increase, which in turn could burn out the sensor with frequent readings. Regardless of the nature of these relationships, the mere existence of a relationship between some events has implications for design philosophy and overall implementation approaches.

VI. DISCUSSION

The design, deployment, and analysis of Makak reveals design recommendations for similar WSN deployments and opportunities for future research.

A. Design Recommendations

Based on the findings described in Section V, we identify the following design recommendations:

- 1) **Sensor selection: the air pressure, air temperature, light, and water temperature sensors we employed demonstrate good performance compared to higher-cost standards.** The combination of air and water pressure sensors also demonstrate a reliable and accurate method of calculating water level change. The dissolved oxygen and relative humidity sensors showed potential for high-quality environmental monitoring, but different physical configurations and further validation are necessary for applications that require high accuracy. Our deployment of the conductivity sensor at the water's surface did not provide valid data; future studies should explore the impact of depth and water flow on the validity of low-cost conductivity sensor measurements.

- 2) Solar panel system design: **When selecting and configuring solar panels, design for voltage in addition to total energy produced.** If a system has a wide tolerance of input voltages, consider a combination of series and parallel configurations to ensure that provided voltage will be high enough on low-light days while also making sure that one low-light panel will not block the current generated by other panels. Alippi and Galperti propose a circuitry solution for the problem [32].
- 3) Location selection for connectivity: **if using LTE-M for connectivity, prioritize WSN placement within 4km of a tower.** If possible, conduct a survey prior to deployment to map the connectivity landscape at sites of interest and acquire accurate fine-resolution coverage maps. We suspect that river deployments present especially challenging connectivity environments because of their location at topographical minima and the large amount of biomass that often grows nearby.
- 4) Subsystem complexity and interaction: **try to limit the overall number of components and system complexity** [12], because even with well-planned system isolation there may still be domino-effect failures between systems. Emulate and test many different failure states and their impact on other subsystems, even when there is no clear causal relationship between those two systems.
- 5) Status metadata: With access to more status metadata, we could have conducted a deeper analysis with less time and effort. Our design relied on system-generated metadata, such as battery percentages, that we trusted without full verification. **We recommend backing up key metadata in multiple places (Flash, SD card, and the cloud).** Take many pictures during assembly and deployment, which can be crucial in characterizing what happened and can provide metadata such as location information and timestamps.

B. Future Work

Our results highlight opportunities to design better tools and frameworks for long-term WSN deployments. Fusing multiple data sources to predict connectivity and energy availability in a nuanced way could improve design and deployment decisions. Synthesizing LiDAR/topographical data, historical weather data, tree and leaf cover data, connectivity survey data, and circuit equations for solar charging may also aid in rural WSN deployments by providing a better chance of remaining powered and connected throughout their deployment. An evaluation framework for extended WSN deployments could provide valuable guidance on how to analyze common data streams like sensor readings, power, and connectivity. If this framework can be general enough to apply to many scenarios and specific enough to provide useful analysis, it would benefit individual deployments and the wider WSN community by standardizing metrics for comparison. Finally, further knowledge based on real-world experiences deploying sensors in harsh (e.g. wet, remote, hot, or cold) environments would be valuable to many in this community.

C. Limitations

This study was based on a WSN deployment primarily intended to provide partner organizations with useful and timely environmental data. Findings are based on a relatively small number of devices that did not experience a representative sample of the environmental conditions in the region. The lack of in-depth logging, battery status, and ubiquitous knowledge about the circumstances Makaks experienced means that we had to reconstruct and derive system statuses and events from other data sources, making informed inferences along the way. Future Makak deployments should strive for improvement rather than perfection, addressing the shortcomings of the past while acknowledging the impossibility of a perfect system.

VII. CONCLUSION

Environmental data from low-cost WSNs present tremendous opportunities to better understand and steward the world's remote natural spaces in a scalable and accessible manner. Few deployments have achieved this promise due to challenges in reliable sensing modalities, power, connectivity, and system complexity, among other socio-technical limitations like alignment with user goals and contexts. The Makak design attempted to address these technical challenges, and the deployment and subsequent analysis of 21 of these devices over a 6 month period in the summer of 2025 provides insight into both the specific shortcomings of the Makak design and general principles of any WSN design. Our analysis on individual low-cost sensing modalities, solar charging, LTE-M connectivity, and unexpected interactions between subsystems lend themselves to design recommendations for future remote environmental sensor network deployments. By increasing the number of scenarios remote WSNs can accessibly be deployed long-term, we hope that embedded systems can play an increased role in promoting sustainable futures.

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REFERENCES

- [1] A. S. Lutakamale and S. Kaijage, "Wildfire monitoring and detection system using wireless sensor network: A case study of tanzania," 2017.
- [2] M. Kaur, K. Singh, and S. Kumar, "Biodiversity sensor: a customized and power efficient solution for biodiversity surveillance," *IEEE Sensors Journal*, vol. 23, no. 24, pp. 31 159–31 170, 2023.
- [3] I. Zaman, J. Dede, M. Gellhaar, H. Koehler, and A. Foerster, "Molenet: A new sensor node for underground monitoring," *IEEE SenseApp*, 2016.
- [4] S. Easterbrook, "From computational thinking to systems thinking: A conceptual toolkit for sustainability computing," in *ICT for Sustainability 2014 (ICT4S-14)*. Atlantis Press, 2014, pp. 235–244.
- [5] L. M. Hilty and B. Aebischer, "Ict for sustainability: An emerging research field," *ICT innovations for Sustainability*, pp. 3–36, 2015.
- [6] M. T. Lazarescu, "Design and field test of a wsn platform prototype for long-term environmental monitoring," *Sensors*, vol. 15, no. 4, pp. 9481–9518, 2015.
- [7] B. Rothrock, E. Greenlee, Y. Sangar, J. McKenna, W. Graveen, K. Hanson, M. Lewis, K. Smith, M. Falck, B. Byrne *et al.*, "Makak: Co-designing environmental sensors to protect manoomin (wild rice)," in *Proceedings of the ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies*, 2025, pp. 115–130.
- [8] D. Ekhajzer, L. Bornes, J. Combaz, C. Letondal, and R. Vingerhoeds, "Decision-making under environmental complexity: the need for moving from avoided impacts of ict solutions to systems thinking approaches," in *2024 10th International Conference on ICT for Sustainability (ICT4S)*. IEEE, 2024, pp. 29–40.
- [9] N. R. Patel and S. Kumar, "Wireless sensor networks' challenges and future prospects," in *2018 International Conference on System Modeling & Advancement in Research Trends (SMART)*. IEEE, 2018, pp. 60–65.
- [10] B. Nardi, B. Tomlinson, D. J. Patterson, J. Chen, D. Pargman, B. Raghavan, and B. Penzenstadler, "Computing within limits," *Communications of the ACM*, vol. 61, no. 10, pp. 86–93, 2018.
- [11] A. H. Dehwah, M. Mousa, and C. G. Claudel, "Lessons learned on solar powered wireless sensor network deployments in urban, desert environments," *Ad Hoc Networks*, vol. 28, pp. 52–67, 2015.
- [12] X. Fafoutis, A. Elsts, R. Piechocki, and I. Craddock, "Experiences and lessons learned from making iot sensing platforms for large-scale deployments," *IEEE Access*, vol. 6, pp. 3140–3148, 2017.
- [13] A. Cabral, V. Ranganathan, and J. Waldo, "Cellular lte and solar energy harvesting for long-term, reliable urban sensor networks: Challenges and opportunities," *arXiv preprint arXiv:2307.04016*, 2023.
- [14] C. Mydlarz, M. Sharma, Y. Lockerman, B. Steers, C. Silva, and J. P. Bello, "The life of a new york city noise sensor network," *Sensors*, vol. 19, no. 6, p. 1415, 2019.
- [15] P. J. Basford, F. M. Bulot, M. Apetroaie-Cristea, S. J. Cox, and S. J. Ossont, "Lorawan for smart city iot deployments: A long term evaluation," *Sensors*, vol. 20, no. 3, p. 648, 2020.
- [16] L. Joris, F. Dupont, P. Laurent, P. Bellier, S. Stoukatch, and J.-M. Redouté, "An autonomous sigfox wireless sensor node for environmental monitoring," *IEEE Sensors Letters*, vol. 3, no. 7, pp. 01–04, 2019.
- [17] E. Kadusic, C. Ruland, N. Hadzajlic, and N. Zivic, "The factors for choosing among nb-iot, lorawan, and sigfox radio communication technologies for iot networking," in *2022 international conference on connected systems & intelligence (CSI)*. IEEE, 2022, pp. 1–5.
- [18] M. Navarro, T. W. Davis, Y. Liang, and X. Liang, "A study of long-term wsn deployment for environmental monitoring," in *2013 IEEE 24th annual international symposium on personal, indoor, and mobile radio communications (PIMRC)*. IEEE, 2013, pp. 2093–2097.
- [19] F. M. Al-Turjman, H. S. Hassanein, and M. Ibnkahla, "Towards prolonged lifetime for deployed wsns in outdoor environment monitoring," *Ad Hoc Networks*, vol. 24, pp. 172–185, 2015.
- [20] C. O. Mathuna, T. O'Donnell, R. V. Martinez-Catala, J. Rohan, and B. O'Flynn, "Energy scavenging for long-term deployable wireless sensor networks," *Talanta*, vol. 75, no. 3, pp. 613–623, 2008.
- [21] S. Sahu and S. Silakari, "Analysis of energy, coverage, and fault issues and their impacts on applications of wireless sensor networks: a concise survey," *network*, vol. 10, p. 13, 2021.
- [22] G. Barrenetxea, F. Ingelrest, G. Schaefer, and M. Vetterli, "The hitchhiker's guide to successful wireless sensor network deployments," in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, 2008, pp. 43–56.
- [23] C. Jamroen, N. Yonsiri, T. Odthom, N. Wisitthiwong, and S. Janreung, "A standalone photovoltaic/battery energy-powered water quality monitoring system based on narrowband internet of things for aquaculture: Design and implementation," *Smart Agricultural Technology*, vol. 3, p. 100072, 2023.
- [24] K. Qayyum, I. Zaman, and A. Förster, "H2o sense: a wsn-based monitoring system for fish tanks," *SN Applied Sciences*, vol. 2, no. 10, p. 1643, 2020.
- [25] G. A. López-Ramírez and A. Aragon-Zavala, "Wireless sensor networks for water quality monitoring: a comprehensive review," *IEEE access*, vol. 11, pp. 95 120–95 142, 2023.
- [26] M. Pule, A. Yahya, and J. Chuma, "Wireless sensor networks: A survey on monitoring water quality," *Journal of applied research and technology*, vol. 15, no. 6, pp. 562–570, 2017.
- [27] K. S. Adu-Manu, C. Tapparello, W. Heinzelman, F. A. Katsriku, and J.-D. Abdulai, "Water quality monitoring using wireless sensor networks: Current trends and future research directions," *ACM Transactions on Sensor Networks (TOSN)*, vol. 13, no. 1, pp. 1–41, 2017.
- [28] A. Delgado, C. Briciu-Burghina, and F. Regan, "Antifouling strategies for sensors used in water monitoring: review and future perspectives," *Sensors*, vol. 21, no. 2, p. 389, 2021.
- [29] M. N. Hussain, M. A. Halim, M. Y. A. Khan, S. Ibrahim, and A. Haque, "A comprehensive review on techniques and challenges of energy harvesting from distributed renewable energy sources for wireless sensor networks," *Control Systems and Optimization Letters*, vol. 2, no. 1, pp. 15–22, 2024.
- [30] J. Amusan and E. Otokunefor, "The effect of cloud on the output performance of a solar module," *International Journal of Engineering Science*, vol. 9, no. 2, pp. 19 665–19 671, 2019.
- [31] D. S. Hasan, M. S. Farhan *et al.*, "Impact of cloud, rain, humidity, and wind velocity on pv panel performance," *Wasit Journal of Engineering Sciences*, vol. 10, no. 2, pp. 34–43, 2022.
- [32] C. Alippi and C. Galperti, "An adaptive system for optimal solar energy harvesting in wireless sensor network nodes," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 55, no. 6, pp. 1742–1750, 2008.
- [33] K. Salemin, D. Strijker, and G. Bosworth, "Rural development in the digital age: A systematic literature review on unequal ict availability, adoption, and use in rural areas," *Journal of rural studies*, vol. 54, pp. 360–371, 2017.
- [34] B. Palacios Abad, E. Belding, M. Vigil-Hayes, and E. Zegura, "Mending the fabric: the contentious, collaborative work of repairing broadband maps," *Proceedings of the ACM on Human-Computer Interaction*, vol. 8, no. CSCW2, pp. 1–24, 2024.
- [35] T. Tamir, "On radio-wave propagation in forest environments," *IEEE Transactions on Antennas and Propagation*, vol. 15, no. 6, pp. 806–817, 2003.
- [36] Federal Communications Commission, "Broadband deployment report," Federal Communications Commission, Tech. Rep., Feb. 2018, accessed: 2026-01-27. [Online]. Available: <https://www.fcc.gov/reports-research/reports/broadband-progress-reports/2018-broadband-deployment-report>
- [37] S. R. Borkar, "Long-term evolution for machines (lte-m)," in *LPWAN technologies for IoT and M2M applications*. Elsevier, 2020, pp. 145–166.
- [38] M. B. Hassan, E. S. Ali, R. A. Mokhtar, R. A. Saeed, and B. S. Chaudhari, "Nb-iot: Concepts, applications, and deployment challenges," in *LPWAN Technologies for IoT and M2M Applications*. Elsevier, 2020, pp. 119–144.
- [39] T. C. Stevenson, "New description of box for holding thermometers," *J. Scottish Meteorol. Soc.*, vol. 1, p. 122, 1864.
- [40] T. Despres, P. Dutta, and S. Ratnasamy, "Make way for ducklings: Centering data files in sensor networks," in *Proceedings of the 26th International Workshop on Mobile Computing Systems and Applications*, 2025, pp. 97–102.
- [41] P. Maistriaux, T. Pirson, M. Schramme, J. Louveaux, and D. Bol, "Modeling the carbon footprint of battery-powered iot sensor nodes for environmental-monitoring applications," in *Proceedings of the 12th International Conference on the Internet of Things*, 2022, pp. 9–16.
- [42] E. Kallitsis, J. J. Lindsay, M. Chordia, B. Wu, G. J. Offer, and J. S. Edge, "Think global act local: The dependency of global lithium-ion battery emissions on production location and material sources," *Journal of cleaner production*, vol. 449, p. 141725, 2024.
- [43] B. Smith, A. Sekar, H. Mirlatz, G. Heath, and R. Margolis, "An updated life cycle assessment of utility-scale solar photovoltaic systems installed

- in the United States,” National Renewable Energy Laboratory, Tech. Rep., 2024.
- [44] J. Malmmodin and D. Lundén, “The energy and carbon footprint of the global ict and e&m sectors 2010–2015,” *Sustainability*, vol. 10, no. 9, p. 3027, 2018.
 - [45] D. H. P. Kang, M. Chen, and O. A. Ogunseitan, “Potential environmental and human health impacts of rechargeable lithium batteries in electronic waste,” *Environmental science & technology*, vol. 47, no. 10, pp. 5495–5503, 2013.
 - [46] S. Mann, M. Karetai, R. Myers, and J. Vaughan, “Story re-telling: A decolonial approach to sustainable ict,” in *2025 11th International Conference on ICT for Sustainability (ICT4S)*. IEEE, 2025, pp. 286–295.
 - [47] D. J. O’Connor, “The temporal and spatial distribution of dissolved oxygen in streams,” *Water Resources Research*, vol. 3, no. 1, pp. 65–79, 1967.
 - [48] R. G. Wetzel, *Limnology: lake and river ecosystems*. gulf professional publishing, 2001.
 - [49] T. H. Moges, D. S. Lakew, N. P. Nguyen, N.-N. Dao, and S. Cho, “Cellular internet of things: Use cases, technologies, and future work,” *Internet of Things*, vol. 24, p. 100910, 2023.