ECOHABIT: A COMMUNITY SCIENCE TOOL FOR HARMFUL ALGAL BLOOM EDUCATION AND IDENTIFICATION

Master's Capstone Submitted to the Faculty of the Bard Center for Environmental Policy

By Robert Howe

In partial fulfillment of the requirement for the degree of

Master of Science in Climate Science and Policy

Bard College

Bard Center for Environmental Policy

P.O. Box 5000

Annandale on Hudson, NY 12504-5000

May 2026

Table of Contents

Acknowledgments

I am extremely grateful to the faculty and staff of Bard, with whom I have had the chance to learn, as well as to my wonderful peers and the Wallkill River Watershed Alliance, who have all been integral to the work. I give my sincerest gratitude to all those who made this possible and those whose names may not appear here, but whose efforts were essential, nonetheless.

To my advisor, Jennifer Phillips, I cannot thank you enough for taking me on, providing me with this hands-on learning experience, and helping me through this process every step of the way.

To Caroline Ramaley, thank you for your constant support, advice, and care.

To Steven Valles, thank you for helping me with technical issues and being a supportive best friend, always willing to help.

To my family, Mom, Dad, Becca, and Grandma, who encourage me to keep pushing forward, thank you for your care, love, and support. Thank you for always being willing to help in any way you could and for providing me with insightful feedback

To my many friends—Cole Ewalt, Shawn Wallbillich, Julian Wilson, and Frank Parasio—I am thankful for the encouragement, feedback, and support along the way.

To my friends at Riverkeeper and Hudson River Watershed Alliance — Shannon Roback, Dan Shapley, and Emily Vail — Thank you for giving me the experience and the opportunity to work on real-world applications in the watershed related to EcoHabit.

To my friends at SUNY Ulster—Mike Burke, Jennifer Guiher, and Telemak Olsen—thanks for giving me the opportunity to learn to use the Water Quality equipment and to help teach the class on GIS aerial mapping.

To Ulster County Department of the Environment — Ella Cattabiani — Thank you for helping me promote EcoHabit and for expressing interest in future iterations.

To Open Space Institute — Thank you for accepting me into the Barnabas McHenry Fellowship; this was the first big step toward understanding the gap in HABs monitoring on the Wallkill River.

To my Bard CEP cohort and fellow graduates, thank you for your emotional support during the capstone process. There is much to be proud of what we have accomplished!

Abstract

Harmful algal blooms (HABs) are an increasing freshwater concern because they can produce toxins that threaten people, pets, and wildlife. Monitoring watersheds at the community level remains challenging because traditional methods depend on trained personnel, field sampling, laboratory analysis, and agency resources, which makes continuous monitoring of every part of the watershed unfeasible. This capstone addresses the gap by developing and evaluating EcoHabit, a replicable community-science web platform designed to help watershed stakeholders recognize potential HABs, interpret environmental data, and understand when local observations warrant reporting. The nine-step, self-paced online exercise was tested in the Wallkill River watershed in the Hudson Valley of New York. The tool included a preliminary survey, a visual HAB identification task, an environmental dashboard interpretation module, a second visual identification scenario, an optional satellite imagery component, and a post-survey with questions about user experience and future improvements. Identification accuracy increased from 61.0% initially to 87.8% in the second scenario. Furthermore, participants reported gaining more knowledge about HABs, rating the overall tool favorably, and being highly likely to report suspected blooms afterward. Open-ended comments suggest that EcoHabit effectively raises community awareness of HABs and encourages watershed stewardship.

Executive Summary

Introduction

Harmful algal blooms (HABs) are toxic cyanobacteria that pose an increasing threat to freshwater systems, producing toxins that affect people, pets, and wildlife (Watson et al., 2016). Growth is associated with nutrient input from agricultural runoff, wastewater treatment, and other land-use pressures. Climate change-related warming and increased carbon dioxide can further exacerbate these effects (Chorus & Welker, 2021; Igwaran et al., 2024; Urrutia-Cordero et al., 2020). In 2025, HAB concerns became especially visible in the Wallkill–Hudson system: The New York State Department of Environmental Conservation (NYSDEC) confirmed a Hudson River HAB report in mid-August and received additional reports through late summer and early fall, while regional reporting documented additional confirmed HABs on the Wallkill River and described the Hudson River bloom as unprecedented and the largest detected by Cary Institute researchers in nearly 40 years (New York State Department of Environmental Conservation, 2025; HVNY, 2025).

Despite the seriousness of HAB risks, community-level monitoring remains difficult (Chorus & Welker, 2021). Conventional monitoring remains essential, but it depends on trained personnel, field sampling, laboratory analysis, and agency capacity that cannot always cover every river segment (Clites et al., 2024). This creates a gap between when community members first notice suspicious water conditions and when institutions can confirm and respond. EcoHabit addresses this gap by testing a web-based community science tool designed to help watershed users recognize potential HABs, interpret environmental

data, and understand when local observations may warrant reporting. Although the tool was tested with adults who use, manage, or live near the Lower Wallkill River in Ulster County, New York, its structure is intended to serve as a replicable model for watershed-based HAB education and reporting preparation. This capstone prefers "community science” over “citizen science" to emphasize that EcoHabit is designed for HAB education for anyone connected to the river, regardless of background, institutional ties, or legal status.

Community Science and Digital Design

This capstone draws on two traditions in public participatory science programs. The first highlights the importance of standardized data collection and scientific rigor, with volunteers assisting researchers in gathering data for analysis and regulation. The second centers on democracy, community empowerment, local problem-solving, shared interpretation, and the use of science to inform decisions (Irwin, 1995; Johnson et al., 2017; Shirk et al., 2012). EcoHabit draws from both traditions by treating HAB monitoring as both a technical challenge and a community learning process.

This integration matters because environmental monitoring is not only a method for gathering information; it can also cultivate stewardship (Haywood et al., 2024). Stewardship is understood here as ongoing action to preserve, restore, or sustainably manage natural resources for community benefit (Bennett et al., 2018). Monitoring is important because it distinguishes active stewardship from general environmental concern. Someone concerned about water quality might be environmentally conscious, but someone who consistently observes, interprets, and reports water conditions assumes the role of a steward. EcoHabit was created to facilitate this shift by providing users with a structured method for practicing

HAB recognition and environmental interpretation within a local watershed setting, while also offering a framework that other watershed organizations could adapt to their own place-based monitoring needs.

Digital tools can support this process when they are designed as learning environments rather than simple data submission forms. EcoHabit's structure reflects evidence-based principles from the community science and digital training literature, including progressive skill-building, self-paced instruction, situated learning, iterative feedback, and tiered participation (Hart et al., 2021; Strobl et al., 2020). Instead of asking users only to submit observations, EcoHabit guides them through a sequence of tasks that build on one another. Participants begin with visual identification, then interpret environmental data, and then apply what they have learned to a new scenario. This design allows users with varying levels of prior knowledge to participate.

The use of "community science" also aligns with EcoHabit's design choices. The tool was built as an asynchronous, browser-accessible platform that does not require specialized equipment, institutional affiliation, or advanced technical training for the core exercise. These features are important because a terminology shift alone does not make a project inclusive, meaning the tool must also reduce structural barriers to participation.

HABs are difficult to monitor because they are shaped by several interacting environmental factors. Nitrogen and phosphorus contribute to bloom growth, while warm temperatures, sunlight availability, elevated pH, stagnant or slow-moving water, and long residence times can create conditions that favor cyanobacterial proliferation in areas with stagnant surface water (Bonilla et al., 2023; Zepernick et al., 2023). Human activities such as agricultural runoff, wastewater discharges, faulty septic systems, altered hydrology, and land-use changes can intensify these conditions (Chorus & Welker, 2021; Igwaran et al., 2024).

While on-site monitoring remains crucial, it faces limitations, including high costs and extensive training requirements (Clites et al., 2024). Remote sensing methods, such as satellite imagery and drone footage, can enhance coverage but cannot confirm toxin production and are difficult for non-experts to interpret (Khan et al., 2021). EcoHabit tackles these issues through a hybrid educational model that enables community members to identify suspicious conditions, analyze environmental data, and know when to report issues. This method combines visual training, environmental data analysis, and optional exposure to remote sensing, making it adaptable for watershed groups aiming to improve community HAB education and reporting readiness.

Methods

EcoHabit was developed as an asynchronous, web-based educational platform and study tool. It aimed to enhance community-level skills in identifying potential HABs and analyzing environmental data. The exercise followed a cumulative learning sequence, with each stage building on the previous one, enabling it to serve both as an educational intervention and as a data-collection tool to assess learning, user experience, and stewardship responses.

The nine-step EcoHabit exercise moved participants through a pre-survey, a reference-guided HAB identification task, an interpretation of an environmental dashboard, a transfer scenario without the original reference guide, an optional satellite imagery module, and a post-survey/debrief. This sequence enabled the tool to function as both an educational intervention and a means to assess learning, user experience, and stewardship-related outcomes.

The study enlisted adults from the Lower Wallkill River watershed, including residents, users, and managers of the area. This local sample acted as a case to test whether EcoHabit's framework could effectively support watershed-based HAB education and community reporting. Recruitment materials were distributed via the Wallkill River Watershed Alliance email list, the SUNY Ulster Environmental Science Department, the Wallkill Valley Land Trust email list, and to attendees of the Water Quality Coordination Committee. Data collection ran over nine weeks, from February 19 to April 23, 2026. To protect identities, each participant received a randomized alphanumeric user ID.

Results

A total of 41 participants completed the exercise. They were divided into two groups based on main river activity: those involved in hiking, walking, recreation, or residency were labeled "Recreators," and those engaged in stewardship or scientific work were labeled "Stewards." The final sample included 34 recreators and 7 stewards or scientific participants.

In Step 3, during the initial visual identification task, 25 out of 41 participants correctly identified the HAB image, resulting in an accuracy of 61.0. After using the environmental data dashboard in Step 5, 34 of 41 participants correctly classified the environmental risk condition, reaching an accuracy of 82.9%. In Step 6, during the transfer scenario without the original reference guide, 36 of 41 participants correctly chose the suspicious image, achieving an accuracy of 87.8%. The increase in performance from Step 3 to Step 6 was statistically significant (McNemar's test, $\chi^2 = 6.67$, $p = .0098$).

Participants reported increased knowledge and willingness to act after completing the tool. Self-rated HAB knowledge rose from 3.02 to 3.66 on a 1–5 scale. Perceived HAB risk in the Wallkill River averaged 4.24 out of 5.0, and confidence in reporting HABs was 7.32 out of 10.0. The likelihood of reporting a suspected HAB was 4.0 out of 5.0, with 27 of 41 participants at the highest levels. Overall, the EcoHabit tool was rated positively, with an average of 4.32 out of 5.0. The stewardship cohort rated it at 4.37, and recreators 4.27.

EcoHabit's tiered design encouraged engagement: 19 of 41 participants, including all seven stewardship members and 12 of 34 recreators, chose the optional satellite imagery module. Observations included phycocyanin signatures, green scum near the low-flow shoreline, and timestamps that matched bloom conditions at Sturgeon Pool in September 2025. Qualitative feedback showed participants valued visual materials, dashboard data, and place-based imagery. In response to the "most helpful" prompt, 38.5% highlighted interactive dashboard data, 33.3% emphasized visual guides and bloom photographs, and 28.2% focused on satellite imagery. Participants found the dashboard helpful, noting that maps, aerial views, and visual interpretations significantly aided in recognizing HAB conditions. They reported that images and visual cues contributed to their understanding. Suggested improvements focused on clearer photographs, stronger dashboard explanations, persistent threshold references, simplified satellite instructions, and better browser/mobile compatibility.

Conclusions and Recommendations

EcoHabit served as both an educational tool and a bridge connecting HAB recognition, data interpretation, and watershed stewardship. It began with simple visual tasks and progressed to complex analysis. Visual training alone wasn't enough; combining photos with environmental data enhanced interpretation, particularly when water conditions are ambiguous. The optional satellite module showed success in tiered participation, with many interested in deeper engagement. Participant feedback highlighted the need for clearer design, including expanding the image library, improving dashboard access, and simplifying the satellite module. As HAB risks increase under nutrient loading, climate change, and changing watershed conditions, tools like EcoHabit can help communities become more prepared and confident partners in protecting freshwater resources.

Recommendation 1: The NYS DEC should Adopt EcoHabit as a Model for HAB Identification Training

The New York State Department of Environmental Conservation should consider EcoHabit-style digital training as a companion resource for HAB reporting groups. By teaching users to distinguish likely HABs from look-alikes, interpret basic environmental data, and build confidence in reporting suspicious observations, EcoHabit could improve front-end reporting quality, especially in flowing-water systems such as the Wallkill River.

Recommendation 2: Develop Localized Watershed Versions of EcoHabit

EcoHabit should also be treated as a replicable model for other watersheds. Localized versions could include site-specific photographs, monitoring points, reporting guidance, and regional HAB look-alikes, helping community members recognize local bloom conditions and participate more confidently in water quality governance. With improvements to its visual library, dashboard guidance, and satellite imagery pathway, EcoHabit could serve as a replicable model for watershed-based HAB education and community reporting preparation.

Recommendation 3: Simplify the Satellite Imagery Pathway.

The final major improvement concerns the optional satellite module, which offered one of EcoHabit's most innovative opportunities for deeper engagement but also created the most technical friction for users. Future iterations should simplify the instructions and include a fallback instructional video so users can access the module even when the live tool is confusing or difficult to load, preserving its exploratory value while reducing accessibility barriers.

Chapter One: Introduction

Water is the keystone of all life on Earth, an essential resource that is becoming scarce amid urbanization and rising global temperatures due to climate change (Liu et al., 2023). Anthropogenic impacts on water quality have heightened demand for local watershed management as a vital and urgent environmental issue (Simon et al., 2023). Studies have linked climate and unsustainable land use to increases in toxic cyanobacteria harmful algal bloom (HAB) outbreaks (Wang et al., 2018). Feedback loops between HABs and climate change pose a significant threat to ecosystems and human health by producing toxins, with microcystin being the most common (Watson et al., 2016). Microcystin can cause physiological harm to humans, such as organ and neurological damage, and may be lethal to exposed wildlife (Watson et al., 2016). In addition to producing toxins, HABs can invade lakes and stagnant rivers by lowering oxygen levels, creating hypoxic environments, and increasing water pH, affecting aquatic life at all trophic levels (Watson et al., 2016).

Addressing systemic watershed issues, such as recurring HABs, is a constant challenge due to insufficient community knowledge and resources (Simon et al., 2023). Government-organized resource management often lacks democratic decision-making, thereby excluding local communities (Medema et al., 2017). However, community-based science programs can increase local stewardship among communities that want to govern the results of shared natural resources. They are local volunteer-driven grassroots projects run by those who use environmental monitoring and community outreach to protect resources such as recreational surface waters. This capstone presents a case study of citizen-science engagement in HABs management within New York's Wallkill River Watershed. It aims to identify a) the most effective online methods for community science projects in environmental monitoring; and b) how public science program design can foster meaningful community involvement in natural resource governance.

HABs proliferate when toxic cyanobacterial contamination from an existing bloom is introduced into a freshwater system with favorable conditions, including warm temperatures, excess nutrients, and stagnant water (Zepernick et al., 2023; Igwaran et al., 2024). Nutrient loading that fuels HABs can be evident through visual signs of eutrophication, or excess nutrients in a body of water that drive algal growth. HAB growth intensifies in stagnant water that receives abundant daily sunlight, especially at temperatures above 25℃. These conditions allow cyanobacteria to develop into an algal bloom, thereby affecting downstream and adjacent surface waters (Yang et al., 2021).

Conventional public science water programs use a combination of in-situ data-collection methods, in which community members take pictures of suspicious activity and upload them to a platform (Saleem et al., 2024). Technicians will then collect samples and perform lab analysis. This framework is problematic because the lab analysis required is resource-intensive for smaller groups. It also creates an information gap between data collectors and data interpretation specialists because scientists are responsible for conveying results to the broader community. Newer strategies for monitoring water quality include using satellite and uncrewed aerial vehicles (UAVs) for remote sensing (Khan et al., 2021). Data are collected using spectral indices that filter light reflectance, which are then used to analyze aerial images to detect phycocyanin, a key indicator pigment of cyanobacteria (Cheng et al., 2020; Khan et al., 2021). Although remote sensing has advanced environmental monitoring capabilities, it still faces challenges in community awareness frameworks that differ from those of on-site data collection. Programs that rely solely on remote sensing can be problematic because they lack consistency due to the need for sufficient cloud-free data (Beaulne et al., 2025). Integrated monitoring solutions include data-collection methods that engage users, promote a sense of communal responsibility, and leverage labor-free remote sensing data, such as that reviewed in van Noordwijk et al. (2021). Janatian et al. (2025) assert that the success of public participatory science projects depends on whether the community has monitoring tools that provide knowledge and awareness of the issue, enabling users to become citizen scientists with data interpretation skills and the capacity to develop coordinated response plans or preventive solutions. Successful small-scale programs can strengthen stewardship capacity through inclusive public activities, environmental education, and efforts to prevent natural resource degradation (Haywood et al., 2024). It also allows state-level environmental programs, such as the New York State Department of Environmental Conservation (NYSDEC), to prioritize economic resources toward other environmental issues less likely to be addressed by community-level programs.

HAB issues across New York have spiked, with NYSDEC reporting the most significant historical cyanobacteria outbreak in 40 years in the Lower Wallkill River and the Hudson River in the summer of 2025 (New York State Department of Environmental Conservation, 2025; HVNY, 2025). The research in this capstone draws from citizen science, community science, and environmental stewardship literature to develop and assess EcoHabit as a model for watershed-based HAB education and reporting. The tool was tested in the Lower Wallkill River area through collaboration with local watershed partners, but its framework is meant to guide similar community science initiatives in other watersheds, exemplified by the partnership between the Wallkill River Watershed Alliance and Bard College.

Approach and Roadmap

This capstone examines EcoHabit, a technology-enabled tool that fosters engagement, education, and community involvement in HAB monitoring within watershed environments. Tested in the Wallkill River area, the tool utilized local imagery and data to evaluate how a place-based digital interface can enhance HAB identification, environmental data analysis, and stewardship activities. Aerial footage of the river from the warmer months in 2025 was rendered onto an interactive map, showing HABS-affected areas. Participants of all backgrounds used the web tool. They were given open-ended feedback prompts about their experience using the tool to gauge the goals of creating an effective online interface for monitoring surface water and facilitating community participation for data collection and interpretation.

Chapter two reviews different frameworks of community science and citizen science, how they are integrated into water quality monitoring, the range of participatory models, and the ways volunteers contribute to collecting and interpreting water quality data. Building on this foundation, chapter three turns to HABs, examining the science of HAB formation in specific watersheds and assessing how these public participatory science approaches can support HAB detection and monitoring. Chapter four explains the methods and limitations for this case study, followed by the results and discussion presented in Chapter five. In the concluding chapter, the key findings and policy recommendations are discussed.

Chapter Two: Citizen Science and Community Science Foundations and the Cultivation of Environmental Stewardship

Introduction

Monitoring environmental quality at the scale necessary to protect human and ecosystem health demands resources that government agencies rarely possess (Conrad & Hilchey, 2011). For instance, in New York State, the Department of Environmental Conservation oversees water quality across thousands of miles of streams and lakes with only a fraction of the staff required for comprehensive coverage. These logistical constraints create information gaps that suggest effective environmental governance cannot rely solely on centralized institutions and necessitate distributed networks of engaged community members with the capacity and motivation to function as stewards of their local ecosystems (Shirk et al., 2012; Allf et al., 2022).

However, simply recruiting the public as data collectors is often insufficient to sustain long-term engagement or ensure rigorous results (Dickinson et al., 2012). The history of citizen science reveals two distinct theoretical traditions that have evolved to address this challenge. These traditions frequently operate at cross-purposes; one prioritizing data, the other democratization. Consequently, the central research question guiding this chapter is: How can technology-interfaced citizen science frameworks be designed to maximize community engagement and promote effective environmental stewardship? To address this inquiry, I synthesize foundational theories, volunteer psychology, and evidence-based design principles to identify the structural requirements for digital platforms that can transform volunteers from passive observers into active environmental analysts (Bonney et al., 2016).

These frameworks are then applied to the specific challenge of monitoring harmful algal blooms in freshwater watersheds, with a focus on the Wallkill River in Ulster and Orange counties, New York.

A Note on the Terminology "Citizen Science"

The terms "citizen science" and "community science" are related but not interchangeable in this capstone. "Citizen science" refers to the established scholarly and historical term for public participation in scientific research, including the data-centered and democracy-centered traditions that shaped the field's development (Irwin, 1995; Bonney et al., 2009; Bonney et al., 2016). "Community science," as used here, refers to EcoHabit's applied design philosophy: an inclusive, place-based approach to HAB education, environmental interpretation, and watershed stewardship that does not depend on legal citizenship, institutional affiliation, or prior technical expertise.

For clarity, this capstone uses "citizen science" when referring to historical scholarship, established frameworks, and published research, but uses "community science" when describing EcoHabit's place-based and stewardship-oriented design. EcoHabit supports this approach through an asynchronous, browser-accessible format.

Theoretical Foundations

Citizen science has deeper historical roots than commonly acknowledged (Dickinson et al., 2012). The first recorded instance of systematic public participation in scientific observation occurred in 1835, when William Whewell organized coordinated data collection on ocean tides across the British coast, enlisting volunteers to contribute observations using standardized protocols. This early effort established a foundational principle: systematic, distributed observations could yield scientifically valuable data when properly coordinated through clear instructions and consistent methodology (Wiggins & Crowston, 2011).

The modern citizen science movement traces its origins to the late 1800s, with the Audubon Society's Christmas Bird Count, initiated in 1900 (Dickinson et al., 2012). This annual project transformed bird monitoring from a specialized scientific domain into a participatory practice involving thousands of volunteers across North America. The Christmas Bird Count persists today, accumulating over 1.4 million observations annually and demonstrating the scalability and longevity possible when programs prioritize volunteer retention and engagement over rapid data extraction (Sullivan et al., 2014). The specific term "citizen science" emerged in 1989, applied to acid rain monitoring initiatives in which residents collected precipitation samples to document atmospheric pollution in areas government agencies had not studied (Dickinson et al., 2012). This usage marked a conceptual shift: citizen science was no longer merely data collection coordinated by scientists but rather a method through which communities generated knowledge about environmental problems affecting their own health and ecosystems (Johnson et al., 2017). The distinction proved foundational to theoretical development: science coordinated by citizens differs fundamentally from science serving citizens' needs.

Two Foundational Models: Data-Centric vs. Democracy-Centric

The field of citizen science has been shaped by two parallel but distinct theoretical traditions, both emerging in the 1990s (Wiggins & Crowston, 2011). Understanding these models is essential because most programs unconsciously favor one approach, often to their detriment (Conrad & Hilchey, 2011).

Rick Bonney, working at Cornell Lab of Ornithology, defined citizen science in 1996 as a research technique that enlists public participation in data collection. This top-down approach conceptualizes citizen science as a solution to research capacity constraints, thereby enabling professional scientists to address research questions that they alone cannot address due to resource limitations (Wiggins & Crowston, 2011). Volunteers serve as distributed sensors, collecting standardized observations under protocols designed by expert researchers (Kosmala et al., 2016). Quality assurance emphasizes expert review, statistical filtering to remove outliers, and methodological reproducibility. Projects following this model involve large-scale geographic or temporal monitoring. The model prioritizes scientific rigor: data appear in top-tier journals and have the potential to influence conservation policy and management decisions (Sullivan et al., 2014; Dickinson et al., 2012).

Cornell Lab's flagship project, eBird exemplifies this model. Launched in 2002, eBird aggregates bird observations from hundreds of thousands of volunteers worldwide into standardized datasets used for peer-reviewed research on continental-scale population dynamics, migratory patterns, and climate change impacts (Sullivan et al., 2014). This rigor has made eBird data acceptable to regulatory agencies, with eBird data appearing in over four hundred peer-reviewed publications and directly influencing conservation policy decisions (Cooper et al., 2014).

However, this approach treats volunteers primarily as interchangeable data points. The relationship between volunteers and scientists becomes extractive: volunteers provide observations, but interpretation, publication, and decision-making remain in the domain of credentialed researchers (Ottinger, 2010). This creates what scholars consider the "black hole" effect. Volunteers submit data but never learn how observations are used, whether their contributions changed scientific understanding, or how findings influenced management decisions. (Crimmins et al., 2017). The result: high attrition, with research showing that 67% of citizen science programs lose more than 50% of volunteers within six months (Robinson et al., 2021). Even successful programs like eBird struggle with retention, with a median participation duration under one year despite years of platform development.

Alan Irwin, a sociologist at the University of Liverpool, offered a contrasting vision in his 1995 book Citizen Science: A Study of People, Expertise and Sustainable Development (Irwin, 1995). Irwin defined citizen science as “science which assists the needs and concerns of citizens” and as “a form of science developed and enacted by citizens themselves.” Unlike Bonney’s definition, Irwin emphasized that scientific knowledge is not merely discovered but socially constructed through processes of negotiation and interpretation. The goal is not to assist scientists but to empower communities to generate knowledge that addresses problems affecting their own lives (Irwin, 1995; Johnson et al., 2017).

In Irwin’s framework, citizen science entails public participation in three domains: setting research agendas (communities identify problems worth studying rather than scientists recruiting volunteers for predetermined projects), interpreting findings (communities participate in data analysis and meaning-making rather than deferring to expert interpretation), and advocating for policy response (communities use data to influence decision-makers rather than waiting for scientists to translate findings into policy recommendations) (Johnson et al., 2017). This approach aligns with participatory action research, in which the research process itself serves as a mechanism for capacity-building, consciousness-raising, and political mobilization.

Irwin-model projects typically address environmental justice issues where communities challenge institutional power (Johnson et al., 2017). When the Flint, Michigan, government denied that lead contamination affected drinking water, residents initiated systematic water testing to generate evidence to the contrary. Community members collected samples from hundreds of homes and partnered with scientists at Virginia Tech to conduct laboratory analysis. They used data to demonstrate that government officials had lied about water safety. This citizen science project became inseparable from political advocacy: data collection served the explicit goal of holding the government accountable, protecting community health, and demanding infrastructure investment. The project succeeded in forcing government action—but only after exposing institutional failure and generating sustained public pressure (Johnson et al., 2017).

Frameworks using Irwin-model for projects face distinct challenges. Participatory processes are inherently time-intensive and complicated to scale (MacPhail & Colla, 2020). Community engagement in research design, data interpretation, and policy advocacy requires sustained relationship-building, multiple stakeholder meetings, and iterative negotiation. These investments limit the number of participants and geographic scope. Data standardization suffers when communities prioritize local relevance over reproducibility. A watershed group monitoring stream health may adapt protocols to address regional concerns rather than following standardized methods, enabling comparison with other watersheds. Regulatory agencies often dismiss community-generated data as “anecdotal” because it conflicts with standardized protocols, potentially undermining the policy influence these programs seek (Ottinger, 2010).

The Irwin and Bonney models are not mutually exclusive. Their strongest overlap appears in citizen science programs that combine rigorous data practices with environmental stewardship principles. Before addressing how to synthesize these models, it is necessary to clarify the relationship between citizen science and environmental stewardship. The two are often conflated but are theoretically distinct (Ballard et al., 2017). Environmental stewardship is defined as "systematic actions by individuals or groups with the intent of preserving, restoring, or sustainably managing natural resources for the benefit of their community" (Bennett et al., 2018). The term emphasizes routine, ongoing commitment rather than one-time volunteer events; it refers to practices that shape identity and behavior over years.

Environmental Stewardship as a Conceptual Bridge

Stewardship has deep historical roots in Indigenous cultures, with reciprocal relationships with nature long before industrialization; rotational harvesting to ensure species regeneration, sacred site protection to prevent overuse, and seasonal closures to allow ecosystem recovery. All were forms of stewardship grounded in intergenerational responsibility and accumulated ecological knowledge (Nikolakis et al., 2023). In modern contexts, Turnbull et al.(2020) use the Local Environmental Stewardship Indicator (LESI), which differentiates active stewards from general environmental sympathizers through a framework of seven defining behaviors. The seven key actions are preservation, restoration, monitoring, advocacy, sustainable use, informal enforcement, and pro-environmental education (Turnbull et al., 2020).

Of these seven actions, monitoring serves as the primary distinguishing factor between passive concern and active stewardship (Bennett et al., 2018). While many individuals express general sympathy for environmental causes, few commit to the systematic rigor of monitoring, which is defined as repeated observation over time using consistent methods to track trends and test hypotheses (Turnbull et al., 2020). This practice bridges the gap between abstract care and concrete agency. The distinction manifests empirically: a resident who worries about water quality remains a sympathizer, while a resident who collects weekly samples to document pollution trends embodies stewardship. Systematic observation thus functions not merely as a technical task but as a transformative act of evidence-based agency.

This insight carries profound implications for program design (Jørgensen & Jørgensen, 2021). Citizen science operates as more than a data-collection mechanism; it functions as a vehicle through which individuals develop stewardship identity (Jørgensen & Jørgensen, 2021). When individuals monitor stream health weekly over extended periods, they cultivate specialized ecological knowledge of that place. They internalize seasonal patterns invisible to casual observers, detect subtle environmental changes signaling emerging crises, and build experiential understanding of ecosystem dynamics. The accumulated knowledge fundamentally transforms their relationship to place: they become recognized local experts whose environmental assessments gain credibility with neighbors and community members (Haywood et al., 2024). Programs using these dynamics have been standardized with unique adaptations to fit specific local needs (Shirk et al., 2012).

The integration of the originally coined term “citizen science” and environmental stewardship has been adopted and standardized by the European Citizen Science Association (ECSA) with ten core principles (European Citizen Science Association, 2015, 2025). These principles establish operational standards grounded in evidence-based practice and serve as a practical checklist for program designers, embedding both Bonney's emphasis on scientific rigor and Irwin's emphasis on democratic participation (Wiggins & Crowston, 2011; European Citizen Science Association, 2015, 2025). The European Citizen Science Association (ECSA) Ten Principles are summarized in Table 2.1, which lists the core principle, operational description, and theoretical alignment.

Table 2.1: ECSA Ten Principles for Quality Citizen Science (European Citizen Science Association, 2015, 2025)

Core Principle	Operational Description	Theoretical Alignment
Involvement	Citizens are active contributors, not just data subjects.	Democratic Participation (Irwin, 1995); Mutual Benefit (Preece & Shneiderman, 2009)
Outcome	Projects produce genuine scientific outcomes (publications, policy).	Scientific Rigor (Bonney et al., 2009); Policy Relevance (Conrad & Hilchey, 2011)
Reciprocity	Participation benefits both professional scientists and citizen scientists.	Reciprocity Principle (Rotman et al., 2012); Mutual Benefit (Preece & Shneiderman, 2009)
Participation	Citizen scientists may participate in multiple stages of the scientific process.	Fluid Engagement (Shirk et al., 2012); Ecosystem of Engagement (Allf et al., 2022)
Feedback	Citizen scientists receive feedback from the project (data use, results).	Feedback Loops (Robinson et al., 2021); Retention (Crimmins et al., 2017)
Data Quality	Data is treated as a scientific resource (quality assurance/control).	Data Quality Mechanisms (Wiggins & Crowston, 2011) Validation (Kosmala et al., 2016)
Open Science	Project data and metadata are made publicly available and open access.	Democratization (Irwin, 1995); Data Transparency (European Citizen Science Association, 2015)
Acknowledgement	Citizen scientists are acknowledged in project results and publications.	Volunteer Recognition (Rotman et al., 2012); Identity Formation (Haywood et al., 2024)
Evaluation	Programs are evaluated for scientific output, data quality, and participant experience.	Holistic Assessment (Jordan et al., 2019); Program Evaluation (Phillips et al., 2019)
Legal & Ethical	Project leaders consider legal and ethical issues (copyright, privacy, consent).	Ethics (Resnik et al., 2015); Data Privacy (Bowser et al., 2020)

These principles operationalize what Jørgensen and Jørgensen (2021) term Environmental Citizenship: participants combining scientific protocols (reproducible, standardized observation) with civic ethics (participation in governance, concern for community benefit, advocacy for policy change). While the ECSA principles provide fixed standards for program quality, they do not account for the dynamic nature of participant engagement.

Shirk et al. (2012) proposed a widely adopted typology based on the level of participant involvement in the research design. Contributory projects are scientist-designed initiatives where the community collects data but has minimal input into research questions, methods, or interpretation (Shirk et al., 2012). Collaborative projects involve scientists and community members who jointly refine protocols; community input shapes data collection procedures and interpretation (Shirk et al., 2012). Co-created projects are community-initiated, with scientists joining as partners rather than leaders, wherein the community identifies problems, designs studies, analyzes data, and leads dissemination (Shirk et al., 2012).

Structural Models: From Rigid Categories to Fluid Ecosystems

Academic literature critiques these rigid categories as overly simplistic (Allf et al., 2022). Real programs demonstrate greater complexity than these categorical boundaries suggest. Individuals move fluidly between engagement levels: a casual observer in one project becomes a data analyst in another; a seasonal participant monitoring only during vacation becomes a year-round analyst after retirement; an analyst becomes a mentor training a new volunteer. Effective programs accommodate this fluidity rather than forcing participants into fixed roles. Scholars now propose an "ecosystem of engagement" model, which views citizen science not as fixed categories but as a spectrum of entry points and roles that individuals navigate over time as interests, skills, and life circumstances change (Allf et al., 2022).

This perspective acknowledges that effective programs must accommodate multiple simultaneous engagement levels without penalizing casual users or compromising the intellectual engagement of committed volunteers (Haklay, 2013; Shirk et al., 2012). An environmental monitoring program exemplifies this multi-level design by offering quick, gamified observations for casual users (reporting single sightings via mobile app), structured protocols for regular contributors (weekly checklists following standardized routes), and advanced analysis opportunities for committed volunteers (identifying migration patterns from aggregated data). This tiered approach enables broad participation while providing advanced pathways for those seeking deeper engagement.

A critical ideal in contemporary citizen science practices is the analyst paradigm, which trains volunteers not merely to collect data but to interpret it (Hart et al., 2021). This shift from data sensors to trained analysts addresses two critical challenges simultaneously. It increases the number of qualified observers available for environmental monitoring, alleviating the capacity constraints that limit traditional research. Concurrently, it sustains long-term participation by providing intellectually engaging analytical work, effectively countering the retention issues plaguing many citizen science programs (Hart et al., 2021). Research demonstrates that technology-mediated training produces analysts with identification accuracy that exceeds that of traditional in-person workshops (Hart et al., 2021).

Training Methods Intended for Effectiveness and Retention

Hart et al. (2021) conducted a comparative analysis of online self-paced learning versus face-to-face training for insect identification. Online learners reached 96% accuracy in identification, similar to professional entomologists, while face-to-face workshop attendees achieved 91.3% accuracy (Hart et al., 2021). Hart et al. (2021) suggest this better performance results from features of self-paced digital tutorials: learners can replay tricky sections, review material as needed and use embedded quizzes for self-assessment before attempting field identification. This personalized pacing better suits different learning speeds and prior knowledge levels than fixed-duration workshops, where everyone progresses at the same rate (Hart et al., 2021). These results have clear implications for designing digital learning platforms (Strobl et al., 2020; Hart et al., 2021). The digital interface functions not merely as a data submission form but as a learning environment that cultivates analyst capacity at scale. Effective platforms incorporate three specific design elements: tutorial videos demonstrating identification in realistic field contexts, comparison galleries that display similar species side-by-side with diagnostic differences highlighted, and interactive quizzes that provide immediate feedback on practice identifications. By integrating these three design components, platforms can achieve identification accuracy comparable to that of professional training while simultaneously addressing the resource constraints that make citizen science necessary (Hart et al., 2021; Strobl et al., 2020). This approach democratizes expertise development by distributing high-quality training to unlimited participants at near-zero marginal cost.

Participation retention is a major component of sustainable program design. Citizen science participation is primarily fueled by intrinsic motivation rather than extrinsic rewards (Ryan & Deci, 2000; Crimmins et al., 2017). This generally manifests as either self-directed learning (curiosity) or altruism (conservation commitment) (Rotman et al., 2012). However, long-term retention depends on a deeper psychological shift: the development of a "stewardship identity." Haywood et al. (2024) quantified the value of this shift, finding that volunteers who internalize a steward identity remain active for a median of 3.2 years, nearly quadrupling the 0.8-year retention span of those retaining a hobbyist identity. To foster this transformation, digital interfaces must go beyond simple data entry to explicitly reinforce user impact and skill development, such as the Local Environmental Stewardship Indicator (LESI) in Turnbull et al. (2020).

Technology-Enabled Learning and Data Quality

The Interface as Learning Environment

Digital interfaces in the context of citizen science are fundamentally educational tools, not merely data submission forms (Strobl et al., 2020). A critical function is training volunteers in visual literacy to interpret environmental cues and distinguish normal variation from concerning anomalies. The goal is to move beyond text instructions (such as "look for green discoloration") to visual-based training that mimics how experts identify phenomena in realistic field contexts (Hart et al., 2021; Starr et al., 2014). Effective tutorial design incorporates four evidence-based principles shown in Table 2.2 that work synergistically to create learning environments that achieve accuracy rates comparable to professional in-person training while serving unlimited participants at near-zero marginal cost (Strobl et al., 2020; Hart et al., 2021)

Table 2.2: Tutorial Design Principles for Digital Citizen Science Platforms

Design Principle	Definition	Implementation	Learning Advantage	Format Type	Supporting Literature
Multi-sensory Approach	Multiple information delivery modes addressing diverse learning styles	Visual demonstrations, audio narration, text annotations, interactive elements	Accommodates visual, auditory, kinesthetic learners; reinforces through multiple modalities	Interactive Media	Strobl et al. (2020)
Situated Learning	Material presented in realistic rather than abstracted contexts	Tutorial videos filmed at actual monitoring sites with typical field conditions	Enables skill transfer to real-world settings; demonstrates contextual variation	Video/Field Simulation	Strobl et al. (2020)
Iteration	Repeated practice with immediate corrective feedback	Practice identifications with instant correction and retry until mastery	Reinforces learning; builds confidence through progressive skill development	Quizzes/ Exercises	Strobl et al. (2020)
Self-paced Instruction	Learner controls progression speed based on individual needs	Progress at individual speed; repeat difficult material; skip familiar content	Accommodates diverse expertise levels; focuses effort on knowledge gaps	Modular Content	Strobl et al. (2020); Hart et al. (2021)

Data Quality: Front-End vs. Back-End Mechanisms

Quality assurance can occur at multiple points along the workflow (Wiggins & Crowston, 2011). Strategic program design prioritizes high-scalability mechanisms because they require one-time development investment but apply automatically to all subsequent users (Kosmala et al., 2016).

The critical insight driving this strategy is investing in robust front-end training effectively crowdsources quality assurance itself by ensuring only qualified observers submit data (Wiggins & Crowston, 2011; Hart et al., 2021). This approach shifts the quality control burden from scientists with limited time to digital systems with unlimited capacity.

Research on learning displays that test-enhanced learning provides dual benefits for citizen science (Roediger & Karpicke, 2006). Test-enhanced learning refers to the phenomenon in which quizzes on material improve long-term retention beyond passive review. Quizzes validate volunteer understanding, serving a quality assurance function, while simultaneously reinforcing learning through an educational function (Roediger & Karpicke, 2006). Volunteers who take quizzes after tutorial videos retain identification skills weeks later better than those who watch videos without quizzes. Platforms incorporating quiz-based training achieve both higher data quality, because volunteers internalize identification criteria, and higher volunteer satisfaction, because quizzes provide competence feedback that reinforces self-efficacy (Roediger & Karpicke, 2006; Strobl et al., 2020). Table 2.3 reviews best practices for web interface design from the literature regarding educational outcomes.

Table 2.3: Quality Contol Mechanisms in Citizen Science: Front-End vs. Back-End Strategies (Wiggins & Crowston, 2011; Kosmala et al., 2016)

Mechanism/ Type	Core Method	Scalability	Deployment Strategy	Supporting Literature
Front-End Training (Preventive)	Video tutorials, interactive modules, skill-building exercises	High (unlimited users)	All participants before field deployment	Wiggins & Crowston, (2011); Hart et al. (2021)
Automated Validation (Preventive)	Form validation (rejecting implausible/out-of-range values)	High (unlimited submissions)	All data submissions in real-time	Wiggins & Crowston, (2011).
Embedded Quizzes (Preventive)	Test questions assessing understanding before field authorization	High (unlimited users)	All participants before field deployment	Wiggins & Crowston, (2011); Strobl et al. (2020)
Real-Time Dashboards (Diagnostic)	Aggregate data quality visualization flagging statistical outliers	High (unlimited data points)	Continuous monitoring of incoming data	Robinson et al. (2021)
Expert Review (Corrective)	Specialist review of individual observations requiring taxonomic/contextu al expertise	Low (labor-intensive)	Flagged submissions only (failed automated checks)	Kosmala et al. (2016)

Digital Feedback Loops: Dashboards as Retention Tools

Real-time dashboards address retention by closing the feedback loop that the black hole effect breaks (Robinson et al., 2021). Real-time dashboards are interactive visualizations that update dynamically as new data arrives.

Key dashboard elements include geographic context via interactive maps to anchor data in place; temporal trends shown in dynamic graphs to help volunteers understand seasonal cycles; and impact narratives that link volunteer data directly to management actions, such as regulatory inspections (Robinson et al., 2021; Haywood et al., 2024). For example, updates such as "data documenting declining water quality at monitoring station 7 triggered EPA investigation of upstream discharge permit violations" validate volunteer effort by showing direct policy influence (Robinson et al., 2021; Haywood et al., 2024).

In contrast to these identity-building measures, the use of commercial gamification strategies such as badges; points, and leaderboards require significant caution (Deterding et al., 2011; Bowser et al., 2013) Specifically, reliance on extrinsic rewards risks triggering the "over-justification effect," where a volunteer's genuine commitment to conservation is displaced by a superficial desire for digital badges (Ryan & Deci, 2000). Furthermore, competitive structures such as leaderboards can introduce a zero-sum mentality, actively undermining the collaborative community culture required for long-term project health (Rotman et al., 2012). To sustain engagement without eroding motivation, Robinson et al. (2021) recommend shifting focus away from "controlling rewards" (arbitrary rankings) toward "informational rewards," such as feedback on skill mastery and research insights.

Technology plays a crucial role in large-scale synthesis (Hart et al., 2021; Starr et al., 2014). The balance of rigor and democracy is achieved across four design levels (Robinson et al., 2021). At the interface, training enhances visual literacy prior to fieldwork, integrating quality assurance into skills rather than treating it as a separate process (Hart et al., 2021; Strobl et al., 2020). On the data level, quality assurance transitions from solely expert review to include volunteer training, democratizing oversight by involving trained community members (Wiggins & Crowston, 2011; Kosmala et al., 2016). At the feedback stage, dashboards provide real-time updates on science and management impacts, offering immediate validation (Robinson et al., 2021). Regarding identity, user profiles and contribution histories foster stewardship by displaying engagement and skill development, visible to volunteers and the community (Haywood et al., 2024; Jørgensen & Jørgensen, 2021). Applying these principles necessitates an understanding of both the scientific processes and the digital platform capabilities (Ballard et al., 2017; Allf et al., 2022).

Conclusion

The literature reviewed in this chapter indicates that public participatory science programs are strongest when they combine credible data practices with participant learning, feedback, and stewardship. Bonney's data-centered model and Irwin's democracy-centered model are therefore best understood as complementary rather than competing traditions. EcoHabit draws from both: it uses structured training to support data quality while also emphasizing place-based learning, accessible participation, and community stewardship.

These ideas provide the foundation for the next chapter, which examines why HAB monitoring requires both technical accuracy and broader community participation. Because HABs can be spatially unpredictable and difficult to confirm through visual observation alone, community-facing tools must help users recognize environmental cues, interpret supporting data, and determine when reporting is appropriate.

Chapter Three: Harmful Algal Blooms and Best Practices for Monitoring

Prehistoric geological and palaeobiological evidence show that cyanobacteria have proliferated the planet's waterways for at least two billion years (Chorus & Welker, 2021). This chapter reviews the characteristics of HABs and their impacts on humans, wildlife, and communities. It presents the literature on environmental conditions that favor bloom colonization and monitoring methods used to detect and assess them.

HABs are cyanobacterial algal blooms that produce harmful toxins, causing devastating impacts on organisms throughout a given ecosystem (Zepernick et al., 2023; Igwaran et al., 2024). The toxins produced by HABs differ by species, affecting various parts of human physiology when exposed. Due to the immense risk factors of HABs' ability to proliferate and cause potential feedback loops linked with climate change, monitoring waters with the potential to become afflicted is becoming increasingly urgent (Chorus & Welker, 2021).

Characteristics and Impacts of Harmful Algal Blooms

Although water with algal growth floating may look suspicious, not all types of algae and cyanobacteria are HABs; normal blooms can still result in unpleasant odors and excess scum without producing toxins (Khan & Mohammad, 2013). Cyanobacteria are not necessarily algae but share the origin as photosynthesizing phytoplankton species. Hodges (2022) states that most phytoplankton species are considered beneficial to aquatic ecosystems with an essential role as an autotrophic primary producer, which converts atmospheric carbon dioxide into oxygen. HABs differ from other cyanobacteria with three characteristics: they release toxic byproducts in the end stage of their life cycle, impacts from the toxins are found in large quantities throughout all trophic levels within the surrounding ecosystem due to bioaccumulation, and they create anoxia in large biomasses (Igwaran et al., 2024). HABs have identifying visuals of looking like pea-soup or spilled paint. Zepernick et al. (2023) identify that this effect on water is due to a self-regulating buoyancy mechanism that allows the cyanobacteria to rise to the top of the water column, ensuring maximum photosynthesis. Other unique genotype-specific adaptations that help them dominate include a broad scope of characteristics ranging from nitrogen fixation to the type of toxin produced as a byproduct due to the degradation phase in their life cycle (Igwaran et al., 2024).

The species of HABs determines how cyanobacteria harm humans due to their genotype-specific toxins. Igwaran et al. (2024) assert the most common HABs include: *Dolichospermum, Microcystis, Aphanizomenon, Nodularia, Cylin-drospermopsis,* and *Planktothrix*. Villalobos et al. (2025) categorized the toxins as cyanotoxins, with human health impacts that vary by species. A common cyanotoxin in *Dolichospermum, Microcystis,* and *Aphanizomenon* is microcystin. Microcystin is the only toxin with specific guidelines from the World Health Organization. (2020) concentrations should not exceed 1ug/liter for lifetime drinking water, 12ug/liter for short-term drinking water, and 24ug/liter for recreational water. This hepatotoxin damages the liver, which can result in everything from chronic kidney failure to flu-like symptoms. *Nodularia* produces Nodularins, a hepatotoxin known to give reactions such as skin rashes, liver damage, and bleeding. *Cylin-drospermopsis* and *Aphanizomenon* create a byproduct called cylindrospermopsin, a hepatotoxin associated with kidney dysfunction, vomiting, and stomach cramps. *Microcystis, Aphanizomenon, Cylindrospermopsis* and *Planktothrix* produce Anatoxin-a, a neurotoxin that can induce convulsions, fatigue, paralysis, and respiratory failure. *Dolichospermum* also produces saxitoxins, a neurotoxin with side effects of paralysis, respiratory failure, and tingling sensations around the lips (Villalobos et al., 2025; Igwaran et al., 2024). Villalobos et al. (2025) explain that the extent of cyanotoxins' effect on human health is dependent on the amount and means of exposure, which can range from inhalation in recreational activities to indirect contact, such as ingesting toxins through the bioaccumulation of consuming food sourced from contaminated environments.

HABs impact the agricultural industry and food security in developing countries with contaminations afflicting crops (Abdallah et al., 2021; Díez-Quijada et al., 2019). Abdallah et al. (2021) found that irrigation systems with contaminated water in Brazil showed microcystin bioaccumulation present in pepper and tomato crops. Additionally, Díez-Quijada et al. (2019) documented microcystin toxin bioaccumulation in crops, including lettuce, cabbage, and water spinach. Contamination in freshwater creates a risk factor for all recreational activities in the afflicted water but also potentially impacts drinking waters in surrounding reservoirs (Goodrich et al. 2024). Igwaran et al. (2024) highlights a historic socioeconomic impact of microcystin contamination, preventing the use of drinking water for two million residents in the Wuxi water crisis of May 2007. Bingham and Kinnell (2020) approximate the economic impacts of HABs on ecotourism services for inland Lake Erie, Ohio, tourism activity of at least $3 million in profits for the summer of 2013. Centers for Disease Control and Prevention (CDC) (2023) state that HABs events burdened communities surrounding Lake Erie with at least $65 million in costs in 2011 and 2014. Goodrich et al. (2024) assert that socioeconomic impacts stem from the environmental impacts, such as fish kills. These events happen when HABs rapidly experience the degradation phase of the life cycle, it is a known stress response when the organisms experience an environmental factor that wipes them out in large masses. The toxins are released all at once, poisoning fish and other aquatic species, but species such as shellfish and crabs can tolerate toxins. However, most wildlife is exceptionally vulnerable to them, and the threat worsens due to bioaccumulation, impacting entire food webs throughout an ecosystem (Villalobos et al., 2025).

Another impact that is triggered by the end stage in a bloom life cycle and separate from direct toxicity, is hypoxia or the depletion of oxygen, which is due to environmental changes driven by the prolific shifts in trophic dynamics throughout freshwater habitats (Zepernick et al., 2023). Igwaran et al. (2024) and Zepernick et al. (2023) explain that the most severe environmental impacts result from HABs' ability to change the water conditions of dissolved oxygen and increase pH in freshwater ecosystems to inhospitable levels. Hypoxia can trigger lethal impacts on competing species such as other phytoplankton and predatory species such as shellfish and crabs, which are the biotic controls for HAB populations, leading to the loss of biodiversity within the freshwater habitat (Villalobos et al., 2025). The unique ability of cyanobacteria to change environmental factors is discussed in Large et al. (2022), showing that they played a primary role in the Great Oxidation Event approximately 2.4 billion years ago, impacting atmospheric oxygen levels.

Most characteristics of HABs influence their immediate takeover in freshwater ecosystems are genotype specific. Self-creating environmental factors that are uniquely favorable to HABs promote the exploitation of ecological niches and have the risk of enabling feedback loops, which can cause permanent damage to surrounding ecosystems

(Zepernick et al., 2023; Igwaran et al., 2024). Conditions for HABs to accelerate into feedback loops can also stem from environmental factors.

Favorable Conditions and Limiting Factors

Bonilla et al. (2023) and Ignatius et al. (2022) identify shallow stagnant water, optimal warm temperatures, and elevated pH as environmental variables that provoke biomass growth in HABs. Zepernick et al. (2023 and Bonilla et al. (2023) explain that Bloom proliferation is controlled by the availability of limiting factors, such as total nitrogen, phosphorus, and light (Table 1). This section examines favorable conditions and limiting factors for HABs from the literature, highlighting anthropogenically driven ones.

Table 3.1. Environmental Variables that Influence HABs

Environmental Variable	Favorable Conditions or Limiting Factor	Supporting Literature
Stagnant Hydrological Landscapes	Favorable Condition	Ignatius et al. (2022), Bonilla et al. (2023)
Optimal Temperature Range 25-30 °C	Favorable Condition	Zepernick et al. (2023), Chorus and Welker, (2021)
Increased Carbon Dioxide Levels	Favorable Condition	Nwankwegu et al. (2019)
Elevated pH (7.5-9.5)	Favorable Condition	Bonilla et al. (2023)
High Levels of Nitrogen and Phosphorus	Limiting Factor	Chorus and Welker, (2021), Yang et al. (2021)
Sunlight Availability	Limiting Factor	Chorus and Welker, (2021), Yang et al. (2021)
Mean Residence Time	Limiting Factor	Kim et al. (2021)

Favorable conditions for HABs are factors in an aquatic ecosystem that allow the cyanobacteria to dominate due to rapid biomass accumulation and ecological competition (Chorus & Welker, 2021; Zepernick et al., 2023). Chorus and Welker, (2021) report that HABs experience rapid biomass accumulation in shallow hydrological landscapes with low turbulence, and optimal temperatures around 25-30 °C. Due to thermal stratification, HABs thrive in heatwaves and droughts, allowing them to float to the top layer and sustain biomass growth more rapidly in waters with a higher residence time (Igwaran et al., 2024). Ignatius et al. (2022) conducted a five-year study of water dynamics, examining water quality and algal bloom events throughout 60 hydro dams constructed in the southern United States. They found that HABs concentrations greater than 100,000 cells/mL, surpassing the WHO threshold of high concentrations, occurred at the headwaters in 59 of the 60 reservoirs. Kim et al. (2021) examine the influence of hydrologic mean residence time within hydro dam reservoirs in the Geum River Basin. Their results showed that when gates were open in the series of upper reservoirs, upstream areas of the watershed experienced annual averages of 55% less blooms, with the unintended consequence of increased intensity of bloom persistence above the lowest dam. Chorus & Welker, (2021) explain that reduced water exchange from flow flushing rates promotes bloom accumulation. With enough sunlight available and warmer temperatures, thermal stratification of stagnant water assists the cyanobacteria in floating to near-surface depths, thus allowing them to colonize the top layer (Igwaran et al., 2024; Zepernick et al., 2023). Increased carbon dioxide levels are also known to promote photosynthetic activity among cyanobacteria residing on the top of water columns, allowing them to accelerate growth further. At the proliferation stage of the bloom, HABs undergo respiration processes that deplete dissolved oxygen levels and increase pH, creating inhospitable environments for most taxa in freshwater systems. The ecological competitive advantage creates a positive feedback loop, ensuring their ecological success (Bonilla et al., 2023; Zepernick et al., 2023).

The environmental variables that restrict the growth of HABs when they are in short supply, otherwise known as limiting factors, are conditional requirements for cyanobacteria to reach the proliferation stage (Bonilla et al., 2023; Kim et al., 2021; Yang et al., 2021). Chorus & Welker, (2021) identified sunlight availability, nitrogen, and phosphorus as limiting factors for HABs to optimize growth. Increased bloom intensity in the lower watershed, as shown by the results from Kim et al. (2021), was believed to be linked to the lower reservoir's eutrophic properties due to nitrogen and phosphorus nutrient loading. Bonilla et al. (2023) examined 464 lakes across five distinct biomes throughout the Americas to study environmental drivers for HABs. Variables included temperature, pH, total nitrogen, and total phosphorus. The sample collection in lakes of equatorial, arid, warm temperate, boreal, and polar climates showed that total phosphorus had the most significant connection with cyanobacterial biomass.

Nitrogen and phosphorus in hypereutrophic freshwater systems are most commonly a result of land use and agricultural runoff (Chorus & Welker, 2021). Yang et al. (2021) analyzed Lake Erhai for patterns between agricultural top dressing and bloom timing using on-site testing and satellite imagery to assess the spike in phosphorus and nitrogen concentrations and bloom intensity in 2003-2011 and 2016-2019. The results illustrate a clear seasonal pattern between top dressing crops, rain events, and bloom intensity, with a week of lag between fertilizer application and bloom initiation. The three main growth patterns, early peak, late peak, and winter max, are associated with agricultural planting and topdressing practices. This supports the authors' suggestion that reducing high-nutrient-loss crops and topdressing activities through planting adjustments can be beneficial (Yang et al., 2021). Not all species of HABs need nitrogen as a limiting factor; genotypes such as *Aphanizomenon, Dolichospermum, Cylindrospermopsis,* and *Nodularia,* can use nitrogen fixation to source the nutrient from the atmosphere (Zepernick et al., 2023; Igwaran et al., 2024).

Anthropogenic activity influences HABs through agricultural runoff, the alteration of hydrological landscapes, urbanization, and industrial pollution (Feng et al., 2024; Nwankwegu et al., 2019). Agricultural runoff's contribution to HABs has become a leading factor (Yang et al., 2021) but Ignatius et al. (2022) and Kim et al. (2021) show that human-constructed hydrological systems, such as reservoirs and dams, can also promote conditions where HABs are likely to thrive. Excess phosphorus and nitrogen introduced to a dammed hydrological landscape are synergistic drivers for HABs from human activities. (Igwaran et al., 2024; Zepernick et al., 2023). Anthropogenic activities mentioned by Nwankwegu et al. (2019) that provoke HABs dominance are wastewater treatment facilities emitting effluent upstream of the reservoir and deforestation adjacent to it. Wastewater treatment facilities and faulty septic systems contribute heavily to phosphorus and nitrogen pollution (Feng et al., 2024). Nwankwegu et al. (2019) explain that deforestation around the watershed increases the amount of sunlight received by surface waters and diminishes riparian buffers, which play a role in natural filtration and prevent erosion.

Throughout the literature, it is stated that global increased atmospheric CO_2 and rising temperatures from carbon emissions are climatic shifts that promote the growth of HABs and feedback loops, creating a significant future threat (Igwaran et al., 2024; Zepernick et al., 2023; Chorus & Welker, 2021). Paerl (2018) explains the future potential feedback loop in detail; as the human population continues to increase, it poses a threat due to environmental changes driven by increased agricultural demand and elevated CO_2 levels. Zepernick et al. (2023) and Igwaran et al. (2024) emphasize that the two anthropogenic inputs from climate change, increased atmospheric CO2 levels and nutrient loading from agricultural runoff, are mitigable through lower carbon emissions and sustainable land-use practices.

Urrutia-Cordero et al. (2020) examine the seasonal impacts of increased temperatures on HABs with a study that explored the effects of a 4°C increase in waters on *Microcystis* biomass accumulation. Their results showed that overall, *Microcystis* increased its growth in these scenarios due to its ability to start accumulating biomass earlier and persist later in the year. In +4 °C scenarios, biomass growth started in mid-May and was able to continue daily growth past September. In comparison, the controlled scenarios showed development starting in early July and complete disbandment of the bloom by September. Additionally, results from the heat treatment had shown that in heatwaves or durations when temperatures were optimal for growth, *Microcystis* and biomass accumulation had intensified. Temperature peaks enabled the establishment of colonies that reached 20mg per liter, persisting from the beginning of August to the end of September. Microcystis biomass peaked at approximately 5mg per liter in the controlled scenario for less than 2 weeks (Urrutia-Cordero et al. 2020). Urrutia-Cordero et al. (2020) summarize that heat treatment scenarios saw an average 724% increase in biomass establishment during the summer months and started their phase in biomass accumulation 6 weeks earlier than controlled scenarios. With climate change exacerbating feedback loops, monitoring HABs has become an important safety precaution.

Methods for Monitoring Blooms

Monitoring HABs can help communities make informed decisions that influence local water quality outcomes, which can impact aquatic ecosystems, public health, and save the lives of pets (Villalobos et al., 2025). Oversights in poor monitoring systems are problematic because the spread of small-scale blooms contaminating downstream water in a watershed can lead to major outbreaks in larger bodies of water with more favorable conditions (Saleem et al., 2024). Clites et al. (2024) research the challenges HABs monitoring programs face, communication barriers being at the top of the list, suggesting the information needs to be timely, accurate, and well communicated. Effective monitoring requires scientists to have plain-language discussions with stakeholders, including policymakers, farmers, students, and fishers, so that information from data collections can be used by all audiences (Clites et al., 2024).

To understand the most effective ways to monitor HABs and communicate results to a broader audience, an evaluation of the literature on methods and strategies is imperative. This section presents literature on the challenges of monitoring HABs, reviews traditional methods for identifying and monitoring them, and discusses current on-site monitoring practices. The second section focuses on literature assessing remote sensing as a method for monitoring HABs, reviewing their strengths and limitations, and concluding with a discussion on integrated approaches.

In-situ Monitoring of HABs

Scientists monitoring cyanobacteria face two significant obstacles: identifying them apart from other phytoplankton and the resources it takes to effectively monitor all waters they could form (Smith et al., 2024). In a USGS study of trying to predict HABs in the Finger Lakes by Johnston et al. (2024), typical water parameters monitored, such as specific conductance, dissolved oxygen, and pH, were not found to be significant indicators for detecting HABs. Smith et al. (2024) asserted that most water quality changes related to HABs are symptoms of proliferation in the aquatic system. Multiparameter Sonde probes were used in the study at various depths to collect water temperature, specific conductance, dissolved oxygen, pH, turbidity, chlorophyll fluorescence, and phycocyanin fluorescence. Results showed most parameters monitored were not helpful in preemptively detecting or determining the presence of HABs at low levels. Variables that showed significance in this study were high surface water temperatures and chlorophyll fluorescence, detected by the Sonde's thermometer and fluorescent sensors. Vuorio et al. (2020) were able to forecast blooms in systems with existing toxic cyanobacteria by monitoring nitrogen, dissolved organic carbon, and especially phosphorus nutrient levels. Monitoring the limiting factors of HABs can help prevent fish-kills and the other prolific impacts when avoiding a bloom. However, the true tribulations come from detecting in the beginning stage, pre-bloom, which starts with identifying them from other phytoplankton (Kraft et al., 2025).

HABs monitoring protocols from Standards and Methods 16th edition (1985) explain that the traditional process for identifying autotrophic phytoplankton was a multistep procedure, which helped determine the taxa and chlorophyll-a content. Standards and Methods 16th Edition (1985) process required an enormous collection of samples, which were first put through a silica-based filtration process to isolate the microorganisms, followed by flashing fluorescent lights at the isolated sample to trigger chlorophyll fluorescent responses, which would indicate the presence of chlorophyll-a. Finally, scientists would use a calcium carbonate buffered solution of hydrochloric acid (HCl) to dissolve organelles, and only chlorophyll-a is left. Established almost 50 years ago, these identification strategies are still part of on-site monitoring practices used today. Johnston et al. (2024) claim that using fluorescent sensors was imperative to monitoring HABs in their study. Modern instruments can detect phycocyanin, an easy identifier, because it is a chemical produced by toxic cyanobacteria that produces a unique pigment. Another traditional, straightforward, and impractical way to identify cyanobacteria is through microscope observations; this method requires the observer to be well-trained in tax identification, but it is an invaluable skill for monitoring HABs. In Antunes et al. (2015), taxa identification allowed studies to trace the migratory path of *Cylindrospermopsis* across the globe. *Cylindrospermopsis* migration patterns suggest it is a resilient cosmopolitan species, meaning its prolific impact can threaten all climates (Antunes et al., 2015). Government organizations and other groups with economic resources that can analyze samples for taxonomic data use a biochemical test called Enzyme-Linked Immunosorbent Assay (ELISA) (Chorus & Welker, 2021). Taxonomic data are important, especially for larger-scale HAB events, because of the different cyanotoxins produced and genotype-specific adaptations like nitrogen fixation and buoyancy regulation.

The Use of Remote Sensing for Monitoring HABs

Although on-site practices are data-driven with empirical results, given the increasing scale of HABs over the past decades, programs solely using on-site methods are unlikely to be as effective as remote sensing ones. In the past few decades, integrating remote sensing has become more practical and less resource-intensive than traditional monitoring (Stauffer et al., 2019). Janatian et al. (2025) demonstrate a review of remote sensing projects where open-source Satellite data is accessible on many platforms, with results that can achieve vast spatial and temporal coverage. In Johnston et al. (2024), a three-year study with DEC and USGS, one of the main points in summarizing their limitations was the restriction of space and time they could cover. Remote sensing allows communities to equip themselves with another tool in their HABs monitoring tool belt.

Remote sensing has changed environmental monitoring for decades, using temporal, spectral, and spatial data sets to help those utilizing it make more informed decisions (Zhang et al., 2024). Satellite data sets, UAVs, and stationary technologies have numerous capabilities; in the context of monitoring HABs, they may be one of our best means of monitoring effectively for preventive actions (Khan et al., 2021). Wang et al. (2025) assert that without remote sensing, the enormous impact of HABs would be uncertain and emphasize that it plays a massive role in communicating the issue to global communities. Satellite and UAV images allow scientists to observe early signs of HABs like chlorophyll-a abundance on surface water, indicating eutrophic activity (Cheng et al., 2020).

In Khan et al.'s (2021) examination of 420 published articles on remote sensing for monitoring HABs, 418 focused on sensor trends, of which 407 used multispectral satellite imagery and seven used UAVs. Multispectral satellite data typically consists of 13 spectral bands, some past the visible light spectrum, sensing near-infrared wavelengths. Unless spectral band outputs match the value for monitoring, algorithms are applied to achieve an output within the range. Algorithms known to reflect only the existence of wavelengths are known as light indices; they are used to quantify parameters for monitoring, such as chlorophyll-a at 700nm and phycocyanin at 620nm (Cheng et al.,2020; Khan et al., 2021). Similarly, equations that emphasize larger ranges of light reflectance are known as proxies and can also be used to indicate parameters monitored for signs of HABs. Khan et al. (2021) found that 80% of spectral data used for HABs monitoring was a variation of the chlorophyll-a index. Monitoring services use remote sensing by leveraging spectral data through processing it into outputs suitable for the intended patrons (Janatian et al., 2025). Once metadata sets are collected, they are added to a GIS program and rendered over the coordinates to illustrate the distribution of a parameter within the area. The processed index map gets uploaded to a community hub in addition to a larger temporal data set of the monitored area (Beaulne et al., 2025). Janatian et al. (2025) reported from a review of programs that use this workflow for their monitoring service that programs overall provide value during seasonal blooms but need to determine a scale that is logical for the program and stay within that scope, with data acquisitions from more than just a single satellite. Beaulne et al. (2025) found in their study that there were issues on orbiting days from cloud cover; of the 334 images Landsat 8 and 9 collected, only 214 were available. Additionally, Beaulne et al. (2025) claim that due to the poor spatial resolution of the data, smaller lake communities had insufficient HABs data.

In recent years, UAVs have been integrated into remote sensing, using light index proxies for smaller-scale HABs monitoring projects (Khan et al., 2021). Byrd et al. (2025) reviewed 27 studies assessing the ability of UAVs to monitor HABs with sampling data, and the results for chlorophyll-a had an overall average of .70 r^2 values, with the highest showing a .92 r^2 value. Khan et al. (2021) and Byrd et al. (2025) explain UAV optical sensing as a four-step process where data collected is through flight paths that are replicable, then you use an image processing software with GIS integration to create an Ortho mosaic. The mosaic is processed with an algorithm to create a light reflectance index, and then the UAV light index results are compared with in-situ sampling data using regression models. Byrd et al. (2025) reference the study Cheng et al. (2020) and declare that this type of workflow was optimized, which pioneered accuracy and potential in UAVs of remote sensing by leveraging a double preflight data validation, where preflight data was compared to in-situ sampling and satellite data, using regression models. The results from the 90 flights over 15 days resulted in an .80 r^2 value from red/blue ratio regression model comparisons. The UAV provided greater temporal and spatial datasets than the satellite during the 15-day study, producing photometry with 3.1 cm/pixel resolution.

Stauffer et al. (2019) assert that UAVs will become more powerful tools for remote sensing, like monitoring HABs with AI/machine learning. Telli et al. (2023) characterize UAV research as a quickly evolving interdisciplinary area that integrates remote sensing, communication systems, artificial intelligence, and hardware/software design. This explains why UAV-based monitoring can be highly effective but also technically complex. The most cutting-edge may simplify remote sensing HABs, but there are always tradeoffs; they are either expensive for their precision monitoring capabilities or extremely involved and require a technological background to operate/navigate them. The Mayfly data collector, evaluated in Horsburgh et al. (2019), is an affordable remote sensing monitoring station with endless capabilities, but only for groups willing to do the work. Installation and upkeep require knowledge of the C++ coding language and a background in environmental science (Horsburgh et al., 2019). There are limitations to all forms of remote sensing and water quality monitoring, especially when dealing with HABs (Janatian et al., 2025). Table 3.2. summarizes the methods identified for monitoring HABs throughout the section.

Table 3.2. Summary of approaches: Instruments used to monitor HABs

Instrument	Parameters Measured	Method of Monitoring	Supporting Literature	Additional Notes	Data Source Reliability
Multiparameter Sonde	Water temperature, specific conductance, dissolved oxygen, pH, turbidity, chlorophyll fluorescence, and phycocyanin fluorescence.	On-site set of Standardized Calibrated Probes	Johnston et al. (2024), Chorus and Welker, (2021)	Real-time data acquisition	High
Microscope	Distinct Physical Characteristics	Samples collected and visually analyzed in lab	Antunes et al. (2015), Standards and Methods 16th edition (1985)	Requires expert interpretation	Moderate
Enzyme-Linked Immunosorbent Assay (ELISA)	Total Toxin Counts	Samples collected and analyzed in lab with biochemical process	Chorus and Welker, (2021)	Specific to certain toxins	High
Fluorescent Lights	Chlorophyll and phycocyanin fluorescent responses	On site initially and brought back to lab for further analysis	Johnston et al. (2024), Standards and Methods 16th edition (1985)	Portable and in-situ capability	High
Satellite Images	Chlorophyll-a and Phycocyanin Light Index	Remotely sensed Through MODIS, Landsat 8 and 9, Sentinel 2 and 3 data collections	Janatian et al. (2025), Beaulne et al. (2025)	Large-scale spatial coverage	Moderate
UAV	Chlorophyll and Phycocyanin Light Index Proxies	Near site imagery	Cheng et al. (2020), Khan et al. (2021)	High spatial resolution	High
Buoys/On-site Monitoring Stations	Water temperature, specific conductance, dissolved oxygen, pH, and turbidity	Deployed On-site, Data collection is remotely accessed	Horsburgh et al. (2019)	Continuous temporal monitoring	High

Satellite and UAV remote sensing are innovative technologies that have proven incredibly useful for environmental monitoring (Khan et al., 2021). These are valuable but still tools nonetheless and are most effectively used in unique scenarios that match their niche (Beaulne et al., 2025) The appropriate monitoring methods and means of communication to the public are important when considering effective monitoring programs (Clites et al., 2024). Remote sensing can detect chlorophyll or surface scums, but it cannot confirm whether a bloom is producing toxins, which is the critical distinction for public advisories. Residents at remote and private lakes frequently encounter opaque green water but lack access to toxin testing, while government monitoring focuses on a limited number of public beaches due to staffing constraints (Roque et al., 2022). This creates a diagnostic gap: communities do not know whether a bloom is benign or hazardous, leading to uncertainty about exposure to toxins such as microcystin. Citizen science programs address this dilemma by leveraging data and engaging their communities to be part of the solution (Simon et al., 2023). This research evaluates EcoHabit Beta, an interactive web-based community science interface designed to teach community members how to identify harmful algal blooms, interpret water-quality sensor data, and make informed reporting decisions. The Wallkill River watershed serves as the test case for evaluating whether this model can support place-based HAB education and stewardship-oriented engagement. The tool was built to test strategies from the literature on citizen science and HABs monitoring that can improve identification accuracy, increase confidence in interpreting water quality data, and foster environmental stewardship among lay community members. Concepts from the literature include utilizing Community-Based Participatory Research CBPR, situated learning, breaking the analyst paradigm, and remote sensing.

In the following chapter, I detail the methods used to apply and test best practices for increasing engagement of watershed community members to improve HABs monitoring for the case of the Wallkill River watershed.

Chapter Four: Methods

EcoHabit was developed as an asynchronous, web-based educational platform to enhance community-level proficiency in identifying and assessing the risk of Harmful Algal Blooms (HABs) within the Wallkill River watershed. The tool functions as an interactive learning environment in which identification and decision tasks become progressively more complex, using best practices from the literature intended to help participants learn throughout their experience. This chapter begins with EcoHabit's framework design, the concepts drawn from the literature that shaped it, the workflow of the nine-step exercise, the code that governs the technical web interface, and the recruitment strategies used for community outreach.

The EcoHabit web interface serves both as an educational exercise and as a data-collection instrument. The overall framework decisions were based on successful mechanisms identified in the literature on community science digital interfaces, which emphasize self-paced, participatory learning and are designed so that each stage builds cumulatively on the one before it. EcoHabit is a cumulative learning environment in which each stage builds on the knowledge and interpretive skills developed in the previous stage (Hart et al., 2021; Shirk et al., 2012; Allf et al., 2022). To avoid relying on a single source of information, the exercise drew on digital citizen science strategies to create a participatory learning environment rather than function solely as a survey instrument. The following learning components are known as evidence-based interface principles identified in the literature: *multi-sensory presentation, situated learning, iterative feedback,* and *self-paced instruction*. Quiz-based prompts also supported test-enhanced learning and knowledge retention (Strobl et al., 2020; Roediger & Karpicke, 2006). In this way, EcoHabit reflects a learning structure in which each step builds on prior decisions, allowing users to progressively develop visual and interpretive skills while supporting environmental literacy and stewardship-oriented learning outcomes (Hart et al., 2021; Strobl et al., 2020). The localized strategy of keeping the exercise scope remote from the Wallkill River draws directly on place attachment theory. Hart et al. (2021) assert that prolonged exposure to a specific environment of sentiment fosters deep emotional and intellectual ties. Cultivated people-place bonds are essential to the platform's success, as they motivate the transition from passive observation to active, long-term environmental stewardship. The web interface accommodates different levels of technical expertise by offering a simple core exercise for all users and optional satellite imagery.

EcoHabit Workflow

EcoHabit's nine-step sequential exercise served as the primary study instrument, guiding participants through a structured learning process and community survey data collection, thereby emphasizing its dual role in education and research. Table 4.1 summarizes each step and its purpose within the tools exercise.

Table 4.1 summarizes each step and its purpose within the EcoHabit exercise.

Step	Name	Purpose
1	Introduction / Captcha	Presents the study overview and consent information. A slider captcha confirms the participant is human before data collection begins.
2	Pre-Survey	Collects demographic and prior-knowledge information: age, primary river activity, visit frequency, citizen science experience, place attachment, perceived HAB risk, and self-rated HAB identification knowledge.
3	Visual HAB Identification	Participants select one of four images they believe shows a harmful algal bloom. A visual reference guide accompanies the choices. This is the first accuracy checkpoint in the exercise.
4	Environmental Data Dashboard	Introduces participants to water-quality sensor data linked to the image selected in Step 3. Data includes real-time water temperature (USGS), specific conductance (sonde station), and streamflow (USGS). Drop-down containers show weekly time series for each parameter.
5	Analysis and Risk Classification	Participants interpret the dashboard data alongside their Step 3 image to classify environmental risk. They identify which sensor metrics indicate HAB-favorable conditions and explain their reasoning in a short open-ended response.
6	Transfer Scenario	A new image set and new dashboard data are presented without the reference guide. Participants select the most suspicious image and rank three possible stewardship actions (Avoid, Report, Share) in priority order.
7	Recap and Branch Choice	Recapitulates core identification and data concepts. Participants choose whether to continue to the optional satellite imagery module or proceed directly to the post-survey.
8	Satellite Imagery Exercise (Optional)	Participants use the Copernicus Browser to locate and document a recent satellite observation of the Wallkill River near Sturgeon Pool. The module introduces a JavaScript-based version of the Phycocyanin Index as a remote-sensing indicator of cyanobacteria in Sentinel-2 imagery (Khan et al., 2021; Janatian et al., 2025).
9	Post-Survey / Debrief	Participants rate their post-exercise HAB knowledge, their likelihood of reporting a suspicious observation, and provide an overall tool rating. Open-ended prompts ask what was most helpful and what could be improved.

Recruitment Strategies

The study targeted adults from the local community who use, manage, or live next to the Wallkill River and are likely to have some connection to the local environment in the New Paltz and Rosendale area. I recruited participants through the Wallkill River Watershed Alliance (WRWA) email list, SUNY Ulster Environmental Science Department, the Wallkill Valley Land Trust email list, and Water Quality Coordination Committee (WQCC) meeting attendees, which shaped the sample's diversity and relevance.

The initial recruitment materials consisted of an IRB-approved recruitment email to be sent to the Wallkill River Watershed Alliance email list, approved by the organization's board. The email invited adults 18 years of age or older to participate in a 40-minute online exercise. The email also described the study purpose, procedures, explained time commitment, and provided contact information for the researcher, faculty advisor, and the Bard IRB. Recruitment materials and process were approved by the Bard College Institutional Review Board under the exempt category 104(d)(2). Each participant was assigned a randomized alphanumeric user ID to ensure that their identity was not revealed during data collection. Data collection lasted nine weeks, from February 19 to April 23, 2026.

Web Interface Design

EcoHabit is designed to move community members from simply observing to actively participating by emphasizing steward-focused engagement. It is not solely a top-down, expert-led data collection tool nor purely a bottom-up method.

Five key considerations were used to develop a model for an effective community science platform to inform future similar initiatives and enhance participant engagement. Table 4.2 summarizes the five design elements from academic literature.

Table 4.2 Concepts used from the Literature on Community Science Tech Interfaces

#	Design Consideration	Supporting Framework
1	Use a progressive, step-by-step exercise structure rather than a static survey	Supports iterative skill-building and self-paced learning (Hart et al., 2021; Strobl et al., 2020)
2	Offer tiered participation pathways for both general and technical users	Reflects fluid engagement models in community science (Allf et al., 2022; Shirk et al., 2012)
3	Design data capture to serve both educational assessment and project evaluation	Ensures the tool generates learning outcomes and research data simultaneously
4	Include qualitative feedback channels within the platform	Enables ongoing, evidence-based improvements to the tool
5	Pair visual reference guides with real-world environmental data	Promotes situated learning and strengthens people-place bonds (Haywood et al., 2024)

Limitations

This study has several limitations, though none undermine the meaningful learning gains observed during the exercise. First, the project measured participants' ability to identify and interpret HAB-related conditions within the tool itself, but it did not test whether those skills were retained over time or transferred reliably to real field encounters. Second, the sample was modest, with 41 participant responses, and recruitment was concentrated through environmentally focused networks such as the Wallkill River Watershed Alliance email list and SUNY Ulster environmental biology students. As a result, participants may have been more environmentally engaged than the broader public. Third, the visual training module was limited by the availability of geolocated photographs of filamentous algae, aquatic vegetation, and other HAB look-alikes. A larger image library would likely help future users more confidently distinguish HABs from non-HAB conditions. Finally, time constraints affected both tool development and participant recruitment. The process of conceptualizing EcoHabit, coding the tool, recruiting participants, and interpreting results limited the scope of the final evaluation.

Chapter Five: Results and Discussion

Participant Characterization

A total of 41 people completed the exercise. When asked, "What is your primary river activity?", most participants, using a drop-down menu, indicated that their primary use of the watershed is hiking or walking. Cohorts were determined by this prompt: users who primarily reported use of the river for hiking, recreation, identified as a resident, or chose other were categorized as a "Recreator" (n = 34), and those who reported primary activities were stewardship or scientific were categorized as being "Stewards" (n = 7). Primary river activity for users is further illustrated in Table 5.1.

Table 5.1. Participant activity distribution and cohort (N = 41).

Activity	n	% of Sample	Cohort
Hiking/Walking	16	39.0%	Recreator
Recreation	12	29.3%	Recreator
Resident	5	12.2%	Recreator
Other	1	2.4%	Recreator
Stewardship	4	9.8%	Stewardship
Scientific	3	7.3%	Stewardship
Total	41	100%	

The age distribution skewed toward younger adults: 46.3% of participants were aged 25–34 (n = 19), 24.4% were 35–50 (n = 10), 12.2% were 65 and older (n = 5), 9.8% were 51–65 (n = 4), and 7.3% were 18–24 (n = 3). Prior citizen science experience was nearly evenly split; 18 participants (43.9%) reported prior experience, 21 (51.2%) reported none, and 2 (4.9%) were unsure.

HAB Visual Identification Performance

Three points in the exercise, steps 3, 5, and 6, required participants to use visual or data information to determine whether a HAB event was likely. Accuracy improved at each of the three checkpoints in the exercise. The three steps are not identical tasks; Step 3 relies solely on visual recognition, Step 5 adds real-time dashboard data, and Step 6 presents a new image and dashboard data without a reference guide. Together, they trace a participant's movement from intuitive recognition toward applied, data-informed assessment.

With only a photograph and a visual reference guide in Step 3, 25 of 41 participants (61.0%) correctly identified the HAB image. In the dashboard integration exercise in Step 5, 34 of 41 (82.9%) cases were correctly classified as the environmental risk condition using the sensor dashboard. In Step 6, 36 of 41 (87.8%) selected the suspicious image in the transfer scenario with no reference guide. Results between the two cohorts were difficult to compare because of differences in sample size, and both showed an increase in accuracy as they progressed through the core educational exercise. The recreator group had slightly lower identification accuracy at 20 of 34 (58.8%) for the visual recognition task, in contrast to 5 of 7 stewards (71.4%). In the dashboard integration step, 28 of 34 (82.4%) recreators answered correctly; similarly, 6 of 7 (85.7%) stewards accurately identified the environmental dashboard concepts. In the final educational step, 29 of 34 (85.3%) recreators correctly identified the HABs image, and the stewards had a 7 of 7 (100%) success rate. Figure 5.1 shows user accuracy at each step.

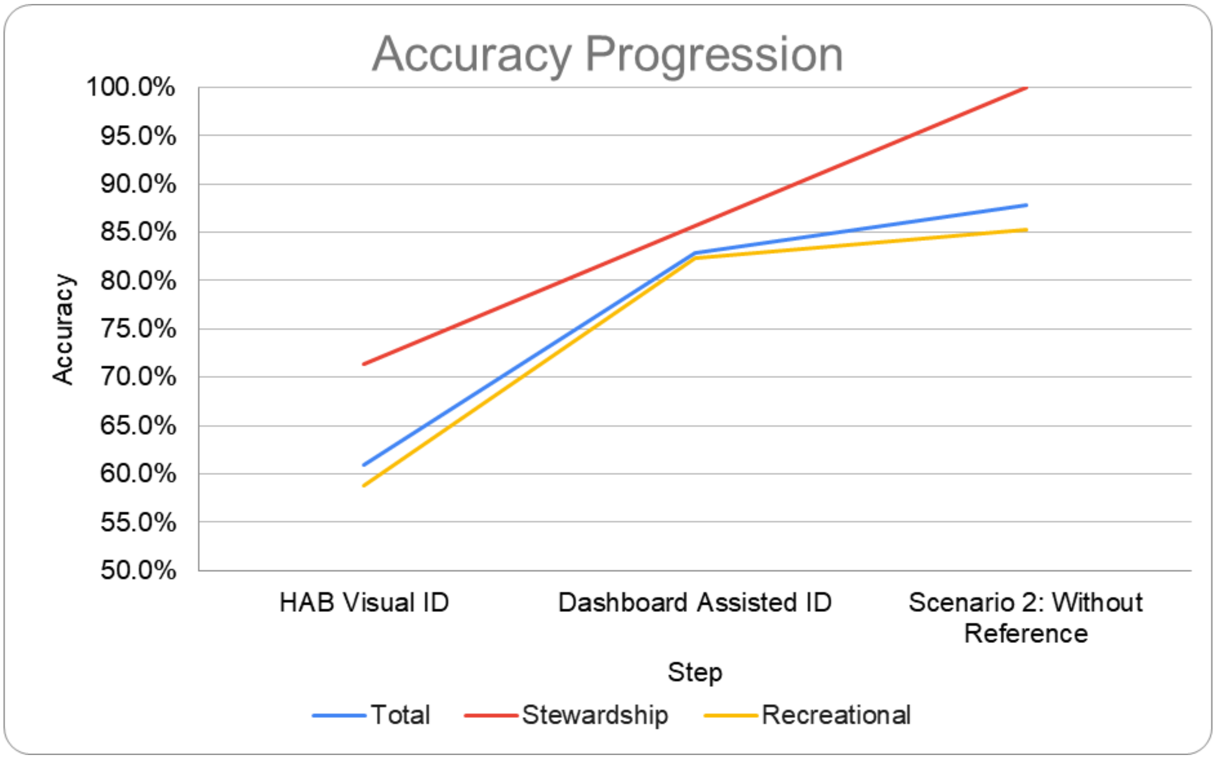

Figure 5.1: Change in accuracy of identifying a HABs event at three checkpoints in the exercise, by participant category.

Remote Sensing Engagement

After completing the core identification and dashboard exercises in step 7, participants chose whether to continue with an optional module on using satellite imagery to identify HAB outbreaks. The module asked them to access the Copernicus browser, locate a specific recent observation of the Wallkill River near Sturgeon Pool, and submit a screenshot along with written observations.

A larger proportion of steward participants opted to proceed to the satellite task compared to recreators. This difference probably indicates that the stewardship group was more comfortable with environmental data tools. However, since over a third of recreators also chose to participate, it shows that the module was not seen as overly technical or difficult to access.

Participants who provided written satellite observations generally described recognizable bloom indicators, including mentions of dark red or orange phycocyanin signatures, suspicious green scum concentrated along low-flow shoreline areas, and timestamps that aligned with known bloom conditions at Sturgeon Pool in September 2025. The qualitative tone of those responses was largely constructive, with participants connecting what they saw in the satellite image to the sensor-threshold logic they had worked through earlier in the exercise.

Table 5.2. Satellite imagery module participation by cohort (Step 8).

Cohort	n (Entered Step 8)	% Participation	Screenshots Submitted
Total	19	46.3%	9 (47.4% of participants)
Stewardship	7 of 7	100%	4 (57.1% of participants)
Recreator	12 of 34	35.3%	5 (41.6% of participants)

Pre- and Post-Exercise Comparisons and Reported Outcomes

Participants self-rated their HAB knowledge on a 1–5 scale at the start and end of the exercise. Mean knowledge before the exercise was 3.02 (SD = 1.29); after the exercise, it was 3.66 (SD = 0.66). At the beginning of the exercise, participants were asked to rate their perceived risk of HABs in the Wallkill River, and across the full sample, the average was 4.24 out of 5.0. When asked in the later steps, their confidence in their ability to report HABs results averaged 7.32 out of 10.0. Both figures suggest that participants took the HAB identification task seriously and answered with at least moderate certainty.

Likelihood to Report

Asked how likely they were to report a suspected HAB after completing the exercise, participants responded on a 1–5 scale with an overall mean of 4.0. 27 of 41 participants

(65.9%) rated themselves a 4 or 5, the highest two levels. The stewardship cohort averaged 4.21 on this item, compared with 3.82 for the recreator cohort. The difference is modest but directionally consistent with the cohort's stronger performance on the identification steps: participants who engaged more deeply with the exercise material also expressed greater willingness to act on what they observe

Overall Tool Rating and Self-reported Outcomes

In the final step of the exercise, participants rated EcoHabit on a 1–5 scale. The overall mean was 4.32 out of 5.0. The stewardship cohort averaged 4.37, and the recreator cohort averaged 4.27. No participant gave a rating below 3, and a majority selected 4 or 5. That pattern of responses aligns with the positive learning trajectories observed in the identification data and with the self-reported willingness to report

Qualitative Feedback Summary

In the final phase of EcoHabit, two prompts gathered feedback on the tool’s strengths and areas for improvement. The "most helpful" prompt received 39 responses. For the improvements prompt, 23 of 41 participants responded, while 18 left it blank or gave unclassified feedback. Percentages in Table 5.3 are based on N = 39 for the “most helpful” prompt and N = 23 for suggestions.

Table 5.3. Qualitative feedback summary by prompt and theme.

Prompt	Topic	N	Percent	Representative quote
What was found most helpful?				
	Interactive dashboard data for supporting visual decisions	15	38.5 %	The environmental data were described as helpful, assisting in supporting or confirming their visual interpretation of possible HAB conditions
	Visual guides, bloom photographs, and identification cues	13	33.3 %	Users reported that the visual guide, bloom photographs, examples, descriptions, and visual cues were useful for recognizing possible HABs.
	Satellite imagery, maps, and aerial views	11	28.2 %	Responses mentioned satellite visuals, maps, aerial imagery, and drone-style perspectives as helpful for seeing HAB conditions spatially.
What improvements should be made?				
	Visual guides and photographs	11	47.8 %	The need for clearer photographs, more close-up images, more consistent image angles, and more examples comparing HABs with look-alikes
	Clarification for directions in the Satellite Imagery exercise, and technical issues	7	30.4 %	Responses mentioned confusion or technical friction in the satellite module, including instructions, browser performance, and mobile-viewing issues
	Interactive dashboard and environmental data	5	21.7 %	a clearer explanation of dashboard metrics, persistent threshold references, and more support in interpreting temperature, conductivity, and flow.

Open-ended responses fell into three themes: (1) visual guides and bloom photos, (2) interactive dashboards and environmental data, and (3) satellite imagery and place-based tools. These groups reflect natural feedback clusters rather than pre-set codes.

My results demonstrate that EcoHabit has strong potential as a community science education tool, particularly in improving HAB recognition, supporting applied interpretation of environmental data, and encouraging stewardship-oriented action among participants. However, the same results also show that the tool's effectiveness depends on several design factors, including clearer photographic references, more accessible dashboard guidance, and a more usable satellite imagery component. With those findings established, the study shifts from results and discussion to a broader consideration of what EcoHabit contributes.

Discussion

The findings indicate that EcoHabit functioned not only as an educational tool but also as a structured bridge between visual HAB recognition, environmental data interpretation, and community-based watershed stewardship. The discussion focuses on three major findings: first, visual reference materials provided an accessible entry point for non-expert HAB recognition; second, environmental data strengthened participants' ability to make more informed assessments; and third, the optional satellite module demonstrated the potential for tiered participation, while also revealing design barriers that should be addressed in future versions of EcoHabit.

Interpreting Qualitative Feedback

Open-ended responses at the end of the exercise in response to the questions” what did you find most helpful?” and “what are improvements that can be made to Ecohabit?” were analyzed across three theme categories: (1) visual guides and bloom photographs, (2) interactive dashboard and environmental data, and (3) satellite imagery and place-based tools. The groupings reflect where participants' feedback naturally clustered, rather than a set of pre-assigned codes.

<u>Visual guides and bloom photographs</u>

What was most helpful, participants consistently pointed to the combination of images and data rather than to encountering these elements alone. Representative responses included: "Combining all 3 things, the data, photos, and the satellite imagery"; "Data analysis with visual guides"; and "I think it focused well on breaking down the false flags that often cause misreporting." Those responses reinforce the situated learning argument behind EcoHabit's design. The value lies not in any single component but in how the components build on one another (Haywood et al., 2024).

On improvements, the most consistent request was for closer or clearer photographs and more visual examples for comparison. One participant asked for "up-close pictures of what's at the surface / along the shore," describing how in-person observation would involve looking closely for filamentous algae and surface color. Another wrote that "all the photos were not equal in visibility," and a third noted that having "overhead on all pictures rather than two overhead and two water level ones" created inconsistency.

Interactive dashboard and environmental data

A wide range of responses was mentioned throughout the qualitative responses. Many participants said the data helped support the photos and made the exercise more analytical, especially when temperature, conductivity, and flow were interpreted together. The data dashboard also prompted some confusion: "Hard to interpret the data when I don't understand the data to begin with" captures a real access challenge that threshold explanations alone do not completely solve. Several participants said the thresholds were hard to remember or interpret as they moved deeper into the exercise, including comments that they could not easily return to earlier sections to reference what they had learned.

Satellite imagery and place-based tools

The satellite module drew both praise and criticism in roughly equal measure. Participants who found it engaging often said so directly and in specific terms, as noted above. Participants who found it confusing or incomplete mentioned that "the requirements of Exercise 8 were slightly confusing" and that the Copernicus browser occasionally froze. Those technical friction points do not invalidate the module, but they do represent a clear boundary condition for the tool's scalability across different devices and connection speeds.

The qualitative feedback helps explain why participants improved: users valued the combination of photographs, dashboard data, and place-based imagery. Participants improved their identification accuracy, expressed willingness to report observations, and rated the tool highly, but they also identified specific design limitations that a second iteration of EcoHabit should address. The most actionable items are: (1) expanding the photograph library to include close-up and in-water perspectives; (2) providing a persistent, accessible reference for dashboard thresholds throughout the exercise, not only at the point of introduction; and (3) streamlining the satellite module instructions and testing compatibility across a broader range of devices.

Visual Identification and Early Learning Outcomes

Performance on Step 3, the visual-only identification task, was 61.0%, well above the 25% expected from random selection among four images. That result supports the argument that visual reference guides and intuitive cues provide non-expert audiences with a meaningful starting point for recognizing HABs, even without formal training. The similar accuracy levels of both the steward and recreator groups at Step 3 indicate that prior experience wasn't the key factor. Even a participant unfamiliar with the term harmful algal bloom could identify one in a photo when provided with sufficient reference material. This finding is significant for any community-based reporting program.

Step 3 data cannot tell us whether that initial recognition would hold up under real conditions, variable lighting, partially submerged blooms, and seasonal color variation. Initial visual identification demonstrates that participants can pick out HAB-relevant features using reference guides and intuitive cues, but visual information alone is insufficient to assess HAB risk in ecologically complex situations. That is exactly why the exercise continued into Steps 5 and 6.

A McNemar's test was conducted to assess whether there was a statistically significant difference in the proportion of participants correctly identifying the target between Step 3 (Reference-Guided Visual ID) and Step 6 (the Second Visual ID). The results showed a statistically significant difference (test statistic = 6.67, $p = 0.0098$). The proportion of correct identifications increased from 61.0% (25/41) in Step 3 to 87.8% (36/41) in Step 6. Participants who completed the dashboard interpretation task and then encountered a second visual scenario performed measurably better than they had at the start. That improvement pattern supports Hart et al.'s (2021) finding that self-paced digital training can enable non-experts to recognize environmentally significant patterns, and it aligns with Strobl et al.'s (2020) argument for iterative feedback as a mechanism for knowledge retention.

Remote Sensing as Tiered Participation

Nearly half of the sample chose to continue into the optional satellite module. The fact that 12 of 34 recreators opted in — participants who had no prior obligation to do so and no technical background suggests the design did what it was intended to do: it created a pathway for deeper engagement without requiring it.

The written satellite observations left by participants who completed Step 8 are particularly insightful. Several described identifying dark red phycocyanin signatures, localized green scum near the northern low-flow section of Sturgeon Pool, and color changes that tracked the September 2025 bloom timeline. One participant wrote that the timestamps appeared to synchronize the satellite data with what they had already learned about bloom development conditions. That is a qualitatively different kind of engagement than selecting an answer from a dropdown list; it is exploratory, place-based, and self-directed. EcoHabit should keep the satellite module in future iterations, and the instructional framing could be tightened to help recreators make the most of it upon arrival.

These results provide the foundation for the final chapter's conclusions and recommendations, which consider how EcoHabit can be refined and adapted for broader watershed-based HAB education.

Chapter Six: Conclusions and Policy Recommendations

Conclusions

Community-based environmental monitoring is most effective when residents and local water users are given tools to recognize environmental change, interpret evidence, and understand how their observations fit into a broader watershed response. EcoHabit indicated that a short, self-paced digital interface can improve community-level HAB recognition and encourage stewardship-oriented activity for local watersheds. The study's results suggest that EcoHabit served as an educational exercise that bridges visual learning and environmental data interpretation, with the potential to influence community reporting behaviors. Overall, with slight modifications, the next version of EcoHabit could become a more effective resource for the Wallkill River Watershed Alliance and wider public education efforts on HABs, DEC reporting, and local watershed stewardship.

The results of the data collection using EcoHabit show that the core educational features produced measurable gains across the exercise, with increased average identification accuracy from 61% in the first identification module (step 3) to 87.8% in the second identification module (step 6). The improvement in accuracy was statistically significant under McNemar’s test ($p = .0098$), reinforcing the claim that the tool enhances educational value through its learning modules.

Self-reported measures are valuable because they indicate that EcoHabit had both educational impact and participant approval. The rise in average self-rated HAB knowledge from 3.02 to 3.66 out of 5 shows that the exercise enhanced participants' perceived ability to recognize and interpret HAB conditions. The average likelihood-to-report score of 4.0 out of

5 suggests that this knowledge gain was accompanied by a moderate-to-strong readiness to act on it in a real-world context. Meanwhile, the overall tool rating of 4.32 out of 5 indicates that participants did not merely learn from the exercise; they also found the platform itself worthwhile. Although EcoHabit delivered strong learning outcomes, participant feedback identified design changes to strengthen future iterations of the tool as it is adapted for other watershed communities facing HAB risks.

Policy Recommendations

Recommendation #1: The NYS DEC should Adopt EcoHabit as a Model for HAB Identification Training.

The first recommendation is directed at the New York State Department of Environmental Conservation. The NYS DEC Roadmap (2026) identifies public outreach and reporting as one of its six focus areas. EcoHabit aligns with the standardized approach by teaching users to visually differentiate likely HABs from commonly mistaken look-alikes, lay a foundation for interpreting environmental data, and build confidence in using reporting systems like NYHABs. This type of digital training could improve the quality of front-end reporting by preparing volunteers before they submit photo-based observations. This is important because DEC primarily relies on visual evidence for bloom reports, and blooms can disappear quickly before staff can verify them in person. A practical extension of this recommendation would be for DEC to treat EcoHabit-style educational tools as companion training for new reporting groups, especially in places like the Wallkill River, where the reporting model is being adapted to a flowing-water system rather than a traditional lake shoreline network.

Recommendation #2: Adapt EcoHabit for Local and Regional Watershed Education by Including Place-based Data and Imagery.

The second recommendation is directed toward local and regional watershed organizations across the nation. EcoHabit is a replicable framework that can be adapted for different watersheds through localized photographs, site-specific monitoring points, regionally relevant reporting guidance, and place-based educational materials. This framing responds directly to the project's broader contribution: EcoHabit was tested in the Wallkill River watershed, but its structure is relevant to other watershed groups that need accessible HAB education and community reporting preparation by utilizing stewardship concepts from the Local Environmental Stewardship Indicator (LESI) in Turnbull et al. (2020). Place-based images and examples are important because participants responded positively to visual materials, dashboard data, satellite imagery, maps, and aerial views. At the same time, participant feedback showed that future versions need clearer photographs, stronger dashboard explanations, persistent threshold references, simplified satellite instructions, and better browser or mobile compatibility.

For that reason, watershed organizations adapting EcoHabit should focus on three design priorities: expanding and standardizing the visual training library, making dashboard threshold guidance easier to access, and simplifying the satellite imagery pathway.

<u>Recommendation 2a. Expand and standardize the visual training library.</u>

Future watershed adaptations of EcoHabit should include a larger and more standardized visual training library. Participant feedback showed that users valued visual guides and bloom photographs, but also wanted clearer images, closer views, more examples of HABs and look-alikes, and more consistent image angles. These responses suggest that the visual identification module was effective as an entry point, but that future versions should reduce ambiguity by giving users more comparable examples. A stronger visual library should include multiple image types: close-up surface photographs, shoreline perspectives, overhead images, and comparison images showing HABs alongside common look-alikes such as filamentous algae, duckweed, sediment, or harmless green discoloration. The goal is not simply to provide more images, but to provide images that teach users what features matter. Standardized image sets would help participants practice recognizing color, texture, surface accumulation, scum formation, and spatial patterns under different viewing conditions. If community members are better prepared to distinguish HABs from non-HAB conditions before reporting, then submitted observations may become more useful for watershed groups and agencies. For local organizations adapting EcoHabit, building a place-based image library will be a core design step rather than an optional enhancement.

Recommendation 2b. Provide interactive data to the dashboard thresholds module with greater accessibility.

Participants were asked to apply temperature, specific conductance, and flow thresholds to a scenario after the instructional reference had disappeared. This likely created a memory burden for some rather than an interpretive, real-life applicable task. The purpose of EcoHabit is to serve as a cumulative learning environment in which each step builds on earlier decisions. Participant feedback suggests that this objective was not fully met for all users. A response implied this in their prompt, asking about improvements: “Maybe provide a bit more explanation about how to use the three metrics for determining algae growth before asking to apply them.” A practical design change would be to keep the benchmark conditions as an optional reference guide for later interpretive tasks. This improvement would shift the exercise away from testing short-term recall and toward applied judgment using environmental information in context.

Recommendation# 3: Simplify the Satellite Imagery Pathway and Improve Accessibility. The final major improvement involves the optional satellite module, where deeper engagement was achievable but not attainable across users and devices. The optional satellite module was one of the tool's most innovative components, but it also generated the most technical friction. The participation data indicated meaningful interest among non-experts, but there was a clear gap in technical expertise and accessibility among users. Qualitative responses indicate that users found the exercise confusing, while others reported mobile-viewing issues, including browser freezing. Feedback also suggests this exercise is valuable for those who want deeper engagement. Practical design changes for the future iteration of EcoHabit will include simplifying the instructions and embedding a fallback instructional video for those whose browsers cannot load the live tool. The goal will be to reduce unnecessary friction while preserving the exploratory depth that added value to EcoHabit.

Bibliography

Abdallah, M. F., Van Hassel, W. H., Andjelkovic, M., Wilmotte, A., & Rajkovic, A. (2021). Cyanotoxins and food contamination in developing countries: Review of their types, toxicity, analysis, occurrence and mitigation strategies. *Toxins, 13*(11), 786. https://doi.org/10.3390/toxins13110786

Allf, B. C., Cooper, C. B., Larson, L. R., Dunn, R. R., Futch, S. E., Sharova, M., & Cavalier, D. (2022). Citizen science as an ecosystem of engagement: Implications for learning and broadening participation. *BioScience, 72*(7), 651–663. https://doi.org/10.1093/biosci/biac035

American Public Health Association, American Water Works Association, & Water Pollution Control Federation. (1985). *Standard methods for the examination of water and wastewater* (16th ed.). American Public Health Association.

Antunes, J. T., Leão, P. N., & Vasconcelos, V. M. (2015). *Cylindrospermopsis raciborskii*: Review of the distribution, phylogeography, and ecophysiology of a global invasive species. *Frontiers in Microbiology, 6*, Article 473. https://doi.org/10.3389/fmicb.2015.00473

Ballard, H. L., Robinson, L. D., Young, A. N., Pauly, G. B., Higgins, L. M., Johnson, R. F., & Tweddle, J. C. (2017). Contributions to conservation outcomes by natural history museum-led citizen science: Examining evidence and next steps. *Biological Conservation, 208*, 87–97. https://doi.org/10.1016/j.biocon.2016.08.040

Beaulne, D., Atarita, F., Fotopoulos, G., & Braun, A. (2025). Simulating at-sensor hyperspectral satellite data for inland water algal blooms. *Science of the Total Environment, 1000*, Article 180313. https://doi.org/10.1016/j.scitotenv.2025.180313

Bennett, N. J., Whitty, T. S., Finkbeiner, E., Pittman, J., Bassett, H., Gelcich, S., & Allison, E. H. (2018). Environmental stewardship: A conceptual review and analytical framework. *Environmental Management, 61*(4), 597–614. https://doi.org/10.1007/s00267-017-0993-2

Bingham, M., & Kinnell, J. (2020). The tourism impacts of Lake Erie hazardous algal blooms. In A. T. Devlin, J. Pan, & M. M. Shah (Eds.), *Inland waters—Dynamics and ecology*. IntechOpen. https://doi.org/10.5772/intechopen.93625

Bonilla, S., Aguilera, A., Aubriot, L., Huszar, V., Almanza, V., Haakonsson, S., Izaguirre, I., O’Farrell, I., Salazar, A., Becker, V., Cremella, B., Ferragut, C., Hernández, E., Palacio, H., Rodrigues, L. C., Sampaio da Silva, L. H., Santana, L. M., Santos, J., Somma, A., Ortega, L., & Antoniades, D. (2023). Nutrients and not temperature are the key drivers for cyanobacterial biomass in the Americas. *Harmful Algae, 121*, Article 102367. https://doi.org/10.1016/j.hal.2022.102367

Bonney, R., Ballard, H., Jordan, R., McCallie, E., Phillips, T., Shirk, J., & Wilderman, C. C. (2009). *Public participation in scientific research: Defining the field and assessing its potential for informal science education*. Center for Advancement of Informal Science Education.

Bonney, R., Phillips, T. B., Ballard, H. L., & Enck, J. W. (2016). Can citizen science enhance public understanding of science? *Public Understanding of Science, 25*(1), 2–16. https://doi.org/10.1177/0963662515607406

Bowser, A., Cooper, C., de Sherbinin, A., Wiggins, A., Brenton, P., Chuang, T.-R., Faustman, E., Haklay, M., & Meloche, M. (2020). *Still in need of norms: The state of the data in citizen science*. CitSci.org.

Bowser, A., Hansen, D., He, Y., Boston, C., Reid, M., Gunnell, L., & Preece, J. (2013). Using gamification to inspire new citizen science volunteers. In *Proceedings of the First International Conference on Gameful Design, Research, and Applications* (pp. 18–25). Association for Computing Machinery. https://doi.org/10.1145/2583008.2583011

Byrd, K., Wu, J., & Lee, J. (2025). Harmful algal bloom monitoring with unmanned aerial vehicles: Tools, challenges, and public health implications. *Toxins, 17*(10), Article 475. https://doi.org/10.3390/toxins17100475

Centers for Disease Control and Prevention. (2023, September 25). *Harmful algal blooms threaten our health, environment, and economy (CS340867-A).* https://www.cdc.gov/harmful-algal-blooms/about/index.html

Cheng, K. H., Chan, S. N., & Lee, J. H. W. (2020). Remote sensing of coastal algal blooms using unmanned aerial vehicles (UAVs). *Marine Pollution Bulletin, 152*, Article 110889. https://doi.org/10.1016/j.marpolbul.2020.110889

Chorus, I., & Welker, M. (Eds.). (2021). *Toxic cyanobacteria in water: A guide to their public health consequences, monitoring and management* (2nd ed.). CRC Press.

Clites, E., Triezenberg, H., & Doberneck, D. (2024). Aligning audience needs with scientists' information in the complex harmful algal bloom outreach to engagement continuum. *Journal of Contemporary Water Research & Education, 181*, 1–10. https://doi.org/10.1111/j.1936-704X.2024.3408.x

Conrad, C. C., & Hilchey, K. G. (2011). A review of citizen science and community-based environmental monitoring: Issues and opportunities. *Environmental Monitoring and Assessment, 176*(1–4), 273–291. https://doi.org/10.1007/s10661-010-1582-5

Cooper, C. B., Shirk, J., & Zuckerberg, B. (2014). The invisible prevalence of citizen science in global research: Migratory birds and climate change. *PLOS ONE, 9*(9), Article e106508. https://doi.org/10.1371/journal.pone.0106508

Crimmins, T. M., Gerst, K. L., Huerta, D. G., Marsh, R. L., Posthumus, E. E., Rosemartin, A. H., Switzer, J. R., Weltzin, J. F., Chuine, I., Mazer, S. J., & Schwartz, M. D. (2017). Short-term forecasts of insect phenology inform pest management. *Annals of the Entomological Society of America, 110*(2), 188–197. https://doi.org/10.1093/aesa/saw088

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining “gamification.” In *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments* (pp. 9–15). Association for Computing Machinery. https://doi.org/10.1145/2181037.2181040

Dickinson, J. L., Shirk, J., Bonter, D., Bonney, R., Crain, R. L., Martin, J., Phillips, T., & Purcell, K. (2012). The current state of citizen science as a tool for ecological research and public engagement. *Frontiers in Ecology and the Environment, 10*(6), 291–297. https://doi.org/10.1890/110236

Díez-Quijada, L., Puerto, M., Gutiérrez-Praena, D., Llana-Ruiz-Cabello, M., Jos, A., & Cameán, A. M. (2019). Microcystin-RR: Occurrence, content in water and food and toxicological studies. A review. *Environmental Research, 168*, 467–489. https://doi.org/10.1016/j.envres.2018.07.019

European Citizen Science Association. (2015). *Ten principles of citizen science*. https://www.ecsa.ngo/10-principles/

European Citizen Science Association. (2025, April 23). *Ten principles of citizen science*. European Climate Pact. https://climate-pact.europa.eu/eu-climate-action-academy-0/resources/ten-principles-citizen-science_en

Feng, L., Wang, Y., Hou, X., Qin, B., Kutser, T., Qu, F., et al. (2024). Harmful algal blooms in inland waters. *Nature Reviews Earth & Environment, 5*, 631–644. https://doi.org/10.1038/s43017-024-00578-2

Goodrich, S., Canfield, K. N., & Mulvaney, K. (2024). Expert insights on managing harmful algal blooms. *Frontiers in Freshwater Science, 2*, Article 1452344. https://doi.org/10.3389/ffwsc.2024.1452344

Haklay, M. (2013). Citizen science and volunteered geographic information: Overview and typology of participation. In D. Sui, S. Elwood, & M. Goodchild (Eds.), *Crowdsourcing geographic knowledge* (pp. 105–122). Springer. https://doi.org/10.1007/978-94-007-4587-2_7

Hart, A. G., Perry, J. R., Sumner, S., & Thompson, C. (2021). “Citizen identification”: Online learning supports highly accurate species identification for insect-focussed citizen science. *Insect Conservation and Diversity, 14*(6), 862–867. https://doi.org/10.1111/icad.12528

Haywood, B. K., Parrish, J. K., Jones, T., & Inman, S. (2024). Shaping people-place bonds in citizen science: A framework for analysis. *Ecology and Society, 29(1), Article 11.*. https://doi.org/10.5751/ES-15041-290111

Horsburgh, J. S., Caraballo, J., Ramírez, M., Aufdenkampe, A. K., Arscott, D. B., & Damiano, S. G. (2019). Low-cost, open-source, and low-power: But what to do with the data? *Frontiers in Earth Science, 7*, Article 67. https://doi.org/10.3389/feart.2019.00067

HVNY. (2025, September 18). *Unprecedented harmful algal bloom affecting Hudson River in multiple locations*. https://hvny.info/news/2025/extensive-algal-bloom-hudson-river

Ignatius, A. R., Purucker, S. T., Schaeffer, B. A., Wolfe, K., Urquhart, E., & Smith, D. (2022). Satellite-derived cyanobacteria frequency and magnitude in headwaters and near-dam reservoir surface waters of the Southern U.S. *Science of the Total Environment, 822*, Article 153568. https://doi.org/10.1016/j.scitotenv.2022.153568

Igwaran, A., Kayode, A. J., Moloantoa, K. M., Khetsha, Z. P., & Unuofin, J. O. (2024). Cyanobacteria harmful algae blooms: Causes, impacts, and risk management. *Water, Air, & Soil Pollution, 235*(1), Article 16. https://doi.org/10.1007/s11270-023-06782-y

Irwin, A. (1995). *Citizen science: A study of people, expertise and sustainable development*. Routledge.

Janatian, N., Raudsepp, U., Broomandi, P., Fickas, K., Olli, K., Heimovaara, T., Mannik, A., Uiboupin, R., & Pahlevan, N. (2025). A review on remote-sensing-based harmful cyanobacterial bloom monitoring services. *Remote Sensing Applications: Society and Environment, 37*, Article 101488. https://doi.org/10.1016/j.rsase.2025.101488

Johnson, M. F., Hannah, C., Acton, L., Popovici, R., Karanth, K. K., & Weinthal, E. (2017). Network environmentalism: Citizen scientists as agents for environmental advocacy. *Global Environmental Change, 29*, 235–245. https://doi.org/10.1016/j.gloenvcha.2014.10.006

Johnston, B. D., Finkelstein, K. M., Gifford, S. R., Stouder, M. D., Nystrom, E. A., Savoy, P. R., Rosen, J. J., & Jennings, M. B. (2024). *Evaluation of sensors for continuous monitoring of harmful algal blooms in the Finger Lakes Region, New York, 2019 and 2020* (Scientific Investigations Report 2024–5010). U.S. Geological Survey. https://doi.org/10.3133/sir20245010

Jordan, R. C., Sorensen, A. E., & Biehler, D. (2019). Adaptive management of urban wildlife: The case of white-tailed deer. In W. C. Pitt, J. C. Beasley, & G. W. Witmer (Eds.), *Ecology and management of terrestrial vertebrate invasive species in the United States* (pp. 301–324). CRC Press.

Jørgensen, F. A., & Jørgensen, D. (2021). Citizen science for environmental citizenship. *Conservation Biology, 35*(4), 1304–1310. https://doi.org/10.1111/cobi.13689

Khan, M. N., & Mohammad, F. (2013). Eutrophication: Challenges and solutions. In A. A. Ansari, & S. S. Gill (Eds.), *Eutrophication: Causes, consequences and control* (pp. 1–15). Springer. https://doi.org/10.1007/978-94-007-7814-6_1

Khan, R. M., Salehi, B., Mahdianpari, M., Mohammadimanesh, F., Mountrakis, G., & Quackenbush, L. J. (2021). A meta-analysis on harmful algal bloom (HAB) detection and monitoring: A remote sensing perspective. *Remote Sensing, 13*(21), Article 4347. https://doi.org/10.3390/rs13214347

Kim, J., Jones, J. R., & Seo, D. (2021). Factors affecting harmful algal bloom occurrence in a river with regulated hydrology. *Journal of Hydrology: Regional Studies, 33*, Article 100769. https://doi.org/10.1016/j.ejrh.2020.100769

Kosmala, M., Wiggins, A., Swanson, A., & Simmons, B. (2016). Assessing data quality in citizen science. *Frontiers in Ecology and the Environment, 14*(10), 551–560. https://doi.org/10.1002/fee.1436

Kraft, K., Haraguchi, L., Hällfors, H., Suikkanen, S., Ylöstalo, P., Kielosto, S., Skyttä, A., Laakso, L., Honkanen, M., Kahru, M., & Seppälä, J. (2025). Monitoring cyanobacteria blooms with complementary measurements—a similar story told using high-throughput imaging, optical sensors, light microscopy, and satellite-based methods. *Harmful Algae, 147*, Article 102865. https://doi.org/10.1016/j.hal.2025.102865

Large, R. R., Hazen, R. M., Morrison, S. M., Gregory, D. D., Steadman, J. A., & Mukherjee, I. (2022). Evidence that the GOE was a prolonged event with a peak around 1900 Ma. *Geosystems and Geoenvironment, 1*(2), Article 100036. https://doi.org/10.1016/j.geogeo.2021.09.003

Liu, J., Fu, Z., & Liu, W. (2023). Impacts of precipitation variations on agricultural water scarcity under historical and future climate change. *Journal of Hydrology, 617*, Article 128999. https://doi.org/10.1016/j.jhydrol.2022.128999

MacPhail, V. J., & Colla, S. R. (2020). Power of the people: A review of citizen science programs for conservation. *Biological Conservation, 249*, Article 108739. https://doi.org/10.1016/j.biocon.2020.108739

Medema, W., Adamowski, J., Orr, C., Furber, A., Wals, A., & Milot, N. (2017). Building a foundation for knowledge co-creation in collaborative water governance: Dimensions of stakeholder networks facilitated through bridging organizations. *Water, 9*(1), Article 60. https://doi.org/10.3390/w9010060

New York State Department of Environmental Conservation. (2025). *Lower Hudson River harmful algal bloom monitoring 2025*. https://dec.ny.gov/sites/default/files/2025-10/hudsonriver_hab_factsheet.pdf

New York State Department of Environmental Conservation. (2026). *Harmful algal bloom (HAB) roadmap: A five-year plan to study, manage, and reduce HABs in New York State*. https://dec.ny.gov/sites/default/files/2026-03/HABroadmap.pdf

Nikolakis, W., Hotte, N., & Innes, J. L. (2023). Indigenous fire stewardship: Federal policy barriers and opportunities. *Land, 12*(1), Article 160. https://doi.org/10.3390/land12010160

Nwankwegu, A. S., Li, Y., Huang, Y., Wei, J., Norgbey, E., Sarpong, L., Lai, Q., & Wang, K. (2019). Harmful algal blooms under changing climate and constantly increasing anthropogenic actions: The review of management implications. *3 Biotech, 9*(12), Article 449. https://doi.org/10.1007/s13205-019-1976-1

Ottinger, G. (2010). Buckets of resistance: Standards and the effectiveness of citizen science. *Science, Technology, & Human Values, 35*(2), 244–270. https://doi.org/10.1177/0162243909337121

Paerl, H. W. (2018). Mitigating toxic planktonic cyanobacterial blooms in aquatic ecosystems facing increasing anthropogenic and climatic pressures. *Toxins, 10*(2), Article 76. https://doi.org/10.3390/toxins10020076

Phillips, T. B., Ballard, H. L., Lewenstein, B. V., & Bonney, R. (2019). Engagement in science through citizen science: Moving beyond data collection. *Science Education, 103*(3), 665–690. https://doi.org/10.1002/sce.21501

Preece, J., & Shneiderman, B. (2009). The reader-to-leader framework: Motivating technology-mediated social participation. *AIS Transactions on Human-Computer Interaction, 1*(1), 13–32. https://doi.org/10.17705/1thci.00005

Resnik, D. B., Elliott, K. C., & Miller, A. K. (2015). A framework for addressing ethical issues in citizen science. *Environmental Science & Policy, 54*, 475–481. https://doi.org/10.1016/j.envsci.2015.05.008

Robinson, L. D., Cawthray, J. L., West, S. E., Bonn, A., & Ansine, J. (2021). Ten principles of citizen science. In K. Vohland, A. Land-Zandstra, L. Ceccaroni, R. Lemmens, J. Perelló, M. Ponti, R. Samson, & K. Wagenknecht (Eds.), *The science of citizen science* (pp. 27–40). Springer. https://doi.org/10.1007/978-3-030-58278-4_2

Roediger, H. L., III, & Karpicke, J. D. (2006). Test-enhanced learning: Taking memory tests improves long-term retention. *Psychological Science, 17*(3), 249–255. https://doi.org/10.1111/j.1467-9280.2006.01693.x

Roque, A., Wutich, A., Quimby, B., Porter, S., Zheng, M., Hossain, M. J., & Brewis, A. (2022). Participatory approaches in water research: A review. *Wiley Interdisciplinary Reviews: Water, 9*(2), Article e1577. https://doi.org/10.1002/wat2.1577

Rotman, D., Preece, J., Hammock, J., Procita, K., Hansen, D., Parr, C., Lewis, D., & Jacobs, D. (2012). Dynamic changes in motivation in collaborative citizen-science projects. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work* (pp. 217–226). Association for Computing Machinery. https://doi.org/10.1145/2145204.2145238

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology, 25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Saleem, U., Torabi Haghighi, A., Kløve, B., & Oussalah, M. (2024). Citizen science applications for water quality monitoring: A review [Preprint]. *EGUsphere, 2024*, 1–18. https://doi.org/10.5194/egusphere-2024-1170

Shirk, J. L., Ballard, H. L., Wilderman, C. C., Phillips, T., Wiggins, A., Jordan, R., McCallie, E., Minarchek, M., Lewenstein, B. V., Krasny, M. E., & Bonney, R. (2012). Public participation in scientific research: A framework for deliberate design. *Ecology and Society, 17*(2), Article 29. https://doi.org/10.5751/ES-04705-170229

Simon, D. F., Munoz, G., Dinh, Q. T., Duy, S. V., Kavanagh, K., Smith, R., Husk, B., & Sauvé, S. (2023). Adopt a Lake: Successfully tracking harmful cyanobacterial blooms in Canadian surface waters through citizen science. *Citizen Science: Theory and Practice, 8*(1), Article 66. https://doi.org/10.5334/cstp.655

Starr, J., Schweik, C. M., Bush, N., Fletcher, L., Finn, J., Fish, J., & Bargeron, C. T. (2014). Lights, ecamera…citizen science: Assessing the effectiveness of smartphone-based video training in invasive plant identification. *PLOS ONE, 9(11), Article e111433*. https://doi.org/10.1371/journal.pone.0111433

Stauffer, B. A., Bowers, H. A., Buckley, E., Davis, T. W., Johengen, T. H., Kudela, R., McManus, M. A., Purcell, H., Smith, G. J., Vander Woude, A., & Tamburri, M. N. (2019). Considerations in harmful algal bloom research and monitoring: Perspectives from a consensus-building workshop and technology testing. *Frontiers in Marine Science, 6*, Article 399. https://doi.org/10.3389/fmars.2019.00399

Strobl, B., Etter, S., van Meerveld, I., & Seibert, J. (2020). Training citizen scientists through an online game developed for data quality control. *Geoscience Communication, 3*(1), 109–126. https://doi.org/10.5194/gc-3-109-2020

Sullivan, B. L., Aycrigg, J. L., Barry, J. H., Bonney, R. E., Bruns, N., Cooper, C. B., Damoulas, T., Dhondt, A. A., Dietterich, T., Farnsworth, A., Fink, D., Fitzpatrick, J. W., Fredericks, T., Gerbracht, J., Gomes, C., Hochachka, W. M., Iliff, M. J., Lagoze, C., La Sorte, F. A., ... Kelling, S. (2014). The eBird enterprise: An integrated approach to development and application of citizen science. *Biological Conservation, 169*, 31–40. https://doi.org/10.1016/j.biocon.2013.11.003

Telli, K., Kraa, O., Himeur, Y., Ouamane, A., Boumehraz, M., Atalla, S., & Mansoor, W. (2023). A comprehensive review of recent research trends on unmanned aerial vehicles (UAVs). *Systems, 11(8), Article 400*. https://doi.org/10.3390/systems11080400

Turnbull, E. A., Knapp, S., & Schroeder, R. (2020). Assessing environmental stewardship: The local environmental stewardship indicator. *Environmental Conservation, 47*(3), 198–208. https://doi.org/10.1017/S0376892920000259

Urrutia-Cordero, P., Zhang, H., Chaguaceda, F., Geng, H., & Hansson, L.-A. (2020). Climate warming and heat waves alter harmful cyanobacterial blooms along the benthic–pelagic interface. *Ecology, 101*(7), Article e03025. https://doi.org/10.1002/ecy.3025

van Noordwijk, C. G. E., Verney, P. J., August, T., Brown, A., Goudeseune, L., & He, Y. (2021). Creating positive environmental impact through citizen science. In K. Vohland, A. Land-Zandstra, L. Ceccaroni, R. Lemmens, J. Perelló, M. Ponti, R. Samson, & K. Wagenknecht (Eds.), *The science of citizen science* (pp. 313–333). Springer. https://doi.org/10.1007/978-3-030-58278-4_17

Villalobos, T., Suárez-Isla, B., & Garcia, C. (2025). Health and environmental impacts of cyanobacteria and cyanotoxins from freshwater to seawater. *Toxins, 17*(3), Article 126. https://doi.org/10.3390/toxins17030126

Vuorio, K., Järvinen, M., & Kotamäki, N. (2020). Phosphorus thresholds for bloom-forming cyanobacterial taxa in boreal lakes. *Hydrobiologia, 847*, 4389–4400. https://doi.org/10.1007/s10750-019-04161-5

Wang, R., Dearing, J. A., Langdon, P. G., Zhang, E., Yang, X., Dakos, V., & Scheffer, M. (2018). Global elevation of algal bloom frequency in large lakes over the past two decades. *Nature, 560*, 494–497. https://doi.org/10.1038/s41586-018-0630-3

Wang, Y., Zhao, D., Woolway, R. I., Yan, H., Paerl, H. W., Zheng, Y., Zheng, C., & Feng, L. (2025). Global elevation of algal bloom frequency in large lakes over the past two decades. *National Science Review, 12*, Article nwaf011. https://doi.org/10.1093/nsr/nwaf011

Watson, S. B., Miller, C., Arhonditsis, G., Boyer, G. L., Carmichael, W., Charlton, M. N., Confesor, R., Depew, D. C., Hook, T. O., Ludsin, S. A., Matisoff, G., McElmurry, S. P., Murray, M. W., Richards, R. P., Rao, Y. R., Steffen, M. M., & Wilhelm, S. W. (2016). The re-eutrophication of Lake Erie: Harmful algal blooms and hypoxia. *Harmful Algae, 56*, 44–66. https://doi.org/10.1016/j.hal.2016.04.010

Wiggins, A., & Crowston, K. (2011). From conservation to crowdsourcing: A typology of citizen science. In *Proceedings of the Forty-fourth Hawai'i International Conference on System Science*. IEEE. https://doi.org/10.1109/HICSS.2011.207

World Health Organization. (2020). *Cyanobacterial toxins: Microcystins: Background document for development of WHO guidelines for drinking-water quality and guidelines for safe recreational water environments* (WHO/HEP/ECH/WSH/2020.6). https://cdn.who.int/media/docs/default-source/wash-documents/wash-chemicals/microcystins-background-201223.pdf?sfvrsn=6d60aa6d_3

Yang, S., Chen, X., Lu, J., Hou, X., Li, W., & Xu, Q. (2021). Impacts of agricultural topdressing practices on cyanobacterial bloom phenology in an early eutrophic plateau lake, China. *Journal of Hydrology, 594*, Article 125952. https://doi.org/10.1016/j.jhydrol.2020.125952

Zepernick, B. N., Wilhelm, S. W., Bullerjahn, G. S., & Paerl, H. W. (2023). Climate change and the aquatic continuum: A cyanobacterial comeback story. *Environmental Microbiology Reports, 15*(1), 3–12. https://doi.org/10.1111/1758-2229.13