Groundwater

Technical Commentary/

Solutions to Current Challenges in Widespread Monitoring of Groundwater Quality via Crowdsensing

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Introduction

Community science, research conducted by members of the general public in partnership with scientists (Kim et al. 2011), can facilitate the widespread collection of environmental data. Crowdsensing serves as a sub-field of community science, in which the participants themselves act as the "sensors," relying on inexpensive (e.g., test strips) or accessible technologies (e.g., smartphones) to provide an easy-to-use detection or sensing method for data collection (Shupe 2017; Muñoz et al. 2019). Recently, crowdsensing has gained attention as a new data collection paradigm across a diverse range of applications, allowing researchers to obtain measurements from nontechnical individuals in a scalable and efficient way (Ganti et al. 2011; Hu et al. 2013; Kawajiri et al. 2014; Wang et al. 2015). The crowdsensing approach is advantageous in that: (1) it provides an infrastructure-free solution; (2) the crowd acts as a "sensor network," providing an efficient way to collect large amounts of data quickly and inexpensively; and (3) active participation in data collection allows the community to become more informed and feel empowered to protect their natural resources.

While crowdsensing has been successfully implemented in many surface water applications (Liu et al. 2005; Shiber 2005; Paul et al. 2015; Boakes et al. 2016), the use of crowdsensing in groundwater applications remains relatively rare, representing a significant opportunity for data collection. In the United States, groundwater is the drinking water source for more than half of the population. However, groundwater is susceptible to contamination (Reynolds et al. 2008), often resulting from human activities and land-use practices (Li et al. 2021). For example, the application of excess fertilizers in agricultural areas (U.S. Geological Survey 2015), improperly constructed or leaky septic systems (Yates 1985), and spills or releases of stored chemicals (U.S. Environmental Protection Agency 2015) can all serve as sources of contamination in groundwater. Depending on the specific nature of the contaminant, dangerously high concentrations can persist for long periods of time in the subsurface and travel large distances (Newell et al. 2020). Across the United States, approximately 40 million people, primarily in rural and suburban communities, rely on private wells (Liu et al. 2005), resulting in the inadvertent pumping and ingestion of groundwater contaminants, exposing residents of well-dependent households to potential health risks unknowingly (Fewtrell 2004, U.S. Census Bureau 2011). A recent study reported that 23% of private wells sampled contained contaminants at levels of concern (Malecki et al. 2017) and the number of groundwater systems in violation of maximum contaminant limits is increasing (Pennino et al. 2017), yet there are no federal laws or central utilities to monitor well water quality.

Without federal regulations in place to ensure access to clean water, community-level monitoring of

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groundwater quality in well-dependent communities is critical to ensure human health and safety. However, unique challenges and limitations exist relative to traditional monitoring approaches at centralized water distribution facilities. Specifically, scaling groundwater monitoring efforts presents a significant challenge in well-dependent communities. It is not feasible to implement both frequent and widespread testing for contaminants in individual wells to ensure water quality standards are routinely met. Additionally, the analytical costs for millions of samples would be exorbitant. Alternatively, sensor networks could be installed to actively monitor groundwater wells; however, the issues of access to, cost, and maintenance of sensor networks prevent widespread implementation. While state and federal agencies may have funding to cover small-scale monitoring, comprehensive monitoring is not feasible, resulting in sparse data in both time and space (Michener et al. 2012).

Using crowdsensing methods to monitor groundwater is novel and provides a straightforward and replicable avenue to collect a vast amount of data. Here, we seek to highlight how crowdsensing can be effectively used to monitor groundwater quality in well-dependent communities. We will address current hurdles to widespread implementation of crowdsensing, including participant recruitment, access to technology, and issues of data reliability, as well as potential solutions that can be used to enhance the efficacy of crowdsensing studies. We will also present a case study from the University of Notre Dame as a simple framework for the execution of large-scale crowdsensing in well-dependent communities that can be translated to other regions and extended temporally to facilitate long-term monitoring via crowdsensing. The adaptation of this framework to other locales can facilitate enhanced communication between local residents and local governments, laying the groundwork for policy change targeted at improving groundwater quality for well-dependent communities.

Current Challenges in Crowdsensing

Participant Recruitment and Biases

Without sufficient participation at the right scale, crowdsensing cannot be a viable way to generate large environmental datasets to adequately monitor environmental resources; therefore, participant recruitment is the most fundamental component to a successful crowdsensing project. Many studies that rely on participation of the public often recruit participants from existing groups (Little et al. 2016, Kim et al. 2011), and individuals who are already involved with established volunteer programs are more likely to participate if their current program is partnered with a proposed project (Alender 2016). However, well-established programs or environmental groups may not exist across all community types. For example, in more spatially dispersed communities, a centralized environmental group may not exist for researchers to use as a framework for a crowdsensing study (Davis et al. 2014). Potential participants may also have concerns over sharing data that could potentially be tied back to their households (e.g., well water quality), so ensuring anonymity in data reporting can be important in making volunteers feel comfortable joining a study. Similarly, obtaining parental consent/assent for crowdsensing studies conducted through the classroom may reduce participation rates.

Additionally, maintaining participant engagement can present a challenge. This can be a significant issue in contributory studies, where volunteers assist in data collection to address scientist-led questions (Lowry et al. 2019). In contributory studies, the interests of volunteers and the general public may not be addressed, which may limit participation and a sense of data ownership in such studies (Cornwall and Jewkes 1995; Shirk et al. 2012). With long-term crowdsensing efforts, volunteer fatigue can occur over time, whereby participants become disinterested and engagement wanes (Deutsch and Ruiz-Córdova 2015). Thus, providing motivation for participants to continue to invest in crowdsensing studies is essential. Because of volunteer fatigue, the average successful volunteer monitoring programs only span three to seven years (Klang and Heiskary 2000; Nerbonne and Nelson 2004; Deutsch et al. 2009). Although short-term studies may successfully identify an issue, repeat monitoring is typically required to assess progress, especially because water quality conditions are transient, and concerns can take decades to resolve. Therefore, overcoming volunteer fatigue is essential in creating and implementing meaningful long-standing crowdsensing studies.

Participation in crowdsensing studies is generally known to be influenced by education level, awareness of an issue, social identities, and the resource type being monitored (Shirk and Bonney 2015). A pre-established interest in the environment will likely generate interest from potential "crowdsensors," as they are more likely to be aware of local environmental concerns (Shirk and Bonney 2015). Lack of interest in the environment or awareness of local issues may be a barrier in using broader public calls for participants through social media or local advertisements. Many communities may not test their water because they simply did not know it was needed (Paul et al. 2015). Additionally, education level may influence the participants' background knowledge on the issue at hand, in turn influencing their willingness to participate. For example, in one study, 38% of participants had a bachelor's degree, which was 16% higher than the city mean, and 57% were at least high school graduates, which was 8% lower than the city mean (Jakositz et al. 2020). This suggests that education level may have unconsciously influenced participants' willingness to join the study. Socioeconomic status, which correlates heavily with education level, should also be considered as a driver for participation (Deutsch and Ruiz-Córdova 2015; Jakositz et al. 2020). This may select against those who hold hourly positions, which may decrease schedule flexibility and the ability to commit time to a crowdsensing project (Spleen et al. 2014). Finally, cultural identity may act as a motivating factor if participants' culture places a high importance on preserving certain natural resources (Ožana et al. 2019).

Access to Technology

Technology serves as the mechanism for participants to become environmental sensors, allowing volunteers to more easily collect, report, and/or share data via websites or smartphone applications (Compas and Wade 2018). Therefore, participants' access to relevant technology is a critical component to all crowdsensing studies. Limited access to enabling technologies, like WiFi or smartphones, may limit participation in crowdsensing studies in low-income or rural settings (Hale et al. 2010), yet these areas are often most susceptible to environmental impacts (Strosnider et al. 2017). Although 93% of Americans use the internet (Pew Research Center 2021a), the availability of at-home broadband connections is lowest in rural communities (only 72% of U.S. adults) compared to urban and suburban communities (77–79% of U.S. adults). Although smartphone usage has increased from 35% in 2011 to 85% in 2021 across the United States (Pew Research Center 2021b), smartphone use is lowest in rural communities as well (80% of U.S. adults versus 84–89% in suburban and urban communities). Therefore, it is possible that using applications or websites for data reporting may bias toward participants with more experience with technology, which may in turn bias data collection and under-represent households with lower incomes or older occupants. It is possible that some participants may not have experience using applications (Kim et al. 2011), which could lead to issues with recruitment early in the project or with data reporting later. Finally, the cost may serve as a barrier to access; the use of smartphone applications or websites may present a financial challenge. Both application and website development will likely require project leads to hire personnel to create platforms for data entry, which may be cost-prohibitive or delay project startup.

Current Limitations for Data Analysis and Reliability

Data reliability is a critical challenge in the data analysis of crowdsensing systems (Wang et al. 2014; Zhang et al. 2018; Liu et al. 2019). This is mainly due to the fact that "crowdsensors" are often the members of general public who may not provide as reliable measurement as professionally trained individuals. Errors in crowdsensing can arise for numerous reasons. For example, issues with data reliability may arise from inaccurate measurements, incorrect operation of sampling equipment, or misunderstanding the instructions. A simple approach to address such problems is to aggregate crowdsensing data by averaging participant reports and leveraging data denoising and smoothing techniques (e.g., majority voting, statistical filtering; Yang and Hong 2017; Chen et al. 2020). However, a key limitation of these approaches is that they treat all crowdsensing reports as equally reliable and do not account for the fact that different participants may have different reliability. For example, the report from a participant who carefully conducts a measurement is likely to be more accurate than a participant who misinterprets the instructions. A report from a reliable participant should not be treated equally to a report from a less reliable one. However, what makes this challenging is that neither the reliability of participants, nor the correctness of their reports is known a priori (Wang et al. 2012). Therefore, it is a critical challenge to develop effective data analytic solutions in crowdsensing systems that accurately estimate both participant reliability and accuracy without a large amount of prior knowledge.

Solutions to Overcome Barriers in Crowdsensing Studies

Participant Recruitment and Biases

To effectively recruit participants and maintain their engagement requires a multi-faceted approach. In fact, most community science projects must be designed using multiple recruitment approaches, attracting participants through social media, word of mouth, public advertising, information stands, and university partnerships (Jakositz et al. 2020). Today, social media is a particularly useful tool to attract individual participants to a research opportunity through posts across several popular platforms (e.g., Twitter and Facebook), allowing interested individuals to find community science research projects relevant to their specific interests with a simple keyword search (Bonnet et al. 2014). Participation via social media platforms can range in success, from a few hundred to hundreds of thousands of participants (e.g., the Zooniverse project; Simpson et al. 2014). Additionally, placing public advertising for participants in highly trafficked areas, such as a local science museum, can be an extremely successful strategy for recruiting participants from a targeted population (Jollymore et al. 2017; Rodriguez et al. 2019), and the use of presentations or interactive displays can inform potential participants about local environmental challenges in their community to help create a common goal between the researchers and volunteers.

Participant engagement should also involve establishing connections with existing local networks and institutions, such as environmental groups or schools. For example, members of environmental groups are generally more likely to have a passion for an environmental subject and an educational background in an applicable field (Paul et al. 2015; Farnham et al. 2017), suggesting they may volunteer as "crowdsensors" more readily than other groups. Schools may also serve as an ideal setting to easily integrate crowdsensing projects directly via the curriculum (Haynes et al. 2019). For example, BirdSleuth from the Cornell Lab of Ornithology (www.BirdSleuth.org) provides lessons and activities that can be incorporated into K-12 curricula that support various community science projects. Working directly with science teachers or hosting outreach events through local schools utilizes an established, centralized infrastructure within the community and can quickly reach a large number of participants both voluntarily or through class assignments (Compas and Wade 2018; Haynes et al. 2019). Additionally, participants with an interest in the subject or providing opportunities for community-based problem solving may result in higher engagement rates and help maintain involvement (Haynes et al. 2019). Therefore, finding novel ways to increase participants' understanding of the issue and centering project goals around community concerns, as well as getting participants excited, is essential (Compas and Wade 2018; Haynes et al. 2019).

Once participants have been successfully recruited, incentivizing participation can maintain engagement and avoid volunteer fatigue. This can be done via educational outcomes, prizes, or data sharing. Prizes, such as monetary compensation, electronics, or books on the subject, offer an alternative incentive that may be especially motivating to younger audiences. Compensating participants for their time with gift card rewards can encourage them to submit their results (Kim et al. 2011). For school settings, creating competitions between classrooms with prizes for the winning classroom may increase completion rates. If prizes can relate specifically to the topic of investigation (e.g., refillable water bottles for a water quality study), then a virtuous cycle of engagement can emerge with prizes further spreading awareness and amplifying recruiting efforts throughout the community. Finally, open and frequent communication via data sharing can motivate participants to stay engaged and offers participants a way to see the outcomes of their efforts (Rotman et al. 2014), as was documented throughout the CrowdHydrology project (Lowry et al. 2019). The use of interactive website features, such as maps, can allow study participants to explore the data they had a hand in collecting, and provide teachers with tools that can augment class assignments. Online platforms can also provide an outlet for "crowdsensors" to share photos and comments about their experiences as well, creating a broader sense of community among the participants and reinforcing the common goal.

Overcoming Limited Access to Technology

Crowdsensing studies inherently rely on some type of technology; therefore, accessibility is key for engaging across community types and gaining a comprehensive understanding of the system of interest. Several studies have shown that useful and uncomplicated technology that has a clear benefit to volunteers is essential for motivating participation (Ali et al. 2021). When using websites or smartphone applications, creating user-friendly interfaces with clear instructions and workflow for data entry is essential, allowing participants to confidently enter their data (Kim et al. 2011). If access to the internet is a barrier to recruitment in a given community, partnering with computer science teachers or local libraries can expand participants' ability to report data. Internet providers may also be willing to sponsor crowdsensing activities and provide enhanced access to WiFi, as we have seen throughout the ongoing COVID-19 pandemic. Using short message service (SMS) technology can be useful in communities where smartphones, and in turn access to applications, are less common, whereby volunteers can then simply text in their measurement results (Fienen and Lowry 2012). This may also expand access to participants who are less technologically adept. Additionally, depending on community-specific challenges, alternative "low-tech" solutions can be adopted as needed, including using pre-paid envelopes to mail in results or creating a centralized datasheet drop-off location within the community.

Data Analysis and Reliability

One of the simplest ways to improve data quality and reliability is to provide adequate training to volunteers. Several studies have shown that with adequate training, the quality of data collected by volunteers is comparable to data collected by professionals across data types (e.g., chemical, physical, and biological; Rodrigues and Castro 2008; Loperfido et al. 2010; Stepenuck et al. 2011). Training participants can range from in-person demonstrations to short training videos (Lowry et al. 2019). Additionally, over the last decade, many innovative algorithms and quantitative frameworks have been developed to ensure data reliability in crowdsensing studies after the data has been collected. For example, technologies called "truth discovery" frameworks address data reliability by jointly assessing the reliability of data sources (e.g., participants) and the correctness of their reported measurements using models based on regression methods, such as principled estimation and machine learning (Wang et al. 2013; Zhang et al. 2018; Sheng and Zhang 2019). Moreover, contextual information can also be used to address data reliability. For example, location information about the data source can be incorporated into "context-aware" data analytic models, which are designed to statistically assess the reliability of a data source and the credibility of the crowdsourced data (e.g., traffic conditions at a specific site and time; Wang et al. 2013). However, as powerful as these approaches are, these methods have their own limitations as they are built using specific and potentially restrictive theoretical assumptions that are required to develop a robust and useable framework. For example, they are not currently suited to dealing with data relating to measured variables that are spatially and temporally correlated (Zhang et al. 2018; Ye et al. 2020). Given that geologic formations and groundwater flows can display a high degree of spatial and temporal correlation (Dagan 1989), which in turn arises in groundwater quality and risk assessment (Bolster et al. 2009), such restrictions may limit the utility of these approaches in groundwater-specific applications. As such, new frameworks that build on these approaches, remove current limitations, and incorporate multiple data sources with differing reliability must be established to jointly estimate both source reliability and accuracy in reporting.

Case Study: SmartWater Crowdsensing Project

Land use in Northern Indiana is primarily agricultural, and the high permeability of the regional aquifer increases the susceptibility of groundwater reserves to

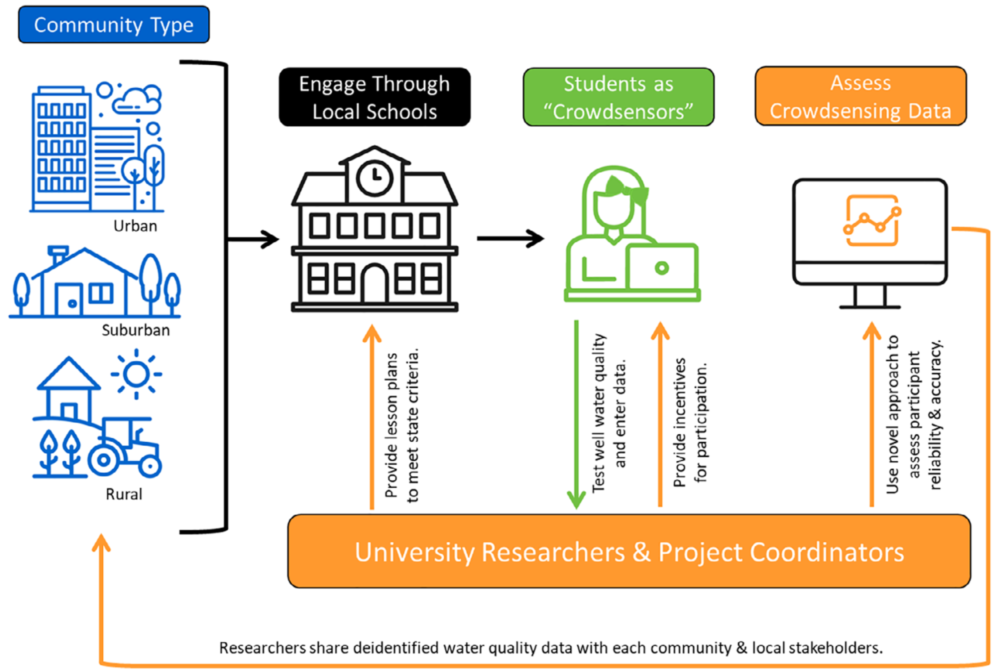

Figure 1. The SmartWater Project's framework to engage local schools in a large-scale crowdsensing experiment to test groundwater quality across community types.

nitrate (NO_3^--N) contamination (Indiana Department of Environmental Management 2016). Many households within the region are well-dependent, and homeowners are singularly responsible for monitoring their well water quality; however, without regular monitoring, residents in well-dependent households are at a greater risk of ingesting water with elevated NO_3^--N concentrations. Additionally, many developments at the rural–urban interface are developed with houses on relatively small lots relying on shallow wells and septic systems for water supply and wastewater treatment, creating further pathways for nitrate contamination. Consuming water with high NO_3^--N concentrations can result in myriad health concerns, including increased risks for certain cancers, birth defects, and thyroid problems with prolonged exposure. It can cause low blood oxygen and lead to methemoglobinemia, which carries a 7–8% fatality rate in infants (Fan and Steinberg 1996). Thus, Northern Indiana presents an ideal geographical setting to test a crowdsensing approach as an efficient and reliable way to monitor NO_3^--N contamination in groundwater wells where a central utility does not exist. Moreover, groundwater contamination is spatially variable across much of Northern Indiana as a result of the influences of both agriculture and contamination from suburban septic systems; for example, only one in three houses in Granger, Indiana, has high levels of NO_3^--N and the mechanisms driving fine-scale spatial patterns are unclear. This highlights the need for individual households in the region to understand their own well water quality, especially as national characterizations of well water quality have not been conducted in the past decade (e.g., Nolan et al. 2002; Rupert 2008; Burow et al. 2010). Thus, researchers at the University of Notre Dame initiated the SmartWater Crowdsensing (SWC) project, which seeks to provide an adaptable framework for monitoring well water contamination by utilizing the collective power of humans as "environmental sensors" through novel recruitment, experimental design, and data analysis approaches (Figure 1). Here, we present preliminary findings and insights from the first round of SWC experiments from Fall 2019, though the experiment has continued through the present. We aim to provide researchers with a generalized crowdsensing framework, which can be adapted to other locales to facilitate both long-term and widespread monitoring efforts.

Using Established Connections to Recruit Local Crowdsensing Participants

In recruiting participants, we sought to have representation from a breadth of well-dependent residential types, including urban fringe, suburban, and rural. Given the interest in replicability, the SWC project approached recruitment through building networks within school districts. Along with university outreach resources, a previous Notre Dame crowdsensing project provided initial connections with science teachers from local elementary schools (Wei et al. 2017) and established a starting point to expand our recruitment efforts in the school district to work with high school teachers in the area. To incentivize teachers to incorporate the SWC project into their curriculum, we provided a mini-lesson, including a presentation covering the importance of groundwater quality and key terms or ideas that met state curriculum requirements (doe.in.gov/standards). We also offered the option for our project coordinator to go to each classroom to present the lesson to enhance in-person engagement with

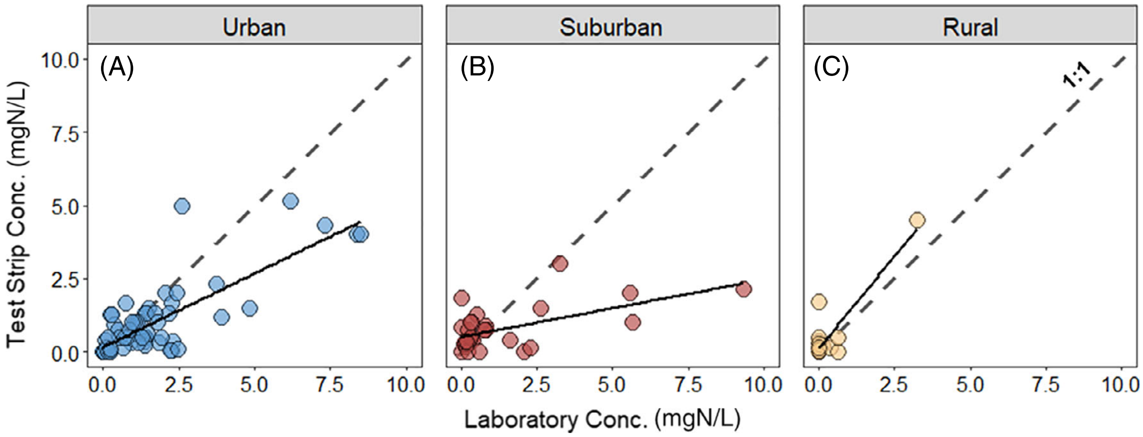

Figure 2. Comparison of test strip NO_3^--N concentrations versus NO_3^--N concentrations measured in the lab by community type: (A) urban, (B) suburban, and (C) rural. The dashed gray line is the 1:1 line, along which laboratory and test strip concentrations would match exactly. The solid black line shows trend in the data for each community type.

the student participants, with the particular objective of minimizing any additional planning or other burdens on the teacher.

Through targeted recruitment in partnership with school programs, we engaged 70 students from well-dependent households in Northern Indiana for our first round of experiments in September 2019; however, our sampling efforts were not evenly distributed across community types. We obtained samples from 35 students representing the suburban residential development, 24 representing urban fringe neighborhoods, and 11 representing rural areas. Students were trained to collect water samples and measure NO_3^--N concentrations with test strips via an in-person demonstration. Additionally, as training videos have been shown to ensure the accuracy of data submitted by volunteers (Lowry et al. 2019), training videos were available on the data submission portal for students to reference as the experiment progressed. Each student received a test kit containing NO_3^--N test strips and sample tubes, as well as instruction sheets and labeling materials. For 4 weeks, students used simple, inexpensive NO_3^--N test strips (approximately 44 cents per test strip), which work based on a colorimetric reaction, to estimate NO_3^--N concentrations from their tap at home three times per week (12 total over the course of the experiment). Their estimated concentration data were directly entered into a web portal that had been created specifically for the project. In addition to test strip data, students also submitted one water sample each week (four total over the course of the experiment) for comparison with the test strip measurement taken on the same day; we then measured the true NO_3^--N concentrations in the laboratory (cadmium reduction method on a Lachat QuickChem Autoanalyzer; American Public Health Association 2017) to assess the accuracy and reliability of each student's test strip measurements using our novel modeling approach (as described below).

Briefly, we found that the students' test strip measurements often underestimated the true NO_3^--N concentrations in the samples (using a simple estimate of mean absolute error). Interestingly, the effect was more pronounced in the urban and suburban communities (Figure 2); however, we are still exploring the drivers of this phenomenon. Additionally, error in test strip measurements increased with NO_3^--N concentration, suggesting that students were able to accurately analyze NO_3^--N concentrations using the test strips when concentrations were low; however, when concentrations increased, students' accuracy declined, and their test strip measurements underestimated actual NO_3^--N concentrations (as measured in the laboratory). This "testing error" may have health implications in households where the true NO_3^--N concentrations are over the 10 mg/L maximum contaminant limit set by the U.S. Environmental Protection Agency, inadvertently resulting in an increased risk of infant methemoglobinemia and some cancers for homeowners using unfiltered drinking water.

Incentivizing Student Participation

While 4 weeks is a relatively short time to engage with participants, we wanted to motivate students to continue participating over the course of the experiment. To ensure continued participation from students, we originally chose to raffle off gift cards from popular food chains to incentivize student engagement, beginning approximately halfway through the experiment. The introduction of incentives increased participation by approximately 12%; however, some students reported that the gift card raffle did not motivate them to submit their data because they felt they were unlikely to win or because the chains chosen were not accessible where they lived. Additionally, we were unable to directly tie incentivization of participation to improved quality in reporting.

Based on this feedback, we adjusted our incentive program for future rounds of SWC experiments. We developed a more inclusive incentive program, where students received groundwater themed stickers for each week they successfully submitted all test strip measurements and water samples. If all test strips and water samples were submitted for the experiment, they receive a reusable water bottle to reward 100% submission. Finally, students received a certificate for participating in the SWC research project that could be listed on a resume or college application.

Technological Barriers in Data Submission

In the first round of experiments, we experienced technological barriers which varied by community type. At the rural school, using the website to enter data was challenging. Many students did not have internet access at home, which forced them to wait for an appropriate time in class to use a school computer. Teachers reported that internet issues resulted in many students forgetting to submit their data or feeling like they did not have adequate time during the school day to enter the results. To adapt for any participants who may not have consistent internet access, a printed data sheet for recording results and a pre-stamped envelope was provided upon request to give students the option to send in their results by mail for future experiments. In contrast, students at the urban school did not find our original website user friendly, despite having internet access. The main critiques were that the website was not smartphone-friendly and appeared outdated. They also found it inconvenient to bring their school laptops home to record their data each week. Based on student feedback, we created a more user-friendly smartphone application with the goal of improved convenience and access for students to report their test strip results.

Assuring Data Privacy and Consent Forms

To address any concerns about data sharing or privacy and to engage minors as participants, student participation in the project was permitted only with parental consent and student assent. Due to possible connections between water quality and property values, we also cannot assume that all homeowners would be amenable to participation, which may result in variable participation rates in other locales. In the consent form, we expressly stated all data would be de-identified and remain confidential due to the connection between well-water quality and property values. Fortunately, we did not receive any negative feedback from concerned parents who did not want their children to participate. However, many teachers did report that it would have been better for students to have additional time to talk through participation with their parents and return the consent form. Therefore, providing ample time (>1 week) for participants to provide consent will be important moving forward.

A Novel Approach to Address Data Reliability

To overcome the challenge of data reliability in crowdsensing, we developed a novel modeling approach that uses a statistical approach (e.g., the maximum likelihood estimation method in truth discovery; Wang et al. 2014) to assess the reliability of participants and correct reported values of nitrate concentrations. As part of this, the model incorporates spatiotemporal correlation in nitrate concentrations at neighborhood scales. Unlike previous approaches assessing reliability in crowdsensing, our solution embraces an interdisciplinary approach, called dynamic latent feature modeling (Zhang et al. 2019), that integrates observations and latent features that may affect NO_3^--N concentrations in the spatiotemporal domain. We first pre-process our raw survey results by converting each context variable (e.g., lawn fertilizer application, pet activities, age of septic tanks, etc.) in the survey to binary data and concatenate them together. With the converted context variables, we derive a set of latent variables through an iterative process called statistical expectation–maximization algorithm (Zhang et al. 2019); we consider these latent variables to be an emergent property of our model. Thus, correlation in nitrate concentrations between physical locations in a neighborhood can be inferred from our crowdsensing data and compared to those predicted by the external databases. This comparison can aid in identifying reliable data sources and reducing “crowdsensor” error. A key benefit of this approach is that it can tackle the data reliability challenge without requiring perfect knowledge of the measured variables a priori (i.e., actual measurements of water contamination, reliability of participants). Furthermore, this estimation framework is flexible and can be further extended to integrate additional physical constraints and expert knowledge (e.g., distance to farms or other sources of contamination along with mathematical estimates of dilution and decay).

The weekly paired test strip and water sample measurements have allowed us to assess and reduce the error on the students’ remaining test strip measurements (Figure 3). Overall, our modeling approach reduced error in individual measurements by 10% (Figure 3A) and error for individual households by 37% (Figure 3B). We also observed a 54% reduction in error in individual measurements in the rural community, compared to 8% and 16% in the suburban and urban communities, respectively (Figure 3A). When pooling results by household, error reductions were similar between rural (47%) and urban (50%) communities, and reductions in error for individual households were less in suburban communities (27%; Figure 3B). Our results suggest that sampling the same household multiple times may result in an overall error reduction and assist in ascertaining the “true” NO_3^--N concentration of an individual’s well water.

Conclusions

Crowdsensing approaches to groundwater monitoring are novel and exciting avenues that can advance our understanding of how to collect a large amount of data that is reliable, scalable, and replicable across communities. Here, we have provided a brief overview of current approaches, highlighting potential barriers to widespread adoption of crowdsensing in environmental monitoring contexts and presented some potential solutions. With thoughtful design, crowdsensing may soon be applied broadly in well-dependent communities across the country. This is particularly promising when partnering with

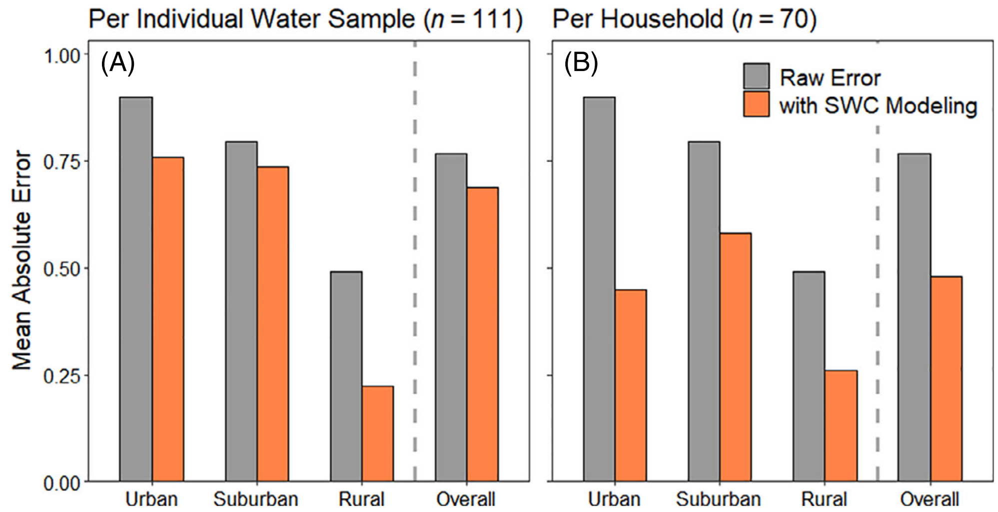

Figure 3. Mean absolute error for test strip NO_3^--N concentrations for both raw data and with the novel SWC modeling approach for both (A) individual water sample ($n = 111$) and (B) households ($n = 70$). Mean absolute error is defined as the average of the absolute difference between each pair of test strip and laboratory measured NO_3^--N concentrations. Data are separated by community type, with overall mean absolute errors shown to the right of the dashed gray line on both panels.

local schools, which act as an ideal centralized infrastructure through which to engage large groups of the population. A clear barrier to the widespread use of crowdsensing is data credibility; therefore, establishing clear methods to assess "crowdsensor" reliability will be essential for implementing this method broadly. The SWC methodology we highlight may offer a scientifically based and formalized approach to "clean" crowdsensing data and ensure its reliability. Such rigorous crowdsensing approaches can enable the community to take a greater stake in the ownership of their local water quality and feel empowered to make improvements to enhance the health of their community.

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Authors' Note

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