# OPEN CITIZEN SCIENCE DATA AND METHODS

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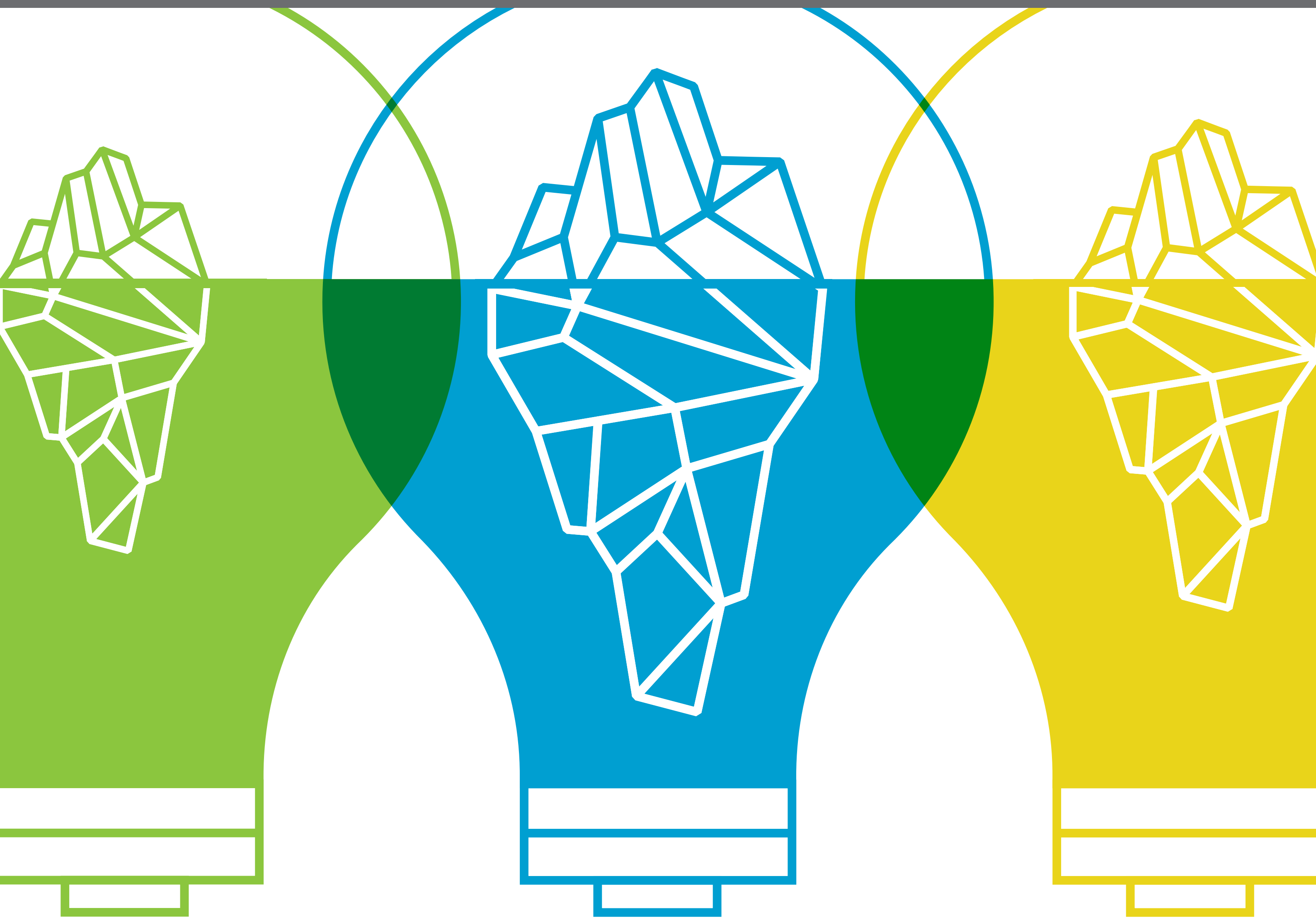

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# OPEN CITIZEN SCIENCE DATA AND METHODS

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EDITORIAL
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# Editorial: Open Citizen Science Data and Methods

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**Editorial on the Research Topic**

**Open Citizen Science Data and Methods**

This Research Topic was launched on April 22nd, 2020, the 50th anniversary of Earth Day, in alignment with the Earth Challenge 2020 initiative. It provides a collection of articles that aim to advance the broader open science agenda by facilitating academic inquiry into open, and findable, accessible, interoperable, and reusable (FAIR; Wilkinson et al., 2016) citizen science data.

Citizen science is a historic paradigm that is growing in importance. It is an approach to science that involves members of the public in voluntarily contributing to the scientific research process, including by asking research questions, collecting data, and/or analyzing and applying results. While citizen science projects can be initiated with a range of goals and outcomes in mind, what distinguishes citizen science from related paradigms—such as Volunteered Geographic Information (VGI), or crowdsourcing—is the emphasis on scientific research. As with other forms of scientific research, citizen science is a multi-disciplinary and increasingly a trans-disciplinary practice.

The articles in this special issue explore key considerations related to the pursuit of strong scientific outcomes, primarily by offering a dedicated platform for discussing both research methodologies (including quality assurance and quality control (QA/QC) practices), and the datasets that result from citizen science research. While not all citizen science can also be considered open science, the vast majority of the articles in this Research Topic bridge both domains. All *Frontiers* titles are offered as open access publications. *Frontiers* also supports open data, including through issuing Digital Object Identifiers (DOIs) to datasets as part of certain publication processes.

This collection contains different types of articles, which are all peer-reviewed. *Methods papers* include those works that describe data collection processes, QA/QC management plans, and other strategies used to produce high-quality citizen science data and research (Paul et al., Herodotou et al., Diviacco et al., Ramírez-Andreotta et al., Moustard et al., Pudifoot et al., Turicchia et al., Kohl et al., Fischer et al.). Describing the methods used in a particular research study is a common practice across scientific disciplines that can enable external parties to evaluate fitness-for-purpose or fitness-for-use of a study's data and other results. Describing methods can also support replication, increasing transparency and trust. In the context of citizen science, methods papers are also particularly beneficial for generating research frameworks that are proven to work in one particular context, and can be customized in other environments to meet local needs.

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A second type of publication, *data reports*, document existing citizen science datasets and provide context to facilitate re-use of the data for scientific purposes (Bonter and Greig, Turicchia et al., Low et al., Carlson et al.). These papers demonstrate concrete alignment between citizen science and broader open science agendas through emphasis on open data. This collection also includes publications that showcase the results of original research that relies on citizen science data in analysis (George et al., Marlowe et al., Bailey et al., Moyo et al., Castell et al., Nuje et al., Møller et al.).

Finally, this Research Topic offers curated *perspectives* on topics including why citizen science data is so important (de Sherbinin et al.), which power dynamics arise at the nexus of citizen science and other open science agendas (Cooper et al.), and data quality (Downs et al.) of citizen science. These perspective pieces also include general reviews on citizen science data quality by type (Stevenson et al.) and perspectives particular to application domains, such as invasive species (Encarnção et al.).

In line with the Earth Challenge 2020 initiative, a priority of this collection is to showcase datasets related to six priority research areas: (1) air quality (Pudifoot et al., Rubio-Iglesias et al., Castell et al.), (2) water quality (George et al., Diviacco et al., Bailey et al., Nuje et al.), (3) insect populations (Møller et al., Encarnção et al.), (4) plastics pollution (Moustard et al., Rubio-Iglesias et al.), (5) food security (Moyo et al., Ramírez-Andreotta et al.), and (6) climate change (Turicchia et al., Low et al., Herodotou et al., Marlowe et al., Bailey et al., Kohl et al., Pudifoot et al.). Overall, this collection also describes research projects that advance knowledge or drive decision-making in scientific disciplines ranging from oceanography (Turicchia et al., Marlowe et al., Turicchia et al.) to ecology (Fischer et al.), to plant sciences (Moyo et al.), among other disciplines. The citizen science data collections more specifically include wildlife (Fischer et al., Bonter and Greig, Turicchia et al.), biodiversity (Rubio-Iglesias et al., Herodotou et al.Møller et al.), landcover (Low et al., Kohl et al.) and green spaces (Pudifoot et al.), hazardous waste (Ramírez-Andreotta et al.), sediments (Nuje et al.), rainfall (Paul et al.), coastal reef monitoring (Turicchia et al.), and water temperature (Carlson et al., Marlowe et al.).

Collectively, these publications reveal a number of cross-cutting themes relevant to the importance of data in citizen science. Information about data quality is essential for the use of datasets. To this end, Findable, Accessible, Interoperable, and Reusable (FAIR) (Wilkinson et al., 2016) principles are guidelines to capture quality information, maximize discovery, and provide access for stakeholders (Peng et al., 2022). Papers in this collection use FAIR principles and while it can be necessary to meet privacy concerns by not having the data open, one can still meet FAIR principles with adequate description (Bailey et al., Ramírez-Andreotta et al.). When citizen science projects communicate their data management practices then data quality can be assessed by what is appropriate for the data type (Stevenson et al.). Quality assessment and quality control can help to improve data quality and offer advice for conducting research on related topics (Downs et al.). The nQuire platform was created to support data quality assurance and control for non-professionals who design their own or take part in existing investigations by providing an expert review on data quality (Herodotou et al.). Besides internal data quality, data fitness for use evaluation methods can help to improve the external quality of a dataset to address particular research or monitoring questions (Fischer et al.).

Papers in this collection also underline important social and ethical implications of citizen science activities including Collective benefit, Authority to control, Responsibility, Ethics (CARE) principles (Cooper et al.). Practices with indigenous communities used CARE principles for data governance which encouraged co-design and consent through a socio-technical approach to establish a participatory science process (Moustard et al.). The Environmental Protection Agencies (EPAs) in Europe demonstrated their use of citizen science along with engagement on best practice to encourage broader adoption for environmental monitoring and policy-making (Rubio-Iglesias et al.). Ethical environmental justice work was demonstrated through a health study that addressed challenges in integrating citizen science and social variables (Ramírez-Andreotta et al.).

This collection welcomed contributions from citizen science researchers, practitioners, and volunteers to bring a diversity of perspectives. The participants in the projects included students in primary (Castell et al.), secondary (Paul et al., Low et al.), and college (George et al.) education, scuba divers (Turicchia et al., Marlowe et al., Turicchia et al.), and indigenous communities (Moustard et al.). Some of the papers are of projects part of the NASA GLOBE program that uses a standard GLOBE Observer (GO) mobile application (Low et al., Kohl et al.) while others use mobile applications developed for their use (Turicchia et al., George et al., Bonter and Greig, Bailey et al., Moustard et al.). Projects collected data through records from visual observation (Bonter and Greig, Møller et al., George et al., Turicchia et al.), sensors (Carlson et al., Diviacco et al.), and image collection (George et al., Low et al., Herodotou et al., Bailey et al.). Many projects perform direct physical environmental sampling using only simple collection devices (Paul et al., Castell et al., Nuje et al., Moustard et al.), and some also involved laboratory analysis in the study (Pudifoot et al.). In addition, through a spatial and temporal sampling approach for citizen science it was demonstrated that standardized data can be produced (Moustard et al.).

At the time of writing, the Research Topic on Citizen Science Data and Methods is not open for submission anymore. Moving forward, the editors believe that research conducted using citizen science methodologies should be published in appropriate disciplinary journals, including through the *Frontiers* journals that published the articles associated with this Research Topic. We encourage journals to consider submissions that use citizen science methodologies as scientific contributions to their fields on equal footing with research conducted through more traditional scientific methods. We believe that research on how to conduct citizen science is perhaps most appropriate to publish in journals such as *Citizen Science: Theory and Practice*, or through titles that focus on outcomes of citizen science that include (for example) enhanced public education or understanding of science.

## AUTHOR CONTRIBUTIONS

CH reviewed the articles in the Research Topic and provided an initial summary. AS, AB, and SS co-edited the Research Topic and provided an analysis of how these articles fit within and help advance the fields of citizen science and open science. All authors contributed to the article and approved the submitted version.

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PERSPECTIVE
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# Citizen Science and Environmental Protection Agencies: Engaging Citizens to Address Key Environmental Challenges

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Environmental Protection Agencies (EPAs) have been involved in citizen science initiatives for decades, engaging with citizens with the goal of protecting and restoring our environment. Yet the data and knowledge generated and the possibilities for engaging citizens have grown significantly in the last decades thanks to the recent developments in mobile technologies and the access to internet, resulting in a transformation of how environmental protection can be done. This perspective provides some examples on how European EPAs and their partners are currently addressing key environmental challenges and exploring new institutional approaches by bringing in citizen science data and methods. It also points out challenges that need to be addressed to fully realize the potential of citizen science as a complement to the monitoring efforts by these agencies. Finally, it presents the Interest Group on Citizen Science of the Network of the Heads of Environmental Protection Agencies (EPA Network), an informal forum where EPAs across Europe share examples and bring together strategic insights on citizen science approaches into their daily activities.

**Keywords: environmental citizen science, environmental monitoring, environmental protection agency, biodiversity, air quality, marine litter, best practices, citizen engagement**

## INTRODUCTION

Citizen science has a longstanding tradition in the environmental domain, dating back to more than 200 years, with networks of volunteers carrying out phenological observations or collecting daily rainfall data. This wealth of information across spatial and temporal scales is extremely difficult to obtain in other ways and comes with increasing citizen engagement in environmental protection. Environmental Protection Agencies (EPAs) are not newcomers in the field of citizen science. In fact, several agencies coordinate or collaborate in long standing initiatives (Nascimento et al., 2018, Owen and Parker, 2018). Yet the growing number of citizen science activities, linked to the possibilities opened by mobile technologies, the pervasiveness of internet connection and the advances in data handling and storage, is a clear game changer. The knowledge generated and the possibilities for engaging citizens can grow exponentially, contributing to the transformation of environmental protection practices (Owen and Parker, 2018). Thus, the current landscape raises the question of how these institutions can best support these initiatives, not only benefitting from their data but also participating actively in the process, while addressing a more demanding citizen-agency dialogue, all in a time of financial difficulties, not the least due to the impact of the ongoing COVID-19 pandemic. In this perspective, we contribute to this discussion by providing some examples on how European EPAs and their partners are addressing key environmental challenges and exploring strategic approaches building on citizen science data and methodologies. We also discuss briefly the challenges faced by these institutions when integrating citizen science in their activities. We conclude by introducing the Interest Group of Citizen Science of the EPA Network, an informal forum where European EPAs share experiences and strategic insights on citizen science.

## THE VALUE OF CITIZEN SCIENCE DATA–TACKLING KEY ENVIRONMENTAL CHALLENGES

While EPAs have diverse mandates and roles, with different national contexts, all of them share the primary goal of the protection of the environment, and are therefore in need of quality assured evidence about the ecosystems, pressures on the environment and the results of the implementation of environmental regulation (Owen and Parker, 2018). Ensuring data is quality assured helps maximize its utility, and besides the use of traditional methodologies and involvement of professional staff, can also be achieved by engaging properly trained citizens, provided with well-developed methodologies, appropriate technology and supported by a wider citizen science community and EPA staff, as we demonstrate below. Hence, the following cases highlight how European EPAs are building on the value of citizen science data and methods to address key environmental challenges of our time.

### Tracking Biodiversity Loss—The Estonian Nature Biodiversity Database

Biodiversity monitoring is one of the areas with a long tradition in citizen science involvement, with time series, coverage and granularity that could not be achieved through official monitoring alone (McKinley et al., 2017). Given the current critical situation of ecosystem collapse and biodiversity loss, with a fall of 60% in the global wildlife populations in the last four decades (WWF, 2018), the need for more data to measure progress toward the relevant policy targets, including the calculation of biodiversity indicators, is more pressing than ever. From a European perspective, this is especially relevant in the context of the recently adopted Biodiversity Strategy for 2030[1], a core part of the European Green Deal[2], the flagship European Union (EU) ambition that inter-alia aims at making Europe a climate-neutral continent by 2050. Citizen science can be instrumental in this process.

In 2006, Estonian Environment Agency (Keskkonnaagentuur)[3], in collaboration with Estonian Naturalists' Society (Eesti Looduseuurijate Selts)[4], developed a platform called Nature Observations Database[5] for volunteers to keep track of their nature observations. The database has grown with each year and now, with more than 230,000 observations and 700 users, it has become a key reference on Estonian nature. Until 2015, all the observations were first recorded by the volunteers on paper before being submitted via an internet form. When this rather cumbersome procedure was replaced by a more user-friendly mobile application in 2015, there was a significant increase in the number of observations (see **Supplementary Figure 1**).

The current wide use of this data clearly demonstrates its value. The data submitted by volunteers to the Nature Observation Database is first checked and validated by specialists at the Estonian Environment Agency, with the help of pictures and descriptions provided by the volunteers. Once accepted, the data is integrated with the national monitoring data, which is then used by environmental officials, municipalities and by researchers.

Taking a step further, in 2019 the Environment Agency decided to launch a pilot project[6] with the objective of assessing the integration of volunteer nature observations into the actual national environment monitoring plan. For this pilot project, amphibians were chosen as they are a small group of protected species in Estonia which are already in a monitoring program. They are widely distributed, easy to find and identify. With 50 volunteers in the first year, more than 170 observations across the country covered mostly common species, but in a much larger area than a limited number of experts would have done in a traditional monitoring campaign. With the results of the second year being even more promising, the project has shown a four-times increase in the number of observations in relation to the previous campaigns. Based on these preliminary results, which also show a high data quality, the campaign is expected to be continued and extended to other species groups in the future, such as otters, dragonflies and pollinators.

### Addressing Marine Litter—Marine Litter Watch

Since litter in general, and plastics pollution in particular, is one of the most prominent and visible problems in the marine and coastal environment, the involvement of citizens in beach litter collection and monitoring is becoming commonplace. The total mass of plastics waste in the ocean is expected to escalate from 50 million tons (Mt) in 2015 to 150 Mt by 2025 (Chamas et al., 2020) which is enormous when compared with the total global

[1] https://ec.europa.eu/environment/nature/biodiversity/strategy/index_en.htm

[2] https://ec.europa.eu/info/sites/info/files/european-green-deal-communication_en.pdf

[3] https://www.keskkonnaagentuur.ee/en

[4] https://www.elus.ee/

[5] https://lva.keskkonnainfo.ee/default.aspx?state=1;877954539;est;lvadb;;&lang=eng

[6] https://www.keskkonnaagentuur.ee/et/kahepaiksete-vabatahtlik-seire (in Estonian)

fish catch value of 96.4 million tons for 2018. Monitoring litter from aquatic environments is very important for generating data on the type and levels of macro and microliter pollution, hot spot areas, identifying threats to ecosystems, pinpointing sources and pathways, assessing the effectiveness of relevant legislation, as well as promoting public awareness (Zettler et al., 2017).

Academic and governmental monitoring efforts for litter data collection are often limited in space and time. Citizen science, especially when undertaken with some training and efficient support, is a cost-effective way to gather data over a large geographical range whilst increasing environmental awareness, spreading scientific knowledge among the general public (Rambonnet et al., 2019) and leading to demands for better and more effective legislation. Such monitoring activities or clean-ups involving large numbers of citizens also result in active clearing of substantial amounts of litter at source.

One of the most popular citizen science actions to tackle litter in Europe is Marine Litter Watch (MLW) coordinated by the European Environment Agency (EEA)[7]. Using a common mobile app developed by EEA, volunteers are collecting beach litter data, mainly from European seas but also rivers and lakes, since 2013. Communities and individuals from dozens of locally organized citizen groups across Europe apply a common protocol and receive permanent online support and training. Under this initiative, volunteers had collected and recorded by the end of 2019 almost two million litter items belonging to tens of types of debris, using a methodology developed by the Technical Group on Marine Litter set up within the scope of the EU Marine Strategy Framework Directive (MSFD) (JRC, 2013). The collected data is available through a dedicated web portal[8] maintained by the EEA (see **Figure 1**).

Despite continuous support from the MLW program, it was recognized that data collected by diverse groups or individual citizens could incorporate a higher margin of error than scientifically acquired data. Therefore, quality assurance through detailed data profiling was undertaken to remove inconsistencies (e.g., removing outliers) and other anomalies within the MLW database.

Recent analyses of MLW data show both spatial and temporal variations in litter composition among different aquatic systems and regions in Europe (Kideys and Aydin, 2020a). Furthermore, this data reveals the shares of certain dominant beach litter items change among distinct European seas (see **Supplementary Figure 2**). MLW data is thus useful for evaluating the efficiency of existing policies (such as the EU MSFD and the EU Strategy on Plastics) and for providing directions to future ones.

## Measuring Air Pollution Together—Samen Meten

Although harmful emissions have decreased over the last decades, air pollution is estimated as causing hundreds of thousands of premature deaths across the EU (EEA, 2019a). Public awareness of this problem has increased in recent years, notably through many citizen science initiatives building on low-cost devices. However, up to very recently only government operated or traditional research networks with reference instruments measured air quality (EEA, 2019b).

Citizen science represents an opportunity to complement the official air quality measurements. Seeing this opportunity, around 2012 the Dutch National Institute for Public Health and the Environment (RIVM)[9], responsible for the official air quality monitoring network in the Netherlands, started to get involved in citizen science projects. The project iSPEX[10], initiated that very year, played a key role in changing RIVM's views on the contribution of citizen science (Volten et al., 2018). The project involved measuring aerosols using iPhones with a small add-on for the camera. More than 3,000 participants took part and over 10,000 observations were taken, demonstrating the value of this data in terms of spatio-temporal resolution, as well as the feasibility of engaging a large audience (Snik et al., 2014). However, the nature of the measurements made them unfit for monitoring purposes, and therefore did not lead to a sustained activity. To address this issue, RIVM turned its focus to low-cost sensors (e.g., nitrogen dioxide and particulate matter -PM- sensors).

In 2016, the RIVM launched the Samen Meten ("Measure Together") program. Samen Meten involves the development of a knowledge portal[11], where citizens can find information on air quality, sensors or citizen science initiatives to team up with, as well as an open data portal[12] (see **Figure 2**). Citizen scientists can either obtain data from the platform or upload it. Data can be exchanged through an Application Programming Interface (API) which is particularly convenient for larger citizen science programs such as Sensor.Community[13] or Hollandse Luchten[14]. Although these initiatives also have their own data platforms, the added benefit of the Samen Meten platform lies in the possibility to combine all available sensor data and to compare with nearby official data. Furthermore, and as the currently most used PM sensor, the Nova Fitness SDS011 sensor[15], is sensitive to relative humidity (RH), the data portal also provides a RH correction to the data (Wesseling et al., 2019). These additional functionalities attract a higher number of participants and boost the number of citizen science projects represented in the fast growing Samen Meten program.

To facilitate the use of the collected citizen science data by RIVM itself, additional efforts are necessary to enhance data by validation methods and corrections (e.g., for RH), using diverse approaches to incorporate the sensor data in monitoring procedures. Initial results show that this represents a valuable addition to traditional air-quality monitoring, providing much more spatial granularity than the official networks. In the case

[7]https://www.eea.europa.eu/
[8]https://marinelitterwatch.discomap.eea.europa.eu/Home.html
[9]https://www.rivm.nl/en
[10]http://ispex.nl/en/
[11]http://www.samenmeten.nl
[12]https://samenmeten.rivm.nl/dataportaal/
[13]https://sensor.community/
[14]https://hollandseluchten.waag.org/kaart/
[15]http://inovafitness.com/en/a/chanpinzhongxin/95.html


**FIGURE 1 |** Marine Litter Watch web application including the list of top 10 items collected, with cigarette butts and filters in the first place **(A)**, and the distribution of events in Europe **(B)**.

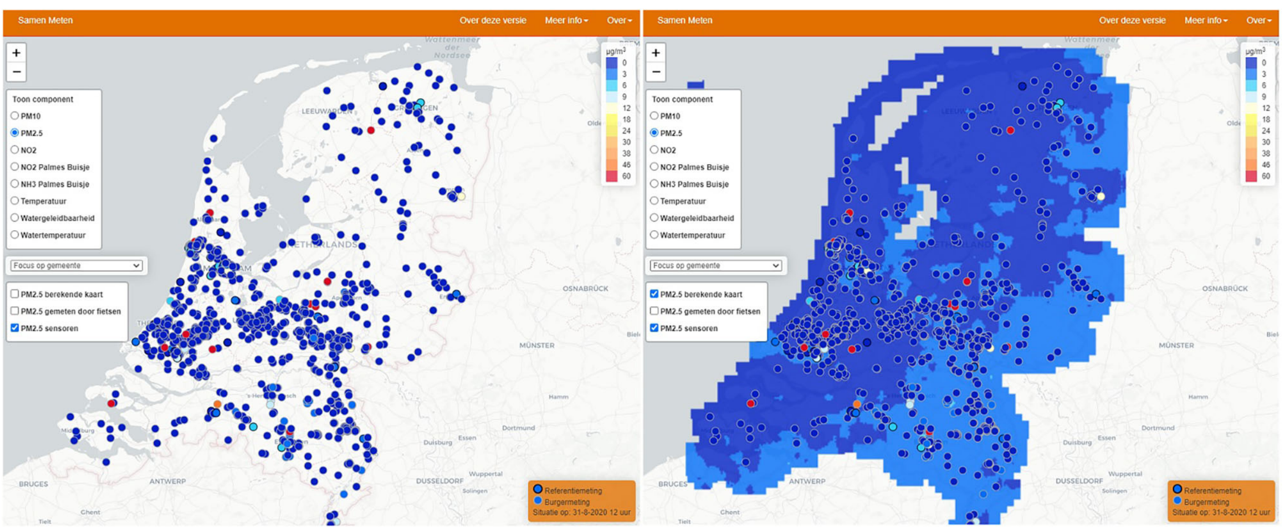


**FIGURE 2 |** Samen Meten data portal showing the density of the PM2.5 sensor locations and reference stations **(A)** on the map of the Netherlands, and the same against a backdrop of air quality model results **(B)**. Colors are an indication of the height of the PM2.5 concentrations.

of particulate matter, for example, the sensor data is now used in air quality models that attain a higher spatial resolution thanks to the many hundreds of sensors uploading to the data portal (Wesseling et al., 2019). Given its positive results, Samen Meten is now being expanded to other environmental areas such as noise and water quality, where the development of relatively low cost (sensor) measurement methods is also advancing at a fast pace.

## THE VALUE OF CITIZEN SCIENCE DATA—FULFILLING OUR CORE MANDATE

EPAs are starting to consider citizen science as instrumental to achieve their core mandate, that is, environmental protection (Hindin et al., 2016, NACEPT, 2016, Owen and Parker, 2018). Many have launched platforms, catalogs and portals to have a better overview of the different initiatives (for example, Scotland's environment Citizen Science Portal[16]) and in some cases are adopting a more strategic approach toward citizen science—such as the Scottish Environmental Protection Agency (SEPA) (Nascimento et al., 2018), RIVM (Volten et al., 2018, Wesseling et al., 2019) or, outside Europe, the US Environmental Protection Agency (NACEPT, 2016). In this section we focus on two cases in Europe: the Finnish Environment Institute and the UK Environment Agencies.

### Serving Our Institutional Goals—The Case of the Finnish Environment Institute (SYKE)

The Finnish Environment Institute (SYKE)[17], as a governmental research and expert institute, has as its main goal to build a sustainable society. In this role it has launched citizen science projects. The data from these projects are considered to contribute to the goals of SYKE in three significant ways.

First, citizen science has enormous policy value as it extends the monitoring capacity of environmental changes and problems. Citizen observations are invited through the Invasive Alien Species Portal[18], for example, to monitor the spreading of crab species (Rhithropanopeus harrisii) in the Baltic Sea (Lehtiniemi et al., 2020). Lake and Sea-Wiki[19] collects data on potentially problematic jelly fish invasions (Aurelia aurita). Data about algal blooms from citizens complements information from official sources, making the review of the cyanobacteria situation in coastal and inland waters more comprehensive.

Second, citizen science data serve innovation purposes. SYKE has developed a new nature-based solution to enhance abatement of diffuse pollution via ecological processes occurring on underwater wood surfaces (PuuMaVesi[20]). Addition of constructed wood bundles to ditches and sedimentation ponds increases simultaneously biological water purification efficiency, biodiversity and carbon storages of aquatic habitats. Collaboration with schools and private land-owners has enabled citizen monitoring of the effectiveness of the method. The results showed high reduction levels of pollutants as well as multiplication in the diversity of species.

Third, citizen science data have institutional service value. SYKE provides environmental information as a public service, enabling citizens, businesses and other public bodies to directly use and benefit from the data. For example, the data submitted by citizens to algal bloom watch can be utilized by everyone who is interested in and use local water bodies. The map-based internet service[21] offers information about locations where and when it is safe to swim, for example. Citizen-contributed data enhance the service making it more comprehensive.

### Citizen Science in a Changing Environment—The UK Environment Agencies

The devolved governments and various environment agencies across the UK, including the England Environment Agency, Natural Resources Wales and Scottish Environmental Protection Agency have traditionally supported a number of well-established citizen science initiatives, especially in weather (e.g., Weather Observation Website[22]) and biodiversity (e.g., the National Plant Monitoring Scheme[23]). Data from these schemes are typically used in a wide range of applications, including reporting on the state of the environment, developing analytical tools and models as well as planning and regulatory activities.

Localness and devolved decision making are becoming increasingly important across the UK. The unique characteristics of citizen science mean it both engages people and empowers them. Citizen science can also augment traditional monitoring. Hence, people can become active in their local environment and it can support local decision-making (UKEOF, 2020a).

However, despite Environment Agencies in the UK supporting a number of longstanding initiatives and the growing importance of localness, there is still no coherent strategy for the development of these initiatives and numerous disparate methods and platforms. At a time of financial pressure, it is not possible to maintain so many different platforms. Government agencies are therefore working together to share information and expertise (e.g., UK Environmental Observation Framework[24]). They are also working with NGOs to develop a data sharing framework to collate and combine data from a wide range of sources (The River Trust, 2020).

Ensuring data is accessible is an important priority for any framework. This requires those involved in the planning, collection, storage or use of data to think about data management at the outset of the project (UKEOF, 2020b), and to develop a plan that considers the whole lifecycle. Data is often one of the lasting legacies of a citizen science project so it must be managed and stored effectively to improve the chance that the project has lasting impact (UKEOF, 2020b).

## DISCUSSION

The previous sections show a snapshot of the rich landscape of citizen science initiatives involving environmental agencies in Europe. However, and despite the opportunities ahead, there are still challenges to be addressed before the potential of citizen science can be fully realized, especially in monitoring (Volten et al., 2018; Wesseling et al., 2019), their policy impact

[16]https://envscot-csportal.org.uk/
[17]https://www.syke.fi/en-US
[18]http://vieraslajit.fi/fi/content/invasive-alien-species-finland
[19]http://www.jarviwiki.fi/wiki/Etusivu?setlang=en
[20]https://www.syke.fi/hankkeet/PuuMaVesi (in Finnish)
[21]https://www.jarviwiki.fi/wiki/Valtakunnallinen_lev%C3%A4seuranta?setlang=en
[22]https://wow.metoffice.gov.uk/
[23]https://www.npms.org.uk/
[24]http://www.ukeof.org.uk/our-work/citizen-science

(Nascimento et al., 2018), but also in its integration at the institutional level.

A representative example of the complex context in which these agencies deal with citizen science is provided by RIVM. Managers at this institution are embracing citizen science as a much-needed way to getting closer to a society where environmental information become more and more available. Likewise, the participation of RIVM experts is warmly welcomed by the citizen scientists, who see them as a reference for questions about air quality. However, and although the participation in citizen science projects was occasionally very successful (e.g., iSPEX), RIVM technical staff expressed some reticence in this new approach. Their concerns referred to valid questions such as how to sustain public trust on official measurements, how to deal with expectation management or how to tackle discrepancies with citizen science measurements not meeting official procedures and regulations. These concerns, together with the perennial data quality discussion, are echoed by other governmental agencies as some of the greatest barriers for adoption (Blaney et al., 2016, Nascimento et al., 2018). While all this needs to be taken into consideration, and as demonstrated by the examples above, the potential of citizen science clearly outweighs the concerns, and in the case of RIVM the institution continues to support and expand the use of citizen science as we have seen with Samen Meten.

Many EPAs have identified common opportunities but also found similar challenges for a wider adoption of citizen science practices. The need for sharing experiences and identifying common approaches across EPAs crystalized in 2014 with the creation of an Interest Group on Citizen Science within the European Network of the Heads of Environmental Protection Agencies, EPA Network[25] The group, with members from 14 EPAs and the EEA, is a forum where EPAs share practical examples, follow policy developments, and bring together strategic insights on citizen science approaches into their daily activities. As a key stakeholder group, the Interest Group is in continuous dialogue with associations and institutions carrying out citizen science, networks such as the European Citizen Science Association (ECSA) and the European Commission. In particular, the group has been very active in contributing to the recently published Commission's "Best Practices in Citizen Science for Environmental Monitoring"[26] The list of recommendations and actions in this document aims at tapping into the potential of citizen-generated data and facilitating their use in environmental monitoring and policy-making, establishing a roadmap to facilitate its adoption and support its integration. Targeting inter alia public institutions such as EPAs and the EEA, these recommendations call for a reflection by the EPAs on further integrating and streamlining citizen science in their daily activities to better harness the potential of citizen science data and methods to make an even bigger and longer lasting impact.

[25]https://epanet.eea.europa.eu/

## DATA AVAILABILITY STATEMENT

The original contributions generated for the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

## AUTHOR CONTRIBUTIONS

TE and TK are the lead authors of section Tracking Biodiversity Loss—The Estonian Nature Biodiversity Database. AK is the lead author of section Addressing Marine Litter—Marine Litter Watch. HV is the lead author of section Measuring Air Pollution Together—Samen Meten, and Contributor to section Discussion. TP is the lead author of section Serving our Institutional Goals—The Case of the Finnish Environment Institute (SYKE) while RG is the lead author of section Citizen Science in a Changing Environment—The UK Environment Agencies. JR-I is the coordinator of the article, lead author of sections Introduction and Discussion and contributor to all the other sections. All authors have reviewed and commented on the full article.

## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fclim.2020.600998/full#supplementary-material

**Supplementary Figure 1 |** Number of observations registered in the Estonian Nature Observations Database over the last 10 years.

**Supplementary Figure 2 |** Comparison of the top ten items of litter collected by the regional sea beaches between 2014 and 2019 (Kideys and Aydin, 2020b).

[26]https://europa.eu/!kk69mB

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frontiers in Water

METHODS
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# Applying Citizen Science for Sustainable Development: Rainfall Monitoring in Western Nepal

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We introduce a case-study agnostic framework for the application of citizen science in a sustainable development context. This framework is tested against an activity in two secondary schools in western Nepal. While the purpose of this activity is to generate locally relevant knowledge on the physical processes behind natural hazards, we concentrate here on its implementation, i.e., to obtain a better understanding of the dynamic of the activity and to learn how it should be implemented. We determined the social capital of secondary schools as a gateway to the local community: they provide a unique setting to bring different stakeholders together. We find that co-designing a teaching programme is an effective means of both complementing local curricula and ensuring continued buy-in of local stakeholders (i.e., teachers). Student engagement depends on the local relevance of teaching materials, with more holistic or global concepts, such as climate change of lesser importance. Our activity focused on rainfall, including student-led data collection. These rainfall data provide a very good fit to co-located rain gauge data, with an average difference on weekly readings of 11.8%, reducing to 8.3% when averaged over all student readings. The autonomous development of student-organized science clubs suggested that our original framework underestimated students' capacity to apply knowledge elsewhere creatively. These clubs may be used to obtain participant feedback to improve and tailor future activities. Quantitative assessment of long-term sustainability remains challenging, due in part to high levels of student turnover. We suggest that integrating scientists wherever possible within a school or local community has a direct and positive result on participant retention.

**Keywords: sustainable development, secondary education, precipitation, participatory monitoring, citizen science**

## KEY POINTS

- We present a framework to apply citizen science in a sustainable development context.
- The framework is tested and refined using an activity in two schools in western Nepal.
- Student-measured weekly rainfall totals are typically within 10% of the rain gauge values.
- Teachers should be involved in co-developing lesson plans to enhance sustainability.
- Informal student-organized science clubs emerged, which develop rapidly and organically.

## INTRODUCTION

### Citizen Science Research Projects

As environmental science and the human development actions increasingly address key challenges in the context of social-ecological systems, there exists a pressing need to understand better how people perceive, operate, learn, and take decisions within those systems. It is increasingly recognized that citizen science can play a role in this process (Buytaert et al., 2014). We define citizen science as scientific research that is carried out by the general public, often in collaboration with professional scientists affiliated to a university or research organization (e.g., Haklay, 2012). Research projects that exploit citizen science also have the potential to mobilize people's involvement in social action and justice, information development, and large-scale information gathering; attempts have been made to formalize the wide variety of terms and expressions that are frequently invoked in the field (e.g., Eitzel et al., 2017). Positioned as a means to accomplish education and conservation science, citizen science projects have increased exponentially in the last decade; it is widely accepted as a fast and economical means of bringing scientific data collection to scale (e.g., Bonney et al., 2014; Theobald et al., 2014; Le Féon et al., 2016; Paul et al., 2018).

Over the past 15 years, technological innovations, such as increasingly sophisticated smartphone apps have enabled citizen scientists to record (or crowdsource) millions of observations of, for instance, the occurrence of seismic activity, or flood duration, magnitude and extent (e.g., Rochford et al., 2018; Seibert et al., 2019). To date, relatively few of these projects have been conceived in developing countries, owing to a range of complex and interrelated hurdles including a lack of local capacity, bureaucratic and financial barriers, inaccessibility, and poorly understood citizen motivation and institutional hierarchies (Bonney et al., 2015; Lukyanenko et al., 2016).

The challenges of citizen engagement and participatory monitoring programmes are increasingly well-documented, including citizen incentivization and project sustainability; and highly variable data quality (in terms of accuracy, completeness, and timeliness) that does not always conform to professional scientific standards (e.g., Bonney et al., 2015; Lukyanenko et al., 2016; Guerrini et al., 2018; Irwin, 2018). Moreover, Bonney et al. (2015) note the difficulty in ascribing "success" to citizen science initiatives; they are often viewed by the professional scientific establishment as "high-risk," rarely achieving all objectives in terms of enhancing public awareness of science, contributing to societal well-being, or providing high-quality, extensive, distributed datasets.

The emerging shift from crowdsourcing (also described as "number-crunching" by Irwin, 2018, or "citizens-as-sensors" by Goodchild, 2007) to more active roles in analysis and interpretation has the potential to enhance and enrich citizen involvement through the entire life-cycle of a research project. In turn, this more active involvement can increase decision-making capacity by enhancing local uptake. However, major hurdles remain in terms of embedding citizen science projects and data into governmental development agendas (Cieslik et al., 2018; Paul et al., 2018).

To avoid that citizen science be seen as a panacea to longstanding agricultural, economic, or social problems suffered by community-level stakeholders, or as an alternative to established programmes that build resilience to natural hazards, it is important to consider it a useful new modality that complements the existing toolkit in such efforts (Cieslik et al., 2018; McCampbell et al., 2018; Paul et al., 2018). In developing countries, and especially in a sustainable development context, citizen science initiatives are often community-based and -led; policy acceptance at higher levels remains poor due to a series of complex and interconnected challenges, such as lack of institutional capacity, mistrust of the motives of project leaders, and potential overlap with existing initiatives (Irwin, 2018; Hecker et al., 2019). Elsewhere, the Extreme Citizen Science (ExCiteS) research group at University College London (UCL) explicitly interrogates the barriers and opportunities toward operationalizing and scaling up citizen science in developing countries (e.g., Stevens et al., 2014).

### Participant Motivations Across Geographic and Temporal Contexts

Even though a number of citizen science projects adopt a global perspective (i.e., addressing the sustainable development goals; Fritz et al., 2019), participant motivation differs significantly between developed and developing country settings. While in Europe and North America citizen-participants enjoy the opportunity to spend time in nature with their friends and families and enhance their relationship with the natural world (Rotman et al., 2014), for citizen-participants in low- or lower middle-income countries, this form of volunteerism is less evident. In a recent paper on citizen-scientist motivations in Sierra Leone, Larson et al. (2016) report that nearly all participants referred to financial compensation as the greatest source of motivation for contributing environmental observations, as "*nearly half of the participants stated they would not voluntarily share information to future researchers without compensation for their time*." They also comment that apart from direct payment, community development and infrastructure like roads, wells and schools were considered sufficient incentives.

While compensating citizen-scientists for their effort remains rare, some citizen science projects in developing countries strive to meet local needs by targeting relevant socio-environmental problems of the local communities, including ecosystems change, resilience to natural hazards and agricultural intensification (Pocock et al., 2018). Despite strong action-oriented framing, however, the potential of science-driven projects to respond to local needs in a timely manner and provide actionable knowledge remains limited (Cieslik et al., 2020).

Citizen-participant motivation also varies across time scales. Rotman et al. (2014) found that even though initial participation in citizen science projects may be fueled by personal interest and altruistic drivers, continued involvement was conditional to merit attribution and acknowledgment. Participant retention is an ongoing challenge for most citizen science projects: largely longitudinal in design, few projects have maintained volunteers' engagement over time.

## Citizen Science in Education

In the context of formal education, citizen science has much to offer as a means of making Science, Technology, Engineering, and Mathematics (STEM) learning accessible, relevant, and meaningful (Ballard et al., 2017). Youth and educators can take part in real-world science that is engaging, that responds to their interests, and that makes connections between science and the world around them, as well as fostering youth participation in current land conservation actions, building their capacity for future conservation actions.

Many studies have reported time-limited interventions in schools that involve a component of teaching, often in the realms of biology or conservation (e.g., Le Féon et al., 2016; Shah and Martinez, 2016; Bracey, 2018). Ideally, such interventions involve the co-generation of new scientific data; for instance, the collection and classification of bees at 20 secondary schools in France (Le Féon et al., 2016). This degree of interactivity ensures that information flow is two-way between the student participant and professional scientist, which has been shown to increase uptake and retention in citizen science projects (Paul et al., 2018). Saunders et al. (2018) note the important role offered by citizen science in school education. It engages students directly with environmental science, offers an understanding of the scientific process, and allows students to observe local representations of global challenges like efforts to mitigate against climate change. Numerous studies describe case studies in the United States specifically, where citizen science has been recognized as a means of enhancing both formal and informal science teaching and learning (e.g., Cooper, 2012; Shah and Martinez, 2016; Bracey, 2018). Indeed, Shah and Martinez (2016) report on the "unexplored" role of citizen science in the classroom, emphasizing its potential role in providing innovative pedagogical methods that could reform the U.S. educational system.

Acknowledging the diversity of motivations that drive citizen science projects is especially important from the point of view of monitoring and assessment. A project is generally considered successful if it manages to generate reliable citizen-sourced data over a period of time, but other benchmarks are also possible, including continued engagement, participant satisfaction and retention rates, knowledge sharing, awareness raising, inciting environmental activism and engagement (Johnson et al., 2014).

Against this background, in this study we target schools as a setting for a citizen science project, to address a number of potential pitfalls (Haywood and Besley, 2014). Since students perform the data collection activities as part of their school curriculum, they are intrinsically motivated and time-unconstrained. The school setting also provides continuity throughout the academic term and generational succession. In developing countries, teachers are generally among the most knowledgeable and respected community members, while children are enthusiastic receptors of new information, which can then be reported back to parents (Cieslik et al., 2019). Finally, skill training and results dissemination allow integration of the educational objectives in a classroom setting, ensuring societal outreach.

## Motivation of the Study

Citizen science has been widely recognized as an effective means of large-scale data collection while also offering novel routes into non-scientist engagement and pedagogy. However, few studies have placed this analysis in a development context (Schuttler et al., 2019). Here, we explore the development of a literature-grounded framework for citizen science in such a context, testing it against a case study of two secondary schools in western Nepal. We seek to operate in the shared space between science and education, i.e., generating new scientific data while also enhancing local environmental awareness (Paul et al., 2018; Cieslik et al., 2019). In addition, we explore how to enhance the longevity of citizen science activities (**Figure 1**) at a community level. More practically, we aimed to develop students' knowledge of the scientific method of structured data collection, as well as practicing the interpretation of data (validity, reliability, accuracy, generalizability, etc.).

We sought to address three points: first, to understand the usefulness and applicability of a framework to guide citizen science in a developing (rather than developed) country; secondly, to explore the potential of citizen science in the disciplines of meteorology and its relation to natural hazards (rather than the fields of biology/ecology); and finally, to maximize the continuing relevance and long-term sustainability of the intervention (rather than a one-off or time-limited survey). Our goal is to analyse the successes and bottlenecks of translating theory into practice at a local level, in order to refine the framework to a set of generalizable and replicable standards. We executed our case study "testbed" in May 2019. Specific local aims were to:

- Sensitize students to aspects of the genesis of natural hazards (Monsoon rains and flooding) in their immediate environment;
- Reinforce STEM education in the schools, and strengthen knowledge about the physical processes underlying natural hazards;
- Collect precipitation data for comparison to a nearby automatic tipping-bucket rain gauge dataset (i.e., an "experiment");
- Generate locally relevant scientific knowledge for development, i.e., generate local data that are of sufficient

quality to be used in decision-making processes on resilience creation to natural hazards.

The specific contribution of this paper is as follows: first, we develop a conceptual framework for designing and conducting citizen science activities for young learners in development contexts. We summarize learnings from the literature and critically assess both the feasibility and salience of involving communities in participatory environmental monitoring. Secondly, we illustrate our model with a case study of a rainfall monitoring project conducted in western Nepal in two local schools. Contrary to the mainstream technocratic approach that relies on ICTs and low-cost connectivity, we demonstrate how the use of locally available tools and instruments can provide accurate and robust environmental measurements of scientific quality. Thirdly, we complement our framework with ready-to use visuals and lesson plans that allow for future replications of our model by scientists and educators alike.

The remainder of the paper is structured as follows. In section Methodology, we describe the construction of our framework and then test it using a case study of two secondary schools in western Nepal. Section Results and Discussion discusses the results of this field experiment, including practical experience of implementing our framework, as a means of refining its validity and applicability. We provide brief conclusions and a future outlook in section Conclusions and Outlook.

# METHODOLOGY

## Framework Construction

Citizen science in its broadest sense may be grouped into three phases: planning, implementation, and assessment (e.g., Bracey, 2018). During the planning, analysis of teachers' expectations and motivations is a widely recognized precondition to citizen science interventions in schools (e.g., Haywood and Besley, 2014; Bracey, 2018; Pocock et al., 2018). The power of such interventions to enrich local curricula has only recently been recognized: it critically depends on the manner of framing or presentation to teachers and students alike (Shah and Martinez, 2016).

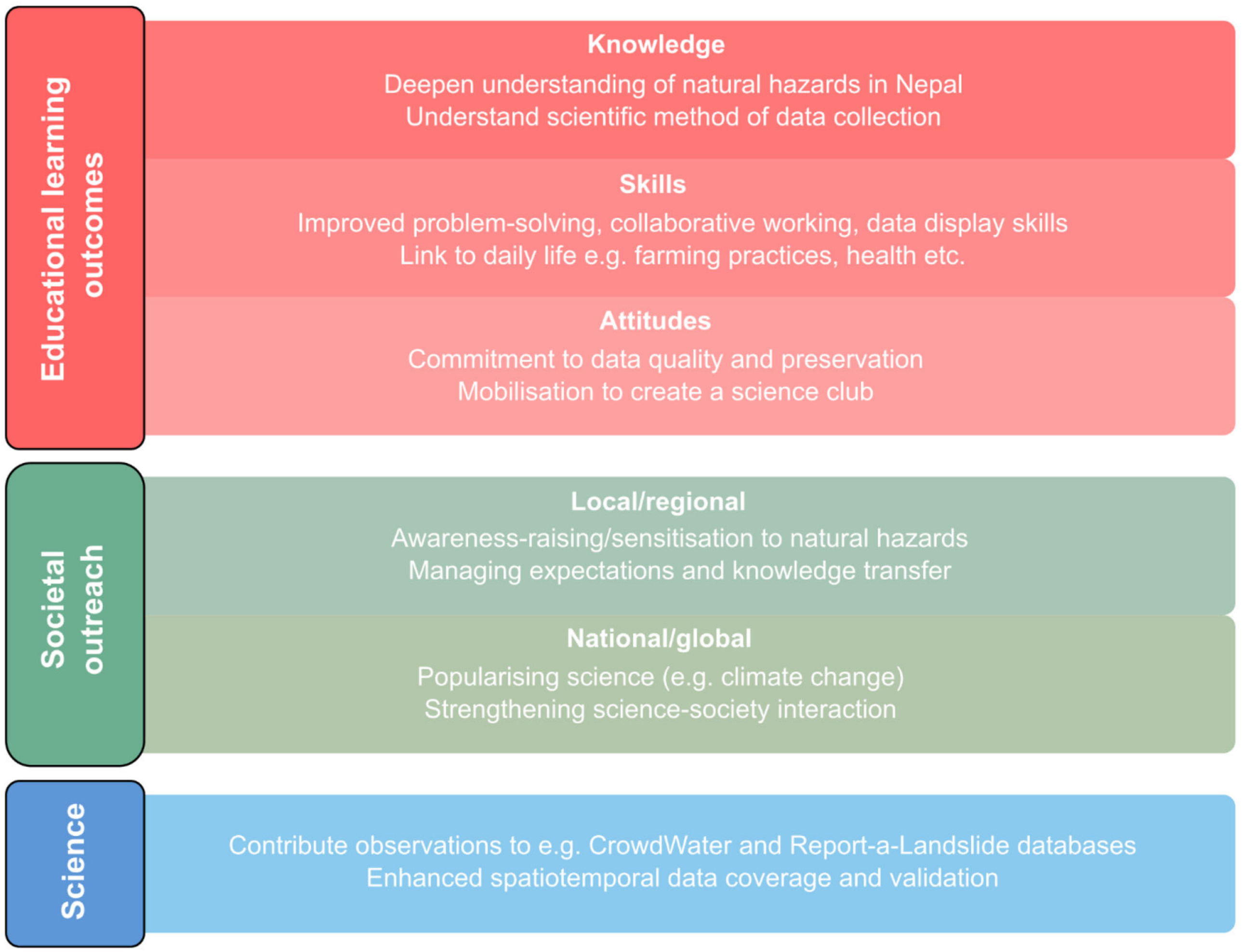


**FIGURE 1 |** Educational, social/societal, and scientific objectives of the case study, used as a "testbed" for the framework (section Framework Construction).

Action-oriented framing—for instance, focusing on combating relevant local socio-environmental problems—has been shown to enhance uptake and participant retention in developing countries (Larson et al., 2016; Pocock et al., 2018; Cieslik et al., 2020). We therefore posit two routes toward enhanced buy-in: (a) co-development, with teachers, of lesson plans and teaching materials that complement local curricula; and (b) framing teaching and data collection in the context of relevant local environmental challenges, such as flooding and landslides.

During implementation of a specific activity, the physical presence of professional scientists has been noted as favorable to both educational and scientific outcomes of many citizen science projects (e.g., Le Féon et al., 2016; Shah and Martinez, 2016; Saunders et al., 2018). Based on post-intervention student interviews, several explanations have been offered (e.g., Haywood and Besley, 2014; Le Féon et al., 2016): the presence of scientists serves as a permanent reminder of the importance of the newly introduced teaching material; participants seek competitively to impress the scientists with increased diligence and attention; and the scientists themselves serve as positive societal role models. In response to these findings, we postulate that professional scientists should be embedded in the social structure of the school as closely as possible. In terms of the activities, students have been shown to be more engaged when a variety of different teaching methods is practiced (e.g., Le Féon et al., 2016). Davids et al. (2019) argue that environmental learning is most effective when local problems, such as Monsoon flooding are placed within a global context, e.g., of climate change. Student-led data collection activities, involving varying degrees of training *a priori*, are likewise a typical component of citizen science interventions in schools (Le Féon et al., 2016; Bracey, 2018; Saunders et al., 2018; Davids et al., 2019). Such co-generation of new scientific data and its dissemination constitutes two-way information flow between scientist and student participant, which enhances uptake and retention rate (e.g., Buytaert et al., 2014; Paul et al., 2018; Cieslik et al., 2019). We therefore propose that activities be balanced equally between classroom teaching, technical training, and scientific data collection. Teaching material should focus on local relevance, but should also be situated within a global context.

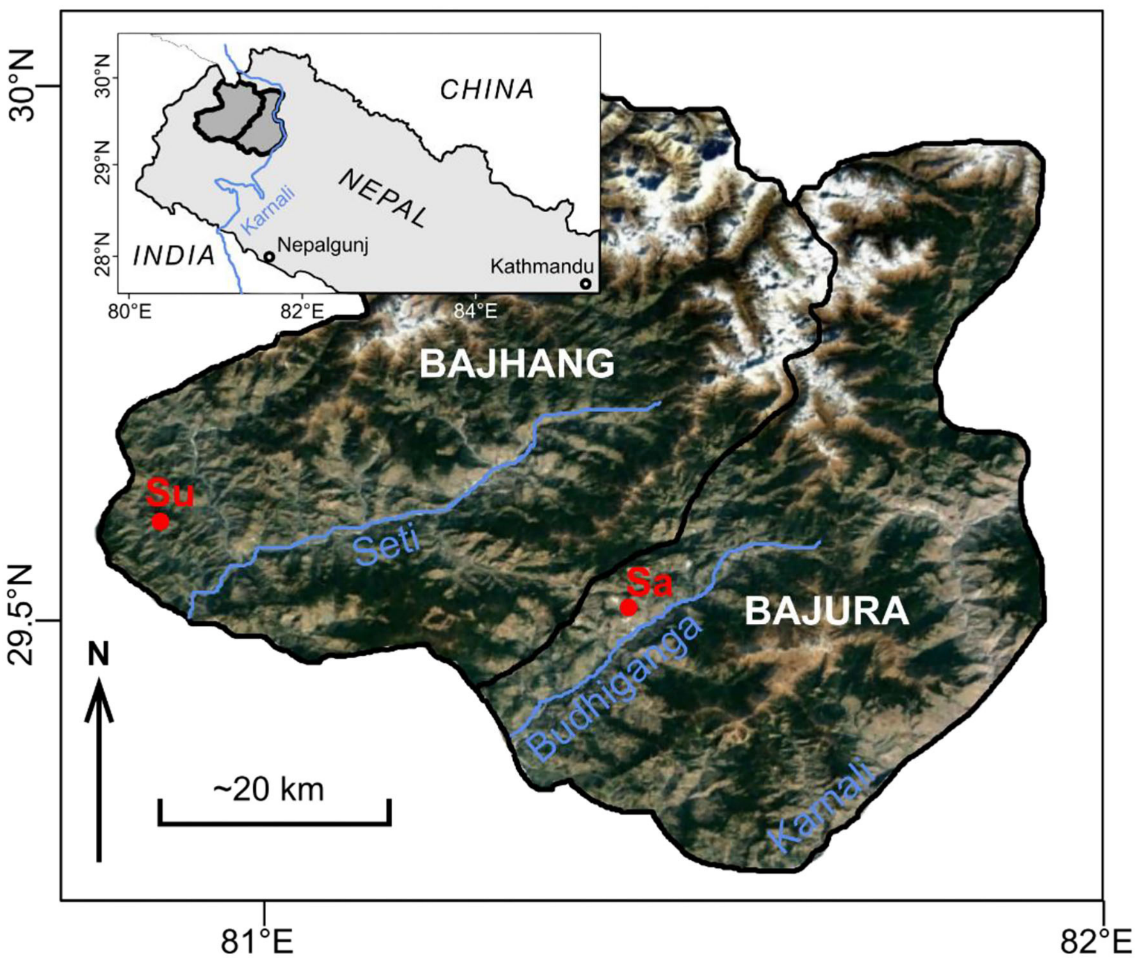


**FIGURE 2 |** Location map showing satellite imagery of Bajhang and Bajura districts within western Nepal. Sa, Saraswati Secondary School; Su, Sunkuda Higher Secondary School.

Less has been paid to the assessment of citizen science interventions, specifically ways in which knowledge generated during citizen science interventions can be sustained (Bracey, 2018). Ballard et al. (2017) emphasize the time-limited, one-off nature of many interventions, usually serving a specific aim that is tied to those of a scientific research project, either in data collection (via crowdsourcing: e.g., Le Féon et al., 2016; Rochford et al., 2018) or outreach (Davids et al., 2019). Participant retention has been recognized as the single most important bottleneck in many citizen science initiatives (Bonney et al., 2015; Gharesifard et al., 2019).

The assessment of citizen science activities is accepted as being of equal importance as the activities themselves, and has been shown to enhance the livelihood relevance of citizen science projects (beyond schools), thus enhancing retention and even allowing such projects to expand via word-of-mouth (e.g., Goodchild, 2007; Haywood and Besley, 2014; Cieslik et al., 2018; Rochford et al., 2018). Based on these findings, we postulate that interviews and questionnaires should be conducted *post-hoc*, the results of which could serve to tailor the local relevance of potential future activities (cf. Kimura and Kinchy, 2016).

## Case Study

Two study sites were chosen targeting local communities vulnerable to flood and landslide hazards. In a remote region of the Lesser Himalayas of western Nepal, these were the municipalities of Sunkuda, Bajhang district; and Bajedi, Bajura district (**Figure 2**). The geological characteristics of these two sites are described in detail elsewhere (Cieslik et al., 2019).

We first identified appropriate secondary schools over the course of three field trips in 2018–2019 based on the following criteria. First, the student cohort needed to be of appropriate size (>20 students in one session) and age (14-/15-years-old, or class 9 and 10 in the Nepal secondary school system, are the most senior students in education through the entire academic year; older students typically take more time off to assist parents with farming activities). Moreover, previous exposure to NGOs or even citizen science initiatives was favorable because roles could more easily be defined and understood, and expectations managed. Lastly, it was thought essential that schoolteachers understood and were enthusiastic about the overall hydrological risk reduction objectives of the initiative. Based on these criteria, as well as proximity to landslides, springs, or rivers, one secondary school at each study site was chosen: Saraswati Secondary School in Bajura, and Sunkuda Higher Secondary School in Bajhang (**Figure 2**; **Table 1**).

We tested our framework (section Framework Construction) at these schools, first developing a set of learning activities for the students (classes 9–10: 14-/15-years-old) that included interactive classroom teaching and data collection. In addition to educational and social objectives (**Figure 1**), the intention of the case study was also to support scientific data collection. As far as possible, we sought to introduce material at a commensurate level with the Government of Nepal (GoN)'s approved curricula on Science for secondary grades. Working with teachers, we identified areas where our intervention could complement the curricula while maintaining local relevance.

**TABLE 1** | Information relating to each school, sourced *a priori*.

| School name | Saraswati Secondary School | Sunkuda Higher Secondary School |
|---|---|---|
| Address | Chhededaha-07, BAJURA | Sunkuda, BAJHANG |
| Coordinates | 29°25′9″ N, 81°19′55″ E | 29°30′13″ N, 80°51′5″ E |
| Preferred session timing | 0.5–3 days | Up to 3 days |
| Best time for intervention? | End-Jan to mid-Feb; and late-Apr to May (exams Mar–Apr) | Mid-April to June |
| Would students be interested in project? (asked to teachers) | Yes because school located in landslide-affected area; rainfall causes landslides; no component on hydrology in Nepali curriculum | Yes; it would complement advanced ICT lessons |
| Strength of local phone signal | Moderate to strong (2G coverage only) | Strong (good 3G coverage for entire school) |
| Local geography | Gumla landslide ∼2.5 km away; Budhiganga river ∼1.5 km away | 400 m to major landslide. Numerous small springs; school on steep valley side overlooking river (2 km below) |
| Commitments | Teachers willing to engage for >3 years, depending on outcomes of initial sessions, if we can build activities into curriculum | Two student helpers and one teacher (ICT specialist) will be available for long-term commitments |
| Possible teaching venue | Main school hall; school ground | School hall; science classroom |
| Nearest guest accommodation | Onsite stay possible in school hall | Guest room in Deulekh (1 km); good hotel in Deura (10 km away) |
| Internet/electricity | No/solar only | Yes/yes (grid and generator) |
| Student cohort | Class 1–10; classes 9 and 10 (14-/15-years-old) = 61 students | Class 1–12; classes 9 and 10 (14-/15-years-old) = 280 students |
| What do teachers teach? | Maths, science, environmental studies (including floods and landslides), health studies | Maths, science, environmental studies, computer studies (ICT) |
| Other details | This school has already formed after-school clubs and has organized activities like whole-school sanitation and tree plantation | Prior exposure to NGOs, e.g., junior Red Cross and child club in place. Teachers keen for activities to contribute to academic syllabus and help with student scientific capacity building |

Data collection in our citizen science activity focused on precipitation measurements for three reasons. First, concepts surrounding (Monsoon) rainfall are locally relevant, tangible, and relatively easy to explain, offering many opportunities for interactive quantitative exercises. Secondly, there is a paucity of ground-based rainfall measurements at a high spatial resolution in western Nepal (and southeast Asia in general: Khatiwada and Pandey, 2019). These data are crucial to increase understanding flood and landslide risk, which are two major natural hazards in the region. Lastly, the measurements can be easily corroborated with data from automatic rain gauges. For this purpose we installed two tipping-bucket rain gauges on each school's roof in May 2018. Focusing on rainfall measurements therefore has the potential to enhance the theoretical grounding behind these installations.

## Application of our Framework

We divide testing the testing of our framework into three phases: planning, implementation, and assessment, as is commonly undertaken in other citizen science projects in sustainable development (e.g., Bracey, 2018).

### Planning

In the planning phase, we began by soliciting interest within our stakeholder consortium, before initiating an extensive consultation exercise with local educators at both schools, culminating in the development of Nepali-language lesson plans and teaching materials that would complement the schools' Science curricula. The intention was that the process be iterative: results from initial or pilot sessions should be used to inform the planning stage of future activities with students (cf. Shah and Martinez, 2016). The planning phase took 4 months and consisted of the following specific activities:

- Circulate concept note to project consortium; solicit interest and marshal ideas for potential school lessons and environmental data collection activities;
- Fieldwork to determine appropriate schools for intervention: ideal conditions include proximity to a potential hazard, e.g., landslide or river that floods regularly; previous exposure to NGOs or citizen science projects; fit to curriculum and school timetable; educators amenable to project objectives; correct number and age of student cohort;
- Co-develop lesson plans and teaching materials with educators and project scientists; translate into local language and dialect;
- Elicit consultations on all project materials in relation to the local context (in particular, linking the material with the appropriate-age national curriculum in environmental science);
- Skype meetings between project scientists to coordinate agendas and determine roles during student activities (e.g., developing oral scripts and planned graphs to draw on the blackboard, checking the veracity and relevance of quantitative exercises);
- Develop assessment forms and protocols per Bracey (2018) and Rochford et al. (2018) for iterative improvement of the citizen science activities.

### Implementation

The next phase, implementation, was tailored to each school's timetable over the course of 2 days. Together with teachers, we developed five sessions for our intervention (**Table 2**). The delivery team comprised a mixture of three professional scientific researchers (two Nepali; one European), two Nepali facilitators from a facilitating NGO (Practical Action Consulting); and Science, ICT, or Geography schoolteachers. Activities with the students commenced with a brief introduction to the project and intended learning outcomes (in English; translated into Nepali), followed by a brief round of introductions from all participants.

Throughout the entire day of activities, interactivity with the student group (30 class 9/10 students in Saraswati, and 45 in Sunkuda) was encouraged through open discussion and question-and-answer sessions that emphasized the immediate local environment (e.g., asking students to locate their houses on a map; suggest reasons for landslide initiation; and debate whether the annual Monsoon rains were increasing or decreasing in magnitude, and whether this was a problem (or not) for their family). We distributed 15 manual measurement cylinders to students at each school that were successfully installed, with help from the schoolteachers, at suitably exposed locations, such as the roofs of students' homes. Students were given specific instructions about rigorous data collection, including the need for an accurate record at a given time each day, and measurement using the volumetric scale on the cylinder. Teachers then took photographs of students' daily rainfall records, which were promptly sent to other project researchers in Kathmandu for data quality control and analysis (monthly smartphone credit was provided to each school to this end).

**Table 2** breaks down the activities over the course of the day, which mixed blackboard teaching with numerical examples, open discussion, and outdoor demonstrations (cf. the "mixed methods" of Le Féon et al., 2016). **Figure 3** is an example of one of the posters (in this case, focusing on the effects of Monsoon rainfall on triggering landslides) that were displayed throughout the day at each school and were used as interactive stimuli for teaching. The design was tailored for the students, with minimal text, bold colors, and attractive graphics (**Figure 3**). Lunch was provided by the research team and taken together; we also sought overnight accommodation as close to each school as possible to foster a sense of community and integration.

### Assessment

Immediately upon the completion of our activities in May 2019, all project participants (i.e., instructors, educators, students, school authorities) were provided with comprehensive feedback forms. Feedback was solicited in three areas: timing and organization of the intervention, the local relevance of scientific content and data collection activities, and suggestions for additional activities that would enhance scientific capacity resilience creation to natural hazards. These forms and interviews will be completed and analyzed in relation to the project's objectives (**Figure 1**), which could then inform the structure of potential future activities (section Conclusions and Outlook).

# RESULTS AND DISCUSSION

## Findings of Case Study Activity

Planning, implementing, and assessing the citizen science activity yielded information about the activity itself, i.e., student engagement levels and the quality and volume of collected data.

**TABLE 2 |** Summary of student activities.

| Session theme | Activities | Learning outcomes |
|---|---|---|
| A: Geographical context (30-min warm-up) | - Locate school and homes on poster map and satellite imagery on phone<br>- Identify local geographical features like rivers, springs, landslides<br>- Discussion on family migration | - Use various GPS-based location apps<br>- Foster greater sense of environmental and spatial awareness (i.e., immediate landscape and hydrology)<br>- Foster student-student knowledge transfer and interaction<br>- Situate students' homes and schools within broader regional/national context<br>- Situate the initiative as a scientific enquiry (managing expectations) |
| B: Rainfall (1 h) | - Teaching on Monsoon: patterns, provenance using worksheets and Q&A<br>- Calculator exercises, e.g., adding up total annual local rainfall figures<br>- Link to local livelihoods: importance of rainfall in farming, health, sanitation | - Importance of collaborative working and problem-solving using incomplete/fragmentary datasets<br>- Ability to quantify rainfall totals—and the importance of figures/calculations<br>- Increased scientific and cultural understanding of uniqueness of Monsoon rainfall |
| C: Hazards (1 h) | - What is the role of water in triggering natural hazards?<br>- Open discussion about landslide perception<br>- Demonstration of causes and triggers of landslides—outdoors<br>- Photos of other natural hazards (e.g., 2015 Kathmandu earthquake) | - Awareness raising and sensitization to flood/landslide processes and associated risk<br>- Awareness of variation in risk and vulnerability, and contributory factors<br>- Behavioral change given certain early warnings |
| **BREAK/LUNCH** | | |
| D: Rainfall trends (1 h) | - Open discussion about local harvests, rainfall—introduction to trends<br>- Introduction (blackboard teaching) to climate change<br>- Some worked examples with calculators | - Knowledge sharing: student/parent knowledge transfer<br>- Farm-level information (scientific measurement) land lost to excessive flooding or landslides<br>- Popularizing science (climate change) and strengthening science-society interaction |
| E: Measuring rainfall (2 h) | - What is the role of technology in understanding hazards and measuring water (rainfall and rivers)?<br>- Interpretation of local automatic tipping-bucket rain gauges<br>- Introduction to manual rain gauges (measuring cylinders)<br>- Outdoor measurement exercises<br>- Outdoor installation exercises<br>- Fieldtrip to demonstrate measurement of river discharge | - Development of skills to locate and use available data sources in students' daily lives<br>- Exposure to scientific data presentation and analysis<br>- Develop understanding of structured data collection<br>- Develop attitudes that support the responsible acquisition and application of scientific and technological knowledge to the benefit of self/society, and the environment<br>- Continue rainfall data collection<br>- Students are mobilized to create a landslide watch group or an environment club in their school to continue the environmental monitoring activities |

## Student Engagement

The intended deliverables were student-collected, daily-recorded precipitation datasets; establishing school-level science and environmental monitoring clubs; and ready-to-use lesson plans with accompanying teaching materials that complement the existing GoN curricula. After 6 months, 12 students continued to record and report data at Saraswati Secondary School; this figure was nine (of 15) students in Sunkuda Higher Secondary School. The nine students who discontinued measurements reported that the measuring cylinders were either stolen, vandalized, or lost due to high winds, rainfall, or livestock movement. Two of these students began to take measurements irregularly in the months prior to cessation. Student selection for manual rain gauge data collection was a source of pride; students worked hard to make accurate daily readings and secure the measuring cylinders to the ground/roof. It is clear that the established social structure of the school, where teachers have a well-defined role relative to the students, was essential in maintaining consistent data collection, as has been reported elsewhere (cf. Shah and Martinez, 2016; Saunders et al., 2018).

## Data Collection and Quality

We compared the student data of weekly precipitation totals for the 2019 Monsoon at Saraswati Secondary School, Bajura, with a locally installed automatic tipping-bucket rain gauge (**Figure 4**). The results of the measuring cylinders agree very well with the rain gauge time series both in magnitude and time. The weekly cylinder measurements differ on average 9.4 mm week$^{-1}$ with the rain gauge measurements, which is equal to a relative difference of 11.8%. This reduces to 6.7 mm week$^{-1}$ (8.3%) if the measurements of all the students are pooled. When aggregated over the entire monitoring period, the difference between the rain gauges and pooled cylinder measurements is as low as 82 mm (2.9%).

In a similar experiment, Davids et al. (2019) describe the use and deployment of repurposed soda bottles for citizen-led rainfall measurements in the Kathmandu Valley. They report a 2.9% error between 154 rainfall measurements and automatic rain gauge data, ascribed to evaporation, condensation, and observational errors.

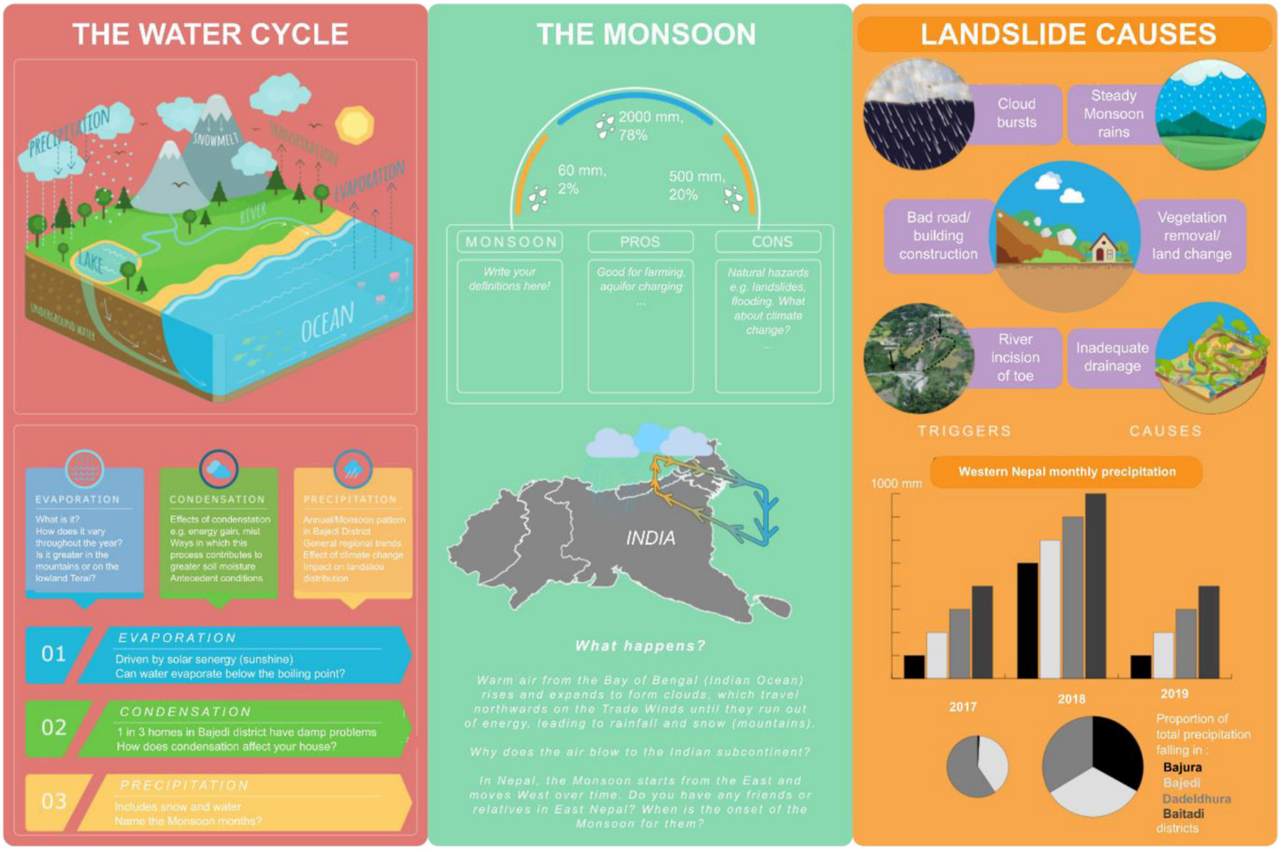


**FIGURE 3 |** Poster before translation into Nepali, used during the Rainfall session (**Table 2**) as a primer for discussion between facilitators and students about Monsoon rainfall. In the first instance, students were asked to write on the poster their own suggestions about the causes, challenges, and potential benefits of the Monsoon. One identified "challenge" was landslides, which led onto the next session (Hazards), where facilitators used the right-hand panel of the poster to teach landslide antecedents (e.g., heavily saturated soil or friable bedrock) and triggers (e.g., cloudbursts or deforestation).

## Evaluation of our Framework

The application of our framework to a specific case study yielded valuable information about its broader applicability and ability to capture properly the impact of the activity (and also, by extension, whether certain effects were missed). We now reflect on lessons that were learned from our experience of translating the generic framework into practice, in order to refine and improve it. In the first instance, the process of co-developing teaching materials that would complement a specific science curriculum was straightforward. From the local teachers' perspective, this was the most salient aspect of our activity, demonstrating the value of their intrinsic involvement throughout the entire life-cycle of such citizen science projects. We found strong complementarity between a fit-to-curriculum and the action-oriented framing of Larson et al. (2016): new learning material introduced to students can be useful both in enhancing their knowledge of prescribed curricula, and in augmenting understanding of the immediate environment (in our case, river development, hillslope processes, and rainfall patterns).

In our framework, we postulated that the physical presence of professional scientists would enhance learning and participant retention. However, in practice, there are few opportunities for such active involvement other than brief (and translated) introductions; students respond more readily to their own schoolteachers, rather than to members of a scientific team. A suite of different scenarios where scientific involvement is varied (i.e., teaching delivery entirely by professional scientists, to none being present at all) would be necessary to evaluate this factor. In terms of our intervention, we found that the continued involvement of teachers extended to their willingness and ability to lead classroom-based sessions (rather than a professional scientist, which we theorized would have greatest impact). The framework should therefore be refined to place greater emphasis on teaching delivery by existing staff. We then analyzed the effect of scientist engagement levels on student retention. While a greater number of students continued data collection activities when we could to integrate more closely with the school and local community (e.g., staying overnight in the school hall, and

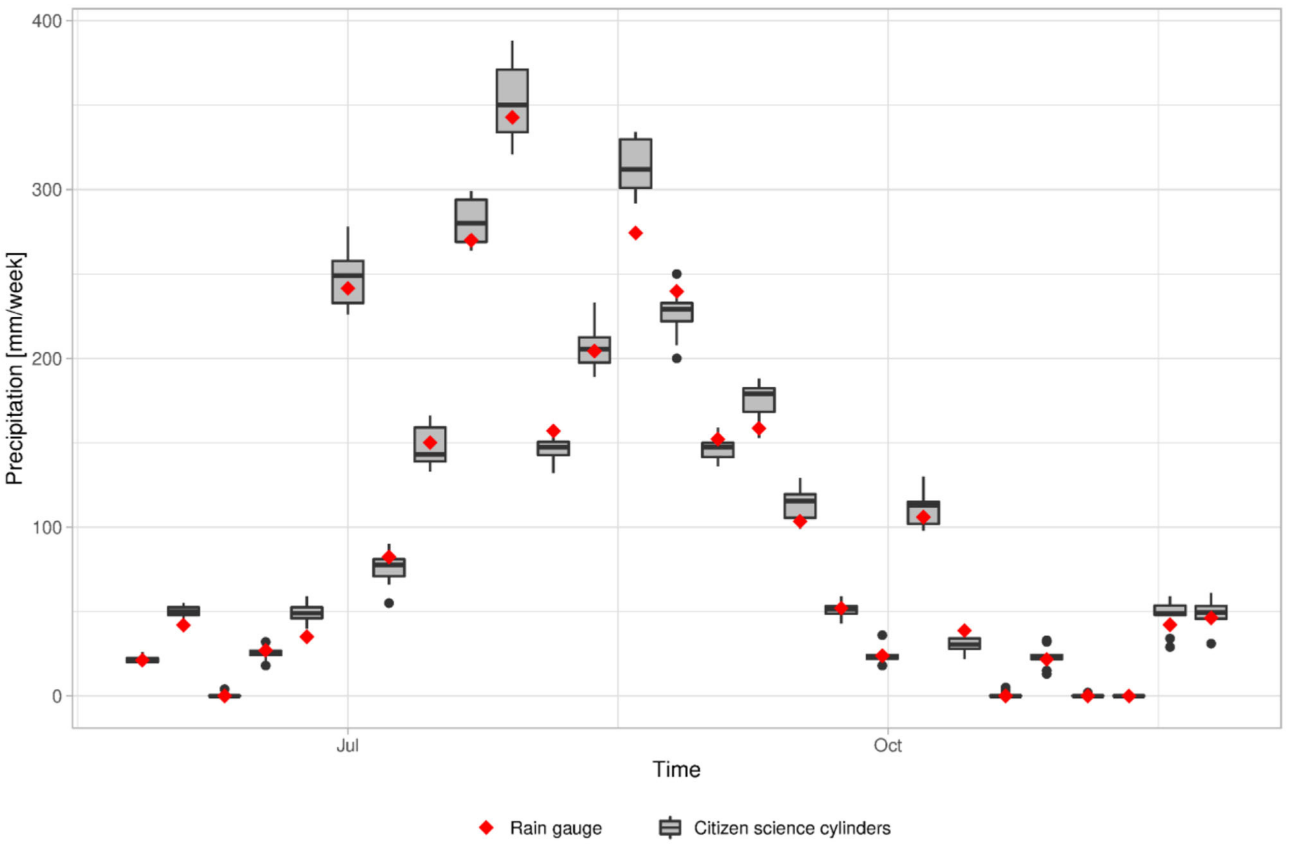


**FIGURE 4 |** Weekly rainfall totals in 2019 Monsoon season (May–December) for Saraswati Secondary School, Bajura district. Red diamonds = automatic tipping-bucket rain gauge data; gray boxplots = weekly totals of the cylinder data recorded by 10–14 students. Black dots = values that fall outside the whiskers, which represent 1.5 times the interquartile range. The mean of the absolute difference between the average of all cylinders reading in a week, and the corresponding rain gauge reading, is 6.7 mm week$^{-1}$ (minimum = 0 mm week$^{-1}$; maximum = 38.7 mm week$^{-1}$).

eating communally with students), additional evidence is needed to establish robustly this theoretical causality (e.g., a greater number of tests with rigidly defined levels of integration: Saunders et al., 2018).

We sought to identify topics of local relevance for students *a priori*; direct measurement of student engagement (relative to, e.g., more holistic concepts, such as climate change) is challenging and has been little explored outside secondary schools in a few developed countries (e.g., Rochford et al., 2018; Saunders et al., 2018).

In the assessment phase, we posited in our framework that student-led "science clubs" represent a means of fostering long-term sustainability. In practice, such groups are more likely to evolve organically with minimal input from a scientific team; in our case study, this process took the form of informal weekly gatherings to collate rainfall measurements. Our framework did not capture the development of a system of monetary prizes for the "best" student data, judged on criteria, such as legibility, accuracy, consistency, and student conscientiousness. This took place independently of data collection and teaching activities and was not directed by project researchers; rather, teachers took the initiative to set up the prizes in order to motivate students to complete their assignments diligently. In future, funding for the prizes could be disbursed during future interventions, to support retention and incentivize continuing data collection. Moreover, we did not envisage a significant externality resulting from the clubs: students also report other environmental metrics (e.g., rice terrace cambering, or development of cracks in the ground) that are well-beyond the scope of our original instruction. The natural development of such information collection suggests that our framework underestimated students' capacity to apply new knowledge elsewhere in a creative manner.

Finally, following common practice in other, non-school-based citizen science initiatives (e.g., Goodchild, 2007; Haywood and Besley, 2014), we also theorized that the results of *post-hoc* questionnaires should allow the implementation of an activity to be improved iteratively (section Framework Construction). This process indeed yielded insights into retention levels or reasons for data collection cessation (such as equipment loss or vandalism, or simple lack of motivation; section Student Engagement). However, the high level of teacher and student turnover is an unforeseen bottleneck that could diminish the "institutional memory" of citizen science activities; also, the GoN's secondary science curricula have experienced dramatic changes in content since federalization in 2017, which could present additional challenges to future continuity in this instance (Davids et al., 2019). Furthermore, we have not yet been able to assess quantitatively the longevity of the science clubs, nor the long-term sustainability of our activities. Our theoretical intention was that feedback solicitation should pose identical scientific questions (such as "when is rainfall heaviest in the year?"; "what are the main causes of river floods?") to respondents in the questionnaires to quantify knowledge and behavioral change (sensu Shah and Martinez, 2016). Instead, one solution could be to consult members of the "science club." While these students will naturally change over time, measuring the retained knowledge in each school is a more practical means of obtaining feedback that can be used to tailor future interventions to reflect more closely students' motivations and livelihood needs.

## CONCLUSIONS AND OUTLOOK

We describe the development of a framework designed to guide citizen science projects in a sustainable development context. We tested the framework by means of a case study at two secondary schools in Nepal, in order to interrogate which elements could successfully translate from theory to practice, and to identify major challenges requiring further refinement. Schools were chosen as a useful "testbed" as they offer an established social structure, ready-made organizational capacity, and high social capital that can usefully be harnessed by a citizen science approach. Our focus on natural hazards (Monsoon and landslides) fulfilled the dual purpose of complementing scientific data collection and improving long-term scientific capacity. Indeed, the student-collected rainfall data provide an excellent fit to gauge data of the 2019 Monsoon, suggesting that our activities could be scaled up to provide good-quality citizen science data elsewhere.

However, our primary aim was to interrogate the implementation of the activity, in order to obtain a better understanding of its dynamics and to learn how it should be implemented. In the planning stage, the involvement of teachers in co-developing learning material was important to secure complementarity between a fit to the local curricula and action-oriented framing, which engaged students. We did not foresee the organic, unregulated development of student-organized science clubs, suggesting that our original framework underestimated students' capacity to apply new knowledge elsewhere creatively. One improvement could be to use these clubs to obtain participant feedback, to ground future activities in greater local importance and foster sustainability. Quantitative assessment of project longevity remains challenging, due in part to high levels of student and teacher turnover.

Our findings and refined framework are generalizable to other student populations, and can be used to guide the application of citizen science in a sustainable development context elsewhere. We plan to complete additional activities (related more explicitly to landslides) at the same schools, which will form additional case studies or "testbeds" to augment and further improve our framework.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

JP drafted the text and prepared the figures. KC, AD, and JP originated the concept. WB and KC provided the input to the structure, text, and figures. JP, NS, PS, BP, and SP executed the field activity, for which we also acknowledge the assistance of Caroline Russell, Clara Rodriguez-Morata, and Alberto Munoz Torrero Manchado. All authors contributed to the article and approved the submitted version.

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# Citizen Science and Biological Invasions: A Review

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Biological invasions are among the most challenging ecological and conservation riddles of our times. Fortunately, citizen science projects became a valuable tool to detect non-indigenous species (NIS), document their spread, prevent dispersion, and eradicate localized populations. We evaluated the most undisputed definitions of citizen science and proposed that a combination of two of them is a better reflection of what citizen science has become. Thus, citizen science is any environmental and/or biological data collection and analysis, including data quality control, undertaken by members of the general public, as individuals or as organized groups of citizens, with the guidance and/or assistance of scientists toward solving environmental and/or community questions. With this review, we also assessed how citizen science has been advancing biological invasions research and its focus, by analyzing 126 peer-reviewed articles that used citizen science methods or data concerning NIS. Most of the articles studied terrestrial species (68%) and terrestrial plants were the most studied group (22.7%). Surprisingly, most first detection reports were of non-indigenous marine fish probably due to the constraints in accessing aquatic ecosystems which delays the detection of new NIS. Citizen science projects running over broad geographical areas are very cost-effective for the early detection of NIS, regardless of the studied environment. We also discuss the applicability and need to adapt the methods and approaches toward the studied ecosystem and species, but also the profile of the participating citizens, their motivations, level of engagement, or social status. We recommend authors to better acknowledge the work done by contributing citizens, and the putative limitations of data generated by citizen science projects. The outreach planning of citizen science projects is also evaluated, including the use of dedicated web platforms vs. pre-existent and disseminated web platforms, while discussing how such outreach actions can be maximized. Lastly, we present a framework that contextualizes the contributions of citizen science, scientific research, and regional and national stakeholders toward the integrated management of biological invasions.

**Keywords: citizen science, invasive species, non-indigenous species, early detection, monitoring, integrated management**

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## INTRODUCTION

Biological invasions are increasingly exacerbated by human activities and their impacts on the environment, as ecosystem degradation, overexploitation of biological resources, or global trade (Pyšek and Richardson 2010; Canning-Clode 2015). Biological invasions usually go unnoticed by the scientific community during the initial period of low abundance and independently of propagule pressure (Simberloff and Rejmánek 2011). A similar process is observed with their impacts, which are only acknowledged by the scientific community and public when impacts are already significant (Pyšek and Richardson 2010; Simberloff 2011). In extreme cases, invasive species may lead to the extirpation of native species and shifts in the functioning of ecosystems (Sousa et al., 2011). The estimated economic impacts are tremendous. For example, the estimates of the economic impact in the European Union ranged between €12 and 20 billion per year (Kettunen et al., 2008; Scalera et al., 2012). On a global scale, the impacts of biological invasions were estimated at US$ 1.4 trillion which in the late 1990s corresponded to 5% of the global economy (Pimentel et al., 2001). Recognizably, prevention, early detection, and localized containment are the most effective measures to minimize the impact of non-indigenous species (NIS), including invasive species (Pyšek and Richardson, 2010).

Given the pervasive nature of biological invasions, citizen science emerged as an additional tool for earlier detection and management of biological invasions. Citizen scientists–as individuals or communities–collect and analyze data, helping to conduct research, generate a new hypothesis, or solving unanswered questions (Eitzel et al., 2017). The Oxford English Dictionary defines citizen science as "scientific work undertaken by members of the general public, often in collaboration with or under the direction of scientists and scientific institutions" (Simpson and Weiner, 2014). However, several other terms exist to describe such activities, as volunteer biological monitoring (Lawrence, 2006), community-based and participatory monitoring (Bell et al., 2008; Danielsen et al., 2009), or community science (Carr, 2004). With so many terms to describe the same topic, the information disperses and is more difficult to find. Citizen science initiatives may also be undertaken entirely and independently, by individuals or communities. Yet, the participation or supervision by scientists is advantageous even when the main objective of a citizen science initiative is to increase public literacy or engagement toward biodiversity and science topics. We advocate that citizen science should merge the definitions of Eitzel et al. (2017) and Simpson and Weiner (2014), mainly if data from citizen science produces new scientific knowledge and are intended to be part of decision-making processes where quality control is required. This combined definition describes citizen science as "any environmental and/or biological data collection and analysis, including data quality control, undertaken by members of the general public, as individuals or as organized groups of citizens, with the guidance and/or assistance of scientists toward solving environmental and/or community questions".

One of the main advantages of citizen science is the ability to cover larger geographical areas, at a significantly lower cost when compared to traditional scientific surveys (Carr, 2004; Crall et al., 2010; Tulloch et al., 2013; Pocock et al., 2017; Simoniello et al., 2019). Thus, citizen science can significantly reduce the time until the first detection of a NIS and track its dispersion with a wide network of citizen scientists. Therefore, eradication, containment, and mitigation measures may occur earlier and eventually be more effective (Gallo and Waitt, 2011; Pocock et al., 2017; Eritja et al., 2019).

Quality control is a theme of recurrent discussion regarding the data produced by citizen scientists (Crall et al., 2010; Ellwood et al., 2017). One should always analyze the scope of each research topic and how a specific project or citizen science initiative may be useful. If scientists are aware of the inherent limitations and acknowledge them, such data are of tremendous value (Bird et al., 2014). Communication and exchange of knowledge with those who are on the field on a daily-basis–e.g., professional fishers, farmers, land managers, forest rangers–provide critical insights into species distribution and behavior. The contributions from such citizens, termed Local Ecological Knowledge, quickly increases the acquisition of information by scientists that otherwise could have taken years to obtain (Davis and Wagner, 2003; Gilchrist et al., 2005; Tiralongo et al., 2019). While not always labeled as such, the sole communication between citizens and scientists toward understanding Local Ecological Knowledge should also be regarded as citizen science, as there is an active collaboration between the two to solve a scientific question or hypothesis. As a broad concept, citizen science can embrace several approaches and methods toward a better understanding of scientific hypotheses, as long as authors maintain similar procedures and nomenclatures.

We have now come to a period when citizen science reached maturity. It is then imperative to understand what we have learned on the use of citizen science to study biological invasions. And above all, what opportunities exist to advance the study of biological invasions with the contribution of citizen science. Thus, in this review, we analyze peer-reviewed articles that used citizen science methods or data applied to study or manage NIS–detection, rate of dispersion, control, and restoration. We discuss the applicability and need to adapt the methods and approaches toward the ecosystem and studied species, but also the profile of participating citizens–motivations, level of engagement, education, and social status. The need for data verification and random audit procedures is addressed, exemplified by different methods where the results obtained by volunteers are compared to those obtained by scientists to evaluate accuracy and efficiency. The outreach plans of citizen science projects are also evaluated, as the use of dedicated web platforms vs. pre-existent and well-established web platforms. The goals of this review are to 1) understand the effective contribution of citizen science toward the detection and monitoring of NIS across a wide range of ecosystems 2) identify the main trends of citizen science focused on NIS, and 3) quantify the efficiency of citizen science (participation of citizens, number of detected NIS) and monitoring outcomes.

## BIBLIOGRAPHIC ANALYSIS

We conducted a bibliographic search with SCOPUS on July 9, 2019, to retrieve research and review articles using three combinations of keywords: "invasive species" and "citizen science"; "non-indigenous species" and "citizen science"; "non-native species" and "citizen science". The search retrieved 233 bibliographic references. The analyzed list consisted of 126 articles after eliminating the articles that do not contain data

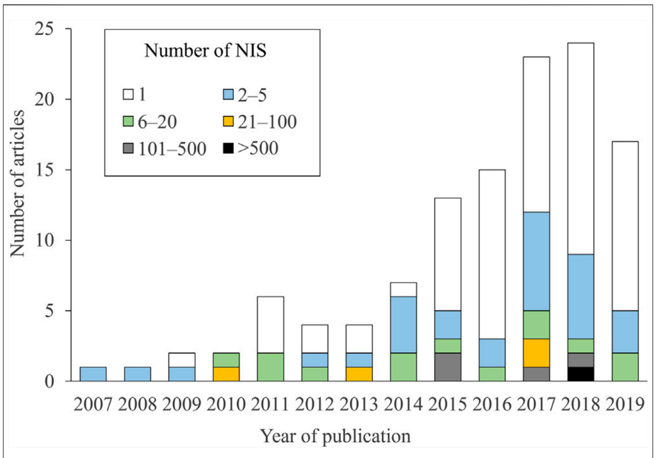


**FIGURE 1 |** Number of articles published on citizen science and non-indigenous species (NIS) since 2007. The number of species studied in each article is also shown and divided into six categories. A total of 126 studies reported information with this issue. Data were retrieved from a bibliographic survey made in July 2019 with SCOPUS using a combination of keywords: “invasive species” and “citizen science”, “non-indigenous species” and “citizen science”, and “non-native species” and “citizen science”.

about citizen science or invasive, non-indigenous, and non-native species. Subsequently, we analyzed the articles according to 18 fields of information:

- Geographic: 1) studied ecosystem (Terrestrial, Freshwater, Marine); 2) country of affiliation of the first author; 3) country where data were gathered; 4) continent where data were gathered; 5) geographic range of the citizen science campaign, divided into five categories according to the maximum distance between data points (<5 km; 5–100 km; 101–500 km; 501–1,000 km; >1,000 km).
- Species: 6) total number of species studied; 7) total number of NIS, divided into six categories (1; 2–5; 6–20; 21–100; 101–500; >500); 8) if species were all NIS or not (yes or no); 9) NIS scientific name list (up to five species; or “Several” if more than five); (10) taxonomic group of NIS (if more than one, classified as “Several”).
- Citizen scientists: 11) training provided to citizens (yes or no); 12) number of citizen scientists that participated in the study; 13) role of citizen scientists in the study (descriptive field on what tasks and actions were performed by participating citizen scientists toward the research question).
- Citizen science initiative or project: 14) duration of data collection (in months); 15) number of records gathered by citizen scientists; 16) how records were transferred from citizen scientists to scientists (personal communication; digital platforms; e-mail or social media post; or combinations of several methods); 17) use of a database to store data (yes or no); 18) source of citizen science data (field sampling campaigns; existent citizen science databases; independent report of data by citizen scientists; questionnaires; evaluation of citizen science projects or data quality; or combination of several methods).

Chi-square tests were done to investigate if the proportions of each category were similar or not, and the results are available as **Supplementary Material**.

We will mainly use the term non-indigenous species (NIS), often also referred to as non-native species, because it embraces both invasive and non-invasive species. However, when appropriate, we will mention if a species is invasive or not. Regarding the type of citizen science activities, our nomenclature will mainly be “citizen science projects” whenever there is an established project behind the data collection, usually with a specific denomination, but not necessarily funded. Still, other actions as one-off data collections will, whenever relevant, be referred to as “citizen science initiatives”.

## OVERVIEW OF PUBLICATIONS

Of the 126 articles analyzed, 76.2% were exclusively on NIS (n = 96), while the remaining also focused on native species. The total number of publications increased consistently since 2007 (**Figure 1**). Significant increases in the number of articles regarding a single NIS ($\chi^2_{(12,68)}$ = 70.4, $p$= < 0.001) and between two and five NIS ($\chi^2_{(12,29)}$ = 26.1, $p$ = 0.010) occurred since 2007 (**Figure 1**). After 2015, most studies focused mainly on one NIS (**Figure 1**).

Most studies delved into terrestrial ecosystems (68.0%, n = 83), followed by marine ecosystems (21.3%, n = 26) (**Figure 2**). Articles on terrestrial ecosystems were the only ones displaying a significant increase with the increase of the study range ($\chi^2_{(4,83)}$ = 11.4, $p$ = 0.022). On the other side, the marine ecosystems showed a trend of reduction in the number of published articles with the increase of the study range (**Figure 2**).

Plants were the most studied group of NIS (22.7%, n = 27), followed by insects (19.3%, n = 23), mammals (10.9%, n = 13), and fish (10.1%, n = 12), while several studies delved into multiple taxonomic groups (11.8%, n = 14) (**Figure 3**). Plants are mostly studied in North America (12.7%, n = 16), while Insects are studied mainly in Europe (11.1%, n = 14). Europe is the continent with most studies (44.4%, n = 56), followed by North America (32.5%, n = 41) (**Figure 3**). Significant changes in the number of published articles across the various taxonomic groups were identified for three study locations: North America ($\chi^2_{(15,41)}$ = 97.5, $p$= < 0.001), Central and South America ($\chi^2_{(15,7)}$ = 27.3, $p$ = 0.026), and Europe ($\chi^2_{(15,56)}$ = 76.0, $p$= < 0.001) (**Figure 3**).

Citizen science databases were the most used source of data (25.4%, n = 32), followed by field sampling activities (22.2%, n = 28), and independent reports by citizens (17.5%, n = 22) (**Figure 4**). The studies that involved some sort of field sampling activity carried out by citizens, were the ones where the highest percentage of training preceded the activities (11.9%, n = 15) (**Figure 4**). Significant differences in the number of published articles across the different data sources were identified for activities with training ($\chi^2_{(6,29)}$ = 44.1, $p$= < 0.001) and without training of citizens ($\chi^2_{(6,97)}$ = 40.3, $p$= < 0.001) (**Figure 4**).

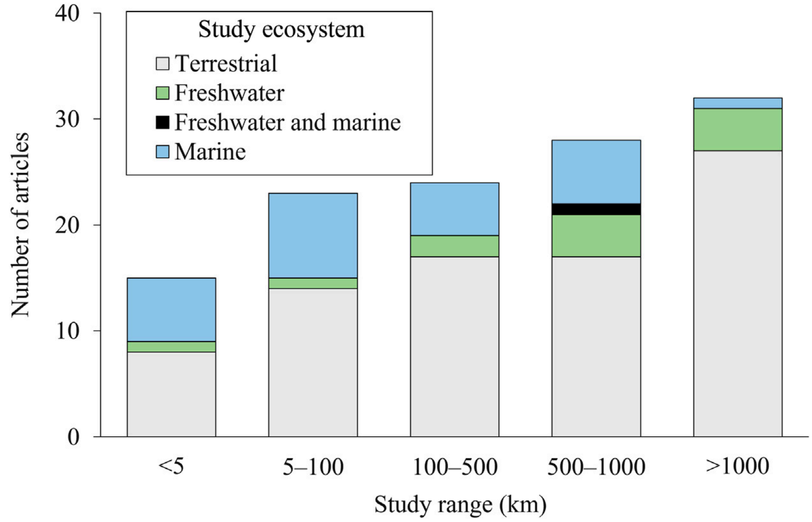


**FIGURE 2 |** Study range of articles published on citizen science and non-indigenous species according to four ecosystem categories (terrestrial, freshwater, freshwater and marine, marine). A total of 122 studies reported information on this issue. Data were retrieved from a bibliographic survey made in July 2019 with SCOPUS using a combination of keywords: "invasive species" and "citizen science", "non-indigenous species" and "citizen science", and "non-native species" and "citizen science".

Data has been transferred to scientists mainly through a digital platform (33.0%, n = 3) (**Figure 5**), either a dedicated website, e-mail, mobile app or a combination of these. Unfortunately, 20.6% of the articles (n = 26) did not specify which type of data transfer method was used, but likely some sort of personal communication was established. Personal communication is the third most common method to report data (16.0%, n = 15). We included in this category the articles that gathered data through in-person surveys or interviews. The reduced diversification of data transfer methods, which reflects how data was gathered in the first place, translates into a significant difference in the number of published articles across these various methods ($\chi^2_{(6,94)}$ = 55.8, $p$= < 0.001). Diversifying the communication channels between citizen scientists and scientists should be established more often, namely combining digital and personal communication, to increase the number of interactions because the use of several methods of communication only represents 9.6% (n = 9) of all published articles (**Figure 5**).

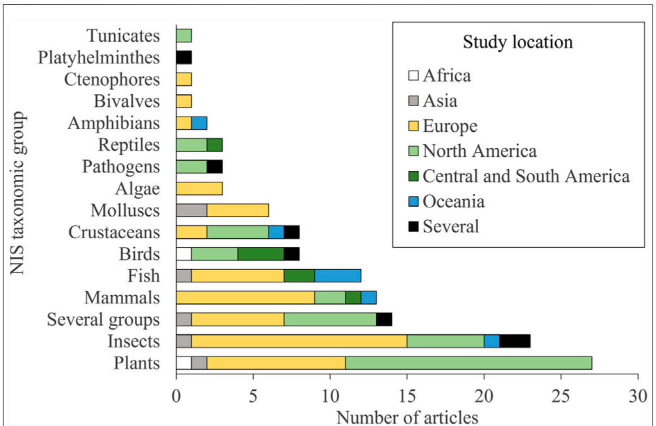


**FIGURE 3 |** Number of articles published on citizen science and non-indigenous species (NIS) according to 16 taxonomic categories. The continent where the studies were made is also included. A total of 126 studies reported information on this issue. Data were retrieved from a bibliographic survey made in July 2019 with SCOPUS using a combination of keywords: "invasive species" and "citizen science", "non-indigenous species" and "citizen science", and "non-native species" and "citizen science".

## UNRAVELING NON-INDIGENOUS SPECIES DISTRIBUTION WITH DIFFERENT CITIZEN SCIENCE APPROACHES

### Supervised Field Actions

A more traditional approach to citizen science projects consists of recruiting citizen scientists, provide them informative materials, develop training sessions, and then finishing with the participatory activities in the field, supervised, or in collaboration with scientists. Yet, only 17.5% (n = 22) of the articles in our bibliographic survey followed this traditional approach. One example consisted of a group of 12 citizens that received a 15-min training session before the one-day field sampling campaign with scientists to document the spread of the hemlock woolly adelgid *Adelges tsugae* (Animalia, Hemiptera) in a forest in Massachusetts (United States) (Fitzpatrick et al., 2009). This type of approach, named bioblitz, is increasingly popular. They are defined as participatory actions to quickly and intensively survey a given area to provide a biodiversity snapshot (Robinson et al., 2013). For example, during the "Marine

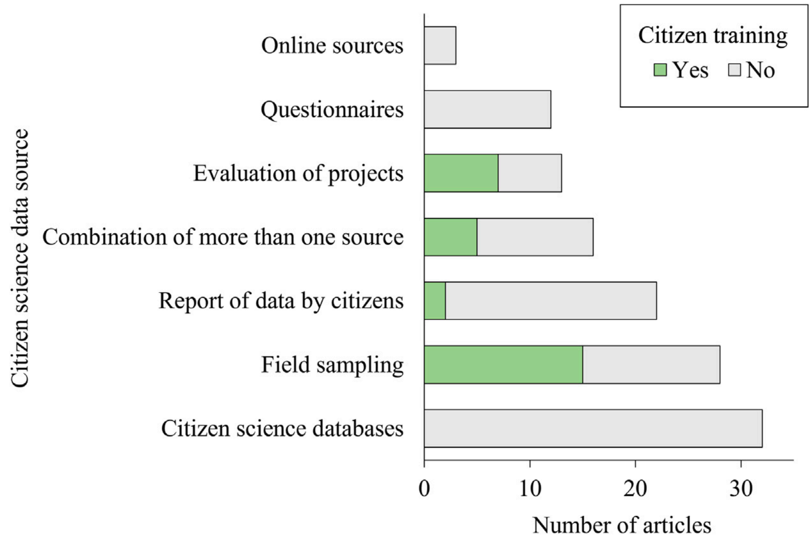


**FIGURE 4 |** Number of articles published on citizen science and non-indigenous species according to the data source used in the study (seven categories) and if citizen scientists received training under the scope of the study. A total of 122 studies reported information on this issue. Data were retrieved from a bibliographic survey made in July 2019 with SCOPUS using a combination of keywords: "invasive species" and "citizen science", "non-indigenous species" and "citizen science", and "non-native species" and "citizen science".

Invasive Species Bioblitz" in Sitka (Alaska, United States), participants received training on the identification of several target NIS which resulted in the detection of a 1000-km northward expansion of the invasive tunicate *Didemnum vexillum* (Animalia, Aplousobranchia) during the 2-days sampling (Cohen et al., 2011). The development of user-friendly tools and metrics enables the participation of a wider range of people. For example, the Metric of Aquatic Invertebrates for Volunteers (MAIV) enabled elementary and middle school students from Southern Portugal to evaluate the ecological status of streams (Pinto et al., 2020).

## Independent Surveys Across Broad Geographical Areas

Citizen science projects may improve the information on the distribution range of known NIS or infer about locations where NIS may expand their distribution. The sampling process of projects studying the distribution range of a NIS, across a broader geographical range, is usually undertaken independently by citizen scientists.

In terrestrial ecosystems, the "Invaders of Texas" project from the United States aims at monitoring invasive plants across the state. Every year, hundreds of citizens receive training through frequent workshops and online training programs. Citizen scientists identified several new locations where the giant reed *Arundo donax* (Plantae, Poales) is present in Texas. In many locations, the new discoveries were done without support from scientific literature or species lists. Then data were submitted to the "Invaders of Texas" database and later validated by professional scientists through photographic evidence (Gallo and Waitt, 2011).

There are numerous examples from aquatic ecosystems–e.g., two gelatinous NIS in the Western Mediterranean Sea (Boero et al., 2009) or freshwater crayfish across Greece and Italy (Faraone et al., 2017; Perdikaris et al., 2017). One of the more successful projects aimed at the early detection and monitoring of the invasive European green crab *Carcinus maenas* (Animalia, Decapoda) along the northern Pacific coast of the United States. Here, trained citizen scientists deployed baited traps and carry visual surveys along 3,000 km of shoreline. Citizen scientists documented the expansion of the European green crab across the state of

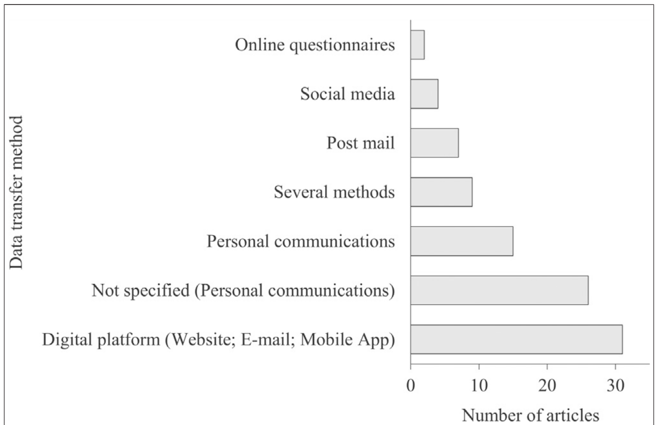


**FIGURE 5 |** Number of articles published on citizen science and non-indigenous species according to the method used by citizen scientists to transfer data to scientists. A total of 94 articles reported information on this issue. Articles based on citizen science databases and evaluations of citizen science projects (n = 32) were not included in this figure because data were not gathered throughout the process of the specific study. Data were retrieved from a bibliographic survey made in July 2019 with SCOPUS using a combination of keywords: "invasive species" and "citizen science", "non-indigenous species" and "citizen science", and "non-native species" and "citizen science".

Washington, which was later confirmed by scientists with rapid assessment surveys (Grason et al., 2018). Such kind of data collection over broad geographical areas may also help predict the areas to where a NIS will expand through species distribution modeling–e.g., two NIS of insects in Sweden (Widenfalk et al., 2014) and several invasive plant species in the United States (Crall et al., 2015) and Portugal (César de Sá et al., 2019).

### Records of Non-Indigenous Species Made by Informed Citizens

Informed citizens should be regarded as citizen scientists that have a strong interest in providing data to scientists even if there is no citizen science project in progress. Frequently, citizen science projects and databases help assess the presence and distribution range of NIS after the first detections were done by scientific surveys–e.g., Asian paddle crab *Charybdis japonica* (Animalia, Decapoda) in Australia (Hourston et al., 2015); Joro spider *Nephila clavata* (Animalia, Araneae) in North America (Hoebeke et al., 2015); monk parakeet *Myiopsitta monachus* (Animalia, Psittaciformes) in Mexico (Hobson et al., 2017). However, extremely relevant information may also arise from sporadic reports made by informed citizens. Such reports may contribute to specific citizen science projects, as the single record reports of two fish NIS in the Mediterranean Sea–the sergeant major *Abudefduf saxatilis* (Animalia, Perciformes) record submitted to the project "Seawatchers" (Azzurro et al., 2013), while the white-spotted puffer *Arothron hispidus* (Animalia, Tetraodontiformes) record was uploaded to the Facebook group "Mediterranean Marine Life" (Bariche et al., 2018). On the other hand, sporadic reports may also trigger the onset of a citizen science project. For example, the first record of weakfish *Cynoscion regalis* (Animalia, Perciformes) in southern Portugal was reported by a fisherman to scientists (Morais and Teodósio, 2016). This led to the development of a citizen science project–through social media and traditional media–which revealed that the species was going unnoticed by the scientific community for years in several locations across Portugal (Morais et al., 2017). Similarly, the first record of Asian bush mosquito *Aedes japonicus* (Animalia, Diptera) in Spain was submitted to the project "Mosquito Alert", triggering scientific surveys that confirmed the presence of the species and suggesting that the establishment had occurred a long time ago (Eritja et al., 2019). Overall, the contributions from informed citizens should be encouraged because it provides unique information that may even trigger the onset of in-depth studies on NIS species.

## SUITABILITY OF CITIZEN SCIENCE METHODS IN DIFFERENT CONTEXTS

### Terrestrial *Versus* Aquatic Ecosystems

The access to different ecosystems requires different logistics and dictates the methods used, both to engage participants and gather data (Cigliano et al., 2015). The number of participants and the amount of data gathered are greater in terrestrial ecosystems (Gallo and Waitt, 2011; Bradley et al., 2018) than in aquatic ecosystems. Still, the number of articles about first records of NIS in marine ecosystems is almost the double of those in terrestrial ecosystems. A search for the keywords "first/new" and "record/occurrence" in the titles of the retrieved articles disclosed five articles done in terrestrial ecosystems (Hoebeke et al., 2015; Maistrello et al., 2016; Mori et al., 2016; Eritja et al., 2019; Schüttler et al., 2019) and nine articles done in marine ecosystems (Boero et al., 2009; Azzurro et al., 2013; Hourston et al., 2015; Bariche et al., 2018; Fernández-Vilert et al., 2018; Giovos et al., 2018; Jurgens et al., 2018; Kleitou et al., 2019; Pearson et al., 2019). This may reflect the inherent difficulty in accessing the aquatic ecosystems by scientific community.

In aquatic ecosystems, data may need to be obtained through SCUBA diving (e.g. Zenetos et al., 2013; Cigliano et al., 2015; Anderson et al., 2017) or fishing (e.g. Danielsen et al., 2009; Morais and Teodósio, 2016; Tiralongo et al., 2019). Our bibliographic survey disclosed that 41 articles (32.5%) delved into an aquatic ecosystem (Marine or Freshwater) (**Figure 2**), but only 25 involved field sampling or the report of observations by citizens. Of these, 11 articles obtained data from marine subtidal areas, either through SCUBA diving (32.0%; n = 8) and/or fishing (20.0%; n = 5). In subtidal aquatic ecosystems, sampling is typically only possible through SCUBA diving which limits the number of participants (Cigliano et al., 2015). Yet, there are several successful examples. Citizen scientists monitored the macroalgae of the Bay of Seine (France) and identified 14 NIS over nine years (Verlaque and Breton, 2019). Also, seven non-indigenous fish were detected on the southern coast of Turkey by volunteer divers across three years of monitoring (Bodilis et al., 2014). The remaining 13 articles included data from shore habitats or intertidal zones. The "Plate Watch" project trained citizen scientists to deploy PVC settlement panels from floating docks and monitor sessile marine invertebrates. The main result was the detection of two invasive colonial ascidians, *Botrylloides violaceus* (Animalia, Stolidobranchia) and *Botryllus schlosseri* (Animalia, Stolidobranchia) (Jurgens et al., 2018).

### Digital Outreach *Versus* Personal Communication

The ease of access to information, through social media platforms, websites, and e-mail, opened new forms of communication between citizen scientists and scientists, as observed in our bibliographic survey. Outreach campaigns, supported by easy-access communication channels, resulted in several opportunities for citizen science projects to obtain new and relevant data, resulting in the detection of invasive species for the first time in several cases–fish species in the Mediterranean Sea (Azzurro et al., 2013; Zenetos et al., 2013; Bariche et al., 2018; Giovos et al., 2018) and in the NE-Atlantic coast and estuarine ecosystems (Morais et al., 2017), crustaceans in the NE-Atlantic (Morais et al., 2019; Encarnação, unpublished data), an invasive mosquito species in Spain (Eritja et al., 2019), or an invasive garden slug in several new locations in Japan (Morii and Nakano, 2017).

Digital outreach should be complemented, whenever possible, with in-person questionnaires to obtain Local Ecological Knowledge from digitally-excluded citizens. Such approach proved its value in detecting and reconstructing the invasion of several freshwater fish in Northern Spain (Clusa et al., 2018), coastal fish in the Mediterranean Sea (Tiralongo et al., 2019), marine mollusks in Greek waters (Crocetta et al., 2017), mammals in the sub-Antarctic Cape Horn Archipelago (Schüttler et al., 2019), and several NIS in the Andaman archipelago, India (Mohanty et al., 2018).

## DATA MANAGEMENT

### Data Quality and Verification Strategies

Several biases may occur when combining data gathered by scientists and citizen scientists. The level of expertize of the participants involved should be accounted for when assessing the presence and identification of a species. First, scientists can detect low-abundant invasive species more frequently than less experienced citizen scientists (Fitzpatrick et al., 2009). Second, the rate of correct identifications is generally higher among citizen scientists that received some sort of training, but this does not exclude the need for the implementation of validation protocols (Crall et al., 2011; Jordan et al., 2012; Goczał et al., 2017). Overall, the amount of data, but also the participation of citizens, will likely be higher when dealing with large, unique, or charismatic NIS, than with small and cryptic species. Regardless data quantity all gathered data are of the utmost importance, particularly at the beginning of a biological invasion when abundances are low. In all cases, data quality protocols should always be implemented, either during or after data collection, and regardless of the project dimension, geographical scope, or methodologies used for data collection (Crall et al., 2010).

In many projects, the validation of NIS records is made with photographs sent to scientists (Gallo and Waitt, 2011; Justine et al., 2018; Eritja et al., 2019; Tiralongo et al., 2019; Johnson et al., 2020). In other cases, all samples may be checked by scientists. For example, the samples collected by 1,000 volunteers to monitor two invasive crustaceans–the European green crab *Carcinus maenas* (Animalia, Decapoda) and the Asian shore crab *Hemigrapsus sanguineus* (Animalia, Decapoda)–were checked and re-counted by the research team after each sampling campaign (Delaney et al., 2008). Another strategy is for scientists to participate in the field sampling along with citizen scientists to make a quality control assessment of a subset of samples and compare it with the data gathered by citizen scientists (Jordan et al., 2012). A third strategy is to analyze a subset of samples once the field sampling is concluded (APA, 2020).

### Dedicated Web Platforms

The use of digital communication channels and new technologies, like smartphone apps, increases participation and engages participants to keep active and motivated (Graham et al., 2011). The importance of digital communications is undeniable since 33.0% (n = 31) of published articles relied on it (**Figure 5**). However, the diversity of communication channels may challenge scientists and data managers on how to standardize this type of data. Indeed, several authors stressed out that standard protocols for gathering and sharing data on public databases must be implemented (Crall et al., 2011; Crall et al., 2012; Adriaens et al., 2015; Johnson et al., 2020). Such recurrent concerns can be partially addressed with an initial assessment of pre-existent standardized protocols and platforms, and an evaluation of their suitability to a new project, resulting in the subsequent integration of citizen science data into public databases and in the decision-making process (Delaney et al., 2008; Crall et al., 2011).

Here are a few examples of the diversity of methods used to collect information provided by citizen scientists. Smartphone apps have been used to detect and monitor NIS in several ecosystems. The app “FrogID” was designed to record and identify the callings of frogs in Australia (Rowley et al., 2019). The app “RINSE That’s Invasive” and “KORINA” were designed to record plant and animal NIS across Europe (Adriaens et al., 2015). The apps “Tigatrapp” and “iMoustique” were developed to detect mosquito NIS in Spain and France, respectively (Kampen et al., 2015). However, the creation and maintenance of a dedicated smartphone app, or a website to submit observations, is expensive and may discourage researchers from exploring such tools. An alternative approach has been the use of generalist and free citizen science online platforms, such as iNaturalist (iNaturalist, 2020). This online platform can be used by any project to record the submissions of citizen scientists. The iNaturalist platform has been chosen by many citizen science projects, including to study the presence of marine species expanding their distribution range and NIS in southern Portugal (Encarnação, unpublished data), the invasive Eastern gray squirrel *Sciurus carolinensis* (Animalia, Rodentia) in Italy (Mori et al., 2016), or reptiles and amphibians in North America (Spear et al., 2017).

## ENGAGEMENT OF CITIZENS

### Managing Expectations and Motivations

Scientific activities involving citizens may fall under three project categories (Bonney et al., 2009): 1) contributory projects–scientists define the research questions and citizens collect data according to pre-defined protocols; 2) collaborative projects–citizens are involved in several research steps, as sample collection and analysis, interpreting data, and presenting results; and 3) co-created projects–citizens usually determine the research question and then work with scientists to solve a specific problem, usually on issues of community concern as environmental or public health.

In each project category, the expectations and motivations of citizens are inherently different and should be accounted for by project managers. The most common motivations to participate in citizen science projects are to learn more about the environment and biodiversity, protect a local area or natural resource, spent more time in nature, or help with community activities (Crall et al., 2012; Tulloch et al., 2013; Merenlender et al., 2016; Frensley et al., 2017). For example, the motivation of Australian fishers to fish the invasive common carp *Cyprinus carpio* (Animalia, Cypriniformes) relied on their desire to remove this invasive species. The common carp is likely to disrupt aquatic ecosystems and removal actions were regarded as socially acceptable–the "ends justify the means" (Atchison et al., 2017). Interestingly, there was a significant difference among fishers' motivations depending on their origin; overseas-born fishers' motivations were mostly based on the joy for recreational fishing, while Australian-born fishers were mainly motivated by environmental reasons due to the species' invasiveness (Atchison et al., 2017).

Although many citizens may be motivated to participate and contribute to a citizen science project, the willingness to spend time making such contributions change from person to person and according to what is expected from citizens. In many contributory projects, participants are not required to attend meetings or training sessions, which simplifies their participation and may increase the amount of data collected (Zenetos et al., 2013; Jordt et al., 2016; Morii and Nakano 2017; Tiralongo et al., 2019). In participative methodologies, as collaborative or co-created projects, citizens receive a higher number of tasks and have more responsibility, which requires that substantial information must be transmitted to participants to keep their motivation high and demonstrate how their actions can impact science and conservation (Jordan et al., 2011). Also, citizen science projects where citizens are active volunteers–i.e., they actively search for citizen science projects to participate–reach higher levels of engagement and retention (Bonney et al., 2009; Andow et al., 2016; Davis et al., 2018).

Finally, once citizen science projects make significant progress, scientists should contact citizen scientists and disclose the scientific progress they helped achieve. This simple action motivates citizen scientists and keeps them engaged with the current project while increasing the chances of having them participate in future projects.

## Becoming Part of the Solution

The implementation of activities to control or eradicate invasive species increase the level of engagement of citizen scientists because they feel being part of the solution. Sometimes of a very noticeable environmental problem. Several examples from our bibliographic survey show this. Motivated volunteer divers and fishers are fundamental in the removal of the invasive lionfish *Pterois volitans* and *Pterois miles* (Animalia, Scorpaeniformes) in the Caribbean Sea, while providing data on the distribution and abundance of the species (Carballo-Cárdenas and Tobi, 2016; Anderson et al., 2017). In the Aviles estuary (Northern Spain), a group of 20 citizen scientists removed 774 individuals of the invasive pygmy mussel *Xenostrobus securis* (Animalia, Mytilida). This removal action effectively controlled the population as confirmed by posterior visual census and eDNA analysis (Miralles et al., 2016). In Portugal, participatory ecosystem restoration efforts to remove the invasive iceplant *Carpobrotus edulis* (Plantae, Caryophyllales) and the giant reed *Arundo donax* (Plantae, Poales) have been regularly performed by citizen scientists, including elementary and middle school students (APA, 2020). Several examples of innovative approaches propose the use of invasive species for human consumption while partnering with Chefs and news media channels to increase awareness on biological invasions (Chapman et al., 2016; Carrillo-Flota and Aguilar-Perera, 2017; Mancinelli et al., 2017; Cerveira, 2019; Leone et al., 2019; Ulman et al., 2020).

Nevertheless, several obstacles may arise when planning the removal or eradication of certain invasive species. For example, public empathy with species may undermine removal actions, namely with species that the public perceives as "beautiful", "domestic", or "useful" (Courchamp et al., 2017)–e.g., invasive gray squirrels *Sciurus carolinensis* (Animalia, Rodentia) in Italy (Bertolino and Genovesi, 2003), feral cats *Felis catus* (Animalia; Carnivora) in Australia (Nogales et al., 2013), or freshwater game fish like the smallmouth bass *Micropterus dolomieu* (Animalia, Perciformes) in several European countries and South Africa (Loppnow et al., 2013).

# DISCUSSION

## A Roadmap to Citizen Science Success

Citizen science is not a perfect science, but perfection is the enemy of good. As described throughout this review, many citizen scientists have contributed significantly to the knowledge of biological invasions and their management. In the following paragraphs, we propose six action items that any citizen science project could adopt to maximize the chances of success.

First, know your audience. At the onset of a citizen science project identify the social, cultural, and environmental awareness background of potential participants. This action will pave the road to success or failure. Bear in mind that a successful citizen science project cannot be mimicked anywhere else because the sociological fabric is different and mutates through time. Even the same project has different levels of success within a population owing to the intrinsic characteristics of the individuals (e.g., age, education, environmental awareness, motivation) and, consequently, also between different regions and countries (Crall et al., 2010; Ganzevoort et al., 2020; Larson et al., 2020).

Second, cherish the contributions from informed citizens and strengthen that partnership. The records provided by informed citizens on non-indigenous and uncommon species are precious information that often ignites research efforts (Morais et al., 2017; Morais et al., 2019), so they must be encouraged. However, given the sporadic nature of such records, they must be part of a broader effort to complement citizen science projects and scientific research.

Third, combine multiple methods of communication with citizen scientists. The methods used in citizen science projects should strive to maximize the reach and engagement of a broader audience (e.g., field sampling, social media, in-person interviews/questionnaires). For example, digital platforms of communication between citizen scientists and scientists

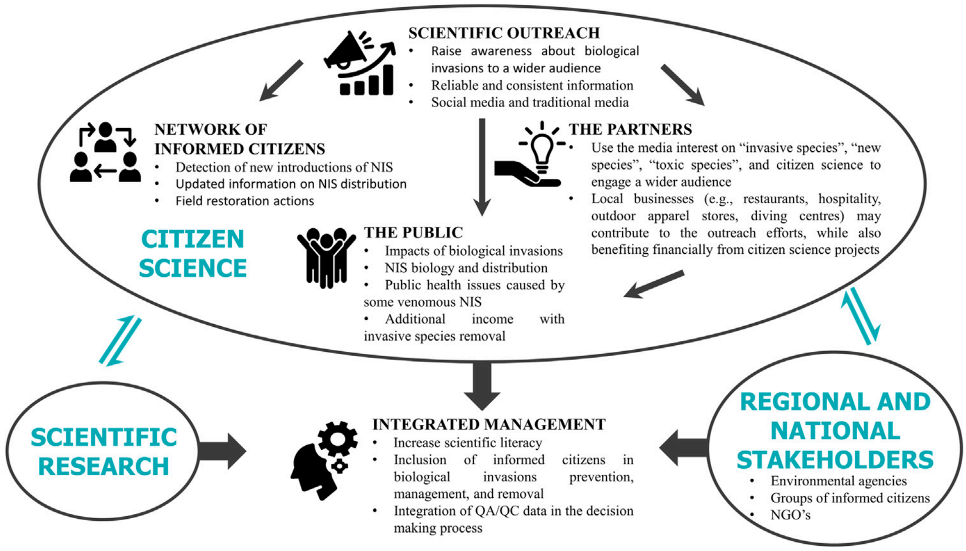


**FIGURE 6 |** Diagram proposing how outreach activities promoted by scientists can be boosted with the aid of the media and local businesses to reach a higher audience and inform several segments of the public with credible information about biological invasions. The media and the public, but also a network of informed citizens, are essential for building a solid citizen science project. The contributions from citizen science and national and regional stakeholders complement those from scientific research to attain a more solid integrated management of biological invasions. Icons retrieved from the Noun Project (www.thenounproject.com).

exclude those that are not technologically savvy, despite being very effective and essential in modern citizen science projects (Spiers et al., 2019). This is a simple example of why multiple methods must be set in place.

Fourth, KIS–Keep It Simple. We advocate that a citizen science project should be kept as simple as possible, regardless of the dimension or scope. The participatory activities of a project should not overload participants with too many tasks or demand a long-term commitment. This will allow citizens with different experiences, motivations, and expectations to custom-tailor their participation and commitment to a project. For example, citizen scientists are generally uncomfortable in making advanced scientific decisions, regardless of their motivations and engagement, so, such kind of requests may limit the number of submitted observations (Gallo and Waitt, 2011).

Fifth, describe the methods clearly and acknowledge the contributions made by citizen scientists. Many articles covered by our review failed to describe basic information on the process of data gathering–i.e., 1) the number of participating citizen scientists, 2) how citizen scientists contributed or gathered data to the project, 3) the amount of data gathered by citizen scientists, and 4) how data were transferred from citizen scientists to the scientists. This undermines the public and other scientists from understanding the role of citizen scientists, the engagement of a project, and its impact. Ultimately, mentioning how each citizen participated and contributed to advance scientific knowledge will encourage citizen scientists to participate in future projects and recruit new volunteers. The outreach channels used to call citizen scientists for action should be used at a later stage of the project to communicate how data gathered by them advanced scientific knowledge.

Sixth, use existing citizen science digital platforms. While conducting this review, we questioned the cost-benefit of developing an app or web platform for the submission of observations in each new citizen science project. Such an approach–one app *per* project–will potentially reduce the participation of citizens in more projects (Johnson et al., 2020). Additionally, the lack of data uniformization can undermine the value of data on biological invasions, while data sharing-policies on commonly available databases will facilitate access to a wider scientific audience and managers. Citizen science projects should firstly consider ready-to-use and free apps, with mobile and desktop interfaces, as these are advantageous in many aspects. For example, it standardizes submission protocols, data-sharing policies, and allows highly engaged citizens to participate in multiple projects while using the same platform. Adopting existing and free platforms (e.g., iNaturalist, Zooniverse, Project Noah) will contribute to advance citizen science as a whole. The platform iNaturalist is one of the best citizen science platforms because it has a user-friendly interface for multiple devices, it features automated suggestions for the identification of species, the validation of species identification is made by a wide array of experts, and the validated records are regularly exported to the Global Biodiversity Information Facility (GBIF) database (iNaturalist, 2020). Automated export of data to centralized databases, such as GBIF, should be a standard procedure, regardless of the used platform (Adriaens et al., 2015). The use of generalist platforms will still require the establishment of QA/QC protocols by each research team before the use of data on a specific project.

## Integrated Management of Biological Invasions

The interest of citizen science in biological invasions has increased steadily, as reflected by the increased number of articles published since 2015 (**Figure 1**). Citizen science has benefited from the easier access of citizens to novel technologies and digital platforms (Eritja et al., 2019; Simoniello et al., 2019), but also to increasing efficiency of the outreach actions of citizen science projects (Nuñez et al., 2012; Chapman et al., 2016; David et al., 2018; Encarnação, unpublished data). As highlighted throughout this review, choosing a method to engage citizens in gathering data will mainly depend on the target taxonomic group, study ecosystem, and social context of the citizen scientists. We do not see this variability in approaches and sociological contexts as negative, but rather as an opportunity to adapt each citizen science project to specific scientific questions, different NIS, ecosystems, and regions/countries.

Several actions can be merged to increase the outreach of citizen science projects and the chance to convey the "right" message about biological invasions to the public and maximizing integrated management of biological invasions (**Figure 6**). Thus, informed citizens with their intrinsic Local Ecological Knowledge can be recruited as citizen scientists and early warning agents to detect the introduction of NIS and track their expansion (Boero et al., 2009; Gallo and Waitt, 2011; Azzurro et al., 2013; Hoebeke et al., 2015; Morais and Teodósio, 2016; Hobson et al., 2017; Grason et al., 2018; Eritja et al., 2019; Encarnação, unpublished data). They can also be recruited to eradicate species during field restoration actions to reduce the impact of invasive species in highly invaded ecosystems-e.g., invasive terrestrial plants (Crall et al., 2010), intertidal invasive invertebrates (Miralles et al., 2016), marine invasive fish (Peiffer et al., 2017). It should be noted that the eradication of edible invasive species may provide additional revenue for local populations, encouraging all stakeholders to contribute to the reduction of invasive species (Chapman et al., 2016; Mancinelli et al., 2017; Rotter et al., 2020), although everyone must be continuously reminded that the overall goal is the effective reduction of invasive species abundance (Nuñez et al., 2012). Again, a well-structured outreach plan will ensure that the "right" message is conveyed to all stakeholders.

Bringing a citizen science project to the next level–i.e., contributing to official national and international monitoring networks of NIS–requires the setup of independent and regular audits (Delaney et al., 2008; Crall et al., 2010). Citizen science should also strive to reduce the gap between the scientific community and the general public and promote scientific literacy while increasing the information obtained by scientists (Bonney et al., 2009; Crall et al., 2012). Reducing this gap should be the overarching goal of any citizen science project while empowering citizens to make effective contributions for integrated management plans of biological invasions.

## AUTHOR CONTRIBUTIONS

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# Consumer Preference Testing of Boiled Sweetpotato Using Crowdsourced Citizen Science in Ghana and Uganda

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Crowdsourced citizen science is an emerging approach in plant sciences. The triadic comparison of technologies (tricot) approach has been successfully utilized by demand-led breeding programmes to identify varieties for dissemination suited to specific geographic and climatic regions. An important feature of this approach is the independent way in which farmers individually evaluate the varieties on their own farms as "citizen scientists." In this study, we adapted this approach to evaluate consumer preferences to boiled sweetpotato [*Ipomoea batatas* (L.) Lam] roots of 21 advanced breeding materials and varieties in Ghana and 6 released varieties in Uganda. We were specifically interested in evaluating if a more independent style of evaluation (*home tasting*) would produce results comparable to an approach that involves control over preparation (*centralized tasting*). We compiled data from 1,433 participants who individually contributed to a *home tasting* (de-centralized) and a *centralized tasting* trial in Ghana and Uganda, evaluating overall acceptability, and indicating the reasons for their preferences. Geographic factors showed important contribution to define consumers' preference to boiled sweetpotato genotypes. Home and centralized tasting approaches gave similar rankings for overall acceptability, which was strongly correlated to taste. In both Ghana and Uganda, it was possible to robustly identify superior sweetpotato genotypes from consumers' perspectives. Our results indicate that the *tricot* approach can be successfully applied to consumer preference studies.

**Keywords: tricot approach, crop evaluation, underutilized crops, *Ipomoea batatas*, West Africa, East Africa**

# INTRODUCTION

Sweetpotato [*Ipomoea batatas* (L.) Lam] is grown as a staple root crop in Ghana and Uganda. It complements cassava and yams and competes with other starchy crops such as maize and plantain/bananas to supplement household income (Abong' et al., 2016; Glato et al., 2017). It is a nutritionally rich, climate-smart crop with good adaptability under low rainfall conditions, poor soils, and minimal farm inputs or labor (Abidin et al., 2017; Low et al., 2020). These agronomic attributes, together with the relatively short growing period, make it an ideal candidate crop for enhancing food security and improving livelihoods in Africa (Orr and Mwale, 2001; Low et al., 2009; Fiorella et al., 2016; Mzali, 2019). The resilient crop displays an array of storage root flesh colors which include various shades of white, cream, yellow, orange, and purple, all with unique nutritional properties (Nabubuya et al., 2012; Ellong et al., 2014; Chandrasekara and Kumar, 2016). The orange fleshed varieties are high in β-carotene, a precursor of Vitamin A in the human body, whilst purple fleshed varieties are excellent sources of anthocyanins with important antioxidant and anti-inflammatory properties (Low et al., 2007; Montilla et al., 2011; Jenkins et al., 2015; Salawu et al., 2015; Zhu et al., 2018; Bao and Fweja, 2020).

Despite the relative importance of sweetpotato to Africa, nutritionally and as a food security crop, it remains generally underutilized by different end-users along the value chain (Andrade et al., 2009; Mwanga et al., 2011). Knowledge gaps due to low investments in sweetpotato research present key challenges to drive demand or adoption of new varieties in most African regions with suitable climatic conditions (Low et al., 2017; Manners and van Etten, 2018). Over the last decade, improvements in demand-led breeding programs, albeit small, have increasingly re-directed research priorities toward stimulating and enhancing variety uptake and adoption along the different nodes of the value chain. Shifting the focus of breeding programs to consumer preferred traits, especially based on sensory acceptance attributes, has been shown to be a worthwhile strategy to drive demand for new sweetpotato varieties along the value chain (Wismer et al., 2005; Jaron et al., 2015; Baafi et al., 2016).

Consumer preference toward a particular crop variety is often influenced by quality attributes such as appearance, smell, texture, and taste, amongst others, which need to be taken into account in such studies (Kihinga, 2007; Siegrist and Hartmann, 2020). Sensory evaluation studies concerning consumer preference are thus important for demand led breeding strategies but remain challenging to perform with low-income consumers in Africa (Kamdem, 2016). In order to identify the most preferred crop variety, for example, consumers would be presented with the varieties to taste and score for best or most preferred variety. Breeding trials often have a large array (sometimes more than 10) of varieties to select from. As a result, these studies are often laborious, time-consuming, and costly. New approaches for acceptability and preference tests based on crowdsourced citizen science can reduce costs and have been successfully applied in agriculture (Minet et al., 2017).

For the field evaluation of varieties, innovation has led to a cost-effective approach that could also be useful for food science applications. Tricot employs a crowdsourcing approach where farmers become "citizen scientists," assisting researchers in data generation and collection (van Etten et al., 2016, 2019). The approach enables large tasks to be split into small, manageable tasks through an incomplete block design, which can be distributed to many participants over large regions. The planting material is randomized into incomplete blocks of three varieties. Each farmer receives a seed package with three coded varieties to plant and score in their own field. Data is then retrieved from the individual participants and processed using the digital platform ClimMob (https://climmob.net) to generate statistical analyses based on models suitable for ranking data (Turner et al., 2020). In this way, a wide array of crop varieties can be analyzed by different farmers within the same region to identify the most suitable and preferred variety for release or promotion. Studies have shown the accuracy of farmer-generated data (Steinke and Van Etten, 2016) and their usefulness to study genotype by environment interactions (van Etten et al., 2019).

The ranking of three items that is core to the tricot approach is equivalent to best-worst scaling (or "maximum difference scaling"), which is a method that is increasingly popular in food science, because it can be easily adapted and applied across cultures since it does not rely on verbal anchors (Moskowitz, 2005; Flynn and Marley, 2014). Using best-worst scaling, the consumer is prompted to select the "least preferred" and "most preferred" variety from a set of samples. When it is done with only three items, best-worst scaling is equivalent to ranking. Best-worst scaling is one option among a large set of methods in affective sensory analysis, including preference ranking, magnitude scales, hedonic scales, and pair-wise comparisons (Coetzee and Taylor, 1996; Hein et al., 2008; Voicu, 2013; Carabante and Prinyawiwatkul, 2018). Preference ranking is often a challenge in studies which involve many samples to evaluate due to consumer fatigue. Elderly consumers and consumers with low literacy levels struggle with magnitude and hedonic scaling. Generally, there is a good understanding of the relative value of each of these methods and best-worst scaling with incomplete blocks of three items does not present a deviation from accepted practice. The novelty of tricot as a citizen science approach is its relatively simple format that provides the possibility to work with large samples of consumers, who can perform the tests in their home environments, which may provide a perspective closer to target use environments of food.

In this study, the tricot approach was applied to evaluate the preferences for boiled sweetpotato of consumers from Ghana and Uganda. In the tricot approach, consumers were "citizen scientists" and generated data on variety preferences based on key quality attributes of boiled sweetpotato. We focused on the boiled root of sweetpotato, which is the most common preparation method in both Ghana and Uganda, even though other methods are also used (such as steaming, frying, roasting, baking) (Oggema et al., 2007). The objectives of the study were to (i) validate the suitability of the tricot tool for evaluating consumer preferences to released and advanced selections of sweetpotato clones, (ii) compare two ways to implement the

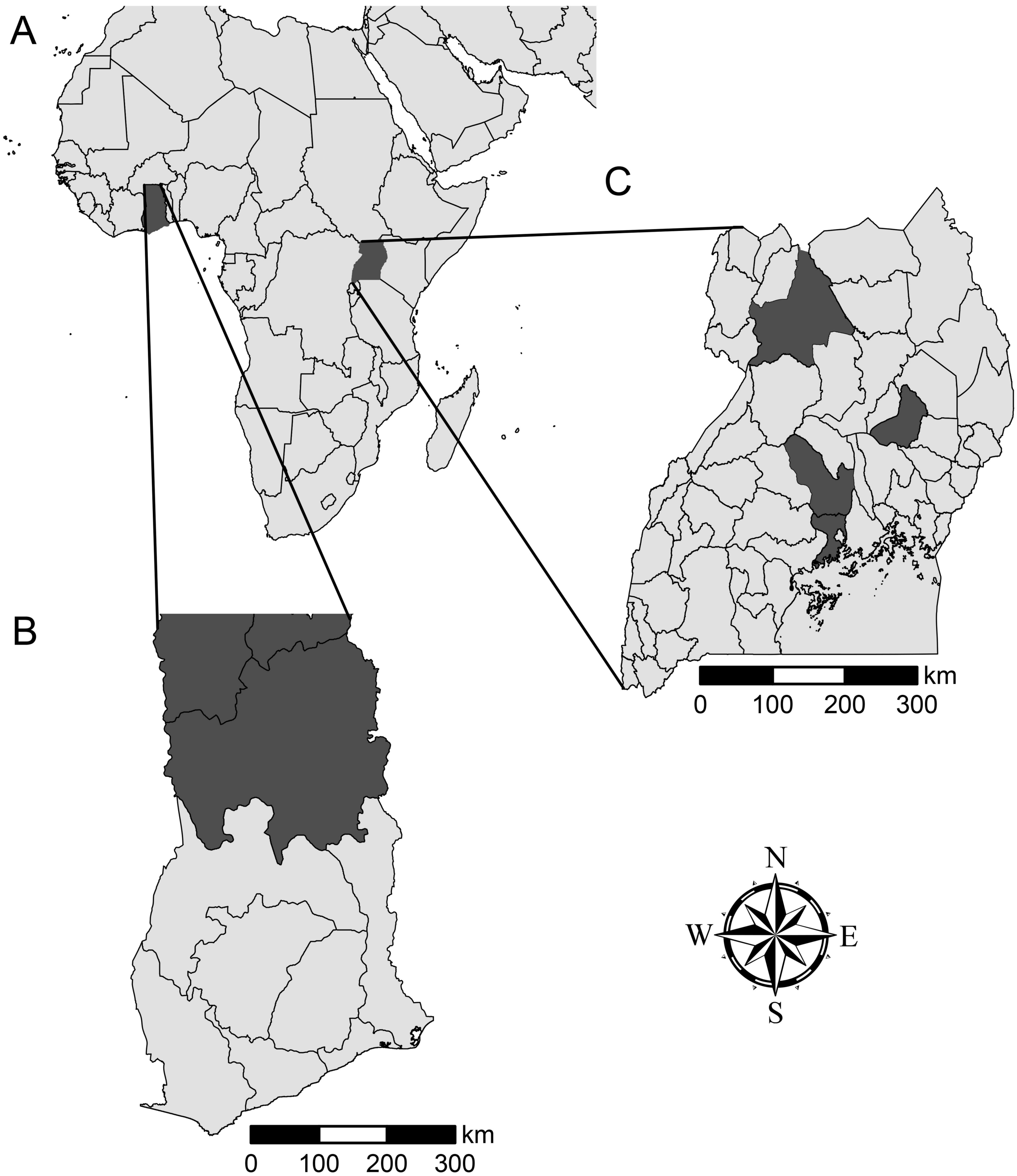


FIGURE 1 | Research sites. **(A)** Overview of Africa with Ghana and Uganda highlighted. **(B)** Overview of Ghana, with the districts of Northern, Upper East, and Upper West highlighted. **(C)** Overview of Uganda, with the districts of Gulu, Soroti/Serere, and Wakiso highlighted.

approach; centralized and home tasting, and (iii) document the key aspects of the method to inform future applications.

## MATERIALS AND METHODS

### Study Sites

The study was conducted in Ghana (West Africa) and Uganda (East Africa) using released varieties and advanced breeding materials of sweetpotato available in the different regions (**Figure 1**). In Ghana, the study was conducted in the Northern, Upper East, Upper West, and Savannah regions. We selected areas known for high sweetpotato production and consumption: Tolon and Kumbungu districts (Northern Region); Bongo, Bawku, and Kasena-Nankana districts (Upper East Region); Sissala West and Wa Municipal (Upper West Region); and Bole and West Gonja districts (Savannah Region). In Uganda, three

**TABLE 1 |** Characteristics of the sweetpotato genotypes utilized in this study.

| Genotype | Status | Country | Flesh color | Dry matter content (%) | Sugar content (%) | Beta-carotene content (mg/100g) |
|---|---|---|---|---|---|---|
| CRI-Yiedie (CIP442162) | RV | Ghana | Yellow | Very high: >35 | 17.54 | 0 |
| PG17362-N1 | AT | Ghana | Orange | Medium: 25–28 | 18.44 | 21 |
| PG17265-N1 | AT | Ghana | Orange | Medium: 25–28 | 22.42 | 17.24 |
| PG17206-N5 | AT | Ghana | Cream | High: 29–35 | 16.68 | 0 |
| PG17412-N2 | AT | Ghana | Orange | Medium: 25–29 | 14.2 | 16.42 |
| PG17136-N1 | AT | Ghana | White | High: 29–35 | 14.64 | 0 |
| PG17305-N1 | AT | Ghana | Cream | High:29–35 | 17.84 | 0 |
| PG17140-N2 | AT | Ghana | Yellow | High: 29–35 | 13.65 | 0 |
| PGN16021-39 | VT | Ghana | Orange | Medium: 25–28 | 20.64 | 16.54 |
| PGN16203-18 | VT | Ghana | Orange | High: 29–35 | 18.32 | 29.42 |
| PGN16130-4 | VT | Ghana | Purple | Very high: >35 | 18.55 | 0 |
| PGN16030-30 | VT | Ghana | Orange | High: 29–35 | 21.54 | 5.46 |
| PGA14011-24 | VT | Ghana | Orange | High: 29–35 | 19.99 | 2.12 |
| PGN16092-6 | VT | Ghana | Yellow | Very high: >35 | 14.42 | 0 |
| PGN16024-28 | VT | Ghana | Cream | High: 29–35 | 22.4 | 14.44 |
| PGN16024-27 | VT | Ghana | Orange | Very high: >35 | 19.52 | 12.43 |
| CRI-Apomuden | RV | Ghana | Orange | Low: <25 | 32.95 | 42.76 |
| SARI-Nyumingre (Obare) | RV | Ghana | White | Very high: >35 | 14.64 | 0 |
| SARI-Diedi (Tu-Purple) | RV | Ghana | Purple | High: 29–35 | 18.56 | 0 |
| SARI-Nan | RV | Ghana | Orange | Medium: 25–28 | 24.42 | 25.6 |
| CRI-Ligri | RV | Ghana | Cream | Very high: >35 | 16.41 | 0 |
| Ejumula | RV | Uganda | Orange | High: 29–35 | 12.54 | 34.6 |
| Kakamega | RV | Uganda | Orange | Medium: 25–28 | 16.84 | 33.32 |
| NASPOT 8 | RV | Uganda | Orange | Medium: 25–28 | 16.47 | 15.11 |
| NASPOT 10 (Kabode) | RV | Uganda | Orange | Low: <25 | 15.55 | 21.3 |
| NASPOT 12 | RV | Uganda | Orange | Medium: 25–28 | 8.79 | 29.39 |
| NASPOT 13 | RV | Uganda | Orange | Medium: 25–28 | 16.73 | 48.75 |

*Information taken from https://research.cip.cgiar.org/sweetpotato-catalog/cip_sp_catalogue/index.php and https://sweetpotatobase.org/. AT, advanced yield trial; RV, released variety; VT, variety trial.*

regions were selected: Gulu (northern Uganda), Soroti/Serere (eastern Uganda), and Wakiso district (central Uganda). Gulu and Soroti/Serere are rural whilst Wakiso is a peri-urban sweetpotato growing region. Consumption of sweetpotato is important in all selected areas in Uganda.

## Selected Sweetpotato Genotypes

We tested 27 sweetpotato genotypes: 21 genotypes (15 at the later breeding stages and 6 released varieties) in Ghana and 6 released and widely grown varieties in Uganda. The roots in Ghana were acquired from on-farm demonstration trials in the different regions whilst the roots in Uganda were acquired from local farmers in each region. In both countries, the roots were harvested at full maturity and utilized within 48 h post-harvest. Nutritional profiles of raw roots of all the genotypes from the different regions are shown in **Table 1**. The study was conducted in the last quarter of 2019.

## Experimental Design

A total of 1,433 participants contributed to the study (**Table 2**). In both Ghana and Uganda, the trials were split into a centralized and a home tasting trial.

**TABLE 2 |** Total number of participants in centralized and home tasting trials in Ghana and Uganda.

| Country | No. of participants *Centralized trial* | No. of participants *Home trial* | Total no. of participants |
|---|---|---|---|
| Ghana | 897 | 118 | 1,015 |
| Uganda | 144 | 274 | 418 |

The tricot approach was used (van Etten et al., 2019) to study consumer preferences. This trial was supported by the ClimMob digital platform (http://climmob.net/), which streamlines the process. The objective of the study was shared with community leaders who also coordinated and interpreted in the local languages to ensure every participant understood the aims of the study. Potential participants who consented to being part of the study and having evidence photographs taken, with possibility of being published for research purposes only, signed up to participate. Sets of three genotypes from the country-specific sets of genotypes listed in **Table 1** were allocated randomly to participants as incomplete blocks, maintaining balance by assigning roughly equal frequencies of each genotype, where possible. In Ghana, some varieties were slightly underrepresented as they were in short supply from the demonstration trials. They were however included for comparative purposes for their flesh colors and nutritional attributes. Genotypes in each incomplete block were labeled as *A*, *B*, and *C* and presented anonymously to prevent bias in the evaluation. Each participant evaluated their assigned set choosing the genotype which, according to their opinion, had the best and the worst characteristic for a given trait. The middle-ranking genotype is inferred from the answers on the best and worst, leading to a complete ranking of each set (incomplete block) of three varieties. In Uganda, three characteristics were evaluated; taste, color, and overall acceptability (OA); whereas in Ghana, only OA was assessed. The decision to exclude taste and color analyses from the Ghana data was based on a high percentage of missing and/or incomplete data. In both countries, participants were asked to provide the reason for evaluating a given genotype as best or worst. **Table 3** describes the frequency, disaggregated by gender and trial, for each genotype tested.

### Home Tasting Trials

In the *home tasting trials*, participating households were identified with the help of local field agents associated with sweetpotato research and development activities and/or community leaders in the respective study areas. In Ghana, samples were distributed to individual households through the help of field agents. In Uganda, participants gathered at common locations within the community for briefing, orientation on the study procedures and distribution of the coded samples to individual household representatives. The genotypes were provided to each household as raw, unpeeled roots. Participants were instructed to prepare the roots following their usual preparation method, keeping the three coded samples distinguishable from each other. Each household was also issued with questionnaires (see the format in the **Supplementary Appendix 1**). Each household representative was requested to have only adult members (≥18 years) within the household complete the questionnaires after tasting. Individuals younger than 18 years old were not included in this study for ethical reasons. In Ghana, the research teams visited all individual households to recover the questionnaires. In Uganda, the research teams visited a representative sample of the households to recover the completed questionnaires whilst the rest were collected at the centralized tasting venues. The differences in the implementation of the study in the two countries were based on pilot studies conducted in the target regions on identifying tailored solutions to collecting consumer preference data.

### Centralized Tasting Trials

The other approach taken was to test in central locations, the *centralized tasting trials*. In Ghana, locations close to fresh-produce markets were visited in the presence of community representatives and sweetpotato buyers were intercepted and requested to participate in the trial. In Uganda, community leaders and local field agents mobilized participants to gather at common locations, such as schools, for the tasting (**Figure 2**). The roots were utilized for the centralized tasting exercises within 48 h post-harvest in all regions. In all regions of Ghana, preparation of the samples included thoroughly washing the roots to remove soil particles and any sprouts and then boiling in plain water until optimally cooked. The same procedure was followed in Soroti/Serere and Gulu in Uganda, except the roots were covered with banana leaves during boiling. In Wakiso (Uganda), the roots were washed, peeled, wrapped in banana leaves, and steamed, as per the local practice. Each individual participant was served with three randomly selected and coded cooked varieties and handed a questionnaire to complete (see the format in the **Supplementary Appendix 2**). Drinking water was provided to rinse the mouth before tasting the next variety. Local community members were recruited as translators to assist those who could not read or write. All questionnaires were recovered at the tasting venues.

## Data Analysis

All analyses were done in R (R Core Team, 2020). Genotype preferences were assessed using the PlackettLuce package (Turner et al., 2020), an implementation of the Plackett-Luce model (Luce, 1959; Plackett, 1975) in R. The Plackett-Luce model estimates the "worth parameter," the probability that a genotype wins against all other genotypes in the set. The model follows the Luce's Choice Axiom, which states that the probability that one item beats another is independent from the presence or absence of any other items in the set (Luce, 1959). To consider explanatory variables, we created Plackett-Luce Trees (PLT) through model-based recursive partitioning (Zeileis et al., 2008). For model-based recursive partitioning with the PLT we used the variables district, age (integer number) and gender (man, woman). Rankings from home and centralized tasting trials were analyzed independently. The PLT models had a cut-off value of $\alpha = 0.1$ and a minimum group size of 10. The procedure to select splitting variables for the PLT are described by Turner et al. (2020). This procedure first fits a Plackett-Luce model to the full data, then assesses the stability of the worth parameters. If there is significant instability, the model splits the full data by the covariate showing the strongest instability. The process is repeated until there is no more significant instability.

## Supporting Software

Organizing the data relied on the R packages gosset (de Sousa et al., 2020), janitor (Firke, 2020), readxl (Wickham and Bryan, 2019), tidytext (Silge and Robinson, 2016) and tidyverse (Wickham et al., 2019). Statistical analyses were performed using the packages gtools (Warnes et al., 2020), gosset (de Sousa et al., 2020), multcompView (Graves et al., 2019), PlackettLuce (Turner et al., 2020), and qvcalc (Firth, 2020). Charts were produced using packages ggparty (Borkovec and Madin, 2019), ggplot2 (Wickham, 2016), and patchwork (Pedersen, 2020). All the data and R code used in this research are available through Zenodo (Moyo et al., 2020). Most methods are also available for automatic report generation in the ClimMob platform (https://climmob.net).

**TABLE 3 |** Frequency of genotypes assessed in this study.

| Genotype | Country | Freq. | Relative freq. (%) | Man ($n$ = 645) | Woman ($n$ = 788) | Centralized ($n$ = 1041) | Home ($n$ = 392) |
|---|---|---|---|---|---|---|---|
| CRI-Yiedie (CIP442162) | Ghana | 113 | 7.90 | 51 | 62 | 98 | 15 |
| CRI-Apomuden | Ghana | 237 | 16.50 | 108 | 129 | 208 | 29 |
| CRI-Ligri | Ghana | 239 | 16.70 | 112 | 127 | 210 | 29 |
| PG17136-N1 | Ghana | 116 | 8.10 | 51 | 65 | 101 | 15 |
| PG17140-N2 | Ghana | 113 | 7.90 | 59 | 54 | 98 | 15 |
| PG17206-N5 | Ghana | 117 | 8.20 | 48 | 69 | 101 | 16 |
| PG17265-N1 | Ghana | 117 | 8.20 | 54 | 63 | 103 | 14 |
| PG17305-N1 | Ghana | 118 | 8.20 | 56 | 62 | 104 | 14 |
| PG17362-N1 | Ghana | 115 | 8.00 | 55 | 60 | 101 | 14 |
| PG17412-N2 | Ghana | 120 | 8.40 | 49 | 71 | 104 | 16 |
| PGN14011-24 | Ghana | 116 | 8.10 | 58 | 58 | 105 | 11 |
| PGN16021-39 | Ghana | 120 | 8.40 | 56 | 64 | 105 | 15 |
| PGN16024-27 | Ghana | 120 | 8.40 | 51 | 69 | 105 | 15 |
| PGN16024-28 | Ghana | 117 | 8.20 | 47 | 70 | 105 | 12 |
| PGN16030-30 | Ghana | 118 | 8.20 | 58 | 60 | 105 | 13 |
| PGN16092-6 | Ghana | 117 | 8.20 | 51 | 66 | 105 | 12 |
| PGN16130-4 | Ghana | 113 | 7.90 | 53 | 60 | 105 | 8 |
| PGN16203-18 | Ghana | 114 | 8.00 | 54 | 60 | 105 | 9 |
| SARI-Diedi (Tu-Purple) | Ghana | 236 | 16.50 | 109 | 127 | 209 | 27 |
| SARI-Nan | Ghana | 234 | 16.30 | 105 | 129 | 206 | 28 |
| SARI-Nyumingre (Obare) | Ghana | 235 | 16.40 | 104 | 131 | 208 | 27 |
| Ejumula | Uganda | 217 | 15.10 | 97 | 120 | 63 | 154 |
| Kakamega | Uganda | 224 | 15.60 | 94 | 130 | 79 | 145 |
| NASPOT 10 (Kabode) | Uganda | 203 | 14.20 | 78 | 122 | 75 | 128 |
| NASPOT 12 | Uganda | 187 | 13.00 | 78 | 106 | 70 | 117 |
| NASPOT 13 | Uganda | 217 | 15.10 | 92 | 122 | 82 | 135 |
| NASPOT 8 | Uganda | 206 | 14.40 | 98 | 108 | 63 | 143 |

*In the tricot approach, genotypes are evaluated as incomplete blocks of three. The relative frequency shows the proportion (out of all participants) that a given genotype was evaluated. Freq., frequency of each genotype being evaluated by study participants.*


**FIGURE 2 | (A)** Community members in Gulu (northern Uganda) gathered for the tasting of boiled sweetpotato. **(B)** Members of the community who could not read or write were assisted by translators to complete the questionnaires (all pictures were taken with consent from participants for research purposes).

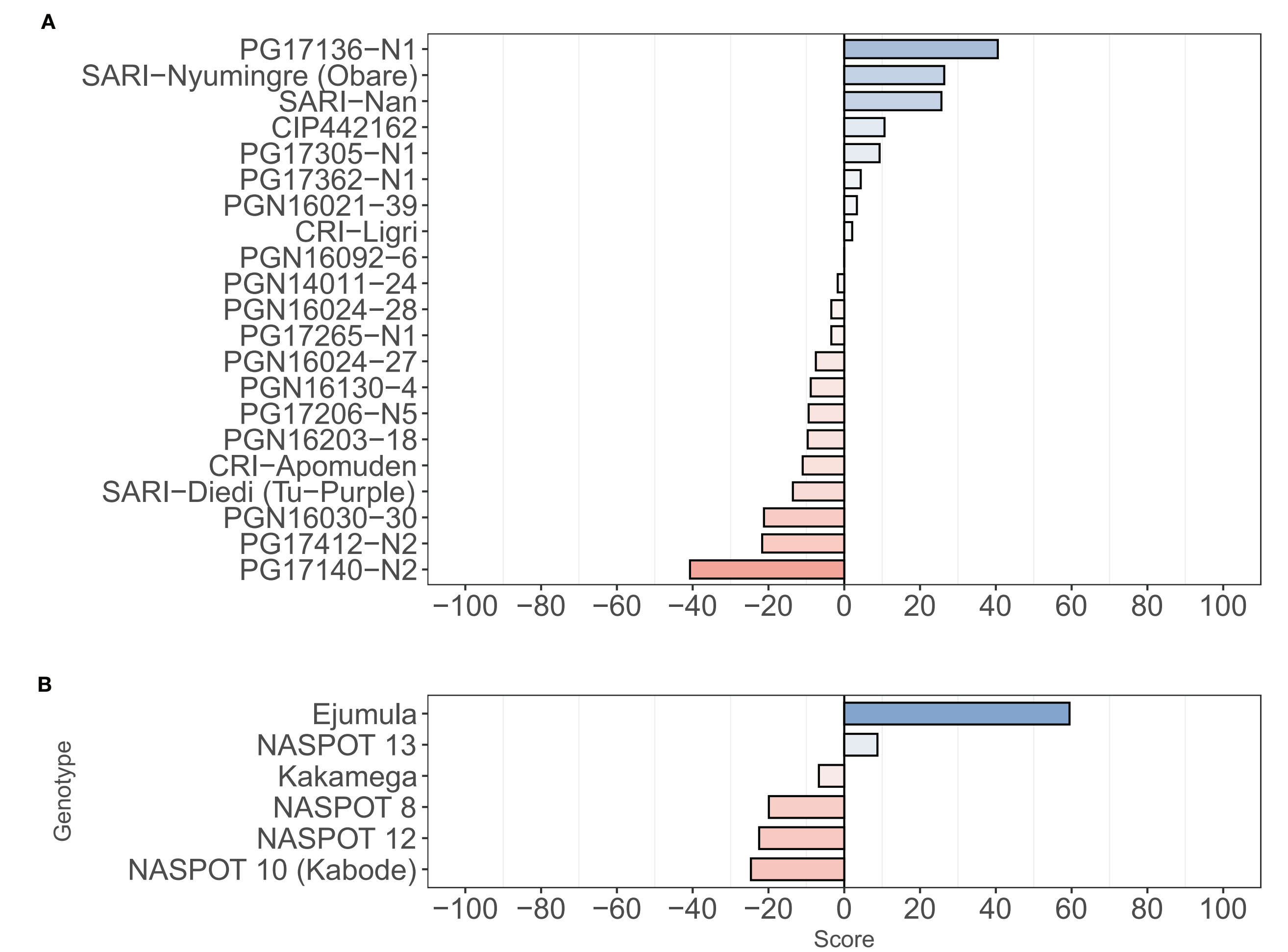


**FIGURE 3 |** Favourability score for the genotypes evaluated in **(A)** Ghana and **(B)** Uganda. Score is based on the relative number of times a given genotype is preferred over the others in pairwise contests in both home and centralized tasting trials.

# RESULTS

## Crowdsourced Citizen Science Supports the Identification of Promising Genotypes

In a first analysis, we aggregated the results from the 27 tested genotypes, and the group of 1,433 total participants from the two target countries from both home and centralized tasting trials (**Figure 3**). In Ghana, eight varieties showed a positive favourability score, which means they were more frequently ranked as better than the other varieties in the incomplete blocks. These included four released varieties SARI-Nyumingre (Obare), SARI-Nan, CRI-Yiedie (CIP442162) and CRI-Ligri; and four advanced clones PG17136 N1, PG17305-N1, PG17362-N1, and PGN16021-39 (**Figure 3A**). In Uganda, only Ejumula and NASPOT 13, displayed positive favourability scores (**Figure 3B**). Reference varieties were identified as NASPOT 8 for Uganda and SARI-Nyumingre (Obare) for Ghana, representing the most commonly planted and consumed varieties in the different communities.

We then disaggregated the rankings among trials (home and centralized) to assess whether the participants ranked the genotypes differently between trials. The relation between model estimates for home testing and centralized testing was assessed using a method proposed by Bland and Altman (1986). In Ghana, a marked difference is shown for the model estimates between the centralized tasting trial (**Figure 4A**) and the home tasting trial (**Figure 4B**). The genotype PG17136-N1 outperformed the reference [SARI-Nyumingre (Obare)] in both trials. However, while in the centralized trial only one genotype (SARI-Nan) had similar performance (same preference) compared to the reference, the home trial shows that other six genotypes performed equally compared to the reference. This weak relationship between estimates is shown in **Figure 4C**, where the genotypes PG17206-N5 and PGN16030-30 had different levels of performance among trials.

The results show a stronger relationship between the home trial and centralized trial for Uganda (**Figures 5A,B**). The genotype Ejumula outperformed all the others in both trials.

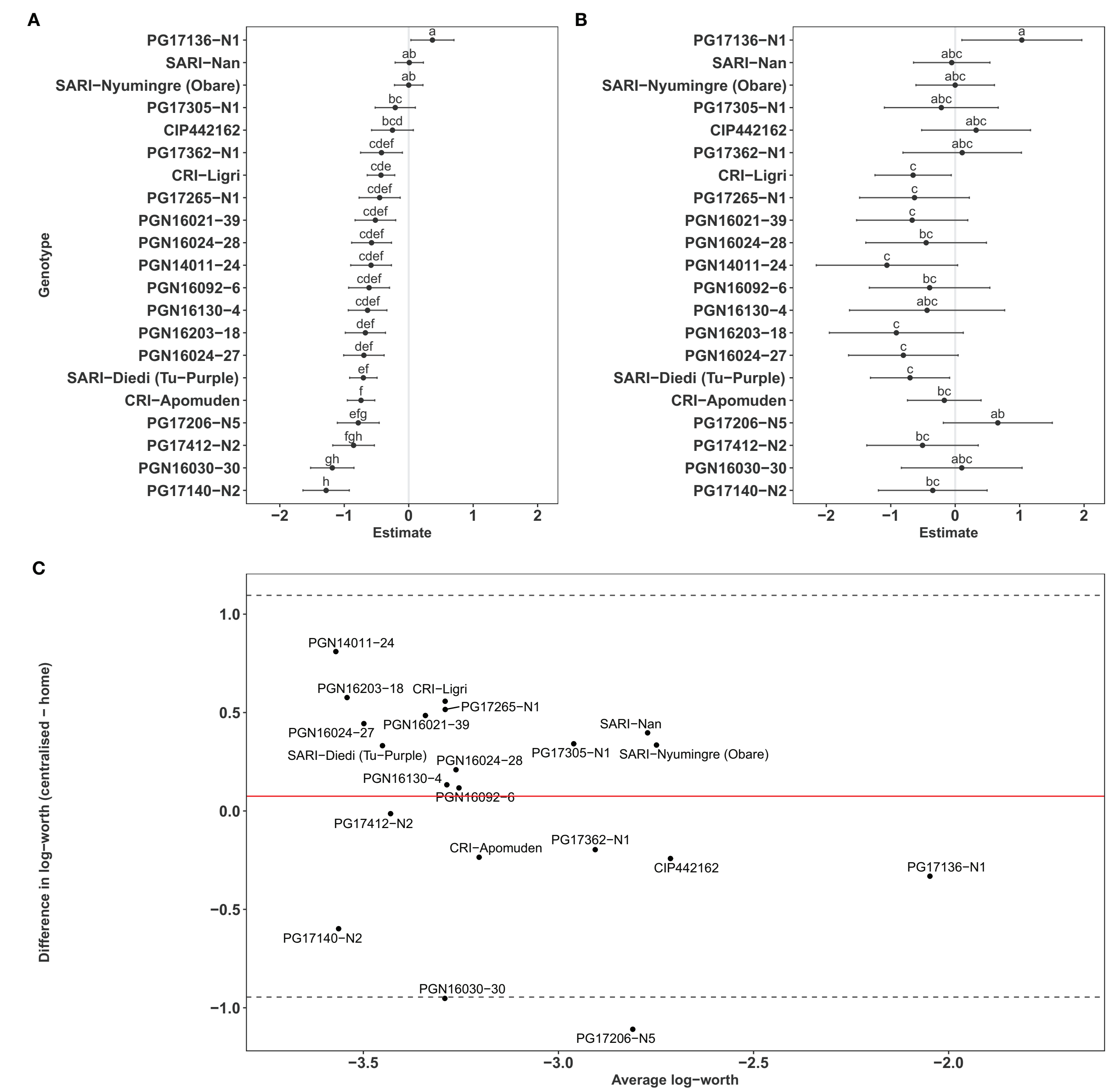


**FIGURE 4 |** Plackett-Luce Model estimates (log-worth parameters) from tested genotypes in Ghana. Different letters indicate significant differences at $p < 0.05$. **(A)** Log-worth parameters from centralized tasting. **(B)** Log-worth parameters from home tasting. **(C)** Differences between log-worth parameters in centralized and home tasting in Ghana. The genotype "SARI-Nyumingre (Obare)" is set as a reference (log-worth arbitrarily set to zero). In **(C)**, solid red line represents the mean of difference in log-worth (centralized–home), upper dashed lines represent the mean + 2SD (standard deviation), bottom dashed line represent the mean−2SD.

The second-preferred genotype was different for each trial. In the centralized trial, Kakamega, NASPOT 8 (the reference) and NASPOT 13 had statistically similar performance. In contrast, in the home trial, NASPOT 13 outperformed the reference for second rank. **Figure 5C** shows the difference in model estimates between the two trials as a comparison for their correlation.

Overall, the Plackett-Luce estimates for the ranked preferences show that in Ghana, PG17136-N1 (an advanced trial variety) outperformed the reference [SARI-Nyumingre (Obare)] and was the most preferred genotype among the participants (**Table 4**). The genotypes SARI-Nan and CRI-Yiedie (CIP442162) were ranked as second and showed no difference compared to

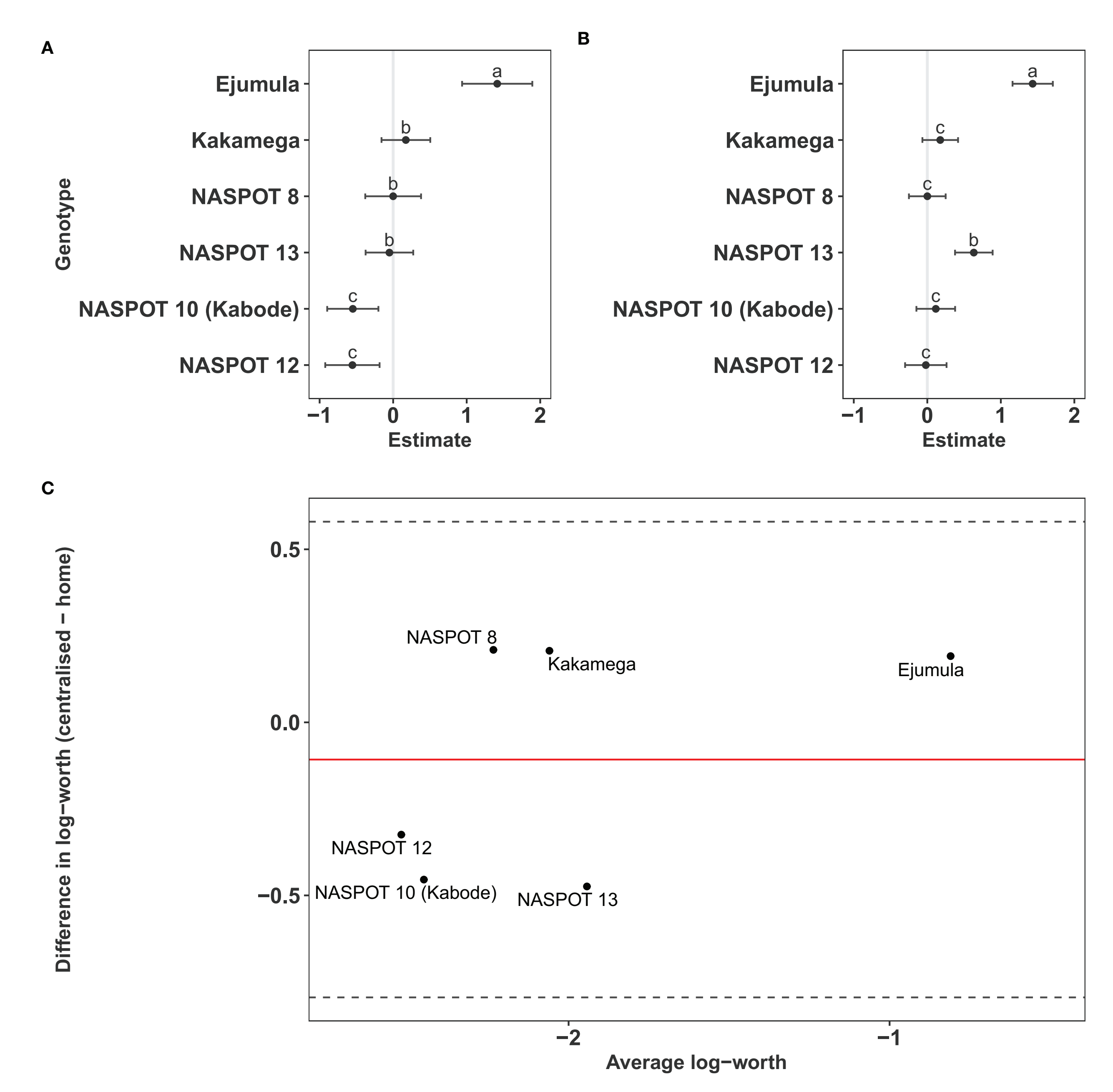


**FIGURE 5 |** Plackett-Luce Model estimates (log-worth parameters) from tested genotypes in Uganda. Different letters indicate significant differences at $p < 0.05$. **(A)** Log-worth parameters from centralized tasting. **(B)** Log-worth parameters from home tasting. **(C)** Difference between log-worth parameters in centralized and home tasting in Uganda. The genotype "NASPOT 8" is set as a reference (log-worth arbitrarily set to zero). In **(C)**, solid red line represents the mean of difference in log-worth (centralized–home), upper dashed lines represent the mean + 2SD (standard deviation), bottom dashed line represent the mean−2SD.

the reference. Least preference was estimated to the advanced varieties PG17412-N2, PGN16030-30, and PG17140-N2.

In Uganda, two genotypes outperformed the reference "NASPOT 8." The genotype Ejumula was the most preferred (**Table 5**). NASPOT 13 is the second preferred genotype, showing significant difference compared to the reference. NASPOT 10 (Kabode) and NASPOT 12 ranked as least preferred genotypes, but with no significant difference compared to the reference NASPOT 8.

## Characteristics That Drive Consumer Preference

In addition to overall acceptability (OA), "taste" and "color" attributes of boiled sweetpotato were also evaluated in Uganda. The Kendall correlation ($\tau$) between the overall acceptability and the other traits, shows that "taste" is the main driver for the participants final decision in ranking a given genotype as best or worst (**Table 6**). In 88% of the times that a given genotype was ranked as best for the trait "taste," the given genotype was

**TABLE 4** | Plackett-Luce Model estimates from genotypes tested in Ghana.

| Genotype | Estimate | Std. Error | *z*-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| PG17136-N1 | 0.4397 | 0.1873 | 2.3474 | 0.0189054* | a |
| SARI-Nyumingre (Obare) | 0 | – | – | – | b |
| SARI-Nan | −0.0212 | 0.1491 | −0.142 | 0.8871026 | b |
| CRI-Yiedie (CIP442162) | −0.1679 | 0.1841 | −0.9121 | 0.3617344 | bc |
| PG17305-N1 | −0.2062 | 0.1811 | −1.1389 | 0.2547537 | bcd |
| PG17362-N1 | −0.3625 | 0.1877 | −1.9315 | 0.0534197. | cde |
| CRI-Ligri | −0.4665 | 0.1465 | −3.1851 | 0.0014471** | cdef |
| PG17265-N1 | −0.4701 | 0.1837 | −2.5582 | 0.0105206* | cdefg |
| PGN16021-39 | −0.5497 | 0.1856 | −2.9623 | 0.0030535** | defg |
| PGN16024-28 | −0.5672 | 0.1817 | −3.1223 | 0.0017943** | efg |
| PG17206-N5 | −0.5966 | 0.1839 | −3.2442 | 0.0011777** | efg |
| PGN16092-6 | −0.6058 | 0.1855 | −3.2651 | 0.0010944** | efg |
| PGN16130-4 | −0.6203 | 0.1833 | −3.3839 | 0.0007146*** | efg |
| PGA14011-24 | −0.6321 | 0.1867 | −3.3863 | 0.0007084*** | efg |
| CRI-Apomuden | −0.6717 | 0.1468 | −4.5773 | 4.710e-06*** | fg |
| PGN16203-18 | −0.6905 | 0.1839 | −3.7551 | 0.0001733*** | efgh |
| PGN16024-27 | −0.7059 | 0.182 | −3.8782 | 0.0001052*** | efgh |
| SARI-Diedi (Tu-Purple) | −0.7078 | 0.1469 | −4.8167 | 1.459e-06*** | g |
| PG17412-N2 | −0.8128 | 0.1859 | −4.3722 | 1.230e-05*** | ghi |
| PGN16030-30 | −1.0499 | 0.1928 | −5.4447 | 5.188e-08*** | hi |
| PG17140-N2 | −1.1462 | 0.1975 | −5.8048 | 6.443e-09*** | i |

*Different letters indicate significant differences at $p < 0.05$. Genotypes are sorted from higher ranked (top) to least ranked (bottom).*
*Significance levels [difference from worth = 0, or SARI-Nyumingre (Obare)]: "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1.*

**TABLE 5** | Plackett-Luce Model estimates from genotypes tested in Uganda.

| Genotype | Estimate | Std. Error | *z*-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| Ejumula | 1.4348 | 0.1587 | 9.0416 | <2.2e-16*** | a |
| NASPOT 13 | 0.3951 | 0.1486 | 2.6586 | 0.007847** | b |
| Kakamega | 0.2005 | 0.1461 | 1.373 | 0.169752 | bc |
| NASPOT 8 | 0.0000 | – | – | – | cd |
| NASPOT 10 (Kabode) | −0.1074 | 0.1506 | −0.7128 | 0.475957 | d |
| NASPOT 12 | −0.1893 | 0.1539 | −1.2297 | 0.218818 | d |

*Different letters indicate significant differences at $p < 0.05$. Genotypes are sorted from higher ranked (top) to least ranked (bottom).*
*Significance levels (difference from worth = 0, or NASPOT 8): "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1.*

also ranked as best for OA. The same is found for the worst performance in 81% of the cases. We identified a negative Kendall correlation between OA and "color," showing that this was not a driver for the participants decision in ranking the genotypes in Uganda.

Participants were requested to use their own vocabulary/descriptors for the best and worst genotypes in both Ghana and Uganda and a summary of these reasons is provided in **Figure 6A**. Results from home and centralized tasting trials were combined for this analysis. Overall, the main driver for the best rankings was that a given variety had a good taste or a preferred level of sweetness. Worst rankings were given by a tasteless flavor, bad appearance, or an excessively sweet flavor. The most common sentiments associated with each tested genotype are shown in **Figures 6B,C**.

**TABLE 6** | Correlation between rankings provided for overall acceptability (OA), Color and Taste assessed in Uganda.

| Trait | Kendall ($\tau$) | Best | Worst |
|---|---|---|---|
| Color | −0.032 | 0.270 | 0.182 |
| Taste | 0.799 | 0.885 | 0.813 |

*Correlation is shown as Kendall rank correlation coefficient ($\tau$) and the proportion of agreement between the genotype ranked as best/worst for OA and also ranked as best/worst for Color and Taste.*

## Socio-Economic and Geographical Segmentation of Consumers

Recursive partitioning trees (Zeileis et al., 2008) were used to distinguish groups of participants with similar preferences using socio-economic and geographical covariates for the home and centralized trials separately. In Ghana, we found groups split by district in the centralized tasting and we found no split in the home tasting trial (**Figure 7**). In the centralized tasting the genotypes PG17136-N1, SARI-Nyumingre (Obare) and CIP442162 outperformed the others among participants in the districts of Bongo and Bole. The genotypes SARI-Nan and PG17136-N1 outperformed the other genotypes among the participants in the districts of Kasena-Nankana West. In the Home tasting trials the genotype PG17136-N1 outperformed all the other genotypes regardless of the district.

For Uganda, the results for both tasting approaches show two groups with different preference split by District (**Figure 8**). In the centralized tasting, the genotype Ejumula showed outstanding performance with a 60% probability in outperforming the other genotypes in all the districts. The difference in performance is shown for the second significantly different genotypes, in Gulu it is NASPOT 12 and NASPOT 8, whereas in Soroti/Serere and Wakiso it is Kakamega and NASPOT 13 (**Figure 8A**). For the home tasting, the genotype NASPOT 12 showed higher probability of winning against the other genotypes in the district of Gulu, while the genotype Ejumula was the preferred one in Soroti/Serere and Wakiso.

We then assessed the averaged probability of winning across the Plackett-Luce nodes shown for Ghana (**Figure 7**) and Uganda (**Figure 8**, **Table 7**). This measure produced similar recommendations for both Ghana and Uganda, recommending PG17136-N1 and Ejumula as the best choices respectively.

## Insights From Implementing Home and Centralized Tasting Approaches

Home tasting was a more independent style of evaluation whilst centralized tasting involved control over sample preparation. Key aspects of implementing the two approaches in Ghana and Uganda are documented in **Table 8**.

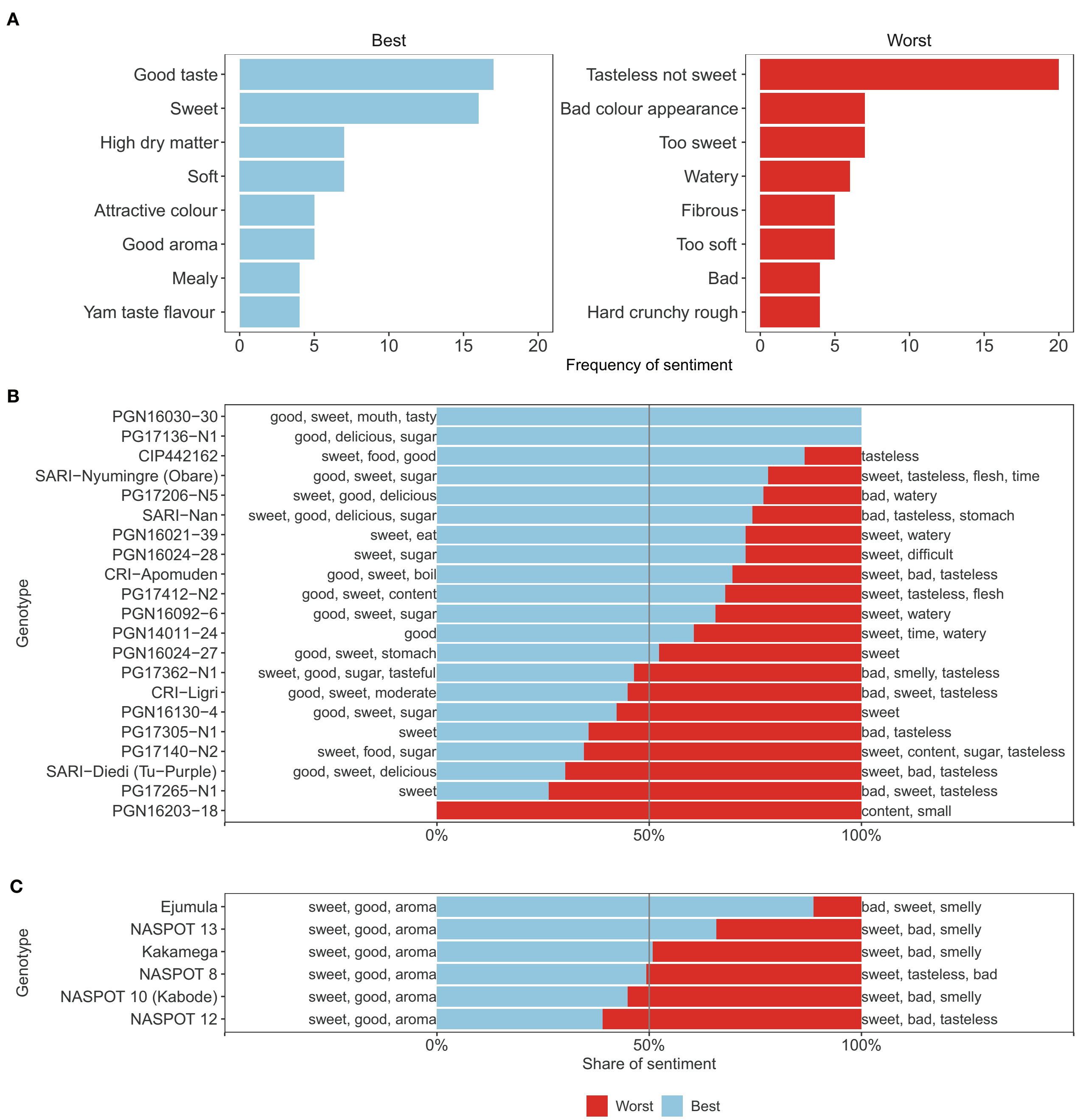


**FIGURE 6 |** Sentiment analysis for the drivers of consumer preference for boiled sweetpotato genotypes. **(A)** Overview of the drivers of best and worst appreciation of boiled sweetpotato genotypes in Ghana and Uganda. **(B)** Share of sentiment for the evaluation of a given genotype as best or worst in Ghana. **(C)** Share of sentiment for the evaluation of a given genotype as best or worst in Uganda. Sentiments on the left side are the most common words associated with a given genotype for best preference. Sentiments in the right are the most common words associated with a given genotype for worst preference.

# DISCUSSION

## Overall Preferences

In Ghana, PG17136-N1, a white fleshed, high dry matter clone at the advanced trial stage of the breeding pipeline, had the highest favourability score from a selection of 21 genotypes, and ranked highest in both home and centralized tasting approaches (**Figure 3A**, **Table 4**). PG17136-N1 was not significantly different statistically from SARI-Nyumingre (Obare), the currently most popular variety in the area, if centralized and home tasting are considered separately. However, if the data from home and centralized tasting are pooled, the difference is statistically

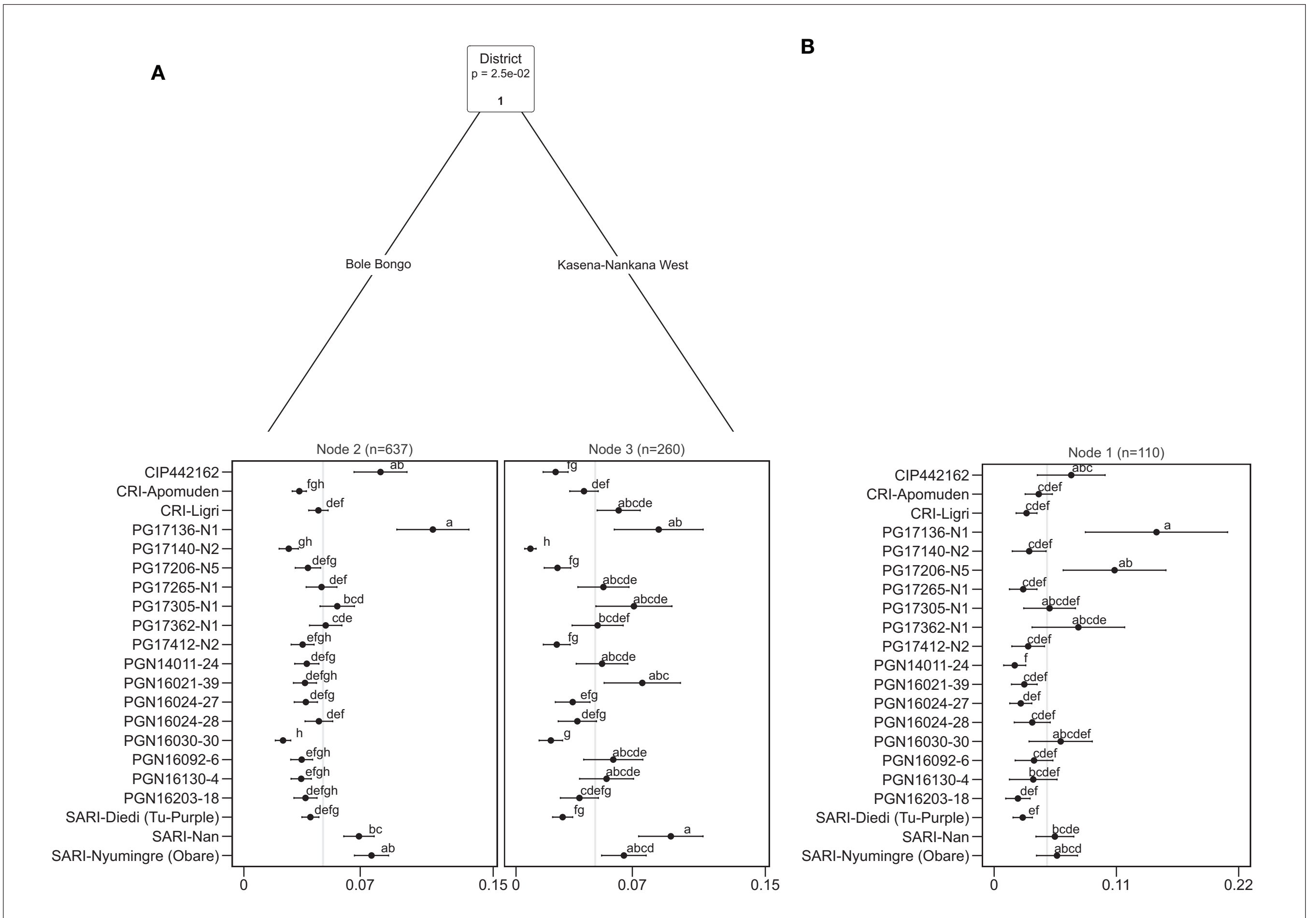


**FIGURE 7 |** Plackett-Luce Tree of crowdsourcing citizen-science evaluation on sweetpotato genotypes in **(A)** centralized tasting and **(B)** home tasting in Ghana. The horizontal axis of each panel represents the probability of winning for the genotypes. Error bars show quasi-SEs. The gray vertical line indicates the average probability of winning (1/number of genotypes). In this case, the model selected the district as the splitting covariate. Different letters indicate significant differences at $p < 0.1$.

significant ($p < 0.05$; **Table 4**). Based on these findings, we consider that the identification of PG17136-N1 as a material that is superior to SARI-Nyumingre (Obare) is robust for the study area.

Consumers in Uganda identified Ejumula, an orange fleshed, high dry matter clone as their most preferred variety, with the highest favourability score amongst the six that were evaluated in both home and centralized tasting approaches (**Figure 3B**, **Table 5**). Ejumula is a local landrace with low field resistance to sweetpotato virus disease (SPVD) and Alternaria blight. Our results support previous reports that the maintenance of this variety by farmers, in spite of its disease susceptibility, is likely due to its superior consumption characteristics (Mwanga et al., 2007). Notably, Ejumula is a donor parent to NASPOT 13 in the breeding pipeline, which was also highly acceptable by consumers. Both Ejumula and NASPOT 13 are ranked superior to NASPOT 8, which is the most commonly cultivated variety within the target communities.

In both Ghana and Uganda, the study has identified a variety that consistently outperforms the local check variety and has the highest score regardless of the method of tasting (home or centralized). While the top varieties were consistent, there were differences in the order of rankings for the remainder of the varieties when comparing the two approaches (**Figures 4**, **5**). More inconsistencies in rank order are expected among lower ranking items, as negative aspects may overwhelm their ability to tease out subtle differences. However, most inconsistencies are within the bounds of the confidence of the parameter estimates. The home tasting results in Ghana display low statistical significance, probably due to the low number of participants ($n = 118$) given the number of varieties that were tested ($n = 21$) (**Table 2**, **Figure 4**). Statistically, this small sample size increased variation and hampered the discrimination power of the trial (Granato et al., 2014). In anticipation of such variation, future studies should aim at increasing consumer population size, particularly for home tasting, than would be required for controlled or lab-based analyses.

Differences are not only random and due to sample sizes, however, as there were important methodological differences between the centralized and home trials. Centralized tasting was

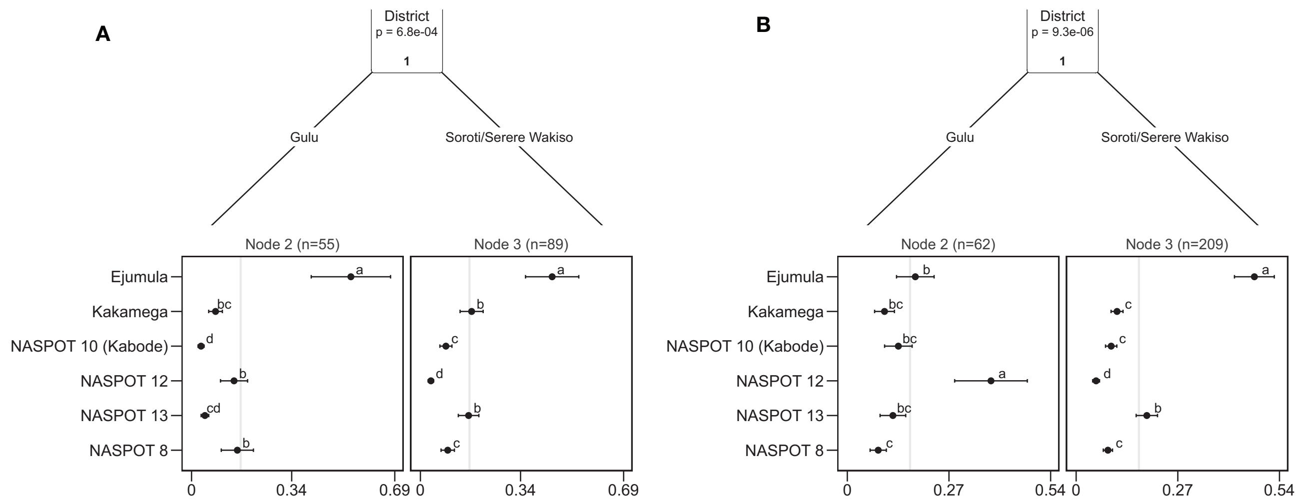


**FIGURE 8 |** Plackett-Luce Tree of crowdsourcing citizen-science evaluation on sweetpotato genotypes in **(A)** Centralized tasting and **(B)** Home tasting in Uganda. The horizontal axis of each panel represents the probability of winning for the genotypes. Error bars show quasi-SEs. The gray vertical line indicates the average probability of winning (1/number of genotypes). In this case, the model selected the district as the splitting covariate. Different letters indicate significant differences at $p < 0.1$.

conducted with experimental control over sample preparation, particularly cooking time and amount of water added to boil the roots. In addition, tasting conditions such as serving temperature and environment were consistent for all the varieties in each location. On the other hand, participants were instructed to follow their usual preparation method for home tasting, with no instruction on conditions under which samples should be evaluated. The possible differences in cooking times and serving temperatures between the two approaches could have affected the sensory attributes of the samples and in turn their perception and appreciation by the consumers. In future studies, it should be attempted to characterize the preparation practices, actual use, and adoption context of the varieties at household level and include these aspects in the statistical analysis.

Another possible explanation for the recorded differences between rank order from home and centralized tasting is a mismatch between the consumer population samples between the two approaches. People with different gender, socio-economic, and age profiles are likely to have been selected in centralized and home tasting trials. We expect that home tasting provides a less biased sample, as selection is more inclusive. However, in future studies, it would be recommended to record these aspects and include them in the statistical analysis as much as possible.

## Factors That Influence Overall Preferences

Apart from overall acceptability, also color and taste attributes were evaluated in Uganda (**Table 6**), but not in Ghana. In Uganda, color was not identified as a driver for the consumers' decision in ranking the varieties. These results could have been influenced by the range of hues in the set of varieties tested. On the other hand, consumers identified taste as the main driver for the rankings with "good taste" and "sweet" being the most common descriptors used for the best ranking variety whilst, "not sweet" and "tasteless" were amongst the most common descriptors for the worst ranking varieties (**Figure 6**). Our results are in line with those reported by Mwanga et al. (2020) for Lira and Kamwenge districts in Uganda, where consumers preferred sweet tasting sweetpotato genotypes. Sweetness is a sensory attribute commonly perceived when consuming foods rich in sugars. Kakamega, NASPOT 10 (Kabode) and NASPOT 13 were described as "too sweet" by some participants and the average sugar content in raw roots is 16.84, 15.55, and 16.73%, respectively (**Table 1**). None of the participants described NASPOT 8 as "too sweet" even though the raw roots display sugar content higher than that of NASPOT 10 (Kabode) at 16.47%. Raw roots contain sucrose, glucose, and fructose whilst the boiling process results in starch being hydrolysed to maltose, a major contributor to the "sweet" taste in cooked sweet potato. Thus, the nutritional profiles of the raw roots do not give a clear picture of the profiles of the boiled samples, especially since sugars are known to leach out during boiling (Lyimo et al., 2010; Guillén et al., 2017). Nutrient retention databases (USDA., 2007) are a useful resource but tend to lack variety specific data on some nutritional components. Generating data on variety specific nutrient retention studies would be important to understand consumer preferences to cooked sweetpotato.

Geographic location was identified as a distinguishing factor for consumer preferences to boiled sweetpotato in both Ghana and Uganda (**Figures 7, 8**). These results highlight the complexity of consumer preferences toward any given product and the need to understand the underlying socio-economic variables of target populations (Rakotosamimanana and De Kock, 2020). Variety promotion may target different varieties in different areas, although in this case, probably the same single variety could be promoted across all study areas if only one variety had to be selected.

**TABLE 7 |** Expected probability of winning (average of all nodes in the Plackett-Luce Tree) across the nodes in the Plackett-Luce Trees for Ghana and Uganda.

| Country | Genotype | Probability of winning |
|---|---|---|
| Ghana | PG17136-N1 | 0.113 |
| | PG17362-N1 | 0.062 |
| | SARI-Nan | 0.072 |
| | PG17206-N5 | 0.038 |
| | CRI-Yiedie (CIP442162) | 0.064 |
| | PG17140-N2 | 0.023 |
| | CRI-Apomuden | 0.036 |
| | PGN16021-39 | 0.045 |
| | PG17265-N1 | 0.044 |
| | PGN16203-18 | 0.033 |
| | PG17305-N1 | 0.058 |
| | PG17412-N2 | 0.032 |
| | SARI-Diedi (Tu-Purple) | 0.035 |
| | PGN16024-28 | 0.042 |
| | PGN16092-6 | 0.040 |
| | CRI-Ligri | 0.046 |
| | PGN16024-27 | 0.034 |
| | PGN16030-30 | 0.024 |
| | PGN16130-4 | 0.039 |
| | PGA14011-24 | 0.040 |
| Uganda | Ejumula | 0.439 |
| | NASPOT 13 | 0.154 |
| | Kakamega | 0.121 |
| | NASPOT 10 (Kabode) | 0.089 |
| | NASPOT 8 | 0.097 |
| | NASPOT 12 | 0.110 |

## Study Execution Aspects

This research enabled us to document and compare key aspects of the two approaches (home and centralized tasting) employed for evaluating consumer preferences to boiled sweetpotato to highlight the dynamics to be considered when conducting similar studies in future (**Table 8**). From both countries, it was evident that centralized tasting gave the researchers more control over sample preparation, tasting environment, and reduced the number of rejected questionnaires since they could supervise every step of the process.

In Ghana, consumers participated in centralized tasting during the course of the day since they were intercepted next to busy sweetpotato markets. This strategy ensured that participants were limited to those who bought sweetpotato for their families and are therefore, likely sweetpotato consumers themselves. Since market sites were centralized, consumers from different villages had more or less equal opportunities to participate making the data generated more comprehensive. One drawback to this approach includes the difficulty to obtain the undivided attention of the consumers who had not anticipated to spend much time at the market. Their lack of attention to details on the questionnaires could have compromised the quality of their responses. In Uganda, venues were pre-arranged, and participants were mobilized to meet at specific times. This increased the likelihood that the researchers had the undivided attention of the consumers during the course of the activity. It also meant, however, that only consumers who were not engaged elsewhere at that particular time could participate and this could have potentially eliminated a valuable segment of consumers. Future studies could conduct centralized tastings over several days and provide options to participate during different time slots to accommodate the schedules of different consumers.

The home tasting trials presented different experiences and challenges in both countries. In Ghana, samples, and questionnaires were distributed to individual households and recovered similarly. This approach ensured that each household had the undivided attention of the research team during the visits and could easily seek clarification on the completion of the questionnaires. The scattered distribution of households in some districts however made it logistically impossible for some consumers to be included in the study, potentially causing a sampling bias. In Uganda, representatives of households congregated at centralized locations for sample collection and briefing on completion of the questionnaires. Whilst this approach saved time for the research team, it potentially excluded households which were engaged in other activities at the pre-arranged time of the meeting day. Future studies should aim at assigning more time and resources to this approach to enable more consumer households to be visited for sample distribution and recovery of completed questionnaires.

# CONCLUSIONS

This study applied the tricot method to consumer evaluation of boiled sweetpotato in Ghana and Uganda. The most preferred genotypes were consistent across different implementations of the tricot approach (centralized vs. home tasting) and user segments. Based on these results, PG17136-N1 is the most preferred genotype in Ghana amongst the communities that participated in this study whilst Ejumula is the most preferred in Uganda. Taste was identified as the main driver for the consumers' ranking of the genotypes with geographic location also playing an important role. Overall, these results prove that tricot is a robust tool which could effectively be adapted to consumer preference studies. Using tricot for both on-farm trials and consumer preference studies provides an opportunity for a single, methodologically consistent approach to inform release decisions for varieties that meet both farmer and consumer expectations. Tricot can therefore contribute to coordinated efforts of breeders and food scientists to deliver varieties that are likely to meet demand along different nodes of the sweetpotato value chain.

Future studies should consider the choice to conduct either home or centralized tasting approaches or a combination of both, each option having strengths and weaknesses. Also, sample sizes and recruitment strategies should be carefully considered. Collecting more contextual data about the food preparation methods and context and socio-economic characteristics of the participants and their households could feed into a more refined

**TABLE 8 |** Comparison between home and centralized tasting as approaches for consumer preference studies using the tricot method.

| Attribute | Home tasting | Centralized tasting |
|---|---|---|
| Duration of study | Home tasting trials required at least 2 days, one for distribution of samples and another day for collection of completed questionnaires. In some cases, multiple visits on different days to homes were necessary to distribute and retrieve all questionnaires | With prior planning in terms of acquiring samples and coding, centralized tasting trials could be conducted in a single day for each area, thus saving time for the researchers |
| Total number of participants | Uganda: High numbers of participants were reached because participants converged at a common place for briefing and sample collection, and even those who missed traveling to the common place still tasted in the evening or the next morning when the families gathered together for meals<br>Ghana: Low numbers of participants were reached especially in sparsely populated communities which made distribution and/or collection of completed questionnaires a challenge | Uganda: A lower number of participants was reached through centralized tasting as most families, especially those from distant locations, sent only one adult representative to participate at the central locations<br>Ghana: A higher number of participants were reached by targeting busy market days and intercepting sweetpotato buyers to participate in the study |
| Age specification for participants | Some participants misunderstood the instructions and allowed household members <18 years of age to fill questionnaires, rendering the questionnaires invalid to the study | Researchers could ensure that only adults above 18 years of age participated with the help of local community members |
| Sample preparation | Each family prepared the roots as per their usual method, giving a good representation of how the genotypes would be perceived at household level. Possibility of overcooking or undercooking samples is high as participants could have cooked samples based on cooking times from local varieties. | Controlled sample preparation, ensuring optimal cooking times is achieved. In this way, overcooking or undercooking was controlled for to ensure that it did not influence the ratings |
| Tasting environment/ venues | Home tasting enabled the participants to consume the samples in a relaxed environment. They could also choose which part of the day to consume the samples as per their family habits | Uganda: The environments were controlled; tastings were conducted in the afternoons at pre-arranged venues.<br>Ghana: There was less control over the environment than in Uganda as participants were sweetpotato buyers who visited the market at different times of the day |
| Quality of responses on questionnaires | In situations where some questions were misunderstood, incomplete and incorrectly completed questionnaires posed a challenge during data curation | Generally, good quality responses were acquired since the researchers were close by to explain each question to the participants as they filled the questionnaire. Lower number of incomplete of incorrectly filled questionnaires. In areas where there were language barriers, translators were recruited to assist |

analysis and a possible correction of participant selection biases. The burden to the participant should be kept to a minimum, however. Also, researchers should resist the temptation to use experimental control to reduce variation and increase statistical power. The strength of the tricot citizen science approach is its potential to bring testing closer to the use context, making it representative of likely future use of the tested materials.

## DATA AVAILABILITY STATEMENT

The data and R code used in this research are available through Zenodo, https://doi.org/10.5281/zenodo.4117591 (Moyo et al., 2020).

## ETHICS STATEMENT

Oral consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

## AUTHOR CONTRIBUTIONS

TM, EC, HL-K, MM, RS, JE, and KS designed the concept of the research study and the research tools. MM, RS, SN, MN, ED, DA, and JA-D conducted the field work. TM and EC supervised the overall research activities. KS and JE analyzed the data. MM, RS, KS, and JE wrote the manuscript. All authors reviewed all versions of the manuscript and contributed by suggesting novel additional analyses and interpretations.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2021.620363/full#supplementary-material

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frontiers in Marine Science

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# Divers as Citizen Scientists: Response Time, Accuracy and Precision of Water Temperature Measurement Using Dive Computers

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There is a lack of depth-resolved temperature data, especially in coastal areas, which are often commonly dived by SCUBA divers. Many case studies have demonstrated that citizen science can provide high quality data, although users require more confidence in the accuracy of these data. This study examined the response time, accuracy and precision of water temperature measurement in 28 dive computers plus three underwater cameras, from 12 models. A total of 239 temperature response times ($\tau$) were collected from 29 devices over 11 chamber dives. Mean $\tau$ by device ranged from (17 $\pm$ 6) to (341 $\pm$ 69) s, with significant between-model differences found for $\tau$ across all models. Clear differences were found in $\tau$ by pressure sensor location and material, but not by size. Two models had comparable $\tau$ to designed-for-purpose aquatic temperature loggers. 337 mean data points were collected from equilibrated temperatures in hyperbaric chamber ($n$ = 185) and sea ($n$ = 152) dives, compared with baseline mean temperature from Castaway CTDs over the same time period. Mean bias, defined as mean device temperature minus baseline temperature, by model ranged from (0.0 $\pm$ 0.5) to ($-$1.4 $\pm$ 2.1) °C and by device from (0.0 $\pm$ 0.6) to ($-$3.4 $\pm$ 1.0) °C. Nine of the twelve models were found to have "good" accuracy ($\leq$0.5 °C) overall. Irrespective of model, the overall mean bias of ($-$0.2 $\pm$ 1.1) °C is comparable with existing commonly used coastal temperature data sets, and within global ocean observing system accuracy requirements for *in situ* temperature. Our research shows that the quality of temperature data in dive computers could be improved, but, with collection of appropriate metadata to allow assessment of data quality, some models of dive computers have a role in future oceanographic monitoring.

**Keywords: citizen science, dive computer, sea temperature, accuracy, response time, precision**

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## INTRODUCTION

The oceans have a critical role in climate change, acting as a heat sink and being responsible for the uptake of more than 90% of the excess heat in our climate system between 1971 and 2010 (Pörtner et al., 2019; Johnson and Lyman, 2020). Warming ocean temperatures are intrinsically linked to sea level rise and projections show the rise accelerating because of non-linear thermal expansion

(Widlansky et al., 2020). In addition, the number and severity of occurrences of extreme events linked to increased sea temperatures, such as heat waves, are expected to increase with global warming (Bindoff et al., 2019). Global sea surface temperature (SST) is projected to rise by up to 6.4 °C depending on the emission scenario (Aral and Guan, 2016); accordingly, both sea surface and subsurface temperatures are defined as essential climate variables (Bojinski and Richter, 2010; Lindstrom et al., 2012). However, there is regional variability (Kennedy, 2014); for example, SST around the British Isles has been increasing at a rate of up to six times the global average rate (Dye et al., 2013) and at twice the global rate in offshore China since 2011 (Tang et al., 2020). In contrast, parts of the North Atlantic have experienced cooling (Wright et al., 2016). Shifts in biodiversity have been seen in response to variations in temperature between 0.1 and 0.4 °C (Danovaro et al., 2020), with shallow seasonal thermoclines being important to ecosystem dynamics, horizontal and vertical distribution of fish (Aspillaga et al., 2017) and biological production (Palacios et al., 2004). Variation and oscillations in thermocline depth and temperature have been recorded during the stratification period (Bensoussan et al., 2010; Aspillaga et al., 2017).

*In situ* data are essential to monitor these local variations, supplement satellite sea surface temperature data and validate ocean models (Brewin et al., 2017), but there are a lack of depth-resolved temperature data (Wright et al., 2016) and few time series on localised variations in thermoclines (Bensoussan et al., 2010). This lack in data is especially true in areas near to the coast which research vessels and Argo floats cannot commonly reach (Wright et al., 2016). Citizen science has been shown to provide opportunities for collecting data at broad spatial and temporal scales, which would not be possible by traditional means because of accessibility and financial constraints (Pocock et al., 2014; Wright et al., 2016). Many case studies have shown that citizen science can provide high quality data (Kosmala et al., 2016) with comparable accuracy to dedicated research studies (Vianna et al., 2014; Albus et al., 2019; Krabbenhoft and Kashian, 2020), but with uncertainty regarding the reliability and quality of data (Burgess et al., 2016; Gibson et al., 2019). To address these concerns, and to increase the value of existing datasets, users require more confidence in the accuracy of these data (Burgess et al., 2016; Kosmala et al., 2016). *In situ* measurements should have associated uncertainty estimates (Barker et al., 2015). *Post hoc* data quality assessment and error detection have been found to dispel doubts about data quality (Burgess et al., 2016).

SCUBA divers (from here on referred to as divers) have been involved in many marine citizen science projects (Thiel et al., 2014; Hermoso et al., 2019) including marine protected area monitoring (Pocock et al., 2014), reef habitat/biodiversity surveys (Branchini et al., 2015; Hermoso et al., 2019) and marine debris collection (Pasternak et al., 2019). Some areas most frequently accessed by citizen scientist divers are the shallow coastal subtidal areas (e.g., to depths < 40 m; Thiel et al., 2014) where reliable physico-chemical data series are sparse. Within the estimated 6–10 million recreational divers globally (Wright et al., 2016) the use of dive computers may be approaching 100% (Azzopardi and Sayer, 2010). Dive computers are worn with the primary purpose of managing decompression limits via algorithms which calculate the level of nitrogen load in tissues. Most modern dive computers record profiles of temperature and depth, with the latter derived from a dedicated pressure sensor. Temperature data are required to correct for non-linear pressure sensor output as ambient temperature changes (Li et al., 2016), but as temperature does not have the same impact on decompression algorithms as pressure, the same level of accuracy is not required. Consequently, temperature data are obtained from thermal corrections applied to the pressure sensor (Azzopardi and Sayer, 2010; Wright et al., 2016), rather than from a dedicated temperature sensor. Temperature readings are not calibrated, and only have an advertised accuracy (where published by manufacturers) of ± 2 °C (Mares, 2020; Azzopardi and Sayer, 2012), or ± 2 °C within 20 min of temperature change (Suunto, 2018). Previous research has explored the possibility of collecting temperature data from dive computers. Wright et al. (2016) concluded that, with processing, temperature data from dive computers could be a useful resource. Other authors recommend that these data be avoided for scientific study (Azzopardi and Sayer, 2012), or state that dive computers do not have sufficient accuracy to measure ocean temperature changes (Egi et al., 2018).

This study builds on the work carried out by Wright et al. (2016) and investigates a range of dive computers in replicated experiments which aim to mimic real-world scenarios, to quantify the temperature responses of different models; aiming to address some of the concerns regarding the potential use of these data. We focus on three objective measures; the time constant $\tau$, accuracy and precision. Time constants are used to measure a sensor's response to change; representing the time taken for 63% of the total step change in temperature to have taken place. $\tau$ is useful in the context of oceanographic temperature change (such as thermocline identification), and, in conjunction with the sample rate, the potential to gather useful data from relatively short dive profiles. Temperature accuracy is defined as the systematic error in the devices' temperature measurement when compared with a reference temperature, such as from a calibrated microCTD. By focusing on these measures, this paper investigates the potential of different devices as alternative sources of *in situ* temperature for oceanographic monitoring. The response to temperature change within and between models and as a function of the dive computer's body material, size, pressure sensor location and attachment to the diver (i.e., worn on the wrist or hanging freely) are analysed to ascertain whether some models or features may offer potential for higher quality data than others.

## MATERIALS AND METHODS

### Equipment

28 dive computers (11 models from 7 brands), along with three Paralenz Dive Camera+ cameras (for the purposes of this study referred to collectively as "dive computers"; see **Table 1**) were analysed. All devices shared the ability to record full profiles of temperature and depth as a function of time, except Suunto

Vypers, which only store a single minimum temperature per dive. All devices were able to sample at intervals of 30 s or less and were set to the highest frequency possible for each model for all dives.

Recorded temperature resolution ranged from 0.1 to 1 °C. The devices were categorised into four "sizes": "Small" (diameter < 5 cm), "Medium" (5 cm < diameter < 7.5 cm), "Large" (diameter > 7.5 cm), and "Camera" and further classified by pressure sensor location based on the identifying small holes in the housing material into "Back" or "Edge" with Paralenzes being defined as "Covered" (**Table 1**). Material was a composite category based on front, edge and back material being metal (m) or plastic (p).

All hyperbaric tests were carried out in a cylindrical two-compartment, 2,000 mm diameter Divex therapeutic recompression chamber, manually controlled to compress to the simulated nominal depths, as described by Sayer et al. (2014). For all baseline temperature measurements with the exception of water bath trials, three SonTek CastAway CTDs (CTD = Conductivity, Temperature, Depth) with 0.01 °C resolution, ± 0.05 °C accuracy, sampling rate of 5 Hz (SonTek CastAway CTD, 2020) were used. For unpressurised temperature comparison a Grant R4 refrigerated bath with TXF200 heating circulator was used.

## Time Constants (τ)

Inside the hyperbaric chamber, all devices and Castaways were immersed to (8.5 ± 2.5) cm in a tub containing 13 litres of cold (10 ± 1) °C fresh water and allowed to acclimatise for 10 min, as high ambient air temperature has been demonstrated to affect temperature profiles for several minutes into a dive. Three further tubs were filled with well-mixed warm water between 18 and 25 °C. Although fitted with an environmental control unit it was not possible to regulate chamber air temperature precisely; varying between 18 and 27 °C over the course of a single dive of 1 h duration, caused by the heating effect of compression and subsequent cooling across the non-insulated chamber walls. To minimise the impact of the changing chamber temperature on tub temperature, warm tubs starting temperatures approximated the mid-point of potential chamber ascent temperatures (as measured with a stick digital thermometer).

Some models allow manual switching between salt and freshwater mode (densities unspecified by manufacturers), but to allow comparison between dive computers which did not have this capability, all dive computers were left in default salt-water mode for all dives with the exception of the *Shearwater Perdix* which was set to "EN13319" mode (1,020 kg $m^{-3}$ water density) (Shearwater, 2020). All devices were allowed to automatically start recording temperature profiles according to their default pressure parameters, except for Paralenz Dive Camera+, which were started manually.

After acclimatisation, all tubs were compressed to a maximum simulated depth of between 9 and 10.4 m. Once the simulated depth was reached, one Castaway was moved from the cold bucket to each of the warm tubs and stirred well, followed by a further 2 min of acclimatisation. One Paralenz Dive Camera+ was then moved into each warm tub and stirred well. Early trials established that all devices reached temperature equilibrium before 7 min. Therefore, after 7 min all Paralenz Dive Camera+ were removed and switched off to conserve battery life. Subsequently, a dive computer was moved into each of the warm tubs, stirred well, then left for 7 min, repeated until all the devices had been transferred. This interval approach was designed to minimise any effect of cold-water ingress by the transfer of devices between tubs, without impacting the temperature response of previously added devices. Two dives were carried out with the same depth/tub protocol using only the three Paralenz Dive Camera+ devices, and nine replicates with all devices (Schema in **Supplementary Figure 1**).

Dive profiles were downloaded from individual devices into the open-source divelog software, Subsurface (Subsurface, 2020). Profiles were then combined in an XML-based format and exported into R Studio for processing. For each dive by device, data were aligned to the start point of the response curve and sliced at the first instance of the maximum temperature, isolating the full temperature response (**Figure 1**). In contrast to the findings of Egi et al. (2018), not all models' temperature response had a single exponential form, and linear regression did not consistently produce a good fit. Time constants were ascertained by exponential fitting via numerical integration as defined by Jacquelin (2009), using the area under the curve to calculate $\tau$, allowing linear regression to be applied to non-linear data without estimation of parameters (Jacquelin, 2009).

## Accuracy

Three protocols were followed to assess the temperature accuracy and consistency of the dive computers.

### Water Bath

Dive computers only start to record profiles once they reach a prescribed pressure, but for safety reasons, it is not possible to put a temperature-controlled water bath in a pressurised chamber environment. Therefore, trials were conducted in an unpressurised environment and the temperatures were visually recorded from the computer displays. Water temperature was controlled using a Grant R4 refrigerated bath filled with deionised water, with the circulation set to maximum and temperature equilibrated to (20.0 ± 0.1) °C. Between 9 and 11 devices could be submerged in the water bath at once, so the experiments were run in a series of batches. An initial batch was submerged in the bath for 15 min (three times the maximum mean model time constant, by which time all devices have equilibrated to final temperature). Temperature was then read from the digital display of each device whilst still submerged, and the device removed from the bath. Once all device temperatures had been read the subsequent batch was submerged for 15 min and the process repeated. The process was then repeated at bath temperatures of 10 and 30 °C. For analysis, the deviation of on-screen temperature display from the water bath temperature was noted. On-screen temperature resolution for all devices is limited to 1 °C, with the exception of the Ratio iX3M GPS Deep which display temperature on-screen at a resolution of 0.1 °C.

**TABLE 1 |** Outlines the models used and their categorisations within this study.

| Model | *n* (devices) | Resolution/°C | Pressure sensor | Size | Material (front-edge-back) | Sampling interval $\Delta T$/°C |
|---|---|---|---|---|---|---|
| Aqualung i750TC | 3 | $5/9 \approx 0.56$ | Back | Medium | ppp | 30 |
| Garmin Descent Mk1 | 3 | 1 | Edge | Small | mpp | 1 |
| Mares Matrix | 2 | 0.1 | Edge | Small | mmp | 5 |
| Mares Puck Pro | 2 | 0.1 | Back | Medium | ppp | 5 |
| Paralenz Dive Camera+ | 3 | 0.1 | Covered | Camera | mmm | 1 |
| Ratio iX3M GPS Deep | 3 | 0.1 | Back | Large | ppp | 10 |
| Scubapro G2 | 3 | 0.4 | Back | Medium | ppp | 4 |
| Shearwater Perdix | 3 | 1 | Back | Large | ppp | 10 |
| Suunto D4i | 1 | 1 | Edge | Small | mmp | 20 |
| Suunto D6i | 3 | 1 | Edge | Small | mmm | 10 (20 for first 3 dives) |
| Suunto EON Steel | 3 | 0.1 | Edge | Large | mpp | 10 |
| Suunto Vyper | 1 | 1 | Back | Medium | ppp | NA |

*In the material column, m denotes metal and p, plastic. E.g., ppp denotes plastic for the front, edge and back of the housing, respectively.*

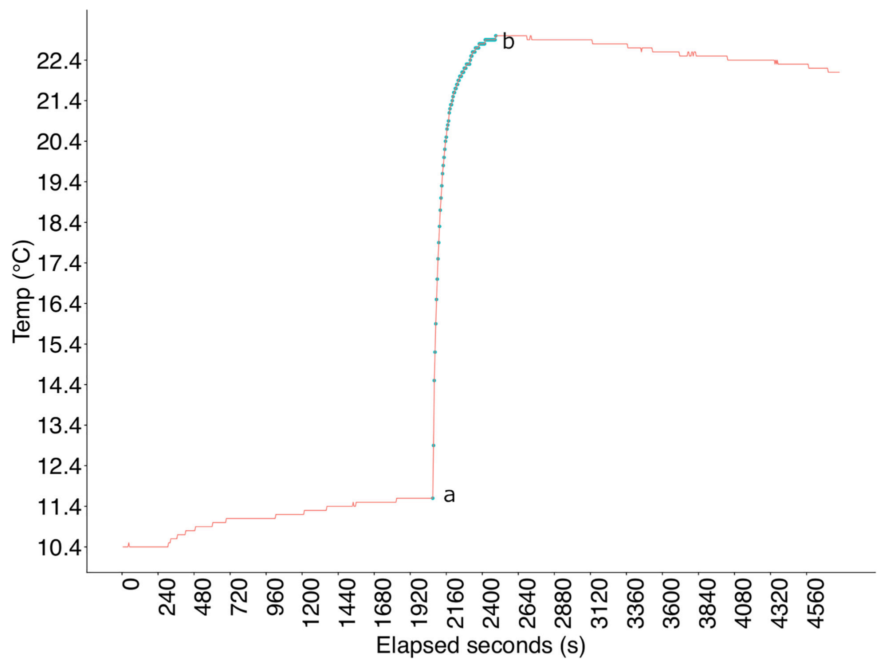


**FIGURE 1 |** Example of response curve for one dive/device. Elapsed seconds is the entire dive profile during which all devices were moved between cold and warm tub at 7 min intervals.

## Chamber

Six replicate dives were carried out in the outer lock of the Divex chamber, with a maximum simulated depth of $(10 \pm 1)$ m. Three dives included a temperature change from a cold to warm environment and three a warm to cold transition, using one tub for the starting temperature and three for the contrast temperature. All devices acclimatised in a single tub for 10 min, unpressurised, to the same starting temperature (cold or warm, depending on dive). Devices were then shared across the three tubs with contrasting temperature; one Castaway CTD in each tub to provide a baseline. All tubs were compressed to the simulated depth for 10 min, then decompressed and removed (Schema in **Supplementary Figure 2**). Over the six dives, cold tub final temperature ranged from 10.4 to 12.6 °C and warm tub final temperature ranged from 16.8 to 19.5 °C.

Raw data output from the Castaways was used, retaining the full temperature profile as a function of pressure and time. Castaway depth was calculated from pressure using the swDepth function in R (swDepth, 2020), which uses Fofonoff and Millard's refitted equation (Fofonoff and Millard, 1983). Device profiles were aligned by depth and time with the relevant Castaway from the same tub. Mean device temperature from the final 180 s at > 2.5 m depth was calculated (to compensate for differences in depth at which devices start recording) by which time all devices had

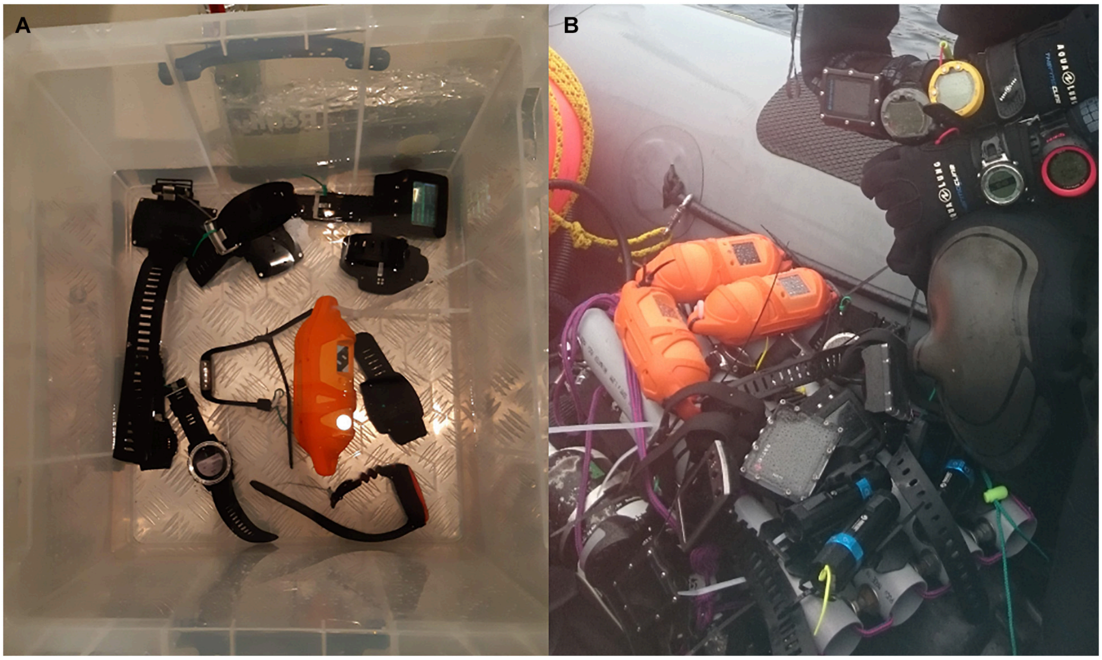


**FIGURE 2 | (A)** Devices in tub with Castaway in chamber dive. **(B)** Diver wearing computers on arms, with frame shown in RHIB.

equilibrated to the change in temperature (**Supplementary Figure 3**). The mean from the equivalent 180 s Castaway data were used as baseline temperature for comparison. Mean bias was defined as mean device temperature minus mean Castaway temperature.

### Sea Dives

Six sea dives were carried out by RHIB at dive sites local to Oban (56.41535° N, 5.47184° W), with maximum depths ranging from 13.5 to 30.7 m (mean: 18.6 m). For each pair of dives, half the dive computers were carried hanging loosely on a frame made from plastic piping, and half were worn on the arms of two divers (**Figure 2**). For subsequent dives in each dive pair, each device was switched to the other mounting position. All Paralenz Dive Camera+ were transported on the frame for all dives (as they were not wrist mountable), along with all Castaways for baseline temperature.

Raw Castaway data was imported, depth calculated as per section "Chamber." The sea dives had a shallow cold surface thermocline from snow melt run-off. The mean temperature below the depth at which the Castaway temperatures equilibrated (top of the bottom mixed layer) was used as a baseline temperature for comparison for each dive (**Supplementary Figure 4**). In dive number order this depth was 5, 10, 10, 10, 10, and 12 m. As the frame was carried by divers, and therefore may not have been consistently horizontal, small variations were seen in Castaway depths. Device dive profiles were imported into R Studio and mean temperatures calculated for each device, Castaway and model for the final 180 s below the specified depth (**Supplementary Figure 5**). Mean bias was defined as mean device/model temperature minus mean Castaway temperature.

## RESULTS

As per Wright et al. (2016), devices and models were categorised as accurate if the mean bias from baseline temperature was $\leq$0.5 °C and as precise if the standard deviation of the mean bias was $\leq$0.5 °C. Devices were defined as having quick, intermediate or slow response to temperature change (respectively $\tau < 60$ s, 60 s $\leq \tau < 120$ s, $\tau \geq 120$ s).

### Time Constants

A total of 239 $\tau$ values were collected from 26 devices over 9 dives plus three Paralenz Dive Camera+ cameras over 6 dives. 13 $\tau$ values were lost because of battery failures or camera recording not initiating correctly. All Ratio iX3M GPS Deep dives and two Shearwater Perdix dives were removed from the analyses because of a poor regression fit (**Figure 3**).

Mean $\tau$ by model ranged from (18 $\pm$ 5) s to (304 $\pm$ 45) s (**Figure 4** and **Supplementary Table 2**). Uncertainties represent 1 $\sigma$ unless otherwise described. Time constants and residuals were not normally distributed; time constants were best fitted to an inverse Gaussian distribution curve. A generalised linear model (GLM) approach was used in R Studio to look for significant differences. Significant between-model differences were found for $\tau$ for all models ($p < 0.001$) [Mares Puck Pro ($p < 0.01$)]. Mean $\tau$ by device ranged from (17 $\pm$ 6) to (341 $\pm$ 69) s (**Figure 5**). S($\tau$ fit) represents 95% confidence intervals in the regression fit, based on the standard error of the regression (full data in **Supplementary Table 3**). S($\tau$ fit) < 10 s was considered to be a good fit and applied to all profiles except for those mentioned in the first paragraph of this section.

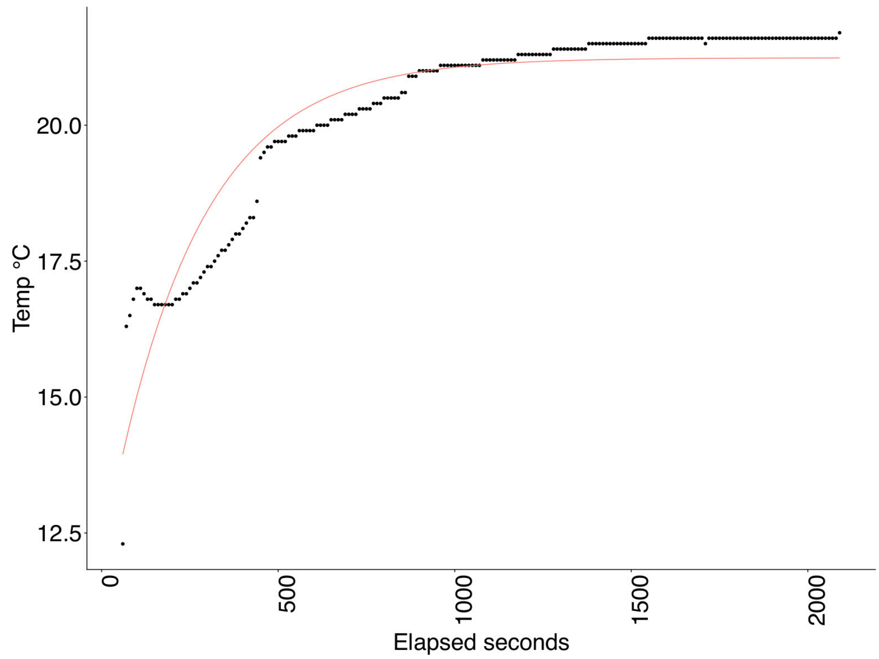


**FIGURE 3 |** Example of a poor regression fit in Ratio iX3M GPS Deep; devices excluded from further analysis.

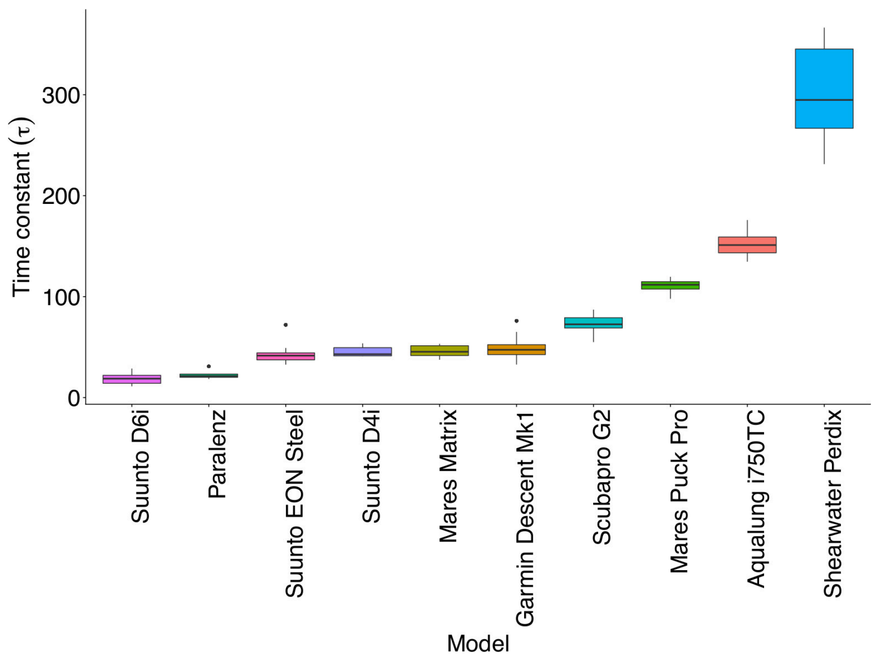


**FIGURE 4 |** Mean response time (τ) by model. The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * inter-quartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers.

Clear differences were found in $\tau$ by pressure sensor location and material, but not by size (**Figure 6**). All devices with the pressure sensor at the edge along with the Paralenz Dive Camera+ were defined as having a quick response (17 s $\leq \tau <$ 52 s) and all with a pressure sensor at the back were classified as intermediate or slow responders. Devices with entirely metal housing had quick mean response (17 s $\leq \tau <$ 24 s), part metal/part plastic were

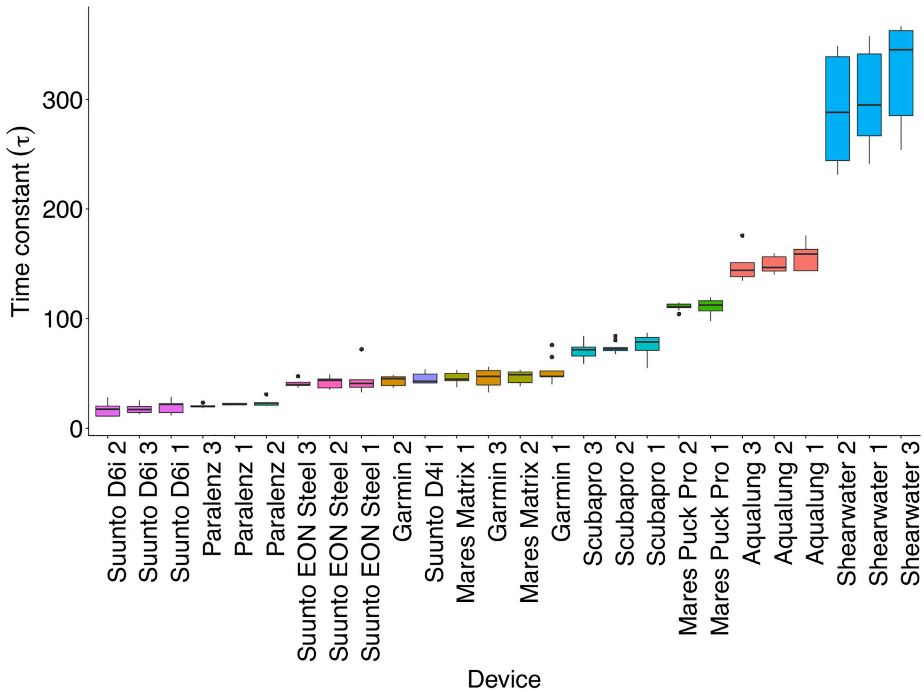


**FIGURE 5 |** Mean response time (τ) by device. The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * inter-quartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers.

intermediate (41 s $\leq \tau < 52$ s) and all plastic were slowest (70 s $\leq \tau < 322$ s).

## Temperature Accuracy

### Water Bath Trials

A total of 78 data points were collected from 29 devices over three conditions (bath temperatures). One Suunto D6i data point was missed because of a dead battery. Paralenz Dive Camera+ were not included in the water bath deployments due to not having an on-screen temperature display. Mean bias is defined as displayed device temperature minus water bath temperature, averaged on a model or device basis. By model, this ranged from 0 to ($-1 \pm 1.7$) °C. The mean bias by device ranged from 0 to ($-2.3 \pm 1.5$) °C (**Supplementary Tables 4, 5**).

### Chamber

The chamber dives investigating accuracy comprised $n$(devices) = 31 and $n$(dives) = 185. Mean bias by model ranged from ($0.1 \pm 0.3$) to ($-1.4 \pm 2.0$) °C and by device ranged from ($0.1 \pm 0.1$) to ($-3.3 \pm 1.4$) °C. Full data on accuracy dives across conditions are shown by model (**Table 2**) and device (**Table 3**).

### Sea Dives

A total of 152 mean bias values were collected from 31 devices over five sea dives. Three values are missing due to failure to recover data from Paralenz Dive Camera+. Mean bias by model, without taking into account experimental condition, ranged from ($0.0 \pm 0.1$) to ($-1.3 \pm 2.2$) °C and by device ranged from ($0 \pm 0.1$) to ($-3.5 \pm 0.1$) °C (**Tables 2, 3**).

#### *"On Frame" vs. "On Arm"*

Wearing a computer "on arm" led to a non-negative mean bias across all models ($0.0 \pm 1.6$) °C (**Table 4**) and devices ($0.0 \pm 2$) °C (**Supplementary Table 6**) when compared to being carried on the frame (**Figure 7**). Brand, housing material, shape or response group were not found to be significant for bias in "on arm"/"on frame" data.

### Overall Accuracy

As depth resolved-temperature data are required for scientific interest and collecting temperature data from dive computers in an unpressurised environment would not be recommended, only data from sea and chamber accuracy dives were combined for overall accuracy results. Across the total $n$ = 337 data points from the two accuracy protocols, overall mean bias was ($-0.2 \pm 1.1$) °C. Mean bias by model ranged from ($0.0 \pm 0.5$) to ($-1.4 \pm 2.1$) °C (**Figure 8** and **Table 5**) and by device ranged from ($0.0 \pm 0.6$) to ($-3.4 \pm 1.0$) °C (**Supplementary Table 7**).

## DISCUSSION

Despite the inherent limitations of the existing technology, our research shows that, while there is wide between-model variation in both temperature bias and $\tau$, there is value in data derived from devices commonly carried by SCUBA divers as a source

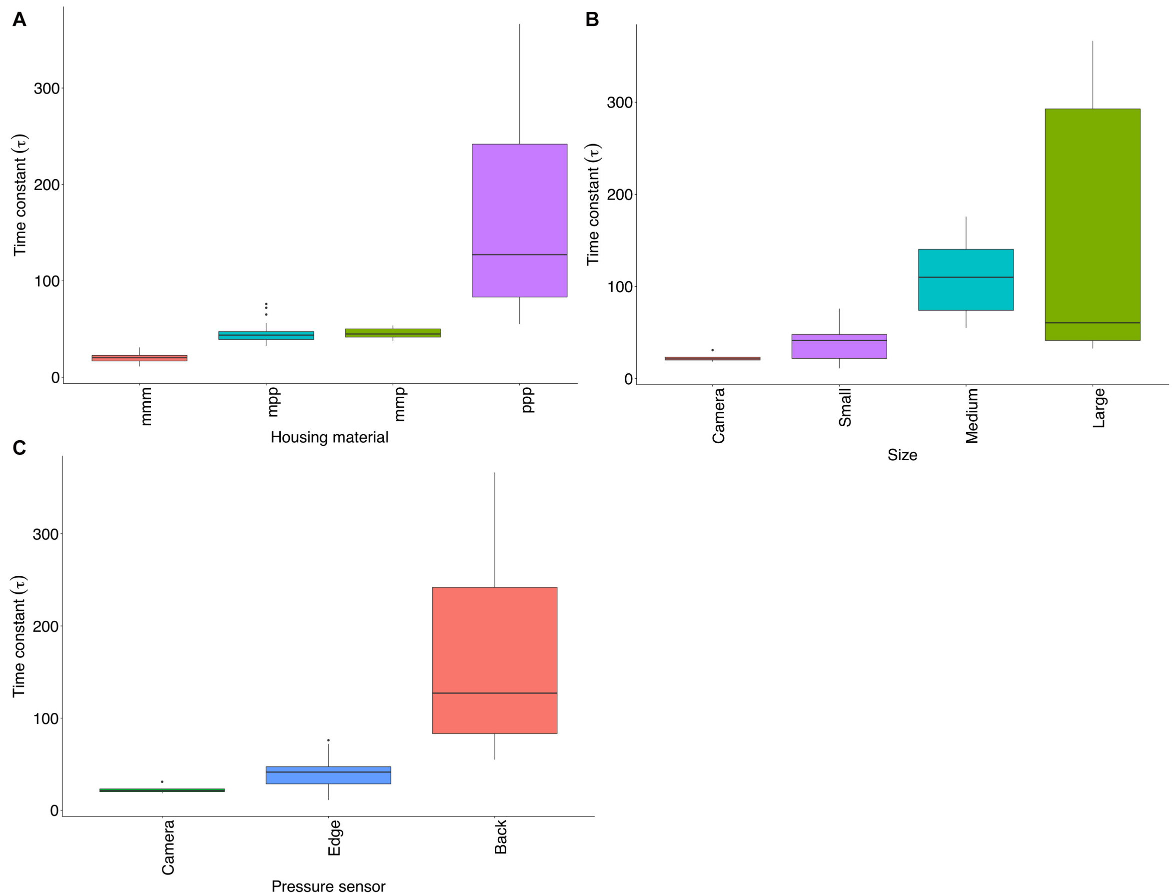


**FIGURE 6 | (A)** τ by material; m = metal, p = plastic. For example; mmm devices comprise metal front rim, edge and back. **(B)** τ by size **(C)** τ by pressure sensor location. The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * inter-quartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers.

of subsurface temperature data in coastal areas. We demonstrate that there is sufficient consistency in bias within some models to offer the potential for bias correction by model. In addition, an overall bias of (−0.2 ± 1.1) °C demonstrates that, with sufficient datapoints, valuable data may be produced irrespective of the models from which data were derived. Due to variation in $\tau$, while not all models would be recommended for use in scenarios of temperature change, some models also demonstrate a $\tau$ which, in conjunction with a sufficiently high resolution, offer the potential for identification of thermoclines.

**TABLE 2 |** Bias by model across the two accuracy conditions.

| Model | Sea dives | | Chamber | |
|---|---|---|---|---|
| | *n*(dives) | bias Δ*T*/°C | *n*(dives) | bias Δ*T*/°C |
| Aqualung i750TC | 15 | −1.3 ± 2.2 | 18 | −1.4 ± 2.0 |
| Garmin Descent Mk1 | 15 | −0.3 ± 0.7 | 18 | 0.1 ± 0.9 |
| Mares Matrix | 10 | 0.1 ± 0.1 | 12 | −0.1 ± 0.7 |
| Mares Puck Pro | 10 | 0 ± 0.1 | 12 | −0.2 ± 0.7 |
| Paralenz Dive Camera+ | 12 | 0.7 ± 0.1 | 17 | 0.7 ± 0.6 |
| Ratio iX3M GPS Deep | 15 | 0.9 ± 0.7 | 18 | 0.1 ± 0.3 |
| Scubapro G2 | 15 | 0 ± 0.6 | 18 | −0.4 ± 0.9 |
| Shearwater Perdix | 15 | −0.3 ± 0.4 | 18 | −0.9 ± 0.6 |
| Suunto D4i | 5 | −0.5 ± 0.2 | 6 | −0.4 ± 0.8 |
| Suunto D6i | 15 | −0.3 ± 0.4 | 18 | −0.2 ± 1.0 |
| Suunto EON Steel | 15 | −0.6 ± 0.1 | 18 | −0.4 ± 0.7 |
| Suunto Vyper | 10 | −0.3 ± 0.4 | 12 | −0.2 ± 2.9 |

## Response Time

$\tau$ varied widely between models, with less within-model variance than between. We saw less within-device variation in $\tau$ than Egi et al. (2018), although a similar mean $\tau$ (46 s compared with 52 s) was seen for the only model used in both papers (Mares Matrix). Within-model consistency is promising for the purposes of citizen science, as it offers projects the potential to select specific models based on the project objectives or run *post hoc* corrections.

Six models were defined as quick responders ($\tau$ < 60 s) (**Supplementary Table 8**). Of these, the two models with the shortest $\tau$ [Suunto D6i (18 ± 5) s and Paralenz Dive Camera+ (22 ± 3) s] have $\tau$ comparable designed-for-purpose aquatic temperature loggers; the plastic Star-Oddi Starmon mini has an 18 s standard $\tau$. Although more commonly used in moored scenarios, Starmon minis have been used to measure lake temperature profiles, with corrections applied (Jóhannesson et al., 2007).

Exponential fits proved consistent across models, exceptions causing poor fit were errant temperature data points recorded in the temperature profile (Suunto EON Steel) or a sharp rise in temperature followed by a levelling or drop before a further rise (Ratio iX3M GPS Deep). In the case of the Ratios, the response seen could be because of intermittent heating caused by internal electronic functions of the model, or, as a slow responding but higher resolution model, the devices may have been affected by cold water ingress introduced by adding additional devices.

When dive computer model was excluded as a parameter from the generalised linear model, pressure sensor location and housing material were also found to significantly influence $\tau$. As the two features are correlated (e.g., all devices with a pressure sensor at the back are entirely housed in plastic, **Table 1**), it is not possible to fully separate the effect of the two variables. Also, while pressure sensor location is identifiable (**Supplementary Table 1**), it is not known whether the temperature sensor is co-located with the pressure sensor in any given model. However, it is logical to postulate that in a small device, or where a sensor is close to the edge of the device housing, a more rapid response to temperature change will be seen than that of a sensor buried deep within a larger housing, where the thermal mass of the dive computer itself may slow the response.

## Temperature Accuracy

All models performed well within the $\pm$ 2 °C advertised accuracy (Mares, 2020; Azzopardi and Sayer, 2012; Suunto, 2018) overall, with only one model having a mean absolute bias $\geq$1 °C (Aqualung i750TC), and only two (Aqualung i750TC, Suunto Vyper) having poor precision. The overall mean bias seen [($-0.2 \pm 1.1$) °C] is comparable with existing commonly used coastal temperature data sets, such as those using handheld digital thermometers for subsurface temperature measurement; Cefas coastal temperature datasets include data from thermometers and

**TABLE 3 |** Bias by device across the two accuracy conditions.

| Model | Device ID | Sea dives | | Chamber | |
|---|---|---|---|---|---|
| | | *n*(dives) | Bias Δ*T*/°C | *n*(dives) | Bias Δ*T*/°C |
| Aqualung i750TC | Aqualung 1 | 5 | −3.5 ± 0.1 | 6 | −3.3 ± 1.4 |
| Aqualung i750TC | Aqualung 2 | 5 | −1.9 ± 0.0 | 6 | −1.9 ± 0.8 |
| Aqualung i750TC | Aqualung 3 | 5 | 1.5 ± 0.4 | 6 | 0.9 ± 0.9 |
| Garmin Descent Mk1 | Garmin 1 | 5 | −0.3 ± 0.4 | 6 | 0.2 ± 0.7 |
| Garmin Descent Mk1 | Garmin 2 | 5 | −0.9 ± 0.3 | 6 | −0.5 ± 0.9 |
| Garmin Descent Mk1 | Garmin 3 | 5 | 0.2 ± 0.7 | 6 | 0.5 ± 0.9 |
| Mares Matrix | Mares Matrix 1 | 5 | 0.1 ± 0.1 | 6 | −0.1 ± 0.6 |
| Mares Matrix | Mares Matrix 2 | 5 | 0.1 ± 0.1 | 6 | −0.1 ± 0.8 |
| Mares Puck Pro | Mares Puck Pro 1 | 5 | 0.1 ± 0.1 | 6 | −0.2 ± 0.8 |
| Mares Puck Pro | Mares Puck Pro 2 | 5 | 0 ± 0.1 | 6 | −0.2 ± 0.8 |
| Paralenz Dive Camera+ | Paralenz 1 | 4 | 0.5 ± 0.0 | 6 | 0.6 ± 0.7 |
| Paralenz Dive Camera+ | Paralenz 2 | 4 | 0.8 ± 0.1 | 6 | 0.9 ± 0.7 |
| Paralenz Dive Camera+ | Paralenz 3 | 4 | 0.8 ± 0.1 | 5 | 0.8 ± 0.5 |
| Ratio iX3M GPS Deep | Ratio 1 | 5 | 1.2 ± 0.7 | 6 | 0.4 ± 0.2 |
| Ratio iX3M GPS Deep | Ratio 2 | 5 | 0.5 ± 0.6 | 6 | −0.3 ± 0.3 |
| Ratio iX3M GPS Deep | Ratio 3 | 5 | 0.8 ± 0.8 | 6 | 0.1 ± 0.1 |
| Scubapro G2 | Scubapro 1 | 5 | 0.2 ± 1.0 | 6 | −0.5 ± 0.9 |
| Scubapro G2 | Scubapro 2 | 5 | −0.1 ± 0.1 | 6 | −0.4 ± 1.1 |
| Scubapro G2 | Scubapro 3 | 5 | −0.1 ± 0.3 | 6 | −0.4 ± 1 |
| Shearwater Perdix | Shearwater 1 | 5 | −0.2 ± 0.5 | 6 | −1 ± 0.5 |
| Shearwater Perdix | Shearwater 2 | 5 | −0.4 ± 0.4 | 6 | −0.8 ± 0.8 |
| Shearwater Perdix | Shearwater 3 | 5 | −0.3 ± 0.5 | 6 | −1 ± 0.5 |
| Suunto D4i | Suunto D4i 1 | 5 | −0.5 ± 0.2 | 6 | −0.4 ± 0.9 |
| Suunto D6i | Suunto D6i 1 | 5 | −0.3 ± 0.4 | 6 | −0.1 ± 1.2 |
| Suunto D6i | Suunto D6i 2 | 5 | −0.3 ± 0.4 | 6 | −0.3 ± 1 |
| Suunto D6i | Suunto D6i 3 | 5 | −0.3 ± 0.4 | 6 | −0.3 ± 0.9 |
| Suunto EON Steel | Suunto EON Steel 1 | 5 | −0.7 ± 0.0 | 6 | −0.6 ± 1 |
| Suunto EON Steel | Suunto EON Steel 2 | 5 | −0.5 ± 0.1 | 6 | −0.3 ± 0.6 |
| Suunto EON Steel | Suunto EON Steel 3 | 5 | −0.6 ± 0.0 | 6 | −0.4 ± 0.6 |
| Suunto Vyper | Suunto Vyper 1 | 5 | −0.3 ± 0.4 | 6 | −0.3 ± 2.2 |
| Suunto Vyper | Suunto Vyper 2 | 5 | −0.3 ± 0.4 | 6 | −0.1 ± 3.6 |

data loggers with accuracies of (± 0.2 to ± 0.3 °C) (Morris et al., 2018). A systematic negative bias of −1 °C has been seen in satellite sea surface temperature (satSST) (Brewin et al., 2017) and up to 6 °C bias between coastal satSST and *in situ* devices (Smit et al., 2013).

Sampling requirements for the global ocean observing system *in situ* SST temperature are 0.2 to 0.5 °C (Needler et al., 1999), and bias-corrected numerical oceanic models have been shown to still have up to −0.86 °C offset from baseline satellite temperature after corrections have been applied (Macias et al., 2018). As nine of the twelve dive computer models were found to have "good" accuracy (≤0.5 °C) overall (**Supplementary Table 8**), these requirements and biases indicate that, with sufficient data points, some models of dive computers can offer an additional source of temperature data to contribute to ocean temperature monitoring, numerical models and composite satellite products.

Differences were found in both bias and variance (accuracy and precision) across the two conditions (sea and chamber). Nine models had the same accuracy categorisation in both sea and chamber dives (**Supplementary Table 8**). Of these, only three models (Aqualung i750TC, Garmin Descent MK1, Scubapro G2) had the same precision across the two conditions. Precision was found to be improved in sea conditions, with eight models categorised as having "good" precision (**Supplementary Table 8**). Only one model (Ratio iX3M GPS Deep) was found to have good precision in the chamber. The reduced precision found in nine of the models in the chamber is likely caused by differences between tub temperatures in dive repetitions, combined with the effect of a static water environment on the Castaway temperature sensor. Castaway CTDs are designed to work with a steady flow of water of around 1 m $s^{-1}$ through the sensor channel. Collection of data in real world scenarios will always lead to differences caused by environmental variation for which it is not possible to control. In the present study, all Castaways were positioned on a frame carried by one diver, while all the dive computers were worn on the wrists of two divers. It is therefore possible that, although precision was better than in the chamber, proximity differences combined with local variations in temperature led to additional variation being seen in the sea dives.

**TABLE 4 |** Comparison of bias by model worn "on arm" with loose on a frame.

| Model | On frame Bias $\Delta T$/°C | On arm Bias $\Delta T$/°C | On arm minus on frame Difference $\Delta\Delta T$/°C |
|---|---|---|---|
| Aqualung i750TC | −1.4 ± 2.1 | −1.2 ± 2.3 | 0.2 |
| Garmin Descent Mk1 | −0.5 ± 0.5 | −0.1 ± 0.8 | 0.3 |
| Mares Matrix | 0.1 ± 0.1 | 0.2 ± 0.1 | 0.1 |
| Mares Puck Pro | 0.0 ± 0.1 | 0.2 ± 0.3 | 0.1 |
| Paralenz Dive Camera+ | 0.7 ± 0.1 | n. a. | −0.7 |
| Ratio iX3M GPS Deep | 0.5 ± 0.3 | 2.0 ± 1.2 | 1.6 |
| Scubapro G2 | −0.2 ± 0.1 | 0.2 ± 0.8 | 0.4 |
| Shearwater Perdix | −0.5 ± 0.3 | 0.0 ± 0.4 | 0.5 |
| Suunto D4i | −0.7 ± 0.1 | −0.4 ± 0.3 | 0.3 |
| Suunto D6i | −0.4 ± 0.3 | −0.1 ± 0.4 | 0.4 |
| Suunto EON Steel | −0.6 ± 0.1 | −0.6 ± 0.1 | 0.0 |
| Suunto Vyper | −0.4 ± 0.4 | −0.1 ± 0.5 | 0.3 |

*Bias is defined as the mean temperature derived from the final 180 s of sea dives below the top of the bottom mixed layer, compared to baseline Castaway temperature data acquired over the same time.*

With the exception of three devices [Ratio iX3M ($n$ = 1), Garmin Descent Mk1 ($n$ = 1), Suunto EON Steel ($n$ = 1)], all individual devices aligned with their model's overall accuracy categorisation, demonstrating positive within model consistency. Similarly, only one device had lower precision than its model's categorisation, with four devices [Suunto EON Steel ($n$ = 2), Aqualung i750TC ($n$ = 2)] having better precision than their model would indicate. This within model consistency is encouraging for *post hoc* bias correction by model. Across both conditions, all models except three showed overall negative bias to the baseline temperature. In contrast, Mares Matrix had an overall bias of 0, whilst Ratio iX3M GPS Deep and Paralenz Dive Camera+ biased warm. This could be caused by an internal heating effect of the electronics due to additional active functions as both Ratio iX3M GPS Deep and Paralenz DiveCamera are both devices with additional functionality in comparison with some smaller devices.

Diver attachment placement also had significant effect on bias in sea dives, with all models "on arm" having a non-negative mean bias compared with than "on frame" (irrelevant of whether the device was biased colder or warmer than the baseline). These differences could be caused by the heating effect of the diver's body, an effect of an additional barrier between the ambient water temperature and the temperature sensor (dependent on sensor location within the housing). All divers were wearing drysuits, but the material and thickness varied (neoprene/membrane).

With the exception of two models (Mares Matrix, Suunto EON Steel) there was greater variation in within-model bias in "on arm" conditions. This could be due to differences in positioning of dive computers on arms, the amount of contact between the device and the diver's arm, or the dive suit material. When collecting or correcting data across different environments, console mounted devices which are mounted on a hose not attached to the diver may be preferable for temperature data accuracy. Alternatively, it is common for divers to have redundancy in kit, carrying two dive computers. The secondary device could be attached safely to the diver but not worn on the arm. It is recommended that attachment mechanism and thermal protection type be noted in data collection from citizen scientist divers so it can be taken into consideration.

## Technology Limitations

Accuracy in recorded or displayed temperature, or response to temperature change does not form part of primary dive computer function and dive computer manufacturers are not providing temperature data for oceanographic purposes. The results found are in no way reflective of the performance of any model in the designed purpose as diver safety devices. Whilst dive computers in the United Kingdom must adhere to standards set in British Standard BS EN13319:2020, which covers functional and safety requirements including depth and time, the Standard does not include temperature (British Standard, 2000).

The greatest potential for temperature data from citizen scientist divers is to address the lack of depth-resolved data in

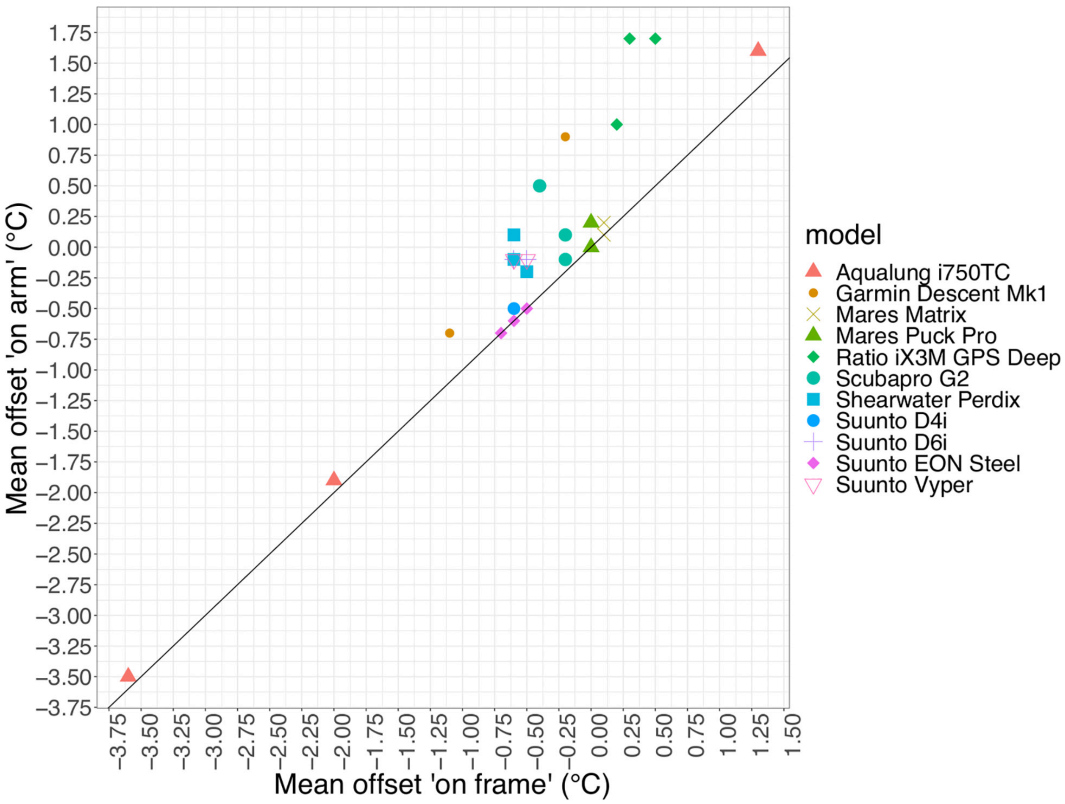


**FIGURE 7 |** Effect of wearing devices "on arm" vs. "on frame." Bias from Castaway baseline data by device, black line represents an equal bias in both conditions.

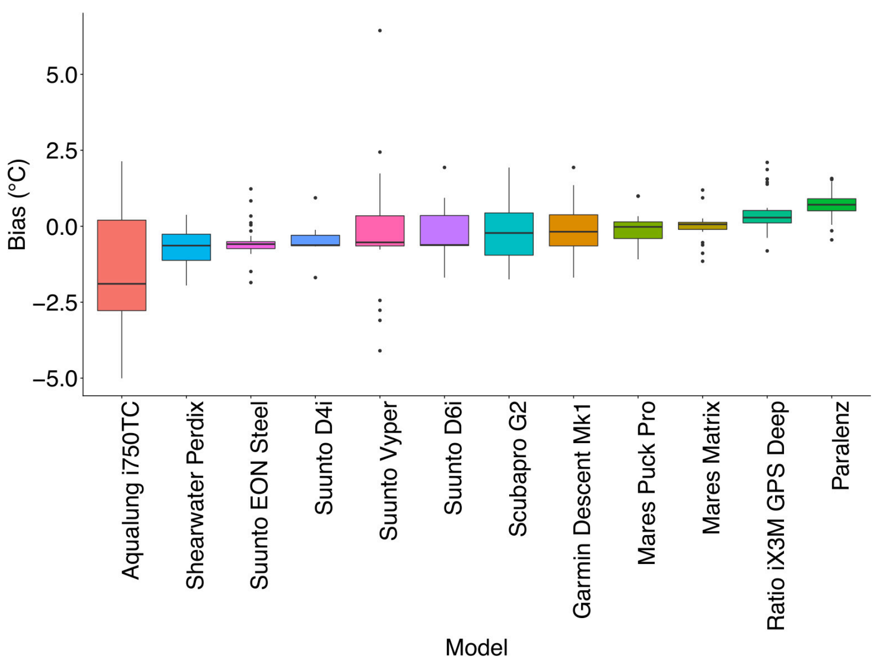


**FIGURE 8 |** Normalised bias by model across sea and chamber dives. The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * inter-quartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers.

**TABLE 5 |** Bias by model, averaged across sea and chamber dives.

| Model | *n*(dives) | Bias $\Delta T$/°C | Resolution/°C |
|---|---|---|---|
| Aqualung i750TC | 33 | −1.4 ± 2.1 | 5/9 ≈ 0.56 |
| Garmin Descent Mk1 | 33 | −0.1 ± 0.8 | 1 |
| Mares Matrix | 22 | 0 ± 0.5 | 0.1 |
| Mares Puck Pro | 22 | −0.1 ± 0.6 | 0.1 |
| Paralenz Dive Camera+ | 29 | 0.7 ± 0.5 | 0.1 |
| Ratio iX3M GPS Deep | 33 | 0.4 ± 0.7 | 0.1 |
| Scubapro G2 | 33 | −0.2 ± 0.8 | 0.4 |
| Shearwater Perdix | 33 | −0.6 ± 0.6 | 1 |
| Suunto D4i | 11 | −0.5 ± 0.6 | 1 |
| Suunto D6i | 33 | −0.3 ± 0.8 | 1 |
| Suunto EON Steel | 33 | −0.5 ± 0.6 | 0.1 |
| Suunto Vyper | 22 | −0.3 ± 2.1 | 1 |

coastal regions. To improve the overall use of dive computers as oceanographic monitoring devices in less-well performing models, manufacturers could look at improving the quality of the out of the box measurements. The addition of an accurate dedicated temperature sensor, with considered placement of the sensor would support unbiased detection of water temperature change. Whilst the majority of dive computer models tested by Azzopardi and Sayer (2010) were found to be consistently within 1% of nominal depth, the addition of conductivity sensors to measure salinity would increase the accuracy of depth values, although this would not affect temperature data quality. Inclusion of geolocation ability would allow easy identification of dive locations. The combination of all of the above would maximise the citizen science potential of divers, due to their access to otherwise hard to reach locations.

Within the limitations of the current commercially available devices, a citizen science project dataset could be improved by calibrating individual dive computers in advance, simply, using an iced bucket of water. As evidenced by the water bath trials—this would be greatly improved by an additional significant figure to the unpressurised temperature display, as currently the majority of models display only positive integers, limiting the potential accuracy by introducing truncation effects.

## Citizen Science and Use of Data

We need to better understand how model type affects temperature profiles so that citizen science diving projects can help fill gaps in coastal temperature datasets. To standardise data, there should be a focus on the models offering the greatest accuracy and shortest temperature response. Only one model (Aqualung i750TC) was found to have poor accuracy and precision across all conditions, along with a slow response to temperature change. Five of the six models with a quick temperature response ($\tau$ < 60 s) were also found to also have good accuracy, with good/moderate precision overall (**Figure 9**). These comprise Mares Matrix (2/2), Garmin Descent (2/3), Suunto D6i (3/3), Suunto EON Steel (2/3) and Suunto D4i (1/1), all sharing promising characteristics as individual devices.

When considering models for citizen science data collection, those with the greatest potential have a high sample rate and resolution, are likely to have a pressure sensor located on an edge and have a metal or part-metal housing. In addition, a standardised model could be used by all volunteers in a project and simple corrections applied for systemic model bias. The most promising model tested here for overall use across citizen science projects is the Mares Matrix. This model had consistently good accuracy and precision and a quick response to temperature change; exhibiting an overall mean bias of (0.0 ± 0.4) °C and $\tau$ = (46 ± 5) s with a recorded resolution of 0.1 °C and a 5 s sampling rate. A close second is the Suunto EON Steel, which has good accuracy overall, moderate precision and a quick response to temperature change, with a recorded resolution of 0.1 °C and a 10 s sampling rate. Other models have shorter $\tau$ (Suunto D6i, Suunto D4i, Garmin Descent), but single degree resolution, making them less useful for monitoring temperature change.

With sufficient data points, we found "good" accuracy, irrespective of originating device. Therefore, data collected by local groups or dive centres in commonly dived, discrete areas, may generate sufficient data points to provide a useful accuracy, irrelevant of model. In addition, not all sampling locations have equal value (Callaghan et al., 2019) and lower quality data may still be of use to support decision making (Buytaert et al., 2016) if uncertainties are quantified. As such, in remote, less widely sampled areas where there are limited pre-existing records, dive computer information may still be of use as indicative data, even with fewer sampling points or from devices with less accuracy/precision.

In addition to the device-related effect, we found that mode of attachment and placement on the diver body had an influence on temperature accuracy. Therefore, for citizen science-derived dive computer profiles to be useful on a wider basis, collection of metadata is crucial. Downloaded profiles already contain metadata such as date, time and model, but diver attachment, placement and diver thermal protection type should be collected in addition, to enable a more comprehensive assessment of data quality on an individual profile basis. An online portal facilitating easy upload of profiles and associated metadata is currently in late-stage development. Ideally, data from different citizen science dive portals should be combined in a global dataset.

Temperature from dive computers could be used to complement biological datasets. For example, thermocline depth affects vertical distribution of fish (Sogard and Olla, 1993), so computer-derived temperature data could contribute to a better understanding of local variability in fish movements. Temperature data can also support regional assessment of hydrological conditions (Morris et al., 2018). In highly dived areas, the data would provide a time series allowing identification of seasonal variation, albeit without complete temporal coverage. They may also be useful for marine recreation (Brewin et al., 2015) or feeding into numerical models and satellite products (Smit et al., 2013) in areas where the accuracy is known to be < 1 °C. They could be especially useful in commonly dived, poorly sampled areas, such as the South Pacific, where the volume of dive profiles could provide data of a useful resolution irrespective of model.

In conclusion, the limitation of divers as citizen scientists for temperature data collection is inherent in the devices themselves.

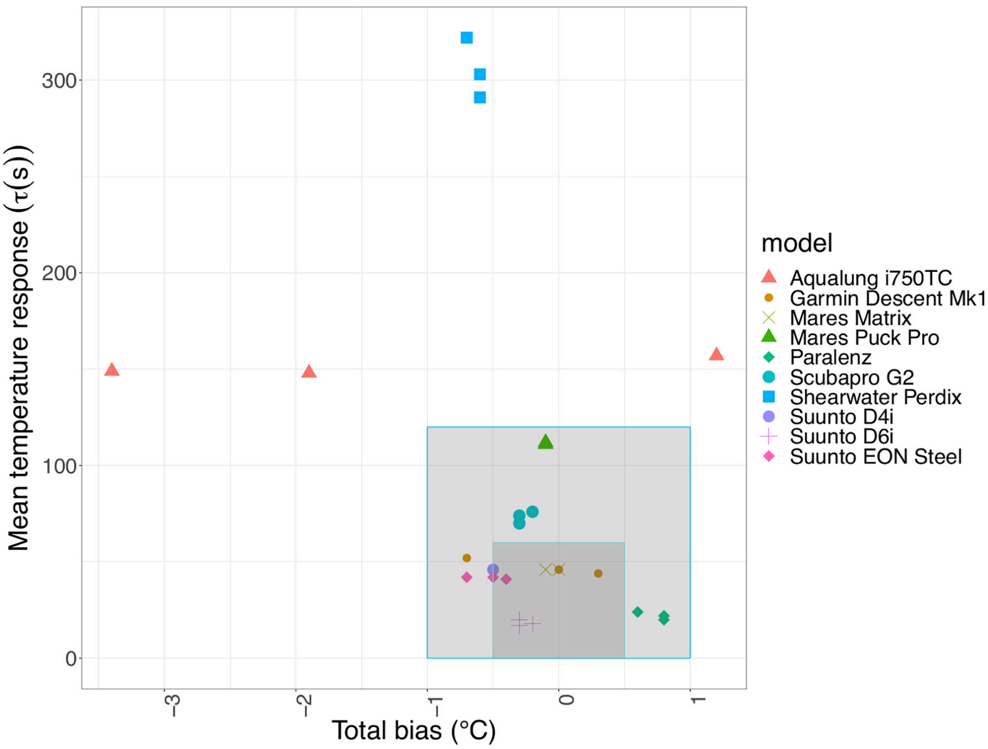


**FIGURE 9 |** Accuracy against bias for all devices; the inner box highlights 0.5 °C bias with 60 s τ. Devices falling in the inner box are defined as having both a quick response and good accuracy overall. The outer box highlights devices which have up to 1 °C bias and 120 s τ: an intermediate response to temperature change, and moderate accuracy.

The challenge is to understand the uncertainty in accuracy and precision recorded by the devices rather than the abilities or knowledge of the citizen science diver. Our research shows that the quality of temperature data in dive computers could be improved, but implementation would need to be driven by manufacturers, or by diver demand. As some models of dive computers can demonstrably provide data comparable to that collected by more traditional methods, within required accuracy levels for some monitoring scenarios, they have a role to play in future oceanographic monitoring.

## DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: British Oceanographic Data Centre; doi: 10.5285/b3c2a748-357b-5fb7-e053-6c86abc05126 and https://www.bodc.ac.uk/data/published_data_library/catalogue/10.5285/b3c2a748-357b-5fb7-e053-6c86abc05126/.

## AUTHOR CONTRIBUTIONS

CM carried out the experiments and analysed the data. CM wrote the manuscript with contributions from all authors. All authors set the conceptual framework of this study.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.617691/full#supplementary-material

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# Implementing Citizen Science in Primary Schools: Engaging Young Children in Monitoring Air Pollution

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Most European cities have air pollution levels that exceed the threshold for human health protection. Children are sensitive to air pollution and thus it is important to ensure they are not exposed to high concentrations of air pollutants. In order to make a positive change toward cleaner air, a joint effort is needed, involving all civil society actors. Schools and local communities have a decisive role, and can, for example, become engaged in citizen science initiatives and knowledge coproduction. In 2019, with the aim of raising awareness for air quality, NILU developed a citizen science toolbox to engage primary schools in monitoring air quality using a simple and affordable measuring method based on paper and petroleum jelly. This is a very visual method, where the students can clearly see differences from polluted and non-polluted places by looking at "how dirty" is the paper. In addition to the qualitative analysis, we have developed an air meter scale making possible for the students to obtain an indicative measurement of the air pollution level. The comparison between the paper and petroleum jelly method against reference $PM_{10}$ data collected at two official air quality stations showed a good agreement. The method is a strong candidate for dust monitoring in citizen science projects, making participation possible and empowering people with simple tools at hand. The toolbox is targeted at primary schools and children aged 6–12 years, although it can easily be adapted to other age groups. The main objective of the toolbox is to involve young children who are usually not targeted in air quality citizen science activities, to develop research skills and critical thinking, as well as increase their awareness about the air they breathe. The toolbox is designed to engage students in hands-on activities, that challenge them to create hypotheses, design scientific experiments, draw conclusions and find creative solutions to the air pollution problem. The toolbox includes all the necessary material for the teachers, including guidance, background information and templates facilitating the incorporation in the school curricula. The toolbox was launched as part of the Oslo European Green Capital in March 2019 and was later included as part of the European Clean Air Day initiative coordinated by the European Citizen Science Association (ECSA) working group on air quality. A total of 30 schools and 60 4th grade classes (aged 8–9 years) participated in the Oslo campaign. The citizen science approach employed in the schools, combined the four key elements that promote knowledge integration: elicit ideas, add new ideas, distinguish among ideas and reflect and sort out ideas. Although the main goal of the study was to provide simple but robust tools for engaging young

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children in air quality monitoring, we also carried out ex-ante and ex-post evaluations in 12 of the participating classes using a 10-question multiple choice test to have an indication of the contribution of the activity to knowledge integration. The results show that there is an increase in the number of correct answers, as well as a reduction in the misconceptions after conducting the activity. These results indicate that applying a citizen science approach improved science instruction and helped knowledge integration by including students' views and taking advantage of the diverse ideas students generated. Citizen science gives learners an insight into the ways that scientists generate solutions for societal problems. But more important, citizen science provides a way to differ from the classic view of the learner as an absorber of information, by considering the social context of instruction and making the topic personally relevant.

**Keywords: air quality, low-tech monitoring, citizen science, primary schools, inclusiveness, knowledge integration**

## INTRODUCTION

Despite long-term efforts across the whole of Europe during the last decades, air pollution is still a reason for concern with regard to health impacts, especially in urban areas. A recent report about the air quality in Europe estimates that long-term exposure to particulate matter was responsible for ~417.000 premature deaths in that area [EEA (European Environment Agency), 2020].

Air pollution is especially harmful to children, as their lungs are still developing. Air pollution has been associated with a wide variety of adverse health impacts in children (Gehring et al., 2013). These include increased acute respiratory disease, increased prevalence of respiratory symptoms and lowered lung function when pollution levels increase (Gehring et al., 2013; Guarnieri and Balmes, 2014).

Radical changes are needed to support the transformation toward a cleaner Europe, which must involve all parts of society. Schools and local communities have a decisive role in this context by promoting knowledge coproduction and citizen science (Harris and Ballard, 2018). Citizen science can be defined as the involvement of non-professionals, i.e., volunteer lay people, in scientific research (Bonney et al., 2009). In citizen science, citizens can contribute to scientific research at different levels, from helping to co-design a citizen science project to collecting data, and/or analyzing results and disseminating them (Haklay, 2013; Irwin, 2018). Citizen science has been described as being beneficial for participants in several ways, including: enhanced science literacy and critical thinking, developing new skills and advocacy/taking action to influence policy (Irwin, 2018, Den Broeder et al., 2018; Harris and Ballard, 2018).

The appearance of low-cost sensor technologies to monitor the environment has opened numerous opportunities for citizens to observe their environment and as part of these activities, monitor air pollution (e.g., Sensor.Community[1], EU H2020 project hackAIR[2]). A number of projects and initiatives show the successful involvement of high school students in citizen science projects, monitoring air quality by help of low costs sensors that have been built and coded by the students independently (e.g., Fjukstad et al., 2018; Grossberndt et al., 2020). However, to our knowledge, there are no specific methods for air quality monitoring with focus on younger children that do not have technology as part of their curricula yet. Other citizen science projects with focus on air quality used active and passive samplers to measure levels of nitrogen dioxide ($NO_2$) and particulate matter (PM) inside and outside the school buildings, developing toolkits and education tools to make children aware of air pollution, its effects on health and the environment and what they can do to reduce it [CleanAir@School[3]; Health and Environment Alliance, 2019]. Even though these citizen science projects focused on younger children, they did not involve the children in building their own devices neither decide about the place where they wanted to measure air quality. Thus, a true involvement of the children in the co-production of scientific knowledge was missing.

This led us to the design of a citizen science toolbox for primary school students, that involved them in all the phases of scientific research, including building their own air monitoring devices (Castell et al., 2020). The main objective of the toolbox was to introduce the concept of the scientific method to young children (aged 6–12 years), raise their awareness about air quality and elicit their imagination on how they can contribute to improve it. We deployed a citizen science approach, including the children in both problem definition and data collection and interpretation. We also empowered them to disseminate their results to local policy makers. The children in one of the participating schools had the opportunity to discuss their ideas with the Governing Mayor of Oslo, and three students from two different schools were invited as speakers to the Urban Future Global conference, where they presented the project results to an international audience mainly composed by public authorities and policy makers.

[1]https://sensor.community/en/
[2]https://www.hackair.eu/
[3]https://www.eea.europa.eu/themes/air/urban-air-quality/cleanair-at-school

# METHOD AND MATERIAL

## Citizen Science School Toolbox

The citizen science school toolbox was targeted toward primary schools and young children (aged 6–12) to engage them in designing their own experiment around measuring air pollution in their local environment. The goal of the toolbox was to engage young children in science, increase their understanding of the relation between air quality and health and encourage positive action toward cleaner air around the school buildings. The material was organized in a manner that students could conduct the experiment the same way it would be done by a researcher, following the scientific method of creating a hypothesis, design the experiment, analyse and discuss the results and extract conclusions.

The citizen science school toolbox was developed together with a master student in Digital Learning at the University of Oslo and was reviewed by several teachers and 4th grade students. In collaboration with the Education Agency in Oslo (Utdanningsetaten i Oslo, UDE) we ensured that the project was in line with the learning objectives in the schools' curriculum. The Environment Agency in Oslo (Bymiljøetaten i Oslo) also reviewed the material, and their help was crucial when reaching out to the schools in Oslo and Akershus county to invite them to participate in a monitoring campaing.

The toolbox contains an air meter (based on paper and petroleum jelly) to monitor dust, a dust scale to compare the air meter and obtain the pollution level, instructions for the teachers, a short introduction to air pollution and health for the students (above 8 years old) and a scientific notebook (above 8 years old) to guide the students in the design of their own experiment.

The teachers can use the materials from the citizen science school toolbox over two lessons, of ∼45 min each. There must be at least 1 week between the two lessons, as this is the time that the air meter needs to be exposed to the air pollution. We proposed to divide the lessons as follows:

- Lesson 1: Elaboration on the background information, preparation, and deployment of the air meters.
- Lesson 2: Collection of the air meters, analysis, discussion, writing the conclusions and registration of the data on the website.

The activity can be conducted by each student individually, or the class can work in groups of 2–3 students. The students can also agree on a research question, and collectively design the experiment to answer it. Examples of experiments can be deploying air meters in different places around the schools to monitor differences in air pollution or deploying the air meter under different weather conditions to measure differences in air pollution over time at the same location.

We also prepared a website (http://luftaforalle.nilu.no) where the participating schools could easily download the citizen science school toolbox materials, upload their data to a GIS map, and see the results from other participant schools. The website was created in Norwegian, as the toolbox was first developed as part of the activities conducted in the Oslo Green Capital 2019. The toolbox materials are currently available in other languages (English, Norwegian, Portuguese, Dutch and German) through the European Clean Air Day website (http://www.ecad.eu), and the EU Citizen Science platform (https://eu-citizen.science/).

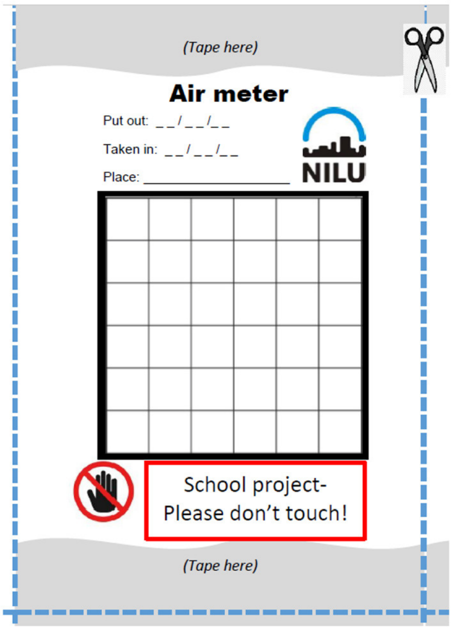


**FIGURE 1** | Air meter to monitor dust levels using petroleum jelly. The air meter can be printed in a normal A4 paper and then cut it to have four air meters.

## Air Meter

The air meter (**Figure 1**) can be printed in regular A4 paper, although it was recommended to use thick paper (160–200g). Each A4 paper has 4 air meters that the students need to cut. Each air meter contains a space on the top to fill in the date it was put out, the date it was taken in and the place it was deployed. The measuring part consist of a square of 6 × 6 $cm^2$, divided into smaller squares of 1 × 1 $cm^2$. In other to make the air meter more resistant to rain conditions, we suggested to first attach the air meter to an empty milk carton by using silver tape and then deploy it outside using also silver tape to fasten it for example to street lights, a tree or a window (**Figure 2**).

The students should grease a thin layer of petroleum jelly covering the full 6 × 6 $cm^2$ square using a brush or their fingers (**Figure 2**). The air meter has to be deployed outdoors for 1 week, this is to ensure that we are measuring over a representative period. As other passive instruments to monitor air pollution, like passive samplers, the air meter needs to be exposed for a sufficient amount of time to obtain a representative sample. We conducted several tests, and concluded that 1 week was an optimal time, as it was allowing to collect enough dust (particulate matter), while also fitting well in the school agenda (i.e., the same class was repeated the same day each week).

During the campaign period, from 27th February to 27th May 2019, we co-located air meters in three reference stations in Oslo (Kirkeveien, Hjortnes, and Sofienbergparken), representative of


**FIGURE 2 | (A)** After printing the air meter, the students can cut it. **(B)** The air meter is attached to a milk carton box using silver tape. **(C)** A thin layer of petroleum jelly is applied using the finger. **(D)** The air meter is deployed outside using silver tape.

traffic and urban background stations. The air meters were placed and collected every week for 11 weeks. **Figure 3** shows the comparison between the weekly average of PM10 at the reference station and the number of dots. The results show that the air meter, even being a very simple method, correlates well with the concentration of PM10 in the air, with a coefficient of dispersion of 0.4.

## Dust Scale for the Air Meter

To elaborate the dust scale, we co-located three air meters at a traffic reference station and three air meters at an urban background reference station for 20 weeks in the period between September and January 2018. We then compared the number of particles fastened to the petroleum jelly with the concentration of particle matter ($PM_{10}$) measured at the reference station. Based on the comparison we linked the number of dots per $cm^2$ with the air pollution level. We divided the scale in four air quality levels: low, medium, high, and very high. In order to facilitate the task of assessing the air quality level, specially to the smaller children, we also added pictures of the air meter, and a description of how the air meter will look like depending on the air pollution level (**Figure 4**).

After 1 week of exposure the students could take down the air meters and compare their air meters with the dust scale to assess the air quality level. To count the gray dots, the student must select three squares from the grid, count the dots in each of the three squares, and calculate the average. Selecting three squares allows to obtain a more representative value, as the particles do not get fastened homogeneously over the full square. As mentioned before, the task of analyzing the air meter can be simplified depending on the children age.

## Notebook: My Air Quality Experiment

As part of the toolbox material we created a two pages notebook for the students with the aim to guide them through the scientific method. The notebook is divided in two parts, one to be completed in the class 1, during the preparation and mounting of the air meter, and one for the class 2, after collecting the air meter and conducting the analysis. During the class 1, the students are asked to write down their research question or hypothesis (e.g., "I think there is more air pollution along St. Andrew Road and on the south side of the playground"), and describe the method about how they prepare the air meter step by step, and the location where they will place them. Then they prepare the air meter and go out to place it at their selected locations. During the class 2, after collecting the air meters, the students count the dots, and write down the results obtained after comparing the number of dots with the dust scale. They can now determine the level of air pollution at their selected locations. They can further discuss if their hypothesis was true or false, write down a conclusion about the air pollution level in the places they measured, and together suggest what can they do to improve air quality.

## Web Portal

The web portal (in Norwegian, http://luftaforalle.nilu.no) has a link to download the material (in Norwegian), a video with the instructions, a link to upload the information from the air meter, and a link for visualizing the results. On the visualization map it

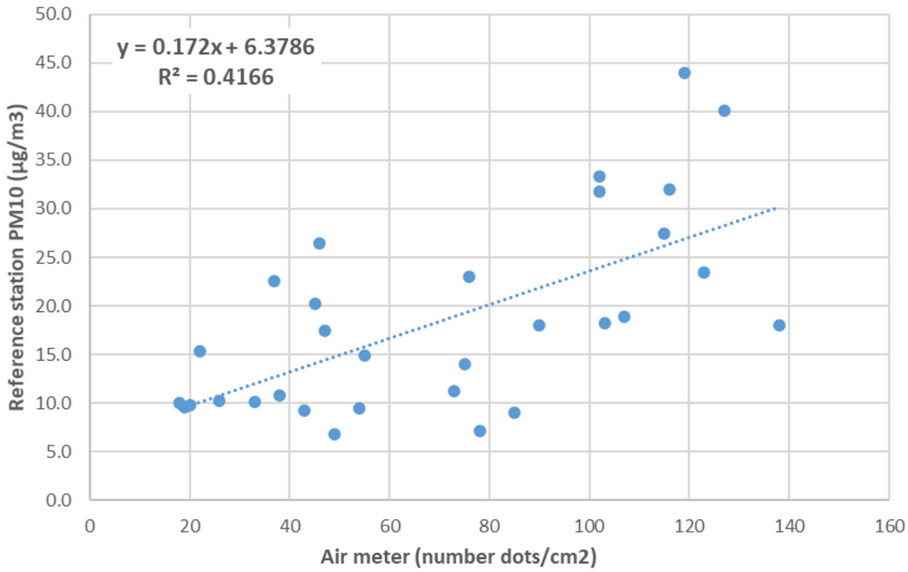


**FIGURE 3 |** Comparison for the air meter against weekly particulate matter concentrations (PM10) measured at the reference stations of Sofienbergparken (urban background), Kirkeveien (traffic), and Hjørtnes (traffic) in Oslo.

## Dust scale

Compare the air meter with the dust scale and select the smiley (emoji) that suits:

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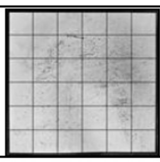
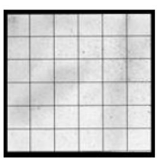
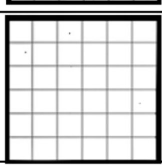
| Picture | Description | Dots pr cm$^2$ | Air pollution level | Smiley |
|---|---|---|---|---|
|  | The paper has many black and grey dots. Large parts of the paper have turned grey. | > 50 | Very high |  |
|  | The paper has quite a few black and grey dots. There are some parts on the paper that have turned grey. | 26 - 50 | High |  |
|  | The paper has black and grey dots all over the surface, but there are no fields that are completely grey. | 11 - 25 | Medium |  |
|  | The paper has only a few black and grey dots, and there are no fields that are completely grey. | < 11 | Low |  |

**FIGURE 4 |** Dust scale to obtain the air pollution level measured with the air meter. Each level is associated with one smiley. The smiley will be used in the website to represent the air pollution level.

is possible to filter the results by time period, school and level of pollution. The parts of the web portal for uploading data and visualizing the results can be accessed independently (http://renluftforalle.nilu.no/markers) and are currently available in English, Norwegian, Dutch, Hungarian, and German (**Figure 5**). They are operative and any school or interested person can upload new data.

The teachers were asked to upload the results in the web portal. In order to register an air meter, the following information needs to be provided: the dates the air meter was deployed, the average number of dots per $cm^2$, the weather conditions (i.e., if it was raining during the time the air meter was outside), and the air quality level (smiley). The registration form has also a free text box to add other relevant comments from the students or the teachers.

The part of the portal dedicated to upload the results has a registration area, where the schools are asked to provide a name for their class and the name of the school. We do not store any private information regarding the students or the teachers. The name of the class is displayed in the visualization map. Through the visualization map the students could see their own results but also the results from other participating schools (**Figure 5**). The visualization portal is open and do not require registration.

## CITIZEN SCIENCE ENGAGEMENT WITH SCHOOLS

### Monitoring Campaign in Schools in Oslo and Surroundings

We prepared a list of the primary schools in Oslo and Akershus county, and sent an email to their directors presenting the campaign and inviting the schools to participate. For that purpose, we prepared a two-page leaflet (in Norwegian) explaining the purpose of the campaign and the tools we had created for the schools to actively participate in measuring air pollution. At the beginning of February 2019, we sent out the invitations.

The measuring campaign was conducted in the period between 15 March and 15 May 2019. This is the high season

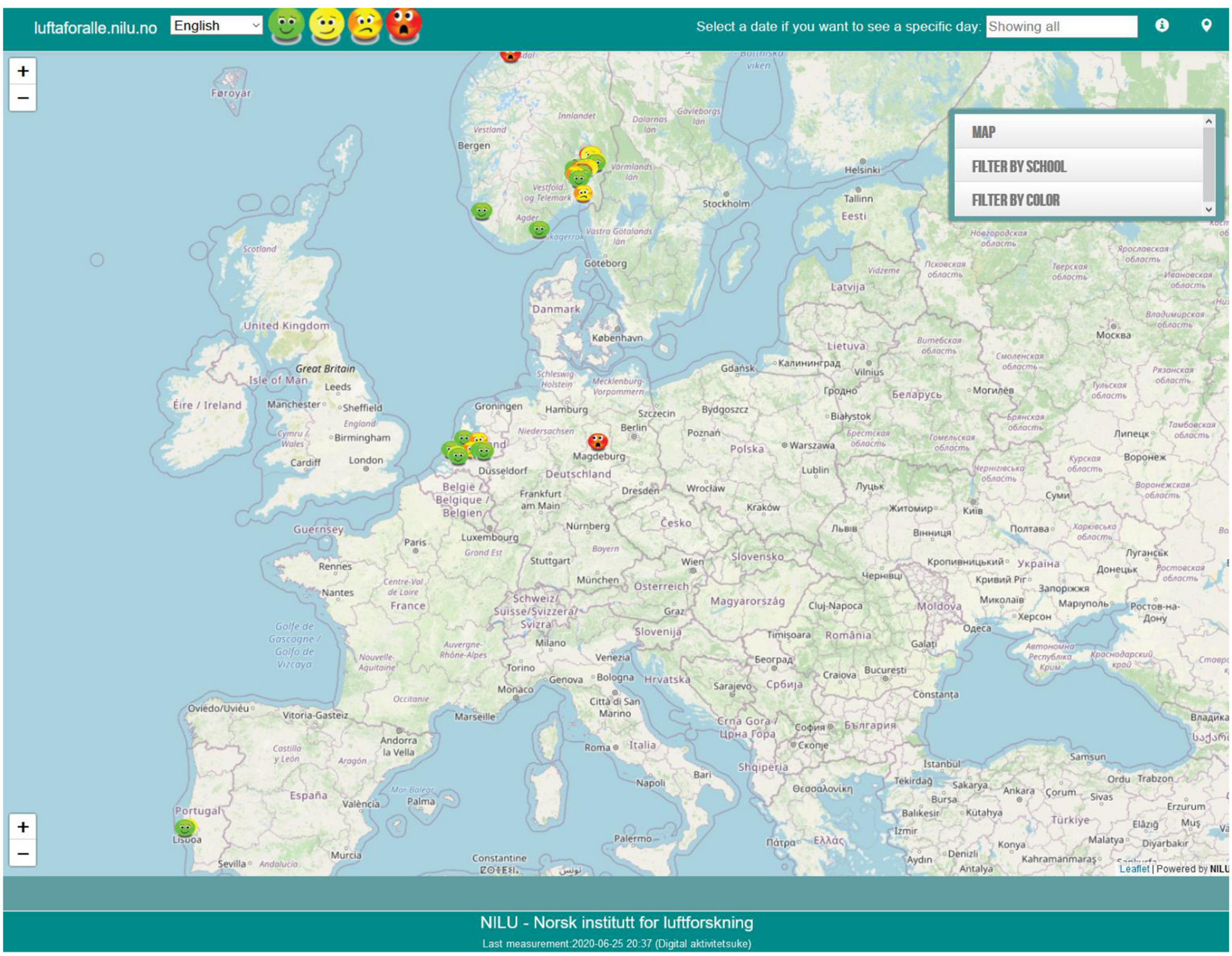



**FIGURE 5 |** Screen shot of the web portal where the schools can upload the data and visualize the results from all the participant schools.

for particulate pollution in Norwegian cities, due to road dust resuspension. The kick-off of the campaign took place on 15th March at a participating school (Årvoll skole) in Oslo. The governing mayor of Oslo, together with a team of researchers from NILU, presented the project to the three 4th grade classes. The students had the opportunity to ask questions about the campaign and build their own air meter. The kick-off was covered by the national TV and regional press and was disseminated through different social media channels. This resulted in more schools registering to participate in the campaign.

A total of 60 4th grade classes from 30 schools in Oslo and Akershus county joined the measuring campaign. During the campaign, a team of one NILU scientist and the previously mentioned master student visited 10 schools (Volla, Munkerud, Tveita, Trasopp, Holmlia, Døli, Ullevål, Råholt, Årvoll, Auli) in Oslo and Akershus county and carried out the activities planned for the first class together with the teachers. Other schools conducted the activity without the assistance from NILU scientists. We collected almost 300 measurements.

In May 2019, the results from the project were presented at the Urban Future Global Conference in Oslo, an international conference for decision makers and city changers. The project was presented by three 4th grade students from Årvoll and Tveita skole.

### Monitoring Campaign During the European Clean Air Day 2019

The citizen science toolbox for schools was selected as one of the monitoring methods for the European Clean Air Day (ECAD, http://cleanairday.eu), organized by the European Citizen Science Association (ECSA) working group on Air Quality and celebrated on 20 June 2019. The toolbox was mainly promoted through science fairs and workshops celebrated on the occasion of the ECAD in Netherlands, Germany, Hungary and Portugal. In Amersfoort (Netherlands) and Lisbon (Portugal), the toolbox was incorporated as part of teaching lessons at schools. In Netherlands, the activity was conducted by one school engaging students aged 12–13 years, while in Portugal, the activity was adapted for adult students participating in night school classes, aged 18–40 years.

## KNOWLEDGE INTEGRATION

In the 10 schools in Oslo and Akershus county that we visited during the measuring campaign, we conducted ex-ante and ex-post questionnaires to evaluate the students' learning outcome and awareness about air pollution, using a 10-question multiple choice test. The ex-ante questionnaire was conducted before the students started the lesson 1 activities, while the ex-post questionnaire was conducted after all activities (lessons 1 and 2) had been conducted. The questions were related to the information that the students read about air pollution during the first lesson, as well as their work as junior scientists collecting and interpreting the data. The questions were checked by a teacher to ensure they were appropriate for the curricula of 4th grade students in Norway.

**TABLE 1** | Summary of the results from tests obtained in 12 primary classes that conducted the activity.

| | Ex-ante | Ex-post | Difference post – ante (%) |
|---|---|---|---|
| Total number of right answers | 1,787 | 1,963 | 10.1 |
| Total number of wrong answers | 601 | 347 | −10.1 |

It is outside the scope of the study to thoroughly evaluate knowledge integration, and the conclusions we can extract from the tests are limited as we did not have any control group. Also, we did not have an individual ex-ante and ex-post evaluation, but we collected all the questionnaires in each class without differentiating who completed them. In some cases, the number of ex-ante and ex-post tests for a particular class did not match, as the number of attendees to the class may vary (e.g., due to sickness). The ex-ante and ex-post evaluations were only conducted in the classes that we visited. During our visit, we observed big differences in the classes (e.g., levels of concentration, reading skills, involvement in the activities), this was also displayed in the results from the questionnaires. In total, from the 12 classes that conducted both, we collected 245 ex-ante and 238 ex-post questionnaires that have been used in the analysis. Seven classes filled in only the ex-ante (124 tests), but did not return the ex-post. We have not used that data in the analysis. The results (**Table 1**) show that there is a 10% increase in the number of correct answers. We can also observe a reduction in the misconceptions, for instance, before performing the activities, 46% of the students thought that particulate matter is bigger than the diameter of a human hair, while after the activities, this wrong answer is only given by 22% of the students. Similarly, most of the students (60%), thought air quality was not a problem in Norway before starting the activities, while after the activities, only 32% of the students replied that air quality was not a problem in Norway. We can also see a decrease of 10% in the number of wrong answers to the question of what we can do to improve air quality.

Even if the conclusions we can extract from the study are limited, the results from the tests indicate that conducting citizen science activities in the classroom can improve science instruction and help knowledge integration by including students' views and taking advantage of the diverse ideas students generated. The citizen science toolbox can help teachers to combine the four key elements that promote knowledge integration: elicit ideas, add new ideas, distinguish among ideas and reflect and sort out ideas (Bonney et al., 2009; Harris and Ballard, 2018).

## CONCLUSIONS

Currently, most of the low-cost sensors used in citizen science school projects require technological knowledge (e.g., electronics, programming) and are not suitable for primary schools. The citizen science toolbox includes a low-tech method based on paper and petroleum jelly (air meter) suited for small children that still do not have technology as part of their curriculum. Despite being a very simple method, the comparison of the air meter against particulate matter measured at the reference stations show that the air meter has a good agreement with $PM_{10}$ concentrations and can be used as an indication of air quality levels.

The citizen science school toolbox has proven to be successful in engaging young children in creating their own scientific experiment and eliciting ideas on how to improve air quality in their local environment. The ex-ante and ex-post evaluation showed that overall the toolbox has contributed to increasing knowledge about air pollution among the participating students.

The teachers evaluated positively the adequacy of the toolbox and the possibility to be further integrated as part of the primary schools' curriculum. The citizen science toolbox is openly accessible, allowing to be translated to other languages as well as adapting it to the specific requirement of national school curriculums.

The results of the campaign show that when we provide tools appropriate to the age of the children, they can participate in knowledge creation processes related to their local environment. Enrolling young children in citizen science can play an important role in addressing local environmental challenges as air pollution.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

NC: project leader, design of Citizen Science Toolbox, preparation of the material, school engagement, data analysis and write manuscript. SG: school engagement, visits to the schools, preparation of the material, web portal, and supervision of manuscript. LG: design of the material for teachers and students, design of the questionnaires, interviews with teachers, and visits to the schools. MF: design of the web portal, including registration and visualization. JS: field work for the co-location of air meters in the reference stations. BH: engagement with authorities, facilitation of work at the schools, and supervision of the toolbox. All authors contributed to the article and approved the submitted version.

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# The Critical Importance of Citizen Science Data

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Citizen science is an important vehicle for democratizing science and promoting the goal of universal and equitable access to scientific data and information. Data generated by citizen science groups have become an increasingly important source for scientists, applied users and those pursuing the 2030 Agenda for Sustainable Development. Citizen science data are used extensively in studies of biodiversity and pollution; crowdsourced data are being used by UN operational agencies for humanitarian activities; and citizen scientists are providing data relevant to monitoring the sustainable development goals (SDGs). This article provides an International Science Council (ISC) perspective on citizen science data generating activities in support of the 2030 Agenda and on needed improvements to the citizen science community's data stewardship practices for the benefit of science and society by presenting results of research undertaken by an ISC-sponsored Task Group.

**Keywords: data management, data life cycle, citizen science, sustainable development goals, applied research**

## INTRODUCTION

Citizen science is an important vehicle for democratizing science and promoting the goal of universal and equitable access to scientific data and information. While the benefits of civic engagement and the contributions of citizen science (CS) to societal goals such as environmental justice are widely recognized, perhaps less understood is the critical importance of data as an output of citizen science projects. Yet, data need to be recognized as a long-lived legacy of CS activities and an important contribution to scientific research. The International Science Council's (ISC; formerly ICSU) acts as the "voice of science", with the vision that scientific knowledge, data and expertise are universally accessible, and their benefits universally shared. Accessibility to scientific knowledge and sharing its benefits are also values associated with citizen science. Through its work the ISC is promoting data stewardship and dissemination in the CS community so as to magnify the impact of citizen science on policy and programs related to (among other things) attainment of the U.N. Sustainable Development Goals (SDGs) (see also Fritz et al., 2019; Fraisl et al., 2020).

To that end, in 2016 the ISC established a joint Task Group on Citizen Science Data under the auspices of its two data-related bodies, the Committee on Data (CODATA), which focuses on data policy and capacity building in data science, and the World Data System (WDS), which focuses on promoting the value and sustainability of Trustworthy Data Repositories (TDRs) that provide data stewardship, long-term preservation, and access to quality-assured data. In its first incarnation, the CODATA–WDS Task Group focused on understanding the ecosystem of data-generating CS and crowdsourcing projects so as to characterize the potential of and challenges for science as a whole and data science in particular.[1] The interest was in evaluating CS practices throughout the data lifecycle. To that end, the Task Group (TG) conducted a survey of data collection, validation, curation, and management practices for a sample of 36 CS projects globally representing different research domains, types of CS practices, and regions (results published in Bowser et al., 2020).

In its second incarnation, with some change in membership, the TG turned to the question of how CS can contribute to the evidence base for monitoring and driving progress toward achievement of the SDGs.[2] To advance research in this area, in 2020 the TG collected data on 44 CS projects in Sub-Saharan Africa linked to the water and sanitation (SDG 6) and urban development (SDG 11) SDGs. The TG also developed guidance for CS groups that wish to contribute data to SDG monitoring efforts by "unpacking" the often opaque language surrounding the SDG goal, target, and indicator framework by presenting key information in layperson's terms. The purpose of this work is to provide "handles" that allow citizen groups to contribute to filling data gaps and tracking the progress of government agencies and other actors in monitoring and fulfilling the SDGs.

This article provides an ISC perspective on the topic based on these efforts and the views of the co-authors, who have all served as TG members. From an ISC perspective, citizen science is an important vehicle for democratizing science and promoting the goal of universal and equitable access to scientific data and information. Beyond evaluating citizen science and its data products from the perspective of its utility to professional scientists (a primary focus of the work of the first TG), the ISC understands that CS can be a vehicle for addressing interlinked environmental and development issues that are of the highest concern to communities (a major focus of the second TG) (International Council for Science (ISC), 2017). These include environmental justice and equitable access to basic services such as clean water, food, education and health services.

It should be noted that CS is an evolving practice that covers many disciplinary areas and types of citizen contributions, from crowdsourcing using online platforms to relatively passive modes of data collection using sensors to extreme CS (often conducted under the auspice of terms like "community based participatory research"), in which citizens are involved in all phases from problem definition to protocol development and implementation (Haklay, 2013). This complexity makes generalizations perilous. Hence findings presented in this perspective must necessarily be seen as partial, though still helpful for highlighting common data practices among CS projects and understanding the potential that CS holds for democratizing data.

## FINDINGS

### Current Data Practices in Citizen Science and Recommendations for Future Activities

In 2017 the TG launched a research project to understand "the State of the Data in Citizen Science." The TG developed a sampling framework for capturing the diversity of citizen science projects, including topical areas, geographic scale or scope, location, type of data collection or data analysis, and project governance model. This resulted in a sample of 36 CS projects. TG members then surveyed CS project principals using an interview instrument designed to elicit self-reported practices on aspects of the data lifecycle and data management, including information on data quality assurance and quality control (QA/QC), technical infrastructure, and data governance, documentation, and access.

Some of the most vocal criticisms of citizen science involve the perceived quality of citizen science data (e.g., Nature, 2015). We found that many of the projects in our sample had robust mechanisms for ensuring data quality −94% of projects surveyed used one method or more, and 56% used five methods or more. This suggests that data quality itself is not a major issue in CS, but rather the documentation (or lack thereof) of publicly reported QA/QC and practices is a main opportunity for improvement. We also found opportunities for improvement around data storage, management, and access. For example, compared to the large number of projects employing a diverse range of QA/QC mechanisms, fewer projects provided easy access to open data, offered a persistent unique identifier (UID), or selected an open license. Still, in line with norms around providing feedback to guide and motivate continued participation, the majority of projects (83%) found some way to share findings with their volunteers.

The complete description of research findings can be found in the journal article by Bowser et al. (2020). In addition, as a complementary practical resource the TG offered a summary of recommendations in six areas of the data lifecycle. Here, based in part on the article and on findings from ongoing work, we offer some updated recommendations for at least two audiences: citizen science projects seeking to improve their own data-related practices, and therefore elevate the value of their data for reuse, and a growing number of supporting platforms, infrastructures, and communities that are supporting citizen science projects in data curation, validation, and management.

### Data Quality

Many projects already ensure that volunteers receive training, sensors undergo initial calibration checks, and assessments are

[1] The full TG remit and membership can be found at https://codata.org/initiatives/task-groups/previous-tgs/citizen-science-and-crowdsourced-data/.

[2] The remit and membership of the second TG can be found at https://codata.org/initiatives/task-groups/citizen-science-for-the-sustainable-development-goals/.

made for individual devices and contributors. Some projects are also leveraging "big data" quality strategies, including methods to flag outliers for further checks, or incorporating uncertainty metrics for devices, volunteers, and individual measurements (e.g., Kelling et al., 2015). For projects that seek to promote the re-use of their data, or for supporting platforms, initial analysis on the quality of the collection, sampling approaches, and triangulation against other datasets encourages reuse and further increases the credibility of CS data in the scientific community. To improve data quality assessments, we recommend that CS projects with minimal privacy concerns could store the data in its most disaggregated form, explicitly state likely biases in sampling [e.g., over-sampling in nature preserves or on weekends (Cooper, 2014)], and document these assessments along with their QA/QC practices on websites and/or through formal QA/QC plans.

## Data Infrastructure

Many CS platforms, such as iNaturalist, OpenStreetMap, BioCollect, and CitSci.org, already offer existing "infrastructures" of technological platforms and communities. Other projects may develop their own technological platforms and systems. To the degree possible, we encourage new projects to consider leveraging existing, already tested infrastructures across the data lifecycle rather than establishing entirely new and distinct platforms. In cases where new developments become necessary, it is critical to partner with existing open-source technology and standards development communities to ensure that best practices are achieved. For example, working groups of the U.S. based Citizen Science Association (CSA) and Open Geospatial Consortium (OGC) have already established guidelines for metadata documentation and/or standards for data collection and sharing.

## Data Preservation

Both within and beyond citizen science, there are benefits to data archiving in large and stable data repositories, where they can be aggregated with data from other CS efforts as well as data from other research methodologies (see data access below). Ideally, to ensure long-term data preservation, an archiving strategy should involve more than one copy, use different media technologies, and preserve the datasets at different locations (Eynden et al., 2011; Parsons et al., 2011). Raw data and metadata should also be retained to allow subsequent reprocessing (Danielsen et al., 2020).

## Data Governance

Relevant considerations include privacy and ethical data use, including ensuring the protection of sensitive location-based information, personally identifiable information (PII), and proper use of licensing. CS projects should carefully consider tradeoffs between openness and privacy. For example, while many citizen science projects embrace openness as a scientific ideal and support data re-use, there are also legitimate concerns around the safety of endangered or threatened species and the privacy of citizen science volunteers who may share data from sensitive locations (Bowser et al., 2017; Johnson et al., 2021). Moreover, CS projects should ensure that data ownership and data use rights are clearly stated and reflect the priorities of the volunteers (see also data licenses below).

## Data Documentation

As discussed earlier, assessments of data quality and fitness-for-purpose can be supported with documentation on QA/QC methods on project websites. Documentation is also needed to describe exactly how the data were collected, including information on specific protocols (Assumpção et al., 2018). One opportunity for sharing this information is posting it along with QA/QC methods on project websites. In addition, as existing work on data and metadata standards and supporting platforms continues to evolve, tools such as data catalogs could document standardized information on methodologies for external parties to discover and assess. The field of CS would benefit from increased resources to support data documentation, which promotes confidence in the data as well as reuse.

## Data Access

In terms of data discovery and access, 28% of projects surveyed made data available through a topical or field-based repository (such as the Global Biodiversity Information Facility), 22% through an institutional repository, 11% through a public sector data repository, and 6% through a publication-based repository. This broadly corresponds with the practices by scientists more generally (Tenopir et al., 2015). CS projects can encourage re-use by providing easy access to their data in standardized formats. Multiple download options such as raw and cleaned data, temporal and spatial subsets, and format options such as spreadsheets, geographic formats, and API access can help to eliminate the barriers to use and meet the needs of data users. The ability to subset the data is particularly beneficial in regions with limited bandwidth. Note that broader open science efforts are required to promote open access to citizen science data, along with other types of scientific knowledge.

## Data Licenses

In addition to making data open, additional mechanisms are required to make data findable, accessible, interoperable, and reusable (FAIR; Wilkinson et al., 2016). We recommend the adoption of open, machine-readable licenses. Our research found that Creative Commons licenses are frequently used in citizen science (e.g., CC BY 4.0, which promotes attribution of the data authors but otherwise does not restrict use). While seemingly "progressive" and in keeping with the community ethos of some CS initiatives, the restriction on commercial uses (such as CC BY-NC 2.0) or the inappropriate application of share-alike licenses (such as CC BY-SA 3.0) can prevent third parties from providing value-added data and services based on raw data that are of benefit to society. Other licenses, such as the Open Data Commons Open DataBase License (ODbL), may also be appropriate for projects seeking to maximize data reuse (see Cooper et al., 2021, this Research Topic).

## The Use of CS Data for the SDGs: Challenges and Opportunities

In 2019, as the above work was being finalized, the TG turned its attention to understanding challenges and opportunities for citizen science to contribute to the SDGs. Our findings in this area, based on a 2020 survey of 44 CS initiatives in Sub-Saharan Africa, are more preliminary. We focused on water supply and access (SDG 6) and urban planning and sanitation (SDG 11) out of a recognition that these two areas are of high concern in Africa (Stren, 2019), and the fact that projects in these domains are more likely to be driven by community concerns rather than donor interests (Jameson et al., 2020). The survey was of a representative mix of projects across regions of sub-Saharan Africa, with roughly 39% of projects from West Africa, 27% each from Central and East Africa, and 7% from Central Africa.[3] The authors identified respondents in a number of countries through TG members and regional CS experts, then employed snowball sampling to identify additional respondents. All respondents were directed to the link for a Google form or interviewed in person using the same instrument.

Examples of surveyed projects include the Nigeria Slum/Informal Settlement Federation, the Clean and Green Congo project in the Democratic Republic of Congo, the Citizen Land and Service Project in Ghana, Map Kibera in Nairobi, Kenya, and the AfriWatSan project in Uganda. Domains represented by the CS projects (in descending order of frequency considered in our survey) include mapping of resources, urban planning, urban sanitation, ecosystems and ecology, disaster risk management, and transportation, among others. Common tools used by the projects include smartphones, sensors, test kits, and a variety of geospatial tools (GPS, GIS, OpenStreetMap, etc.) and the primary purposes were to educate the public, advance research and ensure that evidence-based policies are enacted.

## Findings

Our findings suggest that CS projects have the potential to contribute to SDG tracking through participatory data collection, standardized data collection across cities, and improved data accessibility for decision making and science. Perhaps the two most important contributions from an equity lens are in understanding community perspectives and generating data at local levels (which are critical for the Leave No One Behind focus of the 2030 Agenda), and promoting the empowerment of communities to negotiate with authorities on service delivery. However, barriers still remain to getting citizen science used in SDG reporting, due to issues such as an inherent lack of trust in citizen-generated data, as well as (in some cases) inconsistent adherence to best practices for data management, including those described above.

While the use of citizen-generated data by decision makers is not yet widespread, trust and acceptability have been found to increase the chances of data use. City officials in Lagos have used CS generated data to select communities for revitalization and service provision, and National Statistical Offices (NSOs) in Kenya and Ghana have expressed openness to CS generated data on the grounds that data are scarce, no agency can monitor all 17 SDGs, and such data can mobilize community and government cooperation. Some specific examples of data use by governments came out of SDG6-related projects in southern Africa. For example, the uMkhomazi Landscape Restoration Project in South Africa states that the government is supportive and is seeking to integrate data from citizen science into catchment management, whereas WaterAid in Eswatini (former Swaziland) mentioned decision makers' understanding of the potential to use the data to inform better planning and budgeting for water supplies, however financial constraints have limited government action.

Recognizing that most citizen groups are not trained in the processes developed by NSOs to ensure the consistent collection of robust data, citizen-generated data may need to be validated by an NSO before inclusion in official SDG reporting. It has been suggested that such data may therefore be viewed mainly as a complement to data from conventional sources and could be provided alongside official statistics. Viewed from the CS perspective, Jameson et al. (2020) argue that citizen science in low-income contexts should not only be viewed in terms of the value of data production but also as a means of empowering and engaging communities. Thus, rather than requiring that citizen scientists adhere to rigorous protocols and sustain data collection efforts over long periods, CS projects are perhaps best positioned to identify gaps in data acquisition and to highlight community concerns, and as a tool for lobbying for better services and hopefully sustained and consistent data collection by government agencies on issues of importance to communities.

## Enabling Citizen Science Contributions

The complexity of the SDG indicators suggests that they have not been developed with a view to enabling lay-people to monitor them (Fritz et al., 2019). Where CS groups do wish to contribute to sustained monitoring of SDG progress, they need tools to do so. Thanks to multiple interactions of members of the TG with experts at the UN, governments and NSOs on one side, and citizens in the field on the other, it became clear that some of the limits to engagement and adoption of improved data collection practices lie in misunderstanding and miscommunication between the two groups. The requirements that bodies like the UN and NSOs have for data, including quantity, quality, collection procedures, and the needs for specific measurements are quite strict. For CS data to be useful in this context, CS groups need to be aware of such criteria. However, the jargon and complexity of official requirements is often impenetrable to citizen groups, which can represent a barrier to engagement.

In order to explore the extent of this challenge, we sought to demystify the official requirements for a selection of SDG indicators by translating them into layperson's language. The

[3] Almost half of the projects were in Nigeria and South Africa, which reflects TG member contacts but may also very well reflect high engagement with CS in these two countries. The team found it difficult to locate CS representatives without in-country contacts who could identify the main actors and provide up-to-date email addresses or cell phone numbers, since most information on the Internet is unreliable.

TG worked with five indicators and produced for each a compendium[4] including concepts and definitions of the goal, target and indicator; a global overview on the current progress in attaining the target; the computation method and an example of implementation; the rationale, significance and consequences of implementing the indicator; and suggestions on how a citizen can participate and contribute. Documentation is necessary to raise awareness on how data need to be collected for selected SDG indicators, and to present citizen science projects with clear opportunities for participation.

Also, those seeking to re-use CS data—particularly for national or international reporting and assessment processes—need to meet citizen science projects halfway (Eicken et al., 2021). Even when citizen science projects are following scientific best practices for collecting, analyzing, and sharing data, governing bodies like the UN typically have additional requirements for monitoring and assessment processes. For example, efforts are underway to promote CS contributions to reporting progress on SDG 14.1.1.b, which assesses plastics pollution in oceans, by including an indicator for citizen science collected data on beach litter (Campbell et al., 2019). A UN advisory group produced an 138-page report on plastics pollution (Joint Group of Experts on the Scientific Technical Aspects of Marine Environmental Protection (GESAMP), 2019) that is too dense and detailed for most individuals or citizen science groups. Recognizing a gap to be filled between such detailed guidelines and the need for actionable, on-the-ground guidelines, UNEP convened a workshop in December 2020 to discuss how to effectively leverage citizen science for SDG reporting that considered both UNEP and CS perspectives. Similar efforts around SDGs 6, 11, and others could further bridge lingering gaps.

That said, whereas some types of indicators are amenable to involvement of local stakeholders in their monitoring (Danielsen et al., 2013), others are best suited to expert-driven assessment (e.g., indicators that require a national overview or detailed knowledge of administrative or legislative aspects). This suggests that just as citizen science data may be fit for a particular purpose, participation through citizen science should also be conducted with explicit acknowledgment of achievable end goals that benefit data users and citizens alike.

[4]To access these "how to" guides, follow the link in footnote 2. Goal 3: good health and well-being - target 3.1: by 2030, reduce the global maternity ratio to less than 70 per 100,000 live births—indicator 3.1.1: maternal mortality ratio; Goal 11: sustainable cities and communities—target 11.6: by 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management—indicator 11.6.1: proportion of municipal solid waste collected and managed in controlled facilities out of total municipal waste generated, by cities; Goal 13: climate action—target 13.1: strengthen resilience and adaptive capacity to climate related hazards and natural disasters in all countries—indicator 13.1.2: number of countries that adopt and implement disaster risk reduction (DRR) strategies in line with the Sendai Framework for DRR 2015-2030; Goal 15: life on land—target 15.5: take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species—indicator 15.5.1: red list index.

## DISCUSSION

In order to leverage the potential of citizen science to address grand challenges like the SDGs, more work is needed, both on good data practices, and on alignment between data and decision-making. The ISC's action plan for 2019–2021, *Advancing Science as a Global Public Good* (International Science Council (ISC), 2019), revolves around four domains considered as the major challenges for society to which science—and the ISC as a global voice for science—must respond. The fact that the first of these challenge domains is "The 2030 Agenda for Sustainable Development" highlights the ISC's leadership role in the post-2015 development processes of the United Nations, and its strong commitment to work with its members and other international scientific organizations, funders, government agencies, NGOs and the prívate sector toward meeting the SDGs.

CODATA's strategic plan focuses, among other things, on the contribution of research data and analysis to indicators supporting the 2030 Agenda and the Sendai Framework for Disaster Risk Reduction. This is part of a broader effort on making data work for cross-domain grand challenges, including data interoperability and reuse—i.e., FAIR data. It is important for the CS community and domain experts to continue to develop agreed upon standards and ontologies for data access and integration (i.e., accessibility and interoperability). The CODATA-RDA School of Research Data Science, a strategic program to train early career researchers from low and middle income countries in data skills, has developed short courses and held summer schools over the last 5 years. The school is open to CS practitioners and could be a valuable mechanism for them to gain additional data science skills.

For its part, WDS underscores in its 2019–2023 Strategic Plan the importance of all scientific data being preserved for the long-term in trustworthy data repositories, including citizen-generated data (World Data System (WDS), 2019). This is vital to both the integrity and the acceleration of science, since it moves toward FAIR data practices for current and future generations of scientists seeking to address the grand challenges. WDS encourages citizen science groups that maintain their own data holdings to become TDRs by becoming CoreTrustSeal certified,[5] and ultimately WDS Regular Members. This would ensure that they become more integral parts of the research data infrastructure through involvement in international collaborative programmes sponsored by ISC and beyond.

The work by the Task Group has contributed to a better understanding of the data management practices and needs of the CS community, including practical challenges facing smaller groups with limited financial and human resources. Clearly, given the range in scales and foci of activities among CS groups globally, a one-size-fits-all strategy will not work. And, as mentioned, the primary goal of all CS projects is often not data generation (Johnson et al., 2021). But, for medium- to large-sized data generating CS projects, the TG supports efforts to develop standards and to incorporate CS data into global research data infrastructure–as is already happening with ornithological data

[5]For more information visit https://www.coretrustseal.org/.

collected by eBird, which is deposited in the Global Biodiversity Information Facility (GBIF), a WDS regular member (Chandler et al., 2017). The TG also recognizes that citizen science projects often unfold in environments with limited resources. While we believe that identifying and recommending good data practices will help advance the field and enable more scientific research, we also understand that additional work will be needed to help citizen science projects translate these recommendations into concrete practices.

In 2021, the TG is developing a report on CS for SDGs 6 and 11 in Sub-Saharan Africa that will include practical guidelines for CS groups wanting to contribute to SDG monitoring in the urban water, sanitation and environmental planning domains. This can support the work of urban managers and UN agencies such as UN-HABITAT, as well as highlight the way citizen engagement can improve the lot of millions of urban residents across the continent.

## DATA AVAILABILITY STATEMENT

The data analyzed in this study is subject to the following licenses/restrictions: The data are preliminary. Requests to access these datasets should be directed to pelias@unilag.edu.ng.

## AUTHOR CONTRIBUTIONS

The article development was led by AdS, AB, T-RC, CC, FD, RE, EF, CH, RM, and IP contributed text to the article. AdS, AB, CC, PE, EF, RM, AS, and KS contributed to research efforts the findings from which are presented in this article. All authors contributed to the article and approved the submitted version.

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DATA REPORT
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# Over 30 Years of Standardized Bird Counts at Supplementary Feeding Stations in North America: A Citizen Science Data Report for Project FeederWatch

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**Keywords: birds, citizen science, occupancy modeling, place-based dataset, Project FeederWatch, supplementary feeding**

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## INTRODUCTION

Citizen science datasets are becoming increasingly important means by which researchers can study ecological systems on geographic and temporal scales that would be otherwise impossible (Kullenberg and Kasperowski, 2016). Birds are both a tractable study taxa for citizen science efforts, and an indicator of broad ecological and evolutionary themes such a climate change and anthropogenic habitat modification, invasive species dynamics and disease ecology (Bock and Root, 1981; Link and Sauer, 1998; Bonney et al., 2009), to name a few. Enjoying birds around one's home may seem like an ephemeral pastime, but in the context of citizen science, such a pastime has built a multi-decade long, continent-wide dataset of bird abundance through the program Project FeederWatch (hereafter, FeederWatch).

FeederWatch is a place-based citizen science program that asks participants to identify and count the birds that visit the area around their home, particularly focused around supplementary feeding stations (i.e., bird feeders). Place-based datasets provide a unique view of change through time and engage participants in long-term data collection from a single location, inspiring them to engage more deeply in the preservation of the place they study (Loss et al., 2015; Haywood et al., 2016). The concept of FeederWatch began when Erica Dunn of Canada's Long Point Bird Observatory established the Ontario Bird Feeder Survey in 1976 (Dunn, 1986). Ten years later, in 1986, the organizers expanded the survey to cover all provinces in Canada and states in the United States by partnering with the Cornell Lab of Ornithology to create the program now called Project FeederWatch (Wells et al., 1998). In the winter of 1987-88, more than 4,000 people enrolled and began counting birds following the current counting protocol. Since then, the number of project participants has grown to $>$ 25,000 annually across the U.S. and Canada, approximately half of which submit bird checklists (**Figure 1A**). The program collates ~180,000 checklists annually (as of the 2019-2020 season) with submissions increasing over time (**Figure 1B**). FeederWatch continues to be a cooperative research project of the Cornell Lab of Ornithology and Birds Canada (formerly the Long Point Bird Observatory and later Bird Studies Canada) and has an inter-annual participant retention rate of ~60–70%.

Data from FeederWatch have been used in dozens of scientific publications, ranging in topic from invasive species dynamics (Bonter et al., 2010), disease ecology (Hartup et al., 2001), irruptive movements (Dunn, 2019), predator-prey interactions (McCabe et al., 2018), range expansions (Greig et al., 2017), dominance hierarchies (Leighton et al., 2018) and climate change (Zuckerberg et al., 2011; Prince and Zuckerberg, 2014). Studies use either the standard protocol bird count dataset, which is the dataset we describe here, or supplementary data protocols such as reports of signs of disease (Hartup et al., 2001), reports of behavioral interactions (Miller et al., 2017) or reports of window strike mortality (Dunn, 1993). Irrespective of the exact data type being collected, the strength of the FeederWatch dataset lies in the repeated observations made from the same location over time, which creates a data structure perfectly suited to occupancy modeling or repeated measures analyses. It also cultivates long-term participation in the project, which is predicted to increase data accuracy because participants are expected to improve their data collection skills the longer they participate (Kelling et al., 2015).

# METHODS

## Data Collection Protocol

Participants follow a standardized counting protocol to record all the bird species they see around their count site, typically their home, and typically in the proximity of supplementary feeding stations or other resources (e.g., water or plantings). Specifically, participants count the maximum number of each bird species seen in their count site over a 2-day checklist period. By requiring that participants only report the maximum number of each species in view simultaneously during the checklist period, the protocol ensures that participants are not repeatedly recording the same individuals multiple times within a single checklist. Further, the protocol requires that participants submit complete checklists of all bird species observed, allowing for the inference of zeros (i.e., both detection and non-detection) in all checklists. These checklists are conducted from late fall through early spring in the northern hemisphere (November to April each year, the FeederWatch "season"). Participants can submit checklists as often as once per week within this time frame. For each checklist, participants are required to report two categorical measures of observation effort (detailed below). Participants also record a categorical estimate of snow cover. Historically, participants were asked to record additional weather variables during their checklist periods, but with the availability of large-scale climate datasets, collection of additional weather data has been discontinued. The protocol instructions provided to participants are available on the project web site (https://feederwatch.org/about/detailed-instructions/).

Because the FeederWatch protocol is a repeated measures design, participants are reporting from the same location as often as weekly, with many people reporting for many years. As such, it is useful to capture a description of the participant's count site and supplementary feeding procedures and how those change over time. Annually, participants can describe their count site on a form that records information about habitat, resources, and threats to birds. Completing the site description is not compulsory, so not every location has a complete site description for every year of participation (site description data were provided for 72% of count sites during the 2019-2020 season). Although the site description information is not available for all locations, this information can be useful for addressing specific research questions. For example, researchers may be interested in the effects of supplementary food type or amount on the detectability or occupancy of bird species in the community (e.g., Greig et al., 2017). Details of the 57 data fields recorded by participants on the site description form are available in the data repository.

## Data Validation

All FeederWatch checklists are passed through geographically and temporally explicit filters to flag observations that are unexpected for any species in a particular state/province or month (Bonter and Cooper, 2012). The flagging system takes into account the FeederWatch protocol which instructs that participants record the maximum number of each species in view simultaneously. Because the territorial and flocking behavior of species limits the maximum number of each species that is likely to be viewed in a single location at the same time, the system filters were set to trigger a flag if the count reported exceeded three standard deviations from the mean for each species/state or province combination. Count limits were originally calculated based on FeederWatch data submitted prior to the 2006 season and have been manually adjusted over time (e.g., to allow for range expansions). Therefore, the flagging system is not only triggered by a species reported outside of its typical geographic range (e.g., 1 Verdin, *Auriparus flaviceps*, in Maine), but also by unusually high counts (e.g., 30 Black-capped Chickadees, *Poecile atricapillus*) and by species rarely seen in the context of backyard bird feeding (e.g., waterfowl and migratory warblers). Over time the flagging system has become more sophisticated. Since 2014, a real-time data entry trigger has been used to flag suspect observations, whereby the participant entering the count is immediately asked to review and confirm that their entry is correct. This provides an opportunity for participants to correct typographical errors or identification mistakes before they are entered into the database. If the participant chooses to enter their flagged observation into the database, it is automatically entered into the manual review system to be checked by an expert reviewer before being accepted as valid, corrected, or left flagged as an unexpected observation. Flagged observations are identified in the database as "0" in the VALID field and their status in the review process is described using a combination of the VALID field and the REVIEWED field as defined here:

VALID = 0; REVIEWED = 0; Interpretation: Observation triggered a flag by the automated system and awaits the review process. Note that such observations should only be used with caution.

VALID = 0; REVIEWED = 1; Interpretation: Observation triggered a flag by the automated system and was reviewed; insufficient evidence was provided to confirm the observation. Note that such observations should not be used for most analyses.

VALID = 1; REVIEWED = 0; Interpretation: Observation did not trigger the automatic flagging system and was accepted into the database without review.

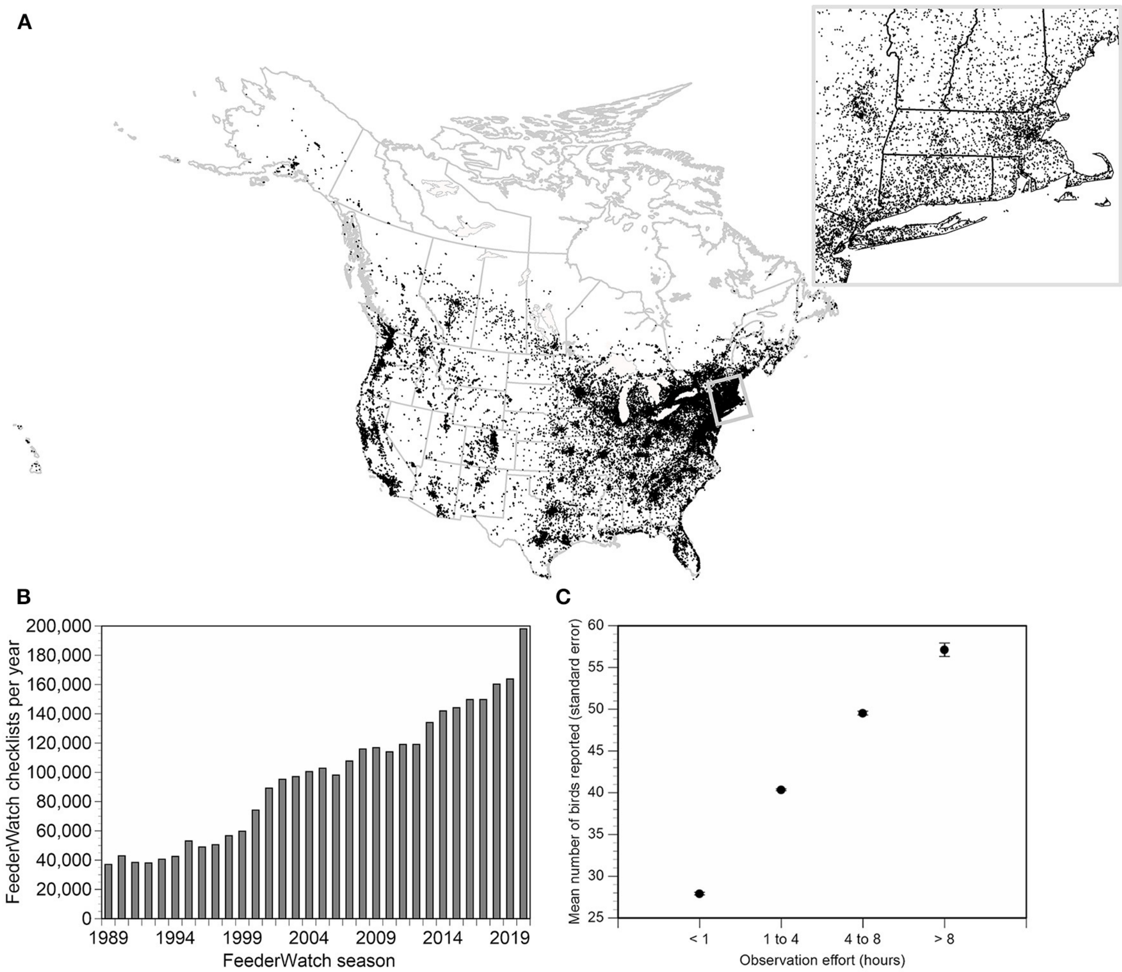


**FIGURE 1 | (A)** Map of locations from which Project FeederWatch participants have submitted data (all sites, 1989–2020, $N = 65{,}237$ locations). The inset box provides detail of an example area of northeastern North America to better illustrate the density of sampling locations. **(B)** Total number of checklists submitted to Project FeederWatch by year. **(C)** Mean (± standard error) number of birds reported per checklist as a function of observation effort (categorical: < 1 h of effort, 1–4 h, 4–8 h, > 8 h). All years and sites combined.

VALID = 1; REVIEWED = 1; Interpretation: Observation triggered the flagging system and was approved by an expert reviewer.

The decisions of expert reviewers are based on a knowledge of bird biology and supporting information from the participant in the form of a description, photo, or confirmation that they are following the counting protocol correctly. All reports irrespective of their VALID or REVIEWED status are included in the full dataset, because incorrect identifications may themselves be of interest to researchers. For example, this dataset could be used to study longitudinal changes through time in participant data collection accuracy. It is up to researchers to appropriately remove invalid and unreviewed sightings from their analysis. Note that the overall proportion of flagged records is small relative to the entire dataset; of the 34,074,558 observations submitted from 1988 to 2020, only 516,614 (1.52%) were flagged for review, and only 48,417 (0.14%) were permanently flagged following review due to lack of supporting evidence.

Undoubtedly, some of the presumed valid reports in the database involve incorrect identifications that have not triggered a flag (e.g., misidentification of one common species for another), or reports by participants who do not correctly follow the FeederWatch protocol but whose incorrect counts are within the range permitted by the filter system. Researchers may want to consider lumping similar-looking species in some analyses depending on their questions, for example Black-capped and Carolina Chickadees (*Poecile carolinensis*) in the areas where populations overlap and hybridize, or Cooper's and Sharp-shinned Hawks (*Accipiter cooperii and A. striatus*), which are difficult to distinguish throughout their ranges. Despite the fact that a dataset of this temporal and geographic scale must contain some imperfections, there is consistency in avian population trends found with FeederWatch and other indices of bird abundance (e.g., Christmas Bird Counts; Lepage and Francis, 2002). This suggests that unidentified errors do not drive broad patterns in the data, and that FeederWatch data provide biologically meaningful insights.

# DATASET

## Dataset Structure

There are two datasets that are the primary Project FeederWatch data: (1) the checklists (i.e., the bird counts) and (2) the site descriptions. The key data fields associated with these datasets are listed in **Table 1**, with a complete dictionary of data fields included with the raw data files in the open access data repository. The "data level" column in **Table 1** defines levels of organization of the dataset, of which there are four levels: (1) "site level," referring to fixed data associated with the site, or location, at which the observations are made (e.g., the latitude and longitude); (2) "season level," which are site-level descriptors that may (or may not) change from one season to the next (e.g., number of feeders maintained), (3) "checklist level," referring to variables shared across a single checklist (e.g., date and sampling effort), and (4) "observation level," referring to aspects of an individual species count within a checklist (e.g., the number of Black-capped Chickadees observed). When combining raw data from the checklists and site descriptions, researchers should link datasets using location (LOC_ID) and year (PROJ_PERIOD_ID). The data are organized for easy incorporation into a occupancy modeling framework (Fiske and Chandler, 2011). Specifically, the site-level variables are static across seasons and equivalent to site-level covariates. Season-level variables are dynamic across seasons and equivalent to season-level covariates. The season-level also includes the year in which a series of checklists were made, equivalent to the primary sampling period. Checklist- and observation-level variables are equivalent to "visits" or "observations" using the occupancy modeling terminology in Fiske and Chandler (2011).

Data are either binary (e.g., whether or not cats are present at the site), categorical (e.g., the approximate depth of snow cover), continuous (e.g., the number of chickadees observed on a checklist), or a date, indicated by the "data type" column in **Table 1**. The data are either entered by participants (e.g., the number of suet feeders provided) or assigned automatically by the database (e.g., the unique LOC_ID for every location), indicated by the "data entry" column in the data dictionary housed with the raw data. Categorical variables entered by participants are constrained by drop-down menu options or check boxes at the time of data entry.

The dataset is stored with all observations of presence recorded, but observations of absence are not recorded. Because the FeederWatch protocol instructs participants to record all species seen within the count area, researchers can infer absence for any species of interest by assuming that if it was not reported on a particular checklist (i.e., a particular SUB_ID), it was not observed. It is necessary for researchers to zero-fill the data themselves for their species of interest. This zero-filling can be accomplished by extracting a list of unique checklists (SUB_ID values), filling the HOW_MANY field for the species of interest with zeros, then overwriting the zeros with actual counts for the species on the checklists (SUB_ID values) in which the species was observed.

## Interpretation and Use

The content of most data fields is self-explanatory from **Table 1**, but there are a few details to be aware of when interpreting some fields. The latitude and longitude fields are identified with varying degrees of accuracy depending upon how participants submitted their data and how locations were estimated. Prior to 2000, all data were submitted on paper forms (identified as "paper" in the DATA_ENTRY_METHOD field) and all sites were given the latitude and longitude of the centroid of the ZIP code (United States) or postal code (Canada), and identified as "POSTCODE LAT/LONG LOOKUP" in the ENTRY_TECHNIQUE field. The online data entry system was developed in late 1999 and, since then, a series of mapping tools with varying degrees of location accuracy have been implemented, most of which tie into Google Maps Application Programming Interfaces (APIs). These systems are identified in the ENTRY_TECHNIQUE field. Researchers seeking high spatial accuracy should exclude sites created using the centroid of the ZIP/postal code (e.g., when linking observations to high resolution land cover and weather datasets). Locations are subject to some degree of error because participants are responsible for inputting their site location and any changes in that location over time (e.g., if the participant moves). However, participants are likely self-motivated to maintain the accuracy of their site location, because they themselves wish to accurately monitor their site's birds through time using the data outputs provided on the FeederWatch website.

While the data collection protocols have remained fixed over time, data entry methods have changed, with implications for data interpretation. Before 2004, the paper data forms had boxes that only accommodated values up to 9, 99, or 999 for some species (the maximum value allowed varied depending on the typical flocking behavior of the species). If the participant observed a larger number of a species than could be accommodated on the paper forms, then they recorded the maximum number permitted on the data form and marked the "Plus_Code" field as "1." These observations should be interpreted with caution because there is no way to know the true number of birds observed by the participant.

In 2018, the Cornell Lab of Ornithology released a mobile phone application for FeederWatch data entry. The mode of data entry is documented in the DATA_ENTRY_METHOD field. The codes are continuously evolving with new releases of the web and mobile apps but should be self-explanatory and can be functionally distilled to the three modes of data entry (web vs. mobile vs. paper). Because the mobile app is a new development, we have not yet attempted to quantify any potential differences in observations submitted using the mobile vs. web-based apps.

Previous research clearly demonstrates the importance of including sampling effort in analyses of FeederWatch data (e.g., Zuckerberg et al., 2011; Prince and Zuckerberg, 2014; Greig et al., 2017). There are two measures of effort within the dataset. The EFFORT_HRS_ATLEAST field records a 4-level

**TABLE 1 |** List of variables provided in project FeederWatch database.

| Variable name | Data level | Data type | Definition |
|---|---|---|---|
| LOC_ID | Site | Categorical | Unique identifier for each survey site |
| LATITUDE | Site | Continuous | Latitude in decimal degrees for survey site |
| LONGITUDE | Site | Continuous | Longitude in decimal degrees for survey site |
| SUBNATIONAL1_CODE | Site | Categorical | Country and State/Province abbreviation of survey site |
| ENTRY_TECHNIQUE | Site | Categorical | Method of site localization |
| SUB_ID | Checklist | Categorical | Unique identifier for each checklist |
| OBS_ID | Observation | Categorical | Unique identifier for each species observation |
| Date* | Checklist | Date | Date of 1st day of checklist (*three fields) |
| PROJ_PERIOD_ID | Season | Categorical | Calendar year of FeederWatch season end |
| SPECIES_CODE | Observation | Categorical | Bird species observed, stored as 6-letter species codes |
| HOW_MANY | Observation | Continuous | Number of individuals seen during observation period |
| VALID | Observation | Binary | Validity of observation based on flagging system |
| REVIEWED | Observation | Binary | Review state of observation based on flagging system |
| PLUS_CODE | Observation | Binary | If number of individuals seen was maximum possible |
| Number of half days* | Checklist | Binary | Time frames the site was observed (*four fields) |
| EFFORT_HRS_ATLEAST | Checklist | Categorical | Participant estimated survey time for each checklist |
| SNOW_DEP_ATLEAST | Checklist | Categorical | Participant estimated minimum snow depth |
| DATA_ENTRY_METHOD | Checklist | Categorical | Data entry method for each checklist |
| Yard type* | Season | Binary | Features of yard (*five fields) |
| Habitat type* | Season | Binary | Features of surrounding habitat (*fourteen fields) |
| Trees/shrubs* | Season | Categorical | Types of surrounding vegetation (*six fields) |
| Brush pile/water* | Season | Categorical | Presence of brush piles or water sources (*three fields) |
| NEARBY_FEEDERS | Season | Binary | If other feeders regularly operate within 90 m |
| Other animals* | Season | Binary | If squirrels, cats, dogs or humans present (*four fields) |
| HOUSING_DENSITY | Season | Categorical | Participant estimated housing density of neighborhood |
| Feeding schedule* | Season | Binary | Which months food is provided (*thirteen fields) |
| Feeder numbers by type* | Season | Continuous | Number and types of feeders provided (*eight fields) |
| POPULATION_ATLEAST | Season | Categorical | Participant estimated population of city or town |
| COUNT_AREA_SIZE | Season | Categorical | Participant estimated area of survey site |
| CREATION_DT | Site | Date | Date of site creation |
| LAST_EDITED_DT | Site | Date | Date of last site location edit |

*Asterisks indicate the information is stored as multiple fields in the database. Variables in all capital letters are the actual field names.*

categorical measure of observation effort (< 1, 1–4, 4–8, > 8 h). The second measure of effort divides the 2-day observation period into 4 half days, with the observer recording whether or not they observed their feeders during each of the four half-day periods. The series of four fields, labeled DAY1_AM, DAY1_PM, DAY2_AM, DAY2_PM, is often aggregated into a derived metric of the number of half-days that the participant spent observing during one checklist. Typically, the greater the sampling effort, the greater the number of species and individuals observed (**Figure 1C**).

Researchers may want to consider using occupancy modeling frameworks (e.g., Fiske and Chandler, 2011) when analyzing FeederWatch data because the data structure is well-suited to this form of analysis. Occupancy modeling allows for inferences about both presence/absence, abundance, and behavior. For example, finding complementary patterns in occupancy and detectability for a species across some environmental gradient may suggest changes in abundance (e.g., Zuckerberg et al., 2011). However, finding contrasting patterns in occupancy and detectability over an environmental gradient may suggest changes in behavior (e.g., Greig et al., 2017). As always, researchers should interpret data with care and within the context of the biological system being studied. Other modeling approaches can also be appropriate, such as generalized linear mixed models (GLMMs) because of the repeated counts from the same locations (e.g., Bonter and Harvey, 2008), as well as general algebraic modeling system (GAMS) approaches.

## Data Access

Raw data from 1989-present are available in the Mendeley data repository with the most permissive open access level (doi: 10.17632/cptx336tt5.1). Data are also available with open access from the FeederWatch website maintained by the Cornell Lab of Ornithology (https://feederwatch.org/explore/raw-dataset-requests/). FeederWatch is an ongoing program and future data updates will be added to the Cornell Lab of Ornithology website. Data are updated annually around June 1.

## DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: https://data.mendeley.com/datasets/cptx336tt5/1.

## ETHICS STATEMENT

The animal study was reviewed and approved by Cornell University Institutional Animal Care and Use Committee (protocol #2008-0083).

## AUTHOR CONTRIBUTIONS

DB conceptualized the manuscript, prepared and revised the presentation of raw data, and revised the manuscript. EG conceptualized the manuscript, wrote and revised the manuscript, and revised the presentation of raw data. All authors contributed to the article and approved the submitted version.

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# Perspectives on Citizen Science Data Quality

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Information about data quality helps potential data users to determine whether and how data can be used and enables the analysis and interpretation of such data. Providing data quality information improves opportunities for data reuse by increasing the trustworthiness of the data. Recognizing the need for improving the quality of citizen science data, we describe quality assessment and quality control (QA/QC) issues for these data and offer perspectives on aspects of improving or ensuring citizen science data quality and for conducting research on related issues.

**Keywords: citizen science, data quality, information quality, citizen science data, citizen science methods**

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## INTRODUCTION

Citizen science (CS) is recognized as having broad potential benefits to society. Citizen science projects are providing unique and sometimes fundamental scientific insights and offer a wide variety of scientific outcomes (Pettibone et al., 2017; Paul et al., 2018; Wiggins et al., 2018; Bautista-Puig et al., 2019; Miller et al., 2019; van Etten et al., 2019). Citizen science also offers opportunities for efficiently collecting data that otherwise might not be obtainable in a practical manner (Li et al., 2019; Van Eupen et al., 2021). Citizen science data (CSD) provides valuable environmental measurements and observations that can be used independently and in conjunction with other data products and services to improve research and decision making capabilities (Robinson et al., 2018; Poisson et al., 2020). Especially given the increased opportunity to supplement traditional scientific data with CSD, it is essential that the CSD be as trustworthy and of known quality as other scientific data (Swanson et al., 2016; Aceves-Bueno et al., 2017; Budde et al., 2017; Burgess et al., 2017; Kallimanis et al., 2017; Steger et al., 2017; Sandahl and Tøttrup, 2020). Information about the quality of CSD builds trust, provides opportunities for potential users to discover CSD that are appropriate for their purposes, and enables users to determine whether and how the data can be used to meet their objectives (Alabri and Hunter, 2010; Hunter et al., 2013; Freitag et al., 2016; Lukyanenko et al., 2016; Stevenson, 2018; Anhalt-Depies et al., 2019). The quality of CSD also can influence the analysis and interpretation of the data (Kelling et al., 2015; Clare et al., 2019). Quality information is important for scientific data, including CSD (Roman et al., 2017; Gharaibeh et al., 2019). Citizen science data contributes to many scientific endeavors that are important for environmental science and for the well-being of society, including sustainable development, humanitarian efforts, and disaster prevention and response (Hicks et al., 2019; Fraisl et al., 2020). Providing data quality information can improve opportunities for CS to contribute to important societal efforts and to the reuse of CSD (Kosmala et al., 2016; Hecker et al., 2019; Shanley et al., 2019).

While CS initiatives offer possibilities for obtaining observations and gathering data that supplement traditional data collection on important environmental issues, there is healthy skepticism about the quality of CSD (Brown and Williams, 2019; Cross, 2019). Fritz et al. (2019) indicate that uncertainty regarding quality of the data is a major barrier to the use of CSD, despite their value for the United Nations Sustainable Development Goals (SDGs). They also provide examples of several activities where steps have been taken to ensure that CSD are of high (and known) quality. Earp and Liconti (2020) describe the disparity between benefits of using marine CSD for research and perceptions of quality. Incompatible design of CS studies and inconsistencies in nomenclature also can affect data quality, resulting in challenges for integrating data from different CS programs (Campbell et al., 2020). User interfaces of digital tools provided to participants also can affect CSD quality (Sharma et al., 2019; Torre et al., 2019). Studying CSD management practices, Bowser et al. concluded: "While significant quality assurance/quality control (QA/QC) checks are taken across the data lifecycle, these are not always documented in a standardized way" (Bowser et al., 2020, p. 12). Recognizing a perceived bias among scientists regarding the use of CSD, Albus et al. (2019) reviewed comparison studies that were conducted on volunteer and professional data collection efforts for large-scale water quality projects, concluding that more comparison studies are needed and that such studies should include accuracy, while controlling for variations among the datasets that are compared.

Considering such concerns about the quality of CSD, as well as other data, and how data quality can affect data and their use, the Earth Science Information Partners (ESIP) Information Quality Cluster (IQC) is attempting to provide recommendations on practices to help ensure or improve CSD quality and build trust for CSD in the scientific community. This manuscript aims to lay out ESIP IQC's perspectives on the existing challenges and important aspects of CSD quality that should be tackled by the community in the near future.

In section ESIP Information Quality Cluster, activities of the ESIP Information Quality Cluster, relevant to CSD, are introduced along with four quality dimensions that occur throughout the data lifecycle. Section Challenges and Approaches for Improving CSD Quality introduces challenges, directions, and approaches for improving the quality of CSD. The first subsection offers a brief overview of opportunities for improving CSD quality during the recruitment, selection, self-selection, and training of CS volunteers. The second subsection describes selected issues that pertain to transparency of information about QA/QC practices during the production of CSD. The third subsection describes the importance of documenting CSD quality. The fourth subsection describes the importance of and need for establishing rubrics for evaluating CSD quality levels. Section Discussion concludes the paper with a discussion of these CSD quality issues and offers recommendations for progressively improving the quality of CSD.

## ESIP INFORMATION QUALITY CLUSTER

The ESIP IQC studies and promotes the awareness of data and information quality (Ramapriyan et al., 2017). Like other ESIP Collaboration Areas (ESIP, 2020), the IQC reflects perspectives of various partner organizations that contribute to the collection, curation, dissemination, and interdisciplinary use of Earth science data. Information Quality Cluster activities include regular meetings, workshops, conference sessions, white papers, and journal publications. Information Quality Cluster activities also leverage the work of the NASA Earth Science Data System Working Group (ESDSWG) on Data Quality, which was active during 2014–2019 and completed its recommendations to the NASA Earth Science Data and Information System Project (NASA, 2020a). The IQC also organized sessions on CS during recent ESIP meetings. Directly related to data quality concerns for CS and other types of studies, the IQC recently began developing guidelines for documenting and enabling the sharing and reuse of data quality information (Peng et al., 2020). The strength of the IQC is in its membership, consisting of experts in data and information quality from various organizations and disciplines, and promoting collaboration among them and resulting in synergy for developing recommendations with broad applicability.

## CHALLENGES AND APPROACHES FOR IMPROVING CSD QUALITY

Applying CSD can be problematic if researchers and other users are not aware of data quality issues that could affect their analyses, contributions, or operational uses. However, there are several challenges for improving CSD quality. Assessing CSD quality can be extremely difficult due to heterogeneous observers and methods and lack of information about such methods. In particular, data bias, errors, uncertainty, and ethical issues pose challenges that should be assessed regularly as part of CS research projects. These and other challenges that occur throughout the data lifecycle are being investigated in an effort to improve the quality of CSD.

Taking a lifecycle approach can help CSD investigators to consider data quality issues and improve the information about data quality that is recorded and provided to users along with the data. The term, data lifecycle, has been defined variously with different levels of detail by different groups. For example, at a very high level, the NOAA Environmental Data Management Framework shows three types of activities—Planning and Production, Data Management, and Usage—in that order, but with feedback from each to the previous type of activity (NOAA, 2013). The US Geological Survey (USGS) defines a science data lifecycle model consisting of the following activities: "Plan, Acquire, Process, Analyze, Preserve and Publish/Share" (Henkel et al., 2015), with cross-cutting activities including "Describe (including metadata and documentation), Manage Quality, and Backup and Secure" (Henkel et al., 2015), thus emphasizing that management of quality cuts across all parts of the lifecycle (Faundeen et al., 2013). Strasser et al. (2012, p. 3) define a data lifecycle with eight components: "Plan, Collect, Assure, Describe, Preserve, Discover, Integrate, and Analyze." Ramapriyan et al. (2017) consider information quality (i.e., quality of information about data quality) throughout the entire lifecycle to be four-dimensional. These dimensions, also referred to as aspects of information quality, are: 1. Scientific quality, 2. Product quality, 3. Stewardship quality, and 4. Service quality. Activities that focus on these four dimensions can be regarded as constituting four stages in the lifecycle. The specific activities of the four stages and their mappings to the four dimensions are: "1. Define, develop, and validate; 2. Produce, assess, and deliver (to an archive or data distributor); 3. Maintain, preserve, and disseminate; and 4. Enable data use, provide data services and user support" (Ramapriyan et al., 2017). **Figure 1** depicts data lifecycle stages with each of these activities represented within the four quality dimensions.

Regardless of the terminology used and the level of detail into which the data lifecycle is subdivided, it is important that characterizing and documenting data quality is considered within each stage of the lifecycle. For convenience of discussion, the terms, stages 1–4, as defined, above, in terms of the four quality dimensions, are used in sections Recruitment, Selection, Self-Selection, and Training of CSD Contributors, Transparency in Information about QA/QC Practices during the Data Production Process, Documenting Data Quality to Facilitate Discovery and Reuse, and Establishing Rubrics for Evaluating Quality Levels of CSD to indicate when the recommended actions need to be taken during CSD projects.

Information about the quality of data, including CSD, should be recorded throughout the data lifecycle to improve data for potential use and reuse. Effective planning is critical to the success of a CS project (Freitag et al., 2016) and improved data stewardship (Peng et al., 2018). Considering data quality during the earliest stages of the data project can improve planning and enable the research team to identify issues that could affect data quality later during the project. A framework for data quality issues to be considered while planning and designing CSD research is offered by Wiggins et al. (2011) for applying data quality and validation methods throughout the research process. In particular, when planning the CSD project, the questions and techniques identified by Kosmala et al. (2016) provide a good starting point for investigators and also provide considerations that can be assessed by evaluators and users of CSD. Such planning would be applicable to CS projects that involve a small number of volunteers as well as to large-scale projects, such as those that were the focus of the study conducted by Albus et al. (2019). A white paper has been developed by NASA's Citizen Science Data Working Group, for the benefit of researchers desiring to incorporate CS and crowdsourcing into their projects (NASA, 2020b). While this white paper is targeted for NASA-funded researchers in the Citizen Science for Earth Science Program, the discussion in the paper is relevant to a much broader audience. Many aspects of CSD management are addressed in this white paper, including a significant amount of detail describing how information about data quality should be handled.

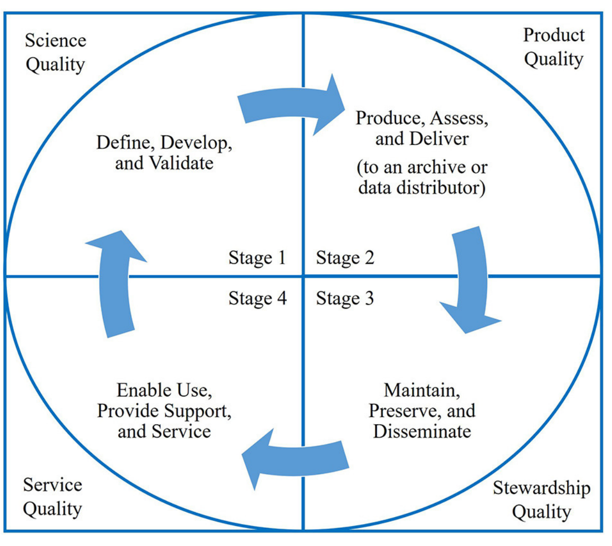


**FIGURE 1** | Information quality dimensions and data lifecycle stages.

The ESIP IQC recognizes some of the challenges in and potential approaches to addressing these data quality issues that are pertinent to CSD. These are discussed in more detail within the following subsections.

## Recruitment, Selection, Self-Selection, and Training of CSD Contributors

Bias, errors, uncertainty, and ethical issues can be addressed through well-designed and documented procedures and proper training by providing volunteers with instructions and written procedures for fieldwork. For studies that involve large numbers of volunteers in additional aspects of the research process besides data collection, training of volunteers contributes to QA (Wilderman and Monismith, 2016). Investigators should consider sources of potential bias when recruiting CS participants and, including recognizing the potential for errors, the proper use of instruments, and techniques for reducing and flagging data uncertainty. Developing a data collection instrument and recruiting volunteers to use the instrument in the field provides opportunities to identify enhancements that can improve the quality of data collected by future volunteers (Compas and Wade, 2018). When engaging volunteers, protecting indigenous people and privacy also must be considered (Bowser et al., 2017; Carroll et al., 2019; Global Indigenous Data Alliance, 2019). Human research subject protections further reduce risks (Resnik, 2019). The NASA Earth Science Data Systems CSD Working Group also offers guidance on these and other relevant issues (NASA, 2020b).

Citizen science data quality efforts for recruitment, selection, self-selection, and training should be initiated during stage 1 (science quality focus) of the data lifecycle, when defining, developing, and validating CSD. These activities also should be pursued during subsequent stages.

## Transparency in Information About QA/QC Practices During the Data Production Process

Uncorrected errors, missing data, and undocumented corrections and modifications could influence findings resulting from the analysis of CSD. Such lack of transparency could result in lost time when exploring whether to use the data. Identified usage limitations should be recorded and, when possible, addressed during research design. Similarly, appropriate uses of data should be identified to reduce the potential for misuse. Verification procedures should be planned and conducted to ensure correctness of data values. Completeness should be ensured by reducing the potential for missing values.

Deploying automated verification and parsing to address data quality issues also could reduce the potential for human errors. However, human oversight is recommended to avoid potential pitfalls of fully-automated systems, such as underestimating extremes. In addition, increasing transparency about pitfalls that have compromised the quality of CSD can avoid a cycle of repeating failures in CS research (Balázs et al., 2021). Enabling volunteers to contribute to transparent validation of observations also contributes to the improvement of CSD quality and to the motivation of contributors (Bonnet et al., 2020).

Considering that CSD is produced largely from voluntary contributions, it is also critical to be transparent about other aspects of CSD that can facilitate use, especially when designating CSD as open data. Providing simple language that enables users to understand their intellectual property rights for using CSD facilitates their use as open data. Ideally, such language should describe permissive intellectual property rights that eliminate restrictions on the use of the data and the documentation (Anhalt-Depies et al., 2019).

Facilitating transparency of information about QA/QC practices should be completed as part of stage 1 (focus on science quality) and stage 2 (focus on product quality) of the data lifecycle. Such transparency also should be facilitated during subsequent stages.

## Documenting Data Quality to Facilitate Discovery and Reuse

Describing the quality of CSD in documentation and metadata improves its potential for use and improves capabilities for assessing whether data are appropriate for reuse by those who did not participate in the original study that collected the data. Furthermore, describing data quality can improve the interoperability and integration of CSD with other data. Documentation of CSD also should describe provenance for collection, validation, curation, dissemination, and use of the data. As data originators, the roles and responsibilities of investigators and volunteer observers for ensuring and documenting the scientific quality of data should be defined (e.g., Peng et al., 2016).

Relevant guidance on practices for managing data also delineate the importance of documenting data quality. These include the FAIR Principles (Wilkinson et al., 2016), the Group on Earth Observations System of Systems (GEOSS) Data Management Principles (Group on Earth Observations, 2016), the TRUST Principles for Digital Repositories (Lin et al., 2020), and data maturity models (Peng et al., 2019).

Data quality documentation should be conducted throughout all four stages of the data lifecycle. The development of data quality documentation should be initiated early during stage 1, delivered to a repository during stage 2, disseminated along with the data during stage 3, and used to support use of the data in stage 4.

## Establishing Rubrics for Evaluating Quality Levels of CSD

To enable and maximize the reuse of CSD in environmental research and other areas, easy-to-understand quality levels that address the specific needs of target user communities, e.g. researchers, decision supporters, and the general public, on CSD will be important. Establishing rubrics to evaluate CSD quality information against such quality levels will be consequential. For example, Balázs et al. (2021) recommend communicating data quality goals to volunteers and providing accessible training materials, guidance, and understandable instructions for data collection to improve the quality of CSD. Tredick et al. (2017) developed a rubric for evaluating CS programs. This structured rubric acknowledges the importance of CSD management, quality assurance, and information integrity to the success of a CS program. The BiodivERsA Citizen Science Toolkit For Biodiversity Scientists (Goudeseune et al., 2020) also described the evaluation of output, including data quality, as one of the ten key principles for successful CS. Vocabularies for CSD quality levels, which link to the needs of diverse user communities and rubrics to assess CSD against such vocabularies, are important next steps to maximize the scientific and societal benefits of CS programs.

Rubrics for information quality levels of CSD apply to the dimensions across all stages of the data lifecycle. However, it should be noted that the development of rubrics should be initiated very early during stage 1, and that such rubrics will support users during stage 4.

# DISCUSSION

Enabling the use of CSD offers opportunities for new research projects to investigate issues while avoiding costly or redundant data collection. To allow for broad use of CSD, data QA/QC should be performed, and information about QA/QC procedures should be captured and conveyed to users. Since improving CSD quality offers opportunities for additional uses, data quality efforts should begin during project conceptualization and planning, continuing throughout the data lifecycle, to enable data reuse. Efforts to improve the quality of CSD should begin during stage 1, when science quality activities are performed and quality information is prepared when defining, developing, and validating the data. Citizen science data quality efforts should continue with stage 2, so that product quality information is prepared, assessed, and delivered along with the data to a repository for dissemination. Citizen science data quality information should be maintained, preserved, and disseminated with the data to ensure stewardship quality during stage 3. Providing quality information along with the data to provide service quality during stage 4 enables and supports the use of CSD.

Furthermore, documenting CSD quality can improve trust in CS within the scientific community and reflects ethical approaches to conducting CS. When preparing CSD for use, investigators should describe data quality in the metadata and data documentation, as well as in data papers and publications. Documentation should differentiate between various quality issues to avoid confusing potential users.

Consequently, we recommend employing a systematic approach for ensuring CSD quality. Future research should consider implications of data quality throughout the data lifecycle and data quality as it pertains to collecting CSD.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

## AUTHOR CONTRIBUTIONS

RD, HR, GP, and YW contributed to conception and design of the manuscript and wrote the first draft and sections of the manuscript. All the authors reviewed and revised the draft with beneficial edits, and approved the submitted version.

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METHODS
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# When It Rains, It Pours: Integrating Citizen Science Methods to Understand Resilience of Urban Green Spaces

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Urban green spaces are often promoted as nature-based solutions, thus helping to mitigate the negative effects of climate change. Estimating the potential environmental benefits provided by urban green space is difficult because of inconsistencies in management practices and their heterogeneous nature. Collecting data across such a spectrum of contexts at a large scale is costly and time consuming. In this study, we explore a novel integrated method for citizen scientists to assess the flood mitigation potential of urban green spaces. In three European cities, citizen scientists measured infiltration rate and associated soil characteristics in managed and unmanaged urban green spaces. The results show that simple citizen science-based measurements can indicate the infiltration potential (i.e., high vs. low) of soil at these sites. Infiltration rate was best predicted by measurements of soil compaction, soil color, air temperature, and level of insolation (i.e., high vs. low). These simple, fast methods can be repeated over time and space by citizen scientists to provide robust estimates of soil characteristics and the infiltration potential of soils that exist in similar temperate urban areas. A classification flow diagram was constructed and validated that allows citizen scientists to carry out such tests over a wider geographical region and at a higher frequency than would be available to research scientists alone. Most importantly, it allows citizens to take actions to improve infiltration in their local green space and support local flood resilience.

**Keywords: citizen science, nature-based solutions, infiltration rate, pluvial flooding, urban trees, green space**

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## INTRODUCTION

By 2050 the global urban population is predicted to be twice that living in rural areas (United Nations, 2019). Whilst social and economic opportunities are driving the move to urban areas, there are clear environmental challenges to maintaining a healthy and habitable urban environment (Elmqvist et al., 2013). Many of these challenges are related to the loss of natural areas that provide ecosystem services e.g., water and air purification, temperature regulation, flood protection, and a range of important cultural services. One example is the loss or modification of former green space to gray infrastructure, resulting in increased impervious surfaces. This in turn increases urban run-off and transport of pollutants, resulting in increased flood risk and degraded water quality (Miller and Hutchins, 2017).

Climate change stands to amplify urban environmental challenges (Emilsson and Ode Sang, 2017), not least regarding urban hydrology. In Northern Europe, rain is predicted to fall more intensely, with the UK having seen a 10% increase in the number of days with widespread heavy rain in the past 30 years (Kendon et al., 2019). An increase in urban flooding across Europe, even under conservative warming projections, will impact soil and water quality (Alfieri et al., 2018), as well as overwhelming drainage systems that were designed for different land cover and climate conditions. For example, in London alone, 1.25 m people and 800,000 properties are at risk from tidal or surface water flooding (Future of London, 2016).

Nature-based solutions (NbS) such as urban green space offers an environmentally friendly method to mitigate urban flood risk (Keesstra et al., 2018). For example, urban trees provide multiple benefits within the hydrological cycle, such as intercepting rainfall with their canopy, absorbing water from the soil for their growth (McElrone et al., 2013) and aiding water infiltration through the modification of soil conditions (Li et al., 2014). In particular, infiltration is related to the magnitude of pluvial flooding as high infiltration arrests the celerity of the flood wave peak and reduces surface runoff (Horton, 1941). Infiltration rate is defined as the rate at which water can enter into soils and filter through subsequent layers (Pitt et al., 2008). It is regulated by soil characteristics such as porosity, bulk density, texture, and mineralogy (Lado and Ben-Hur, 2004; Yang and Zhang, 2011). Thus, infiltration rate can be used as an indicator of an area's ability to deal with heavy rainfall. However, knowledge of how soil and tree management practices affect infiltration of pluvial events and other ecosystem services is limited (Gaston et al., 2013). Moreover, given the wide range of park, garden, or street tree soil characteristics (e.g., compaction, water content, amount of organic matter), understanding the conditions of green spaces across the urban continuum is challenging.

Major urban areas, where gray infrastructure and population numbers are high, require special care and analysis for assigning green spaces to best facilitate their ecosystem services. Greater London, for example, has an estimated 21% canopy cover (Treeconomics, 2015), presenting a diversity of tree species located across a multitude of soil types. Therefore, identifying appropriate land management approaches for a specific location requires information on a fine scale that accounts for the substantial heterogeneity and patchwork make-up of urban green spaces (Gaston et al., 2013). Identifying areas of flood vulnerability or of high potential mitigation value is hampered by this heterogeneity, with data collection at the scale of individual trees and their microhabitat being difficult both logistically and financially (Toms and Newson, 2006; Hobbs and White, 2012). Information at a more detailed scale is key to understanding the capacity of urban green space to process heavy rain events and to be able to manage this NbS effectively.

Citizen science has proven to be an effective method for collecting environmental data. Citizen science involves the collection and/or analysis of data by the general public. Although a long-standing method, over the past decade the number and variety of citizen science projects have increased dramatically (Bonney et al., 2014). Simultaneous to increasing the scale of scientific data collection, the involvement of citizens in the scientific process fosters engagement and promotes education in local environmental issues, as well as opportunities for collaboration between stakeholders within a community (Thornhill et al., 2016; McKineley et al., 2017). Citizen scientists have been shown to enhance the geographical, temporal and contextual scope of data collection at the catchment and sub-catchment scale (Holck, 2007; Szabo et al., 2010; Belt and Krausman, 2012; Hadj-Hammou et al., 2017; Cunha et al., 2019). Citizen science also offers multiple pathways to the provision of real-time flooding data, integrated as part of early-warning systems for pluvial flooding (See, 2019; Pandeya et al., 2020).

Trees and their surrounding soil represent one of the few remaining natural amenities accessible to and managed by local citizens in urban areas, whether they are present in residents' own gardens, line city streets or adorn parks and green spaces. Thus, the activation and participation of citizen scientists to help determine soil conditions with respect to infiltration of high precipitation events might help to close the gap between the modeling and management of green spaces. Furthermore, the identification of sites with poor infiltration capacity could allow citizens to take simple actions in their own green space to improve their status (Soil Association, 2016).

Here we examine a range of simple citizen science methods to measure soil characteristics and assess soil water infiltration rate in urban areas, which could be used to enhance knowledge of pluvial flooding risk for a certain area. We validate these methods under different land management regimes across three European cities to identify if relatively quick and uncomplicated citizen scientist measurements can be used as a proxy for infiltration potential. The methods are coupled with a classification flow diagram that guides a citizen scientist through the process of investigating the flood mitigation capacity of their local urban green spaces. Although the classification flow diagram demonstrated in this study is most suited to the locations and tree species researched here, the workflow can serve as a blueprint to be extended to other contexts in the future.

# METHODS

## Citizen Scientists

Over the course of the 2-year study, 520 citizen scientists were trained and assessed soil characteristics in three urban parks. Following a 1-h training session led by professional physical scientists on the background and methodologies of urban soils, trees, and infiltration processes, participant teams took measurements in urban parks (section Sites) on 2 consecutive days. The total sampling and measurement time was $\sim$2 h per team per day. Over the course of 2 years (2018–2019), each location was revisited by different citizen scientists several times in spring, summer, and autumn (30 events in total).

## Sites

The study sites were located in Birmingham, London, and Chantilly (France), cities which experience similar climatic conditions (Average annual temperature: 9, 11, and 11°C and average annual precipitation: 64.1, 57.5, and 60 mm in

Birmingham, London, and Chantilly, respectively, Climate-Data, 2020). Here, mature (over 30 years old) Linden (*Tilia spp*) trees, one of the most common tree species found in urban environments, were selected in three urban parks, under which measurements were taken. Six Linden trees were located in Cannon Hill Park, Birmingham, a further six in Kew Gardens, London and three Linden trees were selected in Les Fontaines, Chantilly (France). Four sampling sites were identified, two sites due north and two sites due south of each tree ($n = 60$) (**Supplementary Figure 1**). These represented contrasting levels of direct solar radiation, whereby southern (less shaded) sites were exposed to more solar radiation during sampling periods (spring, summer, autumn). We refer to this as level of insolation, with southern sites exposed to high insolation and northern sites, low insolation.

Each sample site was classified in terms of its management regime. Managed sites were defined as those having the majority of leaf litter and undergrowth vegetation cleared, typically these sample sites were located on amenity grass and had no or few nearby trees ($n = 27$). Meanwhile unmanaged sites were defined as having little to no human intervention in the removal of litter or undergrowth thus there was often a mix of herbaceous ground cover, vegetation litter and bare soil with other trees and vegetation close by ($n = 26$) (**Supplementary Figure 2**). Some sample sites ($n = 7$) were identified as intermediate (unmanaged but with a mown path or paved surface immediately nearby) and so were not included in the analyses.

## Citizen Science Methods

At each sampling site, citizen scientists estimated soil color, compaction, texture, moisture content, and infiltration rate. Citizen scientists also collected surface and soil ring samples for subsequent laboratory analysis.

Participants assessed soil color using the Munsell soil color chart 7.5YR, identifying the color that most closely matched their soil sample. Munsell color co-ordinates were later converted to a numerical value (**Supplementary Figure 3**).

Compaction was measured on a patch of undisturbed soil, with the surface vegetation removed, using an Eijkelkamp pocket penetrometer. Participants measured the compaction of the topsoil by pushing the shaft (to a depth of 6.35 mm) of the pocket penetrometer with a constant force into the soil. The internal spring is calibrated such that participants read the compressive force required to insert the penetrometer to the nearest 0.25 kg/cm$^2$.

Soil texture was characterized by participants following a standard soil handling protocol (Yolcubal et al., 2004). Following a decision diagram, participants classified their sample into specific categories of soil texture.

Soil moisture was obtained by measuring conductivity using a Delta-T Devices SM150T probe inserted into the topsoil. The raw data (conductivity) obtained was then converted to moisture content (**Supplementary Material Equation 1**). Participants took conductivity measurements in a radial pattern extending from the trunk of the study tree, which were averaged ($n = 13$) for the north and south sides, respectively.

Participants measured soil infiltration using a mini-disc infiltrometer (Decagon Devices, Inc). Both the upper chamber and lower water reservoir were filled with water, and the bottom elastomer with porous disk firmly replaced. The infiltrometer was placed on a flat surface with any vegetation removed to ensure good contact between the soil and infiltrometer. The suction was set to 1 cm and the water level read every 60 s (unless the infiltration rate was particularly fast, in which case participants recorded at shorter intervals of every 20–40 s). The initial volume of water was recorded followed by 10 additional readings (typically 10 min). The infiltration rate ($Q$) was calculated as follows (Equation 1):

$$Q = v\left(\frac{\Sigma(D_{t+1} - D_t)}{n - 1}\right) \tag{1}$$

where $v$ is a multiplication factor to compensate for the frequency of readings taken ($v = 3$, 1.5, 1, and 0.5 for frequencies of 20, 40, 60, and 120 s, respectively), $D$ is water depth in ml, and $n$ is the number of readings taken.

In addition to the soil characteristics assessed by participants, local temperature, and precipitation data were obtained from the NOAA NCEP climate dataset (NOAA/OAR/ESRL PSL, https://psl.noaa.gov/). Hourly temperature and precipitation data were selected between 0600–1800 on each day of an event at the relevant location, and a daily average calculated.

Laboratory analyses of the soil samples collected by citizen scientists were conducted to assess volumetric water content at saturation, field capacity and sampling. This was used to help validate our citizen scientist collected measurements and eventual analysis of potential differences between sites.

## Data Analysis

*T*-tests and Mann-Whitney tests were used to determine significance in the differences in means and medians of soil characteristics in areas with high and low infiltration and between the two land management types. ANOVAs and Kruskall-Wallis tests were used to compare differences in the measured soil characteristics between different city locations and seasons.

Logistic regression models were used to explore the relationship between infiltration rate and soil and local climate characteristics. Infiltration rate was transformed to a binomial value of low ($<$1.75 ml/min) or high infiltration rate ($\geq$1.75 ml/min) as the dependent variable in the logistic models. This cut-off is the equivalent to a rainfall intensity of 6.6 mm/h, which qualifies as heavy rainfall according to the UK Met Office (McIntosh, 1963).

Independent variables (i.e., soil moisture, soil compaction, soil color, average daily temperature, low or high insolation, and soil texture) were included in the models following normalization. Soil texture was converted to an ordinal factor (**Supplementary Table 1**). All independent variables were standardized using a $z$ score conversion ($z = (x–\mu)/\sigma$) such that their different measurement scales were comparable in the model output. Data analysis was performed in R and using the RealStats extension in Microsoft Excel.

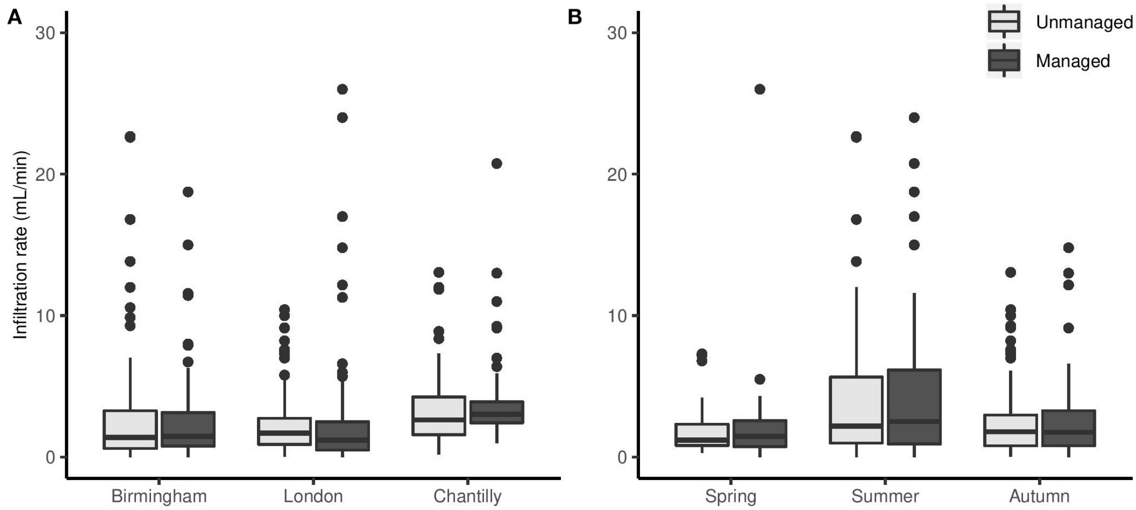


**FIGURE 1 |** Boxplots of raw infiltration rate (mL/min) transformed to positive values, according to management regime (gray = unmanaged; black = managed), by **(A)** location of park where samples were taken, and **(B)** season. Central horizontal line in boxplot = median; box limits = first and third quartiles; whiskers = 1.5 times the interquartile range. Data beyond the whiskers plotted as outliers, with points >30 mL/min not shown.

# RESULTS

## Infiltration Rate

Infiltration rates varied according to location (**Figure 1A**) and the seasons (**Figure 1A**). Soils of the Chantilly park had the highest infiltration rates (mean infiltration rate 3.87 mL/min) compared to those in Birmingham (mean infiltration rate 3.29 mL/min) or London (mean infiltration rate 2.56 mL/min), (Welch *t*-test on log transformed infiltration rate: T = 26.2, df = 2, $p < 0.001$, **Figure 1A**). Summer infiltration (mean infiltration rate 5.29 mL/min) was higher than rates in spring (mean infiltration rate 2.03 mL/min) and autumn (average infiltration rate 2.40 mL/min), (Welch *t*-test on log transformed infiltration rate: T = 11.17, df = 2, $p < 0.001$, **Figure 1B**). Infiltration rates showed no significant difference between the managed and unmanaged sample sites (Welch *t*-test on log transformed infiltration rate: T = 0.23, df = 483, $p = 0.8$). Equally, when categorized as binary infiltration rates (high vs. low), these were also independent of management type (Fisher's exact test, two tails, $p = 0.78$).

## Laboratory Analyses

The categorization of citizen scientist collected measurements of infiltration rate into either a low or high category was validated through laboratory analysis of soil samples. For the managed sites, volumetric water content at saturation showed significant differences between the low (mean: 54%) and high infiltration (mean: 52%) categories (Wilcox test = 3,868, $p = 0.015$). This was also confirmed in measurements of water content at field capacity (Wilcox = 4,025, $p = 0.005$, low infiltration mean: 53%, high infiltration mean: 51%), and sampling (T = 2.28, df = 157, $p = 0.02$, low infiltration water content at sampling mean: 27%, and high infiltration mean: 24%). For unmanaged sites, no significant difference was observed in the laboratory analyses of volumetric water content at saturation (T = −0.86, df = 144, $p = 0.39$), field capacity (Wilcox test = 2650.5, $p = 0.89$) or sampling (T = 0.21, df = 144, $p = 0.83$) between the low and high infiltration rate categories.

Differences in soil characteristics, as collected by citizen scientists, between the managed and unmanaged sites were also examined. Significant differences in soil color (T = 8.15, df = 426, $p < 0.001$), soil compaction (Wilcox test = 9,465, $p < 0.001$) and soil texture ($X^2 = 12.71$, df = 1, $p < 0.001$) were found, with a higher soil color (i.e., darker) for unmanaged soil, higher compaction for managed soils and a higher soil texture (i.e., more aerated) assignment for unmanaged soils. Binary soil infiltration (Fisher's exact test, two tails, $p = 0.78$) and soil moisture (T = 0.37, df = 464, $p = 0.7$) did not show significant differences between land managements.

## Logistic Regression Models

An initial binary logistic regression model aggregating both management regimes (managed and unmanaged sites) provided an estimate of high and low infiltration ($X^2 = 29.43$, $p < 0.001$, $n = 490$; accuracy (percentage of correct predictions by the model) = 0.64, AUC ROC = 0.61). Initially, the model included footfall intensity as a ranked factor according to the observed level of foot traffic each location received. However, this factor was subsequently removed from the model (and subsequent separated managed and unmanaged models), as it was highly correlated with compaction ($r_s = 0.94$, $n = 6$, $p < 0.05$), to avoid collinearity. Air temperature and soil moisture showed some correlation ($r = -0.44$, $n = 488$), although this was considered moderate (Schober et al., 2018); therefore, we retained both factors in the model as they could provide additional information.

Given the relatively low accuracy and specificity/selectivity of the aggregated model and the clear differences between soil

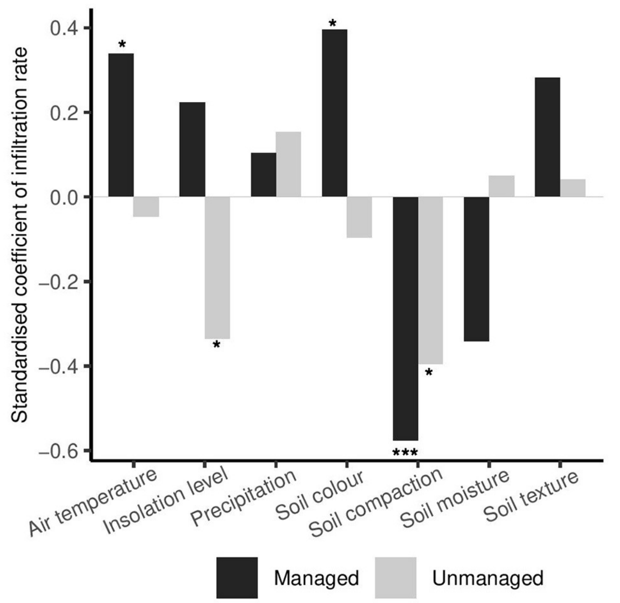


**FIGURE 2 |** Standardized coefficients ($z$ score: $z = (x–\mu)/\sigma$) of binary infiltration rate in the managed (black) and unmanaged (gray) logistic regression models in response to each of the model's independent variables: average daily air temperature, location of sample site relative to level of insolation, average daily precipitation, soil color, soil compaction, average soil moisture, and soil texture. Positive standardized coefficients signify a positive relationship; negative coefficients denote a negative relationship between the independent variable and the likelihood of high infiltration rates (≥1.75 mL/min). Asterisks denote variables that were significant predictors of high infiltration rate in each model (*<0.05, ***<0.001; **Table 1**).

characteristics of the managed and unmanaged sites, separate models were developed. The utility of simple observational data (managed vs. unmanaged) in citizen science has been well-documented elsewhere (Champion et al., 2018; Thornhill et al., 2018; Pohle et al., 2019).

### Managed Model

The model for managed sites demonstrated increased accuracy compared to the aggregated model, with a specificity/selectivity indicating a fair model (Accuracy = 0.69, ROC AUC = 0.72) (Bradley, 1997; Fawcett, 2006). The model distinguished between high and low infiltration rates ($\chi^2 = 38.08$, $p < 0.001$, $n = 255$) based on the suite of measurements made by the citizen scientists (**Figure 2**).

In particular, the measurements of soil color, soil compaction, and average air temperature were the most important for managed sites (**Table 1**, **Figure 2**). The model indicated that low soil compaction, high soil color (i.e., darker; related to organic matter content), and higher average air temperature were associated with high infiltration rates. Soil moisture and soil texture were not found to be significant factors ($p = 0.06$ for both parameters; **Table 1**), while their coefficients suggested that lower soil moisture and sandier soil textures were associated with higher infiltration at the managed sites (**Table 1**).

### Unmanaged Model

For unmanaged sites, the logistic model had lower-than-desired accuracy (Accuracy = 0.60, ROC AUC = 0.65), but remained significant ($\chi^2 = 17.57$, $p < 0.01$, $n = 235$) and had a higher AUC than that obtained in the aggregated model. In this model, soil compaction and location with respect to insolation were the most important variables (**Table 1**). Low soil compaction and sites with low insolation (i.e., samples to the north side of trees) were associated with high infiltration rates (**Figure 2**).

## Soil Characteristics Influencing Binary Infiltration Rate

In both models, soil compaction was the most significant variable with the highest standardized coefficient (**Table 1**). As compaction was negatively correlated with infiltration rate, a 1 kg/cm$^2$ decrease in soil compaction nearly doubled the odds that the site would have a high infiltration rate (1.6 and 1.75 times at managed and unmanaged sites, respectively), all else being equal (**Table 1**). Our measurements confirmed that soil was more compacted at the managed sample sites (Wilcox test = 9,465, $p < 0.001$, **Figure 3A**), a pattern maintained throughout seasons and across locations (**Figures 3A,B**).

Soil color was a predictor of infiltration rate in the managed model only (**Table 1**), where darker soil was linked to high infiltration rates. Soil was generally darker at the unmanaged sites (T = 8.15, df = 426, $p < 0.001$, **Figure 3C**) and showed a higher variance overall (F = 1.87, df = 234, 254, $p < 0.001$). This pattern was most evident at the Chantilly and London sites, but not in Birmingham, where the discrepancy between management type was very small (Two-way ANOVA: $F_2 = 24.05$, $p < 0.001$, **Figure 3D**). Soil color in the unmanaged samples was more heterogeneous and exhibited a greater change between seasons compared to the managed sites (Two-way ANOVA: $F_2 = 4.03$, $p < 0.02$), where lighter colors were evident during the summer.

Daily air temperature was an important factor at the managed sites for predicting infiltration rate. The positive role of air temperature on infiltration was confirmed by the significant difference between managed sites classified as low and high infiltration rate (Wilcox = 6940.5, $p = 0.04$). There was no significant difference in air temperature comparing unmanaged sites with low and high infiltration (Wilcox = 7102.5, $p = 0.7$).

The degree of insolation, determined by the location of the sample site with respect to the tree canopy (north vs. south), was an important factor in the unmanaged sites (**Figure 4**). Southern samples were exposed to more solar radiation, as such the average daytime surface temperature of the southern sites was expected to be higher (Jim, 2015). For managed sites, there was a significant difference in air temperature between sites with different infiltration levels (Wilcox = 6940.5, $p = 0.04$); but these different infiltration levels were independent of the level of insolation ($X^2 = 1.69$, df = 1, $p = 1.9$, **Figure 4**). On the other hand, at unmanaged sites high and low infiltration rate was dependent on the level of insolation ($X^2 = 5.96$, df = 1, $p = 0.01$, **Figure 4**) but there was no difference in median air temperature (Wilcox = 7102.5, $p = 0.7$) between sites with different infiltration levels.

**TABLE 1 |** Comparison of all variables in each of the logistic regression models, showing standardized coefficients ($z$ score: $z = (x-\mu)/\sigma$) for predicting high infiltration rate ($\geq$1.75 mL/min) and their significance level.

| Independent variable | Managed sample sites | | | Unmanaged sample sites | | |
|---|---|---|---|---|---|---|
| | Standardized coefficient | *P*-value | Odds ratio* | Standardized coefficient | *P*-value | Odds ratio* |
| Soil compaction | **−0.58** | **<0.001** | **1.6** | **−0.40** | **0.01** | **1.75** |
| Soil color | **0.40** | **0.01** | **1.9** | −0.10 | 0.50 | |
| Average daily temperature | **0.34** | **0.05** | **1.1** | −0.05 | 0.76 | |
| Level of insolation | 0.22 | 0.10 | | **−0.34** | **0.01** | **1.96** |
| Soil moisture | −0.34 | 0.06 | | 0.05 | 0.75 | |
| Soil texture | 0.28 | 0.06 | | 0.04 | 0.77 | |
| Average daily precipitation | 0.10 | 0.46 | | 0.15 | 0.30 | |

*Odds ratio for a unit change in each variable considering the non-standardized coefficient. For soil compaction, odds ratio = increase in likelihood of high infiltration rate with 1 kg/cm$^2$ decrease (negative coefficient) in compaction. Soil color odds ratio = increase in likelihood of high infiltration rate with an 11-point increase in color, equivalent to one shade darker. The odds ratio of average daily temperature = increase in likelihood of high infiltration rate with a 1°C increase in temperature. Insolation = odds ratio of high infiltration rate on the low insolation (north) side of a tree compared to the high insolation (south) side of a tree.*

*Bold refers to significant ($p$ < 0.05) independent variables in either the managed or unmanaged model.*

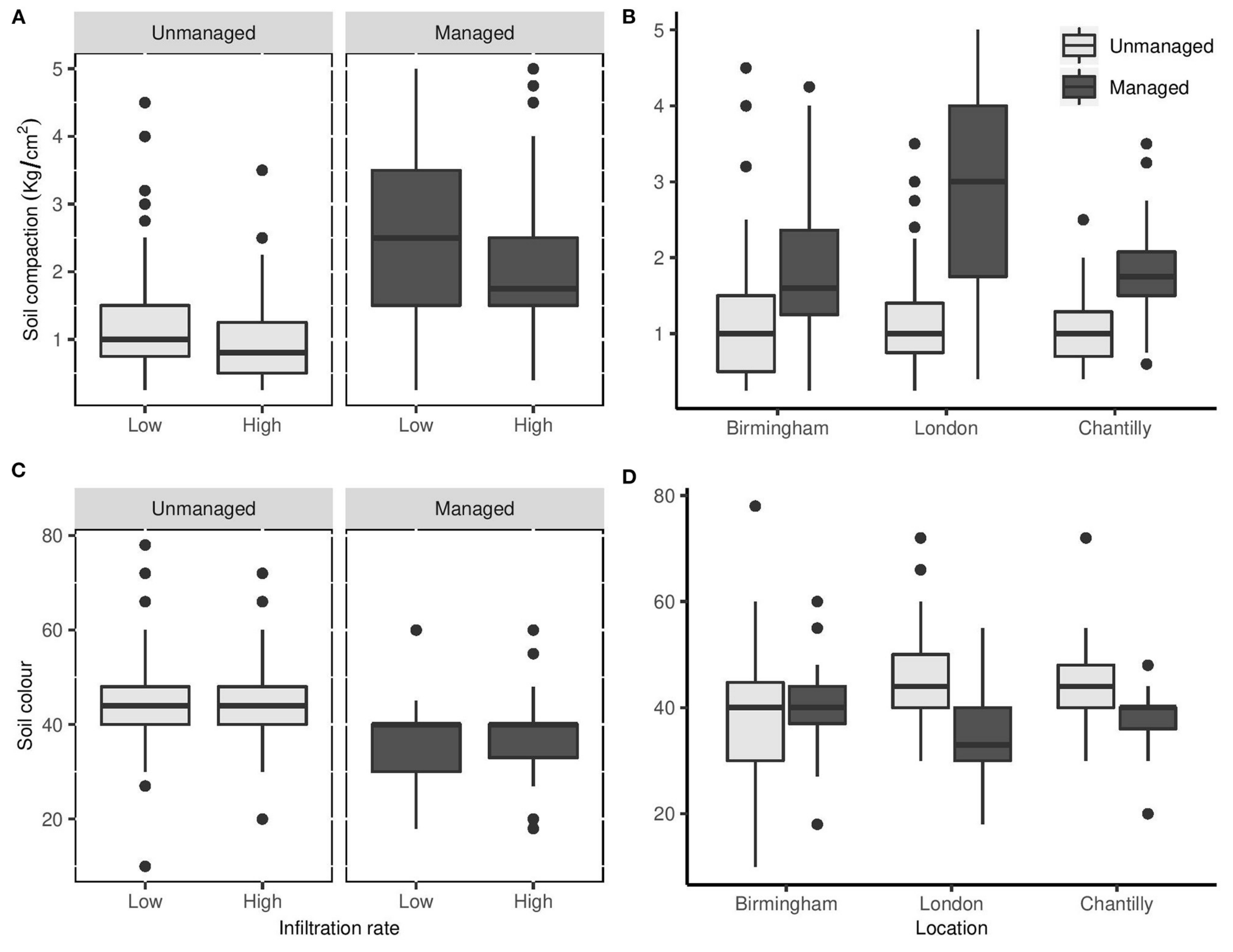


**FIGURE 3 |** Soil compaction (kg/cm$^2$) according to **(A)** management type: unmanaged (gray) and managed (black) in relation to infiltration rate categorized (binary) as low (<1.75 mL/min), or high ($\geq$1.75 mL/min), **(B)** location of the park where sampling took place. Soil color (higher number = darker) in relation to **(C)** management type: unmanaged (gray) and managed (black) in relation to infiltration rate categorized (binary) as low (<1.75 ml/min) or high ($\geq$1.75 ml/min), **(D)** location of the park where sampling took place. Boxplots as per **Figure 2**.

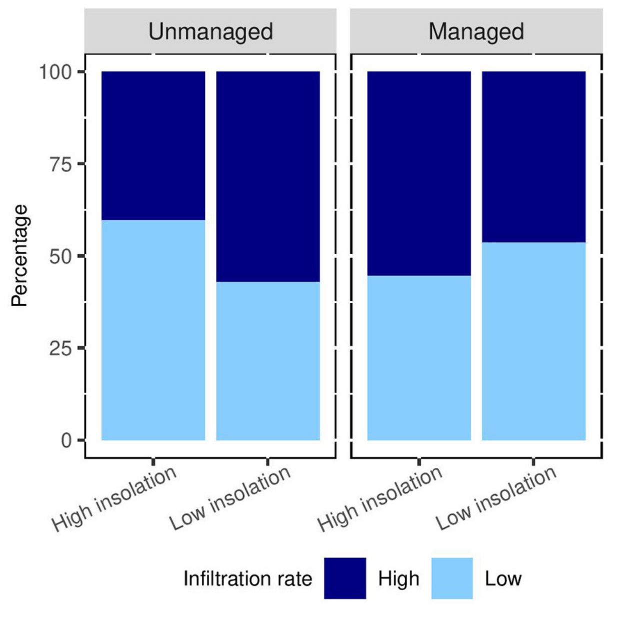


**FIGURE 4 |** Percentage of samples falling in the low (light blue, <1.75 mL/min) or high (dark blue, ≥1.75 mL/min) infiltration rate categories on the low insolation (north) or high insolation (south) side of the sampled trees.

The model indicated that in unmanaged areas, soil samples that were exposed to less insolation were 1.9 times more likely to have high infiltration rates than those that were exposed to more insolation, all else being equal (**Table 1**; **Figure 4**). This was not associated with differences in organic content or soil moisture. In fact, low and high levels of insolation had no explanatory power at unmanaged sites in relation to soil color (Wilcox test = 7,363, $p = 0.32$), compaction (Wilcox = 6,419, $p = 0.41$), texture (Wilcox = 6,865, $p = 0.97$), or moisture (Wilcox = 6,754, $p = 0.86$).

## DISCUSSION

Our results indicate that, using easy to perform measurements (i.e., soil compaction, soil color, air temperature, and level of insolation), citizen scientists can categorize whether an urban green space containing trees (e.g., their garden or local park) had sufficient infiltration capacity to reduce the impact of a heavy rainfall event.

### Soil Characteristics

Infiltration rates measured directly with mini-disk infiltrometers by citizen scientists showed significant variation based on the location and timing of sampling (**Figure 1**), attesting to the heterogeneous nature of urban environments and alluding to the complexity of using an infiltrometer with little prior experience. Soil conditions, location and sampling season of each site were important characteristics with respect to infiltration.

Less compacted soil equates to higher soil porosity and therefore higher infiltration rate (Pitt et al., 2008; Yang and Zhang, 2011; Elliot et al., 2018). Compacted soils have fewer voids that are essential to the movement of water, gases and plant roots, which together influence soil structure and therefore impact root growth and the efficiency of fertilizer, critical for a healthy soil. The more compact nature of the managed sites (**Figure 3A**) in our study could be related to the lack of leaf litter and their higher footfall and the application of machinery for vegetation and litter maintenance (Yang and Zhang, 2011; Elliot et al., 2018). This was particularly evident at the London managed site (**Figure 3B**), located in Kew Gardens, which experiences a high throughput of visitors, 2.36 million in 2018–19 (Kew Royal Botanic Gardens, 2019), leading to high soil compaction.

Darker soils are often associated with higher organic matter content (Fitzpatrick, 1986; Galvao and Vitorello, 1998). In many studies, soils with high organic matter content have a higher infiltration rate than soils with lower organic matter contents (Boyle et al., 1989; Chen et al., 2014; Wang et al., 2018); while other studies have found no influence (Phillips et al., 2019). Our citizen scientists identified a darker soil color in unmanaged sites compared to managed sites (**Figure 3C**), where in the latter organic leaf litter and clippings were regularly removed. However, darker soils were not a predictive factor of infiltration at unmanaged sites (**Table 1**, **Figure 2**). At managed sites that have low litter input, the color of the surface soil is more static (Tóth et al., 2007). Links between soil color, organic matter content, and infiltration are further influenced by a range of other variables including soil bulk density, soil texture, and root paths (Bartens et al., 2008), which are more complex to measure on a large scale.

Soil moisture and texture measured by citizen scientists had limited influence on predicting infiltration, and only at the managed sites. We had expected that soil moisture, in particular, would have played a more important role, as high antecedent soil moisture reduces infiltration rates (Tromble et al., 1974; Pitt et al., 2008). The comparison with the laboratory analyses tends to support this (mean water content at sampling for low infiltration rate was 27% and for high infiltration rate was 24%, T = 2.28, df = 157, $p < 0.02$). Soil texture trends were somewhat unclear, even though soils with high clay or silt content tend toward lower infiltration (Yang and Zhang, 2011). The uncertainty of the relationship between soil texture and infiltration may be related to the complexity of the citizen science soil texture method itself, rather than the parameter and should be analyzed separately.

The effect of the orientation of the soil samples with respect to the trees influenced infiltration in unmanaged areas. Typically, shaded soil exposed to less insolation has higher water content, carbon, nitrogen and phosphorus concentrations, compared to more exposed conditions (Akpo et al., 2005). This favors decomposition of available leaf litter, with positive impacts on infiltration (Anthelme and Dangles, 2012). In fact, an increased likelihood of high infiltration rate was found on the northern sides of trees, with lower insolation, in the unmanaged sites (**Figure 4**).

On the other hand, in the managed sites, overall air temperature played a stronger role on infiltration than level of insolation. One explanation for this could be the lower tree density in managed sites, as infiltration rate has been shown to be sensitive to temperature in some conditions (Jaynes, 1990).

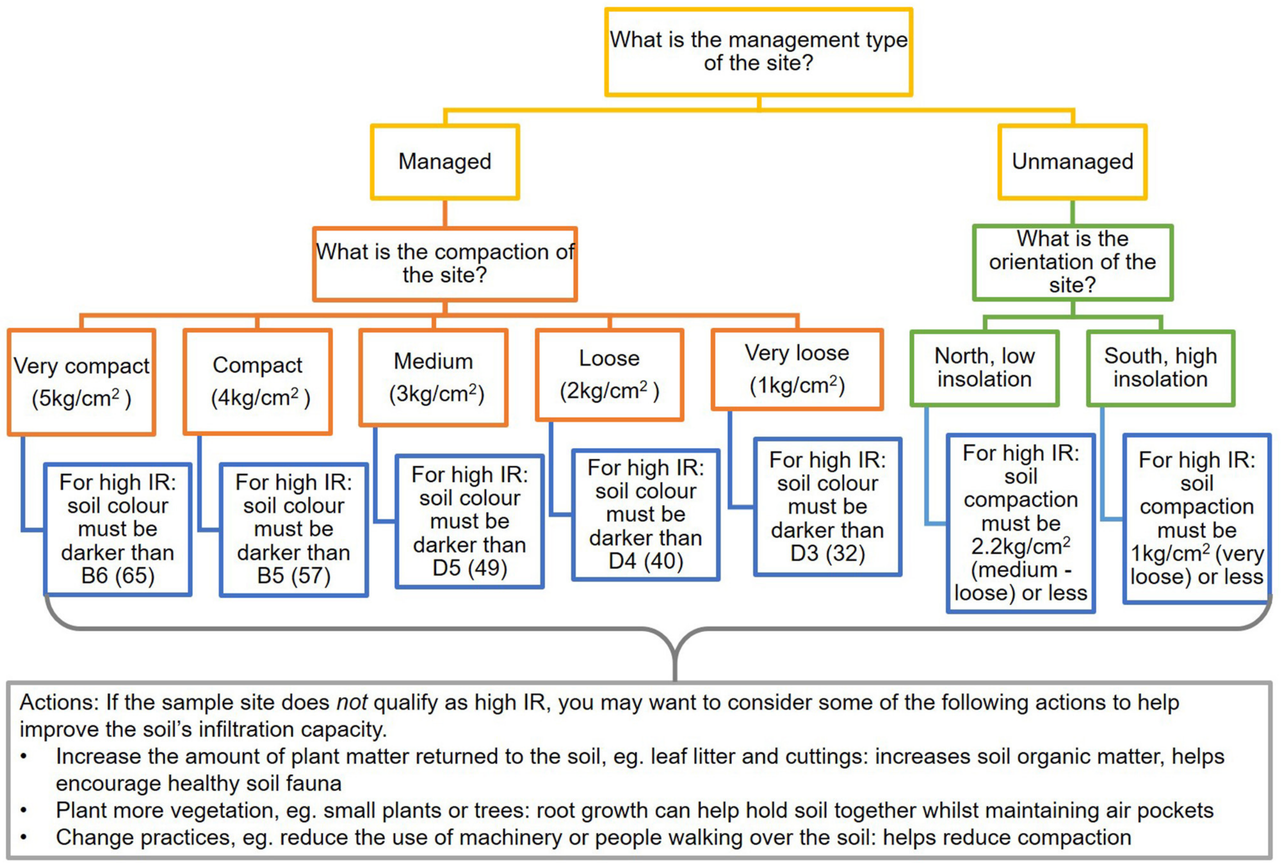


**FIGURE 5 |** Classification flow diagram for citizen scientists to estimate the infiltration potential of their local urban green space, and suggested actions to take to improve infiltration potential if samples cannot be classified as high infiltration rate (Soil Association, 2016). IR = Infiltration rate.

Meanwhile, the lack of influence of air temperature in the unmanaged sites could be the result of soil insulation by leaf litter (Xiong and Nilsson, 1997), although more detailed temperature measurements, specifically at the soil surface, would be needed for confirmation. Together this indicates the importance of fine-scale measurements, as microhabitat differences can influence soil conditions.

## Citizen Scientists' Role

Based on these results, a classification flow diagram was built to allow citizen scientists to differentiate sites that have high or low infiltration potential (**Figure 5**). Construction of this classification flow diagram had two objectives: first, to allow citizens (and planners) to better understand the conditions of their local park or garden with respect to intense rain events; and secondly, to inform management actions to improve flood protection aspects of local green spaces. The classification flow diagram was built based on data from parks with trees (*Tilia spp*) in European temperate areas; thus, its application is defined to areas with similar climatic conditions, soil types and in proximity to similar tree types. Additional data could support the extension of our classification flow diagram for use at other locations in the future.

**TABLE 2 |** Minimum soil colors for classifying high infiltration soils when sampling at 9°C, the mean annual temperature of Birmingham.

| Compaction (kg/cm$^2$) | For high infiltration rate, soil color must be darker than |
|---|---|
| 5 | B6 (69) |
| 4 | B5 (60) |
| 3 | C5 (52) |
| 2 | C4 (43) |
| 1 | C3 (35) |

The classification flow diagram begins by identifying the management type of the green space (managed sites: the majority of leaf litter and undergrowth vegetation cleared; vs. unmanaged sites: little to no human intervention, **Supplementary Figure 1**), and then by presenting the initial factor to be measured (compaction for managed; level of insolation for unmanaged). A threshold value of the second parameter was then defined to allow for the identification of high- and low-infiltration soils. For the managed sites, air temperature was also an important factor. The figures shown in this example diagram are specific to a site at 11°C, the annual mean temperature for both London

**TABLE 3 |** Classification flow diagram validation.

| Management type | Correctly predicted | Incorrectly predicted | Accuracy |
|---|---|---|---|
| Managed | 23 | 11 | 67.6% |
| Unmanaged | 13 | 15 | 46.4% |

*Original data omitted from the model are input into the flow diagram (**Figure 5**). Number of correctly predicted high and low infiltration rate categorizations by the flow diagram compared to the actual measured infiltration rate, and number of incorrect predictions, for managed and unmanaged sample sites. Accuracy = percentage of correct predictions.*

**TABLE 4 |** Estimates of citizen scientist measurement times required to complete the classification flow diagram (**Figure 5**), assuming three repeat measurements within the sampled green space.

| Measurement | Action | Time estimate | Repeats |
|---|---|---|---|
| Define management regime | Observations on how the area is typically managed | <1 min | 3 |
| Soil compaction | Penetrometer or steel rod reading | 2 min | 3 |
| Soil color | Sample compared to Munsell color chart | 2 min | 3 |
| North-South orientation (level of insolation) | Observations of shading/use of compass | <1 min | 3 |
| Temperature check | Check the air temperature via thermometer/app/website | <1 min | 1 |
| Total time | | | ∼19 mins |

and Paris (Climate-Data, 2020). The mean annual temperature for Birmingham is 9°C; therefore, the associated minimum colors required to estimate high infiltration rate are shown in **Table 2**.

Data omitted for the initial building of the model because of their poor match were input into the classification flow diagram in a validation exercise. The classification flow diagram was able to predict high and low infiltration rate correctly in many cases (**Table 3**), despite the limited sample size ($n$ = 7) and the input data being originally discounted due to their unsuitability for the defined management categories. The unmanaged branch of the flow diagram performed less well, resulting from the poorer-fitting unmanaged model, suggesting the influence of additional factors. More data would help to improve the applicability of the classification flow diagram to a wider range of locations and climates. However, particularly in the case of the managed sample sites, the classification flow diagram can immediately be utilized by citizen scientists in areas similar to those used here.

For example, a citizen scientist may be interested in measuring the infiltration capacity of the soil in their garden. As they might mow their lawn and clear the resulting litter, they would consider this site as managed, and thus follow the left-hand branch of the diagram. The citizen scientist would first estimate soil compaction. If the soil were loose (i.e., compaction <2 kg/cm$^2$), the individual would next evaluate soil color. If soil color were then darker than D4 on the Munsell color chart, the site should be considered to have high infiltration rate. Repeat measurements (>3) in close proximity would allow for greater information on site variability. If sampling suggested that the soil had low infiltration capacity, the lower gray box in **Figure 5** provides suggested actions to be taken to improve the infiltration capacity of the urban green space (Soil Association, 2016).

Measuring infiltration rate with an infiltrometer requires more training than is required to estimate soil color, compaction, tree orientation associated to level of insolation, and temperature measurements. Properly setting up and using an infiltrometer can be complex (Kosmala et al., 2016), requires calculations for interpretation *post-hoc*, and takes a minimum of 10 min per measurement. Conversely, measuring several different simple soil parameters to estimate soil infiltration indirectly is simpler and more engaging, offering a learning opportunity that encourages survey completion and commitment to repeated sampling (i.e., retention: Ryan et al., 2001). As an example, a site assessment with three repeat measurements could be completed in 20 min or less (**Table 4**). However, it is worth noting that compaction measurements, although simple in terms of methodology, typically requires the use of equipment which can be associated with a cost (in this study a Pocket Penetrometer was used, costing in the region of £90). Therefore, we suggest two options which could account for this. Firstly, a targeted sampling campaign in a particular area of interest liaised via a central authority or organization could loan equipment such as pocket penetrometers to citizen scientist groups, as the Drinkable Rivers project does for water quality (see https://drinkablerivers.org/). Compared to minidisc infiltrometers, penetrometers are easier to use, requiring minimal amounts of training, offering more robust results, less expensive and more easily shipped or posted to citizen scientists, making them suitable for this type of loan set-up. Alternatively, or as a complementary solution, citizen scientists could use simpler homemade penetrometers, such as from a knitting needle and spool of thread (Science Buddies Staff, 2020), a pointed stick or even using your finger (Davidson, 1965). Both options provide a low-cost means to test relative soil compaction by a citizen scientist.

Furthermore, compaction and soil organic content data might indicate which factors are leading to low infiltration rate and thus provide opportunities for mitigation actions to improve infiltration, empowering the citizen scientist to take action based on their measurements. Citizen science has greatest impact when there is a potential call for action (van Noordwijk et al., 2021) and when that action is simple, engaging, and complies with local social norms (Rare The Behavioural Insights Team, 2019). The opportunity to modify local conditions to improve resilience to pluvial flooding represents a strong potential motivation for continued participation in this kind of citizen science activity.

While this study only looked at soil around trees in urban parks, 29% of the total urban land area in Great Britain is residential gardens (ONS, 2019). In some cities, up to 40% of green space is located on private property, where homeowners have direct control over soil and tree management (Davies et al., 2009; Gaston et al., 2013). Therefore, local knowledge regarding a neighborhood capacity to deal with heavy rain events lies within domestic gardens (Cameron et al., 2012). Participation in citizens' own gardens lends itself to ease of access, and to repeated measurements over time (Toms and Newson, 2006; Williams et al., 2016), throughout all seasons. Furthermore, homeowners and park managers have multiple options for improving soil compaction and organic matter content, including soil aeration, and changing use practices such as vegetation and leaf litter removal practices (Soil Association, 2016).

The information resulting from these measurements is coarse, yet it could enhance the efficient prioritization of resources to improve the utility of green spaces as NbS for flood protection. In particular, if in the future this method were to be used at scale, data collection input via a GIS based survey or app, it would allow for other valuable factors such geo-locating sample points to be easily captured. This would help to build a spatial picture of the flood mitigation potential of urban green spaces, thus achieving an overview of the overall risk of an area. The integration of citizen science-collected data into early warning systems for pluvial flooding is growing (See, 2019); therefore, datasets such as those presented here could, in the meantime, feed into and complement these resources.

Others have demonstrated the value of citizen scientists in collecting soil data over a large area (Bone et al., 2012). More generally, participating in citizen science empowers local residents as they are positively contributing to local decision-making and policy (McKineley et al., 2017). Moreover, citizens also have the potential to learn from the experience at a scale greater than their own survey spot, which translates to enhanced environmental awareness (Hobbs and White, 2012; Geoghegan et al., 2016).

## CONCLUSIONS AND FUTURE OUTLOOK

Considering the increasing importance of climate change on urban environments, the development of simple methods for citizen scientists to assess the capacity of their local green areas to mitigate pluvial flooding could provide valuable new knowledge to local planners, park managers and to the citizen scientists themselves. Through replication over a wide area and range of management types at a high frequency, an overview of the status of soil in terms of protection from pluvial flooding could be developed. This would allow for a better understanding of how different park and garden management regimes function under different climates. These data could be used to identify priority areas at risk of flooding and to help develop more complex models at validation sites. The participation of citizen scientists has additional benefits in being able to generate information from hitherto restricted private green space in domestic gardens, as well as reducing costs and labor inputs, and empowering communities to better manage their local environment.

To achieve this, future sampling should incorporate a greater number of sample sites to account for a greater geographical spread and represent different climatic regions and underlying soil types. Further sampling could also investigate soils from different types of green space, for example including residential gardens as well as urban parks, and consider the effect of different tree species on soil infiltration. The inclusion of greater numbers of citizen scientists would allow for these proposed increases in sampling effort, while reaching a wider audience, who could in turn benefit from the educational and engagement opportunities of citizen science.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

MC, SL, and WB contributed to conception and design of the study. BP performed the statistical analysis and wrote the first draft of the manuscript. SL wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frwa.2021.654493/full#supplementary-material

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DATA REPORT
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# The 2017 Mission Arctic Citizen Science Sailing Expedition Conductivity, Temperature, and Depth Profiles in Western Greenland and Baffin Bay

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## 1. INTRODUCTION

The density of polar waters is controlled by salinity, making them so-called "beta oceans" (Carmack, 2007). Changes in salinity, therefore, can alter stratification, which impacts of a host of physical and biogeochemical processes in beta oceans (Carmack, 2007; Brown et al., 2020). Mass loss from the Greenland Ice Sheet has increased by a factor of six since the 1980s (Mouginot et al., 2019) and freshwater runoff into adjacent fjord and shelf waters has subsequently increased (Sejr et al., 2017; Boone et al., 2018; Moon et al., 2018; Mankoff et al., 2020). The increase in freshwater discharge impacts marine ecosystems (Meire et al., 2017; Cape et al., 2019; Seifert et al., 2019; Hopwood et al., 2020; Oliver et al., 2020), and density stratification and circulation in fjords and Baffin Bay (Castro de la Guardia et al., 2015; Sejr et al., 2017; Boone et al., 2018; Moon et al., 2018; Monteban et al., 2020; Rysgaard et al., 2020). The contribution of freshwater runoff from the Greenland Ice Sheet to the freshening observed in the North Atlantic remains an area of active research that relies heavily on numerical ocean models (Liu et al., 2018; Dukhovskoy et al., 2019; Zhang et al., 2021). Synoptic hydrographic observations can aid in quantifying the magnitude and spatial distribution of glacial meltwater in fjord and ocean waters around Greenland to provide much-needed benchmarks for ocean models that attempt to simulate the effects of this added freshwater on ocean circulation, heat transport, and climate (Gillard et al., 2016; Little et al., 2016; Dukhovskoy et al., 2019).

Observations in remote and harsh Arctic environments can be difficult and costly. Additionally, the number of research vessels that operate in Greenlandic waters are limited and are highly sought after. Sailboats have been used as measurement platforms in the region (Miller et al., 1995; Karnovsky et al., 2010; Johannessen et al., 2011; Fenty et al., 2016; Nicoli et al., 2018; Aliani et al., 2020; Bouchard et al., 2020) and marine monitoring programs should leverage the increase in Arctic tourism aboard cruise ships and private yachts (Dawson, 2019; Leoni, 2019; Palma et al., 2019) to increase the spatiotemporal coverage of ocean observations in Greenlandic waters. While sailboats lack the resources of dedicated research vessels, they are small, maneuverable, and flexible, and therefore, are well-suited for citizen science (Simoniello et al., 2019).

Here, we present a pilot project that demonstrated the ability of citizen scientists aboard a sailboat to independently acquire hydrographic data in remote marine environments that are impacted by glacial runoff. The Mission Arctic citizen science sailing expedition collected profiles of temperature and salinity from July to September 2017 in the upper ∼60 m of the water column in western Greenland, Nares Strait, and Baffin Bay (**Figure 1**). This report describes the expedition, hydrographic data collection and quality control procedures, the final data set, and presents preliminary results.

# 2. METHODS

## 2.1. Expedition Summary

The Mission Arctic Science Sailing Expedition to western Greenland and Baffin Bay took place aboard the sailboat *Exiles* in summer 2017. *Exiles* departed St. John's Newfoundland, bound for southern Greenland, in late June 2017. *Exiles*' route can be traced in **Figure 1** following a counter-clockwise path from Paamiut in southwest Greenland, north along the west coast of Greenland, and back south along the Canadian Arctic. Scientific activities were coordinated by Dr. Daniel Carlson from the Arctic Research Centre at Aarhus University in Denmark. Dr. Carlson met *Exiles* in Paamiut and disembarked in Upernavik, in northwest Greenland. During July 2017, the Mission Arctic crew conducted conductivity/temperature/depth (CTD) surveys (see section 2.2) of fjords in contact with the Greenland Ice Sheet, acquired low-altitude aerial imagery of coastal macroalgal beds, and recovered moored instruments. Here, we focus on the CTD observations.

After Dr. Carlson disembarked in Upernavik in late July *Exiles* continued north, through Melville Bay and into Nares Strait. *Exiles* proceeded as far north as possible, reaching 80°N, until sea ice forced the vessel to turn around. *Exiles* then turned southwest, following the coast of Ellesmere Island to Craig Harbor and Grise Fjord. *Exiles* sailed southward along the western boundary of Baffin Bay, with stops in Pond Inlet and Clyde Harbor on Baffin Island. *Exiles* returned to Newfoundland in late September, completing a circuit of Baffin Bay, collecting 98 CTD profiles on this leg. In total, 147 CTD profiles were collected during the 2017 Mission Arctic Citizen Science Sailing Expedition. The CTD profiles are described here and they are available for download from the Greenland Marine Ecosystem community data repository on Zenodo (https://zenodo.org/record/4597385#.YF2cPF1Ki8U). The Greenland Marine Ecosystem community data repository (https://zenodo.org/communities/greenmardata/) is a curated repository for relevant datasets collected by professional and citizen scientists. The repository also contains other datasets that were collected during the expedition as well as datasets from other research cruises. A daily summary of activities aboard *Exiles* during July 2017, as well as plots of each fjord transect, are provided with the dataset.

## 2.2. CTD Profiles

A RBR Concerto CTD (https://rbr-global.com/) that measured conductivity, temperature, and pressure was used in fjords from Paamiut to Upernavik in July 2017. A Sontek CastAway CTD (https://www.sontek.com/castaway-ctd) was used for all stations north of Upernavik in western Greenland and on the return leg along the western shore of Baffin Bay to St. John's, Newfoundland (**Figure 1**). The CastAway features a built-in GPS and liquid crystal display (LCD) screen, and Bluetooth data transfer, which make it relatively easy to use in citizen science field campaigns. The built-in GPS minimizes record-keeping requirements and the LCD screen allows the operator to verify that the instrument is functioning properly, both before and after each profile and the wireless Bluetooth data transfer reduces the risk of flooding the pressure housing when connecting data transfer cables. The CastAway CTD has a maximum operating depth of 100 m, records data at 4 Hz, and has accuracies of ±0.05°C, ±0.1 psu, and 0.25%, for temperature, salinity, and depth, respectively.

## 2.3. CTD Data Processing

All CTD profiles were quality controlled, binned, and stored in a single network common data form (netCDF; https://www.unidata.ucar.edu/software/netcdf/) file using a template provided by the National Oceanographic and Atmospheric Administration's National Centers for Environmental Information (https://www.nodc.noaa.gov/data/formats/netcdf/v2.0/). NetCDF provides self-describing data in a format that is compatible with popular analysis tools like Ocean Data View, Python, Matlab, and R-Studio.

The raw CTD measurements were processed to remove the surface soak (e.g., a period of several minutes that allows the sensors to acclimate to the ambient water temperature) and the upward segment of the profile. The downcast conductivity data were de-spiked and the conductivity, temperature, and pressure data were used to compute salinity, depth, density, potential temperature, conservative temperature, and potential density. Salinity, density, potential density, potential temperature, and conservative temperature were computed using the Gibbs Seawater Oceanographic Toolbox for Matlab (McDougall et al., 2012).

# 3. PRELIMINARY ANALYSIS

The CastAway CTD profiles that were acquired by the crew of *Exiles* in August and September 2017 were used to compute the freshwater content (FWC) of the upper 40 m. This depth limit was selected as the glacial meltwater signal is thought to be confined to the upper 30 m (Castro de la Guardia et al., 2015). The FWC was computed following de Steur et al. (2009),

$$FWC = \sum_{z=-40}^{z=0} \frac{S_{ref} - S(z)}{S_{ref}} \Delta z \tag{1}$$

where $S_{ref}$ and $S(z)$ are a reference salinity and a given depth profile of observed salinity, respectively. The reference salinity was computed using a Bootstrap resampling of the mean salinity (Efron and Tibshirani, 1986) at 40 m depth in Melville Bay ($S_{ref} = 33.25$), Nares Strait ($S_{ref} = 31.54$), and off Ellesmere ($S_{ref} = 31.91$) and Baffin Islands ($S_{ref} = 31.51$). The estimates of FWC in the region during August and September 2017 are shown in **Figure 2**. **Figure 2** reveals FWC of ∼2–3 m near the outlets of fjord systems in western Greenland and Ellesmere and Baffin Islands. The FWC in Nares Strait ranged from 1–2 m. Thus, these

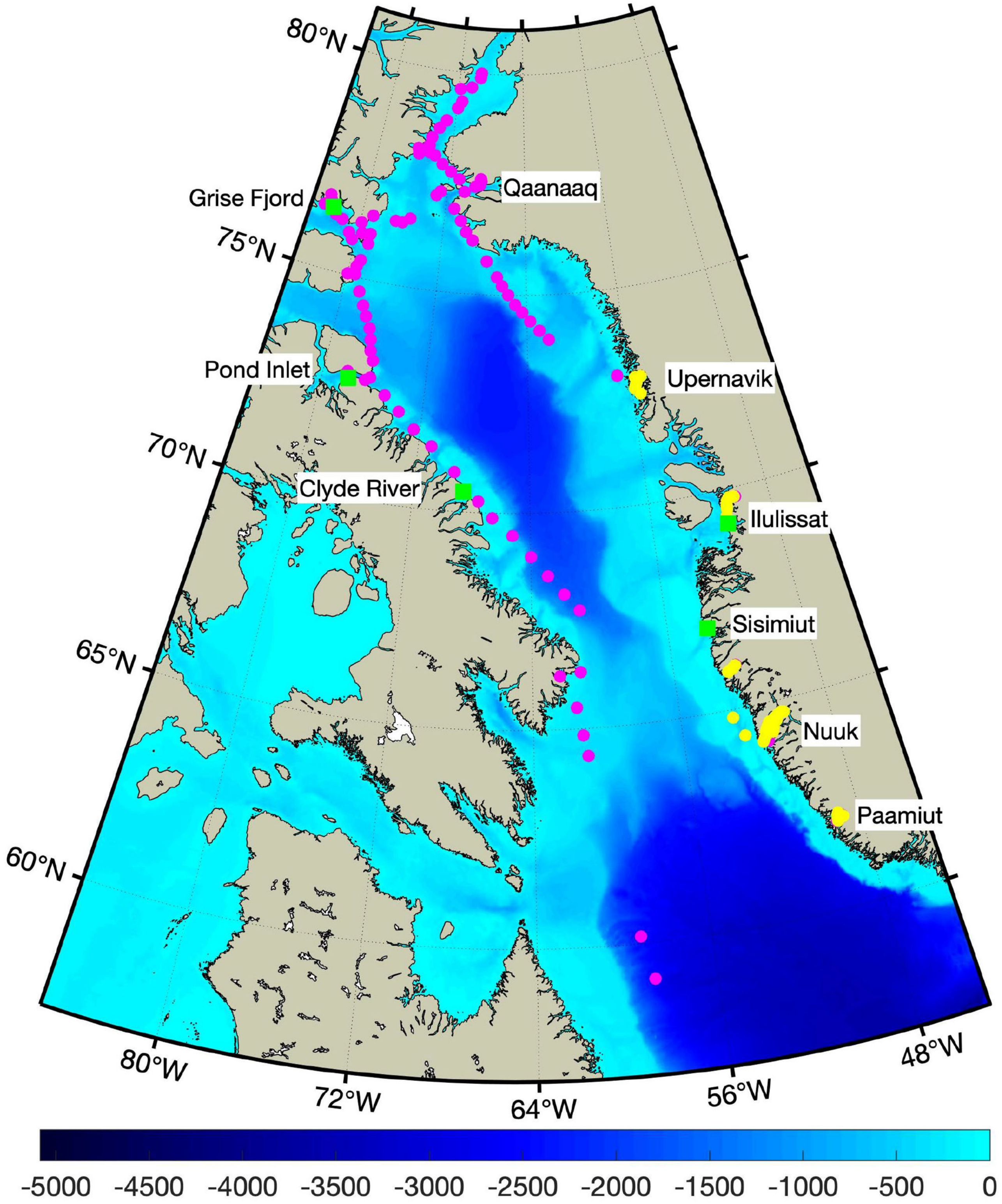


**FIGURE 1 |** A map of Baffin Bay and the Labrador Sea, bordered by Greenland on the east and Canada to the west. Circles are used to indicate CTD profile locations colored to represent the instrument that was used. Yellow circles correspond to the RBR Concerto and pink circles correspond to the Sontek CastAway. Colored contours indicate ocean bathymetry (meters below sea level) derived from ETOPO1 (NOAA National Geophysical Data Center, 2008).

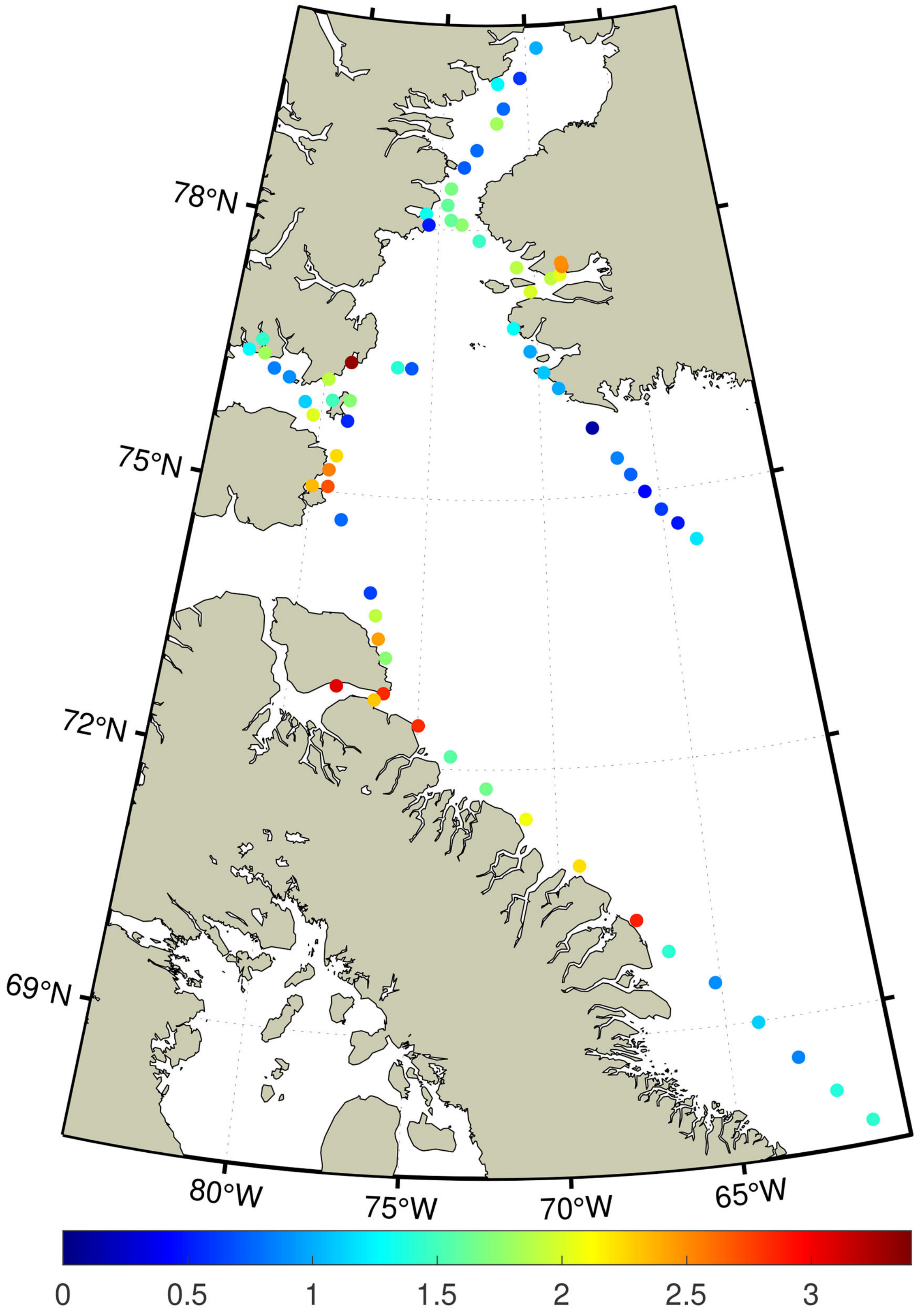


**FIGURE 2 |** The freshwater content (FWC; units of meters) of the upper 40 m in northern Baffin Bay is indicated by color-coded circles. The FWC ranged from 0.12 to 3.33 m during the 2017 survey.

observations quantify shallow FWC in a data-scarce region of the Arctic.

## 4. CONCLUSIONS

These preliminary results, therefore, demonstrate the potential for citizen science initiatives to contribute observational data to the ongoing effort to observe and understand the rapidly changing marine Arctic environment. These preliminary results also demonstrate that visiting sailboats can be effective data collection platforms in remote and harsh polar environments. Furthermore, Greenland is the world's largest island and the culture and economy of its citizens are inexorably linked to the sea. In addition to visiting yachts and cruise ships, which only visit Greenlandic waters in the warmer months (Leoni, 2019), citizen science CTD observations should be expanded to acquire data year-round.

## DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: https://zenodo.org/record/4597385#.YF2cPF1Ki8U.

## AUTHOR CONTRIBUTIONS

DC, NP, and SR conceived the study. DC, NP, PL, PP, WT, JC, and GC collected the data. DC performed the quality control and wrote the first draft of the manuscript. SR provided the funding. All authors contributed to the article and approved the submitted version.

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METHODS
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# GLOBE Observer and the GO on a Trail Data Challenge: A Citizen Science Approach to Generating a Global Land Cover Land Use Reference Dataset

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Land cover and land use are highly visible indicators of climate change and human disruption to natural processes. While land cover is frequently monitored over a large area using satellite data, ground-based reference data is valuable as a comparison point. The NASA-funded GLOBE Observer (GO) program provides volunteer-collected land cover photos tagged with location, date and time, and, in some cases, land cover type. When making a full land cover observation, volunteers take six photos of the site, one facing north, south, east, and west (N-S-E-W), respectively, one pointing straight up to capture canopy and sky, and one pointing down to document ground cover. Together, the photos document a 100-meter square of land. Volunteers may then optionally tag each N-S-E-W photo with the land cover types present. Volunteers collect the data through a smartphone app, also called GLOBE Observer, resulting in consistent data. While land cover data collected through GLOBE Observer is ongoing, this paper presents the results of a data challenge held between June 1 and October 15, 2019. Called "GO on a Trail," the challenge resulted in more than 3,300 land cover data points from around the world with concentrated data collection in the United States and Australia. GLOBE Observer collections can serve as reference data, complementing satellite imagery for the improvement and verification of broad land cover maps. Continued collection using this protocol will build a database documenting climate-related land cover and land use change into the future.

**Keywords: citizen science, community engagement, science technology engineering mathematics (STEM), reference data, geotagged photographs, land cover - land use**

## INTRODUCTION

Global land cover and land use (LCLU) mapping is critical in understanding the impact of changing climatic conditions and human decisions on natural landscapes (Sleeter et al., 2018). Modeling the biophysical aspects of climatic change requires accurate baseline vegetation data, often from satellite-derived global LCLU data products (Frey and Smith, 2007). Satellite-based global LCLU products are generated through classification algorithms and verified through the visual interpretation of satellite images, detailed regional maps, and ground-based field data (Tsendbazar et al., 2015). However, an assessment of such LCLU data products found that land cover classifications agreed with reference data between 67 and 78% of the time (Herold et al., 2008). Some classes, such as urban land cover, are more challenging to accurately identify. At high latitudes, where land cover change has the potential to generate several positive feedback loops enhancing $CO_2$ and methane emissions, field observations agreed with global LCLU data as little as 11% of the time (Frey and Smith, 2007). The high volume of reference data needed to refine global LCLU products can be impractical to obtain, but geotagged photographs may have potential to inform multiple global LCLU products at relatively low cost (Tsendbazar et al., 2015).

Citizen science can be a tool for collecting widespread reference data in support of studies of land cover and land use change, particularly if multiple people document the same site (Foody, 2015a). For example, both the Geo-Wiki Project (Fritz et al., 2012) and the Virtual Interpretation of Earth Web-Interface Tool (VIEW-IT) generated early citizen science-based land cover and land use reference datasets by asking volunteers to provide a visual interpretation of high-resolution satellite imagery and maps (Clark and Aide, 2011; Fritz et al., 2017). Other citizen science efforts, such as the Degree Confluence Project (Iwao et al., 2006), GeoWiki Project (Antoniou et al., 2016), Global Geo-Referenced Field Photo Library (Xiao et al., 2011), and PicturePost (Earth Observation Modeling Facility, 2020), have built libraries of geotagged photographs that may also serve as reference data. In this paper, we present a subset of GLOBE Observer Land Cover citizen science data as another potential LCLU reference dataset of geotagged photographs collected following a uniform protocol.

GLOBE Observer (GO) is a mobile application compatible with Android and Apple devices used to collect environmental data in support of Earth science (Amos et al., 2020). GLOBE Observer includes four observation protocols, one of which is called GLOBE Observer Land Cover. The land cover protocol first trains citizen scientists and then facilitates recording land cover with georeferenced photographs and classifications. GLOBE Observer is a component of the Global Learning and Observations to Benefit the Environment (GLOBE) Program (https://www.globe.gov), an international science and education program in operation since 1995 (GLOBE, 2019). As such, GLOBE Observer Land Cover data is submitted and stored in the GLOBE Program database with the GLOBE Land Cover measurement protocol data, in addition to 25 years of student-collected environmental data (biosphere, atmospheric, hydrologic, soils). The GLOBE Observer Land Cover protocol, which launched in September 2018, is built on an existing paper-based GLOBE Land Cover measurement protocol that has its roots early in the GLOBE Program (Becker et al., 1998; Bourgeault et al., 2000; Boger et al., 2006; GLOBE, 2020b). The connection to this deep history and well-established, experienced volunteer community makes GLOBE Land Cover unique.

This paper documents the method used to collect geotagged land cover reference photos through citizen science with GLOBE Observer, including data collection, the use of a data challenge to motivate data collection, and a description and assessment of the data collected in one such challenge, GO on a Trail, held June 1 through October 15, 2019.

## MATERIALS AND EQUIPMENT

All GLOBE Observer Land Cover data, including the data resulting from the GO on a Trail challenge, were collected through the NASA GLOBE Observer app. Data collection is contained entirely within the app to ensure that data are uniform following the defined land cover protocol. No external equipment is required. The app automatically collects date, time, and location when a user begins an observation. Location is recorded in latitude and longitude coordinates determined through the mobile device's location services [cellular, Wi-Fi, Global Positioning System (GPS)]. The accuracy of these coordinates is shown on-screen, providing the user the opportunity to improve the location coordinate accuracy, with a maximum accuracy of 3-meters, or the option to manually adjust the location using a map.

The collection of geotagged photographs also builds on embedded phone technology. The GLOBE Observer app integrates the phone's native compass sensor with the camera sensor to help users center the photographs in each cardinal direction. The direction is superimposed on the camera view; the user then taps the screen to capture a photograph when the camera is centered on North, South, East, or West. To collect uniform up and down photos, the phone's gyroscope sensor detects when the phone is pointed straight up and straight down and automatically takes a photo when the camera is appropriately oriented. Users may also upload photos directly from their device, a measure put in place to allow participation on devices that do not have compass or gyroscope (Manually uploaded photos are flagged in the database.). Direction indicators on the bottom of the screen turn green when a photo exists so that the user can clearly see if more photos are needed to complete the observation. The end user may review all photos and retake them as needed. Both the location and photography tools are shown in **Figure 1**.

## METHODS

### GO Land Cover Protocol

Volunteer-collected geotagged photographs have been shown to provide useful reference data if a protocol is followed (Foody et al., 2017). At minimum, photos should include date, location, and standardized tags; ideally, a photograph should be taken in each cardinal direction to fairly sample the land cover at that

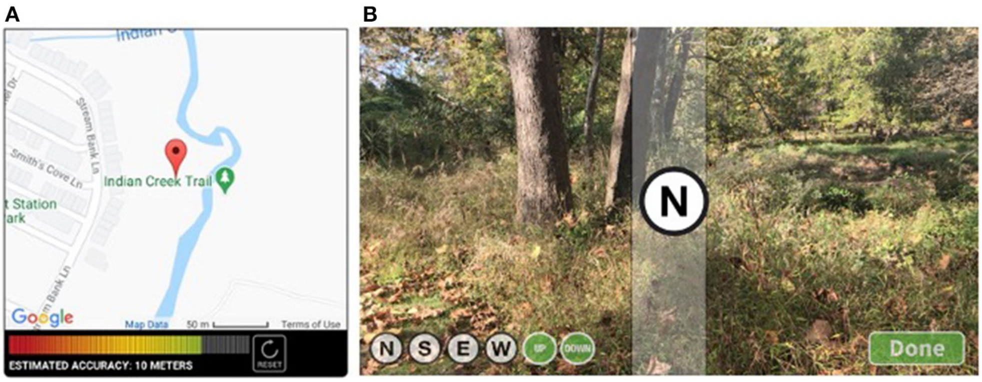


**FIGURE 1 |** Screenshot of the location accuracy interface **(A)** and the photo collection tool **(B)** in the GLOBE Observer app. These tools integrate the phone's functions (GPS, compass, and gyroscope) to ensure land cover photographs are collected uniformly.

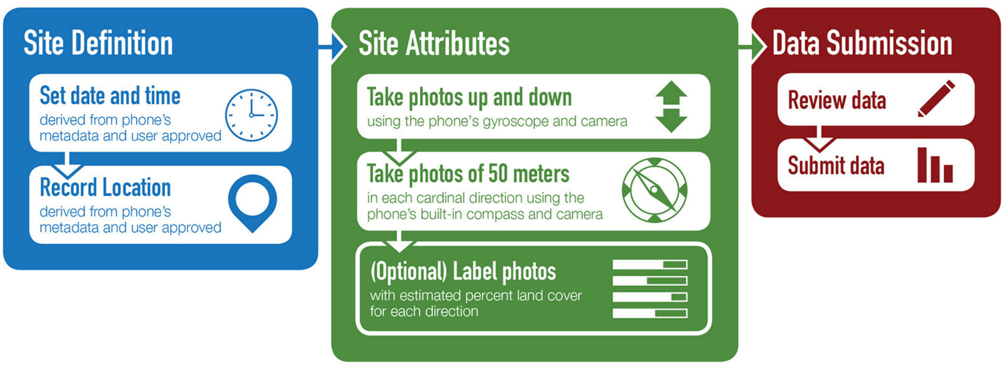


**FIGURE 2 |** Task flow for a GLOBE Observer Land Cover observation. Users review all data submitted, including metadata.

location (Antoniou et al., 2016). The GLOBE Observer Land Cover protocol meets these requirements. The protocol contains two components: definition of the observation site and definition of the attributes of the site.

Data collection begins with the definition of the observation site, a 100-square meter area centered on the observer. The date, time, and location derived from carrier and phone settings are autofilled and verified by the user.

Site attributes identified in the second phase of the data-collection protocol include ephemeral surface conditions (snow/ice on the ground, standing water, muddy or dry ground, leaves on trees, raining/snowing), site photos, and optionally, land cover classification labels. Up to six photographs are taken at each location: horizontal landscape views focused on the nearest 50 meters and centered on each cardinal direction, up to show canopy and cloud conditions, and down to show ground cover at the center of the site. Volunteers may label each N-S-E-W photo with the primary land cover types visible in the image and estimate the percentage of the 50-meter area includes that land cover type. The classification step is optional, and an observation may be submitted without classifications.

To collect high quality data, users are trained before data collection and are required to review data before submission. Before data collection begins, users complete an interactive in-app tutorial to unlock the protocol tools. Training includes definitions of land cover, animations demonstrating how to photograph the landscape, and an interactive labeling exercise. The animation screens cannot be advanced until the animation finishes, preventing the user from skipping the training. The tutorial and a simple land cover classification guide with photo examples are accessible from any screen during data collection and classification. After collecting data, the volunteer sees a summary of the observation and has the opportunity to correct errors before final submission. The data collection process is documented in **Figure 2**.

## Method of Managing Data Storage and End User Privacy

Upon submission, all data are stored in the GLOBE Program database. Before storage, data, including metadata, are lightly sanitized for privacy. Quality assessment/quality control measures are performed on subsets of data and published separately, **Figure 3**.

Photos are manually reviewed by GLOBE Observer staff daily. If a staff member sees a photo with an identifiable person, identifying text (primarily car license plate numbers), violence, or nudity, the photo is moved to a non-public database. During the GO on a Trail challenge, 1% of

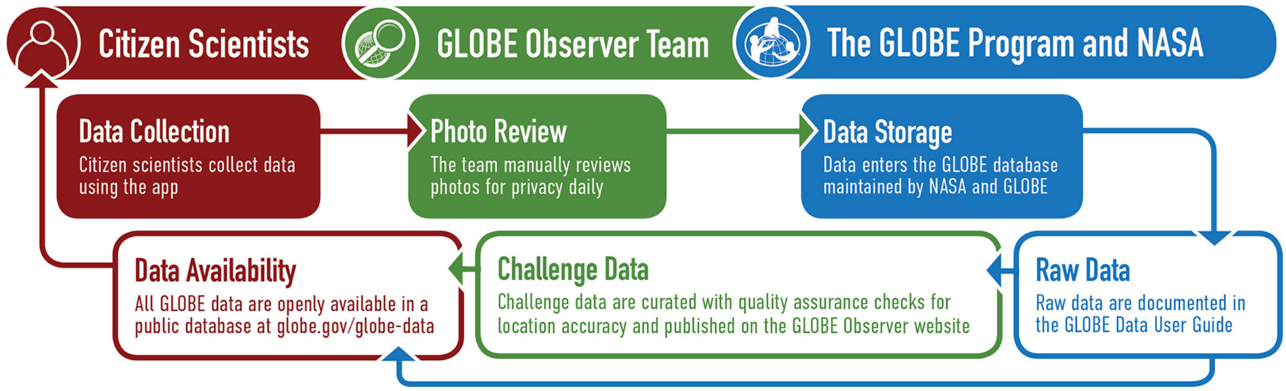


**FIGURE 3 |** Data collection and data management workflow. Raw data are sanitized to ensure volunteer privacy, and are entirely user-inputted data. Challenge data and other curated datasets include quality assessments done after data submission.

photos (234 photos) were rejected. All remaining photos are entered into the public database. Photos taken with the app's camera plugin are compressed to a standard size (1920 by 1,080 pixels), while manually uploaded images maintain their original size.

Camera Exchangeable Image File Format (EXIF) metadata is stripped from the photos to maintain user privacy before images are stored in the system. Relevant metadata (date, time, location) are contained in the user-reviewed data entry. The app's location accuracy estimate is also stored with the location data. The app requests location from the phone up to 10 times or until repeat measurements are <50 meters apart. The distance between repeat measurements is the location accuracy. The location and accuracy estimate is visible to the end user on the location screen, and the user has the opportunity to repeatedly refresh the location to improve accuracy. This means that the volunteer sees and approves all metadata associated with each observation to ensure accuracy and privacy.

Volunteer privacy is further protected in the database through anonymity. Each observation is associated with a unique number assigned to each person that is not publicly associated with their name or email address. For quality assurance, it is possible to gauge a volunteer's experience level by looking at all data associated with the anonymous user number, but a volunteer's name or contact information is never made public.

Approved photos and all inputs from the volunteer are available through the GLOBE Program database (globe.gov/globe-data) as a comma-separated values (CSV) file. The file includes fields for date, time, location, user ID, elevation (based on the location, not from the phone's metadata), URLs to each photo within the database, LCLU overall classification, classification percent estimates for each photo, and user-submitted field notes. These data should be viewed as "raw" primary data. Subsets of data on which additional quality assurance or data validation analysis has been done after submission, such as the GO on a Trail data described in this paper, are provided on the GLOBE Observer website (observer.globe.gov/get-data). GLOBE Observer Land Cover data and data access are documented in the GLOBE Data User Guide (GLOBE, 2020a).

## Method of Motivating Data Collection

While GLOBE Observer Land Cover data collection began in September 2018 and continues through the present, this paper focuses on applications of the method to generate data during a citizen science challenge called GO on a Trail and held June 1 through October 15, 2019. The challenge was modeled on other successful challenges conducted through GLOBE Observer, particularly the Spring Clouds Challenge held March-April 2018 (Colón Robles et al., 2020), which resulted in increased rates of data submission during and after the challenge period. During the GO on a Trail challenge, citizen scientists from all 123 countries that participate in The GLOBE Program were encouraged to submit observations of land cover (The GLOBE Program, of which GLOBE Observer is a part, operates through bi-lateral agreements between the U.S. government and the governments of partner nations.). GLOBE countries are grouped into six regions. To motivate data collection, the three observers who collected the most data in each region during the challenge period were publicly recognized (if they wished to be) as top observers for the challenge and awarded a certificate.

To collect regions of geographically dense data within the challenge, GLOBE Observer partnered with Lewis and Clark National Historic Trail (LCNHT) and requested data at specific locations of historical and scientific interest along the Trail, and with John Pring of Geosciences Australia and Scouts Australia for data in remote locations in Australia. Top participants in the partner-led challenges were awarded a Trail patch and poster (LCNHT) or recognized in a formal ceremony (Scouts Australia).

In the United States, the GO on a Trail data challenge was planned and implemented as a partnership between the NASA-based GLOBE Observer team and Lewis and Clark National Historic Trail (LCNHT) under the U.S. National Park Service. LCNHT was deemed an ideal education partner because the trail covers ∼7,900 km (4,900 miles) over 16 states, transecting North America from Pittsburg, PA, to Astoria, OR. The Trail crosses eight ecoregions, encompassing a variety of land cover types, and consists of 173 independently operated partner visitor centers and museums that could support volunteer recruitment and training.

Interested visitor centers and museums were trained on the land cover protocol and given challenge support material including data collection instructions and a large cement sticker to be placed at a training site near the building. Called Observation Stations, the stickers were designed to be locations where on-site educators could train new citizen scientists how to collect data. Observation Stations were intended to generate repeat observations to gauge the variability in data collection and classification across citizen scientists. More than 150 Observation Station stickers were distributed, but it is unclear how many were placed.

Acknowledging that many successful citizen science projects use game theory to improve volunteer retention and to increase data creation (Bayas et al., 2016; National Academies of Sciences Engineering, and Medicine, 2018) and to encourage data collection at Observation Stations, a point system was implemented to award the most points (4) for observations collected at an Observation Station. Participants could earn 2 points per observation taken at designated historic sites (United States Code, 2011) along the Trail, and 1 point per observation taken anywhere else along the Trail. While the single point was meant to enable opportunistic data collection, we also awarded a single point to data collected at the center points of Moderate Resolution Imaging Spectroradiometer (MODIS) pixels to encourage observations that could be matched to the global 500-meter MODIS Land Cover Type (MCD12Q1) version 6 data product. The participants with the most points were recognized as the challenge top observers and received a Trail patch and poster.

Concentrated data collection in Australia resulted from a land cover data collection competition for youth participating in Scouts, an organization for children and youth (male and female) aged 5–26, and associated adults. John Pring, Geosciences Australia, hosted the competition, which ran June 15–October 15, timed to coincide with both state-based school holidays and cooler weather. The competition incorporated a points system intended to encourage observations in non-metropolitan settings and with value increasing with distance from built up areas. While 23 scouting-based teams registered through the GLOBE Teams function and contributed data, two were extremely active, adding nearly 200 observations across 5 Australian states and territories. The winning team of three [aged 10, 11 (Team Captain) and 15] collected 111 LCLU observations. They also ranked among the top GO on a Trail observers in the Asia and Pacific region, contributing just over a quarter of all data submitted from the region during the challenge.

## Method for Conducting Quality Assurance on Challenge Data

To prepare data for scientific use, challenge data were assessed for quality assurance focusing on location, data completeness, and classification completeness. All data with location accuracy error > 100 meters were removed as were submissions that lacked photographs. Ninety percent of the observations submitted passed screening. QA fields include location accuracy error, image count (0–6), number of images rejected (0–6), image null (0–6), classification for each direction (0–4), completeness (image count + classification direction count/10, range of 0–1), presence/absence for each directional photo (1 is present, 0 is blank), and the sequence of values for image presence/absence to indicate which directions are absent in the observation.

As an initial assessment of user classification labeling, the MODIS/Terra + Aqua Land Cover Type Yearly L3 Global 500-meter classification data are included in the final data file for each GO observation site. A mismatch between user classification and MODIS data does not necessarily indicate that the volunteer incorrectly labeled the land cover. Differences can also result from LCLU change, differences in scale, or errors in the satellite data product. Discussion of additional planned quality assessment of user classifications follows.

GLOBE Observer Land Cover GO on a Trail challenge data are in the supplemental data and are archived on the GLOBE Observer website, https://observer.globe.gov/get-data/land-cover-data, as a CSV file. An accompanying folder of GO on a Trail photos is provided on the website.

# RESULTS

## GO on a Trail Data Description

GO on a Trail data were collected opportunistically between June 1 and October 15, 2019, by a group of 473 citizen scientists that created 3,748 (3,352 after QA/QC) LCLU point observations consisting of 18,836 photos and 906 classification labels using the GLOBE Observer mobile app with the Land Cover protocol. Observations were submitted from 37 countries in North and South America, Africa, Europe, Asia, and Australia with concentrations in the United States (70% of all data) and Australia, **Figure 4**. Other top contributors included Poland, United Kingdom, and Thailand. Participation varied throughout the period, with a peak in late June when the challenge was heavily promoted, as shown in **Figure 5**. Most of the data were collected by experienced volunteers. As is typical in many citizen science projects, 6% of the participants (super users) collected 75% of the data, while 54% of users submitted just one observation, **Figure 6**.

Twenty-seven percent (902) of the total observations were within the focus area of the LCNHT, defined as an area five kilometers on either side of the Trail, as shown in **Figure 7**. Ten percent of the LCNHT observations came from visitor centers (potential Observation Stations), resulting in 578 images collected within 500 meters of the visitor centers. Too few repeat observations were submitted from Observation Stations to do the intended assessment of variability in data collection and classification across citizen scientists.

In Australia, the challenge resulted in 183 new land cover observations with 1,028 photos. Teams traveled more than 20,000 kilometers between them based on known home locations and the farthest data point from home collected by each team. New data includes contributions from extremely remote locations where other LCLU reference data are scarce, **Figure 8**.

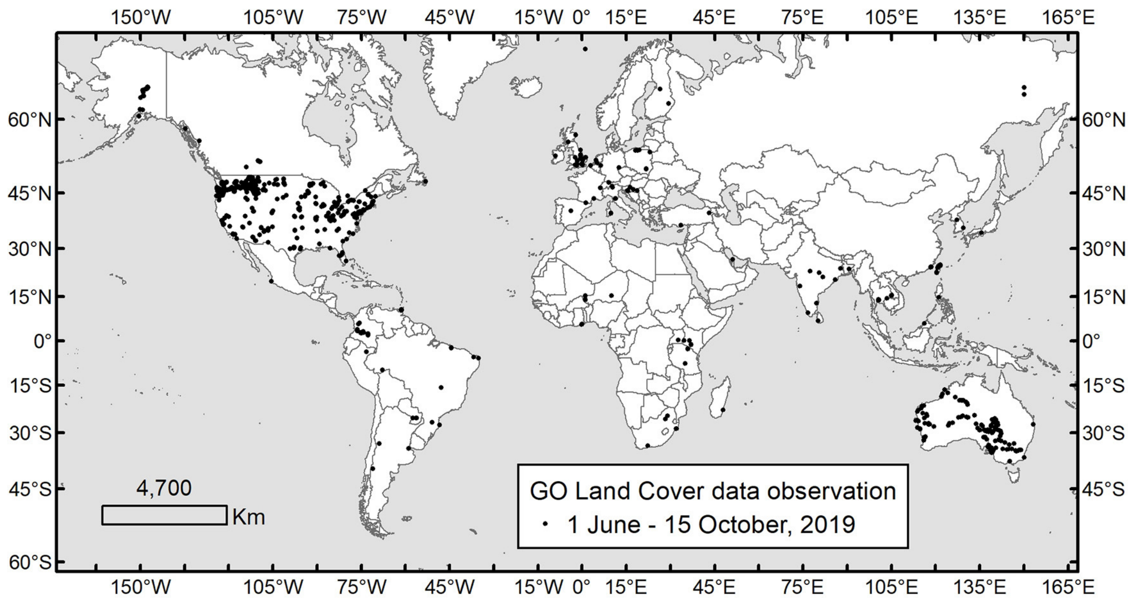


**FIGURE 4 |** Distribution of ground reference images collected globally using the GLOBE Observer mobile app with the Land Cover protocol during the GO on a Trail data campaign that occurred from June 1 to October 15, 2019. Observations were reported from every continent except Antarctica, but are most concentrated in North America and Australia where partner-led challenges drove data collection.

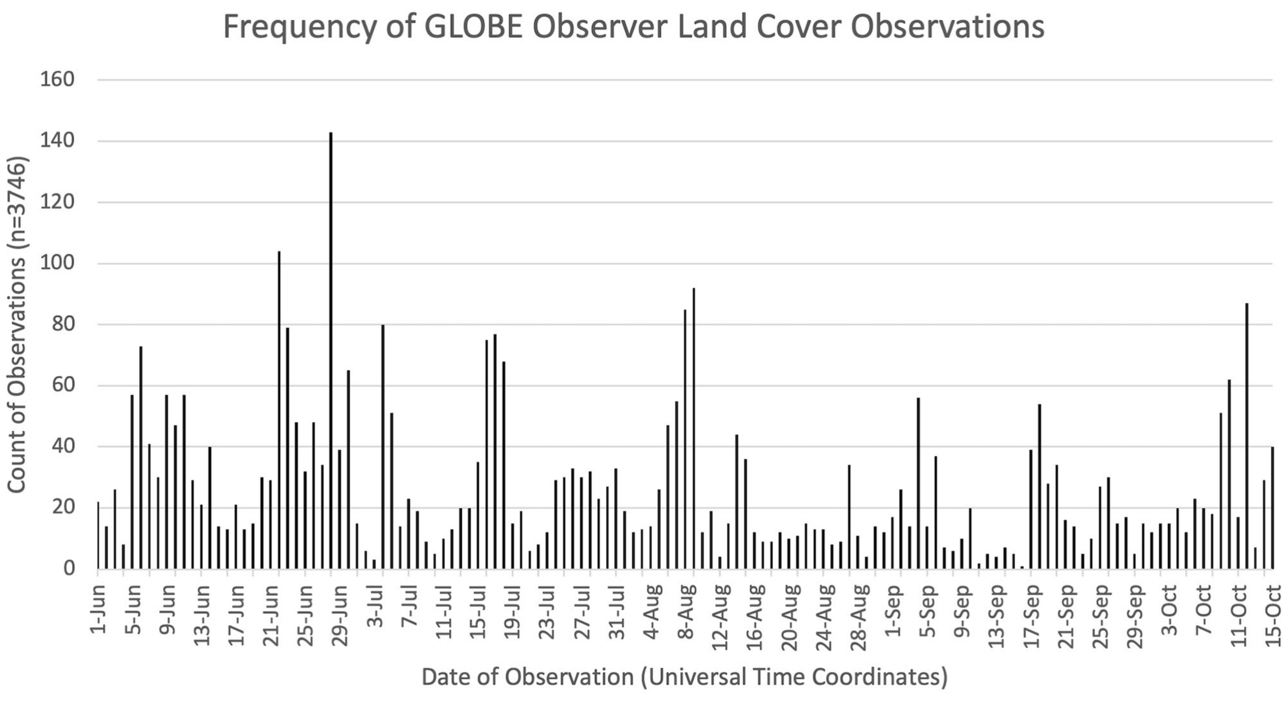


**FIGURE 5 |** Participation of citizen scientists in data collection varied but was consistent throughout the time period of 1 June–15 October, 2019.

Most observations were collected in dry conditions when leaves were on the trees, **Table 1**. Twenty-five percent of the observations include optional classification data, **Table 2**. For all observations with classification labels submitted during this data challenge, the most common LCLU type mapped was herbaceous land (grasses and forbs, 387 sites) followed

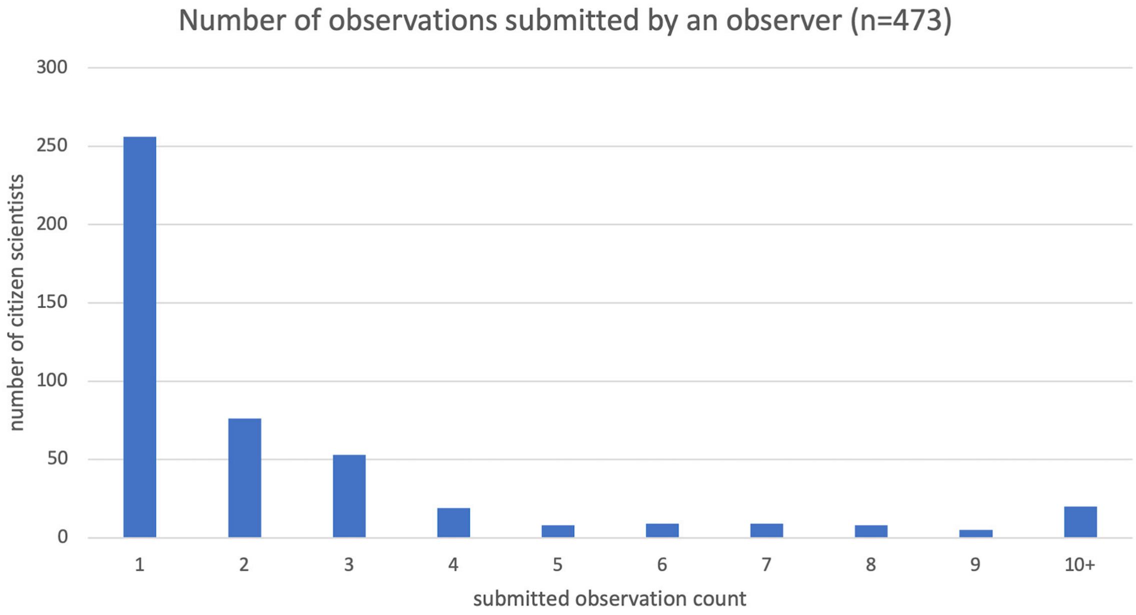


**FIGURE 6 |** The overall challenge engaged 473 citizen scientists who primarily submitted between 1 and 9 observations while there were 20 highly-engaged participants who each contributed >10 observations.

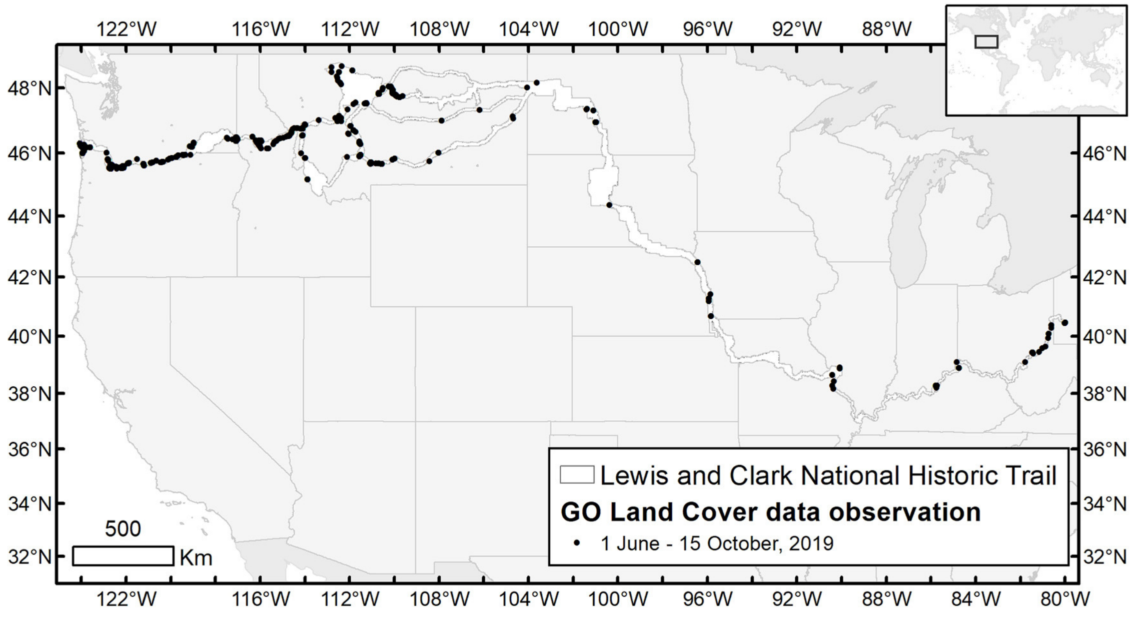


**FIGURE 7 |** This map shows the results of a geographically-focused portion of the data challenge with partner Lewis and Clark National Historic Trail (LCNHT) under the U.S. National Park Service.

by urban/developed land (197 sites). The high number of urban/developed land likely reflects opportunistic data collection, meaning participants received "credit" for data collected anywhere and these land cover types are most accessible to volunteers. Along the LCNHT, classified sites were also primarily herbaceous, followed by open water and urban. Considering that grassland is the dominant land cover type (78%: MODIS IGBP) and that the Trail itself is defined by roadways along rivers, these LCLU class results are not surprising.

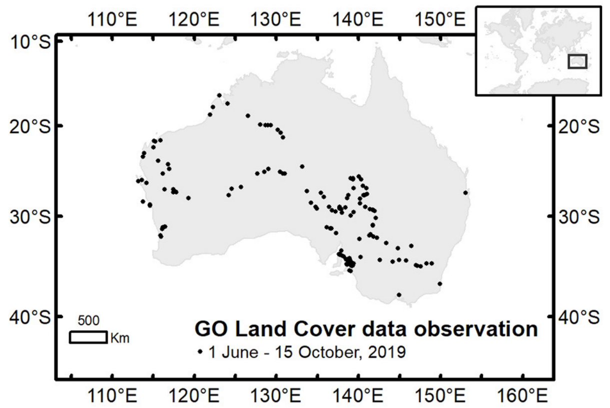


**FIGURE 8 |** Distribution of GLOBE Observer Land Cover observation sites during the geographically-focused Australian data challenge June 15–October 15, 2019.

**TABLE 1 |** Surface conditions are recorded with each GLOBE Observer Land Cover observation.

| Type | True | False |
|---|---|---|
| Snow/ice | 87 (3%) | 3,265 (97%) |
| Standing water | 481 (14%) | 2,871 (86%) |
| Muddy | 328 (10%) | 3,024 (90%) |
| Dry ground | 2,718 (81%) | 634 (19%) |
| Leaves on trees | 3230 (96%) | 122 (4%) |
| Rain/snow | 141 (4%) | 3,211 (96%) |

*Most citizen scientists made observations during "dry ground" periods.*

**TABLE 2 |** GLOBE Observer volunteer classifications.

| MUC description | Count | % of total |
|---|---|---|
| Barren | 48 | 5% |
| Cultivated | 73 | 8% |
| Herbaceous | 387 | 43% |
| Shrubs | 34 | 4% |
| Trees | 112 | 12% |
| Urban | 197 | 22% |
| Wetlands | 13 | 1% |

*Nine hundred six of 3,352 observations include optional classifications. Eight hundred eighty-five records have classifications in all N-E-S-W directions and 21 have classifications in three directions.*

## DISCUSSION

### Data Quality Analysis

The data that results from the GO Land Cover protocol is a series of six photographs tagged with date, time, location, and, in some cases, land cover classification estimates. Other projects create collections of similar geotagged photographs. The Degree Confluence Project encourages users to photograph integer latitude-longitude confluence points in each cardinal direction. By the nature of the project, the spatial density of the photographs is limited (Fonte et al., 2015) to 24,482 potential points on land (Iwao et al., 2006). The Geo-Wiki Project also accepts geotagged photos of specific, pre-defined locations for brief project periods during which users upload a single photo from a requested location or land cover type (Fonte et al., 2015).

GLOBE data offers photographs of the four cardinal directions and adds up and down photos for additional context. **Figure 9** and **Table 3** show the raw data from a single user-submitted observation. While this paper focuses on data collected during the GO on Trail challenge in 2019, GLOBE data collection is ongoing with data reported at more than 17,000 locations in 123 countries.

Since the primary data are geotagged photos, location accuracy is the most significant data quality check done on the GO on a Trail data to facilitate mapping the photos to other LCLU data. Further, a published quality assessment of all GLOBE Observer land cover data collected between 2016 and 2019, including GO on a Trail data, found that location errors are the most common errors (Amos et al., 2020). The GLOBE Observer app reports location accuracy estimates based on repeated queries of the phone's GPS receiver. The minimum accuracy error is 3 meters and the maximum is 100 meters with an average error of 14.7 meters, **Table 4**. Data with location accuracy errors > 100 meters (242 observations, 6%) have been eliminated from the dataset.

The dataset may include a degree of LCLU bias introduced by citizen observers. Foody (2015a) notes that a weakness of citizen-collected geotagged photos, such as GLOBE Observer photos, is that certain types of land cover may be over-represented. People are known to show preferences for visiting particular land cover types. Han (2007) highlighted a preference for coniferous forest landscapes compared to grassland/savanna biomes. Buxton et al. (2019) noted preferences for greener landscapes in urban neighborhoods. White et al. (2010) observed preferences for water landscapes. Kisilevich et al. (2010) highlighted a trend to visit and document scenic locations. Understanding these potential biases, LCNHT staff used the GO on a Trail challenge to identify particularly scenic locations along the trail. Also, because the data collection was more directed in this area, this sample of land cover types observed by citizen scientists along the LCNHT have more heterogeneity than in the global GO on a Trail data. This bias will be mitigated in future challenges by encouraging data collection at pre-selected sites within the app in addition to allowing user-driven opportunistic data collection.

The third area to assess is the quality of volunteer-assigned land cover classification labels. The optional land cover labels are adapted from a hierarchical global land cover classification system (UNESCO, 1973) developed for the GLOBE Program's 1996 land cover protocol, on which GLOBE Observer Land Cover is based, and named the Modified UNESCO Classification (MUC) system (Becker et al., 1998; GLOBE, 2020b). The subsequent GLOBE Observer land cover data labels were required to be consistent with historic GLOBE data to maintain continuity.

As stated in the GLOBE MUC Field Guide, the original goal of the GLOBE Land Cover measurement protocol was

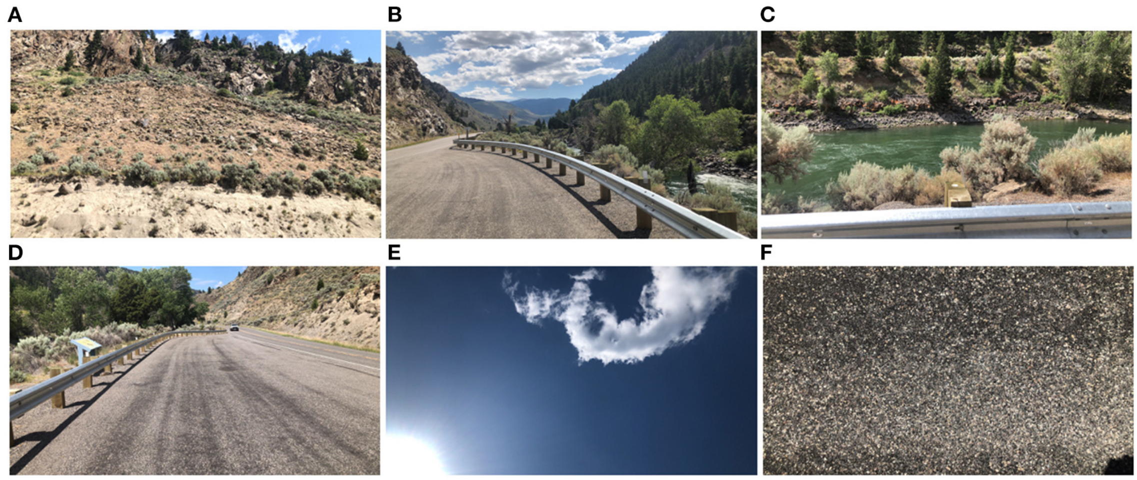


**FIGURE 9 |** Sample GLOBE Observer land cover photos: **(A)** North, **(B)** East, **(C)** South, **(D)** West, **(E)** Up, and **(F)** Down.

**TABLE 3 |** GLOBE Observer sample summary data table for a single raw data point.

| | |
|---|---|
| Land Cover Id | 26199 |
| Data Source | GLOBE Observer App |
| Measured At | 2019-07-30 17:50:00 |
| Overall Land Cover (MUC) Classification | Shrubs, Loosely Spaced, Short Evergreen |
| Field Notes | Highway along river in steep canyons |
| North | 20% MUC 56 (Barren, Dirt/Other); 30% MUC 31 (l) (Shrubs, Loosely Spaced, Short Evergreen); 40% MUC 43 (Herbaceous/Grassland, Short Grass); 10% MUC 93 (Urban, Roads and Parking) |
| East | 40% MUC 93 (Urban, Roads and Parking); 20% MUC 02 (b) (Trees, Closely Spaced, Deciduous - Broad Leaved); 30% MUC 31 (l) (Shrubs, Loosely Spaced, Short Evergreen); 20% MUC 42 (Herbaceous/Grassland, Medium Grass) |
| South | 40% MUC 71 (Open Water, Freshwater); 30% MUC 42 (Herbaceous/Grassland, Medium Grass); 30% MUC 31 (l) (Shrubs, Loosely Spaced, Short Evergreen) |
| West | 50% MUC 93 (Urban, Roads and Parking); 30% MUC 31 (l) (Shrubs, Loosely Spaced, Short Evergreen); 20% MUC 42 (Herbaceous/Grassland, Medium Grass) |

*The complete data file has 55 fields, including location, surface conditions, and anonymized user identification information. Data are fully documented in the GLOBE Data User Guide, https://www.globe.gov/globe-data/globe-data-user-guide.*

**TABLE 4 |** Location accuracy estimates are derived by pinging the phone's GPS location service up to 10 times or until the accuracy error is <50 meters.

| Accuracy method | Count | Average (m) | StdDev (m) | Minimum (m) | Maximum (m) |
|---|---|---|---|---|---|
| Automatic | 2,958 (88%) | 14.7 | 19.5 | 3 | 100 |
| Manual | 394 (12%) | – | – | – | – |

*Users can improve location accuracy by requesting a new location, thus allowing the app a longer time to get repeat location measurements. Users may also edit the location to improve accuracy, resulting in a manual flag with unknown accuracy.*

"the creation of a global land cover data set to be used in verifying remote sensing land cover classifications." Selecting a land cover classification system for citizen science poses a challenge because many of the current global LCLU datasets (e.g., the Moderate Resolution Imaging Spectroradiometer, or MODIS) employ different classifications systems (Herold et al., 2008), making them difficult to compare without harmonizing to similar land cover definitions (Yang et al., 2017; Li et al., 2020; Saah et al., 2020). To make GLOBE Observer Land Cover data comparable to global LCLU maps central to NASA-funded science while maintaining continuity with prior GLOBE Land Cover measurement data, the MUC system was cross-mapped with the International Geosphere-Biosphere Programme (IGBP) Land Cover Type Classification (Loveland and Belward, 1997) used in the MODIS Land Cover Product (Sulla-Menashe and Friedl, 2018). MODIS pixel-level LCLU values are reported for each observation site in the GO on a Trail data. The MODIS Land Cover Product was selected because it was the highest resolution global NASA product available at the time. Alignments are shown in **Supplementary Table 1**. Because GO data include raw percent estimates in addition to the overall land cover for each photograph, a similar process could be used to harmonize with other classification systems, such as the Land Cover Classification System used by the Food and Agriculture Organization of the United Nations.

Since building a library of geotagged photos is the primary objective of the protocol and classification is optional, only 25% of the data includes classification labels. Fifty-three percent of the volunteer labels match the IGBP classification for that location, **Table 5**. The remaining 37% of classifications do not match because of LCLU change between 2018 and 2019 (i.e., GO-classified cultivated vs. IGBP forest), volunteer misclassification (i.e., GO-classified herbaceous grassland vs. IGBP urban), or

**TABLE 5 |** Confusion matrix for GLOBE Observer Land Cover classes based on comparison with IGBP classification.

| GO MUC classification | MCD12Q1_006 IGBP classification | | | | | |
|---|---|---|---|---|---|---|
| | **Forests** | **Shrublands** | **Herbaceous** | **Croplands and mosaics** | **Seasonally or permanently inundated** | **Unvegetated** |
| Forests | 65 | 0 | 11 | 4 | 3 | 29 |
| Shrublands | 14 | 0 | 9 | 1 | 1 | 10 |
| Herbaceous | 96 | 0 | 118 | 78 | 7 | 88 |
| Cultivated | 8 | 0 | 5 | 31 | 0 | 11 |
| Wetlands | 6 | 0 | 1 | 3 | 0 | 3 |
| Unvegetated | 44 | 3 | 67 | 22 | 13 | 155 |
| Not labeled | 840 | 82 | 431 | 224 | 63 | 806 |

*Fifty-three percent of user classifications directly match IGBP classifications with an additional 10% that may match.*

differences in scale (GO-classified barren vs. IGBP sparse herbaceous). An additional 10% of volunteer classifications may match such as a volunteer classification of herbaceous land cover being assigned to a location classified as savanna or open forest in the MODIS product. In this case, grasses may cover a greater percentage of the 100-m area mapped with GO than trees. Of the observations that are classified, it's unclear how well volunteers are estimating percent cover. Dodson et al. (2019) reported that GLOBE citizen scientists estimating percent cloud cover in the GLOBE Observer Clouds tool tend to overestimate percent cover compared to concurrent satellite data. This means that GLOBE Observer Land Cover percent estimates, which are done following a similar protocol, may also be high and should be viewed not as quantitative data, but as a means to gauge general land cover representation in the area.

GLOBE Observer is implementing two initiatives to further assess and remove errors in classification. First, GLOBE Observer is exploring the potential use of artificial intelligence/machine learning (AIML) to identify land cover in the photos. The second initiative is a secondary classification of the photos by other citizen science volunteers, an approach such as those employed by Geo-Wiki Project's Picture Pile (Danyo et al., 2018) or classification projects on the Zooniverse platform (Rosenthal et al., 2018). Further analysis is required to compare the accuracy of AIML classification and secondary classification to primary classification.

AIML and secondary classification will also expand the number of geotagged photos that include classification labels. GLOBE Observer is additionally pursuing incentives to encourage volunteers to submit complete and accurate observations by completing phase two of data collection. While recognition for "winning" does motivate people to participate in challenges, feedback may provide a more powerful mechanism for encouraging routine data completeness and accuracy. A survey of GLOBE Observer users found that the majority of active participants contribute because they are interested in contributing to NASA science and that some that stop participating do so because they feel that a lack of feedback from the project indicates that their contributions aren't useful (Fischer et al., 2021). Clear feedback will help users understand the value of complete and accurate data and will improve data accuracy by identifying classification success or offering correction.

Bayas et al. (2020) report significant improvement in the quality of volunteers' land cover classifications when users were provided with timely feedback. As documented in Amos et al. (2020), GLOBE Observer provides such feedback for volunteers who submit clouds data. Volunteers are encouraged to take cloud observations when a satellite is overhead through an alert that appears 15 min before the overpass. Data concurrent with an overpass are matched to the satellite-derived cloud product from that overpass, and the user is sent an email that compares their observation to the satellite classification. Daily cloud data submissions peak during satellite overpass times, indicating that the alert combined with feedback motivate data collection. We are exploring mechanisms to provide a similar satellite match email for land cover data. Such a system would not only provide feedback, but also flag observations that report land cover that differs from the matched data product. These sites could be reviewed by experts to identify volunteer errors and offer feedback or to identify change or errors in the satellite-based land cover product.

Since a desire to contribute meaningfully to science motivates GLOBE Observer users, data completeness may also improve if volunteers are asked to collect specific types of data to meet a particular science objective. To that end, an in-app mechanism is under development to enable scientists to request observations at designated observation sites. By communicating the scientific need for data and making it simple for volunteers to identify where to collect the most useful data, we will provide motivation for complete and accurate data collection.

## Data Applications

The GLOBE Observer Land Cover dataset is a relatively new but growing data set and the authors suggest some potential data applications. First, the photos could be used on their own in a standard photo monitoring approach (e.g., Sparrow et al., 2020) to estimate current conditions or for tracking LCLU changes over time. Second, if a photo was not classified by a GO citizen scientist, there are improvements in computer vision processing to automatically identify land cover (Xu et al., 2017) or elements like woody vegetation (Bayr and Puschmann, 2019) and thus be incorporated in a variety of software workflows.

Third, the ground reference photos could support remote sensing activities that rely on human cognition (White, 2019) and readily-accessible datasets to accurately label satellite imagery such as developing datasets for LCLU mapping and monitoring with tools such as TimeSync (Cohen et al., 2010) and Collect Earth (Bey et al., 2016; Saah et al., 2019) or in the attribution of land cover change (e.g., Kennedy et al., 2015). The growing dataset could support both of these examples via the provision of landscape level observations across widely dispersed areas. A deep review is underway to assess how well the GO photos map to satellite data which of these applications are most viable.

Foody (2015b) and Stehman et al. (2018) both note the potential large impact on statistical or area estimation in LCLU mapping if reference data is not collected in a specific manner. The increasing temporal and spatial breadth of the GO Land Cover dataset should support the verification of remote sensing Land Cover mapping and the determination of "error-adjustment[s]" suggested by both Foody and Stehman. Indeed, use of geotagged photos as a supporting data source to inform land cover maps is not without precedent, and LCLU data could be "radically improved" with the introduction of more quality volunteer-produced data (Fonte et al., 2015). Iwao et al. (2006) established that photos collected in the Degree Confluence Project provided useful validation information for three global land cover maps. The Geo-Wiki Project also demonstrated the potential value of geotagged photos in a handful of case studies (Antoniou et al., 2016).

The GLOBE Land Cover photo library similarly has the potential to contribute quality reference data to the land cover and land use research community. The location accuracy of GLOBE Observer georeferenced photos is 100 meters or better for 80% of the data and 10 meters or better for 60% of the data. This is sufficient to place the photos within a single pixel of moderate-resolution satellite-based LCLU products, such as the MODIS Land Cover Map. Up to 63% of volunteer classification labels align with the MODIS Land Cover product. Cases of mismatched labeling require deeper investigation, but ongoing assessment of volunteer and expert classification labels will add value to GO on a Trail data.

## DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://observer.globe.gov/get-data/land-cover-data.

## AUTHOR CONTRIBUTIONS

HK and KW manage GLOBE Observer and conceived of the GO on a Trail data challenge. HK, PN, and DO designed the GLOBE Observer Land Cover protocol, and DO led the development of the app data collection tool. AD, RC, and DW planned and implemented the LCNHT portion of the GO on a Trail challenge, contributed to communications, and supported trail partners. ML did the secondary classification of trail data. JP led the Australia Scouts challenge. PN, AD, and ST collected the most GLOBE Observer land cover data along the LCNHT. MH, SH, and JL were the Scouts who collected the most data in the Australia data challenge. AB managed communication to recruit citizen scientists to participate in the challenge. PN did much of the data analysis presented in this paper. HK wrote most of the manuscript, and PN contributed significantly, particularly to the discussion. JP and KW also contributed to the text. HM designed challenge graphics and **Figures 2**, **3**. All authors contributed to the final manuscript.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fclim.2021.620497/full#supplementary-material

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# Development of Privacy Features on Anecdata.org, a Free Citizen Science Platform for Collecting Datasets for Climate Change and Related Projects

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The Anecdata website and its corresponding mobile app provide unique features to meet the needs of a wide variety of diverse citizen science projects from across the world. The platform has been developed with the help of continuous feedback from community partners, project leaders, and website users and currently hosts more than 200 projects. Over 8,000 registered users have contributed more than 30,000 images and over 50,000 observations since the platform became open to the public in 2014. From its inception, one of the core tenets of Anecdata's mission has been to make data from citizen science projects freely accessible to project participants and the general public, and in the platform's first few years, it followed a completely open data access model. As the platform has grown, hosting ever more projects, we have found that this model does not meet all project needs, especially where endangered species, property access rights, participant safety in the field, and personal privacy are concerned. We first introduced features for data and user privacy as part of "All About Arsenic," a National Institutes of Health (NIH)/National Institute of General Medical Sciences (NIGMS) Science Education Partnership Award (SEPA)-funded project at MDI Biological Laboratory, which engages middle and high school teachers and students from schools across Maine and New Hampshire in sampling their home well water for analysis of arsenic and other heavy metals. In order to host this project on Anecdata, we developed features for spatial privacy or "geoprivacy" to conceal the coordinates of samplers' homes, partial data redaction tools we call "private fields" to withhold certain sample registration questions from public datasets, and "participant anonymity" to conceal which user account uploaded an observation. We describe the impetus for the creation of these features, challenges we encountered, and our technical approach. While these features were originally developed for the purposes of a public health and science literacy project, they are now available to all project leaders setting up projects on Anecdata.org and have been adopted by a number of projects, including Mass Audubon's Eastern Meadowlark Survey, South Carolina Aquarium's SeaRise, and Coastal Signs of the Seasons (SOS) Monitoring projects.

**Keywords: citizen science, data privacy, geoprivacy, anonymity, data to action**

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# INTRODUCTION

## Citizen Science and Evolution of Anecdata

Citizen science, or the involvement of citizens in scientific research, is an effective strategy for expanding capacity for science and fostering the use of science in decision-making about complex problems (Wals et al., 2014; Dillon et al., 2016). Anecdata.org is an online platform developed at the MDI Biological Laboratory's Community Environmental Health Lab for the collection of observational data from citizen scientists that is uniquely designed to enable project leaders and participants to utilize their data to enact change (Disney et al., 2017).

The development of Anecdata started in 2014 to provide a data management system for several citizen science projects run by the Community Environmental Health Lab, ranging from bay monitoring to seagrass restoration. Until then, the projects used a combination of Microsoft Excel sheets and Access databases to store data, which became very prone to errors as projects scaled up and made it difficult for the administrative and research team to effectively share data with collaborators and community members in a timely fashion.

Over the years, Anecdata evolved as an online platform for citizen science data collection, aggregation, and analysis through continuous feedback and suggestions from community partners who reached out to our team to host their projects. The development of the platform has followed an Agile software development methodology as defined in the Agile Manifesto, where features are developed by prioritizing and valuing "individuals and interactions over process and tools, working software over comprehensive documentation, customer collaboration over contract negotiations, and responding to change over following a plan" (Hazzan and Dubinsky, 2014).

Today, Anecdata is freely available to citizen groups and community partners around the world. As of publication, it is home to more than 200 projects, where more than 8,000 registered users have contributed over 30,000 images and more than 50,000 observations. Anecdata also continues to serve as a key platform for projects at the Community Environmental Health Lab, especially "All About Arsenic," a 5-year National Institutes of Health (NIH)/National Institute of General Medical Sciences (NIGMS) Science Education Partnership Award (SEPA)-funded project that focuses on building data literacy among middle and high school students while engaging them in sampling their home well water for arsenic and other contaminants and sharing their findings within their local and regional communities. This is the project that provided the impetus for the development of data privacy features on Anecdata.

## Privacy Features on Anecdata

Managing a large repository of online citizen science datasets opens many avenues for developing best practices for citizen science digital data management, including ensuring privacy of certain data types. A high-level overview of data management in citizen science includes individual research topics such as data acquisition, data quality, data infrastructure, data security, data governance, data documentation, data access, data services, and data integration (Bowser et al., 2020).

**TABLE 1** | Definitions of privacy features on Anecdata.org.

| Privacy feature on Anecdata | Definition |
|---|---|
| Geoprivacy | The partial obscuring of geographic coordinates using an algorithm to make observations appear in the general area of the actual observation but shifted by a random distance to obscure the precise observation location. |
| Private fields | A feature that redacts certain datasheet questions from the publicly available dataset. |
| Anonymity | A feature that obscures the user account that was used to create an observation. |

Many projects on Anecdata have informed the development of new functionalities on the platform. "All About Arsenic"[1] is the first project where we systematically developed three such features: (1) "geoprivacy," so that sample site coordinates could be obscured; (2) "private fields," so that certain data fields could be concealed from public view; and (3) "participant anonymity," so that the identity of the person who originally registered a sample is not revealed. These features, defined in **Table 1**, subsequently became available for all projects on Anecdata. Although most data are available for the public to view and download, fields that have been marked as private are only available to project administrators.

Privacy features are critical components of many citizen science projects where protecting the privacy and security of individual participants is essential. Incorporating these features in the design and development of the citizen science platform allows project leaders to support their project participants in making informed and safe decisions about their personally identifiable information (Bowser et al., 2014).

There are multiple reasons why "All About Arsenic" project participants want their personal information obscured. The potential health impacts of arsenic exposure raise issues of medical privacy. In addition, high levels of arsenic in well water could affect property values. A study on the effect of elevated arsenic levels in well water on home values in two Maine towns showed no significant negative impact after 2 years (Boyle et al., 2010). However, a later survey of private well owners in Maine revealed the belief that mitigating arsenic in well water would increase the value of their homes (Flanagan et al., 2015). The relationship between well water quality and negative impact on home values has been documented in other parts of the nation as well (Guignet et al., 2016).

The new privacy features stemming from the "All About Arsenic" project are now available and accessible to all projects on Anecdata and provide vital functionality for groups that are crowdsourcing a wide variety of information that requires data privacy. For these projects, datasets (which are considered privileged) can be downloaded by project administrators but not the general public.

[1] https://www.anecdata.org/projects/view/299

One of the first projects to adopt new data privacy features after they were introduced on the Anecdata site was Coastal Signs of the Seasons (SOS) Monitoring. This program is an offshoot of a New England-wide phenology program that engages citizen scientists in observing 19 upland and coastal indicator species with two main objectives. The first is to characterize the biological effects of climate change through the collection of phenology data and the second is to empower citizens to become a part of the solution to climate change by participating in research comparing the current timing of life cycle events for individual species with historically documented events such as leaf-out, flowering, and gamete production (Stancioff et al., 2017). Other climate change and related projects on Anecdata soon followed suit and adopted privacy features.

While individual projects may have policies that adhere to laws and ethical standards (Guerrini et al., 2018), technology platforms such as Anecdata have a role to play in promoting ethics in citizen science by building in features that provide options and support for privacy controls at both the individual and project levels (Bowser et al., 2014).

As we enter an era where citizen science and open science receive greater recognition, we can celebrate that information is more freely available to everyone for use in advocacy, to promote environmental improvements, to enhance human health, to protect wildlife, and more. At the same time, there are concerns about data quality, stewardship, privacy, security, and control (Bowser et al., 2020), particularly in the case of data that relate to human health (Majumder and McGuire, 2020). Anecdata is in the company of several citizen science platforms that have aimed to achieve a balance between unrestricted public access to data and levels of privacy for project leaders and data contributors, such as CitSci.org (Wang et al., 2015; Lynn et al., 2019), Open Humans (Tzovaras et al., 2019), and iNaturalist (Bowser et al., 2014).

Anecdata supports location and user privacy features and provides the option for any additional data fields to be kept private. In this paper, we present our "All About Arsenic" project as a case study in data privacy and relate it to an early adopter of data privacy features on Anecdata.org, SOS Monitoring.

# METHODS

## Anecdata Technology Stack Description

Anecdata is an online platform composed of a server-side data management system, a public Web interface, and mobile apps for iOS and Android. Anecdata was designed to manage and publicly share our project data at the Community Environmental Health Lab. It is freely available for others to use for projects that serve the public good. While originally envisioned for use with environmental and conservation data, it is now being used by project leaders and participants to collect and share a range of dataset types, including public health, and city planning.

Both the website and the mobile app exchange data with the Anecdata server using the same application programming interface (API) endpoints, which send and receive structured data such as lists of observations, chat messages, or user profiles. The Anecdata server is written in PHP using the CakePHP framework and uses the MariaDB relational database for data storage. The Anecdata website and mobile app are both developed in TypeScript using the Angular framework. The mobile app additionally uses the Ionic framework to provide a native user experience and interface with the device's hardware. By using Angular across all platforms (both mobile and website), the shared code reduces the overall development time when introducing new features. All features developed for one project can be easily replicated across and made available to all projects on the platform.

## Data Collection Schema on Anecdata

The sequence of steps for setting up a new citizen science project or getting involved in an existing project on Anecdata is depicted in **Figure 1**. For everyone, the first step involves creating a user account with an email address and password. A date of birth column is captured during user account registration to ensure that all users are above the age of 13, as US federal law requires that anyone using online platforms collecting personally identifiable information be at least 13 years of age.

Projects, in the context of Anecdata, are pages that have been created by one or more project administrators with the purpose of gathering observations to fill a data need. Data are shared with these projects by participants in the form of observations.

Project administrators use the project designer tool to enter information about their project's goals, protocols, and other essential information for project participants. This generates a custom project page from an established project page template (**Figure 2**). The data schema of a project can be customized to suit the needs of the project using the "datasheet" designer tool.

The "datasheet" designer tool provides an interface for creating a list (rows and columns) of named datasheet fields that participants use to enter data and offers multiple base data inputs that project administrators can choose, including text inputs, numbers, yes/no checkboxes, controlled-vocabulary dropdown menus, date, time, and geospatial coordinates. The datasheet designer also offers templates for common use cases such as litter cleanups, animal observations, water quality monitoring, and collecting biological specimens in the field.

The structure of the Anecdata datasheet system allows for the entry of two categories of data:

1) **Parent fields**, which are fields that pertain directly to all data on the datasheet. In the case of the "All About Arsenic" project, examples of these fields include the name of the student's school, the name of the legal guardian, and well type.
2) **Child fields**, which are repeating blocks of questions that allow the participant to log multiple entries. In the "All about Arsenic" project, students may submit multiple water samples (pre- and post-filtration, or from different locations in the house, such as the kitchen sink and outside faucet), and the child fields on the datasheet pertain to an individual water sample. Examples of these fields include the sample vial ID number, where the sample was collected in the home, the type of filtration system used (if any), and additional comments.

Every time participants visit an Anecdata project page and begin a new observation, they are presented with a blank datasheet with the data fields that project administrators have designed. After

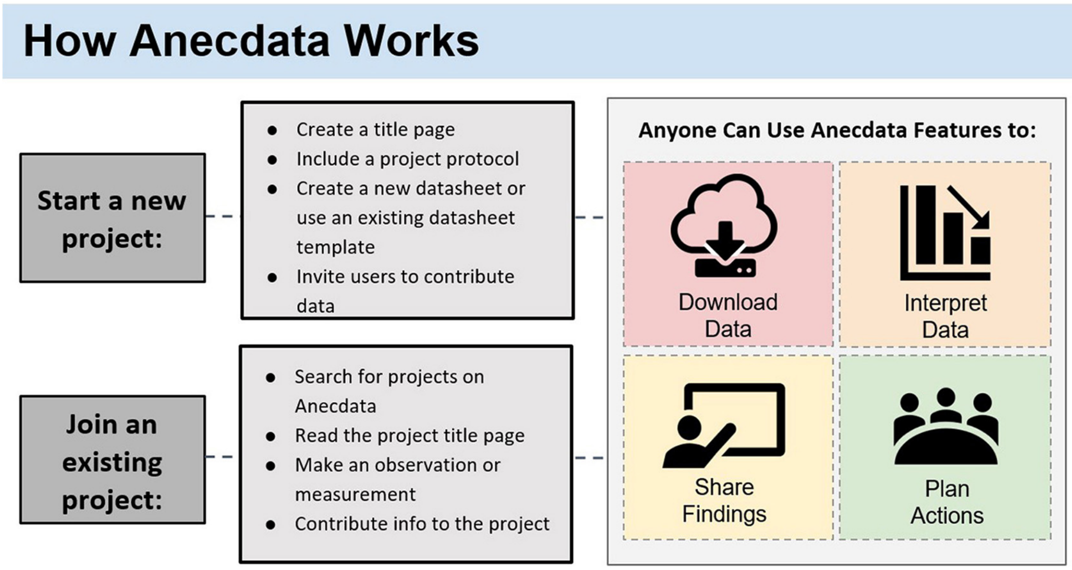


**FIGURE 1 |** How Anecdata works. Anecdata is a citizen science platform that welcomes new projects, some of which are open to new participants joining. Anyone can download non-private data for analysis and interpretation, share the data with others, and use the data to plan actions aimed at effecting change at any societal level.

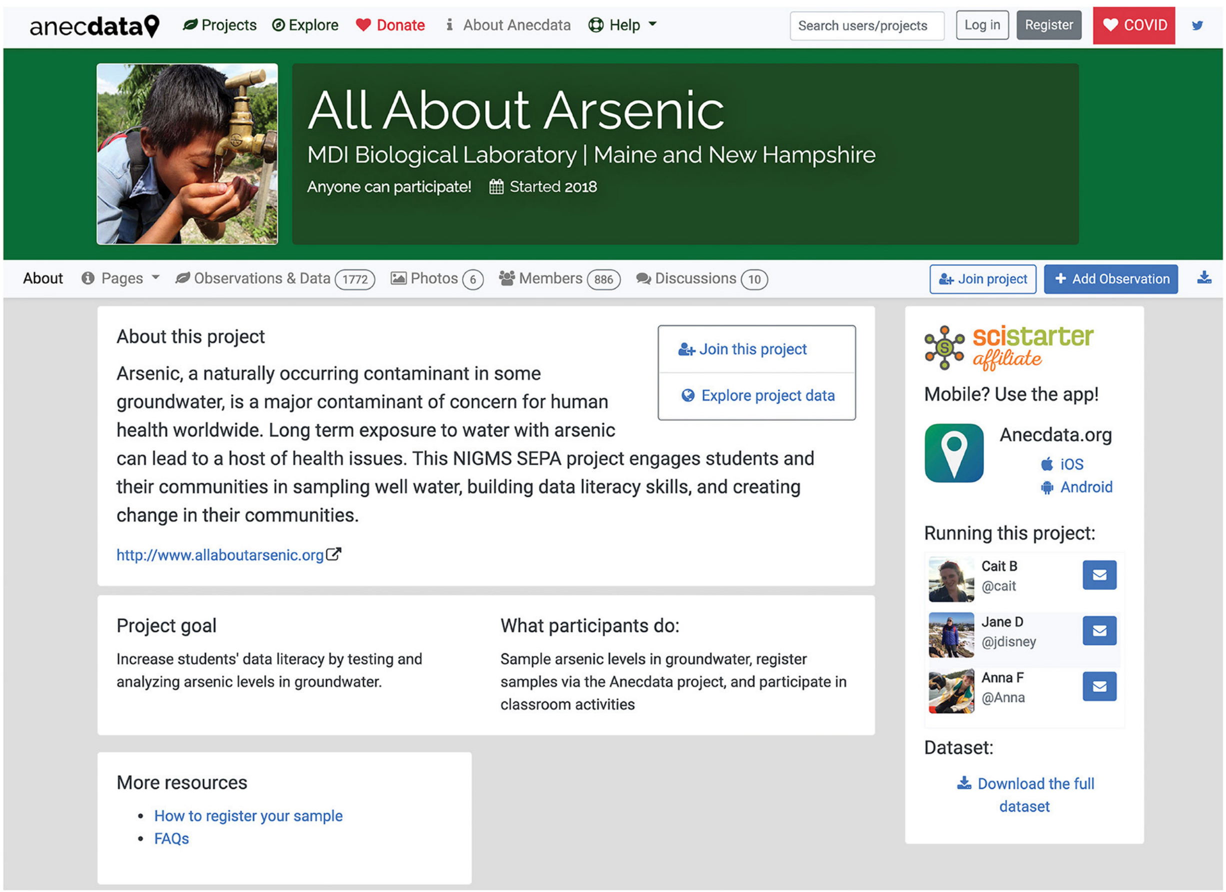


**FIGURE 2 |** A typical project page on Anecdata describes the project and the project goals and provides instructions to participants. In the case of "All About Arsenic," more details about the project are provided in a link to the project website.

TABLE 2 | Metadata in "All About Arsenic" project.

| Personal information | Sample metadata |
|---|---|
| Associated school | Sample number |
| Name | Sample location |
| Street and mailing addresses | Sample filtration (Y/N) |
| Previous arsenic test | Type of filtration |
| Permission to share data | Water filtration description |

all data have been entered and saved, the observation becomes publicly visible on the Anecdata website.

The "All About Arsenic" project workflow provides project participants with the option to share their private data with a state agency; in Maine, well water analysis and associated metadata are shared with the Maine Center for Disease Control (CDC), and in New Hampshire, they are shared with the New Hampshire Department of Environmental Services (DES). Before entering any data into the "All About Arsenic" data form on Anecdata, the project participants encounter a disclosure question that requires them to provide or deny permission for the sharing of their private data (exact latitude and longitude, parent and student first name and last name, and home address).

Participants fill out the datasheet to register the spatial coordinates of where their sample was collected, indicate whether the sample was filtered, and share other related metadata (**Table 2**). The well water samples are brought to school and then shipped by teachers to the Community Environmental Health Lab where the labels on each tube are cross-checked with teacher log sheets and sample registrations on Anecdata. Cross-checked batches of well water samples from one or more classrooms are sent to the Trace Element Analysis Core (TEAC) at Dartmouth College for analysis of 14 variables including antimony, arsenic, barium, beryllium, cadmium, chromium, copper, iron, lead, manganese, nickel, selenium, thallium, and uranium.

Datasets for each batch are returned to the Community Environmental Health Lab from TEAC in Excel file format. Using a unique uploader feature on Anecdata, the analytic results are aligned with the metadata in the "All About Arsenic" project. Teachers alert students when sample results are ready for viewing. Parents and students use a sample lookup tool on the "All About Arsenic" project website[2] to retrieve their well water test results. When they enter their sample number, a pop-up display informs them of whether their sample data are available or not; if results are available, the user is automatically redirected to the Anecdata observation page for their well water test results. We added a data validation feature to the "All About Arsenic" project, which displays the maximum contaminant level (MCL) for each analyte next to the result, highlighting samples that are below the EPA MCL in green and those that are at or above the MCL in red. The complete dataset for each sample can be downloaded as a PDF so that each family has a record of its individual water sample results and associated metadata. These customized features were developed for the "All About Arsenic" project and are now available options for other related projects on Anecdata.

[2]http://www.allaboutarsenic.org/

## Development of Data Privacy Features on Anecdata

From a data management and privacy standpoint, the implementation of the "All About Arsenic" project posed several challenges because at the time, Anecdata had an open model whereby all observations were visibly linked to the participant who shared them. We recognized that for the purposes of this project, we needed to protect the locations of participants' homes as well as make sure the identities of sample registrants were protected. We developed a way to obscure this information while retaining the ID of the original observer, so they can update their sample registration later if needed.

We addressed the issue of participant privacy by obscuring the account that registered a sample and questions on the sample registration that would require personally identifiable information. By obscuring this information, effectively making it inaccessible upon public download, we anticipated that more individuals would feel comfortable about participating in the "All About Arsenic" project or other projects with similar data privacy needs.

## Development of the Anonymity Feature

In order to make observations anonymous, the first step was to add a Boolean variable to the project's settings, called **anonymize**, which defaults to **false** in all projects unless otherwise selected by a project administrator. The Anecdata software checks this variable when saving new observations:

1. When **anonymize** is **false**, it stores the ID of the currently logged-in user with the observation data as it normally would.
2. When **anonymize** is **true**, **a special account called @Anonymous** is displayed as the creator of the observation (**Figure 3**). We also add a record to a table with two values, **post_id** (the ID of the observation) and **user_id** (the ID of the currently logged-in user). Data from this table are never displayed directly from any of Anecdata's API endpoints.

When retrieving an observation from the Anecdata API, we set an additional **edit** variable in the payload returned by the server that informs the user interface whether to display an Edit button that the user can use to correct any mistakes they may have made. For every observation displayed to the user, the Anecdata server-side software checks multiple conditions and sets edit accordingly (**Table 3**).

The benefit of this approach is that instead of needing to filter observations every time they are read from the database to ensure that the link to the originating user's account is removed, we simply never store the link at all in the standard table of observations and only refer to the original table when we need to check access permissions for the purposes of editing an observation.

## Development of Spatial Privacy Feature

Our approach to spatial privacy, also known as geoprivacy, is similar to the spatial privacy model used by iNaturalist for

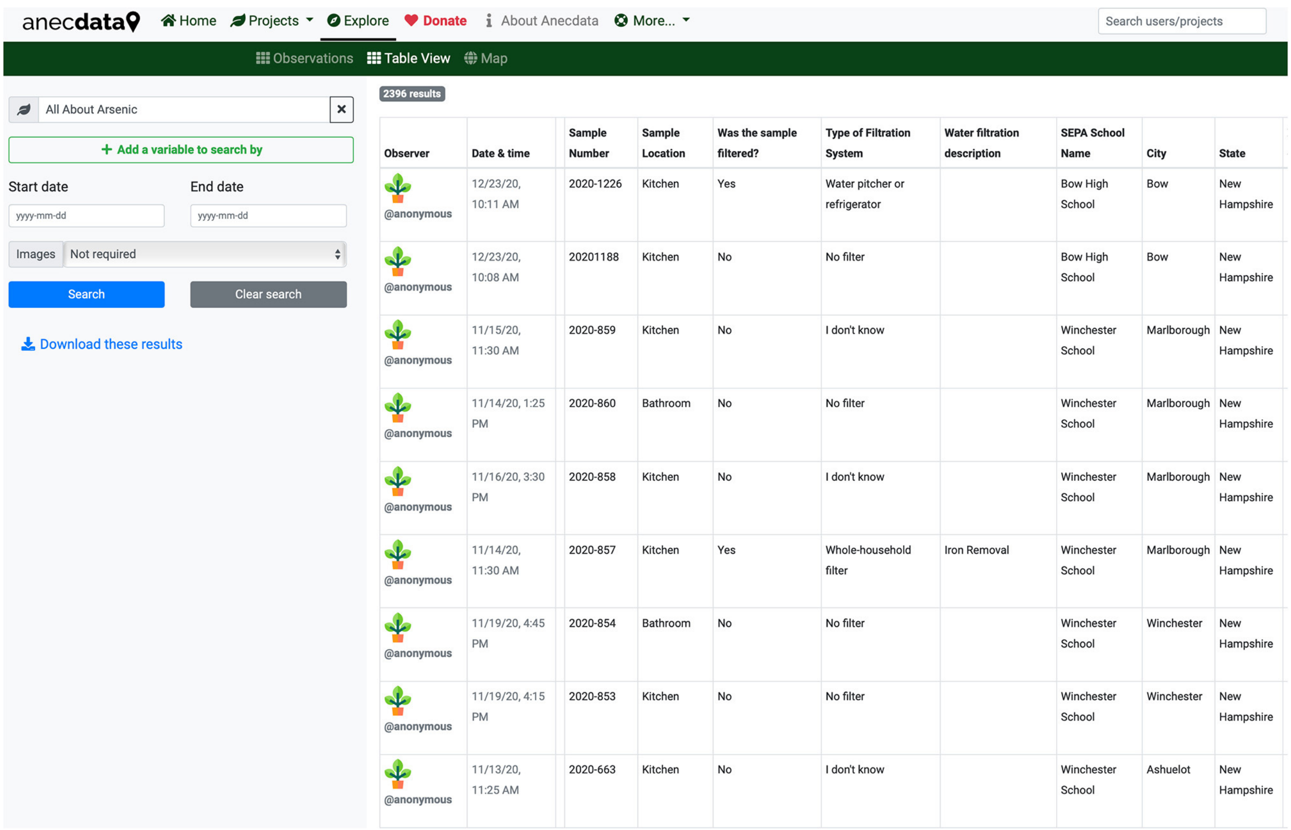


**FIGURE 3 |** This screenshot of participant information on Anecdata shows that each participant is identified as @anonymous.

**TABLE 3 |** Anonymity conditions and user access.

| Condition | Can the user edit the observation? |
|---|---|
| The user is an administrator in the observation's project | Yes |
| The user created the observation (the observation's **user_id** is the same as the logged-in user) | Yes |
| The user created the observation (There is a record in **anonymous_post_owners** with a **post_id** matching the observation's ID and a **user_id** matching the logged-in user's ID) | Yes |
| Default if no other condition is met | No |

**TABLE 4 |** Obfuscation algorithm.

```
<? php
  function roundCoord($number = 0){
    // Handle missing coordinates correctly:
    if(empty($number)){
      return 0;
    }
    // Generate a random floating-point
    // number between−0.1 and 0.1
    $randomNumber = (rand(0, 2000) - 1000) / 1000;
    return $number + ($randomNumber / 10);
  }
```

the protection of endangered species (iNaturalist, 2019). While the exact coordinates of observations are available to project administrators, the publicly available coordinates are obscured by adding a random floating-point number between −0.1 and 0.1 to the latitude and longitude (**Table 4**). This random number is stored when the observation is saved and not generated each time the observation is read from the database, thereby preventing users from guessing where an observation is by refreshing the page repeatedly to deduce the exact coordinates.

The first step in implementing this feature was adding a new Boolean switch on projects, **geoprivacy**, which defaults to false unless otherwise chosen by a project administrator.

All Anecdata observations are located spatially using **lat** and **lng** decimal columns to store latitude and longitude in the database. We added two new columns, **private**_lat and **private**_lng, to store the exact unobscured coordinates of every observation.

We then added a function to the Anecdata server-side software that checks when saving an observation whether the corresponding project's geoprivacy is true or false (**Figure 4**).

The result of this is that all observations in the project have publicly displayed latitudes and longitudes that are (+/−) 0.1 degrees away from their actual location. These can be thought of as "boxes of uncertainty" on a map (**Figure 5**).

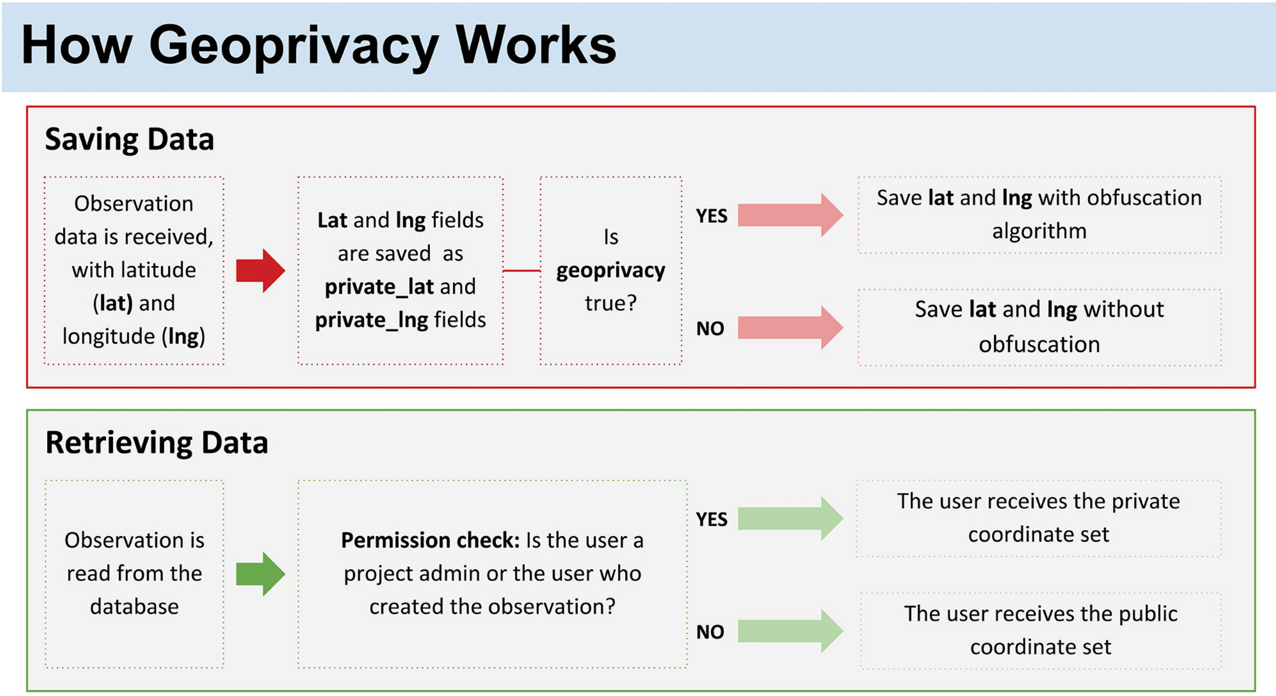


**FIGURE 4 |** How geoprivacy works. When geoprivacy is needed for a project, the lat and lng are saved with an obfuscation algorithm. When data are retrieved with geoprivacy options in place, there is a permission check to ensure that privacy is maintained.

## Development of the Private Fields Feature

A key privacy concern in the sample registration process for the "All About Arsenic" project is protecting the identities of participants. We needed to collect the names and home addresses of participants and keep these data private while keeping other aspects of their sample registrations, such as sample number, well type, and sampling date, public.

To implement this, we added an additional column to our table of datasheet template fields called private. In order to prevent a data breach, fields that have been marked as private are not saved to the standard fields table that all other data are saved in, but rather a separate table that is not normally accessed while viewing and analyzing data.

When a user or project administrator edits an observation or when a project administrator downloads a privileged dataset, the Anecdata software checks the user's privileges before running a separate data query that loads all the private fields from a separate table and displays them on the data entry form or in the export CSV file as if it were any other column. This approach is similar to the one we use for anonymity; instead of marking data as private and actively removing them every time observations are accessed, we store it in a separate table and only include them when the data endpoint explicitly needs it and we have ascertained that the user has access privileges.

After privacy features were developed and available to all project administrators on Anecdata, numerous projects began to adopt these features. In order to understand how these features were helpful, we asked project leaders for feedback. A feedback survey was emailed to all project administrators who had signed up to receive updates from our team. The feedback survey was sent *via* email to project administrators in line with Agile principles for providing a sustainable means for the users of privacy features to reflect on how they could be made more effective and efficient (Hazzan and Dubinsky, 2014). The following three questions were asked of 200 project administrators:

1. Can you comment on how privacy features such as geoprivacy and/or anonymity have been helpful in your work?
2. How satisfied are you with the current privacy features on a scale of 1–5? (1, low—5, high)
3. What can we do to improve the privacy features on Anecdata?

## RESULTS

While we designed privacy features with our "All About Arsenic" project's needs in mind, many other projects on Anecdata are now using these same features. Since privacy features were introduced with the "All About Arsenic" project in 2018, 22 additional projects have begun using one or more privacy features (**Table 5**). Of these projects, 10 are using private fields, 15 are using geoprivacy, and five are using the participant anonymity features.

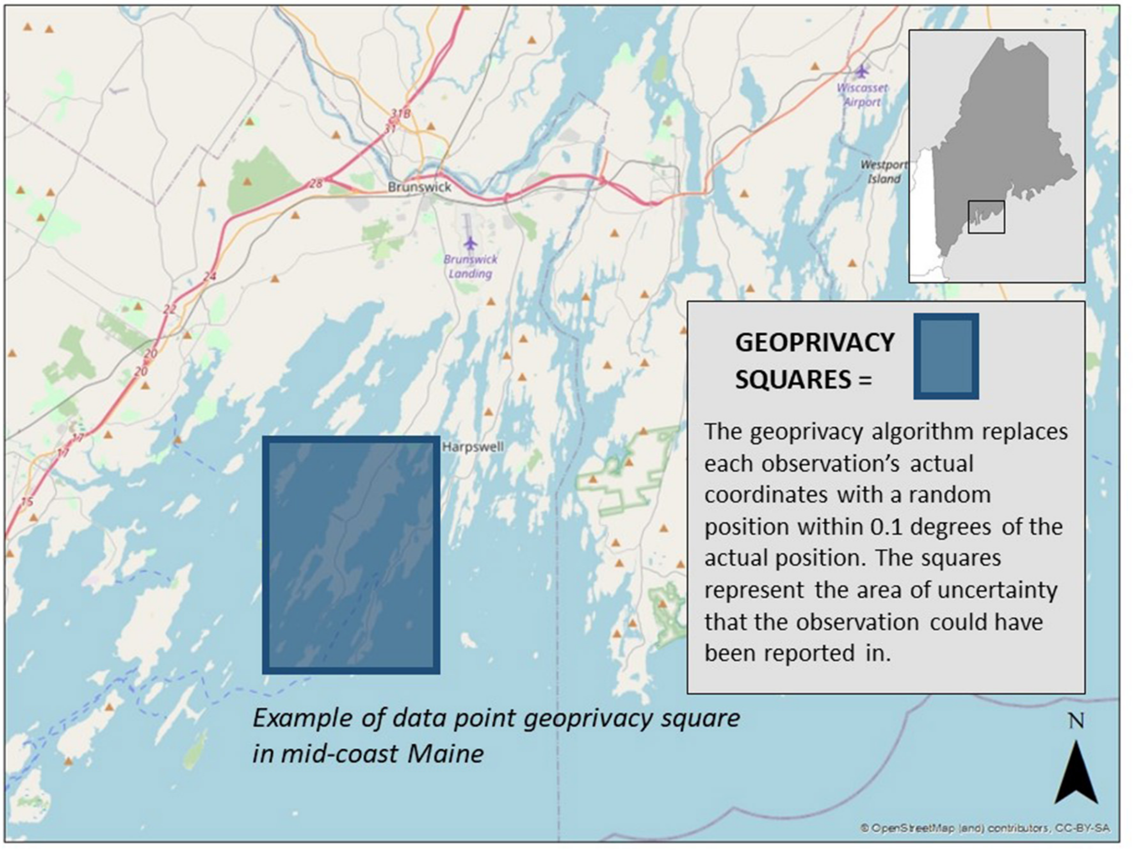


**FIGURE 5 |** Geoprivacy squares. All well water variables are associated with obfuscated lat/long measurements that put the data point somewhere within each square, not close enough to the actual location to reveal the address or identity of the project participant.

Climate change-related projects using private fields include "MaMA (Monitoring and Managing Ash) Monitoring Plots Network"[3] in which participants monitor ash trees on an annual basis to determine mortality due to the invasive insect, emerald ash borer, and "Great Green Crab Hunt,"[4] which involves monitoring coastal New England habitats for the invasive green crabs. Projects using geoprivacy to obscure the exact coordinates of observations include Mass Audubon's "Eastern Meadowlark Survey,"[5] which collects observations of meadowlark presence and absence at 434 sites across Massachusetts, and the University of Maine's "Coastal SOS Monitoring" project,[6] which collects phenology data on rockweed as an important climate change indicator along the coast of Maine.

We note that participant anonymity is not used as frequently as other privacy features, accounting for only five of the 23 projects on Anecdata that are utilizing these features. Three of the five are school-based such as our "All About Arsenic"[7] project, which engages secondary school students in collecting private well water samples for analysis of arsenic and other contaminants, the "Dartmouth Dragonfly Mercury Project,"[8] which involves students in collecting dragonfly larvae from streams for mercury analysis, and "NASA's Lower the Boom" project,[9] which enlists high school students in collecting measurements of background noise samples to determine how quiet supersonic jetliners would have to be in order to not cause a disturbance when flying across the continental US. Without the anonymity feature, locations could be deduced even with the geospatial privacy feature in place, such as Mass Audubon's "Barn & Cliff Swallow Nesting Sites" project,[10] which asks local birders to identify farm buildings and other structures that may be used by nesting swallows. Given that some project participants might identify their own farm buildings, participant anonymity is as necessary as geoprivacy in order to protect the location of these nesting sites.

[3]https://www.anecdata.org/projects/view/319
[4]https://www.anecdata.org/projects/view/521
[5]https://www.anecdata.org/projects/view/187
[6]https://www.anecdata.org/projects/view/301
[7]https://www.anecdata.org/projects/view/299
[8]https://www.anecdata.org/projects/view/791
[9]https://www.anecdata.org/projects/view/473
[10]https://www.anecdata.org/projects/view/710

**TABLE 5 |** Projects with privacy features on anecdata.

| Project | Organization | Project location | #Of observations | #Of participants | Uses private features | Uses geoprivacy | Uses participant anonymity |
|---|---|---|---|---|---|---|---|
| Downeast Maine Smelt Monitoring | Downeast Salmon Federation | Eastern Maine | 225 | 32 | No | Yes | No |
| Eastern Meadowlark Survey | Mass Audubon - Bird Conservation Department and Mass Division of Fisheries & Wildlife | Massachusetts | 992 | 117 | No | Yes | No |
| All About Arsenic | MDI Biological Laboratory | Maine and New Hampshire | 2,255 | 959 | Yes | Yes | Yes |
| Coastal SOS Monitoring | Maine Signs of the Seasons | Maine | 670 | 29 | No | Yes | No |
| Beaver Survey | The Wetlands Conservancy | Oregon | 383 | 110 | No | Yes | No |
| MaMA Monitoring Plots Network | Ecological Research Institute | Eastern United States | 668 | 158 | Yes | No | No |
| Salamander Crossing Brigades | Harris Center for Conservation Education | New Hampshire | 68 | 10 | Yes | No | No |
| NASA's Lower the Boom | NASA | United States | 296 | 100 | No | No | Yes |
| Terrapin Tracking Team | The Maritime Aquarium, CT DEEP, WCSU, CT DOT | Southwestern Connecticut | 89 | 22 | Yes | Yes | No |
| Great Green Crab Hunt | Kejimkujik National Park | New England | 114 | 72 | Yes | No | No |
| The Great Canadian Green Crab Hunt | | Kejimkujik National Park Seaside, NS | 24 | 8 | Yes | No | No |
| VietFarm Network Update | VietFarm | Vietnam | 58 | 56 | Yes | No | No |
| Cover It Up: Using plants to control buckthorn | University of Minnesota, Department of Forest Resources | Minnesota | 381 | 110 | No | Yes | No |
| Barn & Cliff swallow nesting sites | MASS AUDUBON | Massachusetts | 31 | 25 | No | Yes | Yes |
| Copper River Steward's Clean-up Journal | Copper River Watershed Project and Eyak Preservation Council | Alaska | 16 | 7 | No | Yes | No |
| Spidey Senser | University of Maryland, Baltimore County | United States | 17 | 8 | No | Yes | No |
| What is in my Backyard? | GreenDubs, University of Washington | Washington | 335 | 87 | No | Yes | No |
| Arsenic in All Seasons | College of the Atlantic | Mt. Desert Island, Maine | 361 | 4 | Yes | Yes | Yes |
| Dartmouth Dragonfly Mercury Project | Dartmouth College | Hanover, NH | 715 | 7 | No | No | Yes |
| Crowd the Tap Maine | Schoodic Institute at Acadia National Park | Winter Harbor, Maine | 160 | 12 | Yes | No | No |
| Rumex Hypogaeus around Christies creek | | Christies Beach, South Australia | 49 | 1 | No | Yes | No |
| WildCam Vashon | Vashon Nature Center | Vashon Island, Washington | 19 | 9 | No | Yes | No |
| Salt Marsh Restoration and Citizen Science in Charleston, SC | South Carolina Sea Grant Consortium | Charleston, SC | 36 | 32 | Yes | Yes | No |

## Feedback on Privacy Features

We requested feedback from over 200 project administrators, 22 of whom (aside from our own "All About Arsenic" project) are currently using privacy features. We wanted to know how helpful the features were, the level of satisfaction with the features, and suggestions for improving the features. We received feedback from 11 project administrators over a 2-week period. Based on our analysis of project leader feedback on privacy features, we learned that these features are useful for reasons that we did not necessarily anticipate. We also learned about barriers and challenges for Anecdata users. Of the 11 respondents, seven currently use privacy features, two do not use the features because they are too restrictive, one does not use the features for reasons that were not stated, and one has intentions to use features in the


**FIGURE 6 |** Themes emerging from project administrator feedback. Expressed needs for data privacy included private fields for species data, geoprivacy for private property and sample site locations, and anonymity for project participants, in particular, schoolchildren.

future. One respondent commented, "I think the fact that you are asking is pretty stellar."

Three themes emerged from the feedback. These themes relate to protection of endangered species and their habitats, privacy of students involved in school-based projects and other project participants, and maintenance of property owner privacy and rights. **Figure 6** depicts how a suite of complementary privacy features can help to address multiple concerns across multiple projects with common reasons for wanting to preserve data privacy.

## Flexibility for Privacy Settings

We learned from project administrator feedback that more flexibility is needed in privacy controls. Several project leaders indicated that they would like a higher level of control in project settings that allow them to set the degree to which location data are obscured:

> "For our measurements, it would be good if indeed you wouldn't see the actual house or garden where a measurement was taken but the current rounding of the GPS coordinates is too much. If it would be possible to choose a certain level of geoprivacy and the coordinates could for example also be rounded to two decimals that would be better."
>
> "We use Anecdata for our precipitation measurements... However, we realized that there could be some privacy issues. Activating the geoprivacy feature doesn't help in our case, since precipitation can change over small spatial units. Long story [short], it would be very handy to have the option of geoprivacy with different rounding options."

In addition, a respondent suggested using avatars or nicknames instead of names as an alternative to having "anonymous" as the default designation in the participant privacy feature. This could also be useful if only some people need or would want to have their names obscured on the project page.

## Communicating Data Privacy Features to Project Participants

A conversation with the "Coastal SOS Monitoring" project administrator informed us of the process used to make property owners and data collectors aware of the importance of data privacy, especially as it relates to location of sampling sites on private shorelines. Project leaders or participants inform property owners that their site location is not shared and that no one can access the participant data portal without permission from a project coordinator. This gives many coastal property owners a sense of security that their site location will be obscured and kept confidential by the Anecdata system. One concern for coastal private property owners who give permission for volunteers to access the shoreline adjacent to their property is that other people will then view their property as open and accessible to the general public. Information about data privacy is provided to participants in both their in-person and online trainings. While "Coastal SOS Monitoring" project data are shared with scientists studying climate change as it relates to coastal ecology, site locations are not revealed. Privacy features can address different kinds of issues that come up related to private property. Based on feedback from project leaders using the Anecdata platform, it is clear that a formal usability study on privacy across this broad range of projects will help us to better understand why data privacy features are being used and how they can meet the growing needs for data privacy by various citizen science projects.

## Technological Solutions to Human Errors

Early in the "All About Arsenic" project, non-obfuscated latitude and longitude data were inadvertently uploaded to our private arsenic platform on the Tuva data literacy website. During the time the actual coordinate data were accessible, it would have been possible for a student or other project member to use the mapping feature on the Tuva website and determine the well water quality status at points on named streets and possibly deduce the homeowner's identity. However, since there are no property lines on Tuva maps, it was unlikely that points could be correlated with individual households. Nonetheless, this made it clear to us that we needed to address this potential for error.

In order to address this, we updated the standard CSV downloader used by all projects on Anecdata to include a toggle switch for administrators that lets them switch between downloading their publicly available dataset and their privileged dataset. In order to help prevent the inadvertent sharing of datasets after they have been downloaded, privileged dataset downloads have their filenames prefixed with "**admin**" and the headers of all private columns are prefixed with "**private**".

# DISCUSSION

We recognize the role that technical platforms play in ensuring that citizen science projects are undertaken in responsible and ethical fashions that ensure privacy and/or anonymity of participants, permissions by participants for disclosure of data in private fields, and location privacy where necessary. When these features are made available, then project leaders setting up

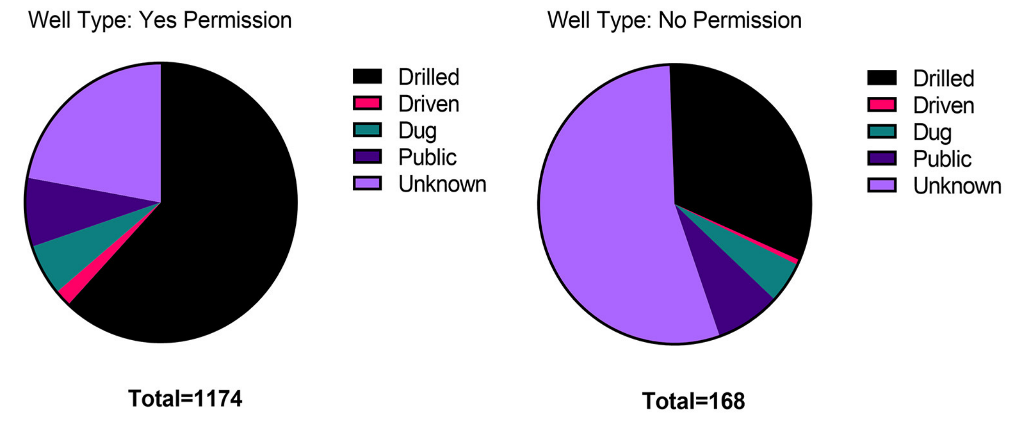


**FIGURE 7 |** Permissions on Anecdata. A permission form was included in the datasheet for the "All About Arsenic" project, so that private data could be shared with state agencies charged with protecting public health. People who did not know much about their wells tended to not give permission for sharing any data.

projects on these platforms can be guided toward more ethical projects by virtue of these available options.

"All About Arsenic" is an example of how metadata privacy can be achieved in an otherwise public-facing project. By combining geospatial, anonymity, and private field features in this project, with an option for providing permission for full disclosure of all project data, we have made it possible for this emerging citizen science dataset to affect change at the community level, protect public health, and inform public health policy. We have anecdotal reports of families installing well water filtration systems to deal with high arsenic levels in their drinking water. We are planning a follow-up study with all participants to determine actions taken in response to receiving well water test results and receiving informational materials and/or attending community outreach events hosted by students involved in the project.

In analyzing the data from those participants who gave permission to share their private data with the Maine CDC or New Hampshire DES, we noted that a higher percentage of people who did not provide permission to share their data did not know the source of their drinking water as compared to those who did provide permission to share their data (**Figure 7**). We are interested in pursuing the link between participant confidence in their data reporting and their willingness to have their private data shared. There may be information or features on Anecdata that could be provided to project participants that would increase their confidence in their data reporting and sharing.

Additional features that were developed for Anecdata resulted from addressing challenges related to the "All About Arsenic" project, such as ways to safely export data for use on other platforms like Tuva without disclosing information in privileged datasets. Though these features were created for the "All About Arsenic" project, all current and future projects have access to them as well.

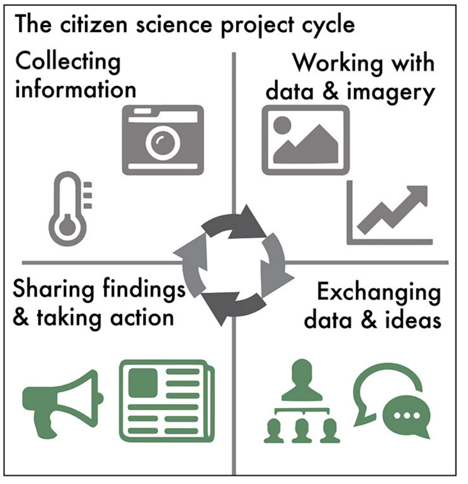


**FIGURE 8 |** The citizen science project cycle. For citizen science data to have broad usage and applicability at various societal levels, technology platforms need to provide more than a way to set up projects for data collection. Project participants need a way to download and work with data and imagery to be able to tell data-supported stories that will lead to action.

## Power of Public Data

Data collected by citizen scientists have power to effect change when there is broad access to the data (Garbarino and Mason, 2016). Researchers can download the data and use it to guide their own research. In one example, a researcher at Maine Medical Center used the "All About Arsenic" dataset when they could not find the information that they needed in the Maine CDC's Environmental Tracking Network dataset. In particular, the lead data in the well water dataset informed this researcher about the scope of lead problems across Maine and New Hampshire, and findings were incorporated into a grant application. In another example, staff from South Carolina Aquarium were able to use data collected as part of their "Litter-Free Digital Journal" project to testify to the city council in Folly Beach, South Carolina, leading to a ban on Styrofoam and reusable plastic bags.

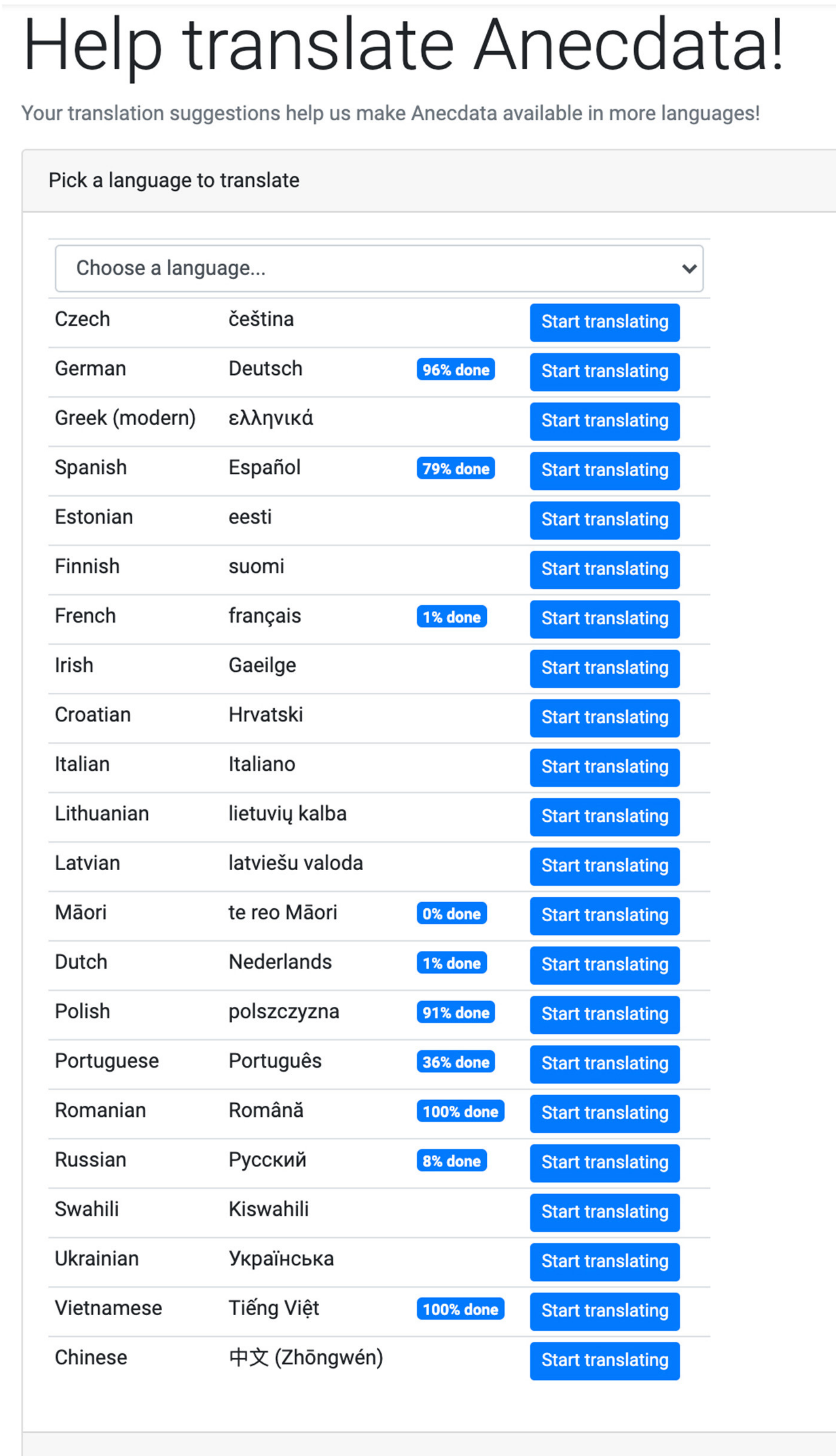


**FIGURE 9 |** Translating Anecdata to promote findability, accessibility, interoperability, and reusability (FAIR) principles. Anecdata users are invited to help translate data into any of 22 languages.

### Future Directions

Anecdata is committed to offering features to ensure that citizen scientists have access to the data that they submit and that they can act on it when necessary. In an expansion of our thinking about "closing the citizen science data loop" (Disney et al., 2017), we plan to add improved data visualization, mapping, and communication features and a civic action toolkit to Anecdata to facilitate the use of data for improving public health, addressing issues like climate change, and informing public policy. Along these lines, we plan to add new types of spatial data collection (line and polygon) and new ways to interact with and map project data. Adding tools and new Web map functionality will allow project leaders and users to study the patterns of their project directly in the project without needing external software or accounts. We believe that this work is important, as maps can be strong communication tools especially for visual learners and communicators.

As we develop features for Anecdata, one of the key concerns is to ensure that their Agile development happens in a manner to support the privacy needs of **all stakeholders** involved in citizen science projects. The data access, visualization, and communication needs of the project administrators, the citizen science participants, and the general public need to be properly researched to ensure the **right balance of privacy features for individual stakeholders** across projects.

Our vision is for Anecdata to provide the tools needed to assist users with engaging throughout the citizen science project cycle (**Figure 8**) not only in data collection and visualization but also in communicating with each other to make data-driven decisions and participate in civic action that leads to impactful and lasting change.

Although privacy is clearly an important feature for many projects, as evidenced by the rapid adoption of new privacy features by projects on Anecdata, project leaders should consider the extent to which data need to remain private. There will always be tension between data privacy and openness (Anhalt-Depies et al., 2019). The question emerges, what is the motivation for privacy of particular data types, and in what instances does it really confer any benefit to the parties involved, the place where data are being collected, or the species being documented. In the case of climate change, there is a lot at stake for the future of landscapes, habitats, and species. In trying to protect species by obscuring their location, for example, specific areas of concern (such as those impacted by flooding) may not be addressed. In these types of instances, the need for privacy must be balanced with the need for openness of data.

Our collective experience with the development of privacy features has led us to explore ways to promote scientific data management and stewardship through adherence to principles of findability, accessibility, interoperability, and reusability (FAIR) (Wilkinson et al., 2016). Along these lines, we have facilitated collaborative efforts by the Anecdata community to provide translation of Anecdata into multiple languages to improve its **accessibility** across diverse geographic locations worldwide (**Figure 9**). Anecdata also has a "CSV Data uploader" feature available for project administrators that allows them to format and upload **legacy data** (from old datasets such as Excel sheets and databases) directly into Anecdata and make them i**nteroperable and reusable** with existing datasets. Anecdata provides APIs to researchers upon request that allow them to easily **access and reuse** anonymized datasets across projects.

Additional research and development efforts are currently underway to ensure that we enhance **findability (search), accessibility, interoperability, and reusability** of datasets across all projects on Anecdata, while ensuring that "private fields" and sensitive data (like personal information and geolocation) are only accessible to project administrators (or organizations) running citizen science projects on Anecdata.

Even though some projects may choose to make data open to the public for moving data to action, adequate information and support in terms of privacy, safety, and security of sensitive information must be provided to project administrators at regular intervals to further the Agile development of the Anecdata platform to meet privacy needs of various projects.

The development of privacy features for the "All About Arsenic" project set the stage for other projects to use privacy features across various local contexts and in support of different needs. Our journey into the development of privacy features showcases a genuine need for investment of time and effort into a usability study to help improve privacy features on Anecdata, which we plan to implement as a "next step" for Anecdata. We anticipate that continued development and refinement of key privacy features will be essential to supporting the diverse projects currently on Anecdata and those that will use Anecdata in the future. By providing an array of refined options for data privacy, Anecdata may be able to serve as a platform for a myriad of data collection projects that would benefit from but otherwise not be amenable to a citizen science approach.

## DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found at https://www.anecdata.org.

## AUTHOR CONTRIBUTIONS

CB provided methods, results, graphics, and editing. AF provided graphics, results, and editing. TP contributed research findings, a literature search, and editing. AT provided maps and editing. JD provided a literature search, results, and discussion and editing. All authors contributed to the article and approved the submitted version.

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frontiers in Water

ORIGINAL RESEARCH
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# Citizen Scientists Contribute to Real-Time Monitoring of Lake Water Quality Using 3D Printed Mini Secchi Disks

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Citizen science aims to mobilise the general public, motivated by curiosity, to collect scientific data and contribute to the advancement of scientific knowledge. In this article, we describe a citizen science network that has been developed to assess the water quality in a 100 km long tropical lake-estuarine system (Vembanad Lake), which directly or indirectly influences the livelihood of around 1.6 million people. Deterioration of water quality in the lake has resulted in frequent outbreaks of water-associated diseases, leading to morbidity and occasionally, to mortality. Water colour and clarity are easily measurable and can be used to study water quality. Continuous observations on relevant spatial and temporal scales can be used to generate maps of water colour and clarity for identifying areas that are turbid or eutrophic. A network of citizen scientists was established with the support of students from 16 colleges affiliated with three universities of Kerala (India) and research institutions, and stakeholders such as houseboat owners, non-government organisations (NGOs), regular commuters, inland fishermen, and others residing in the vicinity of Vembanad Lake and keen to contribute. Mini Secchi disks, with Forel-Ule colour scale stickers, were used to measure the colour and clarity of the water. A mobile application, named "TurbAqua," was developed for easy transmission of data in near-real time. *In-situ* data from scientists were used to check the quality of a subset of the citizen observations. We highlight the major economic benefits from the citizen network, with stakeholders voluntarily monitoring water quality in the lake at low cost, and the increased potential for sustainable monitoring in the long term. The data can be used to validate satellite products of water quality and can provide scientific information on natural or anthropogenic events impacting the lake. Citizens provided with scientific tools can make their own judgement on the quality of water that they use, helping toward Sustainable Development Goal 6 of clean water. The study highlights potential for world-wide application of similar citizen-science initiatives, using simple tools for generating long-term time series data sets, which may also help monitor climate change.

**Keywords: citizen science, mini Secchi disk, TurbAqua, Vembanad lake, FU scale, turbidity**

## INTRODUCTION

Sustainable Development Goal (SDG) indicator 6.3.2 (on the "proportion of bodies of water with good ambient water quality") (UN Water, 2017) aims to address the lack of data from less developed countries on water quality indices. Satellite remote sensing has global reach, and has made important strides in data collection on synoptic scales, but validation and formulation of appropriate, often regionally-tuned, algorithms are required to enhance the quality of regional products. Satellite data are also constrained by operational difficulties such as cloud cover, the limited frequency of passes of certain satellites, difficulties with atmospheric correction, and the optical complexity of nearshore and fresh waters, which hamper the performance of satellite algorithms in such waters. Citizen science data carves out a separate niche of observations which can supplement satellite and *in-situ* measurements. Globally, there are established programmes for time-series measurements of water properties using sensors such as Argo, Global Alliance of Continuous Plankton Recorder Service (GACS), Global Ocean Observing System (GOOS) and many more (Belward et al., 2016). Such networks serve a very useful service, but when dealing with local studies at locations out of the range of such networks, other solutions are needed, such as data collection by citizens (HLPF, 2018; UN Water, 2018; Quinlivan et al., 2020).

The involvement of citizens in hydrological studies has a long history. The earliest prototype is probably the drift bottles used to study surface current patterns in the 1960s (Njue et al., 2019). Monitoring turbidity of the Lake George, New York is cited as one of the long-term citizen science activities wherein the turbidity measurements from various parts of the lake have been continuing since 1986 and improving public awareness of the water quality (Boylen et al., 2004). Engaging citizens in a project activity not only provide additional manpower but also serve to educate them. Abbott et al. (2018) have successfully used 18 years of riverine nutrient data collected by secondary school students and community volunteers to assess how improvements in land management affect the interannual trends and seasonality of river nutrient concentrations in western France. Water quality monitoring of seven rivers and streams in Hong Kong (Ho et al., 2020) is proof for the reliability of the data collected by citizen scientists. They obtained moderate to strong correlations in pH, turbidity and dissolved oxygen (DO) data collected by citizen scientists and professional scientists. To evaluate the performance of citizen scientists and to design strategies for efficient water quality monitoring by citizens, various scientific projects have been implemented. In the SIMILE Interreg Italy-Switzerland project, smartphone applications were employed and analysed (Carrion et al., 2020). Realising that none of the applications for water quality monitoring are open-source ones, SIMILE team designed a new free, open-source application with the option for the users as well as the developers to customise and improve it. Oberoi et al. (2018) call the citizen scientists as "sensors" who can supplement advents in internet and mobile technology. Location sensors (GPS) and cameras on board the mobile devices equip the citizens to collect geotagged data and store them. The use of smartphones and digital cameras in citizen science programmes are improving day by day, an example of which is the mobile application HydroColor that derives water leaving reflectance from digital images (Gao et al., 2020). Most of the citizen science programmes in hydrology from 2001 to 2018 seem to have focused on the monitoring of water quality (Njue et al., 2019), probably due to the increased global awareness on the deterioration of water quality plus the availability of low-cost kits to measure basic water quality variables.

Citizen science offers a way to collect large sets of temporal and spatial data at minimal cost; and can therefore bridge the data gap that the international community faces (Loperfido et al., 2010; Buytaert et al., 2014; Hulbert, 2016; Walker et al., 2016; Ballard et al., 2017; Assumpção et al., 2018; Carlson and Cohen, 2018). However, the quality of citizen-derived data has to be assured, and can be promoted through training programmes (Brouwer et al., 2018). But the expenditures related to citizen science are modest compared with those needed for more sophisticated water quality data collection. Involvement of the general public or stakeholders in scientific data collection process will not only help in the generation of time-series of scientific information, but also promote awareness among the public on the need to protect the water bodies from pollution. This will eventually lead to stakeholder-based evaluation of the quality of water they use and prevent usage of un-safe water, and degradation of water quality. Such improvements are essential to the reduction in water-borne disease incidences from unhygienic or contaminated water.

Awareness raising among the general public, and their participation in conservation efforts have been shown to be important for the successful restoration of many ecosystems (Suman, 2017). Wetlands are an example of sensitive ecosystems whose conservation can benefit from public participation. In this paper, we describe the establishment of a citizen-science network used to monitor the water quality of Vembanad Lake, a large fresh and brackish water lake and one of the three Ramsar sites in Kerala, India. Around 10 rivers drain in to this lake. Vembanad Lake is classified as a critically vulnerable coastal area (CVCA) under Coastal regulation zone (CRZ) notification of 2011. The lake is rich in biodiversity and plays a major role in the livelihoods of 1.6 million people, which ranges from agriculture and fishing to tourism. Anthropogenic activities of different scales, such as construction of a barrier controlling the exchange of water between the northern and southern parts of the lake, dumping of domestic wastes and industrial pollutants, eutrophication, faecal contamination, and aquatic weed infestation, have imposed multiple stresses on the lake, leading to its deterioration. This in turn has led to the proliferation of disease vectors such as mosquitoes, and the lake has become a source of infection for water-associated diseases. The lake is narrow and sinuous in the north, but much broader, with a maximum width of 14.5 km in the south (**Figure 1**). Running parallel to the sea from Azhikode to Alappuzha, the lake is connected to the sea at two places, Azhikode and Kochi. Routine sampling along the entire extent of the lake, that includes many polders or "*padasekharams*" (vernacular for agricultural fields) surrounded by narrow inlets, is cumbersome and expensive.

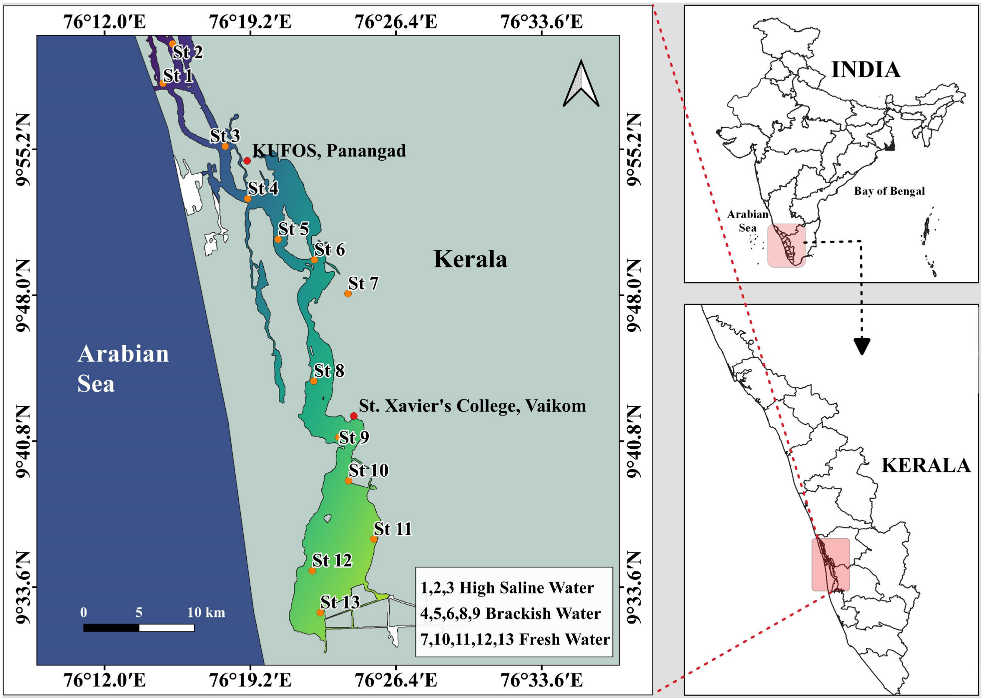


**FIGURE 1 |** Study area—Vembanad Lake showing the 13 stations from which water quality data were collected by scientists at 20 days interval for one and half years. The two academic institutions—KUFOS and St. Xavier's College where we initiated the pilot study are also indicted in the map.

The lives of the people in the vicinity of the lake are intimately linked to the lake. It is used for bathing, washing, cooking, and is an important means of local transport. The southern part of the lake, Kuttanad, is known as the rice bowl of Kerala where cultivation is done below mean sea level. The lake and the surrounding low-lying regions are subject to frequent flooding, especially during the monsoon season. The high literacy (96.2%) and willingness to obey the instructions given by experts is perhaps the reason for this. It is imperative that such a literate society be educated about the deterioration of the water body, which is their lifeline. This aspect is being addressed in the present study under the India-UK water quality initiative, which combines *in-situ* and remote sensing approaches to understand the relationship between water-borne diseases and environmental conditions, and aims to propose remedial action for microbial contamination in the lake, to enhance social welfare by improving public health.

The citizen-science network established in connection with this study aims to increase scientific understanding by enabling public participation in data collection and monitoring. With public support a database on the water clarity of Vembanad Lake was created, which has the potential to grow into a time-series, which can aid climate-related research in the long-term.

## METHODOLOGY

The Secchi disk is a standardised method to measure the transparency of water bodies in a simple, quick and accurate way (Secchi, 1885; Wernand, 2010). One of the traditional measurements of light attenuation in water, it is simple, inexpensive and provides an informal visual index of the optical properties of the water body (Preisendorfer, 1986). Optical properties of a water body can be used as indicators of biological activity, sediment load, and even pollution, and hence can provide a direct indication of the water quality. Change in optical properties cause change in the colour of the water. The Forel-Ule (FU) colour scale is another traditional tool used to quantify the colour of water, with a scale of 21 colours ranging from blue to brown (Forel, 1890; Ule, 1892), with the observations typically taken using a submersed Secchi disk, at roughly half the Secchi depth (Wernand and van der Woerd, 2010). Both the Secchi disk and the FU colour scale have proven to work successfully in many citizen-science projects monitoring water quality (e.g., Lottig et al., 2014; Garaba et al., 2015; Busch et al., 2016a,b; Seafarers et al., 2017). Recently, a miniaturised 3D-printed Secchi disk tool (3DMSD), with a FU colour scale sticker, has been developed (Brewin et al., 2019). Building on the traditional Secchi disk and FU colour scale, the pocket-sized 3DMSD was modified for ease of operation in smaller water bodies, such as lakes, and from small watercraft and platforms (Brewin et al., 2019). It is a small, light and convenient-to-use device, designed specifically for citizen science projects. The device is primarily manufactured using a 3D printer and basic workshop tools, meaning any citizen has the potential to make the device (see instructions and files provided in Brewin et al., 2019). It also offers potential for large-scale bespoke manufacture. Designed specifically for use in lakes and estuaries, where the water is typically more turbid than in the ocean, the device has a smaller disk size of 10 cm (see justification for this decision in section 2.1 of Brewin et al., 2019). Should data be compared with Secchi disk measurements that used a large disk (not conducted here), one might need to consider a small correction in measurement for a change in disk size, but this would be possible given knowledge of Secchi depth theory (e.g., Preisendorfer, 1986), if required at all [see discussion of this in Hou et al. (2007), whose results suggest the disk size does not significantly alter the Secchi depth].

As part of the India-UK water quality initiative, under the project REVIVAL, 85 3DMSD were produced and distributed for the citizen science activity. Combining the data with a smartphone app that collects information on GPS, time and date, geolocated and time-stamped Secchi depth and FU data were collected by the citizens.

The smart-phone application named "TurbAqua" can transfer photos taken using a mobile camera, the GPS locations of the measurements, and the 3DMSD data (Secchi depth as well as colour code) to a central database. In the following sections, we describe the research design of the citizen science network, the development and implementation of the network, data generated by the network, the scientific analysis undertaken, and the effectiveness and the economic benefits of citizen science data collection.

## Strategy

As a first step, a number of 3DMSDs were handed over to selected faculty members of St. Xavier's College, Vaikom, Kerala and Kerala University of Fisheries and Ocean Studies (KUFOS), Panangad, Kerala both situated along the banks of Vembanad Lake. These 3DMSD were then distributed to students living on the banks of the lake. They were trained near their campus premises to collect data using the 3DMSD on Secchi depth, select the FU code corresponding to the water colour when the Secchi disk is submersed (at half the Secchi depth) and to take a photo of the water surface using the smartphone camera. Data recorded using the app TurbAqua were uploaded onto the server when the phone had an internet connection. The initial pilot study proved successful, as data began to flow into the server. However, teething issues on the handling of the 3DMSD led to errors in measurement and in the usage of the mobile application TurbAqua. Following the pilot study, these issues were rectified by providing additional training for all student stakeholders, and by improving the TurbAqua app.

## Organisation of Citizen Science Network

A training programme was organised for college students. We sent invitations to all the colleges located in the vicinity of the lake with under-graduate programmes in fisheries, biology, or environmental sciences. We also sought and received media support in informing the public about the training programme held at the Indian Council of Agricultural Research—Central Marine Fisheries Research Institute (ICAR-CMFRI) as part of the citizen science initiative. Sixteen colleges/research institutions responded to be part of the Vembanad Lake citizen science network (**Table 1**). College students were selected for building the network because it became part of their education, with support at the very highest levels in the colleges.

A brochure for citizen science training workshop was prepared (**Supplementary Material 1**) and circulated among the colleges conducting undergraduate (UG) and postgraduate (PG) courses in biology, fisheries and environmental sciences in the districts Ernakulam, Alappuzha and Kottayam straddling the lake. A training manual with detailed instructions on the operation of the 3DMSD and TurbAqua was prepared (**Supplementary Material 2**).

The first training workshop was conducted at ICAR-CMFRI, Kochi on 9th August, 2019 in which 282 students from 16 colleges and institutions (**Figure 2**) participated. Both theoretical and practical training on the operation of the 3DMSD and TurbAqua were given to trainees (programme schedule as **Supplementary Material 3**). After the training, 3DMSDs were distributed to some of the students, who also installed the mobile application on their smart phones. From August 2019 to March 2020, continuous data inflow began from the student activity.

Encouraged by the success achieved in the first training workshop, a second training workshop was organised for different stakeholders of the Vembanad Lake, such as fishermen, boat owners, NGOs, farmers, social scientists and environmentalists. The programme was hosted on 20th December, 2019 and was attended by 46 participants from different sectors. Secchi disks were distributed to participants after the successful training (programme schedule as **Supplementary Material 3**). Boat owners were asked to encourage their passengers to use the 3DMSD for measuring water transparency and colour. The activity details of the stakeholders other than students are summarised in **Table 2**.

## Print, Visual, Social Media, and Follow-Up Interventions

The local community residing along the vicinity of the lake is highly literate and we used a two-pronged strategy to sustain the enthusiasm among the citizen scientists. First strategy was to keep the faculty among the colleges linked to us, scientists with the help of a WhatsApp group, where we regularly started posting information on our initiative and sensitising them about the need and progress of our scheduled activities. We provided lectures to the participating students both online and in person, to keep them interested in the network and to continue to contribute data. In all citizen-science-related scientific presentations, we involved them online by providing them with links to the seminars (**Supplementary Material 7**). Many of them attended the seminars, and video links were provided to the network mostly for the benefit of those who were unable to attend. The second strategy was to use print, visual and social media to impress the network and the general public on the need for generating scientific information related to the Vembanad Lake and popular dailies produced separate supplements highlighting the need for supporting this project (**Supplementary Material 4**). Further, we encouraged personal interviews with visual media on the training sessions held and circulated the same using Facebook and WhatsApp which

**TABLE 1 |** Activity summary of the colleges along the vicinity of the lake who participated in the citizen science programmes.

| Sl. No. | College/institution | Trainees attended | No. of equipment distributed | No. of students provided data | Discipline of course | No. of data procured |
|---|---|---|---|---|---|---|
| 1 | St. Xavier's College | 26 | 10 | 7 | B.Sc Zoology | 18 |
| 2 | Cochin College, | 33 | 1 | 4 | B.Sc Zoology | 66 |
| 3 | UC College | 14 | 1 | 3 | B.Sc Zoology | 4 |
| 4 | Nirmala College | 27 | 1 | 22 | B.Sc Zoology | 58 |
| 5 | SH College | 58 | 3 | 36 | B.Sc Environmental Science, Botany, and Zoology | 105 |
| 6 | St. Xavier, Aluva | 9 | 1 | 6 | B.Sc Zoology | 22 |
| 7 | Mar Athanasius College | 11 | 1 | 4 | B.Sc Zoology | 6 |
| 8 | KUFOS | 26 | 1 | 2 | Aquatic health management | 32 |
| 9 | CUSAT | 10 | 1 | 2 | M.Sc Marine Biology | 2 |
| 10 | St. Albert's College | 12 | 1 | 2 | B.Sc Zoology | 6 |
| 11 | Maharaja's College | 14 | 1 | 4 | B.Sc Botany | 6 |
| 12 | St. Michel's | 7 | 1 | 4 | B.Sc Botany | 4 |
| 13 | SD College | 7 | 1 | 0 | B.Sc Botany | 0 |
| 14 | NERCI | 1 | 1 | 1 | MSW | 4 |
| 15 | CMFRI | 15 | 2 | 5 | Research Scholars | 282 |
| 16 | NIO | 12 | 2 | 1 | Research Scholars | 3 |
| | **Total** | **282** | **27** | **103** | | **618** |

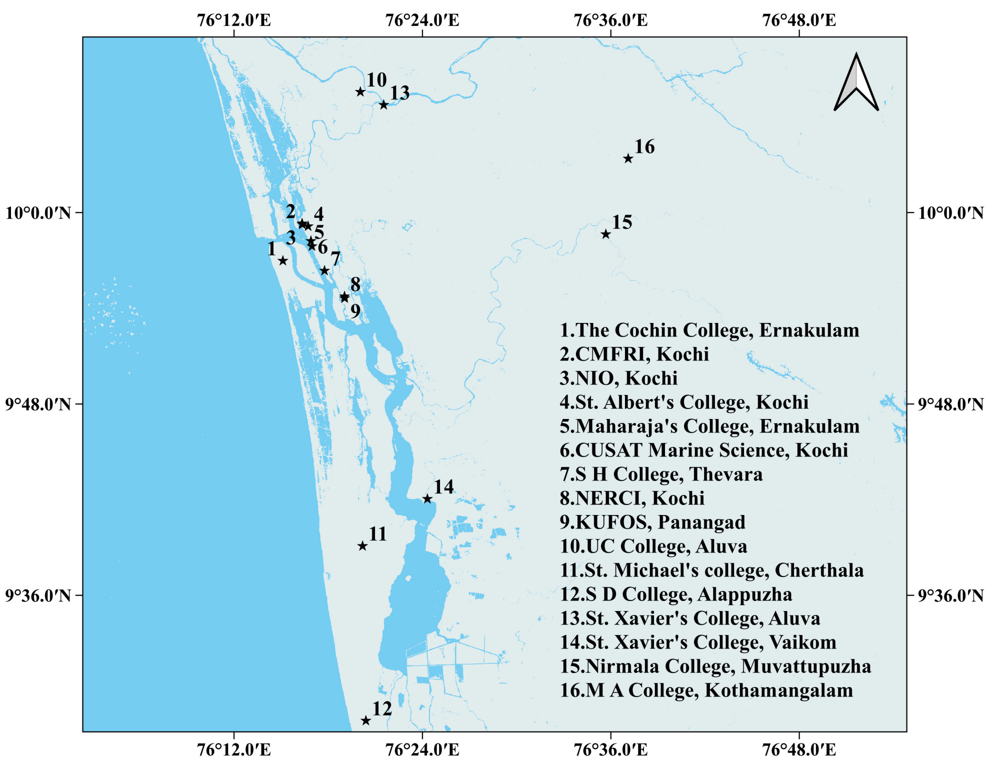


**FIGURE 2 |** The spatial spread of 16 academic institutions which were part of the citizen science network.

seemed to create a good-will for the programme. There are 29 participants in the WhatsApp group named Citizens Science Secchi who are the coordinators of the entire network. Further, an oral feedback survey was conducted among the citizens who provided data using "TurbAqua" app to assess the good-will generated. The results show that 46% of the participants rated the

**TABLE 2 |** Activity summary of the stakeholders other than students.

| Sl. No. | Occupation/organisation | No. of participants | Equipment issued | Data points | Location |
|---|---|---|---|---|---|
| 1 | Sociologist | 1 | 1 | 1 | North |
| 2 | Doctor | 1 | 1 | 0 | |
| 3 | Mahatma PrakrithiKrishiSamithi | 2 | 2 | 25 | Middle |
| 4 | Social worker | 4 | 1 | 28 | North |
| 6 | Lecturer | 8 | 2 | 45 | North, Middle |
| 7 | Fishermen | 4 | 0 | 0 | |
| 8 | Boat operators | 10 | 1 | 2 | South |
| 9 | Technical staff | 2 | 1 | 3 | North |
| 10 | NGO | 4 | 0 | 0 | |
| 11 | Media | 1 | 0 | 0 | |
| 12 | Business | 2 | 1 | 4 | North |
| 13 | Others | 7 | 5 | 9 | North |
| | **Total** | **46** | **15** | **117** | |

programme as excellent, 51% as good and only 3% rated it as not useful. In the case of students, main reasons for discontinuing the activity were either the restrictions imposed as part of fighting the COVID pandemic (43%) or course completion (23%) following which they left the institution (**Supplementary Material 8**).

## Preliminary Validation Exercises

The data collected by the citizens were examined by us and to assure the quality of the data collected, few simple statistical analyses and comparison with our data were done. The CTD measurements (SEABIRD CTD Model SBE 19plus V2 SeaCAT Profiler) taken during our routine survey of the lake provided data on turbidity also as it carries a turbidity metre. Turbidity data from CTD was correlated against the Secchi depth data obtained through citizen science measurements.

Optical properties of the lake water such as absorption by CDOM, phytoplankton and detrital material measured (Bricaud et al., 1981, 1995; Kishino et al., 1985) regularly during our lake sampling were also used for comparison. The absorption co-efficient at 440 nm of the phytoplankton, CDOM and detritus were plotted as a ternary plot, in which the axes represent the fractional contributions due to each of the three components (Prieur and Sathyendranath, 1981). The ternary plot thus prepared was compared with the FU codes reported by citizens so as to check if the maximum represented colour codes matched with the dominating component in the ternary plot.

Another method adopted was to cross-check the colour codes reported by the citizens with that of the respective photos provided by them. The mismatches in data were removed and the correlation between Secchi depth and FU colour code was estimated before and after removal of the outliers.

# RESULTS

## Citizen Science Observations

Over a period of 17 months from August 2019 to December 2020, college students acquired continuous data reaching a total of 735 readings (618 from the student team and 117 from other stakeholder team) taken from different parts of the lake (**Figure 3**), of which 643 data points were found to have all requisites needed for our analysis. The complete data set received as part of the study is provided as **Supplementary Material 5**. Out of the total photos taken by the citizen scientists and saved in the server, those representing each water colour code has been given as a collage in **Supplementary Material 5a**. National lockdown announced on 24th March 2020 in the wake of COVID-19 pandemic put an unexpected sudden stop to the citizen science activity, but it picked up again when the lockdown was lifted. The complete time-series data were partitioned into three phases—pre-lockdown, lockdown and post-lockdown to show the variability in data acquisition in these phases (**Figure 4**).

In contrast to the 13 stations sampled by the scientific team of the project for 16 times over a period of one and half years, the citizens collected 735 sets of data from over 100 points along the length and breadth of the lake. The size of the circles in **Figure 5** indicate the frequency of measurements in each location. Citizens deployed the 3DMSD from the banks of the lake and along the tributaries which are inaccessible by our research vessels. Further, the map used in **Figure 5** was overlaid on the study area map procured from Landsat 8 satellite, which did not highlight each and every inlet and tributary. Hence the data points seem to be on the land, whereas in reality they are not.

The Secchi depth data collected by scientists during regular sampling of the Vembanad Lake was compared with that of the data collected by citizen scientists. There was high complementarity of citizen and scientist measurements in the case of Secchi depth (**Figure 6A**), whereas the relation was not very good in the case of water colour (**Figure 6B**).

## Validation Results

Secchi depth data collected by the citizen scientists were validated using the turbidity values measured simultaneously by marine scientists using CTD. **Figure 7A** shows that the relation is statistically significant with r-value of $-0.75$ ($N = 64$). Further, using the equation given by Anon (2012), turbidity was derived from Secchi depth measured by citizen scientists. **Figures 7B,C** show the similarity in turbidity profile of the lake plotted using the CTD data (**Figure 7B**) as well as the citizen science data (**Figure 7C**).

The FU colour codes recorded by the citizens (**Figure 8A**) were compared with the optical characteristics of the lake measured by scientists. Around 44% of the total measurements

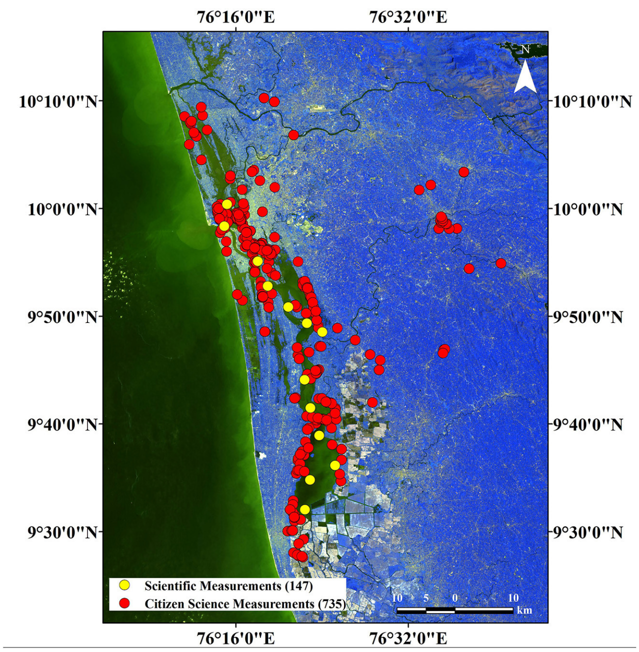


**FIGURE 3 |** Total number of data points collected by the citizen scientists from the Vembanad Lake.

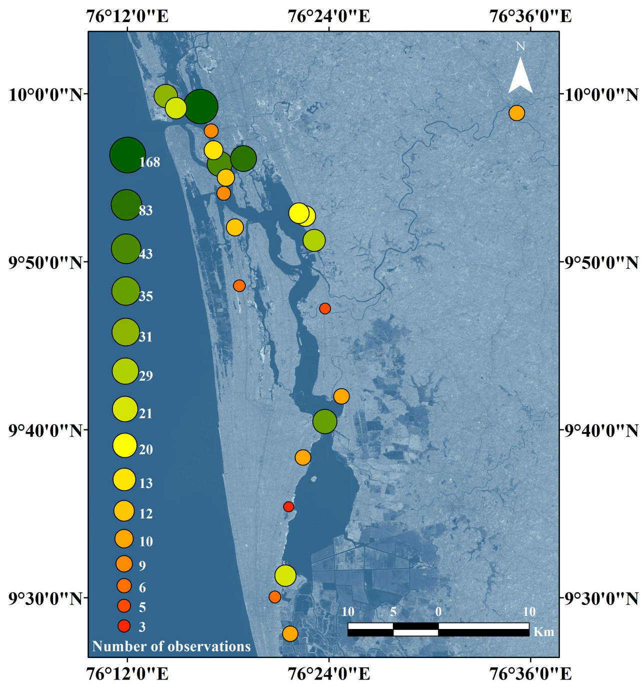


**FIGURE 5 |** Number of observations made by citizen scientists from each point of the lake.

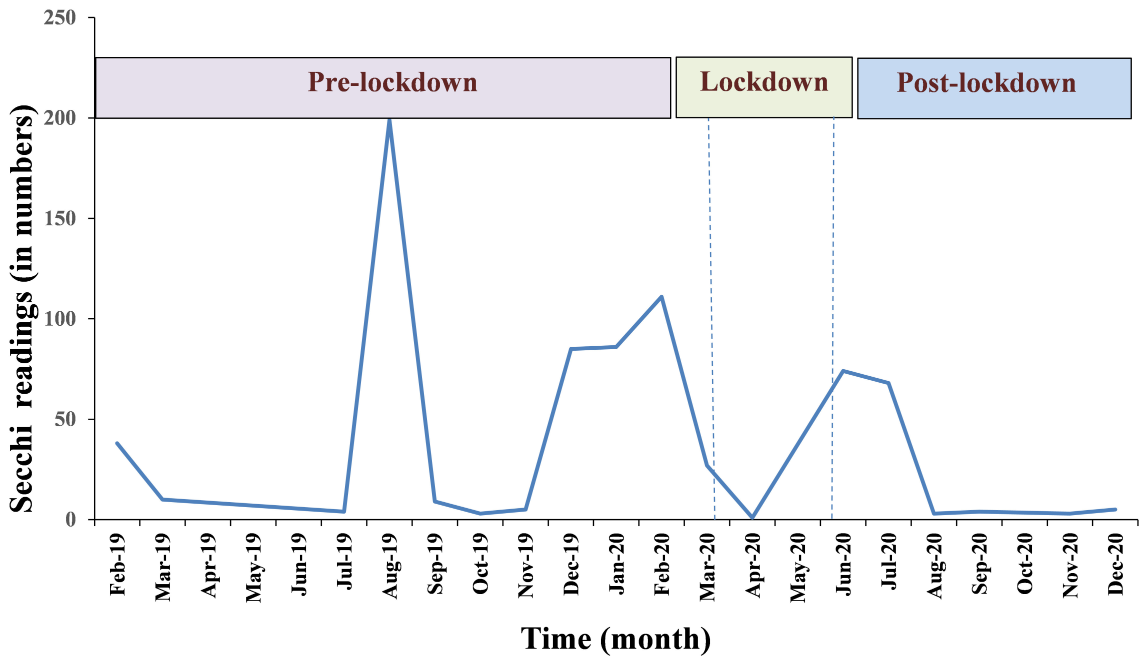


**FIGURE 4 |** Variability in the number of Secchi readings during different phases of COVID related restrictions—pre-lockdown, lockdown, and post-lockdown.

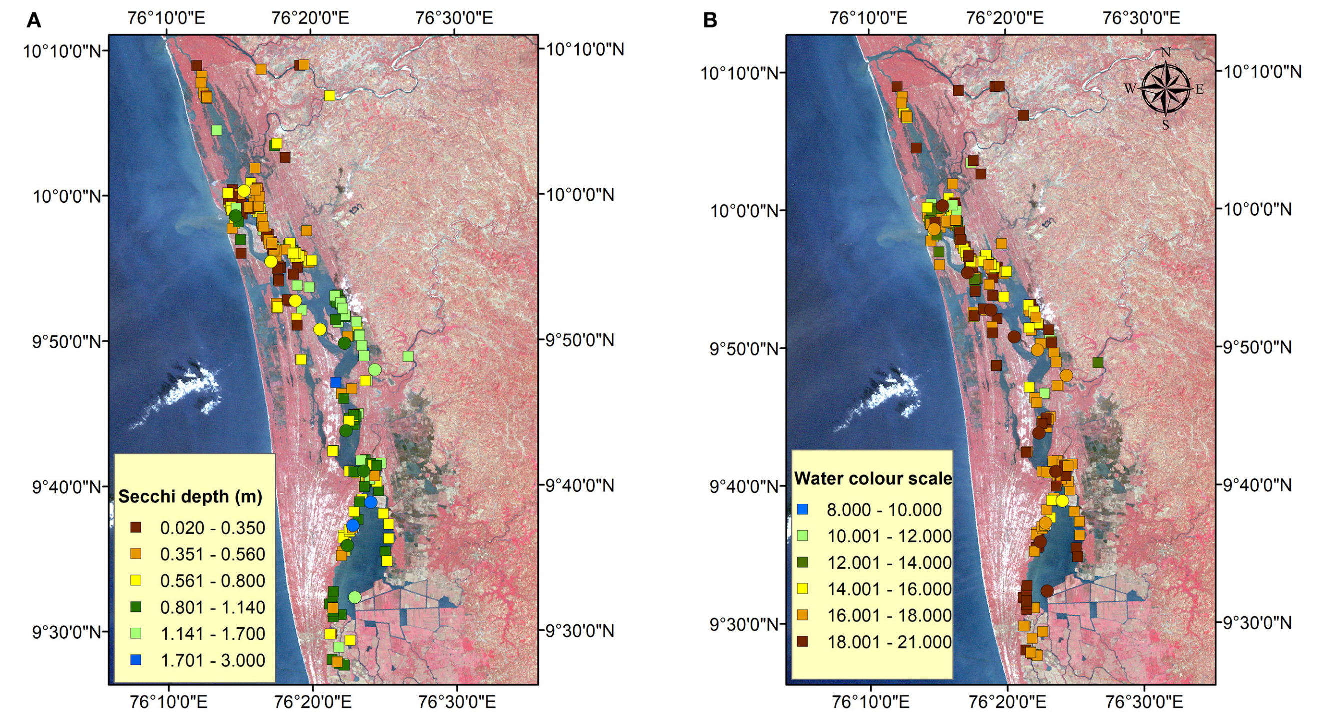


**FIGURE 6 | (A)** Secchi depth observations and **(B)** water colour codes obtained from the measurements of both scientists from 13 locations as well as citizens in the Vembanad Lake for 17 months of citizen science activity during August 2019–December 2020. Circles represent the measurements by scientists and squares represent citizens' observations.

belonged to colour codes in the range 19–21 (brownish green to cola brown) that represent murky yellow to brown colours. Ternary plot (**Figure 8B**) of bio-optics of Vembanad Lake also show the dominance of absorption by detritus in the lake, which typically colours the water yellow or brown.

Correlation measurement between the FU index and Secchi depth obtained using the 3DMSD showed that the results improved significantly when the outliers were removed (**Figure 9**).

## Economics of Citizen Science Activity

A comparison was done to assess the economics of citizen science data collection in comparison with their professional counterparts. Here, we compared the costs per data point. **Table 3** gives an overview of the expenses incurred for data collection by citizens and scientists, and demonstrates how costs for data collection are lower when using the network of citizen scientists. Detailed economic analysis worksheet is given as **Supplementary Material 6**.

## DISCUSSION

Terrestrial citizen science networks are more prevalent globally, but in recent years, marine and freshwater citizen science endeavours have been gaining momentum (Ceccaroni et al., 2020). With our coastal environments in peril due to increased anthropogenic impacts, citizen science provides a platform to address challenges such as deterioration of water quality for which there is scarcity of data. Citizen science projects to measure lake water transparency started as early as 1938 (Lottig et al., 2014). One of the recently successful projects of estimation of ocean transparency is the seafarer citizen science Secchi disk study that began in 2013 (http://www.secchidisk.org) which has demonstrated how the Secchi disk measurements of ocean transparency by citizens could help assessments of climate-induced changes in the phytoplankton (Seafarers et al., 2017). In the REVIVAL project, the 3DMSD designed and fabricated in a high school in the UK (Brewin et al., 2019) was combined with a free mobile application "TurbAqua" for android operating systems. The biggest advantage of the mobile application is the hassle-free collection of data and the immediate receipt of the readings and photographs on the server. Students actively supported the project by providing most of the *in-situ* data (727 out of 826 readings). The number of data generated in the short time of 17 months is testimony to the success of the network.

Vembanad Lake and the surrounding areas constitute a dynamic ecosystem containing elements of fresh water, brackish water, and saline water so that the lake can be treated as a prototypical tropical system. The dense population along its shoreline is vulnerable to periodic flooding and consequent deterioration of the local sanitary conditions. Dry summers followed by heavy rains during monsoons, lead to strong seasonal variability in flushing rates, salinity, temperature, and pH. River discharges into the lake also follow a seasonal pattern:

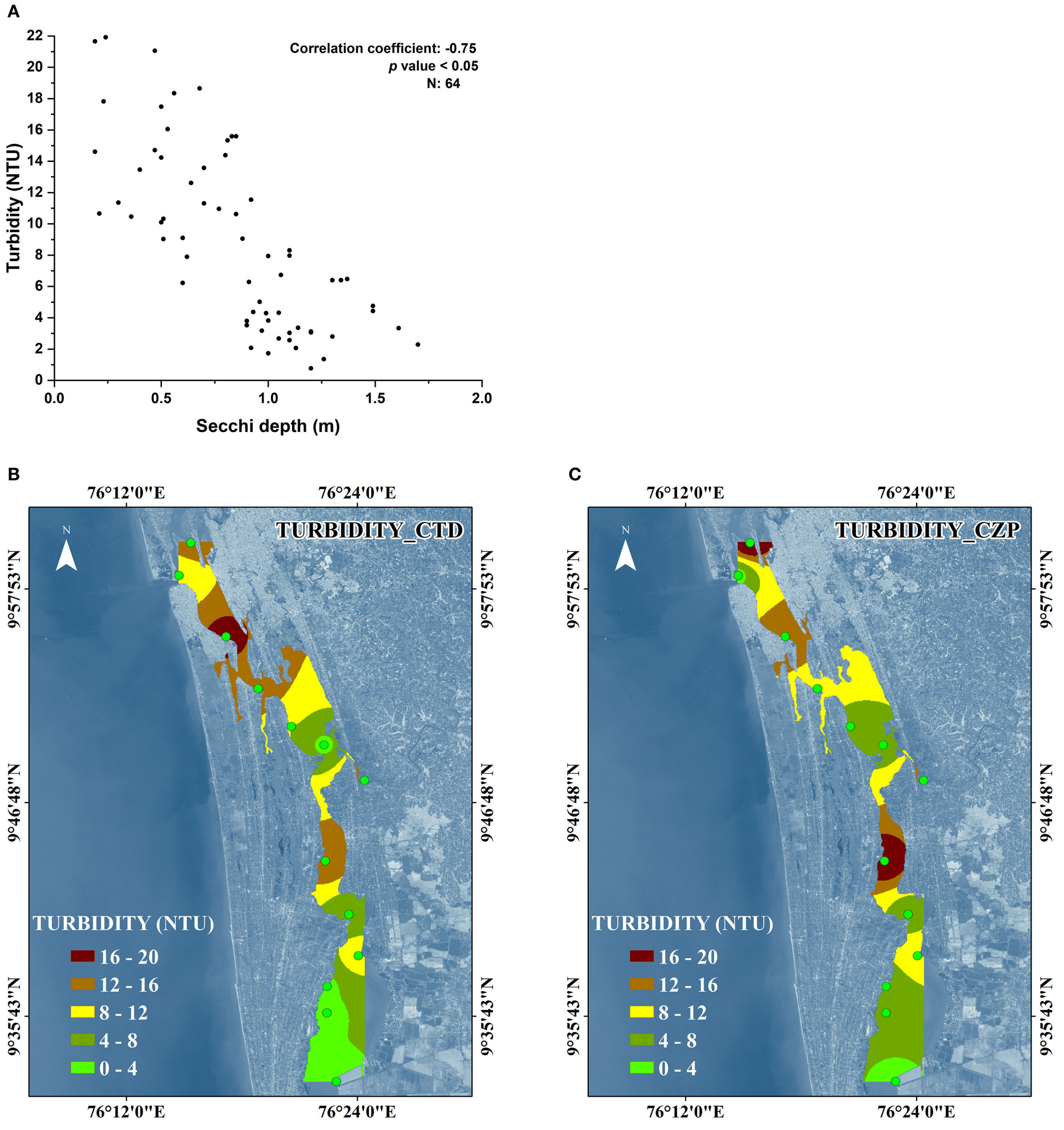


**FIGURE 7 |** **(A)** Correlation between Secchi depth measured by citizens and turbidity measured simultaneously using the CTD instrument by scientists. **(B)** Spatial turbidity profile of Vembanad Lake based on the CTD data. **(C)** Spatial turbidity profile of Vembanad Lake based on the turbidity derived from Secchi depth data, using the model of Anon (2012). Average of data collected from August 2019 to December 2020 are used.

sluggish in summer, and torrential during the rainy season. The stressors that have been imposed on the lake by humans in the form of industrial pollution, agricultural pollution, reclamation, tourism, construction of bunds, and barriers preventing free flow of water, have all had their share in deteriorating the water quality of the lake. The lake is now a breeding ground of mosquitoes that act as vectors for many diseases such as Chikungunya, malaria, filariasis, and microbial pathogens such

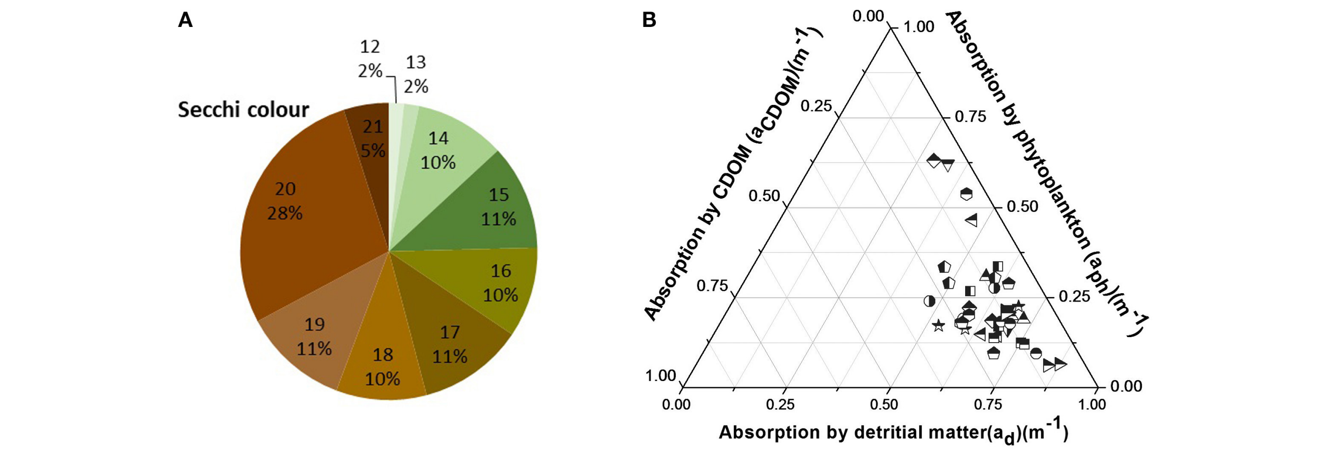


**FIGURE 8 | (A)** Percentage contribution of FU colour codes obtained from citizen science data (colour code and percentage are given in each division). **(B)** Ternary plot showing absorption properties of Vembanad Lake.

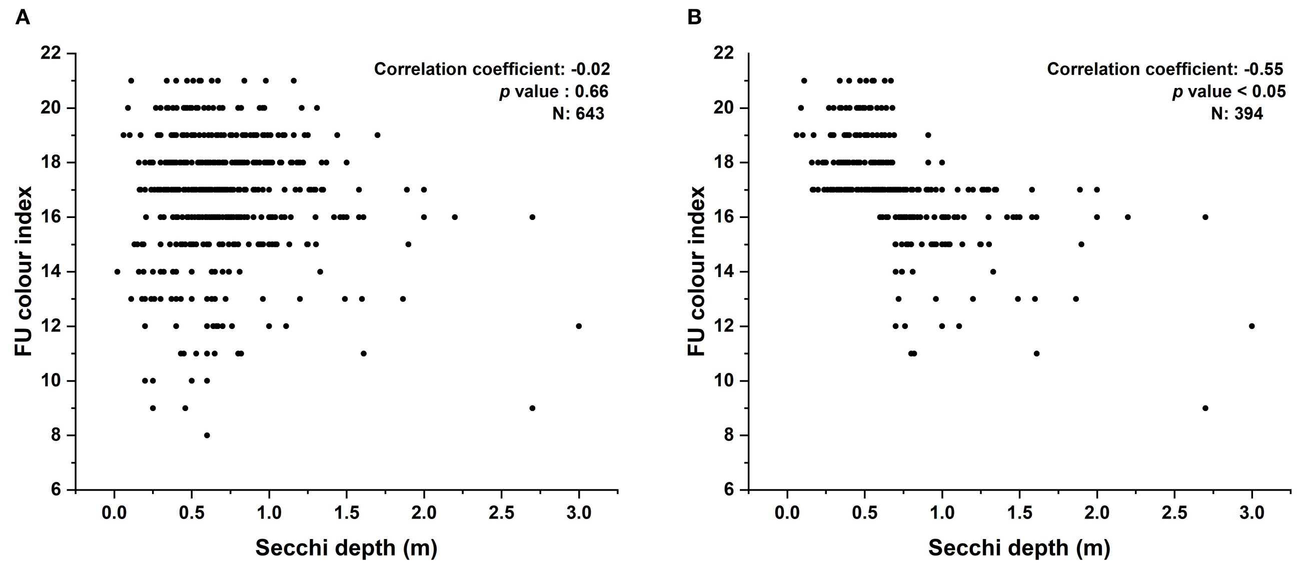


**FIGURE 9 |** Correlation between FU index and Secchi depth obtained using the MSD. **(A)** Using the entire data collected by citizens ($N = 643$). **(B)** After removing outliers ($N = 394$). Relation became statistically significant ($p < 0.05$) after removal of outliers.

**TABLE 3 |** Comparison of the relevant variables and cost associated with data collection using 3DMSD by citizens and scientists.

| Group | Training | Participants | Equipment | Locations sampled | Expenditure (INR) | Cost per data point (INR) |
|---|---|---|---|---|---|---|
| Citizens | Before data collection | 328 | 3DMSD | 735 | 2.11 lakhs | 287 |
| Scientists | Already trained | 12 | 3DMSD + CTD | 147 | 13.9 lakhs | 9,456 |

as *Vibrio cholerae* that cause water-borne diseases impacting the health of the population (Sathyendranath et al., 2020). Water quality determines its suitability for human consumption and the ecological status of the water body. The elongated and indented shape of the lake with its narrow channels makes it difficult for monitoring. In light of this, the citizen science network was established to operationalise monitoring of water quality, specifically the water clarity and colour. Water clarity is controlled by the scattering and absorption of light by particulate dissolved matter in the water, including phytoplankton, dissolved and suspended organic and inorganic matter, and by pure water itself. The simplest way of measuring it is by using the Secchi disk. The change in water colour with the concentrations of these optically-active substances can be obtained using the FU scale. Sensors on satellites and *in-situ* sampling devices are used for estimation of water clarity and colour. Multispectral Imager (MSI) on two Sentinel-2 satellites used to determine seasonal variation in the colour of water of 170 Italian lakes in 2017 showed that while 13 lakes moved from blue to yellow, indicating reduction in water clarity, another 16 lakes showed transitions in the opposite direction, from green to blue or from yellow to green, suggesting improved water clarity from spring to late summer (Giardino et al., 2019). Li et al. (2016) based on the study of the largest 10 lakes in China in 2000–2012 are of the view that the relations of FU index with water clarity and trophic state are not accurate, as the FU index reflects both Secchi depth and chl-*a*, which are important input parameters in trophic state assessment models. A rough classification of water body into oligotrophic, mesotrophic, and eutrophic is the only possibility. Comparative evaluation of three sensor-based models from Landsat ETM+-VNIR data and two smartphone apps—EyeOnWater and HydroColor—to predict the water quality of Kesses Dam in Kenya showed that the estimation of turbidity from the EyeOnWater app, which is based on the FUI-XYZ colour space, was marginally lower than from the HydroColor app which uses the RGB colour space, possibly due to the error contribution by the *x*-chromaticity coordinate conversion process (Ouma et al., 2018).

The measurements on Secchi depth and FU index obtained with the help of crowd sourcing are used in REVIVAL project to validate the satellite-derived water colour and turbidity (Van der Woerd and Wernand, 2015) which we employ as an innovative pathway to monitor water quality.

When scientists monitor the lake, there are limitations to the number of data points that can be procured by deploying the small number of trained manpower available, but when citizens are involved, there is scope to procure more data. The difference in the number of data points recorded in the REVIVAL project by scientists and citizens testifies to this. **Figures 6A**, **7A** show the accuracy of Secchi depth data collected by citizens in comparison with those collected by scientists. The initial training that was provided to the college students and stakeholders have helped in achieving this success rate. Capdevila et al. (2020) also are of the view that "knowledge and experience on data gathering," which comes from initial training prior to data collection and feedback after collection, definitely improves the quality of the data collected. We have also provided feedback and follow-up to rectify the practical difficulties faced by the citizens during initial stages of data collection. However, it was found that the training as well as the follow-ups provided did not meet the required standard as far as the FU indices were concerned. FU colour index recorded by the University students as well as stakeholders had many mismatches with the corresponding Secchi depths. As noted by Weeser et al. (2018) in Kenya, the educational background of the citizens had no impact on the quality of the data collected with regard to this variable. The difference in the FU indices recorded by both citizens and scientists (**Figure 6B**) and the lack of significant correlation between Secchi depth and FU colour code derived using the entire data ($N = 643$) received in the server (**Figure 9A**) prove this. Significant relationship was obtained between Secchi depth and FU index only after the removal of outliers ($N = 394$). But, Chase and Levine (2017) disagree with us and are of the opinion that highly educated volunteers enhance the output of a project.

Motivation is an important factor influencing the continued participation of a person in a citizen science project. Maintaining enthusiasm of participants over long periods is particularly challenging (Bear, 2016). To combat this challenge, we selected University students for the first phase of our citizen science programme. The advantage is that new participants are added to the network every year as the student population turns over, and the average number of participants does not decline. Our strategy matches the view of Thiel et al. (2014) wherein they state that greater understanding of the scientific processes, development of a skill base and social commitment act as motivators. For students, it is a chance to understand the environment and contribute to scientific research for its conservation (Domroese and Johnson, 2017). Further, the data will help to monitor unusual and long-term changes in water quality and validate satellite data which provide a synoptic view of the study area. In addition, as pointed out by Bonney et al. (2009), we also realised that engaging with academic institutions provide a way for collaboration, improving the reach of the activity and easy communication about the areas and frequency of measurements.

The success of the activity depends on how it influences the outcome of the projects of which citizen science is a part. To maintain data quality, statistical comparison of results reported by citizen scientists with those by scientists is desirable as a means of data validation (Thiel et al., 2014; Earp et al., 2018). The citizen science data being collected using a simple equipment is prone to human errors. Our study showed that the Secchi depth data collected by citizens were comparable to that collected by scientists. Step by step instructions given to the citizens on how to measure the Secchi depth helped ensure data quality. Reviews also have shown that data collected by citizen scientists can meet, or surpass, accepted quality standards, or be used to detect important ecological trends (Cox et al., 2012; Forrester et al., 2015; Kosmala et al., 2016; Schläppy et al., 2017). However, the wide variation in the FU colour index measured by the citizens is a matter of concern. In our study, the citizen reports a FU colour code, supported by a photo taken using his/her smartphone camera. It was found that in ~40% cases, the code reported by the citizen and the photo were different. Significant filtration was needed to obtain data points which really fulfilled the scientific criteria for a research study (**Figure 9B**). In a similar citizen science project using FU index to measure water colour of Australian inland waters, Malthus et al. (2020) have reported difference of more than 2 FUI units between the observer data and the photo-based colour code in only 3% of the cases. Therefore, the reason for the larger bias in our case needs to be investigated. Further, we have only 17 months data from August 2019 to December 2020, out of which many months had

<50 data points. This scanty data are insufficient to make any inference on the temporal fluctuations in water quality of the dynamic lake system, which is a limitation of the paper. In our experimental design, the photograph of the water along with the FU colour index provides another avenue for testing the quality of the colour scale reported by the citizen scientists. In the next step of the project, we plan to undertake a detailed comparison of the two, to establish deviations between the two, and propose improvements to the protocol, as needed.

Cost effectiveness of the citizen science activity (**Table 3**) shows that citizen science data has been acquired at virtually no cost, in comparison with the samplings conducted by scientists. This reiterates the need and relevance of citizen science programmes for regions where funding for scientific monitoring is low. Before the advent of citizen science, building a monitoring infrastructure and collecting time series data required a colossal pool of capital. The value of citizen science in meeting the objectives at a lower cost is well-recognised, with the European Commission dedicating several million euros to initiate citizen science work, through projects such as Citclops (Ceccaroni et al., 2020). Data collection in an aquatic environment is often tiresome and expensive. Modelled and satellite remote sensing data validated for time and space can supplement observational gaps in assessing water quality in aquatic environment (George, 2014). But *in-situ* observations are often insufficient to meet the scientific requirement for the validation processes also. Citizen science data carves out a separate niche for such observational lacunae in *in-situ* experiments which seems to be cost effective and feasible.

The model that is worth reproducing in this arena is the global citizen science network "eBird." The provision of mobile application to enter information regarding birds has led to an exponential growth in citizen participation, leading to over 1 million observations of birds in India alone. But as correctly stated by Capdevila et al. (2020), water quality is an invisible subject, calling for specific equipment whose handling can be particularly challenging. Nevertheless, water is fundamental for life and has enormous impacts on health and well-being of the people. Therefore, monitoring the quality of the waterbody in your backyard and rejuvenating it oneself can be the biggest motivation for citizens to take up this programme and expand the network. Our experience shows that citizen science has a strong potential to address the lacunas in water quality research and address the SDG indicator 6.3.2 (UN Water, 2018). Encouraged by the success of the first phase of citizen science programme, we have taken steps to diversify the citizen science activities. Another mobile application on sanitation, "CLEANSE" is in the experimental stage. Step by step improvements in the reliability and utility of the apps, further studies including seasonal observations, calibration, and validation in different geographically homogeneous case studies using satellite sensor-derived water quality parameters are being conducted. Expertise of global scientists working in the field of water quality and human health is also being explored with the establishment of an open network called "ONWARD." As an imminent outcome, we could provide a scientific correspondence to an anthropogenic event that occurred in the lake as a follow-up to this study (Menon et al., 2021). Further, our researchers in the team could come up with possible links which can be utilised for using such time-series datasets for identifying environmental reservoirs of cholera in a tropical lacustrine system such as the lake Vembanad (Racault et al., 2019; Anas et al., 2021).

To conclude, the quality of Vembanad Lake water is under pressure and a dedicated monitoring effort is needed to evaluate changes and detect rapid changes. A strong and constructive association of citizen science is required for further deliberations with support from the localities especially youngsters who are the backbone of the society. Working hand in hand with scientists, our network of citizens can help revive Vembanad Lake and potentially expand to a global network.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Materials**, further inquiries can be directed to the corresponding author.

## AUTHOR CONTRIBUTIONS

GG implemented the programme, developed TurbAqua application, wrote, and revised MS. NNM analysed the data, wrote, and revised the MS. AA resource person for citizen science and edited the MS. SS and TP introduced the concept and supervised the activity. Revised the MS. RJWB developed the 3DMSD and edited the MS. AG, KGM, and SK co-ordination of citizen science workshop, storage and retrieval of data, and logistics for the programme. PP analysed the data and plotted the graphs. All authors contributed to the article and approved the submitted version.

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# Methods of Promoting Learning and Data Quality in Citizen and Community Science

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Citizen science or community science (CS) programmes are engaging volunteers in specific stages of the scientific research, mostly data collection and processing. They are less likely to have an explicit objective to support and promote volunteers' learning. In response to that, "citizen inquiry" emphases citizens' learning and community education, by viewing CS as an opportunity to educate the general public in thinking and acting scientifically. In citizen inquiry, citizens can take part in all the stages of the scientific research, from setting up an inquiry of personal interest, to deciding on the methods of data collection, analysis, and reporting. To ensure data quality when non-professionals design their own or take part in existing investigations, we have designed a bespoke online technological solution, the nQuire platform (nquire.org.uk), with support from the Open University/BBC partnership. nQuire scaffolds the design of high quality scientific inquiries through an authoring functionality and a process of data quality review by experts. In this paper, we detail how nQuire can support data quality assurance and control. We present case studies of how data quality was managed in two projects: "Heatwaves: Are you coping?" and "Pollinator Watch."

**Keywords: data quality, volunteers, learning, online community and citizen science, temperature data, biodiversity data**

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## INTRODUCTION

Citizen science or Community science (CS) is a research paradigm in which members of the public or citizens, often referred to as volunteers or amateurs, take part in scientific activities initiated by scientists and/or community members depending on the CS form. CS can be initiated by scientists in contributory projects (Shirk et al., 2012) where the public primary contributes data, or be the result of a collaboration between members of the public and scientists where the former are involved in most or all aspects of research (co-created projects, see Shirk et al., 2012). These activities are described as "communal experiences" that bring the community together to examine and understand a topic of interest (Audubon Center, 2018). CS has been viewed as a distinct field of inquiry which can engage volunteers with "relevant, authentic, and constantly changing dimensions of primary research" (Jordan et al., 2015, p.211). It can support and extend research in any discipline including social, natural and physical sciences, such as helping scientists identify species (Herodotou et al., 2017). There are subtle differences between a CS activity and more traditional ways of engaging people with research such as a survey or workshop and these should be considered before naming an activity as CS (ECSA, 2020). Documents defining CS and its characteristics such as the "Ten Principles of CS" by ECSA (2015) could help with making this distinction.

The degree of volunteers' engagement with CS activities varies. For example, in some projects, volunteers decide what should be studied, while in others they contribute to specific aspects of the scientific method such as collecting or processing data (Shirk et al., 2012; Haklay, 2013). Most projects engage citizens in the processes of data collection (Hecker et al., 2018), such as making observations of biodiversity, or data processing such as transcribing specimens. Recently, there has been a shift from scientist-led approaches to CS to a more active engagement of the public in scientific activities that are not restricted to processes of data collection and analysis (König, 2017; Herodotou et al., 2018). In particular, the importance of devising personally-meaningful investigations, by having citizens set their own research agendas that match their needs and interests has been highlighted (Anastopoulou et al., 2012). Efforts are also made to expand the application of CS across disciplines, including for example social sciences (e.g., Dunn and Hedges, 2018), while ways to engage diverse demographics with CS activities such as young people are explored (Herodotou et al., 2020).

CS projects are designed with the aim to solve problems or improve science in ways that would not have been possible without the support of volunteers. Yet, an intentional integration of learning objectives for volunteers is less likely to be found in the design of CS programmes, nor the possibility to participate in all the stages of the research process and contribute to decisions and outputs (Edwards, 2015; Herodotou et al., 2020). Assessment of volunteers' learning in CS projects is showing promising outcomes such as educating themselves in scientific thinking and how science works, appreciating nature and contributing to science initiatives (Freitag and Pfeffer, 2013; Aristeidou and Herodotou, 2020). CS could democratize research by allowing citizens to "take agency in the research process" and by directing research toward solving prominent societal problems such as enabling sustainability transitions toward, for example, renewable energy sources and sustainable agriculture (Sauermann et al., 2020). Despite significant benefits, CS programmes designed with an explicit focus on citizens and their growth and development remain scarce; such projects could involve citizens in the problem identification and framing of sustainable solutions, aligning policy agendas with the interests of the public, contribute own socio-political understanding of a topic, and help generate solutions and behavior change (Sauermann et al., 2020). CS benefits are often a "by-product" of citizens' engagement with scientific activities. It still remains to design and assess CS projects that have explicit objectives to support citizens' learning and agency, while also produce quality datasets that can be used to inform research and policy.

## Citizen or Community Inquiry

Citizen or community inquiry (CI) is an innovative approach to inquiry learning located at the intersection between "citizen or community science" and "inquiry-based learning" (e.g., Quintana et al., 2004). It refers to the distributed participation of members of the public in joining and initiating inquiry-led scientific investigations. Unlike the majority of CS projects that engage citizens in data collection activities, it aims to engage citizens in all the stages of the scientific research, from setting up personally meaningful projects to collecting and analyzing data (Herodotou et al., 2017). Specifically,

> *"It fuses the creative knowledge building of inquiry learning with the mass collaborative participation exemplified by citizen science, changing the consumer relationship that most people have with research to one of active engagement"* (Sharples et al., 2013).

Citizen or community inquiry emphasizes the intentional integration of inquiry-specific learning objectives into the design of community science activities. It aligns to a degree with Wiggins and Crowston (2011) categorization of education projects in which "education and outreach" are the primary goals of CS, as opposed to, for example, investigation projects the focus of which is to achieve certain scientific goals. What is distinct with "community inquiry" is the focus on a specific set of learning objectives that enable the development of inquiry skills. These learning objectives could be described using Bloom's updated taxonomy for teaching, learning, and assessment (Anderson et al., 2001) and categorized into (a) remember (recognizing/identifying, recalling), (b) understand (interpreting, exemplifying, classifying, summarizing, inferring, comparing, explaining), (c) apply (executing, implementing), (d) analyse (differentiating, organizing, attributing), (e) evaluate (checking, critiquing), and (f) create (hypothesizing, designing, producing). These learning objectives could be grouped into four major knowledge dimensions: (1) factual knowledge—knowledge of terminology, specific details and elements, (2) conceptual knowledge—knowledge of classifications, principles, theories, (3) procedural knowledge—knowledge of subject-specific skills, techniques, criteria for deciding when to use specific techniques, and (4) metacognitive knowledge- self-knowledge in relation to a subject matter.

Community inquiry could initiate with engaging volunteers in discussions about their own experiences and observations in relation to a topic of interest (remember/call). These discussions could result in brainstorming and elaborating on specific research questions that could be answered through one or more CS projects (understand). The next step is for volunteers to define the research method for collecting and analyzing data such as types of data collected, questions asked, methods of data analysis, and collect the actual data (apply). Following data collection, volunteers are involved in the process of data analysis and interpretation (analyse) during which they sort collected data, compare and contrast findings. This step should be followed by a process of evaluation of the findings (evaluate) in terms of answering the research question, relating findings to existing studies, and demonstrating new understandings. The final step is to promote impact by finding ways to share findings (reporting, publications, social media etc) with different audiences (create).

The community inquiry paradigm shifts the emphasis of scientific inquiry from scientists to the general public, by having non-professionals (of any age and level of experience) determine their own research agenda and devise their own science investigations underpinned by a model of scientific inquiry. Such an approach may sound visionary and particularly challenging, given that some volunteers may not have the necessary skills and training to take part or initiate scientific activities. As explained by Gura (2013), it is difficult to ascertain the quality of the data when you do not know if data were collected by a botany professor or "a pure amateur with an untrained eye" looking at wildflowers. Thus, volunteers' involvement may bias or undermine the scientific process and the production of valid and reliable outcomes. In the next section, we present an overview of how scientists could support volunteers' participation and learning in CS in ways that can result in high quality datasets. We then show how an online technological solution, nQuire, can be combined with a review and approval process to scaffold the design of community inquiry investigations.

## Data Quality in CS

There is often skepticism as to whether data generated by or collected from volunteers are accurate enough to inform future research and policy initiatives. Although considerably large in quantity, such datasets are often heterogeneous and hard to scale up to the population (Kelling et al., 2015). The accuracy of collected data should be judged project-by-project, considering several factors. In large-scale CS projects, high quality data can be achieved through a simple process of data collection and *post-hoc* data quality controls such as computational modeling, while in small-scale CS projects with complex data collection processes, expert-led training, and good quality materials can generate good quality science outcomes (Parrish et al., 2018). Kosmala et al. (2016) showed that a growing number of CS projects have managed to produce data with accuracy equal to, or in some cases, superior to that of scientists and proposed a set of strategies that when followed can enhance data accuracy. These refer to piloting and improving the design of a project, considering the level of difficulty of tasks, making systematic the tasks and data entry (e.g., selection from a predefined list of options), ensuring calibration of equipment used, recording of metadata that may influence data capture such as contextual factors or volunteers' characteristics, standardizing when data should be captured such as place, time, duration of recording, comparing findings to those of professionals in project reporting, allowing for sufficient data quantity and diversification (e.g., covering a range of geographic areas) as per the research questions, and storing data in a concise format to allow for interpretation and easy use. Adding simple instructions that model best practices, alongside technical enhancements that can support correct recording (e.g., status indicator of GPS availability), have also been shown to improve the measurement processes and reduce errors (Budde et al., 2017).

Technology becomes increasingly important in improving data accuracy. Certain technological features or solutions can help to overcome accuracy errors by, for example, systematizing methods of data collection and providing automated ways of giving feedback to volunteers about the quality of collected data. For instance, online social trust models were shown to effectively measure the trustworthiness of citizen generated data, while filtering was used to remove unreliable data (Hunter et al., 2013). A data quality measure framework has been proposed consisting of four steps: (a) identification of data quality dimensions, (b) application of data quality measures, (c) analyzing data and identifying errors, and (d) implementing tools and approaches that can improve data quality (Hunter et al., 2013). Scientists should consider data quality assurance as part of the process of designing a CS project, by identifying possible quality problems and how the project could be adopted to accommodate these. For instance, they should define the minimum sample size and the sampling sites from which data should be collected, that best address project objectives (Weigelhofer and Pölz, 2016). In the next sections, we present how we considered data quality issues in the design of the nQuire platform and we detail data quality and control issues in two nQuire projects related to temperature and biodiversity datasets.

# nQuire

Citizen or Community Inquiry has been operationalised in a bespoke, online solution, the nQuire platform (www.nquire.org.uk). nQuire has been designed with support from the BBC Tomorrow's World initiative to explicitly scaffold citizen-led investigations and inquiry learning processes (Herodotou et al., 2014). At the moment, it hosts 39 investigations with contributions ranging from 100 to 230K. These investigations have been initiated by mainly scientists (from across different universities), organizations such as the the Royal Meteorological Society and the Young Foundation, and individuals with an interest in science or research. The nQuire functionality allows members of the public, from lay individuals to scientists, to set up their own investigations, discuss and negotiate their ideas, and reach a consensus. In particular, nQuire facilitates inquiry learning by enabling citizens to brainstorm and collect potential research questions through, for example, contributing to investigations where data are open to anyone to read, comment, and discuss (see Bloom's objectives of remember and understand), define research methods and collect data in the form of texts, images, and sensor data (e.g., light, sound) through the use of an authoring functionality (apply), analyse and interpret collected data in the form of graphs and narrative that can be open to anyone to access (analyse), and write and share findings in the form of an interim or final report directly with participants (via email) or anyone visiting the platform through publishing a Pdf document on nQuire (evaluate and create). The platform supports two types of investigation: confidential missions and social missions (see **Figure 1**). In confidential missions, all data are private and only accessed by the mission author. In social missions, data are open for other people to view and discuss online. nQuire could potentially support the development of all five CS project types as proposed by Shirk et al. (2012) including contractual, contributory, collaborative, co-created and collegial projects. Yet, the vision behind nQuire is to enable the design of "extreme citizen science" projects (Haklay, 2013), or co-created and collegial projects (Shirk et al., 2012).

An example of a confidential mission is the "What's your chronotype?" mission for people to explore their sleep patterns. The mission attracted 6,700 contributions. Participants entered some personal details such as age and gender, and then responded

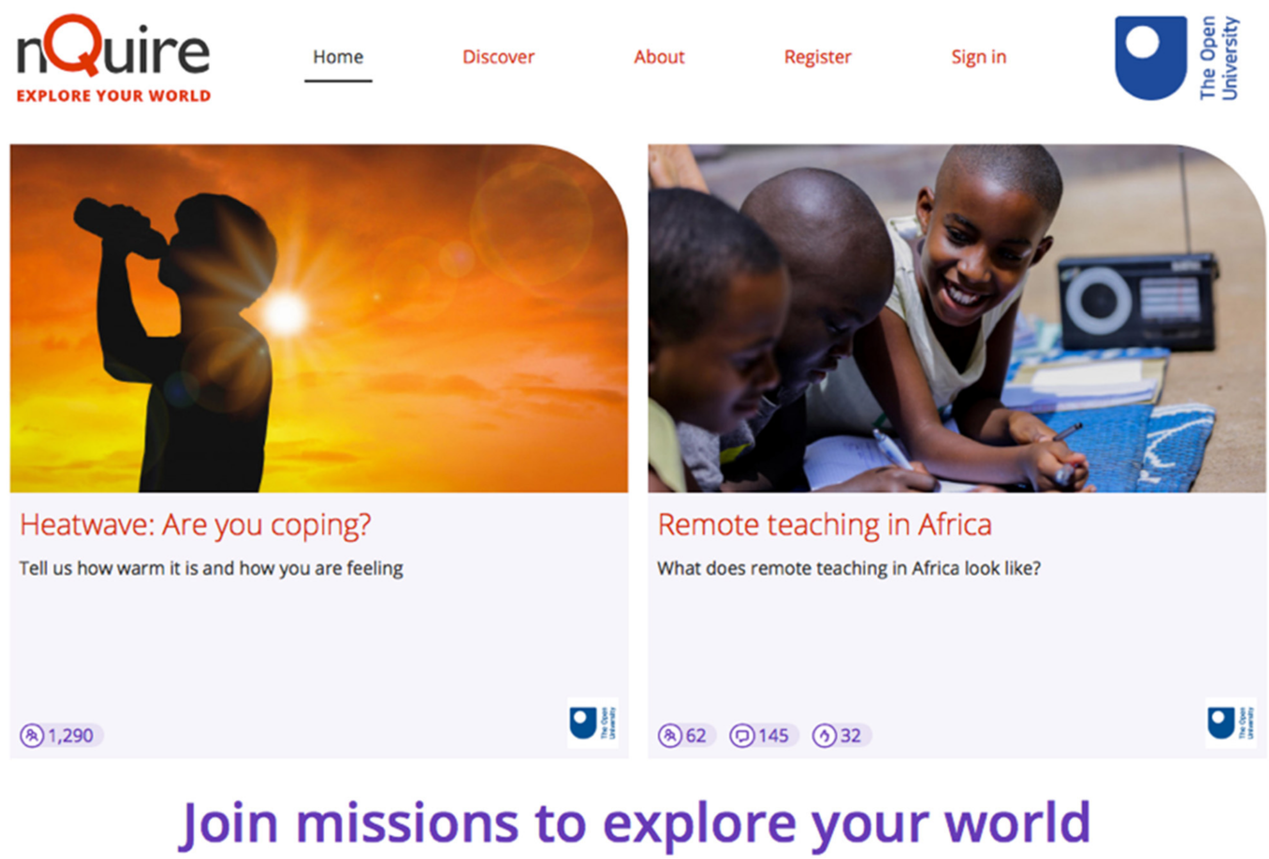


**FIGURE 1 |** A confidential and a social CS investigation on nQuire.

to a series of questions to uncover whether they are e.g., a "morning" or an "evening" person. Each participant received instant and personalized feedback based on their responses, immediately after they submitted their answers. An example of a social mission is "Remote teaching in Africa." Teachers from Africa were asked to share the challenges they faced due to Covid-19 and ways they overcome these. Responses were public. This enabled participants to communicate and learn from colleagues who may be facing similar issues. The mission contributed original insights about the educational situation in Africa as affected by the pandemic and produced guidelines as to how to support learners and teachers in this context.

Missions can include a rich mix of elements, such as: sounds or images as prompts; the ability of participants to upload a picture or sensor data as a response; and a variety of response types, such as slider scales, dropdown lists, and Likert scales. The platform provides an authoring tool to create new missions by setting up a "big question," an outline of the mission, adding a variety of response types, scoring each response category, and authoring customized feedback to the participant based on their scores. The mission can be divided into sections, with separate feedback from each section. All missions are checked by the nQuire research team at The Open University before they go live, to make sure they are safe, ethical, and legal. Owners of the mission (for a confidential mission) or any user (for a social mission) can download data in spreadsheet format. Results from a mission can be published on the platform.

## DATA QUALITY IN DESIGNING CS PROJECTS ON nQuire

A significant factor that could determine the quality of data collected is how a CS project is designed, in particular, what questions volunteers are asked to address and how well these are formulated, how methods of data collection are explained to them, what tools are available to enable accurate data collection, and what benefits there are for volunteers to motivate participation and quality of data collection. CS projects work better when they have defined and clear goals that are communicated to volunteers from the start, scientists with appropriate expertise are involved, the approach can be trialed and improved, participants understand the value of the project and the benefits they get out of it, and the quality of collected data can be measured (Tweddle et al., 2012). In technology-enhanced CS projects, issues of easy and accessible interface design, use of conventional language, easy registration, real time communication functionality, visualization of data collected, and motivational features are amongst the issues to be considered (Skarlatidou et al., 2019). In particular, what can support citizen-centered scientific investigations are mobile affordances, scaffolding the process of scientific inquiry, enabling learning by doing, and being a part of a community (Herodotou et al., 2018). Collective motives, that is the importance one assigns to the collective goals of the project, as well as reputation were found to be positively related to the quality of contribution (Nov et al., 2014), suggesting that benefits to volunteers should be considered when designing a CS project and explicitly shared with them to promote high quality data collection. In nQuire, these benefits are found in mechanisms that promote learning from participation, detailed in section The Process of Review and Approval (second paragraph).

In the case of nQuire, we set in place two mechanisms that support the design of scientifically robust and ethical CS projects: an authoring tool that scaffolds the process of design and a process of review and approval that ensures data quality and control over published investigations.

## The Authoring Tool

The authoring tool is free to access after registration with nQuire. It has been designed to scaffold the process of setting up a CS investigation from start to end. It enables any individual, scientist or citizen, to set up, manage, pilot, and launch an investigation of personal interest and share findings with volunteers. It is structured around four steps (see **Figure 2**):

### Start

The first step asks for details about the investigation including its name, a big question, an outline of the mission, benefits to science, benefits to citizens, time to be completed, and a mission image. It prompts authors to think of these aspects through structured forms, accompanied by explanations and examples.

### Build

In the second step, the author decides whether data from the mission will be confidential or open to the public to read and comment on, whether to score responses to specific questions and provide immediate and personalized feedback to participants based on their responses, and whether they intend to show the contributions on a map that is visible to participants. In this step, authors can set up the questions of the investigation (see **Figure 3**). Participants can contribute data in the form of text, images, geolocated and sensor data. For example, they can be asked to collect sound or light data using the sensors of their personal mobile device. A graph of the recorded data will be captured and uploaded to the investigation. Authors can enable data visualizations for specific mission questions. This feature enables the production of graphs that can be shown live on the nQuire platform while the mission is running. They can be automatically updated, the more data are collected.

### Enhance

The third step enables enhancements to the investigation, including the use of a customized splash screen, social sharing details, a custom consent form, and drafting feedback for volunteers. In the feedback form, authors are asked to provide details around the importance of the investigation, some interesting facts about it, and prompts for participants to read relevant information from specific websites or completing similar investigations on nQuire.

### Finish

The fourth step enables piloting of the investigation through the provision of a unique URL that can be shared with a small group of participants for testing, and a request for launch, which triggers the process of review and approval (see next section).

## The Process of Review and Approval

The process of review and approval is managed by academics in the nQuire team who are responsible to review the investigations and make requests for changes if they deem appropriate. The process entails checks on aspects that include:

- Ethics: Appropriate ethical approvals should be in place. In cases when authors have no access to an ethics board, the process can be managed by the Open University's ethics board.

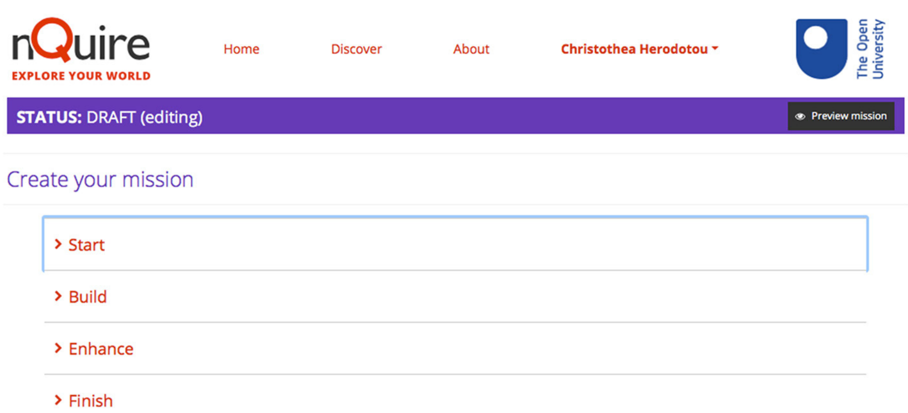


**FIGURE 2 |** The authoring tool enabling design of high quality CS projects on nQuire.

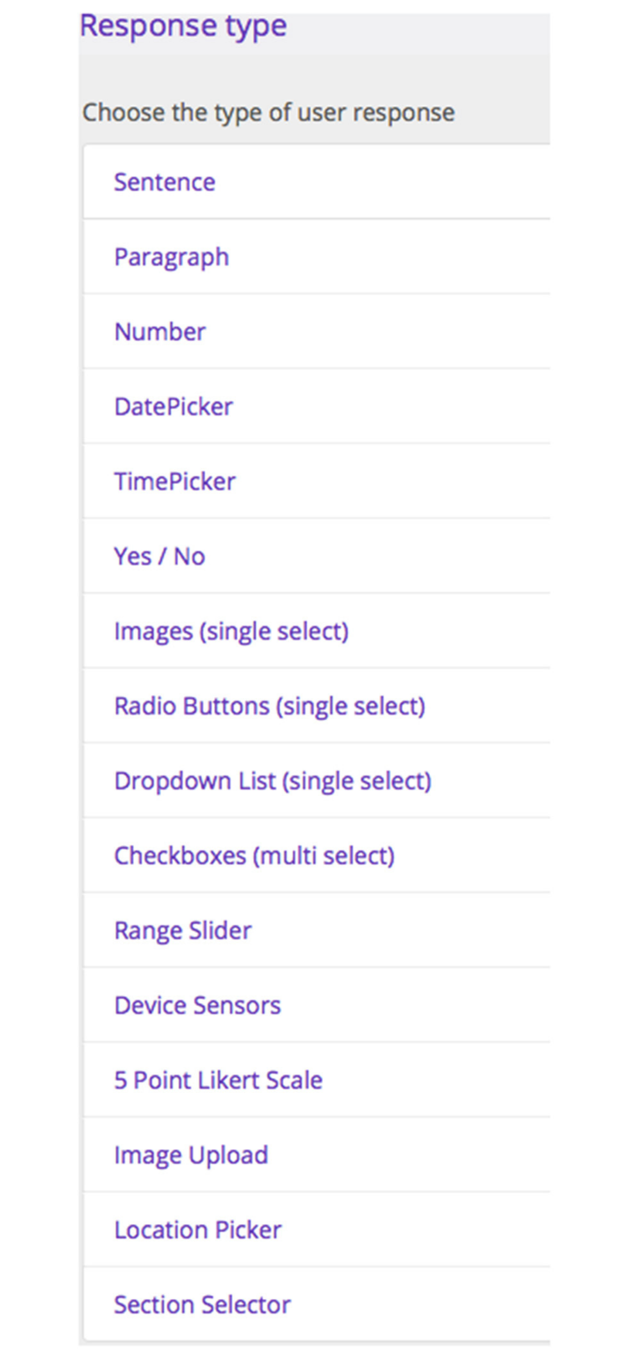


**FIGURE 3 |** Types of responses on nQuire.

- Author: Details about the author/s of the investigation should be legitimate and accurate.
- Originality: The investigation should build on appropriate and relevant literature and have the potential to produce original insights contributing to authentic science. To accomplish that, we engage with scientists who have expertise in the area of investigation and who can assess its originality.
- Mission brief: The mission brief should state clearly what the investigation is about, the benefits from taking part and the value to science, what volunteers will be asked to do and for how long, and how data will be analyzed.
- Language: The language used should be accessible (understandable by most people) and not offensive in any ways.
- Questions: Any predefined responses to questions should be distinguishable and all possible options should be considered and provided.
- Copyrights: Images or any other material used should be clear of any copyright restrictions.
- Piloting: The investigation should be piloted with a few participants and feedback should be sought after prior to launching that can inform the design of questions and ensure that content and tasks are understandable and easily implemented.
- Publishing findings: When the investigation reaches a certain number of contributions, authors are asked to prepare and share an interim report with preliminary findings via nQuire. This report is free to access and ensures that citizens gain access to findings.

The authoring tool and the process of review and approval are two mechanisms that promote data quality controls, support the design of scientifically robust investigations and can foster learning for volunteers. In particular, in terms of the latter, learning is scaffolded through: (a) the provision of immediate and personalized feedback. For example, one of the nQuire investigations is asking volunteers to assess the degree to which a number of statements about Covid-19 are valid. Based on the responses, participants receive personalized feedback about the correctness of those statements and the degree to which they may be prone to misinformation in news. (b) clearly defined and explicit benefits to citizens stated in the mission brief and explained further in the feedback form, (c) for social missions, opening up, and visualizing data, allowing volunteers to comment on the data and communicate with others about the interpretation of outcomes, (d) engagement with hands-on activities for collecting data such as taking pictures of biodiversity or making temperature measurements or assessing the therapeutic impact of sounds from nature on well-being, and (e) the process of designing an investigation from scratch with support from the authoring tool and communication with the nQuire team that reviews and approves missions.

In the next sections, we detail how data quality issues were monitored in two nQuire investigations about heatwaves and pollinators. In particular, we comment on how the design of the investigations was informed by best practice in CS quality assurance, evidenced in the literature, and how we plan to analyse collected data considering for issues of data control.

## QUALITY OF TEMPERATURE DATA

The "Heatwave: Are you coping?" investigation has been designed in collaboration with the Royal Meteorological Society and support from the BBC Weather (see https://nquire.org.uk/

mission/heatwave-are-you-coping/contribute). The mission was the outcome of a workshop with citizens and organizations interested in weather issues, which was organized by the Open University UK, as part of the UKRI funded project EduCS: EDUcating Citizens and organizations in Citizen Science methodologies. Workshop attendees were asked to brainstorm, vote, and rank ideas for research investigations they would like to design using nQuire. How comfortable people feel in extreme weather conditions was one of the two most popular investigations (alongside the impact of climate change). The investigation with more than 1,200 responses, was launched on the 7th August 2020, during which England experienced a heatwave and was ended in September 2020. The purpose of the mission was to explore how people's experiences of hot weather may differ depending on where they live and work, and how people are able to adapt their routines to heat. Citizens were asked to take their first temperature recording around 3–4 pm, when maximum daily temperatures are normally observed. The rationale behind the mission was to collect data about how different people are affected by extreme weather conditions and how working and living conditions could be improved. Results could, for example, help people plan for heatwaves in the future. In terms of the learning benefits for citizens, the mission was an opportunity to learn about what forecast temperatures mean in practice, how to make and record measurements, and how to increase personal comfort in a heatwave.

CS temperature measurements have the unique value of providing data about air temperature on scales smaller than those measured by the official meteorological service, and such data could be possibly used in weather monitoring or even forecasting (Cornes et al., 2020). Yet, the quality of weather data collected is a major challenge and a source of bias, often related to possible overheating of the thermometer by, for example, not being shielded. This was an issue raised and discussed during the workshop, with weather scientists expressing concerns about the quality of data collected and whether amateur scientists could actually offer reliable recordings. To address these concerns, we first reviewed relevant literature about methods for improving weather data accuracy. Amongst the proposed approaches was to collect information about the instrument used and the conditions it is exposed to, that when considered could improve data accuracy (Meier et al., 2017) and consider for the use of a statistical correction—Generalized Additive Mixed Modeling (GAMM)—developed to improve accuracy when analyzing weather data (Cornes et al., 2020).

Considering these insights, we devised a number of mechanisms that could help improve the data accuracy of weather measurements. In particular, (a) in the mission instructions, we included top tips about how to capture the temperature, especially tackling the issue of overheating of the instruments, written in an accessible language and avoiding technical terminology (see **Figure 4**), (b) the Royal Meteorological Society developed an online guide about how to capture temperature and humidity in gardens which was attached to the mission instructions, and which provided technical details about different devices and their accuracy, (c) in the mission questions, citizens were asked to report on contextual information such as the instrument they used

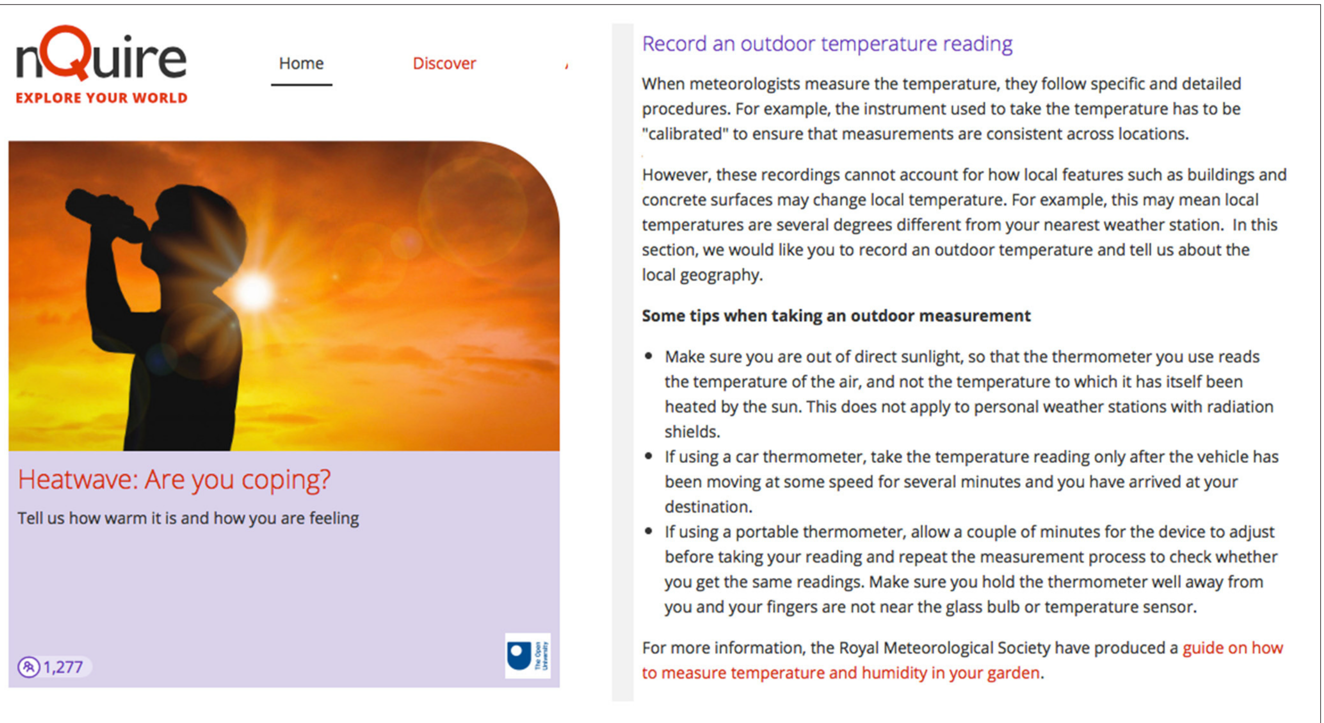


**FIGURE 4 |** Instructions about how to measure temperature in the Heatwave: Are you coping? mission.

to collect data, distance from nearest buildings, area density, relative humidity and their clothing. These data could inform data analysis and be considered in assessing the accuracy of the data collected. (d) During the process of data analysis we plan to undertake a number of checks to enhance the quality of collected data including data cleaning (that is removing data points that are not valid due to mistakes during data collection or reporting), and removing duplicate cases or extreme cases ("outliers") by plotting the data and inspecting for points that are far outside the majority of contributions. We will draw from existing studies such as Li et al. (2020) to get the best possible outcome. (e) We plan to compare data points reported in the same geographic location (postcode) and identify the degree of agreement amongst them. The more accurate the data, the more likely those points will overlap. This is similar to the approach adopted in other CS platforms such as the iNaturalist where species identifications is graded based on whether community members agree and confirm the given identification, and (f) we will compare citizens' recordings to the official weather data for a specific area and identify the degree of agreement or distance between the recordings.

## QUALITY OF BIODIVERSITY DATA

The mission "Pollinator Watch" was designed by the Open University (OU) and promoted by the BBC 2 Springwatch series in 2020, attracting more than 7,800 contributions. The OU has a long lasting collaboration with the BBC for over 40 years for the production of television and radio series. As part of it, in 2019 it designed and launched, with support from the British Trust of Ornithology, the Gardenwatch mission attracting more than 200K contributions. Following this successful collaboration, the nQuire team was asked to design a mission for the 2020 Springwatch series. To identify and set up a relevant mission, a team of scientists from the OU with expertise in biodiversity was brought together. Insect pollinators was the chosen topic as pollinators are essential for many flowers, carrying pollen between plants and enabling seed production, and are under extinction due to several threats such as the destruction of wild habitats and pesticides (e.g., https://bit.ly/3g7ww1Z). The mission could help citizens to learn about different types of pollinators, the benefits they bring and how they can be protected (see **Figure 5**). Citizens were asked to share their observations (upload photographs) of insect pollinators they see and answer some questions. These data would help scientists understand which pollinators are commonly observed and where, especially in the UK, as well as how much citizens know about these important species. In addition to that, scientists were interested in capturing any effects of the government's restricted movement due to the Covid-19 lockdown in the UK, in particular whether citizens' interactions with nature have changed. Preliminary data analysis has been published on the mission page and emailed to consented participants (see https://nquire.org.uk/mission/oupollinatorwatch).

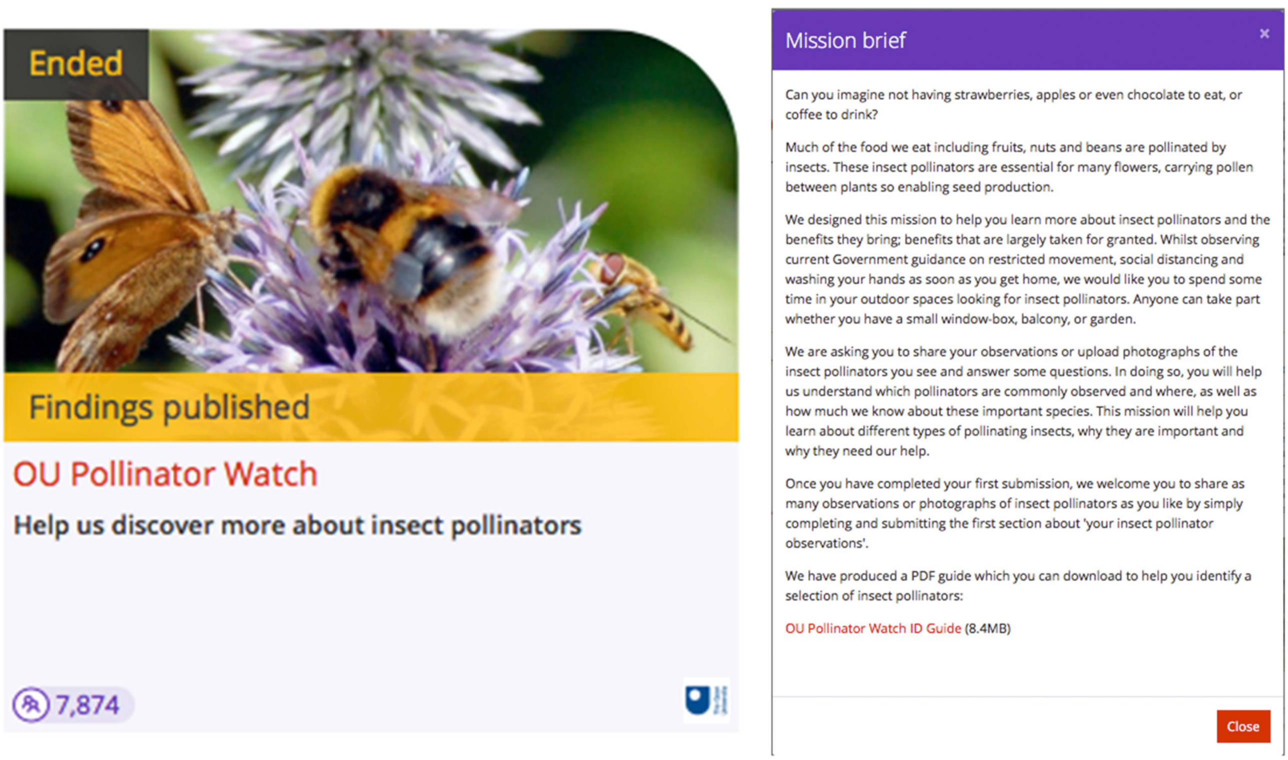


**FIGURE 5 |** The mission brief of the Pollinator Watch investigation on nQuire.

To enhance the quality of data collected, a visual guide with images and names of pollinators was designed and attached to the mission's instructions, encouraging people to use it when they are observing pollinators. This was a document with sample images from each category of pollinator and relevant information. A more dynamic guide such as an online interface with an open choice of filters, rather than directed filtering or direct visual comparison, could have improved further the accuracy of a species identification (Sharma et al., 2019). Also, citizens were asked to assess the degree to which they are confident that the identification they made is correct and state whether they normally observe and identify pollinators. These data will inform our approach to checking the correctness of the identifications; given the large size of contributions, we plan to sample a subset of them based on a set of criteria including previous experiences of identifying pollinators and confidence, general interest in environmental issues, age, and gender. Biodiversity scientists will then make their own identifications of the pollinators in these photographs, compare their identifications to those of citizens and ascertain the degree of correctness. An alternative option would be to upload or share the images with a biodiversity platform such as iNaturalist or iSpot. Such CS platforms make use of a combination of human and machine learning mechanisms for identifying species observations. For example, in iNaturalist, when uploading an observation you receive automatic recommendations as to what the species may be, generated by machine learning algorithms. In addition to that, a community grading system is in place which assesses data quality. An observation is verified when 2/3 of the community agrees on a taxon. In the case of nQuire, this was not feasible due to image copyright issues; participants were given the option to maintain or release rights from the images they took.

To enable easy access to the pollinators investigation, we allowed users to take part without registering with nQuire, yet noting that this would not allow them to access their data after submitting them. A registered user has access to their own private dashboard where they can see all the missions they took part in, their responses, as well as any missions they may have created or launched. Non-registered users raised a data control challenge as it became impossible to infer or identify duplicate responses in the dataset (and remove them) or identify whether a participant submitted more than one observation. We plan to treat non-registered users as a separate category and run the analysis considering for these limitations.

## DISCUSSION AND CONCLUSIONS

In this paper, we have argued that the participation of volunteers in authentic scientific activities is a great learning opportunity that can promote development of scientific thinking skills and community inquiry. Such skills are particularly relevant to, not only those planning to follow a STEM career, but every individual, no matter what their career may be. Scientific thinking is a tool that can help with approaching and solving everyday problems. It is about how one looks at the world, questioning what others say, approaching problems in organized and creative ways, learning to analyze why things went wrong and being open to new ideas that can change the way we think and act (The Royal Society, 2020). Community inquiry can raise awareness, drive behavior change and support transitions toward more sustainable ways of living in areas such as public health and environmental conversation (Sauermann et al., 2020). It can enhance the sustainability of research projects and democratize science, especially when communities are invited to take part in all stages of the scientific research, projects are locally relevant and are addressing both the social and technical aspects of sustainability, and by eliminating tensions between traditional science and CS (Sauermann et al., 2020; Froeling et al., 2021).The significance of developing community inquiry though participation in CS activities comes with a major challenge, that of producing high quality datasets that can be used to inform future research and policy initiatives (Kosmala et al., 2016; Parrish et al., 2018). Citizens are often not trained, or do not have the skills, to conduct scientific activities and thus their involvement is often faced with skepticism. To address this challenge, we detailed how nQuire, an online CS platform, and a process of review and approval by scientists can promote high quality data collection and help volunteers learn from participation in CS.

A number of mechanisms can help to achieve quality assurance and control in CS projects, while at the same time prompt learning and participation. These mechanisms should be made explicit to enable volunteers to reflect and improve their practices over time, and scientists to assess the quality of data collected. There is yet a need for transparent and accessible data management standards that can help assess CS projects and the degree to which they produce reliable results (Borda et al., 2020). Toward that direction, technology plays a major role in producing high quality datasets. In the case of volunteers who are designing their own investigations, it can support the design and management within a single environment and help to standardize processes of data collection. In particular, the authoring tool in nQuire scaffolds the process of designing, managing, piloting, improving, and launching a CS project, by structuring the project around four stages and giving guidelines as to what is required in each stage. For projects focused specifically on biodiversity and species identification, it could be used alongside other platforms that scaffold the identification process through community contributions or machine learning algorithms such as iNaturalist and iSpot. Also, it scaffolds decisions around data collection by offering participants a library of tools they can use to collect data including, for example, image, geolocation, sensor, and text data. This enables any individual with or without expertise in science to initiate a project they or their communities are personally interested in. The process of review and approval is an opportunity for volunteers to communicate and learn from scientists about how they can improve their designs and create scientifically robust investigations. It is a quality assurance process which ensures that the content and structure of the investigation are appropriate by, for example, reviewing the questions, language, ethics, originality, and others. In terms of the data collected, these can be visualized in graphs while the mission is running and shown live on nQuire. Also, data can be downloaded at any time by mission authors in the form of a CSV file for further analysis. Platforms such as PlutoF could be used for organizing and managing databases from across different projects or for making raw data available and open access.

Reflecting on two CS projects related to temperature and biodiversity, what became evident is the importance of providing instructions and modeling participation to enable volunteers to collect data in a consistent manner, by for example creating a relevant guide (e.g., Budde et al., 2017) of how to take temperature or showcasing what pollinators look like. Also, it is important to collect contextual information related to the project such as geographic information or volunteers' demographics (Meier et al., 2017; Parrish et al., 2019) that could help scientists assess the quality of measurements, for example, details about the device used to collect temperature or expertise in identifying species. The quality of data can be further enhanced at the point of analysis by considering for data cleaning and filtering as well as more specialized approaches to statistical analysis (e.g., Parrish et al., 2018) that may be specific to a field of study. Existing literature should also be considered, as lessons learnt from other studies can inform the design and implementation of a project or how data are analyzed and reported. Finally, CS projects should make explicit (state clearly) the benefits to science alongside the benefits to volunteers, as the latter can support data quality contributions (Nov et al., 2014), while project findings and interpretations should be shared with participants (Robinson et al., 2018) and if possible, encourage feedback and communication around then.

As a next step, the nQuire team aims to assess the actual data quality of the Heatwaves and Pollinator Watch projects by following the *post-hoc* data control procedures detailed above. Also, we seek to assess the quality of data across CS projects on nQuire by collating and reviewing publications that have emerged from these projects, and by interviewing the scientists behind each investigation. Of special interest to the nQuire team, is the analysis of data that have captured impact on participants' learning from taking part in CS projects. Early findings show increased awareness about the topics under examination and improvement of skills such as how to identify correctly pollinators. It remains to examine how such learning benefits are developing over time, how they may relate to improved data quality contributions, and other contextual factors such as previous experiences of CS and demographics. Also, we aim to engage with volunteers to identify the challenges they may face when taking part in CS and the errors they see happening when collecting data or designing an investigation, and use these to optimize the design of nQuire and the process of reviewing and approving investigations.

## AUTHOR CONTRIBUTIONS

CH produced a first draft of the manuscript after discussions with ES and MS about quality issues that could be discussed and reported in the paper. ES and MS reviewed and revised the paper, included additional literature, and elaborated on the arguments made. All authors contributed to the article and approved the submitted version.

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METHODS
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# A New Collection Tool-Kit to Sample Microplastics From the Marine Environment (Sediment, Seawater, and Biota) Using Citizen Science

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Microplastics (plastic particles $\leq$ 5 mm) have been studied extensively in coastal areas around the world in several habitats. Nevertheless, understanding and explaining the temporal and spatial occurrence and dynamics of microplastics is challenging. For the first time, three environmental variables were studied at six locations at the same time for each season over a year, along the North and West coasts of Scotland. Surface water was collected with a pole water sampler from the shore whilst beach sediment was sampled using glass jars, and mussels were the target organism collected. Concentrations of microplastics ranged from 0 to 6 $\pm$ 1.50 particles per l of surface water. In beach sediment, microplastics concentrations ranged from 0 to 0.37 $\pm$ 0.12 particles per g.dw, whilst for mussels it ranged from 0 to 23.81 particles per g.ww. This study was designed to determine the presence of microplastics as well as extend the temporal and geographical scales. We developed a simple, cost-effective and practical tool-kit to collect microplastics from the coastal environment and engaged the public in scientific research. The tool-kit was designed to take into account the latest recommendations for sampling each environmental substrate, whilst being practical for citizen scientists to use. This research demonstrates that using a semi-structured to structured project with a defined sampling approach including the participation of the public with local knowledge can be an effective way to monitor microplastics in the marine environment along the Scottish coastline. This approach, can be adapted to other projects monitoring microplastics to increase the use of citizen science in projects, allowing more studies to take place, more samples to be collected, and a greater understanding of the occurrence and the potential impact of microplastics in the environment.

**Keywords: citizen science, microplastics, mussels, sampling, sediments, tool-kit, surface waters**

## INTRODUCTION

Plastics have become a worldwide pollutant with an estimated 19–23 million metric tons entering aquatic ecosystems globally each year (Borrelle et al., 2020). Plastics currently constitute ~80% of the total litter found in the marine environment (Moore et al., 2002; Galgani et al., 2015). Borrelle et al. (2020) predicted an annual plastic emission of up to 53 million metric tons in 2030, based on the current decisions and waste strategies decided by governments. Due to the plastic presence observed from terrestrial (Zhu et al., 2019; Kumar et al., 2020; Sarker et al., 2020; Schell et al., 2020) to freshwater environments (Lassen et al., 2015; Kanhai et al., 2017; Li et al., 2020; Szymanska and Obolewski, 2020) as well as in a number of marine habitats including the deep sea to surface waters (Lusher et al., 2014; Thompson, 2015; Courtene-Jones et al., 2017; Jamieson et al., 2019); geologists have proposed the use of plastics as a marker for the Anthropocene era (Waters et al., 2016).

Frias and Nash (2019) have given a general definition for microplastics that are "any synthetic solid particle or polymeric matrix, with a regular or irregular shape and with a size ranging from 1 μm to 5 mm." Microplastics can be classified as either primary or secondary plastics (Frias and Nash, 2019), with primary microplastics being intentionally-manufactured small pieces, whilst secondary microplastics are the result of fragmentation of larger pieces (Thompson and Napper, 2018). These particles continue to degrade over time due to physical, biological and chemical processes (Frias and Nash, 2019) and consequently, they may become available for ingestion to an increasingly wide range of marine organisms, which could result in physical/physiological disturbances (Auta et al., 2017; Avio et al., 2017). Microplastics vary in type, shape, color and chemical composition (Frias and Nash, 2019; Rochman et al., 2019).

Meijer et al. (2019) have estimated that 1,000 rivers are responsible for 80% of global annual emissions of plastics to the marine environment, ranging from 0.8 to 2.7 million metric tons per year. Thus the coastal zone is a clear interface between land (representing the main sources of plastic debris input) (Jambeck et al., 2015) and the oceans, where the majority of microplastics mix prior to dispersing to other habitats such as the deep sea (Courtene-Jones et al., 2017; Jamieson et al., 2019), sea ice (Kanhai et al., 2020; Kelly et al., 2020), the open ocean (Desforges et al., 2014; Gago et al., 2016; Frére, 2017), coastal areas (Blumenröder et al., 2017; Graca et al., 2017; Yu et al., 2018) or interacting with marine organisms (Cole, 2014; Rezania et al., 2018). Microplastics in sediments, water and fauna have been extensively studied globally over the past few years, and appear prevalent in these systems (Rezania et al., 2018). Increasing knowledge of the occurrence and dynamics of microplastics in the intertidal area is a key challenge that needs to be addressed by developing monitoring programs at a national scale (Zhang, 2017). It is essential to examine the fluctuating composition of plastic particles by specifically looking at temporal variations in several environmental variables (e.g., fauna, sediment, and water).

Citizen science is a powerful tool involving and engaging the public with scientists in research projects to help monitor environmental markers (Cohn, 2008; Wiggins and Crowston, 2011). The word "citizen" is used as part of "citizen science" meaning a member of the wider community (Eitzel et al., 2017). Welvaert and Caley (2016) explained that "citizen science" is generally, and commonly, understood to mean "the public participation in scientific research." Citizen science based studies grew exponentially over the past few years contributing to several publications (McKinley et al., 2017). To allow projects to develop robust monitoring and be comparable, Kelling et al. (2019) suggested a studies' classification based on clear and simple elements: structured, semi-structured and unstructured. All three groups have their advantages, however, a semi-structured project is considered to be a good mix between a flexible and attractive method for the public with a recorded observation process, clear scientific objectives as well as rigorous and well-defined data collection. This therefore allows for effective and valuable monitoring of microplastics along the coastline (Kelling et al., 2019).

Zettler et al. (2017), described citizen science as a resource to increase spatial coverage, enhance sample size, create big datasets, raise awareness and limit financial costs. Some initiatives have proven to be successful, e.g., International Pellet Watch (Zettler et al., 2017) engaging hundreds to thousands of volunteers in scientific studies. The inclusion of citizen science in research projects is undoubtedly facilitating the collection and analysis of a high quantity of samples, as well as enhancing the spatial and temporal breadth of areas studied (Hoellein et al., 2015; Jambeck and Johnsen, 2015; Zettler et al., 2017). Other projects focussing on plastic marine debris have also recommended using citizen science for monitoring and collection of data (Syakti et al., 2017). Trained volunteers and professional scientists' data collection are comparable in terms of size composition of plastic debris and time efficiency of collection (Van der Velde et al., 2017). Nevertheless, concerns regarding the involvement of volunteers for microplastic studies include the quality control of data. However, the creation of simple, reliable and reproducible protocols should result in little sample contamination by the volunteer scientists (Hidalgo-Ruz and Thiel, 2013; Van der Velde et al., 2017; Barrows et al., 2018; Forrest et al., 2019). Forrest et al. (2019) demonstrated that citizen science provides numerous advantages including producing reliable results when studying microplastics in water samples, even if challenges were encountered such as choice of sampling point by volunteers, field blanks missing and limitation of the water volume collected. Bosker et al. (2017) also pointed out the powerful use of citizen scientists in the collection of microplastics data from beach sediment at a global scale by covering 42 beaches including sites in Europe through to the East coast of America. Lots et al. (2017), confirmed the benefit of collecting sediment samples at a European scale using volunteers by designing simple collection methods to investigate microplastic pollution.

Beach sediment has been collected to investigate the presence of microplastics in a plethora of studies, using a range of methods from direct sampling with forceps, volume-reduced sampling by sieving or using bulk sampling (Prata et al., 2019). Bulk samples seemed to include the broadest size range for microplastics compared to sieving (Brander et al., 2020). Blumenröder et al. (2017) suggested that the mechanical action of sieving would create artificially more microplastics leading to an inflation in the number recorded. Sieving would also potentially increase the risk of contamination from the personnel or the environment. It is also recommended to collect the top 5cm of beach sediment using five replicate samples where microplastics seemed to be more abundant (Brander et al., 2020). Marine surface waters collection could be achieved by reduction *in situ* using nets (i.e., neuston or manta), sieves or pumps. Those techniques would allow for large volumes of water to be analyzed thus, outputs should be more representative of the environment being sampled (Prata et al., 2019). However, these techniques require considerable means to deploy the equipment, i.e., a boat, or the need to transport pumps to several sites across hundreds of km, which is not practical for citizen science project. This is therefore perhaps not the best method to be employing when citizen scientists are involved. Nets can also clog easily causing a loss of particles collected (Prata et al., 2019). Alternative techniques such as the use of bulk samples (i.e., bottle and bucket) are preferred with regards to the feasibility of sampling by citizen scientists especially where large distances need to be covered as well as for reducing contamination (Prata et al., 2019). Although small volumes may not be accurate in representing the concentrations observed in the environment, Prata et al. (2020) indicated that low volumes allowed for the geographical and temporal range of a study to be greatly extended.

The current published marine plastic studies have only used citizen scientists to collect macroplastics or microplastics from a single environmental variable through different time scales, e.g., sediment (Hidalgo-Ruz and Thiel, 2013; Bosker et al., 2017; Lots et al., 2017; Nelms et al., 2017; Ambrose et al., 2019; Doyen et al., 2019; Carbery et al., 2020; Nel et al., 2020), water (Barrows et al., 2018; Forrest et al., 2019; Sanders and Brandes, 2020), or biota (Liboiron et al., 2016). Moreover, Blumenröder et al. (2017) highlighted that a lack of protocol standardization, combined with reduced numbers of quantitative spatial and temporal studies are an limitation for the study of microplastics in the environment. Marine Strategy Framework Directive (2013) provided recommendations described protocols to allow monitoring of marine litter and microlitter, in European seas. There is a requirement to develop and apply standardized methods to establish national microplastic database in European Member States (Marine Strategy Framework Directive, 2013).

This study presents a methodological approach that is both simple yet standardized based on the recommendations for the collection of microplastics in coastal seawater, intertidal sediment and wild blue mussels (*Mytilus edulis*). Sampling has been undertaken in different locations over a distance of ∼400 km at the same point in time, over a 12 months period to take into account seasonal variation. To enable this, citizen scientists followed the same protocols as the lead author for the collection the environmental samples to determine the concentration of microplastics in these three matrices and to contribute to the creation of a reliable database. Thus, interacting with volunteers, enabled a broader geographical region to be covered and allowed the sampling campaign to be repeated through time to include a temporal scale as recommended by Brander et al. (2020). This paper demonstrates the potential use of citizen science as a method to generate standardized data on the concentrations and temporal variation of microplastics found in three environmental matrices (water, sediment, and biota) along the North and West coasts of Scotland.

## MATERIALS AND METHODS

### Study Area

Scotland has ∼18,000 km of coastline on the mainland alone with some areas inaccessible or not easily reached due to lack of infrastructure. To assess microplastics contamination along the West and North coasts of Scotland (**Figure 1**), samples were collected from six contrasting sites based on several parameters, hydrodynamic activity (i.e., annual mean wave power, annual mean significant wave height, wave exposure index), anthropogenic activity (i.e., population number and density) and the tidal range (i.e., mean spring tidal range) that defined the sites (**Table 1**). The general description of the sampling sites was based on the Marine Scotland, 2021 Maps National Marine Plan Interactive (NMPI) (Marine Scotland (2021) Maps NMPI part of Scotland's environment).

### Citizen Science

To be able to cover this large region, citizen scientists were recruited based on their educational background, science knowledge, interest in the topic and field/monitoring experiences, through professional contacts via emails, combined with the Natural Environment Research Council (NERC) funded Capturing Our Coast (2016) [CoCoast; (Capturing Our Coast (2016): An innovation in marine citizen science)] citizen science project. The team of citizen scientists ranged from postgraduate students at UHI partner institutes, Islay Natural History Trust volunteers and those who had been directly involved in the CoCoast programme (10 participants in total).

The initial exchange with volunteers introduced them to the topic, type of locations needed and why additional help was required. Volunteers based at Thurso, Islay and Mossyard (**Figure 1**) were asked to identify suitable sampling locations, which combined selection criteria such as accessibility of the site, sandy beaches with rocks present, the presence of blue mussels, closeness to the volunteers' home's for safety reasons and transport time of samples. Volunteers' local knowledge was invaluable in aiding site selection. Prior to any sampling being undertaken, the citizen scientists took site photographs, recorded GPS location data, provided detailed descriptions of proposed locations, along with information on the selection criteria. Sites were deemed acceptable once the research team and volunteers were happy that the locations fulfilled the requirements for the science to be valid. Simple protocols were designed and initially field tested by the research team. Non-scientific personnel were drafted in to review the protocol in the field so that issues could be addressed prior to sampling kits being posted to the volunteers. Additional information was also provided including sampling

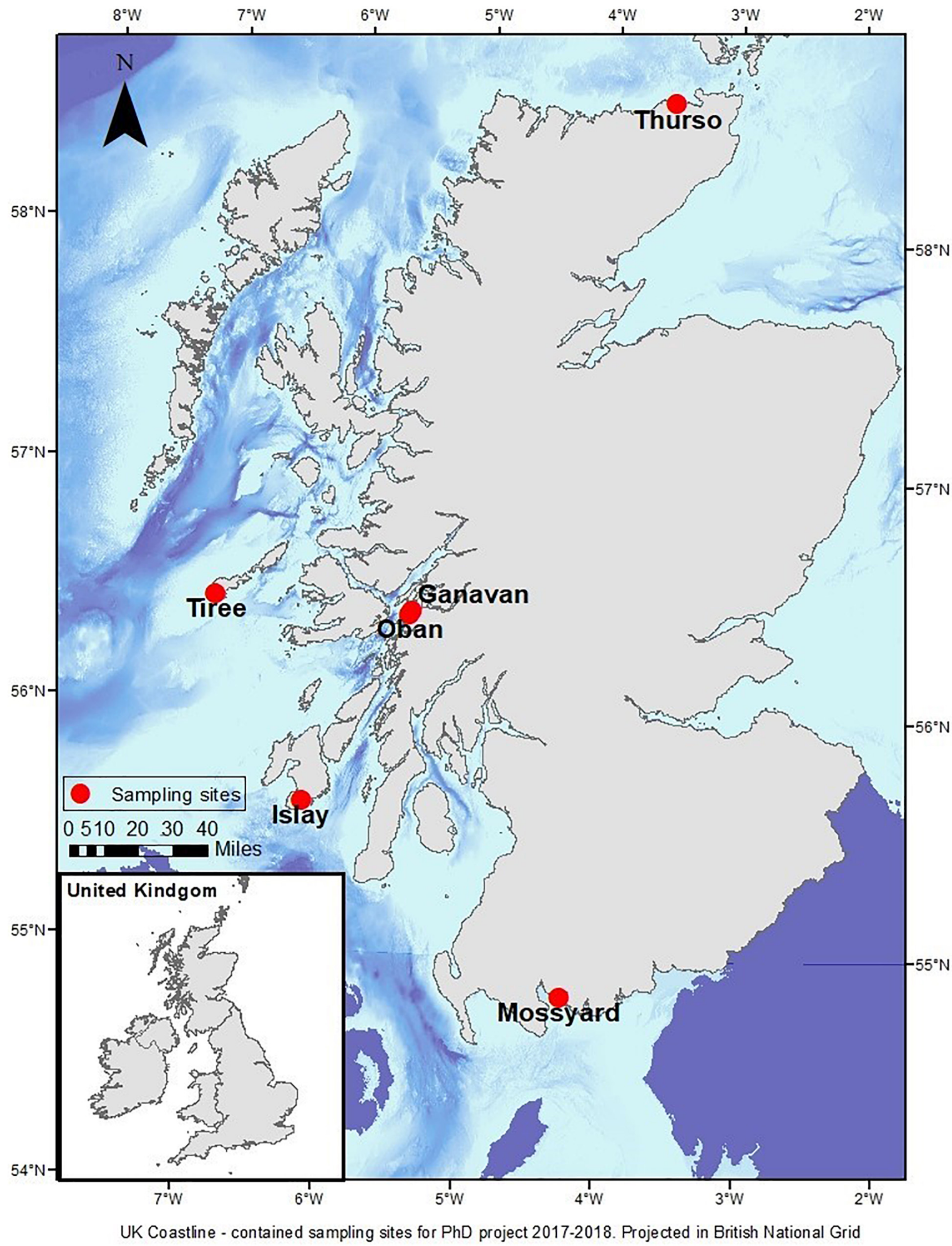


**FIGURE 1 |** The six sampling sites around the West and North coasts of Scotland.

schemes, pictures and a video explaining the methodology, what clothing they should/should not wear (i.e., wellington boots, waterproof jacket and natural fabrics as much as possible to prevent contamination) as well as a reminder to work in pairs to meet health and safety protocols. Volunteers were required to read and accept SAMS' risk assessment prior to any fieldwork commencing. Before each sampling event, a video-conference/telephone-call was organized between the lead author and each of the volunteers allowing for any questions/queries to be addressed. The lead author was also reachable by telephone during each sampling campaign in case any problems were encountered by the volunteers.

## Sampling Kit

Sampling kits were designed to be simple tool-kits, easily used by all volunteers. The tool-kit consisted of a pole-water sampler, glass jars (15 of 7 ml), plastic bottles (5 of 500 ml), sealable plastic bags, filter paper already placed in Petri dishes, aluminum

**TABLE 1 |** Coordinates and general description of sampling locations based on the three main parameters of interest.

| Sites | Latitude | Longitude | Mean spring tidal range (m) | Description |
|---|---|---|---|---|
| Islay – Carraig Fhada | 55° 37′ 16.392″ | −6° 12′ 53.9994″ | 1.1–2.0 | Control site |
| Thurso | 58° 36′ 6.8034″ | −3° 32′ 31.5234″ | 3.1–4.0 | High hydrodynamic activity, Highly populated |
| Oban – town center | 56° 25′ 15.132″ | −5° 28′ 55.4874″ | 4.1–5.0 | Low hydrodynamic activity, Highly populated |
| Oban – Ganavan sands | 56° 26′ 20.0394″ | −5° 28′ 8.3634″ | 4.1–5.0 | Low hydrodynamic activity, Low populated |
| Tiree -Balephuil | 56° 27′ 34.0194″ | −6° 57′ 37.26″ | 3.1–4.0 | High hydrodynamic activity, Low populated |
| Mossyard | 54° 50′ 24.5034″ | −4° 15′ 26.316″ | 6.1–7.0 | Low hydrodynamic activity, Low populated |

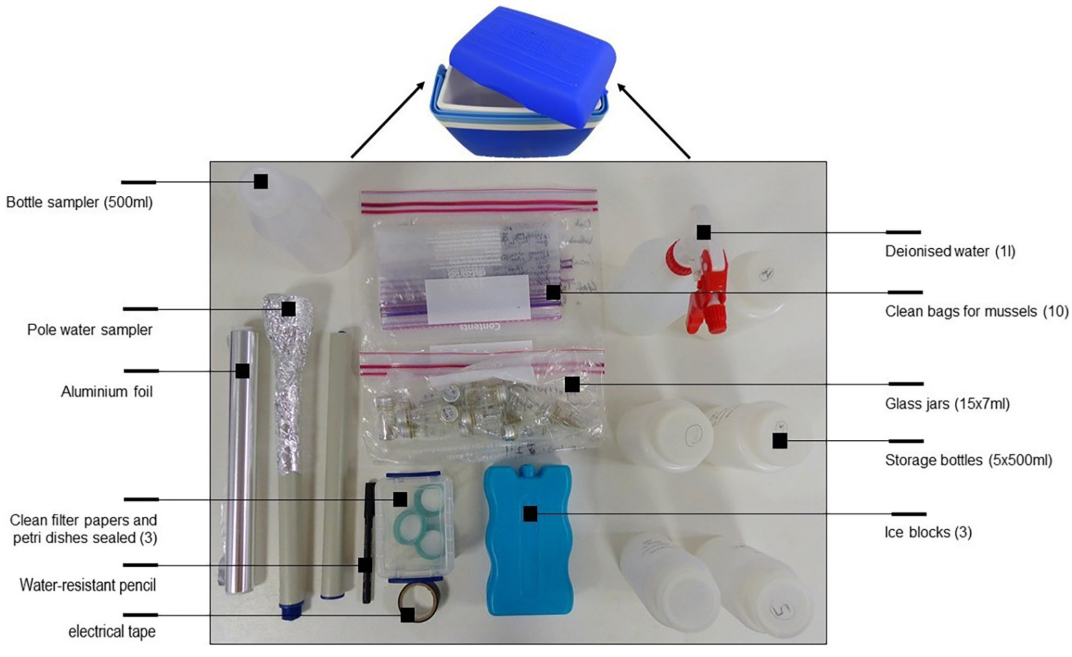


**FIGURE 2 |** Sampling tool-kit compiled before sending the cool-box to citizen scientists.

foil, deionised water (1l), electrical tape, water-resistant pencil, ice blocks (3) and a cool box (**Figure 2**). The water-sampler, bottles, bags and jars were rinsed and cleaned with deionised water and 70% ethanol prior to being sealed. The filter papers and Petri dishes were examined using a stereomicroscope 37.5× magnification prior to sealing with electrical tape to ensure no contamination. Bottles, bags and jars were partially labeled to facilitate the work in the field by the volunteers. All materials were stored in an insulated cool-box immediately after collection and during transport of samples to the laboratory, which allowed safe transportation of materials. The cool-box provided thermal insulation for the samples, resulting in slower development of organic matter, as well as a convenient way to transfer materials to and from the site. The volunteers were asked to take a knife (Swiss army type knife) prior to going into the field, to be able to remove the mussels from their substrate.

## Sampling Collection

At all six locations, intertidal sediment (i.e., sand), coastal water and benthic organisms (i.e., *M. edulis*) were collected four times during the year (every 13 weeks) i.e., April 2018, July 2018, October 2018, and January 2019, to investigate seasonal variability in microplastic abundances, polymer types and shapes. All the sites were sampled at the same time (e.g., over the same weekend) to avoid large weather and tidal disparities between locations.

### Intertidal Sediment

The most recent high tide line was the focus of this study, to look at actual microplastic deposition rather than accumulation over time as suggested by Hidalgo-Ruz et al. (2012). Avoiding the springtide lines would allow the samples to be more representative of the actual microplastic accumulation (Blumenröder et al., 2017). The aim was to investigate the effect of the tide, hydrodynamic and anthropogenic activities on microplastic deposition on sandy beaches.

Three sampling points were randomly chosen using the website Random.org True Random Number Service (1998) and in this instance the points were 8, 12, and 21 m (**Figure 3**),taking into account the length of the six beaches, to allow a coverage of the microplastic variability in beach sediment. The top 5 cm

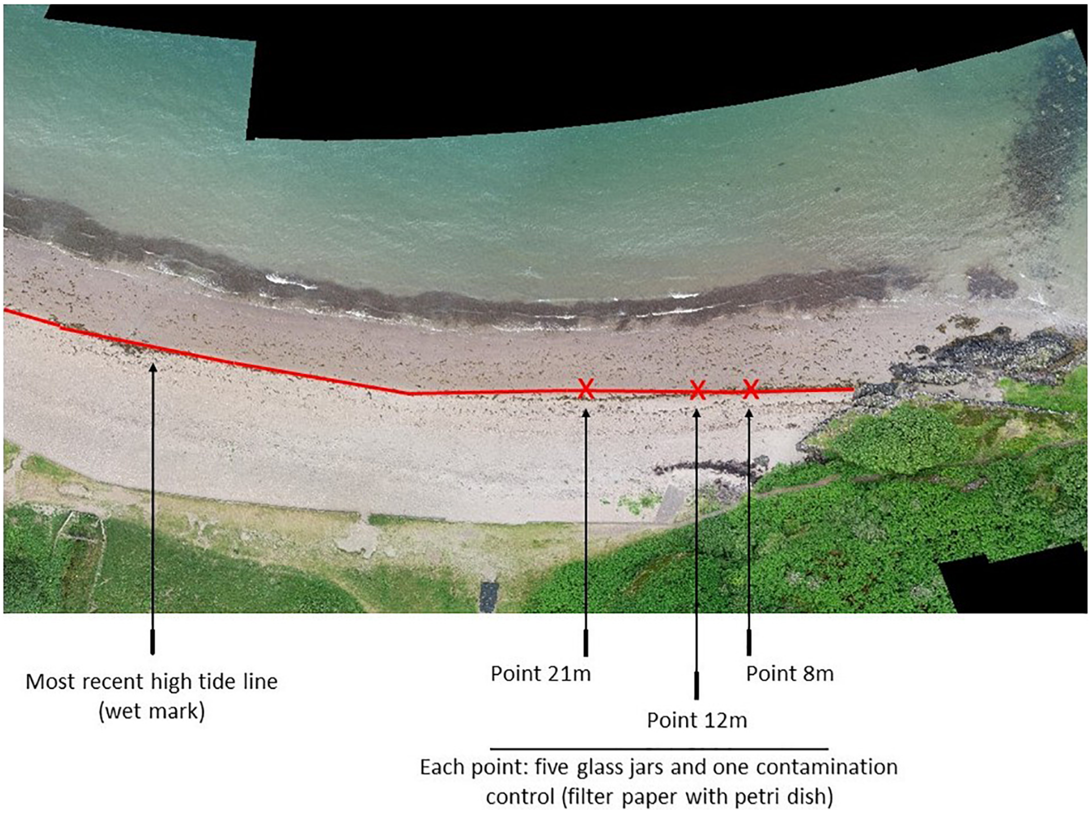


**FIGURE 3 |** Collection of intertidal sediment at the most recent high tide line displaying the three points on Ganavan sands beach. The red line indicates the high tide line.

of beach sediment was collected from five replicates at each sampling point using a 7 ml metal-capped bijou glass jar (**Figure 4**) as recommended by Brander et al. (2020). The five replicates were collected perpendicular to the wet high tide mark. A small petri dish with dampened filter paper (Whatman grade 1, 30 mm diameter) was left open next to the sampling point during the process to assess for any air contamination (**Figure 4**). A total of 15 samples were collected per location and per season. The collection method was adapted from Blumenröder et al. (2017).

### Surface Water

Coastal water was surveyed at the same site after the intertidal sediment had been collected. Surface water was sampled using a pole-water sampler and a sample bottle capable of holding 500 ml previously rinsed and cleaned with deionized water and 70% ethanol (**Figure 5**). After walking into the water to a depth of ∼30 cm to avoid, as much as possible, the mixing area of sand and coastal water, the water sampler was deployed to collect the surface water (i.e., top 15 cm). Five replicates of 500 ml were collected per site with a total of 2.5 l of water per location per season as suggested by Prata et al., 2020. The pole water sampler was wrapped in aluminum foil between collection of each sample to avoid air contamination. In addition, between each replicate, all material was rinsed with deionised water to avoid environmental contamination. The quantity of water collected was limited by the size of cool-box and the practicality of posting the samples back to the laboratory. Plastic bottles were preferred for sample collection compared to glass bottles in this study for safety and practical reasons (i.e., price and fragility).

### Biota: *Mytilus edulis*

Blue mussels (*M. edulis*), are commonly observed along the shore in Scotland (Svåsand et al., 2007). *Mytilus edulis* were collected from the rocky shore directly adjacent to the sampled beach. Adults ranging in size from 2 to 5 cm were collected to facilitate the statistical comparison of results between locations. *M. edulis* were removed from the substrate using a knife rinsed with deionised water prior to being used and any encrusting organisms were detached from the shell of the mussel. Each individual was rinsed with deionised water to remove any potential contamination before being wrapped in aluminum foil and individually stored in a plastic bag. Ten replicates were collected for each site in each season.

## Sample Storage

In the laboratory, water and sediment samples were stored in a fridge at 5°C for a few days or up to 6 months, respectively, until the extraction and filtration processes could take place, to decrease the development of organic matter in the samples. This step also facilitated the recovery of microplastics using oil. To

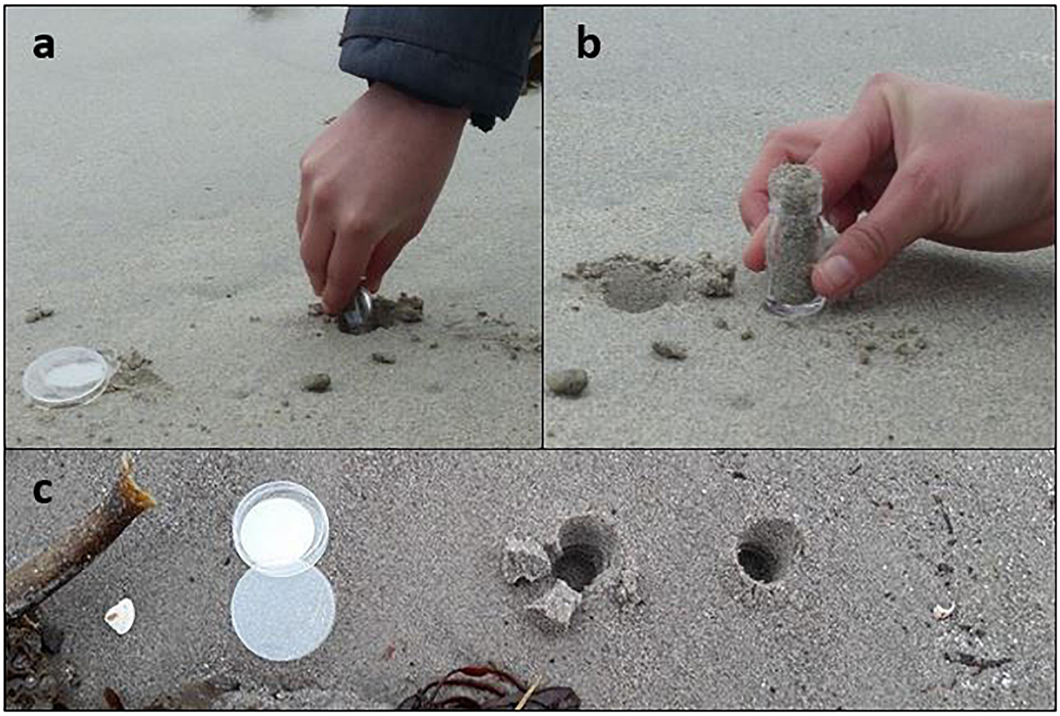


**FIGURE 4 |** Demonstration of sediment collection using a glass bijou jar as a scoop **(a,b)** with a dampened filter paper **(c)** to assess air contamination during the sampling.

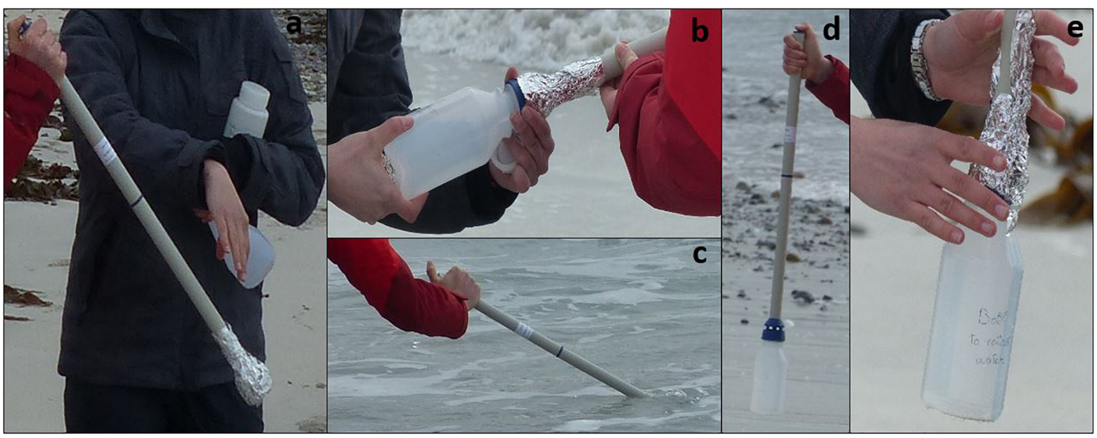


**FIGURE 5 |** Collection of surface seawater with a pole-water sampler using aluminum foil to avoid air contamination, **(a)** pole-water sampler protected from the air with aluminum foil, **(b)** remove aluminum foil at the end of pole and screw the bottle sampler, **(c)** put pole in the water, release the button to collect water, **(d)** press the button to avoid air coming into contact with the seawater, **(e)** put aluminum foil around the apertures to prevent air contamination and release the button prior to transferring the water to the container.

ensure no loss of ingested microplastics from *M. edulis*, they were frozen (−20°C) to keep the shells closed until extraction.

## Sample Processing

### Intertidal Sediment

Glass jars were placed in a drying oven for 48 h at 50°C with a 140 μm metal mesh placed on top of them to reduce air contamination. Blank samples were run at the same time to assess potential airborne contamination in the oven. The sand contained in the glass jar was weighed individually to record the dry mass (g) of each sample. The sand from each glass jar was mixed with 3 ml of canola oil combined with 25 ml of deionised water and placed in a 250 ml conical flask [this method was adapted from Crichton et al. (2017) and Courtene-Jones (2019)]. The quantity of canola oil was adapted to the sand mass content of one glass jar (approximately 10 g) and sand grain size [less fine than Courtene-Jones et al. (2017)]. Following the extraction, a cleaning step was added using an ethanol (99%) 1:1 isopropanol (99%) solution to ensure that the oily layer adhering to the particles was completely removed. Using the ethanol–isopropanol solution resulted in successful analysis of the polymer type using a Fourier Transform Infrared spectrometer (FTIR) (Courtene-Jones, 2019). Each potential microplastic was stored on a separate gridded filter paper and labeled prior to FTIR analysis.

### Surface Water

Water samples were filtered as soon as possible after the storage step using a Buchner funnel with filter paper (Whatman qualitative grade 4, 20–25 μm pore size), coupled to a vacuum pump. The bottle containing the water sample was rinsed three times with deionised water and then poured onto the same filter paper to ensure that all potential plastic pieces were recovered. The wet filter paper was stored and sealed in a glass petri dish and labeled prior to observation and analysis.

### Biota: Wild Mussels

Prior to enzyme digestion, individual mussels were measured (length and width) using dial metal calipers to assess the size ranges within and between locations. Individual mussel flesh was placed onto a pre-weighed glass petri dishes to determine the flesh mass (i.e., wet mass in g). The flesh of each mussel was cut into five pieces, placed into a glass beaker and covered with aluminum foil. A 0.625% Trypsin solution (following the methodology of Courtene-Jones et al., 2016) was added to the mussel flesh (i.e., 25 ml per mussel). The beaker was put onto a hot plate (38–42°C) with a magnetic stirrer for 30 min, after which the contents were poured through a filter paper (Whatman qualitative grade 4, 20–25 μm pore size). After filtration, the beaker was rinsed three times with deionised water to recover all particles from the sample and this solution was also poured through the same filter paper. The filter paper was stored in a glass petri dish, sealed with electrical tape and labeled. These steps were repeated for each individual mussel.

## Microplastic Identification and Characterization

Following quickly the filtration step, the filter papers (Whatman qualitative grade 4, 20–25 μm pore size) were visually inspected for microplastics using a dissecting microscope (WILD M5, 75×) and particles were transferred manually with tweezers (TAAB – High precision Stainless steel Anti-mag Type 3) to be stored on separate gridded filter paper and labeled. The particles were counted, photographed (Zeiss Stemi 2000-C microscope coupled with a Zeiss Axiocam camera), measured (i.e., ocular scale) and characterized by shape, color, length and polymer type. Each potential microplastic was scanned to confirm its polymer type using the FTIR in reflection and μATR collection mode (wavelength ranging from 4,000–600 per $cm^{-1}$) of an Attenuated Total Reflection-Fourier Transform Infra-Red spectrometer (ATR-FTIR Thermo scientific Nicolet iN10 and iZ10, software Omnic Picta). Each final spectrum was the product of 16 co-added spectra with a spectral resolution of 8 $cm^{-1}$. Spectra were compared with five inbuilt polymer libraries (Thermo Fisher) to aid identification and processed through the atmospheric suppression and baseline correction when necessary.

## Contamination Control

A strict process was followed to avoid airborne contamination during the sampling campaigns and in the laboratory. In the field, volunteers wore natural fabrics when possible and collected samples whilst facing into the wind. The material was rinsed with deionised water and 70% ethanol if necessary and wrapped in aluminum foil. The environmental contamination in the field and the air contamination during laboratory work, were assessed with petri dishes and dampened filter paper (Whatman grade 1, 30 mm) left on the bench or near the collection point (Courtene-Jones et al., 2016). In the laboratory, a 'clean room' was allocated to study microplastics (Lusher et al., 2017), air vents were covered and the door remained closed during the experiment. Benches were cleaned with 70% ethanol three times prior to starting work (Murphy et al., 2016). Personnel wore natural fabrics and a 100% cotton lab coat; long hair was tied back and numbers were restricted in the laboratory. All apparatus were washed with deionised water and 70% ethanol prior to use, and materials were inspected under a dissecting microscope to ensure that they were free of any contamination (Lusher et al., 2017). Wherever possible the use of metal and glassware were preferentially chosen over plastic. These steps were repeated each day and for each extraction type. Procedural blanks were run for each protocol and taken into account in the results by subtracting the particles recorded from the database.

# RESULTS AND DISCUSSION

Scientists often have to make a choice between the representativeness and the precision of a sampling design to answer scientific questions. In this study, the sampling protocols for biota and sediment were adapted from Courtene-Jones et al. (2016), Blumenröder et al. (2017), and Crichton et al. (2017). This approach favored the accurate assessment of microplastic concentrations at several locations and the feasibility of sample transportation, over the collection of a high volumes of samples that can be difficult to process due to time limitations. The bulk technique to collect surface seawater from the shore using a pole sampler worked well, as 100% of bottles were filled to the top and sent back to the laboratory from all the six locations. All cool-boxes were received in the 48h after each campaign and there was no suggestion that volunteers had contaminated the samples after following the strict protocol as described in the method section. The order of magnitude of microplastics numbers within each site per seasons was very similar ranging between 0 and 6 particles per l between the different samples, which demonstrated no major contamination during the collection process (**Table 2**). The minimum and maximum concentrations registered in this study were 0 to 6 ± 1.50 microplastics per l, all sites and seasons combined. Li et al. (2018) have observed similar concentrations in coastal waters around the United Kingdom (UK) with a range of 1.5–6.7 items per l. However, McEachern (2018) recorded

**TABLE 2** | Minimum and maximum of microplastic concentrations in seawater (number of particles per l) with the standard errors for each site and season.

| Sites | Microplastic concentrations (N° min–max per 1 ± SE) | | | |
|---|---|---|---|---|
| | **Spring** | **Summer** | **Autumn** | **Winter** |
| Thurso | 0–2 ± 0.49 | 0–4 ± 0.80 | 0 | 0–2 ± 0.49 |
| Ganavan sands | 0–6 ± 1.50 | 0–2 ± 0.49 | 0–2 ± 0.40 | 0–2 ± 0.49 |
| Oban | 0–6 ± 1.16 | 0–2 ± 0.40 | 0 | 0–6 ± 1.17 |
| Tiree | 0–6 ± 1.09 | 0–2 ± 0.49 | 0–2 ± 0.40 | 0 |
| Islay | 0–6 ± 1.20 | 0 | 0–4 ± 0.63 | 0–4 ± 0.98 |
| Mossyard | 0–4 ± 0.98 | 0–2 ± 0.49 | 0–4 ± 0.80 | 0–6 ± 1.36 |

lower concentrations in surface waters in Florida, United States of America, compared to this study with an average of 0.94 particles per l for discrete samples, while in Korea the average concentration was 1.736 particle per l (Song et al., 2018). It seemed that the concentrations observed in this study are of the same order of magnitude as other studies around the world, meaning that the protocol put in place could be suitable for microplastics monitoring.

However, a high standard error between replicates at each site over the year was obtained (**Table 2**) that may be the result of the relatively small volume of water (2.5 l) collected. It would not reflect the actual variability of microplastics in surface waters (Brander et al., 2020). Work undertaken by Barrows et al. (2018), demonstrated the difficulty of maintaining accuracy when collecting small volumes of water, especially when microplastic concentrations are already low (Barrows et al., 2018). The results for water samples did give representative values from the environment for small microplastics (Prata et al., 2020). Those relative values are useful for monitoring, understanding the potential impact of plastic particles and informing measures to reduce this pollution (Prata et al., 2020). Prata et al. (2020) collected surface waters with glass bottles of 1 l in four replicates and extracted subsamples volumes of 0.1, 0.25, 0.5, 1, and 2.5 l, to investigate the minimum volume required to detect the small microplastics considered the most abundant fraction in the environment. Taking into account the feasibility of collecting and processing, Prata et al. (2020) suggested that 0.5–1 l of filtered water would be recommended for future research. Their study concluded that the utilization of small volumes would allow for studies looking at the temporal and geographic scales of microplastic studies to be undertaken with readily available materials (Prata et al., 2020).

Nets could be considered as a mechanism for collecting microplastics from the water as they filter greater volumes of water but could underestimate the number of fibers sampled due to larger mesh sizes. It is also more time consuming to analyze the substantial quantity of particles due to the higher volume of water filtered, even if it was more representative of the environment (Prata et al., 2019). The nets would also be difficult to deploy in shallow water along the shore and would not recover the smaller microplastic sizes (Vermaire et al., 2017; Prata et al., 2019). Grabs are more versatile and easy to use by anyone thus more viable for citizen science studies despite the lower volume collected and the potential of over-estimation of microplastic concentrations due to contamination (Brander et al., 2020). The results of this study support the recommendation by Barrows et al. (2017, 2018) to investigate greater volumes of seawater to define a minimum volume of samples that would be representative of the environment using grabs or other collection techniques (Prata et al., 2019).

One alternative would be to use a pump to collect a greater volume of water and filter the surface water on-site prior to laboratory analysis (Lusher, 2015; Zhao et al., 2015). This technique would not only allow a greater quantity of water to be collected but would also allow easy transportation of samples (filters) to the laboratory and potentially avoid environmental contamination. However, pump systems are expensive to purchase and difficult to transport to different locations (Zhao et al., 2015). Also, using a pump system would require an energy supply for it, which is not practical for use in a citizen science project. Therefore, a balance needs to be maintained based on finances, practicality for collection, working with numerous volunteers and collecting water samples from multiple areas, versus water collection from limited sites. Brander et al. (2020) suggest a combination of grab and net techniques to analyze a wider quantity and range of plastic particles in seawater. For example, McEachern et al. (2019) combined discrete samples (i.e., 1 l per site using a Van Dorn sampler) and plankton tows (i.e., 330 μm net). No significant differences were observed in microplastic concentrations between stations or regions (McEachern et al., 2019), perhaps highlighting that the two techniques could give the same outputs.

The bulk sampling approach to collecting beach sediment worked, with 100% of the glass jars filled to the top, labeled correctly and sent back to the laboratory from all six locations. There was no evidence of volunteers indirectly contaminating the samples thanks to the air contamination assessment in the field with the dampened filter paper while collecting the sediment. The order of magnitude of microplastic concentrations within each site and season was similar ranging from 0 to 0.37 particles per g.dw between the different locations and seasons which seemed to reveal no major contamination during the process (**Table 3**). The standard errors were smaller compared to the water samples confirming that this technique was suitable to look at microplastics in the sediment (**Table 3**). In **Table 3**, the low number of microplastics recorded in samples could be justified by the lack of samples analyzed. Indeed, 20% of all samples collected were analyzed due to the closure of the laboratory as a result of the COVID-19 pandemic. It affected the processing steps of sediment samples. The concentrations recorded in beach sediment for this study were more important than the concentrations observed in Germany with 0.007 particles per g and 0.002 – 0.011 fibers per g (Stolte et al., 2015). Meyer (2015) highlighted similar amount of microplastic fibers in beach sediment in the North of Scotland with a range of 0.015–0.155 fibers per g, while Blumenröder et al. (2017) recorded a an higher amount of microplastics in beach sediment in Orkney, with 0.73 particles per g and 2.3 fibers per g. However, in China, the microplastic concentrations registered in beach sediment were very high

**TABLE 3 |** Minimum and maximum concentrations of microplastics in sediment (number of particles per g of dry weight) with the standard errors for each site and season.

| Sites | Microplastic concentrations (N° min–max per g.dw ± SE) | | | |
|---|---|---|---|---|
| | Spring | Summer | Autumn | Winter |
| Thurso | 0–0.15 ± 0.05 | 0–0.14 ± 0.04 | 0 | 0–0.14 ± 0.05 |
| Ganavan sands | 0 | 0–0.09 ± 0.03 | 0–0.11 ± 0.04 | 0 |
| Oban | 0–0.11 ± 0.03 | 0–0.19 ± 0.06 | 0–0.26 ± 0.08 | 0–0.14 ± 0.03 |
| Tiree | 0 | 0 | 0 | 0–0.13 ± 0.04 |
| Islay | 0–0.25 ± 0.08 | 0–0.11 ± 0.04 | 0 | 0–0.15 ± 0.05 |
| Mossyard | 0–0.12 ± 0.04 | 0.12–0.30 ± 0.06 | 0–0.37 ± 0.12 | 0–0.25 ± 0.07 |

**TABLE 4 |** Minimum and maximum concentrations of microplastics recorded per g of soft tissue wet weight with the standard errors for each site and season.

| | Microplastic concentrations (N° min–max per g.ww ± *SE*) | | | |
|---|---|---|---|---|
| | Spring | Summer | Autumn | Winter |
| Thurso | 0–1.37 ± 0.17 | 0–8.62 ± 0.84 | 0–23.81 ± 2.36 | 0–6.50 ± 0.61 |
| Ganavan sands | 0–1.29 ± 0.13 | 0–4.72 ± 0.56 | 0–2.25 ± 0.23 | 0–0.99 ± 0.10 |
| Oban | 0–0.80 ± 0.10 | 0–0.67 ± 0.07 | 0–0.83 ± 0.09 | 0–7.56 ± 0.92 |
| Tiree | 0–1.18 ± 0.15 | 0–0.66 ± 0.07 | 0–0.44 ± 0.05 | 0–0.72 ± 0.09 |
| Islay | 0–3.94 ± 0.44 | 0–1.22 ± 0.18 | 0–2.00 ± 0.20 | 0–1.20 ± 0.17 |
| Mossyard | 0–0.71 ± 0.07 | 0–1.08 ± 0.11 | 0–0.49 ± 0.05 | 0–0.48 ± 0.06 |

compared to this study with a range of 5.04–8.72 particles per g (Qiu et al., 2015).

Bulk sampling produced the biggest range of size classes of microplastics reporting particles from 1 μm to 5 mm (Brander et al., 2020). This technique was chosen as it was a good method to recover all sizes of microplastics from an area never studied before. Moreover, as the bijou jars used to collect the sediment were not plastic and no sieving step was applied this allowed for a reduction in potential air contamination. Sieving could artificially create more microplastic particles due to mechanical action that would be avoided using bulk samples (Blumenröder et al., 2017). As a result of their smaller volumes compared to other techniques, bulk samples are more easily transported back to the laboratory. All the recommendations cited by Brander et al. (2020) have been respected such as collecting the first 5 cm of sediment, making a transect, a minimum of five replicates per point and approximately 10 samples per 100 m of beach.

When the volunteers collected biota such as wild mussels, all the mussels were cleaned from their byssus and barnacles attached to them and wrapped into aluminum foil to be stored separately in a cleaned plastic bag. No liquid coming out the mussels was visible when the cool-box arrived at the laboratory, which meant that the transport went well and no potential microplastics were lost. Again there was no concern raised that volunteers had contaminated the samples because some of the steps in the protocol were designed to clean and rinse the mussels prior to storage. In **Table 4**, the standard errors were low demonstrating that this technique was suitable to look at microplastics in mussel. In **Table 4**, the variability of concentrations of microplastics per g.ww could be explained by the physiology and the size of the organisms (Brander et al., 2020). The recommendations of Brander et al. (2020) have been respected such as collecting 10 individuals per site or area. Lastly, the volunteers respected the specific guidance provided regarding the collection of adult specimens where possible, with 97% being included between 2 and 5 cm in length as mentioned in the protocol. The concentrations observed in wild mussels all sites and seasons combined were ranging from 0 to 23.81 microplastics per g.ww for this study. These results seemed to be similar to the concentrations observed in Oban area, Scotland with a range of 1.05 to 4.44 per g.ww (Courtene-Jones, 2019). Catarino et al. (2018) have found similar level of microplastics in wild mussels around Scotland with an average of 3.0 ± 0.9 particles per g. Those concentrations matched the observations of microplastics in wild mussels in China with a range of 0.9–4.6 particles per g (Li et al., 2016), whereas the concentrations recorded in France were lower with an average of 0.23 ± 0.20 microplastics per g.ww (Phuong et al., 2017). Therefore, microplastic concentrations observed in wild mussels in this study seemed to be similar to other studies in Scotland and Europe, which means that the protocol could work for bigger citizen science project.

Citizen science can be a powerful research tool enhancing spatial and temporal coverage (Pocock et al., 2017), increasing access to sites and samples (Honorato-Zimmer et al., 2019), reducing financial project costs, raising awareness regarding research or conservation aims (Eaton et al., 2017) and providing opportunities for people to become involved in science projects (Cohn, 2008; Bonney et al., 2009; Bosker et al., 2017). Calculations were made for this study (**Table 5**) to confirm the extent to which volunteers helped reduce the financial costs, time and carbon footprint of the campaign. **Table 5** demonstrates that for this study using citizen scientists (10) helped decrease the sampling time by 73%, lowered the carbon footprint by 65% and reduced the overall financial cost by 63% by using this new methodological development. Including more citizen science in research would, potentially, allow more studies to take place, and more samples to be collected. It could reduce the impact on the environment and support the movement toward more sustainable research.

These results indicate that in order to create and develop a baseline monitoring for plastic pollution along the coastline, as well as for studies that want to cover large spatial and temporal scales, it is essential to have citizen scientists involved in the project. Based on the definition of citizen science projects by Kelling et al. (2019), this study would be classified in the semi-structured to structured categories due to its well-defined objectives, a rigorous protocol with open recruitment and recorded observations during sampling. This type of project has been recommended for the future due to the good collection of scientific values, enough bias control, but still able to attract a large number of volunteers (Kelling et al., 2019).

However, there are some drawbacks including difficulties in finding volunteers without a pre-established network, training and managing citizen scientists (which can be time-consuming),

**TABLE 5 |** Calculations of carbon footprint, time and expenses for this study sampling campaigns done by the lead author alone or combined with citizen scientists.

| Sites | Car distance (km) | Ferry distance (miles) | Car carbon footprint ($kgCO_2$) | Ferry carbon footprint ($kgCO_2$) | Coolbox transport carbon footprint (kgCO2) | Ferry price (£) | Hotel price (£) | Food price (£) | Petrol price (£) | Coolbox transport price (£) | No. days |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Sampling event (lead author alone) for this study** | | | | | | | | | | | |
| Oban → Tiree → SAMS (1× return) | 64 | 123.20 | 9.15 | 92.4 | – | 112.9 | 95 | 70 | – | – | 2 |
| Ganavan → SAMS (2× return) | 32 | – | 4.58 | – | – | – | – | – | – | – | 1 |
| Oban → SAMS (2× return) | 24 | – | 3.43 | – | – | – | – | – | – | – | 1 |
| Oban → Thurso | 348 | – | 49.76 | – | – | – | 154 | 80 | – | – | 2 |
| Thurso → Port Ellen (Islay) | 435 | 34.90 | 62.21 | 26.18 | – | 82.4 | 160 | 80 | – | – | 2 |
| Port Ellen (Islay) → Mossyard | 347 | 34.90 | 49.62 | 26.18 | – | | 150 | 80 | – | – | 2 |
| Mossyard → SAMS | 305 | – | 43.62 | – | – | – | – | 20 | – | – | 1 |
| TOTAL | 1555.00 | 193.00 | 222.37 | 144.75 | – | 195.30 | 559 | 330 | 96.35 | – | 11 |
| **TOTAL sampling 1 season (six sites)** | **1555.00** | **193.00** | **367.12** | | | **1180.65** | | | | | **11** |
| **TOTAL sampling 4 seasons (six sites)** | **6220.00** | **772.00** | **1468.46** | | | **4722.6** | | | | | **44** |
| **Sampling event with citizen scientists and lead author for this study** | | | | | | | | | | | |
| Oban → Tiree → SAMS (1× return) | 64 (*52) | 123.20 (*none) | 9.15 (*7.44) | 92.4 (*none) | (*0.06) | 112.90 (*none) | 95 (*none) | 70 (*none) | 1.54 (*none) | (*42.24) | 2 (*1) |
| Ganavan → SAMS (2× return) | 32 | – | 4.58 | – | – | – | – | – | – | – | Same weekend |
| Oban → SAMS (2× return) | 24 | – | 3.43 | – | – | – | – | – | – | – | Same weekend |
| Thurso | On site | – | – | – | 0.40 | – | – | – | – | 55.92 | Same weekend |
| Islay | 77 | – | 11.01 | – | 0.22 | – | – | – | – | 54.54 | Same weekend |
| Mossyard | 34.80 | – | 4.98 | – | 0.36 | – | – | – | – | 42.24 | Same weekend |
| TOTAL | 231.80 (*219.80) | 123.20 (*0) | 33.15 (*31.44) | 92.4 (*0) | 0.98 (*1.04) | 112.9 (*0) | 95 (*0) | 70 (*0) | 1.54 (*0) | 152.70 (*194.94) | 2 |
| **TOTAL sampling 1 season (six sites)** | **231.80 (*219.80)** | **123.20 (*0)** | **126.53 (*32.48)** | | | **432.14 (*194.94)** | | | | | **2–3 days** |
| **TOTAL sampling 4 seasons (six sites)** | **927.20 (*879.20)** | **492.80 (*0)** | **506.12 (*129.92)** | | | **1728.56 (*779.76)** | | | | | **8–12 days** |

*The lead author sampled the Tiree site themselves coming from Oban, (*) identifies the same sampling events if they had been done by a volunteer based on Tiree (so no transport between Oban and Tiree). The car model used to calculate the carbon footprint and petrol price estimations was a Nissan Micra. The websites that were used to enable all the calculations were [Carbon Independent (2009) – Ferry sources, Dhl Carbon Calculator (2021) – scenarios, Petrol prices. UK (2008), Caledonian MacBrayne Ferries (2021) – Timetable and fares, Car Emissions (2021) – car MPG, $CO_2$ and emissions data]. The car carbon footprint ($CO_2$) was calculated by multiplying the distance in km (car) by the $CO_2$ car emissions per km [Car Emissions (2021) – car MPG, $CO_2$, and emissions data]. The same calculation was made for the ferry in miles [Carbon Independent (2009) – Ferry sources]. When not using the car, the carbon footprint of cool-box transport were estimated with [Dhl Carbon Calculator (2021) – scenarios].*

sampling accuracy, as well as ensuring quality control in the field and blanks for the assessment of environmental contamination (Forrest et al., 2019). In our particular study, based on feedback, all the volunteers had some previous field experience, a great engagement with the topic, and a precision and rigor in applying the methods. If this protocol was to be used again, it would be useful to include video or live training through different media platforms. The advantage of pre-recorded would be that the volunteers could go back and have another look at the file. Communicating positively with the public would potentially interest more volunteers, especially if it fits their beliefs and values (Domroese and Johnson, 2017).

Research teams planning to use citizen scientists in future programs would benefit from accessing larger networks, creating an online platform to facilitate the data collection from volunteers as well as to showcase the results to a wider audience, developing a promotional strategy which could recruit volunteers more efficiently and be less time consuming (Bayas et al., 2017; Barrows et al., 2018; Sanders and Brandes, 2020). Recording field site data is also important for future studies. This should include metadata such as wind speed, wind direction, wave height, wave strength, substrate type and weather forecast which can all provide useful information for the background understanding of samples (Herrera et al., 2018). Barrows et al. (2018) also suggested creating a smartphone application which could be used by volunteers to easily record all useful site information.

Assessing the temporal variation of microplastics along the coastline is one of the biggest challenges that coastal microplastic researchers face. However, a 1-year study may not be long enough to accurately assess the seasonal trends of abundance, or composition, of microplastics in the environment. Barrows et al. (2018) collected microplastics at multiple sites and found both a significant annual and seasonal difference when comparing samples from the same location over 2 years.

Heigl et al. (2019) suggested moving toward a global and general definition based on scientific standards, communication, collaboration and ethics of a citizen science project to ensure standardization and higher quality of studies as more and more research projects involve citizen scientists.

## CONCLUSION

Concentrations of plastic in surface waters ranged from 0 to 6 microplastics per l depending on the sites and seasons. The concentration of microplastics in beach sediment fluctuated between 0 and 0.37 particles per g.dw for all sites and seasons combined, while in wild mussels the number of particles ranged from 0 to 23.81 per g.ww. From the results, the low volumes for water and sediment samples seemed to be a good compromise between the feasibility of the study and the approximation to the real concentration for small microplastics. Using low volumes combined with strict contamination process and good identification protocols allowed us to extend the temporal and geographical sampling of microplastics. The novel aspect of this study was the collection by citizen scientists of three different types of samples at several sites that spanned ∼400 km of coastline, fundamentally at the same time (i.e., the same weekend), several times a year in Scotland. We proposed and deployed a simple, cost-effective and practical collection method that facilitated microplastic sampling for several matrices to enhance the knowledge of microplastic distribution, fate and dynamics in the marine environment. The practical tool-kit was designed to be easy to use, small enough to be posted, and readily used and understood by non-scientific personnel. This technique could be adapted for projects in different environments and countries due to its simplicity, showing the feasibility of monitoring microplastics on a large spatial scale as well as on a temporal scale at low cost.

## DATA AVAILABILITY STATEMENT

The original contributions generated for this study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## ETHICS STATEMENT

The animal study was reviewed and approved by University of the Highlands and Islands.

## AUTHOR CONTRIBUTIONS

BN, NJ, BQ, and AD conceived the project aim. LP, BN, and AD designed the methodology. BN and NJ provided help finding citizen scientists. LP collected and obtained the samples. LP collected and obtained the samples, carried out the sample processing work and the analysis, and led the writing manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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REVIEW
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# Seven Primary Data Types in Citizen Science Determine Data Quality Requirements and Methods

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Data quality (DQ) is a major concern in citizen science (CS) programs and is often raised as an issue among critics of the CS approach. We examined CS programs and reviewed the kinds of data they produce to inform CS communities of strategies of DQ control. From our review of the literature and our experiences with CS, we identified seven primary types of data contributions. Citizens can carry instrument packages, invent or modify algorithms, sort and classify physical objects, sort and classify digital objects, collect physical objects, collect digital objects, and report observations. We found that data types were not constrained by subject domains, a CS program may use multiple types, and DQ requirements and evaluation strategies vary according to the data types. These types are useful for identifying structural similarities among programs across subject domains. We conclude that blanket criticism of the CS data quality is no longer appropriate. In addition to the details of specific programs and variability among individuals, discussions can fruitfully focus on the data types in a program and the specific methods being used for DQ control as dictated or appropriate for the type. Programs can reduce doubts about their DQ by becoming more explicit in communicating their data management practices.

**Keywords: citizen science, data quality, data type, data quality requirment, data quality methods**

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## INTRODUCTION

Citizen science encompasses a variety of activities in which citizens are involved in doing science (Shirk et al., 2012; Haklay, 2013; Thiel et al., 2014; Cooper, 2016). Part of the excitement about CS is the number of scientific disciplines that have adopted a citizen science approach. For instance, astronomy has used CS to map galaxies (Galaxy Zoo), chemistry to understand protein folding (FoldIt), computer science to refine algorithms (SciPy), ecology to document coral reef biodiversity (REEF), environmental science to monitor water quality (Acid Rain Monitoring Project), and geography to map features of cities (OpenStreetMap). CS is a rapidly expanding field involving over 1,000 advertised projects (Scistarter websites). Pocock et al. (2017) identified over 500 CS projects in the ecology and environmental area alone.

At the center of many citizen science programs is the contribution citizens make to gathering and/or scoring observations (Miller-Rushing et al., 2012; Shirk et al., 2012; Bonney et al., 2014, 2016), but concerns regarding citizen contributions arise for several reasons (Cohn, 2008; Riesch and Potter, 2014; Burgess et al., 2017). By definition, participants share a common interest to participate but are not trained experts (Thiel et al., 2014; Cooper, 2016; Eitzel et al., 2017) leading to inherent doubt about their abilities (Cohn, 2008; Bonney et al., 2014, 2016). Citizen science participants may be trained for the specific tasks of the programs in which they participate, but there is often no requirement for them to have formal training, accreditation, or a degree (Freitag et al., 2016). Furthermore, there may be no requirement for participants to regularly practice the skills needed.

In our experience, CS program managers are well aware that the quality of the scientific data their programs produce is paramount to success. A survey by Hecker et al. (2018) suggests that after funding considerations, data quality is the most important concern for program managers (also see Peters et al., 2015). Significant progress is being made in understanding and improving DQ in citizen science. Many papers have been written assessing the DQ of a specific project, and papers starting around 2010 have provided broader context (Alabri and Hunter, 2010; Haklay et al., 2010; Sheppard and Terveen, 2011; Wiggins et al., 2011; Goodchild and Li, 2012; Crowston and Prestopnik, 2013; Hunter et al., 2013; Thiel et al., 2014; Kosmala et al., 2016; Lukyanenko et al., 2016; Muenich et al., 2016; Blake et al., 2020; López et al., 2020). Also, there have been efforts to compare data quality across projects (Thiel et al., 2014; Aceves-Bueno et al., 2017; Specht and Lewandowski, 2018).

A number of papers have focused on DQ as part of the process of data collection/data life cycle (Wiggins et al., 2011; Kelling et al., 2015a; Freitag et al., 2016; Parrish et al., 2018a), and some have examined the variability of individual contributors (Bégin et al., 2013; Bernard et al., 2013; Kelling et al., 2015b; Johnston et al., 2018). Kosmala et al. (2016) and Parrish et al. (2019) emphasized the importance of individual program's protocols for DQ. In this paper, we examined citizen science programs from the point of view of the kinds of data they produce with the goal of informing the strategies of DQ control. This reasoning leads to the questions addressed here, "Are there primary types of data produced by citizen science projects?" and if so, "What are the ramifications of these types for DQ analysis and project design?"

# METHODS

Scopus literature searches were performed using the term "data quality" in combination with the terms "citizen science," "volunteered geographic information," or "volunteer monitoring." A total of 293 papers were found from the published literature between the years 1994 and 2020. Papers were reviewed and discussed among our team using the general data quality framework provided by Wiggins et al. (2011). Investigations were performed using categorical analysis and decision trees. Additional efforts were made to collect the needed information from project web sites, but these sites proved difficult to navigate from the perspective of locating information about data quality methods. It was often unclear whether the information we sought was available or not. Our lack of success in searching on project websites leads us to look more carefully into the heterogeneity of citizen science projects, and specifically into the heterogeneity of data produced by CS projects. An iterative process of re-reading the literature, investigating papers cited in the literature, and re-examining project web sites produced the categorization of the primary data types reported here.

# RESULTS

## Categories of Data From Citizen Science Projects

Our review identified seven primary categories of data contributions made by people to citizen science projects (**Table 1**). Citizens can carry instrument packages, invent or modify algorithms, sort and classify physical objects, sort and classify digital objects, collect physical objects, collect digital objects, and report observations. In the following paragraphs, we describe each of these types and then turn to the implications for DQ requirements and project design.

In the simplest data type, a citizen's designated role is limited to transporting and/or maintaining standard measurement devices (**Table 1**). People carry instrument packages (CIP) or pilot vehicles that carry instrument packages. There is no active role in monitoring or recording data once the instrument is in place. Citizens also bear the cost of carrying the sensors. Weather Underground is an example of such a program. The benefit to the project is that no investment is needed other than arranging the transport of or giving advice about device options, installation, and providing a data sharing and storage website. With this limited role for participants, there are fewer concerns about data quality. Projects can rely on strategies normally employed by scientists when monitoring instrument packages that are deployed.

The second category of participation involves the invention or modification of algorithms (IMA) such as the Foldit project in which citizens help discover the sequence of proteins folds or a search such as the Great Internet Mersenne Prime Search in which citizens help search for class of prime numbers. This kind of citizen science project may take the form of a game or contest. The contributions of participants are explicitly recorded and tested in a public arena. The success of algorithms is usually known to all, and the insights of a citizen or citizen team can often be incorporated by others in subsequent submissions. Data quality is not an issue for these projects. Keeping track of the history of the algorithm submissions is part of the process, so provenance is also inherently addressed.

The third type of project involves the sorting and classifying of physical objects (SCPO). In these projects, scientists already have an existing source of data but need help organizing the collection. Fossils or archeology artifacts are two examples of

**TABLE 1 |** Seven basic types of data contributions made to citizen science projects with examples.

| Data category | Data contribution | Example 1 | | Example 2 | | Example 3 | |
|---|---|---|---|---|---|---|---|
| | | **Project name** | **Description** | **Project name** | **Description** | **Project name** | **Description** |
| Carry Instrument packages (CIP) or pilot vehicles that CIPs | Indirectly through deployment of instrument package | Air Quality Citizen Science | Monitor environmental air quality | SeaKeepers International | Works with NOAA and WMO and deploys Seakeeper Difters and Argo floats | Weather Underground | Connects consumer weather instruments in a network |
| Invent or modify algorithms, IMA | Algorithms, beat the best computer algorithms | Fold-It | Submit steps for protein 3-D folding to understand protein function | MATLAB Online Programming Contest | Develop and share code to solve computing challenge | EteRNA | Submit steps for RNA 3-D folding to understand RNA function |
| Sort and classify physical objects, SCPO | Object categorized | Passport in Time | Contribute to field archeology program with the USFS | Field Museum Collection Center Volunteers | Count, sort and digitize artifacts and specimens | American Museum of Natural History | Volunteering in the Division of Paleontology |
| Sort and classify digital objects, SCDO | Digital object categorized | Galaxy Zoo | Classify galaxies from digital images | EyeWire | Map neurons in the eye of *Drosophila* | Old Weather | Transcribe weather records from ships' logs |
| Collect physical objects, CPO | Sample obtained and submitted, collection process documented | Florida LakeWatch | Collect water samples for analysis | School of Ants | Collect ants around schools that are submitted for identification | The Bighorn Basin Dinosaur Project | Find and collect dinosaur fossils |
| Collect digital objects, CDO | Digital object obtained and submitted, collection process documented | Juneau Humpback Whale Flukes | Collect images of whale flukes | BatME | Collect audio recordings of bats with mobile devices | PicturePost | Contribute digital images of landscape |
| Report observations, RO | Text from instrument readings, counts, classifications, and/or descriptions | Great Sunflower Project | Record pollinator activity in gardens | CoCoRaHS | Submit data about rainfall, hail events, and snow fall | Feeder Watch | Counts bird species that visit bird feeders |

physical objects that can be organized in this type of project. The projects are location-specific, and citizens are usually part of the local science team. Citizens and scientists work together closely, and questions about data quality are quickly resolved because people with appropriate expertise can be easily consulted.

In the fourth type, the digital cousin of the third category, participants sort and classify digital objects (SCDO). Objects are in the form of photographs, audio recordings, or videos that were collected and organized by scientists, and they need to be sorted and classified. These data can be easily shared electronically using the internet. This approach has greatly expanded the opportunity for participation because the activities of the citizens and scientists no longer need to be tightly coordinated. Indeed, this category has some of the largest and best-known citizen science projects in existence such as GalaxyZoo and EyeWire. The Zooniverse platform that evolved from the GalaxyZoo program now hosts dozens of projects that require the classification or interpretation of digital objects collected by scientists.

For SCDO projects, scientists are no longer nearby to review the data classification. In fact, the scale of the project may prevent systematic review because the large classification task that scientists alone were unable to complete is what motivated the use of the citizen science approach in the first place. The digital nature of the project allows scientists to engage a much larger audience and allows multiple people to complete the same task. Scientists can verify the abilities of participants by asking them to classify objects that have been previously classified by experts. If the results from participants disagree, then software can increase the number of replications to get a statistically confident classification, define the object as unclassifiable, or flag the results for review by experts. Hybrid models have arisen in recent years because of the rapid advances in the success of deep learning algorithms.

In the fifth type, citizens help scientists find and collect physical objects (CPO) at temporal and spatial scales that cannot be achieved through other methods. The objects are typically submitted to a science team for further analysis and archiving. Data quality issues may arise regarding sampling location and time or the collection and processing procedures. Scientists can address data quality issues by making citizens provide information about the collecting event or submit duplicate samples.

The sixth category is the digital equivalent of the fifth category. Citizens collect digital objects (CDO) instead of physical objects. Mobile smartphones, with their internal clocks and GPS units, make it easier to record the time and location for all digital objects collected. The digital record of what the observer saw may bolster data quality. The advantage of this category is that electronic samples can be easily shared, thereby allowing multiple people to classify and review the same observation. Thus, the statistical approaches for data quality used in other types that use digital objects, such as category four, can also be applied to this category.

In the seventh and last category of contribution, citizens report observations (RO), including quantitative measurements, counts, categorical determinations, text descriptions, and metadata. The skill of the participants directly affects data quality because more sophisticated tasks and judgments are required. Because these observations are typically numeric or text data, it is easier to store and collect them than it would be for physical or multimedia objects. The inexpensive recording of these observations via the web makes these projects easy to start and support over the long term.

## Data Type and Data Quality Strategies

The different categories of data contribution to CS (**Table 1**) are subject to different types of data quality issues (**Table 2**). When carrying an instrument package or creating new algorithms (CIP, IMA), data quality controls and procedures would be very similar to or the same as in scientific study without citizens. When sorting, characterizing, and categorizing objects (SCPO, SCDO), the objects have already been collected using standard scientific protocols, so their origin and provenance is not in question. If the citizens are working on physical items (SCPO), they are usually working with teams of scientists so when questions arise with a particular item, they can be referred to more experienced team member. Classification of digital objects (SCDO) collected and managed by scientists offers the great advantage that they can be scored by more than one person, which means that statistical techniques can be used to assess data quality and find outliers. The Galaxy Zoo/Zooniverse team has offered several approaches to check data quality (Lintott et al., 2008; Willett et al., 2013).

The collection of specimens for scientific analysis (CPO) seems that it could be very easy if one can accurately record the time, place, and method of collection. In some instances, this can be challenging (Chapman, 2005), and it can be more challenging if the specimens need to be processed in the field. A noted case with a long history of such challenges is the collection of water samples. Here duplicate samples are sometimes used to help ensure data quality, and the US Environmental Protection Agency developed the Quality Assurance Project Plan (QAPP) approach to help bring standard procedures to the process. When people collect digital samples (CDO) (photographs, videos, sound recordings, etc.), there seem to be fewer concerns because collecting digital objects has become so much easier with the growth of smartphones. Today's smartphones commonly time-and-place stamp digital objects automatically with high degrees of accuracy and precision. Time and location, outside of the object itself and the collector, are the most valuable pieces of metadata.

The last instrument type (RO) includes the input of data and metadata by humans and is, therefore, the most prone to data quality issues. Because of the large number and varied protocols and requirements of these projects, it is more difficult to make specific comments about data quality. However, using cell phones when recording data is having a large impact because it allows people to record data as they observe using forms based on pick lists that significantly reduce data input errors. Data can then be shared almost immediately because it can be uploaded directly from the cell phone, reducing chances that data will not be shared or that errors will creep in before data is shared.

The Galaxy Zoo project stands out in its ability to measure observer errors and bias (**Table 2**). The high-quality analyses by the Galaxy Zoo project are possible because they have large data sets, a small number of objects to classify, a large number of

**TABLE 2 |** Characteristics of seven data types related to data quality.

| Data category | Format of primary data | Data quality comments | Data quality approaches | Examples of papers about data quality strategies | Concerns about data quality |
|---|---|---|---|---|---|
| Carry Instrument packages (CIP) or pilot vehicles that CIPs | Digital files | Citizens may determine location of the instrument and some initial metadata | Calibration before and after deployment. Locality and quality of instruments employed can be ranked. Using time series and other data to check sensors over time | Bell et al. (2013) | Minimal, because the citizen's contribution to each observation is minimal. Sensor placement and sensor aging are issues |
| Invent or modify algorithms, IMA | Calculation result, Algorithm | The interactive nature of the process controls data quality. Algorithms are usually tested in a standard environment | The openness of the process allows others to see what is happening and duplicate results | None found | Minimal concerns, because the process is self-correcting. Testing, sharing and archiving solutions along the way is important |
| Sort and classify physical objects, SCPO | Tagging and describing objects | These projects are usually situated in a collection facility such as a museum or as part of scientific team making it easy for citizens and scientists to interact frequently and for citizens to be incorporated into the scientific team | Because they work closely with experts, it is relatively easy for volunteers to be given tasks that are appropriate for their skill level and for any questions about sorting or classification to be answered by experts within a short period of time | Obrecht et al. (1998), Herron et al. (2004) | Minimal, because volunteer's work is closely integrated within a scientific team |
| Sort and classify digital objects, SCDO | Groupings, lists or tags | Citizens are only responsible for determining what the object is. It is relatively easy to crowdsource the task using the internet to a large number of interested people | Calibrate each citizen with known objects, classification of real and test object by multiple citizens, statistical evaluation of classification by multiple citizens, expert review, use AI to narrow the range of possible choices | Lintott et al. (2008), Hansen et al. (2011), Fortson et al. (2012), Swanson et al. (2016), Willett et al. (2016), Jiménez et al. (2019), Walmsley et al. (2020) | High to low, will depends on the difficult of the classification task, the experience of the participants and the number of experienced participants who view each object |
| Collect physical objects, CPO | Physical object or sample | Some objects such as pottery chards or a feather are very stable and the interpretation depends on the circumstances of discovery. Other objects such as water or soil samples may also depend critically on the sampling, storage and transport methods | Replicate samples, for lab processing use splits, blanks and standards for water analysis, expert review | Obrecht et al. (1998), Williams (2000), EPA (2002) | High to low, depending on the documentation of the provenance of the object, specific documentation of the sampling, storage and transport methods and examination by experts can resolve questions |
| Collect digital objects, CDO | Image, video, or sound recordings | Recent technological advances, especially embodied in smart phones, have allowed citizens to readily capture still images, video, and sounds and share them via the internet | Digital objects without accompanying metadata are almost worthless but cell phones or simple digital camera usually record time and place, making it relatively easy for projects to automate collection of the most salient metadata | None found | High to low depending on the contextual data provided; minimal, when digital objects come with the time and location of the observation based on embedded sensors in the recording instrument |
| Report observations, RO | Text | The observer provides the description of the observation and the data that describe the context of the observation | Pseudo-replication, technical difficult of the history of individual contributors, project specific knowledge, machine review, expert review | Yu et al. (2010, 2012), Kelling et al. (2012, 2015a,b) | High to low, will depends on the skill required for the observation, extent of training of the observer, knowledge about the skill of the observer |

*Primary data denotes the focus of the project, the what of the study. Participants may often also report the who, when, where, how, and by whom. These supporting data can be essential to the value of the observation.*

classifications per object (>30), reference images to test users, and expert reference datasets to compare with participant results. Calibrating projects without repeated measures is more difficult, but the eBird project is making progress by analyzing individuals capabilities based on the total number of birds they see and their cumulative sampling records (Yu et al., 2010, 2012; Kelling et al., 2012, 2015a,b). Program leaders are aware of these issues and have practiced improving data quality approaches (Wiggins et al., 2011), but it is not always clear in papers or on project websites what steps have been taken or corrections made.

# DISCUSSION

## Data Types

Wiggins et al. (2011) gave an overview of many approaches used in citizen science for data quality and validation. However, the seven types of data contributions defined here indicate a more refined approach is possible (**Table 1**). The lens of data types offers a new dimension to understand DQ and to compare projects. In the following paragraphs, we offer suggestions about what this typing can offer to the discussion of data quality and project design.

## Criticism of Data Quality in Citizen Science

As described in the introduction, DQ has been a major concern in CS programs. Scientists and others naturally question DQ because of minimal training and a lack of formal accreditation by citizen participants (Freitag et al., 2016). Our findings of different data types (**Table 1**), however, suggest that CS activities that involve carrying instrument packages or inventing or modify algorithms will not have data quality issues beyond what scientists normally encounter. We also believe that projects that sort and classify physical objects are unlikely to have significant data quality issues because of the close physical presence and access to collection managers and experts during the sorting process. The very nature of a physical collection requires collection infrastructure in the form of museum facilities and collection managers to maintain it.

Our analysis suggests that the general criticism about data quality in CS programs is more of a concern in the four remaining data types (sort and classify digital objects, collect physical objects, collect digital objects, and report observations). For instance, collecting physical objects such as water samples for water quality programs often requires a special collection process to prevent contamination and/or special storage procedures to reduce deterioration of the samples. In the case of reporting observations, there are a wide range of DQ issues that stem from the complexity of procedures and human judgment required of specific programs. Unlike the collection of physical or digital objects or the classification of digital objects, there is no direct way to judge the quality of the observation. One must use pseudo-replication techniques or knowledge about the history of an individual contributor. Scientists and others have leveled general criticism of the DQ of CS programs, but consideration of these different types makes it clear that DQ assurance is closely tied to the type of data being gathered, and thus criticism should be more specific now.

It is important to note that the seven data types discussed above, in themselves, do not constitute an exhaustive list for information sharing within projects. Project organizations may use multiple forms of communication, including personal conversations, telephone calls, websites, email, email servers, blogs, and chat rooms to guide projects and monitor the collection of data. These auxiliary information channels may play a critical role in triangulating on data quality but may not be part of the formal records of the project or linked to the scientific data.

## Single Projects May Use More Than One Primary Data Type

It is also important to observe that a single project can include more than one of these basic instrument types. For instance, OpenStreetMap participants can collect data by using a hand (RO), a GPS unit, and more advanced instruments (CDO). They use these data and data from satellites to map additions, corrections, and annotations onto the OpenStreetMap map layers (SCDO) (OpenStreetMap Wiki, 2016). COASST has an extensive protocol to monitor seabirds that includes observation data (RO) but can also include submitting photographs (CDO) and dead birds for archiving (CPO) (Parrish et al., 2018b). eBird was initially designed to collect text reports of people's observations (RO) but since 2015 also supports submissions of digital recordings of sounds, images, and videos (CDO) (Weber, 2019). iNaturalist combines the collection of digital objects (CDO), and the classification of digital objects (SCDO), with the possibility to simply report observations (RO) (Saari, 2021).

## Data Types Are Not Unique to a Scientific Discipline

Different projects within a science discipline may use different types of citizen science data to advance their research. For instance, BatME has recruited citizens to collect audio recordings of bat calls (CDO), while Bat Detective uses citizens to classify bat calls (SCDO). Marshall et al. (2014) give an overview of the multiple ways that citizens contribute to astronomy, focusing on the original observations of amateurs (RO) and the contributions and classification of digital images (CDO & SCDO). St. Fleur (2016) reported that citizens are working with scientists to collect meteors (SCPO). One way for citizen science projects to grow within a scientific discipline would be to develop projects that contribute classes of data that have not been applied to that discipline before. For example, in astronomy, scientists and citizens could work together to catalog meteors and micrometeorites (CPO), or perhaps astronomers would include instrument packages to SpaceX launches (CIP).

## Data Types and Implications for Project Design

What is the implication of these data categories for the design of citizen science projects? One obvious answer is that data categories will define the requirements for handling data for a project. This suggests that a single software platform dedicated to one instrument type could serve the needs of other projects that share the same data type and accelerate the growth of similar citizen science programs.

The clearest example of reusing project software is for the classification of digital objects in which the Galaxy Zoo project has been generalized into the Zooniverse platform. Zooniverse is designed to be readily customized, and it now supports the classification of digital objects from many domains. An example of the lateral transfer of citizen science approaches is the adoption by the eButterfly platform of the eBird sampling protocols (Kelling, personal communication). eBird is an example of a general text collection instrument, but it was designed specifically for bird biodiversity surveys. It is likely that the eBird structure could be generalized for biodiversity surveys of other taxonomies but not other citizen science tasks. A number of efforts, including Anecdata, ArcCollector, BioCollect, CitSci.org, Cybertraker, EpiCollect, FieldScope, GIS Cloud, and OpenDataKit, were built with the goal of allowing people to customize the software for specific field projects. These platforms have been used for numerous projects that collect text and images, but it seems unlikely they would be a good choice to support other instrument types we have outlined.

A general strategy for improving data quality in field collection is to check for errors as early in the process as possible. Specific strategies include (1) requiring users to choose from pick lists rather than using free form input fields, (2) using electronic input via mobile devices (3) checking input immediately from users to give feedback if values seem questionable given the context of the situation (4) taking input such as time and location from sensors when possible, etc.

Another widely accepted approach for data quality is provenance tracking. iNaturalist keeps track of the history of identification for its observations and CoCoRaHS keeps track of instances in which original observations are updated.

Sorting and classifying and/or finding and archiving physical objects (SCPO, CPO) requires a sophisticated infrastructure to manage the objects. Although they may exist, we are not aware of any examples of citizen science platforms that specialize in helping citizens find and archive or sort and classify physical samples most likely because collection management software tools are common in science and largely domain-specific. Instead, citizen science programs would be likely to adapt to interface with established collections software such as Specify (Specify Collections Consortium, 2020), which is used in natural history collections. The scale of these projects is currently bound by citizen proximity to the collection and the space that is needed for work. Sorting and classifying or finding and archiving digital objects (SCDO, CDO) are much more scalable than projects based on physical objects because citizens can be recruited from a larger pool, and expert involvement is not required to assert data quality.

## CONCLUSION

This review of the literature and program websites identified seven primary types used in CS programs (**Table 1**). We conclude that blanket criticism of the CS data is no longer appropriate because data types vary widely in their requirements for DQ needs (**Table 2**). DQ is not needed in the invention or modification of algorithms type because DQ is inherent in the process while plans from a variety of approaches are needed and being employed.

Ultimately citizen science has been practiced in a societal context in which there are tradeoffs with DQ (Anhalt-Depies et al., 2019), but at the moment, we believe that significant progress can be made with a simple focus on DQ. We conclude that discussions about the data types in a program and the specific methods being used for DQ control as dictated or appropriate for the type will be fruitful. Information scientists, domain scientists as well as program designers and managers can use the data types as a lens to compare DQ practices and DQ issues across domains. The seven primary data-type lenses can reduce doubts about DQ for funders, participants, and third party data consumers and help managers be more explicit in communicating their data management practices.

## AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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METHODS
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# Alleviating Environmental Health Disparities Through Community Science and Data Integration

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Environmental contamination is a fundamental determinant of health and well-being, and when the environment is compromised, vulnerabilities are generated. The complex challenges associated with environmental health and food security are influenced by current and emerging political, social, economic, and environmental contexts. To solve these "wicked" dilemmas, disparate public health surveillance efforts are conducted by local, state, and federal agencies. More recently, citizen/community science (CS) monitoring efforts are providing site-specific data. One of the biggest challenges in using these government datasets, let alone incorporating CS data, for a holistic assessment of environmental exposure is data management and interoperability. To facilitate a more holistic perspective and approach to solution generation, we have developed a method to provide a common data model that will allow environmental health researchers working at different scales and research domains to exchange data and ask new questions. We anticipate that this method will help to address environmental health disparities, which are unjust and avoidable, while ensuring CS datasets are ethically integrated to achieve environmental justice. Specifically, we used a transdisciplinary research framework to develop a methodology to integrate CS data with existing governmental environmental monitoring and social attribute data (vulnerability and resilience variables) that span across 10 different federal and state agencies. A key challenge in integrating such different datasets is the lack of widely adopted ontologies for vulnerability and resiliency factors. In addition to following the best practice of submitting new term requests to existing ontologies to fill gaps, we have also created an application ontology, the Superfund Research Project Data Interface Ontology (SRPDIO).

**Keywords: citizen science, community science, interoperability, FAIR principles, environmental health, community resiliency**

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## INTRODUCTION

### Research Context

Pollution is now the leading global cause of premature death and disease (Landrigan et al., 2018). This crisis is currently being addressed through environmental monitoring and public health surveillance efforts that are conducted by local, state, and federal agencies. Most states have environmental quality and health departments, which have the major responsibility for environmental protection and the health and safety of the population. The U.S. federal government has a number of overarching environmental and public health agencies, including the Centers for Disease Control and Prevention, the National Institutes of Health (NIH), the Food and Drug Administration, the Environmental Protection Agency (USEPA), Geological Survey (USGS), and Department of Agriculture (USDA). In addition, two other entities can play important roles in environmental quality and public health; non-governmental organizations (NGOs) and universities, both public and private, that receive extramural funding to conduct environmental quality and public health research.

One of the challenges with these efforts is that the datasets generated by each group are independent and siloed from one another, leading to a lack of standardization, interoperability, application of FAIR (Findable, Accessible, Interoperable, and Reusable) principles of data management, and stewardship (Wilkinson et al., 2016). A second challenge is that community members are rarely involved in environmental monitoring projects. Professionally paid researchers are missing key opportunities to partner with vulnerable communities, collect high resolution data, and incorporate potential exposure routes that may otherwise be overlooked (e.g., Garcia et al., 2013; Ramirez-Andreotta et al., 2013a,b; Ramirez-Andreotta et al., 2014; Dhillon, 2017; Manjón et al., 2020).

Public Participation in Scientific Research (PPSR) efforts such as citizen and community science programs (referred to as CS hereafter) can be used to address the latter challenge. PPSR is broadly defined as partnerships between scientists and non-scientists in which authentic data are collected, shared, and analyzed (e.g., Shirk et al., 2012). Such efforts have dramatically increased in the past few years (Pocock et al., 2017), and it is anticipated that this approach will permanently change the face of how scientific data are collected and who collects it. Incorporation of CS into research efforts has exciting potential due to the vast amount of data and observations that can be collected by the general public. What is most remarkable about this methodology, is the potential to redistribute power, democratize science and achieve environmental justice (Ottinger, 2010; Pandya, 2012; Allen, 2018). CS efforts are increasingly being directed toward environmental monitoring and will be key and necessary to fully understanding the environmental determinants of chronic disease. Such monitoring information will provide the scientific basis for future prevention of environmental exposures and motivating action (Morello-Frosch et al., 2009).

The critical obstacle to using CS data in assessment of environmental exposure is data management and interoperability. As laid out in the 2016 report, "Stakeholder Analysis: International Citizen Science Stakeholder Analysis on Data Interoperability" there is empirical evidence for the importance of data standards in CS, most noteworthy is that some authorities may not use CS data because of "uncertainty about data quality assurance and quality control measures, and a lack of data standardization practices" (Gobel et al., 2016). Yet studies have confirmed that CS models can provide accurate and reliable data (e.g., Haklay, 2010; Gollan et al., 2012; Nagy et al., 2012; Tregidgo et al., 2013; Hecker et al., 2018). In order to move these data beyond disciplinary and stakeholder boundaries, data management and quality assurance is required (Haklay, 2017; Hecker et al., 2018), along with internal support and tools to effectively address the problems identified by CS. For example, the USEPA is supporting CS projects and has generated quality assurance guidance documents that include templates and handbooks to inform community members and other federal and state agencies (USEPA, 2020).

The scarcity of FAIR data (Wilkinson et al., 2016) in CS is not only unfortunate for the progression of science, but unethical. Thousands of people are contributing/participating to CS programs and co-generating datasets; dedicating their time and resources hoping that their efforts will create change and positive social-ecological outcomes (e.g., Shirk et al., 2012; Ramirez-Andreotta et al., 2015). The lack of data standardization and application of FAIR principles in government-, NGO-, university-, and CS-based efforts slows down the ability and efficiency to address environmental health disparities. Further, most public health environmental health monitoring efforts use an epidemiological approach, but it is known that epidemiology alone cannot adequately detect the effects of toxic exposures on human health (Brown, 1992; Brown and Mikkelsen, 1997). Specifically, a fundamental and critical challenge that exists in environmental justice communities is the need to account for interrelated effects of culturally-diverse and economically-disadvantaged groups with toxic exposures. Another challenge is accounting for community resiliency: the sustained ability of a community to withstand and recover from adversity (Plough et al., 2013). Community resiliency comprises the enduring capacity of geographically, politically, or affinity-bound communities to define and account for their vulnerabilities and develop capabilities to prevent, withstand, or mitigate (Abramson et al., 2015).

We hypothesize that FAIR principles can be applied to facilitate the seamless integration of CS/government/NGO/university datasets and allow the inclusion of both community vulnerabilities and resiliencies in the environmental health assessment process. This approach will allow incorporation of all viable data as well as scaling of datasets, a process that can be expected to increase the efficiency and impact of public health intervention efforts.

To address this hypothesis, we have developed a methodology to make environmental health CS data FAIR. This methodology: (1) integrates CS environmental monitoring data with other data sets to enhance discoverability and reuse of data for research translation and (2) enables better hypothesis generation. An anticipated result of this integration effort is that it will help determine if and how community-level resiliencies may combat environmental health vulnerabilities. In this methodology, we use ontologies to combine a CS dataset with existing governmental environmental monitoring and community resiliency data. An ontology is a forma specification of the concepts in a domain and the relationships among them (Gruber, 1993). The use of ontologies is a key component of FAIR data, because ontologies can transform free-text descriptions into structured, standardized machine-readable data, improving findability, interoperability, and reusability.

The CS dataset used in this research is Gardenroots, a co-created CS program. Gardenroots sees gardens as hubs for environmental health research and literacy with the goals of: engaging community members in the environmental monitoring and exposure science process; evaluating environmental quality (water, soil, and homegrown vegetables) and potential exposure routes; and designing personalized and community-based data sharing experiences to support environmental action and decision-making (Ramirez-Andreotta et al., 2013a,b; Ramirez-Andreotta et al., 2015; Sandhaus et al., 2019). CS programs such as Gardenroots demonstrate how community-engaged environmental monitoring efforts have informed local food gardening practices. By working together to determine soil quality and contaminant concentrations, Gardenroots helps sustain community and home gardens efforts while reducing chemical exposures. This is critical because community and home gardening efforts help address social and economic constraints on health by increasing access to wholesome foods, improving community building efforts, enhancing emotional well-being, creating green space, and reducing the cost of food (Ness and Powles, 1997; Armstrong, 2000; Teig et al., 2009; Ramirez-Andreotta et al., 2019). Gardenroots builds on individual- and community-level resiliencies and combats environmental health vulnerabilities, helping to ensure pollution does not interfere with local gardening efforts. However, Gardenroots is site-specific. We use this dataset to demonstrate the possibility of integration of these data with other state and federal datasets related to soil quality, food production, health, etc. This integration not only increases the spatial resolution and understanding of pollution, but also has the potential to increase environmental health decision-making capacity.

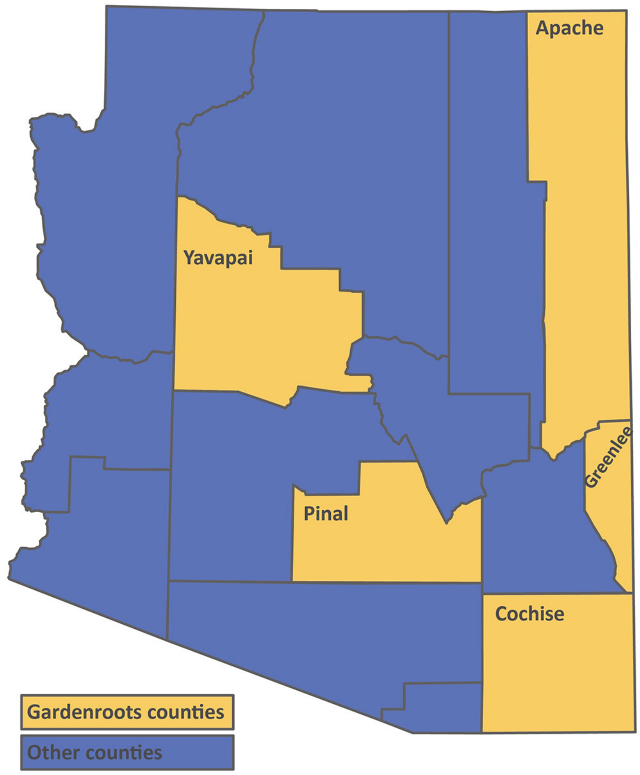


**FIGURE 1 |** Map of participating Gardenroots communities in Arizona.

# MATERIALS AND EQUIPMENT

## About Gardenroots

Gardenroots was established in 2010 in collaboration with a rural community neighboring a USEPA National Priorities List site under the Superfund program slated for cleanup due to uncontrolled hazardous waste (Ramirez-Andreotta et al., 2013a,b). The site comprises a large mine tailings pile that has been barren and subject to wind and water erosion since the 1960s as well as a closed smelter facility site. Both the mine tailings and the smelter site are contaminated with high levels of arsenic, lead, and zinc (USEPA, 2013). More recently, based on the results of a community needs assessment and ongoing community engagement in Arizona, Gardenroots was continued in summer 2015 and 2019 to help address additional community concerns regarding their soil, water, and/or plant quality. Since inception, Gardenroots has been implemented in nine communities nationwide and in AZ alone, more than 120 participants have been trained. Each Gardenroots participant completed a 2-h training on how to properly collect samples from a self-selected area. Community recruitment, trainings, and retention procedures have been previously described (Ramirez-Andreotta et al., 2015; Sandhaus et al., 2019). Typical locations included residential areas, community or school gardens, and local farms. Participants collected water, soil (yard and garden), and/or edible plant samples and submitted them to a centralized location for transport to the University of Arizona (UA). The dataset set reported here is from the following Arizona counties: Apache, Cochise, Greenlee, Pinal (Superior), and Yavapai (Dewey-Humboldt) (**Figure 1**). Each sample submitted and included in this dataset was analyzed for aluminum, arsenic, barium, beryllium, cadmium, chromium, copper, lead, manganese, nickel, and zinc concentrations in water (micrograms per liter, $\mu g\ L^{-1}$), soil (milligrams per kilogram, $mg\ kg^{-1}$), and/or plant samples ($mg\ kg^{-1}$). Field and laboratory methodologies have been previously described (Ramirez-Andreotta et al., 2013a,b; Manjón et al., 2020). All Gardenroots participants received their data (individual and aggregated) via visually-rich results booklets distributed at data sharing and community gathering events or by mail (Ramirez-Andreotta et al., 2015; Sandhaus et al., 2019). In this Methods paper, the Gardenroots CS data is being used as an example to generate a methodology for others to use and allow the seamless integration of other CS collected data with existing state and federal agency datasets.

## Data Management Materials and Equipment

We are using CyVerse (Merchant et al., 2016; https://cyverse.org/) as the primary data storage platform. CyVerse allows all project members to access and analyze data from a shared directory, thus reducing the risk of forking

**TABLE 1 |** Vulnerability datasets.

| Data description | Dataset source | Year | Variable categories ($n$ = number of variables in the category) |
|---|---|---|---|
| Social attributes | USEPA's EJSCREEN | 2019 | Linguistically isolated ($n = 3$) |
| | | | Low income ($n = 3$) |
| | | | Minority population ($n = 3$) |
| | | | Less than highschool education ($n = 3$) |
| | | | Under age 5 ($n = 3$) |
| | | | Over age 64 ($n = 3$) |
| | American Community Survey | 2019 | Poverty status ($n = 11$) |
| Quality of environment | *Gardenroots* Data | 2011–2019 | Concentrations of metal(loid)s in water ($n = 11$) |
| | | | Concentrations of metal(loid)s in soil ($n = 11$) |
| | | | Concentrations of metal(loid)s in plants ($n = 11$) |
| | | | Concentrations of metal(loid)s in dust ($n = 11$) |
| | USEPA's EJSCREEN | 2019 | Proximity to sources of pollution ($n = 30$) |
| | | | Air pollution ($n = 21$) |
| | | | Ozone level in air ($n = 3$) |
| | | | PM 2.5 in air ($n = 3$) |
| | | | Lead paint indicator ($n = 3$) |
| | National Water Quality Monitoring Council | 2018 | Water quality ($n = 22$) |
| | U.S. Geological Survey | 2013 | Soil characteristics ($n = 42$) |
| | Arizona Department of Health Services (ADHS) | 2019 | Arsenic in community water systems ($n = 1$) |
| | Environmental Health Public Tracking | 2019 | Proximity of population and schools to highways |
| Quality of health | Behavioral Risk Factor Surveillance | 2018 | Diabetes ($n = 1$) |
| | | | Cancer ($n = 2$) |
| | | | Asthma ($n = 2$) |
| | ADHS Environmental Health Public Tracking | 2016 | Incidence of cancer ($n = 14$) |
| | | 2019 | Hospitalizations for asthma ($n = 3$) |
| | | | Emergency department visits for asthma ($n = 3$) |
| | National Center for Health Statistics | 2020 | Prevalence of obesity or severe obesity among adults ($n = 1$) |
| Access to food | U.S. Department of Agriculture's Economic Research Service (USDA ERS) | 2020 | State food insecurity ($n = 6$) |

*The most recent data available was used, with the exception of Gardenroots data, that spans from 2011 to 2020. Since the majority of the datasets had a large amount of measured variables, variables are grouped in categories in this table. The n value represents the number of variables in each category.*

(having multiple, divergent copies of the same dataset). Python code for data cleanup and processing are hosted on GitHub at https://github.com/UA-SRC-data/data_loaders. The combination of shared storage and public code allows us to track exactly what processing steps were carried out on each dataset and allows others to reproduce our results. Details on the usage of these platforms is included in section Integrating CS and Federal and State Data Sources.

# METHODS

## Federal and State Datasets

In addition to the Gardenroots CS dataset, data were pulled from existing state and federal programs (**Tables 1**, **2**). These datasets were selected to provide a comprehensive understanding of the possible vulnerabilities and resiliencies in Arizona rural, with special attention on medically-underserved communities that neighbor resource extraction activities. With an understanding of the possible vulnerabilities and resiliencies, efforts will be placed on gathering and juxtaposing variables to see for example, where a community has a tremendous amount of resiliency that has not been tapped for sustainability, environmental quality, and/or justice purposes or vice versa, where an area is suffering and community capacity efforts are in need.

### Vulnerability Datasets

To determine vulnerability (function of the exposure and sensitivity of system, e.g., Cutter, 1996; Adger and Neil Adger, 2006; Cutter et al., 2008), datasets selected include (**Table 1**):

- Quality of Environment
- Quality of Health
- Social Attributes
- Access to Food.

**TABLE 2 |** Resiliency datasets.

| Data description | Dataset source | Year | Variable categories (*n* = number of variables in the category) |
|---|---|---|---|
| Economic capital | American Community Survey | 2019 | Mortgage (*n* = 3) |
| | | | Employment (*n* = 782) |
| | | | Labor force status (*n* = 279) |
| Human capital | American Community Survey | 2019 | Education attainment (*n* = 27) |
| | | | Healthcare coverage (*n* = 25) |
| | | | Presence of computing device (*n* = 11) |
| | | | Internet service/subscription (*n* = 57) |
| | USDA ERS | 2020 | Access to women's infants and children program (*n* = 15) |
| | | | Access to supplemental nutrition assistance program (*n* = 20) |
| Political capital | Arizona Secretary of State | 2018 | Registered voters (*n* = 1) |
| | | | Ballots casted (*n* = 1) |
| | | | Access to polling places (*n* = 1) |
| Social capital | *Gardenroots* Data | 2013–2019 | Number of *Arizona* communities participating in *Gardenroots* (*n* = 5) |
| | USDA ERS | 2020 | Proximity to grocery stores (*n* = 41) |
| | | | Store availability (*n* = 35) |
| | | | Food assistance (*n* = 59) |
| | | | Local foods (*n* = 96) |
| | | | Restaurants (*n* = 15) |
| | Human Resources and Service Administration-Health Professional Shortage Area | 2019 | Federally qualified health center (*n* = 1) |
| | | | Indian, tribal, and urban Indian organizations (*n* = 1) |
| | | | State mental hospital (*n* = 1) |
| | | | Rural health clinic (*n* = 1) |
| | ADHS Environmental Health Public Tracking | 2019 | Access to parks and elementary schools (*n* = 1) |
| | | 2013 | Land use (*n* = 2) |

*The most recent data available was used, with the exception of Gardenroots data that spans from 2011 to 2020. Since the majority of the datasets had a large number of measured variables, the variables are grouped in categories. The n value represents the number of variables in each category.*

### Community Resilience Datasets

Abramson et al. (2015) proposed the Resilience Activation Framework, a conceptual model of how access to social resources promote adaptation and rapid recovery within individuals and communities. This framework rests on six described principles and assumes that access to social services can activate resilience characteristics that are inherent in both individuals and communities, and that once activated, lead to better mental and physical health and well-being (Abramson et al., 2015). Using this proposed design, community resiliencies were collected from diverse datasets and are divided here into (**Table 2**):

- Economic Capital
- Human Capital
- Social Capital
- Political Capital.

## Integrating CS and Federal and State Data Sources

### Data Processing SOP

To maximize the FAIRness of the data collected and analyzed as part of this project, we established a standard operating procedure (SOP) for all datasets that stores raw and processed data in shared folders, tracks all data processing steps, standardizes variables to existing ontologies wherever possible, and publishes standardized data to trusted repositories. Individual technologies in this SOP could be replaced with others of similar functionality. The full SOP is available at https://github.com/UA-SRC-data/data_loaders/blob/master/README.md, but in brief it describes how to:

1. Ensure a copy of the raw data is preserved and sufficiently documented: Gather raw data and store data in a shared CyVerse folder under use case name, under "raw-data."

Include a readme file to readme in each raw folder with the link to the data source and a data dictionary defining variables if needed. Also document data sources in the readme file in the appropriate directory in the data_loaders code repository. Documenting each step of data analysis, including raw data, is crucial for reproducibility.

2. Convert all data to a common format so that it can be integrated: Preprocess data to convert to CSV files with a single sheet per file and a single header row. Standardize column headers by mapping to ontology templates. Output as a CSV file and store on CyVerse under "pre-processed." Data processing scripts are available on a per dataset basis at https://github.com/UA-SRC-data/data_loaders
3. Visualize and validate data: Loading data into the project MySQL or other database allows for preliminary visualization, the first step in most big data projects. This acts as a validation step that allows us to identify outliers and errors in the data such as incorrect units, mapping errors during step 2, or incorrect datatypes.
4. Run data through the Ontology Data Pipeline (https://github.com/biocodellc/ontology-data-pipeline) to convert to graph format. In addition to standardizing the data, the ontology can infer new facts such as hierarchical classification, which enhances searching. More details on the use of ontologies is included in section Standardizing Vulnerability and Resiliency Variables to Ontologies.
5. Output final datasets including standardized versions of datasets for publication as well as complete versions of dataset to use in the visualization portal.

## Decision-Making and Standardization Practices

Integrating data from multiple databases requires many decisions regarding which data to include, how to carry forward missing or other special values, and how to harmonize data collected at different spatial scales or time points. It is critical to document these decisions and ensure that documentation accompanies any published datasets.

### *Managing Non-numerical Values in Numerical Fields*

It is common for data sources to include non-numerical values in certain cells where a numerical value is expected. Data from the National Water Quality Monitoring Council includes values like "$<0.02$" to indicate metal(loid) concentrations below the limit of detection (LOD). Such values will not pass validation and cannot be computed on, so researchers must decide how to use them, which is challenging for data that were collected by a third party. In the Gardenroots dataset, all values below LOD are recorded as LOD/$\sqrt{2}$ so that they can be included in analyses (USEPA, 1991; Helsel, 2011). Because our database (step 3 in section Data processing SOP) specifies datatypes (e.g., float, string) for each field, it will automatically find values of this type that need to be addressed.

### *Variation in Spatial Granularity*

Spatial resolution varies among datasets, including both point locations and shape files at the census block, block group, and tract level or county level. We chose the census block group as our preferred spatial resolution because it strikes a good balance between specificity and availability among different data sources, and because it is the resolution of Gardenroots data (see section below on privacy). Furthermore, for some datasets, such as the USEPA's Environmental Justice Screening tool (EJSCREEN), limited data availability at finer resolution can lead to unacceptable levels of uncertainty (USEPA OECA, 2014). Some datasets are only available at the county level (e.g., USDA data), so any analyses at finer scales must include the uncertainty that comes from using county level data. Data at the point level (e.g., USGS water monitoring data) can be converted to block group using standard code libraries (see https://github.com/UA-SRC-data/data_loaders/tree/master/point2shape), with the recognition that this introduces uncertainty for that block group. Therefore, processed datasets must include annotations that data were converted from point to shape file. In addition to the spatial resolutions listed above, we are also adding spatial files for different boundary types, to represent, for example, tribal homelands and Primary Care Areas.

### *Variation in Temporal Granularity*

The time of data collection also varied among datasets. Gardenroots data were collected over multiple years (2010–11, 2015–16, 2019), sometimes with multiple data points for the same location. Some federal datasets are available for multiple years, while others are available for a single year only. For those that are available over multiple years (e.g., EJSCREEN), we chose to use only data from the most recent year. Because our integration uses only datasets from the period of 2010–2020, we make the assumption that they are comparable, but variation in year collected introduces additional uncertainty. Often, when data at a broader temporal resolution are combined with date where an exact date is known, a specific date will be assigned. For example, a data point for 2018 might be assigned a date of January 1, 2018, to be compatible with other data points for which the day of the year is known. This introduces a false sense of precision. When integrating data at different scales (spatial or temporal), the integration must usually happen at the largest scale, even if this means losing information from more precise dataset.

## Protecting Privacy of CS Data

When working with CS data such as Gardenroots, it is critical to preserve the privacy of participants. Before data collection, all participants were consented under the University of Arizona Institutional Review Board as an approved project for learning research. Although the UA currently does not see environmental monitoring as a "type" of human research, the name, location, and reported-back environmental monitoring data were deidentified to preserve participant privacy. It is clear that there is an ethical duty to report data back to participants, but once the participant has that data, are there ethical or legal implications? Do they have to disclose when selling their home? Renting? Having family members visit who are considered a member of the sensitive population (i.e., under five, over 65, and/or have a preexisting condition)? Goho (2016) reviewed and explored the potential legal duties of study participants once they have participated in a residential exposure study and have received their personalized data results. It was concluded that there are both ethical and legal implications that researchers and community researchers need to consider, highlighting how data privacy and preservation is critical to CS data science efforts. Based on the above and previous efforts, a solution was reached where community data reported herein was kept to the geographic resolution of the census block when the census block includes at least 10 residences and the census block group otherwise.

### Standardizing Vulnerability and Resiliency Variables to Ontologies

Ontologies are standardized terminologies that provide logical (understood by computers) and text (understood by humans) definitions to reduce ambiguity about the meaning of data. A key challenge in integrating such disparate datasets (with variables ranging from metal(loid) concentration in garden soil to median household income to proximity to grocery stores) is the lack of widely adopted ontologies for vulnerability and resiliency factors. Environmental vulnerability terms for chemical exposures have the best existing coverage in ontologies, due to chemical terms in Chemical Entities of Biological Interest ontology (CheBI, de Matos et al., 2009) and environmental quality terms in the Environment Ontology (ENVO, Buttigieg et al., 2013, 2016). We follow the best practice of submitting new term requests to existing ontologies to fill gaps, but that process can be slow. Therefore, we have created an application ontology, the University of Arizona Superfund Research Project Data Interface Ontology (SRPDIO, https://github.com/UA-SRC-data/srpdio) to meet our pressing data integration needs. Superfund Research Project Data Interface Ontology reuses terms from the ENVO, CheBI, the Exposure Ontology (Mattingly et al., 2012), and other ontologies to standardize variable names across datasets. We are working with ENVO curators to move physio-chemical parameters such as metal(loid) concentration or electroconductivity into ENVO, where they can be more broadly reused. For variables that have no ontology (e.g., number of registered voters or proximity to EPA Risk Management Plan Facilities), we are creating terms within the SRPDIO to explicitly define each variable. We plan to work with the larger environmental health community to develop ontologies around social vulnerability and resiliency factors in the future.

## RESULTS

### Integrated Datasets That Permit New Environmental Health Studies

The Gardenroots CS data were integrated with existing governmental environmental monitoring data to create a more holistic story that includes vulnerability and resiliency data from these rural, medically-underserved communities. We integrated typically siloed/separated datasets including datasets that are intentionally segregated based on who collected the data. The integration of these datasets allowed for the generation of the proposed questions in **Table 3** that we anticipate answering (see **Figures 3–5** for examples). The vulnerability and resiliency data in **Tables 1**, **2** are in various stages of processing with the SOP described in section Data processing SOP. Metal(loid) concentration data from Gardenroots, National Water Quality Monitoring Council, and USGS; pollution-related data from US EPA's EJSCREEN; and social data from the U.S. Census Bureau's American Community Survey (ACS) have been preprocessed, and validated using our internal database (step 3 in section Data processing SOP). These datasets are available in an archived release of our GitHub repository (Youens-Clark et al., 2020) in files named "scrutinizer.csv" under their corresponding directories, along with the code that generated them. Because Gardenroots contains multiple datasets, the pre-processed data are instead in a directory named "scrutinizer," with separate files for plant and soil data. Food access data from USDA's Economic Research Service, health data from the National Center for Health Statistics, and NIH's Health Resources and Service Administration's Health Professional Shortage Area data have been downloaded and stored in our shared CyVerse directory, but still require standardization. We do not publish those datasets, as they are available from the original sources, listed in **Tables 1**, **2**. To access data from the Center for Disease Control's Behavioral Risk Factor Surveillance System (BRFSS), we will need to submit a request and complete an application. CDC restricts re-publication of BRFSS data, so although we plan to use them in our integrated data modeling work, we will not be able to publish them. Recognizing the need for privacy, FAIR principles do not require that data be open, but they do require adequate description. Therefore, we will provide full metadata for any BRFSS data we use. Arizona voter data, available from https://azsos.gov/precinct-level-results-county-2018-general-election, will require additional processing for some counties to extract the desired variables, because county-level data are not reported consistently.

Though we have not yet used this methodology extensively, **Figures 3–5** are example visualizations generated from the integration of selective datasets at the county level, demonstrating initial and further anticipated results. We recognize that causality cannot be inferred, but these examples show how the database can help inform hypothesis generation and identify counties that are suffering more from selected health outcomes and/or environmental quality challenges. These visualizations were created to align with the questions posed in **Table 3** to illustrate the breadth of this methodology. For example, arsenic and chromium (inhalation route only) are recognized as human carcinogens by USEPA, while cadmium and lead are classified as probable carcinogens (e.g. USEPA Integrated Risk Information System, USEPA, 2021). **Figure 3** supports hypothesis generation, specifically asking whether arsenic, cadmium, chromium, and/or lead soil concentrations occur in counties with high incidence rates of the most commonly observed cancer types, informing questions 3–4 in **Table 3**. We see that Mohave county experiences bladder, lung, kidney and pancreatic cancers, but is only impacted by chromium in soil, whereas Yavapai county is impacted by all metal(loid)s except cadmium and the bladder and lung cancer incidence rates are among the top five. Greenlee county has the highest concentrations of cadmium, chromium, and copper (currently not classified as

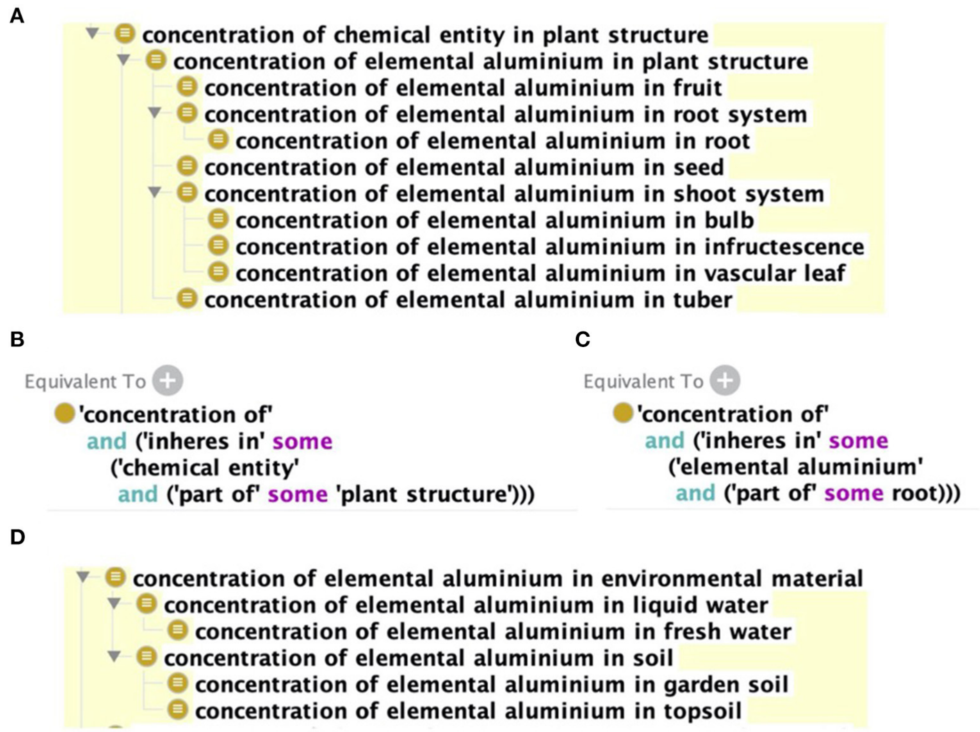


**FIGURE 2 | (A)** The hierarchy of terms for the "concentration of aluminium in plant structure." Plant structure terms are imported from the Plant Ontology (Cooper et al., 2013) and chemical terms are imported from ChEBI. **(B)** The logical definition of "concentration of chemical entities in plant structure." **(C)** The logical definition of "concentration of elemental aluminium in root." An ontological reasoner uses these logical definitions to infer the hierarchy shown in **(A)**. **(D)** The hierarchy for "concentration of elemental aluminium in environmental material" is generated similarly to the hierarchy for concentrations in plant structures. Note that ChEBI is an international ontology that uses the British spelling "aluminium" shown in the figure, but our search engine includes the American spelling "aluminum".

a human carcinogen), however the Arizona Department of Health Services dataset is missing selected cancer incidence rates, which we will gather from another source listed in **Table 1**.

In addition to cancer, studies have also observed that arsenic exposure is associated with an increased risk of developing a number of diseases, including cardiovascular disease and type II diabetes (Sears and Genuis, 2012; Naujokas et al., 2013). Currently, University of Arizona Superfund researchers are working to determine how chronic exposure to mine wastes that contain arsenic contributes to the development of diabetes. **Figure 4** examines the prevalence of diagnosed diabetes and obesity along with major mining activities in Arizona (Niemuth, 2015; Centers for Disease Control and Prevention, 2016; Richardson et al., 2019). Mining and industrial processes are primary sources of arsenic and heavy metal contamination in soil (Lee et al., 2005). Greenlee, Gila, Pinal, Navajo, Graham, La Paz, and Mohave populations have an incidence rate of diabetes and obesity at the medium level, 9–13.9 and 29.1–36.0%, respectively, as well as at least one major mine, informing questions 3–5 in **Table 3**.

**Figure 5** highlights a human capital form of resiliency—the percent of internet subscriptions (dial-up and broadband, cellular data plan, and satellite internet services) in Arizona counties. Internet service is a form of resiliency, indicating potential technical literacy and access to information. The highest percentage of internet service is 35.88% in Yavapai county, followed by Pima, Mohave, and Maricopa counties. This information indicates that researchers, government agencies, and other organizations cannot solely rely on websites for information dissemination, informing question 11 in **Table 3**.

## New Ontology Terms

### Metal(loid) Environmental Monitoring Data

The initial draft of the SRPDIO and the code used to generate it are available at https://github.com/UA-SRC-data/srpdio, with the first official release in November 2020. A key component of the SRPDIO is the creation of new ontology terms for concentrations of metal(loid)s in environmental materials and plant structures. We use logical definitions for these terms that allow the ontological reasoner to automatically build complex hierarchies of metal(loid) concentrations (**Figure 2**). The logical definitions (**Figures 2B,C**) follow an ontology design pattern established in ENVO and the Plant Trait Ontology (TO, Cooper et al., 2018) to define terms for concentrations. "Inheres in" comes from the widely used Relations Ontology (Wg, 2020). It is used to relate a quality (in this case, "concentration of") and the entity that has that quality (in this case a "plant structure" or a

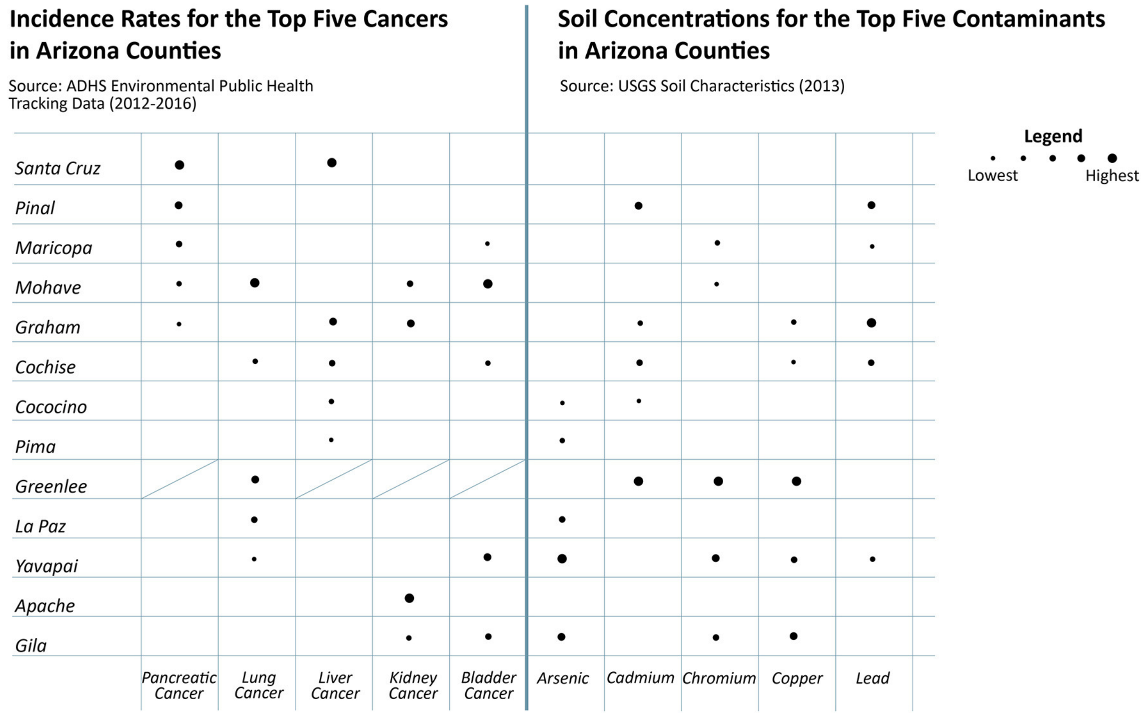


**FIGURE 3 |** A visualization generated from selective datasets to qualitatively describe cancer incidence rates and soil contaminant concentrations.

"material entity"). The ontological hierarchies support advanced queries, such as "find all data on any metal in a plant structure" or "find all data on zinc contamination in any material." These terms and definitions were created in the SRPDIO but will be moved to the Environment Ontology with an upcoming ENVO release.

### Sociodemographic Data

Another key component of the SRPDIO is the development of new ontology terms for sociodemographic variables. Currently, there is not a fully developed ontology for sociodemographic data, such as the information collected in the U.S. Census Bureau's ACS. This was acknowledged as a main concern in Gobel et al. (2016), where interviewed stakeholders reported that current interoperability efforts are biased and limited to the natural sciences. Interviewees were critical that social science standards were absent from discussions, highlighting that any proposed interface and standardization effort would need to be accessible to a wide range of projects and research methodologies. Here, we acknowledge this bias and that the data science efforts have traditionally focused on the natural sciences, entailing observational data, and are not applicable to all forms of knowledge (Gobel et al., 2016). Another issue highlighted by interviewees in the aforementioned Stakeholder Analysis, was the lack of clarity on how to treat data gathered on participants including sociodemographic information and participant evaluations. As highlighted in section Protecting privacy of CS data, we have proposed a solution where community data can be reported while protecting privacy.

## DISCUSSION

### Solving Environmental Health Challenges With Transdisciplinary Data Science

This data science methods paper demonstrates the integrated framework needed to solve the challenges of interoperability within the environmental health sciences as well as how to integrate CS data. We have developed a methodology to make environmental health CS data FAIR, while also integrating other types of environmental health and social data to enhance discoverability, reuse of data for research translation, and enable hypothesis generation. We are, to the best to our knowledge, among the first to develop ontology terms for: contaminant concentrations in various environmental media, and sociodemographic data. This effort is advancing the field, while also demonstrating how the designed data management system can be applied to other research questions and scenarios. An anticipated result of this integration effort is that it will help the field determine if and how community-level resiliencies may combat environmental health vulnerabilities.

The complex challenges associated with environmental health and food security are influenced by current and emerging political, social, economic, and environmental contexts. To solve these "wicked" dilemmas (Rittel and Webber, 1973), we need methods to harness the public's participation in research, conceptualize solutions, and strategize implementations at all levels of the ecological model of health to effectively design interventions (Bronfenbrenner, 1979; Richard et al., 2011). These challenges do not respect disciplinary boundaries. Therefore,

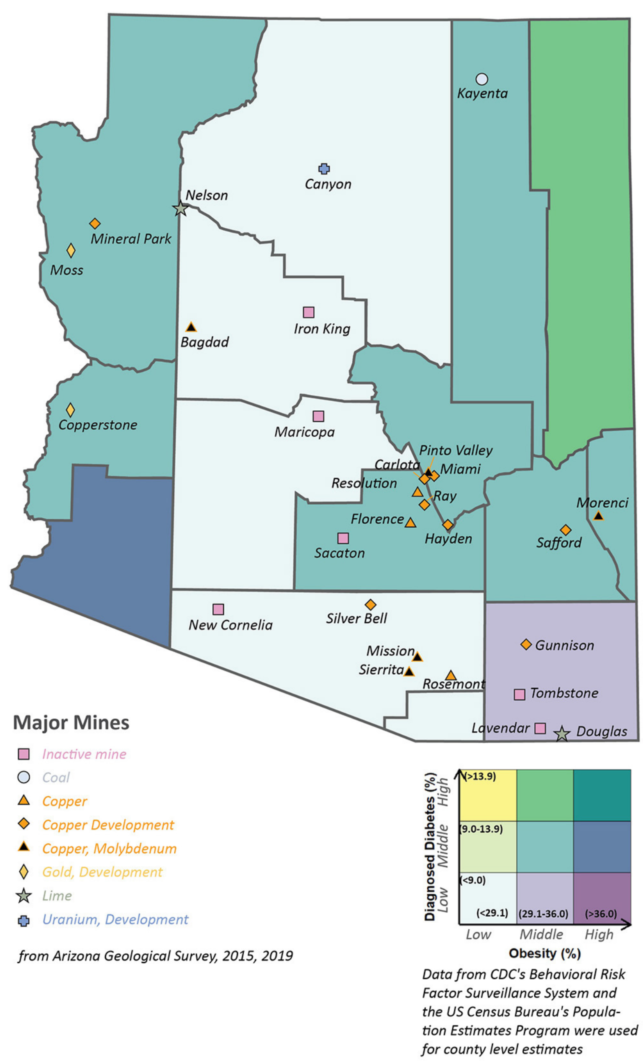


**FIGURE 4 |** Major mines and prevalence of diagnosed diabetes and obesity in the state of Arizona.

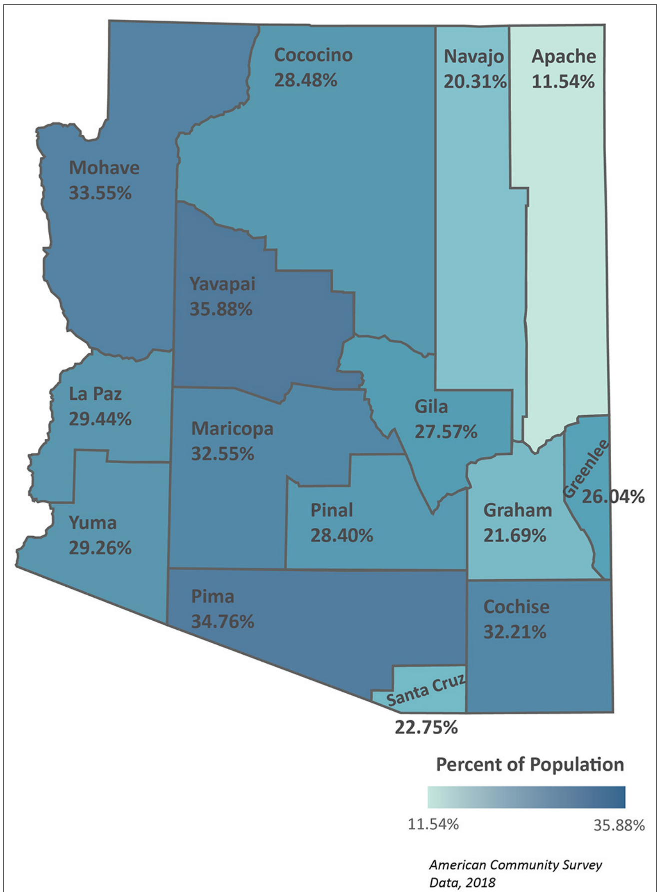


**FIGURE 5 |** The percent of county populations with internet access.

transdisciplinary research efforts are needed (e.g., Ramirez-Andreotta et al., 2014; Anderson et al., 2015; Pohl et al., 2017) that follow FAIR principles so that the varying knowledge sources can be interwoven (Anderson et al., 2015; Pohl et al., 2017). Based on the datasets highlighted and integrated in our case study, we do not necessarily need more data, we need integrated data management practices to solve the challenges of interoperability of CS data within the environmental health sciences.

## Place-Based Strategies to Mobilize Resiliencies

The data science methods reported here go beyond simply integrating CS environmental vulnerabilities datasets. Citizen and community science efforts can be viewed as place-based strategies to address public health challenges such as health promotion and environmental exposures. To build upon place-based strategies and social processes (e.g., Ness and Powles, 1997; Armstrong, 2000; Teig et al., 2009), we combined CS data with data on the communities' human, social, and political capital to help inform how rural mining populations can mitigate potential chronic exposures and rebound when their ecosystem has been negatively impacted. For example, to combat natural disasters, Bergstrand et al. (2015) mapped social vulnerability and community resilience to visualize community risks as well as their capacities for recovery and adaptation.

Regarding enabling hypothesis generation, we anticipate that the integrated Garderoots and government datasets will reveal new forms of community resiliency that can be mobilized to support and protect ecosystem services. Community resilience theory has become a key component of national policies across federal agencies because it provides a framework that embraces principles of equity and justice with a focus on building the capacities of populations both to mitigate disasters and to successfully rebound (Norris et al., 2008; Plough et al., 2013). Our methodology builds on this theory and can ultimately help to directly inform decision-making in these communities and identify critical areas for further study (**Figures 3–5**). Further, we anticipate that an understanding of soil quality

**TABLE 3 |** Questions to ask of the vulnerability and resiliency dataset to achieve environmental justice in communities neighboring active and legacy mining activities.

| Questions | Dataset used |
|---|---|
| 1. What is/are the major:<br>a. Vulnerability(ies)<br>b. Resiliency(ies) | All datasets in **Tables 1**, **2** |
| 2. Are we (all stakeholders) addressing them?<br>a. If not, how can we? | N/A |
| 3. Are mining communities disproportionately exposed to Arsenic?<br>a. If so, what is/are the major arsenic contributor(s) to daily dose of arsenic? | • *Gardenroots Data*<br>• USEPA's EJSCREEN<br>• National Water Quality Monitoring Council<br>• U.S. Geological Survey |
| 4. Are mining communities suffering/experiencing cancer/diabetes/obesity/asthma disproportionately?<br>a. Why?<br>b. Is it due to rural health disparities?<br>c. Access to nutritional foods and public health programming? | • ADHS Environmental Health Public Tracking<br>• Behavioral Risk Factor Surveillance<br>• National Health and Nutrition Examination Study<br>• USDA ERS |
| 5. Are mining communities with elevated arsenic concentrations suffering/experiencing cancer/diabetes/obesity/asthma disproportionately?<br>a. If so, what is/are the major arsenic contributor(s) to daily dose of arsenic? | • Gardenroots Data<br>• USEPA's EJSCREEN<br>• National Water Quality Monitoring Council<br>• U.S. Geological Survey<br>• ADHS Environmental Health Public Tracking<br>• Behavioral Risk Factor Surveillance<br>• National Health and Nutrition Examination Study<br>• USDA ERS |
| 6. Can we assign an index value (Bergstrand et al., 2015)? | All datasets in **Tables 1**, **2** |
| 7. Once we combine the vulnerability and resiliencies, can we rate and compare communities? | N/A |
| 8. How can we leverage the resiliencies to address the vulnerabilities? | All datasets in **Table 2** |
| 9. When considering ecosystem functions, what function(s) are in deficit/not working? Which functions are working?<br>a. Provisioning<br>b. Regulating<br>c. Cultural<br>d. Supporting | All datasets in **Tables 1**, **2** |
| 10. When considering sustainability practices, what needs to occur:<br>a. Economically—new job opportunities?<br>b. Socially<br>c. Environmentally | All datasets in **Tables 1**, **2** |
| 11. How can we successfully communicate with these communities at the local community and government level? | • American Community Survey |

from combining Gardenroots and USGS datasets will support provisioning services and inform where local food production efforts should be invested, addressing food deserts that have been highlighted in the USDA data. Alternatively, if local soils are not suited for crops, affected families can be connected to the Supplemental Nutrition Assistance and/or the Woman's Infant and Children Programs for nutritional assistance. As a second example, in one community we had monthly meetings dedicated to identifying local concerns and priorities. A discussion regarding the need for occupational diversity has been initiated. The community does not want to be solely dependent on a local copper mine for economic prosperity as they recognize that copper ore is a finite resource. Thus, the community is interested in diversifying the types of jobs available in their community. Understanding current employment rates and labor force status, educational attainment, and the presence of a computing device and internet service/subscription at home, in the context of community educational, recreation and tourism, aesthetic, and cultural heritage values, can illuminate the best investments to make in social and human capital to facilitate occupational and economic diversification while protecting cultural resources.

## Determining Community-Level Resiliencies and How They May Combat Environmental Health Vulnerabilities

The resiliency literature has demonstrated that individual, family, social, and environment resources are critical for the successful recovery of a community or cultural system. Resiliency allows a given community to absorb a disturbance. This includes the ability to reorganize to meet the challenges of a change while still retaining the elements that make a community distinct (e.g., Healy, 2006; Fleming and Ledogar, 2008). Unfortunately, past efforts to understand resilience have focused on ecological systems and include socio-ecological systems to a much lesser extent (Bhamra et al., 2011). We anticipate that the lack of consideration of socio-economic systems is due to the absence of available information at different scales and research domains. But we argue that sustained community resiliency heavily relies on the improvement of social factors and this is a missed opportunity. Among these social factors are education, employment, and population well-being (Abramson et al., 2015).

The most important single predictor of health is socioeconomic status (e.g., Singh-Manoux et al., 2018; Kivimäki et al., 2020). Thus, one cannot separate socioeconomic status from environmental health vulnerabilities. However, efforts to improve environmental health need to include a better understanding and mobilization of current community-level resiliencies to help improve the socioeconomic status of the community as a whole. **Table 3** illustrates the type of questions related to vulnerability and resiliency that our proposed framework and methodology would enable exploring. The anticipated outcome is illumination of improved and placed-based solutions to environmental health vulnerabilities (see section Place-Based Strategies to Mobilize Resiliencies).

### Power and Challenges of Interoperability

We have developed a method to provide a common data model that allows environmental health researchers working at different scales and research domains to exchange data. This method provides the ability to usefully incorporate such data, scaling the impact of any single dataset, be it from a single government, NGO, university, or CS source. We are currently working on an end-user/stakeholder analysis to determine "what works," "what is missing," and how to create the interactive data visualization approach that can be used for exploratory analysis and dissemination.

Key tasks for this goal include (Sedlmair et al., 2012): (1) Observations of current end-user/stakeholder's analytical workflow and data visualization practices to prepare a validated visualization system; (2) Formative evaluation and usability studies of the validated visualization system with new end-users/stakeholders to ensure the visualizations meet stakeholder's needs and answer their research questions; and (3) Development of a user-friendly web application that will support efforts to streamline data access, visualization, and analyses. In February 2021, we received University of Arizona Institutional Review Board Approval to start this analysis with local, state, federal, and community stakeholders. The new knowledge gained will aid in the creation of similar tools and workflows for use in other scientific contexts.

Modeling population- and factor-wide environmental effects using existing datasets from academia and federal agencies currently faces a number of challenges, including a limited number of samples in environmental datasets, which may prevent researchers from obtaining robust statistical confidence. Our method, which combines multiple data sources, helps to overcome the lack of power in an individual dataset by increasing the number of datasets available. Another key challenge in integrating CS data with public data and making it FAIR is the lack of existing standards and ontologies for environmental health data. The Children's Health Exposure Analysis Resource ontology (Balshaw et al., 2017) provides broad coverage of environmental health indicators but lacks coverage of many important vulnerability and resiliency terms. We encourage environmental health researchers, especially those with knowledge of social and economic factors (which have the poorest ontological coverage) to get involved in community ontology development in order to support future data standardization and integration efforts. Our future work includes contributions to community ontologies such as ENVO and refinement of the SRPDIO.

## CONCLUSION

This effort has allowed for the development of a transdisciplinary data management (and eventually visualization) tool that we anticipate, will: (1) Help mitigate the human impacts of exposure to environmental contamination through effective research translation and community engagement driven by stakeholder-engaged research, and (2) Serve as a global resource for human and environmental health issues associated with contamination whether it is from a legacy site (as described in the Gardenroots example) or from a new or ongoing data source. It is expected that the interoperability efforts discussed herein, combined with the future end-user/stakeholder informed and validated data visualizations, will yield new insights into the factors that affect environmental health—both positively and negatively in communities.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author/s.

## AUTHOR CONTRIBUTIONS

MR-A: conceptualized the study and designed it with RW and writing-original draft preparation. MR-A and RW: investigation, supervision, and project administration. RW, KY-C, KB, MR-A, and KI: methodology. RW, KY-C, and KB: data curation. DK: visualization. RM, RW, MR-A, KB, and KI: writing-review and editing. RM (administrator), MR-A, and RW: funding acquisition. All authors contributed to the article and approved the submitted version.

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# Monitoring of Suspended Sediments in a Tropical Forested Landscape With Citizen Science

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Catchments are complex systems, which require regular monitoring of hydro-chemical parameters in space and time to provide comprehensive datasets. These are needed to characterize catchment behavior on a local level, make future projections based on models, implement mitigation measures and meet policy targets. However, many developing countries lack a good infrastructure for hydrological monitoring since its establishment is costly and the required resources are often not available. To overcome such challenges in data scarce regions like Kenya, a participatory citizen science approach can be a promising strategy for monitoring water resources. This study evaluates the potential of using a contributory citizen science approach to explore spatiotemporal turbidity and suspended sediment dynamics in the Sondu-Miriu river basin, western Kenya. A group of 19 citizen scientists was trained to monitor turbidity using turbidity tubes and water levels with water level gauges in six nested subcatchments of the Sondu-Miriu river basin. Over the course of the project, a total of 37 citizen scientists participated and contributed to the overall dataset of turbidity. The sampling effort and data contribution varied from year to year and among participants with the majority of the data (72%) originating from 8 (22%) citizen scientists. Comparison between citizen-scientist collected suspended sediment data and measurements from automated stations showed high correlation ($R^2 > 0.9$) which demonstrates that data collected by citizen scientists can be comparable to data collected using expensive monitoring equipment. However, there was reduced precision of the measurements of suspended sediment concentrations at low and high levels attributed largely to the detection limitations of the turbidity tubes and citizen scientists not capturing major sediment export events. Suspended sediment concentrations were significantly higher downstream ($109 \pm 94$ mg $L^{-1}$), a subcatchment dominated by agriculture and rangeland with low forest vegetation cover, as compared to a subcatchment with high forest cover ($50 \pm 24.7$ mg $L^{-1}$). This finding indicates that forest cover is a key landscape feature to control suspended sediment concentrations in the region.

Future citizen science projects should focus on motivation and engagement strategies and the application of robust methods with improved detection limits and resolution to advance hydrological monitoring.

**Keywords: catchment, citizen science, suspended sediments, turbidity, Sondu-Miriu river basin, Mau Forest Complex**

## INTRODUCTION

In the tropics, natural ecosystems and water resources are increasingly threatened by several factors including growing human population, climate change, deforestation, and increased cropping and grazing intensities (Smith et al., 2016; Shupe, 2017; Berihun et al., 2019). Consequently, many tropical forest ecosystems have been subject to disturbances, which vary through time and space. Previous studies have demonstrated the effect of land use change on soil erosion and sediment yield, with conversion of forest to agricultural or grazing land yielding the highest soil loss due to changes in soil properties such as reduced infiltration rates and water retention capacity (Owuor et al., 2018; Stenfert Kroese et al., 2020b). Increased surface runoff may lead to flooding and accelerates sediment transport processes, resulting in amplification of the sediment load in rivers (Pacheco et al., 2014; Owuor et al., 2018). Monitoring of sediment loads in catchments is important for the development of soil erosion management and control strategies, to inform policies for water resources management and for the validation of spatially distributed sediment delivery models (Akrasi, 2005; Kuhnle and Wren, 2005; Gao et al., 2007).

Much of the recent focus in hydrogeochemical research has been on the use of models, remote sensing and high resolution automated monitoring systems to further improve our understanding of ecological systems (Baldyga et al., 2008; Jacobs et al., 2018; Esteves et al., 2019). Although these approaches have been widely used to inform decision making for environmental management, they are expensive and their application within most developing countries is still hampered by poor infrastructure and technical capabilities (Olang and Fürst, 2011; Nardi et al., 2020). As a consequence, relatively few hydrogeochemical datasets exist (Zheng et al., 2017). As the acquisition of field data with high spatial and temporal resolution is very important for sustainable water resource management and governance, this clearly raises the need to explore alternative cost-effective approaches for data collection (Njue et al., 2019; Malthus et al., 2020).

Advances in technology and the rise of robust simple and cheap sensing equipment provides unprecedented opportunities for data collection using citizen science in hydrological sciences and water resources management, especially in data scarce regions (Buytaert et al., 2014; Zheng et al., 2017). Citizen science refers to the involvement of the general public within the scientific research process for the generation of new scientific knowledge (Bonney et al., 2009b; Buytaert et al., 2014). Although citizen science is still uncommon practice in water research, we recognize that its uptake in low-income countries such as Kenya is gradually rising (Njue et al., 2019), especially in monitoring of precipitation, water levels and water quality (Gomani et al., 2010; Kongo et al., 2010; Walker et al., 2016; Weeser et al., 2018). As a scientific method, citizen science is acknowledged to play an important role in delivering valuable and robust environmental data from local to national scales, increasing knowledge of science and reducing monitoring costs (Bonney et al., 2009a; Silvestro et al., 2012; Haklay, 2015). Moreover, citizen observations can provide quality and detailed ground-based data for calibration and validation of satellite-based earth observation and high-resolution automated stations (Fritz et al., 2017; Nardi et al., 2020). Njue et al. (2019) present a comprehensive review on the successful implementation, contribution, and significant growth in application of state-of-the-art citizen science approaches in hydrological monitoring in the past two decades. Looking ahead, citizen science could be used cost-effectively not only to fill data and information gaps, but also to work collaboratively with communities to generate relevant management-oriented knowledge.

This study aimed to evaluate the potential of using citizen science to explore spatiotemporal suspended sediment dynamics using turbidity as a proxy in the Sondu-Miriu river basin in Kenya. The Sondu river originates in the Mau Forest Complex, which is one of Kenya's remaining indigenous tropical montane forests. The Mau Forest Complex experienced a significant loss of 25% forest cover between 1973 to 2013 through illegal logging, forest excisions, charcoal burning and encroachment for settlement and subsistence farming by smallholder farmers (Olang and Kundu, 2011; Otuoma et al., 2012; Swart, 2016; Brandt et al., 2018). Previous studies have linked deforestation in the Mau Forest Complex, to changes in hydrological processes such as changes in flow regimes, soil and water quality deterioration in the catchment (Masese et al., 2012a; Otuoma et al., 2012; Jacobs et al., 2017; Owuor et al., 2018). Masese et al. (2012a) highlight that due to the combined effects of human activities in the Sondu-Miriu river basin, turbidity has more than doubled in 30 years from a mean of 60 NTU in 1988 to 130 NTU in 2012. This could contribute to the accumulation of sediments in Lake Victoria at a rate of 2.3 mm year$^{-1}$ and its effect on eutrophication (Verschuren et al., 2002; Zhou et al., 2014). Additionally, there has been a growing concern amongst the local officials in the water sector and water resource users on the significant increase in sediment transport in the Sondu river basin, which could be linked to high levels of encroachment (Kinyanjui, 2009).

Being the primary catchment area of the Sondu river, the Mau Forest Complex plays a critical role in the management of water resources, water quality and erosion. The Sondu river is not only important as a source of water for commercial (tea and forestry plantations) as well as smallholder agricultural and domestic use, but also for hydropower production. Improving the knowledge on water flows and suspended sediments dynamics in catchments with hydroelectric power plants is crucial (Esteves et al., 2019). Therefore, the collection of data to evaluate the spatial and temporal variability of sediment loads with the Sondu-Miriu river basin is needed to establish a proper baseline to assess alternative future management strategies. We hypothesized that citizen science is a cost-effective, and robust approach for data collection for sustainable water resource management, as it reduces the costs of suspended sediment monitoring and significantly improves data coverage. To our knowledge, this study presents the first analysis of community-based monitoring of sediment dynamics in a tropical forested catchment in East Africa.

# MATERIALS AND METHODS

## Catchment Description

The study was carried out in the Sondu-Miriu river basin (3,450 km$^2$) which originates in the Mau Forest Complex and drains into Lake Victoria at an elevation range of 1,140 to 2,900 m a.s.l (**Figure 1A**). The temporal rainfall distribution in the basin is driven by the intertropical convergence zone, generally exhibiting a bimodal rainfall pattern. A longer rainy season occurs from April to July, with rainfall peaks in April and May (>250 mm per months) in the upper part of the catchment, and a shorter rainy season between October and December. During the dry season in January and February the area receives the lowest amount of rainfall (<75 mm per months). The annual average rainfall ranges from 1,300 mm year$^{-1}$ in the lowland areas to 1,900 mm year$^{-1}$ in the highlands. Mean annual temperatures range from 16°C to 22°C (Stephens et al., 1992; Vuai et al., 2012), with a potential evapotranspiration rate of 1,400 to 1,800 per annum at the uplands and lower altitudes, respectively (Krhoda, 1988).

The Sondu-Miriu river basin is characterized by diverse land use types. The upper highland zone is dominated by small-scale farming in the eastern part and indigenous forest and woodlands, which are part of the Mau Forest Complex, in the central part (**Figure 1B**). From the edge of the forest to the west, the land opens up to a rich upland agricultural area characterized by commercial tea and tree plantations. Moving downstream to the lower midland zone, a mixed land use pattern comprising of smallholder agriculture predominate with more settlements. In this area most of the natural vegetation has been replaced by exotic tree species interplanted with crops (Jaetzold and Schmidt, 1983; Masese et al., 2012b). The lateral and longitudinal distribution of the riparian zones varies in terms of their structure, with severely degraded flood plains in some sites and those adjacent to agricultural land dominated by exotic tree species such as *Eucalyptus* spp. The riparian zones adjacent to the tea estates are well-maintained with dense native vegetation forming a buffer up to 30 m distance (Njue et al., 2016). Farming of crops such as maize, beans and potatoes as well as livestock keeping by smallholder farmers plays an important role in the area for both subsistence and economic purposes.

Generally, the soils are well-drained, deep (>1.8 m), fine textured with humic topsoil of high agricultural potential (Jaetzold and Schmidt, 1983). The predominant soils are humic Nitisols in the upper zones and Acrisols in the middle and Regasolos in the lower zones. Mollic Andosols, Cambisols, Phaeozems, Planosols, Vertisols, and Ferralsols are found in smaller proportions (Sombroek et al., 1982; Jaetzold and Schmidt, 1983; Ouma et al., 2011; Vuai et al., 2012) (**Table 1**).

## Citizen Science Recruitment and Training

The study was designed as a "contributory" citizen science monitoring program, i.e., a scientist-directed program with citizen scientists primarily contributing to data collection (Bonney et al., 2009a). We selected six monitoring sites for turbidity monitoring out of the existing 13 sites for citizen science water level monitoring described in Weeser et al. (2018) (**Figure 1A**). During selection, we considered the accessibility and proximity to potential citizen scientists. Physical characteristics for the sites and their corresponding subcatchments are provided in **Table 1**.

With the help of local administration and Water Resource Users Associations (WRUAs), sensitization meetings with the local community members were conducted at the selected sites. WRUAs were considered a good entry point to reach the community members as these are community groups formed out of local water users to promote sustainable and equitable water use through management and conservation of water resources (Richards and Syallow, 2018). The aim of the sensitization meetings was to promote the project and identify potential participants who would volunteer in the water quality monitoring program. To understand the local knowledge, level of awareness and perception of the local community on water quality and supply, sensitization meetings allowed interactive discussions between citizens and scientists. Besides, a conceptual model of a river system representation in a poster was used to help the participants understand the basic concepts of what a catchment is and how it generally works. Beyond contributing data for scientific purposes, the participants were sensitized on the importance of community-based monitoring in generating data to inform policy, conservation and land management at local level.

Following the sensitization meetings, 19 citizen scientists, ∼3 participants per site (21% female and 79% male), were recruited from the local community based on their interest and willingness to participate and contribute to the monitoring program. Even though participation was open to all community members, several factors may have influenced the citizen's decision to participate in the project and this could explain why more men participated than women. The majority of the citizen scientists were between 25 and 34 years old (42.1%, $n = 8$) with 21.1% ($n = 4$) of the participants between 45 and 54 years. Respectively, 15.8% ($n = 3$) and 10.5% ($n = 2$) were above 55 years and below 24 years. 31.6% ($n = 6$) of the participants had primary education, 52.6%, ($n = 10$) had secondary level of education, and 15.8% ($n = 3$) were college educated (e.g., vocational training and University) (**Table 2**).

At each site, a 1-day training session was conducted during which the participants were informed about the research design, and trained on sample collection and measurement procedures,

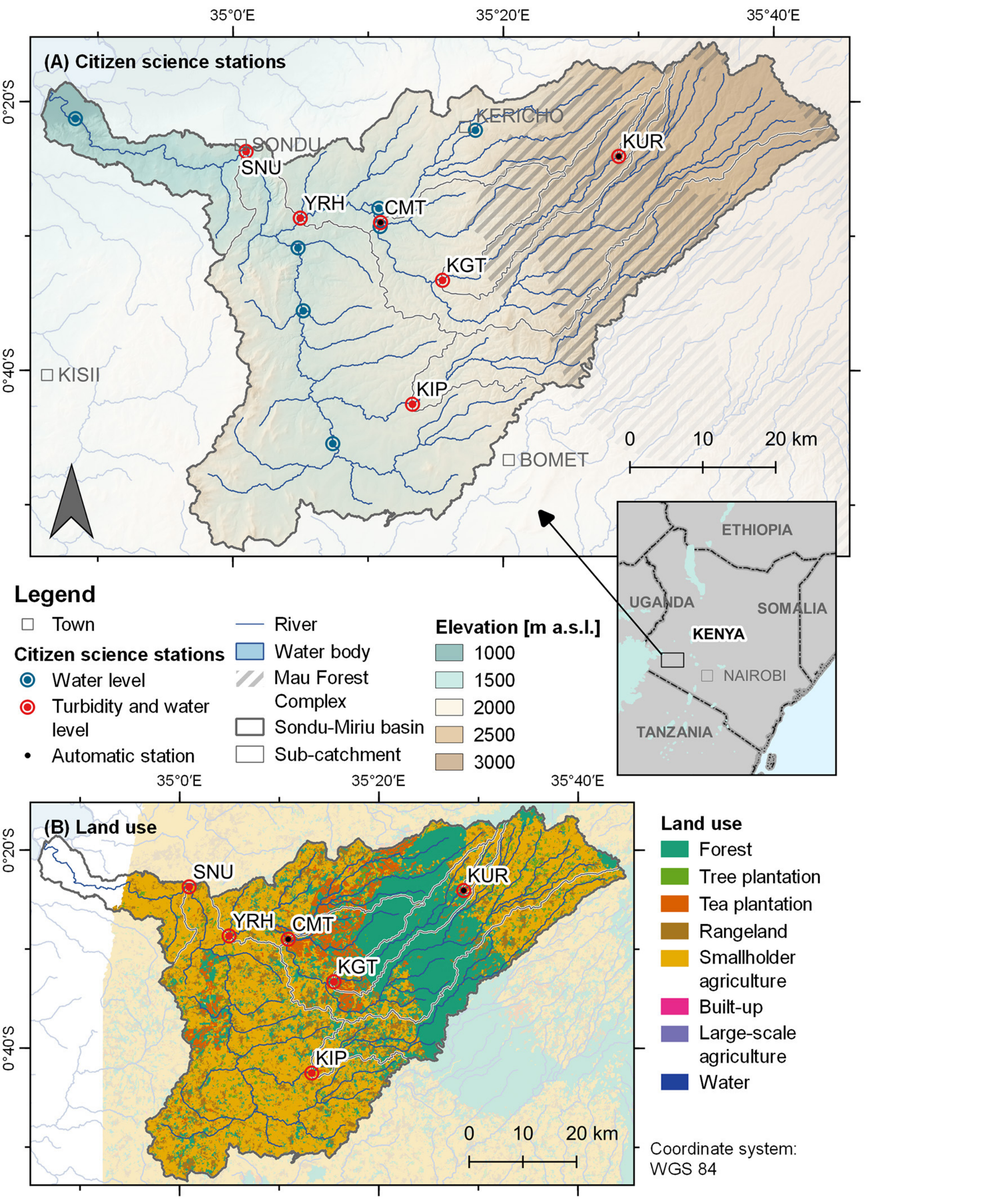


**FIGURE 1 |** Map of the study area showing **(A)** elevation (SRTM digital elevation model 30 m resolution; USGS, 2000), citizen science stations and automatic water monitoring network and **(B)** land use within the Sondu-Miriu River Basin.

data recording and submission Following training, multiple test measurements were made by the team of participants and compared to those taken by instructors. Each citizen scientist was equipped with a turbidity tube, water-sampling device, and an instruction manual in simple language. To avoid communication barriers the trainings were carried out in Swahili. Moreover, the measurement process was explained in the manual using pictures and instructions written in English as well as Swahili. Citizen scientists were encouraged to send water level and turbidity data at least twice per week. To encourage sustained engagement, we implemented a reimbursement of cell phone credit worth US$ 0.50 monthly (equivalent to 50 text messages) to the participants to compensate the costs incurred by sending the text message.

**TABLE 1 |** Catchment characteristics of the monitoring subcatchments in the Sondu-Miriu river basin, Kenya.

| Station name | Chemosit 1JB03 | Kipsonoi 1JF06 | Kiptiget 1JA02 | Kuresoi | Sondu 1JG05 | Yurith 1JD03 |
|---|---|---|---|---|---|---|
| Site-ID | CMT | KIP | KGT | KUR | SNU | YRH |
| Coordinates[a] | 0°28'59.628"S 35°10'52.956"E | 0°42'30.768"S 35°13'16.704"E | 0°33'17.358"S 35°15'29.820"E | 0°24'4.024"S 35°28'31.733"E | 0°23'42.426"S 35°0'57.540"E | 0° 45' 26.820" S 35° 7' 22.788" E |
| Area [km²] | 1,021 | 393 | 185 | 27 | 3,252 | 1,569 |
| Elevation range [m.a.s.l] | 1,721–2,932 | 1,841–2,934 | 1,890–2,692 | 2,389–2,692 | 1,504–2,932 | 1,632–2,932 |
| Mean slope [°] | 7.4 | 8.5 | 7.6 | 6.6 | 6.7 | 6.9 |
| Land uses[b] | Forest cover (51%), rangeland 8%), Smallholder agriculture (32%), tea plantation (7%), and tree plantation 2%) | Forest cover (47%), rangeland (14%), smallholder agriculture (37%), tea plantation (1%), and tree plantation (1.3%) | Forest cover 65%), rangeland 7%), smallholder agriculture (22%), tea plantation (4%), and tree plantation (1%) | Forest cover (16%), rangeland (15%), smallholder agriculture (64%), and tree plantation (4.4%) | Forest cover (36%), rangeland 13%), smallholder agriculture (45%), tea plantation 5%), and tree plantation (2%) | Forest cover (48%), rangeland (9%), smallholder agriculture (33%), tea plantation (8%), and tree plantation (2%) |
| Dominant soil types[c] | Humic Nitisols (68%) and Mollic Andosols (30%) | Humic Nitisols (47%) and Mollic Andosols (49%) | Humic Nitisols (100%) | Humic Nitisols (98%) | Humic Nitisols (46%), Eutric Planosols (12%), Rhodic Ferralsols (11%), and Vertic Luvisols (10%) | Humic Nitisols (99%) |

[a]*Coordinate system: WGS 1984.*
[b]*Swart (2016).*
[c]*KENSOTER Geology data from the Soil and Terrain database for Kenya (KENSOTER) version.*

**TABLE 2 |** Diversity in gender, age, education level, and distance to the monitoring station of the 19 trained citizen scientists.

| Variable | Category | % Citizen scientists |
|---|---|---|
| Gender | Male | 78.9% |
| | Female | 21.1% |
| Age | 24 or younger | 10.5% |
| | 25–34 | 42.1% |
| | 35–44 | 10.5% |
| | 45–54 | 21.1% |
| | 55 or older | 15.8% |
| Education Level | Primary school | 31.6% |
| | Secondary school | 52.6% |
| | College education | 15.8% |
| Distance to the station | <0.5 km | 42.1% |
| | 0.5–1 km | 36.8% |
| | 1–2 km | 5.3% |
| | >2 km | 15.8% |

## Field Data Acquisition and Transmission

Citizens measured turbidity using a modified Wagtech turbidity tube (Total Ex-Works Wagtech Projects, Thatcham UK). The viewing disk of the turbidity tube was modified to a yellow background colored with a black checker pattern to increase visibility. Turbidity was measured by filling the turbidity tube with river water, collected off the riverbank without disturbing the sediment, until the pattern on the disk fixed at the bottom of the tube was no longer visible when viewed from above. Turbidity was then estimated by reading the water level in the tube against the scale on the turbidity tube with values ranging from 5 to 500 TU (see details on calibration of turbidity tubes given below). In cases where the bottom was clearly visible when the turbidity was full, the turbidity reading was recorded as zero to indicate that the measurements were below the detection limit of the turbidity tube. Although Mitchell et al. (2007) advises to take the upper mark when the water level falls between two scale marks, this approach seems to underestimate suspended solid concentrations. Instead, we used a second commonly used approach which is to estimate a fractional value between the two scale marks, assuming a linear scale. In addition to turbidity, citizen scientists took water level data by reading the value from a water level gauge installed at the site.

After taking the measurements, the citizen scientists sent a text message containing the records and a site-specific ID using their mobile phones to the central database. The submitted data was then parsed by a script (using open source programming languages—Python and JavaScript) and interpreted to associate measurements with the specific monitoring station and parameter. Further information on data transmission and processing is detailed in Weeser et al. (2018). Additionally, the participants recorded data onto a standard form in the field. The data collection started in September 2017 and is still ongoing. For the present study we compiled and processed the dataset collected up to September 2019, covering a representative range of hydrological variations coinciding with seasonal changes in the Sondu-Miriu river basin.

## Analysis of Level of Engagement

To gain a deeper understanding of the citizen scientists' participation pattern over time we used several measures. These include counting the total valid data records of individual participants submitted over the monitoring period from

September 2017 to September 2019, analyzing the participation of each participant per site over time, classification of activity of participants, and computing the corresponding Gini coefficient using the approach frequently used to determine inequality of income (Atkinson, 1970). The latter approach has been applied in other citizen science projects to evaluate participants' contributions (Sauermann and Franzoni, 2015; Scott and Frost, 2017). A Gini coefficient is based on the Lorenz curve, which indicates the cumulative data contribution (y-axis) that is made by a cumulative share of participants (x-axis). A 45° line corresponds to total equality, i.e., all participants contribute the same amount of data. The Gini coefficient was then calculated as the ratio of the area between the 45° line and the Lorenz curve over the total area under the 45° line. A Gini coefficient of 0 expresses perfect equality, i.e., equal sampling among participants during the entire monitoring period, whereas a coefficient of 1 expresses maximal unequal sampling effort among participants (Atkinson, 1970).

To provide insight into individual's micro-level participation pattern, we categorized the degree of participation into very active, active, moderate, and less active participation, based on the frequency of participation over time and total data contributions. The very active participants are defined as those that sampled more intensively over a longer period (at least 20 months over a minimum of 25 consecutive months), characterized by more monthly contribution (at least 8 measurements per month) and a dataset exceeding 100 records. Active participants are those that contributed data consistently on multiple days in a month (at least four measurements per month) during the first 10 months after inception and characterized by a dataset ranging from 50 to 100 records. Moderately active participants are those that contributed data occasionally with few very active months (contributed at least 2–4 measurements in active months) and characterized by a dataset ranging from 20 to 50 records. Less active participants are those whose participation was infrequent (had not contributed data for over 12 months continuously after their initial month of participation) and of low intensity (contributed 1–2 measurements in active months), with a dataset of <20 records over the monitoring period.

## Calibration

Calibration of the turbidity tubes was conducted and a relationship between turbidity and suspended sediments concentrations (SSC) was established from all the datasets obtained from the six citizen science monitoring stations and two automated monitoring stations, respectively. This was achieved by preparing suspensions covering a range of suspended sediment concentrations using fine sediments collected from different locations in the riverbed at each sampling site. We took the site-specific samples to account for potential differences in the physical and geochemical characteristics of the catchment and have a reasonable representation of the sediment transported in the catchment. The fine sediment material collected was first sieved to remove gravel and particles larger than 0.5 mm. Then a suspension was prepared in a bucket using the fine sediment material and river water. Further separation was done after 100 s, corresponding to a theoretical grain size of >50 µm following Stoke's law (Equation 1) by decanting the suspension in another bucket. The decanted suspension was used for the calibration. The settling time was calculated using the equation:

$$t = \frac{\mathbf{18}\boldsymbol{\eta} h}{(\boldsymbol{\rho}_{\mathbf{s}} - \boldsymbol{\rho}_{\mathbf{l}})\, X^2 g} \tag{1}$$

Where $t$ is the settling time, $\eta$ is the fluid viscosity [kg/ms], $h$ is the settling depth [m], $\boldsymbol{\rho}_{\mathrm{l}}$ is the liquid density [kg/m$^3$], $\boldsymbol{\rho}_{\mathrm{s}}$ is the particle density [kg/m$^3$], $g$ is the acceleration due to gravity [m/s$^2$], and $X$ is the particle diameter [m].

To obtain the required range of turbidity and suspended sediment concentrations, dilutions were made from the main suspension using clear water. The unit scale of the turbidity tube ranging from 5 to 500 TU was used to guide the calibration process. For each stepwise dilution, the suspension was homogenized by stirring the suspension continuously to prevent settling of sediments, filled in the tubes and the tubes' turbidity was recorded. We then calibrated the suspension in two ways. In the first one, 250 mL of the suspension was taken for the analysis of the suspended sediment concentration (mg L$^{-1}$), which was determined gravimetrically, to determine the relationship between turbidity and SSC (Gray et al., 2000; Anderson and Davie, 2004). In a second approach, we measured the turbidity using the spectro::lyser installed at the two monitoring sites at KUR and CMT. The turbidity values recorded with the turbidity tube and spectro::lyser were calibrated against suspended sediment concentrations for each site using empirically derived linear regression models to allow for statistical prediction of these parameters.

## Data Validation

Two sites (KUR and CMT) were located next to automatic monitoring stations measuring turbidity in FTU (formazin turbidity unit) using a UV-Vis based sensor (spectro::lyser, SCAN Messtechnik, Vienna, Austria) and water level with a radar-based sensor (VEGAPULS WL61, VEGA Grieshaber KG, Schiltach, Germany) at 10-min interval. Stenfert Kroese et al. (2020a) provide a detailed description of the stations. Turbidity data from the sensors were calibrated following the same approach as described in Section Data Validation. These data were used to evaluate the accuracy of the citizen-science data using a linear regression model. For each data point in the citizen science dataset, the corresponding measurement at the same day and time (±10 min) was obtained from the automated stations. Following the assumption that citizen scientists would not measure after sunset, measurements received by the SMS server past 6 pm were omitted to control sources of variability between the actual time the measurement was taken and when it was submitted, as this may account for differences when comparing the two datasets. Additionally, measurements which were taken at the same time by different participants but did not match or those that did not have a valid measurement from the automated station were excluded.

## Quality Control and Assurance

Our study adopted multiple quality control measures to ensure the production of valid data that can yield both scientific and educational outcomes as proposed by (Wiggins et al., 2011). This involved developing simple and standardized data collection protocols and monitoring tools (manual containing instructions and water sampling equipment) that were essential for the process. Further, we trained the participants before embarking on the monitoring program and tracked their performance through follow-up meetings once per month. Additional quality control measures include replication through multiple measurements by the same participant and by having 3 or 4 participants per site to reduce sampling error and bias, submission of data to the central database along with field data sheets for verification, as well as manual screening and identification of outliers in the dataset. Furthermore, the citizen science generated data was compared and validated with the data recorded by the spectro::lyser sensor of the automated stations.

Due to the low number of cases of data replication, we filtered outliers by visually inspecting of the time series data and removed spurious data points. From over 1,300 measurements, 80 (6%) measurements contained invalid data and were not included for further analysis. The invalid data were due errors associated with typing, omitting of site-ID or sending the measurement to a wrong code e.g., submitting water level data using the code for turbidity.

## Statistical Analyses

The suspended sediment concentrations were tested for normality using Q-Q plots and the Shapiro-Wilk test ($P < 0.05$) which revealed non-normal distribution of data. Therefore, all tests used in this study are non-parametric. To test for significant differences in the suspended sediment concentrations among different sites, the Mann-Whitney $U$ test was used at $P < 0.05$. Spearman's correlation coefficients were calculated to identify the strength and direction of significant relationships ($P < 0.05$) between SSC concentrations and explanatory variables.

# RESULTS AND DISCUSSION

## Relationship Between Turbidity and Suspended Sediment Concentration

To visualize the relationship between suspended sediment concentrations and the measured turbidity values from both turbidity tubes and automated stations measurements, the calibration dataset was pooled to obtain one rating curve for the turbidity tube and one for the automated stations. In the view of the potential loss of information through pooling of the data from the six subcatchments, we further compared the resulting regression statistics and found no significant difference between the slopes for each site-specific calibration ($P > 0.1$). Pooling data allows to establish one common calibration which can be used in case turbidity tubes are used in additional so far not measured subcatchments. The relationship between turbidity and suspended sediment concentrations showed a strong linearity (**Figure 2**). The strong relationship indicates a high predictability of SSC from turbidity tube readings and automated stations. Studies conducted to evaluate the use of turbidity tubes to predict total suspended solids concentrations in streams in northeast Ohio revealed also a highly predictive correlation ($R^2 = 0.896$) (Anderson and Davie, 2004). Similarly, Stenfert Kroese et al. (2020a) reported a strong correlation between turbidity readings (FTU) and suspended sediment concentrations for the automated stations used in this study ($R^2 = 0.98$).

## Validation of Citizen Science Data

A comparison between citizen scientist collected data and measurements obtained with automated stations at KUR and CMT showed high correlation of 0.95 and 0.94, with a root mean square error (RMSE) of 40.2 and 33.1 mg $L^{-1}$, respectively (**Figure 3**). However, citizen scientists measurements at KUR tended to deviate from the 1:1 slope to a great extent and the suspended sediment concentration was found to be more likely to be underestimated at higher concentrations ($>50$ mg $L^{-1}$, $P < 0.05$), a bias observed in other citizen science datasets as well (Ho et al., 2020). For data comparability and quality between participants, the relative difference between suspended sediment data collected with the turbidity tubes by the two most active participants per site and the data measured by the automated station was calculated (**Figure 4**). The results show that the citizen scientists at KUR underestimated SSC by ∼30% and generally overestimated low SSC values at CMT, but there was no significant difference in measurements between the participants ($P > 0.05$). Other studies suggest that turbidity tube readings can over- or underestimate actual turbidity values for particular locations due to site-specific characteristics such as particle size, composition of particulate matter, lighting conditions and error between different observers (Dorea and Simpson, 2011; Rügner et al., 2013; Scott and Frost, 2017). We found no significant difference between the citizen scientists' data and automated stations data at CMT ($P > 0.05$), indicating consistency in suspended sediment concentrations between the two methods. Scott and Frost (2017) reported a good relationship between turbidity measurements taken by volunteers using turbidity tubes and lab measurements of total suspended solids ($R^2 = 0.68$). This is an indication that measurements taken by citizen scientists using turbidity tubes can provide useful information on the concentration of suspended sediments in rivers in the Sondu-Miriu catchment, as found elsewhere (Anderson and Davie, 2004).

Our results indicate that the lower detection limit for SSC under field conditions for our turbidity tubes is about 25 mg $L^{-1}$. Anderson and Davie (2004) reported that an accurate estimation of SSC in the lower ranges (10–20 mg $L^{-1}$) is more difficult due to low repeatability owing to the detection limits of the turbidity tubes. Also, the scale on the turbidity tube, especially for larger values, is so rough that some detail is lost at this range. A similar observation was reported by the Forest Water Watch project in Toronto, Canada (Scott and Frost, 2017). Additionally, only very few SSC values >200 mg $L^{-1}$ were recorded by the citizen scientists, thus failing to capture major sediment export events, a sampling bias frequently reported with citizen science approaches (Thornhill et al., 2016;

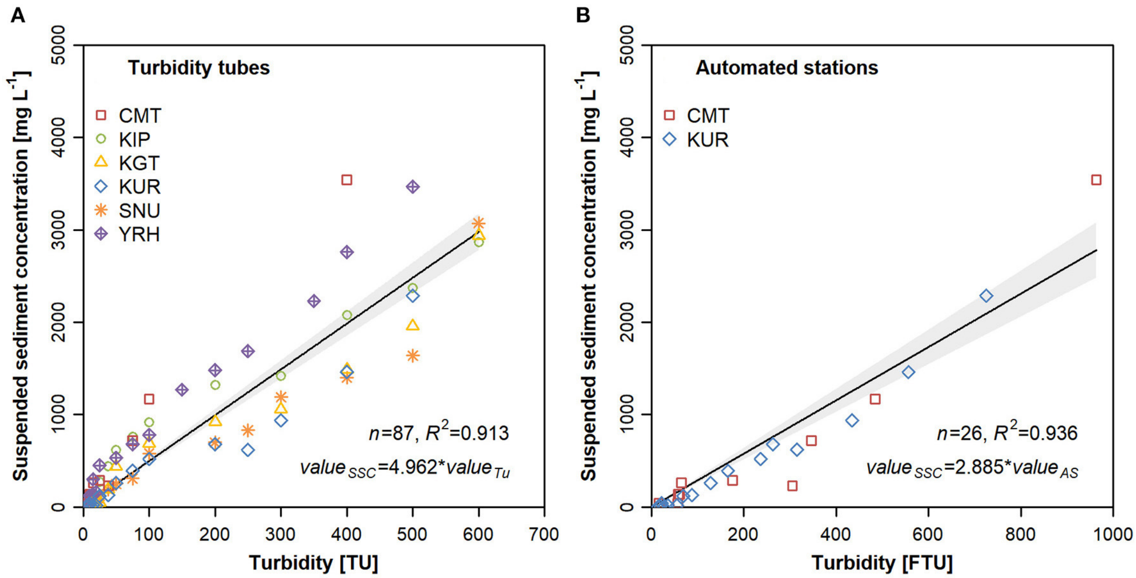


**FIGURE 2 |** Relationship between suspended sediment concentrations (SSC) (mg $L^{-1}$) and turbidity measurements using **(A)** turbidity tubes (Tu) at the six monitoring sites and **(B)** automated station (AS) at two monitoring sites (KUR and CMT) in the Sondu-Miriu river basin, Kenya.

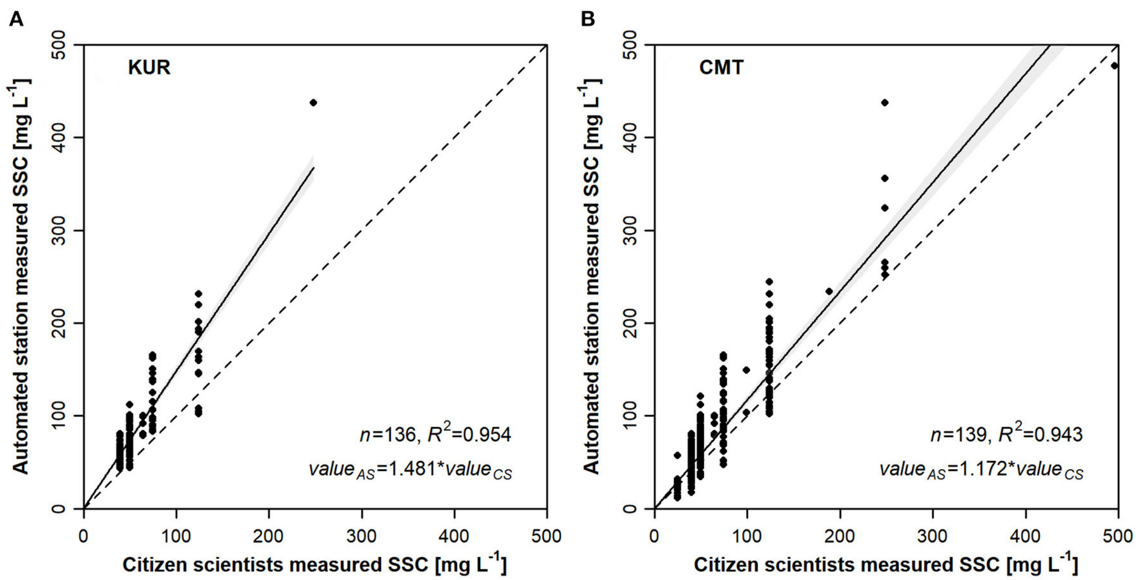


**FIGURE 3 |** Comparison of the suspended sediment concentration (mg $L^{-1}$) calculated based on calibrated turbidity measurements collected by citizen scientist and automated stations between September 2017 and September 2019 for **(A)** KUR and **(B)** CMT in the Sondu-Miriu river basin, Kenya. The dashed line represents the 1:1 relationship.

Miguel-Chinchilla et al., 2019). We attribute this to individual preferences of citizen scientist as high SSCs are likely correlated with increased water levels, rainfall and "bad weather." It is very likely that citizens simply avoid sampling under these conditions. This could have resulted in the underestimation of SSC from each of the monitored subcatchment by an unknown proportion (Ziegler et al., 2014; Dutton et al., 2018).

Rapid developments in technology and rise of low-cost robust sensors with improved detection limits and resolution could be suitable for citizen science studies to complement already existing crowdsourcing efforts (Buytaert et al., 2014; Scott and Frost, 2017). Recently, an improved quantification of both turbidity and concentration of suspended particular matter by use of smartphone applications such as HydroColor has been

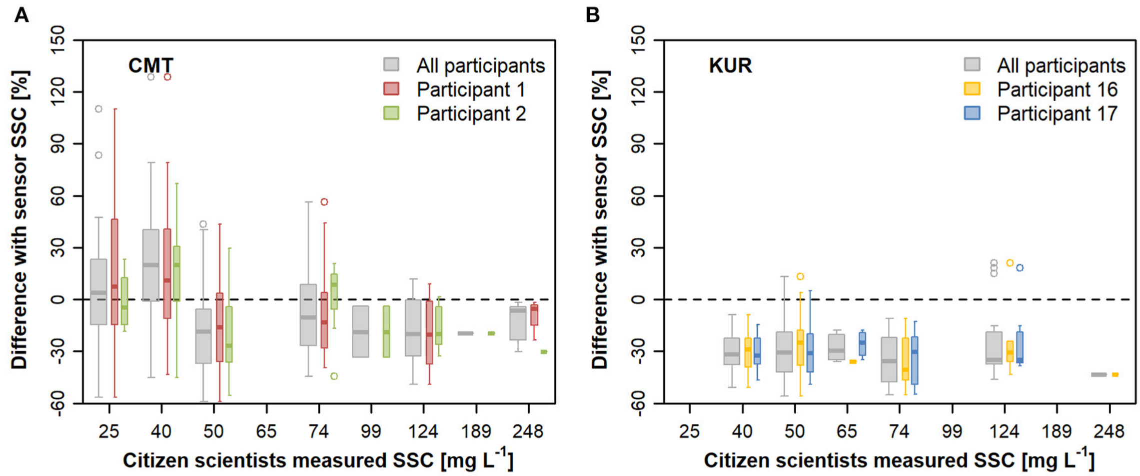


**FIGURE 4 |** Relative difference between citizen scientists measured SSC (mg $L^{-1}$) using turbidity tubes and the SSC (mg $L^{-1}$) obtained from turbidity data recorded by an *in situ* UV-Vis sensor at the corresponding automated station for **(A)** CMT and **(B)** KUR. The gray boxplots show the relative difference for all participants at a given site. Participant number corresponds to the participant ID shown in **Figure 6**.

successfully tested in Australia and USA to monitor inland waters (Leeuw and Boss, 2018; Malthus et al., 2020) and in Myanmar to monitor Ayeyarwady river (Thatoe Nwe Win et al., 2019). Other studies have demonstrated working methods using digital cameras in Wisconsin for water quality mapping (Compas and Wade, 2018).

## Participation Rate

Sustained engagement and generating the required participation levels in citizen science are of primary importance in contributing to data quality and should therefore be carefully considered (Scott and Frost, 2017; Moor et al., 2019; Serret et al., 2019). To evaluate this, we used data on the participation of the citizen scientists from the six monitoring sites. We noticed that the number of participants, of which 19 participated in 1-day training meetings held at the monitoring sites, increased to 37 during the project. Unlike the original 19 participants, these 18 "new" citizen scientists were not followed up intensively during the project. We assume that some of the 18 "new" participants borrowed the tubes and received training from the original participants during their weekly sampling and contributed to the dataset out of intrinsic motivation. This is consistent with other research that reported on citizen science behaviors as a potential avenue for recruiting new members to the program and diffusion of knowledge, for example the Wabash Blitz volunteer experience (Church et al., 2019). Alternatively, the original participants changed their cellphone numbers during the monitoring period and were consequently considered as "new" participants. However, since none of the "new" participants showed a sudden and strong activity in the middle or toward the end of the study period, it is unlikely that such cases occurred as the trained participants consistently contributed most of the data each month. Additionally, there are those participants who contributed data occasionally during the training, and/or monthly sensitization meetings.

The sampling effort and data contribution varied over time with noticeable spikes (Sauermann and Franzoni, 2015). **Figure 5A** reveals that the highest level of participation was recorded during early stages of the project with October 2017 having the highest number of measurements ($n = 101$) followed by a decline in the subsequent months. This could be attributed to the initial novelty when the project activity started and the motivation of the community to learn a new skill (Raddick et al., 2009; Rotman et al., 2012). The monthly spikes can be explained by subsequent growing interest among participants as they became more experienced in the monitoring, new participants who joined later in the project phase or by monthly sensitization meetings undertaken by the project to encourage engagement. All of the participants at sites KUR, CMT and KIP that contributed large numbers of readings lived within 1 km distance from the monitoring station and visited the river more often as they depend on river water for domestic use (**Table 3**). In contrast, reduced motivation over time due to limited ease of access and proximity to monitoring stations could be associated to the low participation rate thus a smaller amount of data at sites SNU, and YRH where 4 out of 6 of the participants lived more than 2 km away. Besides, one of the participants at SNU mentioned that monitoring water level was easy as the staff gauges alongside signboards were installed at designated gauging station, whereas the water quality measurements required bringing own equipment to the site. A reducing interest in long-term citizen science based research is a typical pattern found in other projects as well. Volunteer Lake Monitors in Minnesota and Alabama Water Watch programs reported an overall increase in number of dropouts after the 1–3 years of the monitoring program (Klang and Heiskary, 2000; Deutsch and Ruiz-Córdova, 2015). Notwithstanding, the

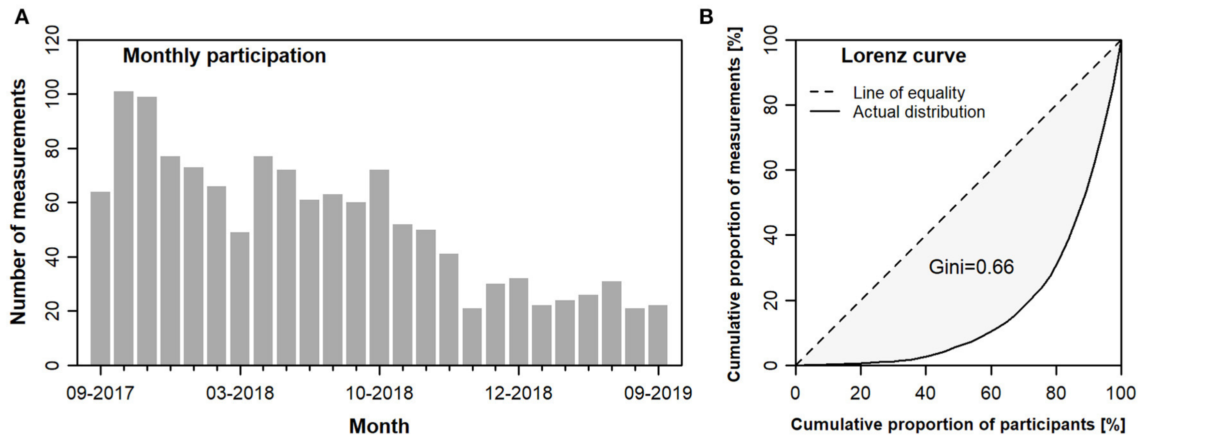


**FIGURE 5 |** Participation of citizen scientists in data collection and cumulative for the monitoring period from September 2017 to September 2019 in the Sondu basin, Kenya: **(A)** total number of measurements per month **(B)** Lorenz curve representing inequality in data collection by all participants.

**TABLE 3 |** Demographics of the 19 trained citizen scientists in relation to the level of engagement based on the total number of valid measurements contributed over the entire monitoring period between September 2017 to September 2019 (Very active: >100, active: 50–100, moderately active: 20–50, less active: <20).

| Variable | Category | Level of engagement | | | |
|---|---|---|---|---|---|
| | | Very active | Active | Moderately active | Less active |
| Gender | Male | 10.5% ($n = 2$) | 21.1% ($n = 4$) | 26.3% ($n = 5$) | 21.1% ($n = 4$) |
| | Female | 10.5% ($n = 2$) | | 5.2% ($n = 1$) | 5.2% ($n = 1$) |
| Age | 24 or younger | | | 10.5% ($n = 2$) | |
| | 25–34 | 15.8% ($n = 3$) | 10.5% ($n = 2$) | 5.2% ($n = 1$) | 10.5% ($n = 2$) |
| | 35–44 | | | 5.2% ($n = 1$) | 5.2% ($n = 1$) |
| | 45–54 | | 5.2% ($n = 1$) | 10.5% ($n = 2$) | 5.2% ($n = 1$) |
| | 55 or older | 5.2% ($n = 1$) | 5.2% ($n = 1$) | | 5.2% ($n = 1$) |
| Education level | Primary school | 15.8% ($n = 3$) | 5.2% ($n = 1$) | 5.2% ($n = 1$) | 5.2% ($n = 1$) |
| | Secondary school | 5.2% ($n = 1$) | 10.5% ($n =2$) | 26.3% ($n = 5$) | 10.5% ($n = 2$) |
| | College education | | 5.2% ($n = 1$) | | 10.5 % ($n = 2$) |
| Distance to station | <0.5 km | 10.5% ($n = 2$) | 10.5% ($n =2$) | 1 0.5% ($n = 2$) | 10.5% ($n = 2$) |
| | 0.5–1 km | 10.5% ($n = 2$) | 5.2% ($n = 1$) | 10.5% ($n = 2$) | 10.5% ($n = 2$) |
| | 1–2 km | | | 5.2% ($n = 1$) | |
| | >2 km | | 5.2% ($n = 1$) | 5.2% ($n = 1$) | 5.2% ($n = 1$) |

last phase of the project was characterized by a more stable monitoring effort as compared to other phases with an average rate data contribution of 25 measurements per month over all the sites.

As noted by Wilkinson (2008), participation follows a power law of distribution in which a small number of very active participants account for most of the activity. This is reflected in the Gini coefficient of 0.66 (**Figure 5B**). While still being relatively high and indicating the dominance of a few participants providing most of the data, our Gini coefficient is somewhat lower than those reported for other projects such as the Toronto Forest Water Watch project and Zooinverse with Gini coefficients of 0.84 and 0.85, respectively (Sauermann and Franzoni, 2015; Scott and Frost, 2017). Analyzing individual-level total data contribution, we find that the very active participants (11%, $n = 4$) and active participants (11%, $n = 4$) contributed 72% of the data. The remaining data were collected by moderately active members (19%, $n = 7$), and less active participants (59%, $n = 22$), most of whom we presume belong to the group of new participants. Of all the participants, four (11%) contributed data consistently for the entire monitoring period (25 months), indicating a long term-commitment from participants residing near to the monitoring locations. 35% ($n = 13$) of the participants dropped out of the program after 1–2 months of monitoring, while 30% of the participants monitored for a period of 11–25 months (**Figure 6**). The greatest proportion of participants with the highest level of engagement were between 25 and 34 years with primary education, even though most of the citizen scientists had secondary school education (**Table 3**). The findings resonates with other studies that observed a similar pattern in which younger (<35 years) and lower educated people showed active participation and long-term commitment

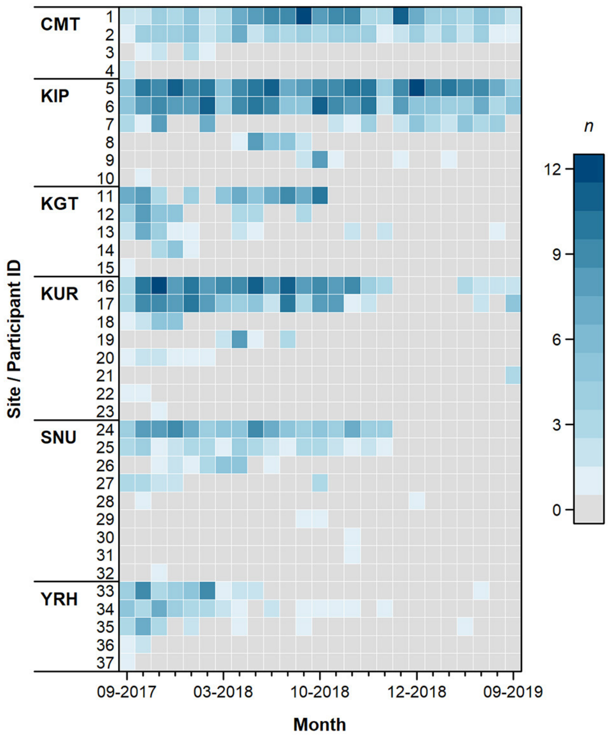


**FIGURE 6 |** Temporal distribution of data collected by all participants at all the monitoring sites for the monitoring period from September 2017 to September 2019. Level of engagement is based on the number of measurements (*n*) contributed per month.

in citizen science projects (Brouwer and Hessels, 2019; Weeser et al., 2021). Nevertheless, even occasional participants can successfully contribute to the monitoring program as most contributions in citizen science are attained by returning participation (Sauermann and Franzoni, 2015).

## Method of Engagement

In addition to generating relevant research data and increasing scientific knowledge, designing, and building a citizen science project requires the consideration of social aspects to sustain user motivation and achieve project goals (Shirk et al., 2012; Domroese and Johnson, 2017). The decline in participation rate and drop out of citizen scientists in the study could have been contributed by the cost of 0.01 USD involved in the transmission of data (Weeser et al., 2021). Additionally, a delay in the reimbursement of credit after submission of data, as this was done at the end of the month, could have demotivated participants thus resulting in declining participation (Wald et al., 2016). Other studies have identified financial incentives as a significant barrier for participation in developing countries where citizen scientists expect to derive income from their engagement (Hobbs and White, 2012; Buytaert et al., 2014). Another challenge in engaging long-term participation could be attributed to the disconnect between the projects objectives and needs of the community as well as interests of the participating group (Wald et al., 2016; Church et al., 2019). According to Golumbic et al. (2020), identifying and addressing a community need can ease the challenging process of participant retention and support sustained engagement.

To minimize barriers for participation we kept the method of sending data as simple as possible. As mobile phone coverage and usage become a more established method of communication in East Africa (Krell et al., 2020), we chose the text message service since it is easy to use, user-friendly, stable, and inexpensive (Weeser et al., 2018). Delivery of feedback is a fundamental element of a successful citizen science program (Brouwer et al., 2018). In this study we incorporated an automated feedback built into the central server to provide an immediate feedback to the citizen scientists and appreciation message of "Thank you" based on the participant's measurements. Such an engagement strategy has a positive influence that could keep the citizen scientists motivated as it acknowlegdes their contribution and indicates the level of activity (Lowry and Fienen, 2013; Weeser et al., 2018). Additionally, two meetings at two sites (KUR and SNU) were organized to communicate preliminary results to the citizen scientists and to other local community members. This provided a platform for interactive feedback between the researchers, citizen scientists and community members after which some participants would be motivated and encouraged to continue sending data. Majority of the volunteers who participated in the water level monitoring program in the same catchment reported that such meetings were powerful means to reach out to the community and engage motivated volunteers (Weeser et al., 2021). Furthermore, visualization and communication of results through meetings or other virtual platforms such as web-based technologies could incentivise citizen scientists for further engagement as they can directly gain from participation (Buytaert et al., 2014; Golumbic et al., 2020).

## Spatial and Temporal Trends of Suspended Sediment Concentrations

Suspended sediment concentrations in the Sondu-Miriu river basin ranged from 25 to 496 mg $L^{-1}$ with an average of 75 $\pm$ 56 mg $L^{-1}$. The data revealed significant differences among sites ($P < 0.05$). The suspended sediment concentrations were significantly higher at SNU than at all other sites (109 $\pm$ 94 mg $L^{-1}$) while KGT had the lowest SSC (50 $\pm$ 25 mg $L^{-1}$), ($P < 0.05$) (**Figure 7**). The proportion of smallholder agriculture ($r = 0.11$) and catchment area ($r = 0.17$) were positively but weakly correlated with SSC concentrations ($P < 0.05$). There is a large body of literature that shows a tight relationship between land use and erosion rates. Particularly, agriculture is associated with increased erosion rate due to arable practices, loss of soil structure and reduced forest cover (Ou et al., 2016; Poudel, 2016; Tanaka et al., 2016), that limit infiltration rates and soil hydraulic conductivity properties in the catchment (Nadal-Romero et al., 2018; Owuor et al., 2018). Earlier studies in the neighboring Mara river basin found that unregulated livestock grazing and agricultural land conversion may have increased erosion and contributed to the higher than expected sediment yields from the catchment (Dutton et al., 2018). Stenfert Kroese

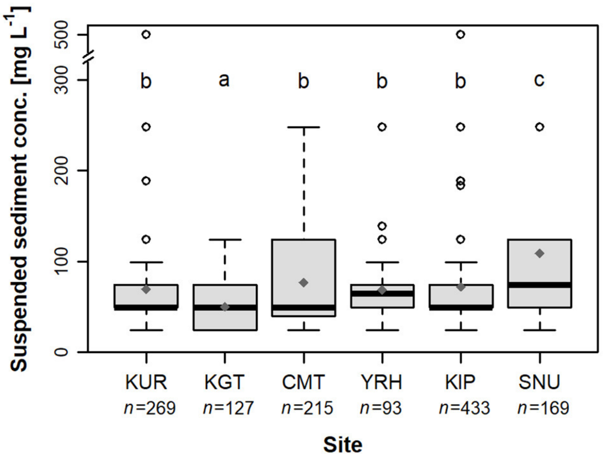


**FIGURE 7 |** Variation in suspended sediment concentrations across the monitoring sites for the sampling period September 2017 to September 2019. The lower and upper lines of the boxplots correspond to the 1st and 3rd quantile ($Q_1$ and $Q_3$), respectively, while the solid horizontal line inside the box represents the median value ($Q_2$). The lower and upper whiskers show the minimum and maximum values within 1.5 times the interquartile range, while the circle markers represent extreme values outside of that range. Significant differences among sites are indicated with different letters ($P < 0.05$).

et al. (2020a) observed that agriculture and unpaved tracks, which are pathways for people and livestock to the streams, in a smallholder catchment in the Sondu-Miriu river basin could be another driving force for the total sediment load into rivers, due to more overland flow. The presence of intact riparian zones, characterized by mixed dense indigenous vegetation, and commercial tea plantation and forest plantation practices around KGT may explain the low suspended sediment concentrations. In contrast, the longitudinal quality of the riparian zone at SNU is degraded with limited ground cover and disturbed banks due to cultivation of crops and plantation of woodlots with exotic tree species. Forests and riparian buffer zones can act as a filter, controlling and decreasing the sediment load by surface runoff (Mello et al., 2018). Similar effects were reported in previous studies that found forested watersheds to have lower suspended sediment concentrations as compared to agricultural landscapes (Tu, 2013; Zhang et al., 2017; Mello et al., 2018; Stenfert Kroese et al., 2020a). Contrasting the effect of land use, we have no clear explanation for the positive correlation with catchment size. Even though increasing catchment area is correlated with larger suspended sediment loads (Göransson et al., 2013; López-Tarazón and Estrany, 2017), we would have expected higher SSC with smaller catchment size, due to higher stream velocities, as well as larger variability and extremes of discharge.

Visual assessment of the hydrological time series data shows seasonal variability in both suspended sediment concentration and water level (**Figure 8**). YRH was omitted from the analysis as it had a short time series because the installation of water level gauge and monitoring of the water level started later in March 2018. The time series of citizen science generated water level and SSC data at sites KUR and CMT show similar trends with the data from the automated station in relation to high and low flow conditions (**Figures 8A,C**). Nevertheless, the citizen scientists did not manage to capture the same degree of variability in SSC concentrations, especially during the rainy season. Peak SSC concentrations were reached in early to mid-rainy season (in the months of April-July for long rains and September to October for short rains), in some instances prior to peak flow, and decreased in the transition from rainy to dry season (in the months of December-March). The higher concentrations of suspended sediments during the rainy season and the lower concentrations in the dry season in this study are consistent with other rivers studied in the Mau Forest Complex (Dutton et al., 2018; Stenfert Kroese et al., 2020a). Also notable are the considerable high SSC even in times when flows were consistently lower in March and May 2019 at site CMT and KIP. This could be due to the time lapse between the rains and their respective effect on the concentration and water level (Göransson et al., 2013). Other studies have reported similar results showing that the SSC did not necessarily change with discharge values which is an indication that other factors besides rainfall such as natural and anthropogenic disturbances control the SSC in small catchments (Ouellet-Proulx et al., 2016; Rodríguez-Blanco et al., 2018). Stenfert Kroese et al. (2020a), in a study in the same catchment, reported that the impulse response between the peaks of discharge and sediment concentration was in general longer compared to the rainfall peak.

Overall, citizen science project in Kenya indicate a promising new approach for recording water quality data in a remote tropical environment. The study also reveals that, when appropriately used, turbidity tubes can be an effective and inexpensive monitoring tool to estimate relative sediment concentrations from different catchments. The total cost for setting up and operating the entire citizen science based network for 1 year cost ∼\$10,000 (including cost for the purchasing of sampling materials, meetings and on-site visits, and maintenance of the data server). In contrast, setting up an automated station at one site cost ∼\$50,000, which is much more expensive as compared to operating a citizen-science approach. Furthermore, extra costs incur annually for security and regular maintenance of automated stations, despite of malfunctioning of sophisticated analytical instruments due to harsh environmental conditions in tropical ecosystems.

## CONCLUSION

This study evaluated the potential of citizen science to monitor suspended sediment concentrations in a remote tropical river basin using turbidity measured with turbidity tubes as a proxy. The citizen science generated data showed a good relationship with the automated measurements of suspended sediment concentrations, which reveals that turbidity tubes can be an effective and inexpensive tool to estimate relative differences in suspended sediment concentrations between catchments with contrasting conditions. This is at least the case under low to moderate water levels. Limitations such as sampling biases attributed to underestimation and the precision of measurements

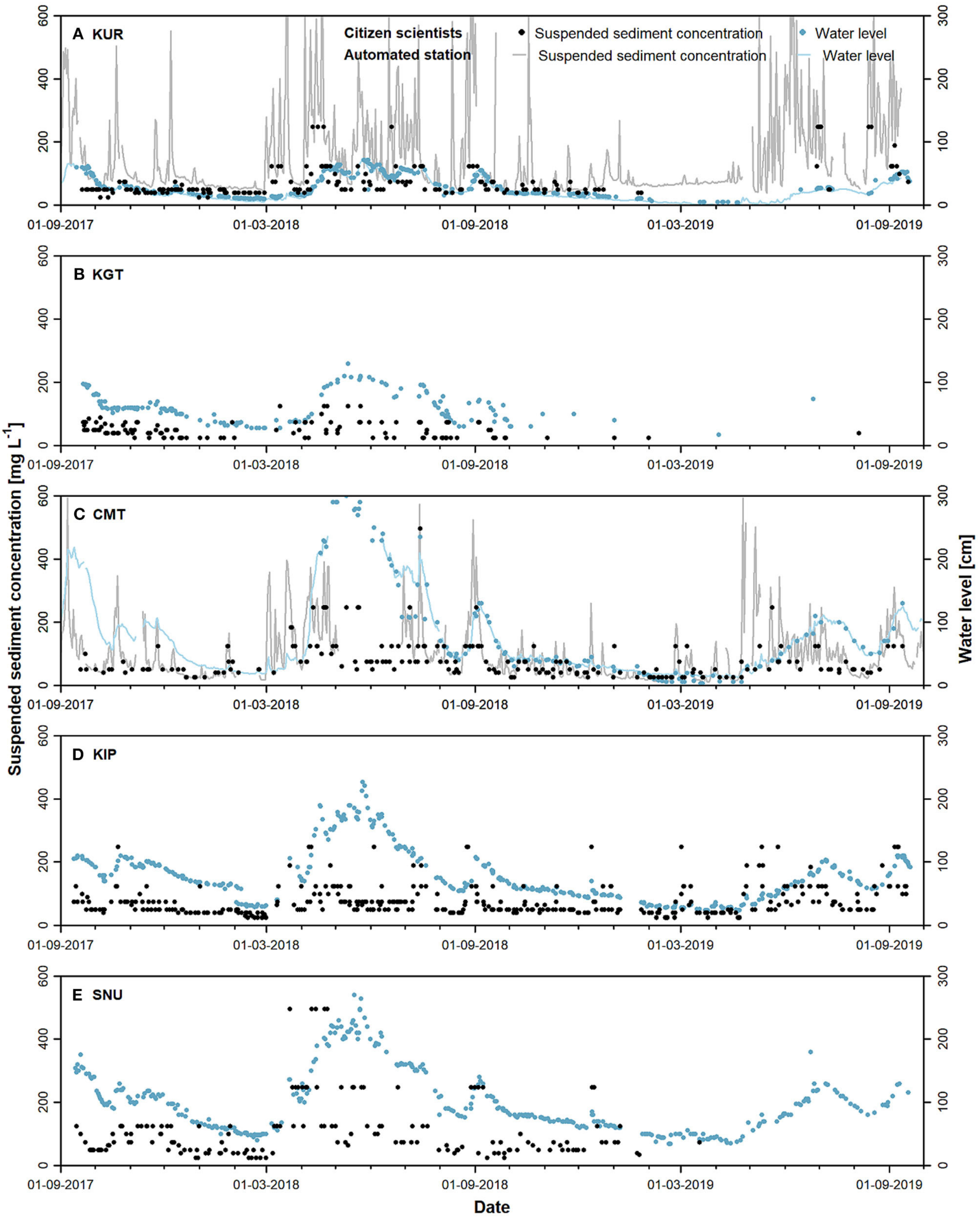


**FIGURE 8 |** Time series of suspended sediment concentration and observed water level transmitted by citizen scientists at five sites and measured by automated stations at sites KUR and CMT in the Sondu-Miriu river basin over the monitoring period between September 2017 to September 2019: **(A)** KUR, **(B)** KGT, **(C)** CMT, **(D)** KIP, **(E)** SNU.

due to low repeatability owing to the detection limits of the turbidity tubes were observed. Notwithstanding, understanding the error and bias associated with citizen science generated data in estimating suspended sediments, the data can be used to provide baseline information on concentrations and support implementation of catchment and land use best management practices. Where the purpose of the data is to calculate sediment yields, further investigation through extensive sampling and increased spatial and temporal resolution is recommended. The possibilities of sampling even extreme events might be even more difficult. On the one hand, because it is difficult to take representative water samples from the middle of stream where sediment loads are likely highest and, on the other hand, because the willingness of the citizens to voluntarily work outside under extreme weather conditions is low.

Despite the limitations of the data collected with the turbidity tubes, the data provide good insights of the spatial and temporal dynamics of sediment concentrations in the Sondu-Miriu river basin. Our findings highlight the forest cover as a key landscape feature as low levels of suspended sediment concentrations were recorded in areas with high forest cover. In contrast, suspended sediment concentrations in the downstream subcatchment dominated with agriculture and rangeland was significantly higher as compared to other subcatchments upstream, indicative of the impacted state of the river ecosystems in the Sondu-Miriu river basin.

Prospective future works should consider employing smartphone applications and robust sensors with improved detection limits and resolution that are suitable for citizen science studies in order to increase the precision of concentration measurements, allow for higher sampling rates and less subjective readings. We particularly see an advantage of those systems that will allow contact-free, remote measurements of the river through taking pictures or video-taping from remote places such as a bridge.

Finally, long-term participation of citizen scientist remains a challenge. While the participation and sampling equality rates were comparable to other citizen science projects, only 11% of the participants remained engaged for the full monitoring period, an indication of a high dropout rate. However, both long-term and short-term monitoring efforts from the participants can increase the spatial and temporal coverage of the overall dataset. Increased collaboration between researchers and the citizen scientists through interactive feedback and communication strategies could be an incentive to promote sustained participation. This study emphasizes the need for further empirical research on the social processes within the context of citizen science in low-income regions to understand in depth the motivations and engagement dynamics to minimize barriers and improve overall participation.

Overall, the results indicate that citizen science is no panacea but is a promising new cost effective approach that affords a unique opportunity for monitoring hydrological and water quality data in a remote tropical montane rainforest environment.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

## AUTHOR CONTRIBUTIONS

NN, JG, LB, BW, SJ, and MR designed the study. NN, JG, and BW implemented the study. NN analyzed the data and drafted the manuscript. SJ, BW, MR, and LB reviewed and edited the manuscript. All co-authors read the manuscript.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frwa.2021.656770/full#supplementary-material

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METHODS
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# Using Sapelli in the Field: Methods and Data for an Inclusive Citizen Science

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The Sapelli smartphone application aims to support any community to engage in citizen science activities to address local concerns and needs. However, Sapelli was designed and developed not as a piece of technology without a context, but as the technical part of a socio-technical approach to establish a participatory science process. This paper provides the methodological framework for implementing and using Sapelli in the field. Specifically, we present the role of Sapelli within the framework of an "Extreme Citizen Science" (ECS) methodology that is based on participatory design. This approach enables Sapelli's users to decide, with the help of professional scientists, which challenges they wish to address, what data to collect, how best to collect and analyse it, and how to use it to address the problems identified. The process depends on the consent of participants and that the project is shaped by their decisions. We argue that leaving ample space for co-design, local leadership and keeping Sapelli deployment open-ended is crucial to give all people, and in particular non-literate people who we have found are often the most ecologically literate, access to the power of the scientific process to document and represent their concerns to outsiders in a way that all can understand, and to develop advocacy strategies that address the problems they identify.

**Keywords: citizen science (CS), Extreme Citizen Science, participatory design, Sapelli, non-literate people, indigenous communities**

## INTRODUCTION

The current era is marked by multiple social and environmental challenges that human society must resolve if it wishes to ensure a sustainable and prosperous future (Ehrlich and Ehrlich, 2013). Challenges of ecological degradation, mass extinction, over-consumption of natural resources, and climate change require coordinated action across society, something that is well recognised in reports such as the Global Environment Outlook 6 (Ekins et al., 2019). Environmental problems require scientific data collection, as well as multi- and inter-disciplinary collaboration to explore and effectively address them. However, the collection of these data relies on the availability of methodologies to engage a wide range of stakeholders to conduct scientific activities. Citizen science, or the meaningful participation of the general public in appropriate elements of a research project, such as in the design of a project, or in collecting and analysing data, or in acting on the results, is recognised as key to addressing the scale of these environmental challenges (Ehrlich and Ehrlich, 2013; Daguitan et al., 2019).

Citizen science can be used to address societal problems and explore fundamental scientific questions at the same time. This global approach promises to bridge the gap between professional researchers and interested members of the public by generating information and knowledge from multiple perspectives (Parlee et al., 2005; Pulsifer et al., 2012; Johnson et al., 2015). To fully achieve its potential, citizen science needs to recognise that scientific insight and discovery can emerge anywhere, regardless of the topic, and be produced by anybody (Liebenberg et al., 2017). While citizen science may encompass a wide range of activities, from data collection to data analysis (Bonney et al., 2009; Shirk et al., 2012; Haklay et al., 2018), this paper focuses on the methodology of "Extreme Citizen Science" (ECS) that specifically seeks to make scientific tools and methods available to anyone. ECS proposes that all people, regardless of literacy levels, should be able to benefit from the scientific process, from the definition of local problems and collaboration in data collection, to the use of the results to address and resolve issues identified by the communities themselves. This methodology has been developed iteratively during 15 years of work begun by Lewis in Congo-Brazzaville in 2005 and further developed and refined by the ECS research group since 2010 mostly working with hunter-gatherer and other rural communities in Central Africa on environmental justice issues identified by local participants (Lewis, 2007, 2012b; Lewis and Nkuintchu, 2012), but now expanded to work in over 20 projects with communities in twelve countries: Congo-Brazzaville, Cameroon, Central African Republic, DR Congo, Ethiopia, Ghana, Kenya, Namibia, Nigeria, Zambia, Brazil and Cambodia (see https://uclexcites.blog/; Skarlatidou and Haklay, 2021 for details).

In contrast with the traditional projects of citizen science, the professional scientists of ECS work to support others instead of focussing on their own projects. Characteristically in citizen science projects, scientists set the research question and then enlist the public to carry out data collection or basic analytical tasks, but in the context of identifying environmental justice issues that are impacting ecosystems and local livelihoods in remote locations, local communities often have the greatest insights. That is why ECS scientists begin by asking community members how they understand the issues they face. As a consequence, we recognize the importance of ensuring that participants from the indigenous groups and other local communities with whom we collaborate retain full control of the data that they facilitate collecting (Johnson et al., 2021). Given the dependence of these communities on local ecosystems for their culture and livelihoods, their concerns often focus on environmental issues. If they consent to collaborate, ECS scientists work with participants to refine research questions that will document issues raised, agree on the data sets required to investigate the questions, and the research strategy to collect the data.

To understand how ECS is positioned with respect to citizen science activities, we can look at Haklay (2013) typology of four levels of participation in citizen science. First, "Crowdsourcing" (Howe, 2006) describes the scientific practice of citizens as sensors, where the level of participation is minimal and mostly focuses on access to data recording resources (e.g., the use of automatic sensing with a mobile phone whilst engaging in outdoor activities). The second level involves the cognitive skills of participants. Sometimes referred to as "Distributed Intelligence," participants not only collect data, but also analyse it to some extent, as occurs in Galaxy Zoo where participants classify images of galaxies (Raddick et al., 2009). At the next level, participants contribute to problem definition and are engaged in data collection, although professional scientists control the development of the protocol, and do most of the analysis. Such "Participatory Science" approaches usually require the assistance of experts to ensure that the research is conducted according to recognised scientific protocols and standards. In ECS research processes, "Extreme" represents the extremities of the citizen science process, whereby participants take the lead on all stages of the scientific process, with professionals available to guide or support when requested (**Figure 1**). Taking citizen science to "extremes" means putting local people at the centre of the research process: they decide what data to collect, how best to collect and analyse it, who to share it with, and how to use it.

The methodology of ECS is dedicated to giving all people access to the scientific method. It brings together scholars from diverse fields such as anthropologists, conservation biologists, ecologists, geographers, and data scientists to develop and contribute to guiding theories and methodologies that promote citizen engagement to address pressing environmental issues. With an interdisciplinary research approach, the ECS methodology aims to provide a set of tools that can be used by anyone regardless of their background and level of literacy. In summary, the adjective "extreme" conveys that: (1) all people can be included in the scientific process, even those who are non-literate and marginalised, (2) participants are involved throughout the scientific process, from problem-definition to problem resolution, (3) it aims to decolonise research by guiding scientists to act in support of others instead of focussing on their own projects, and (4) that the tools and methodologies work in extreme environments such as dense remote rainforests, deserts or places with limited or non-existent infrastructure, since such places are often home to important biodiversity. It is critical to stress that ECS should be seen neither as a critique of, nor in opposition to other citizen science practices, since there are many situations in which other citizen science approaches are both fit for purpose and suitable for participants' needs and interests.

But how to enable such levels of engagement? Professional scientists usually conduct their research using a wide range of precision instruments, tools, and machines to record, generate, visualise, and analyse data. In our work we supply non-professional scientists, even when non-literate, with smartphones—if they do not already own one. Given the range of sensors they contain, smartphones are extremely powerful

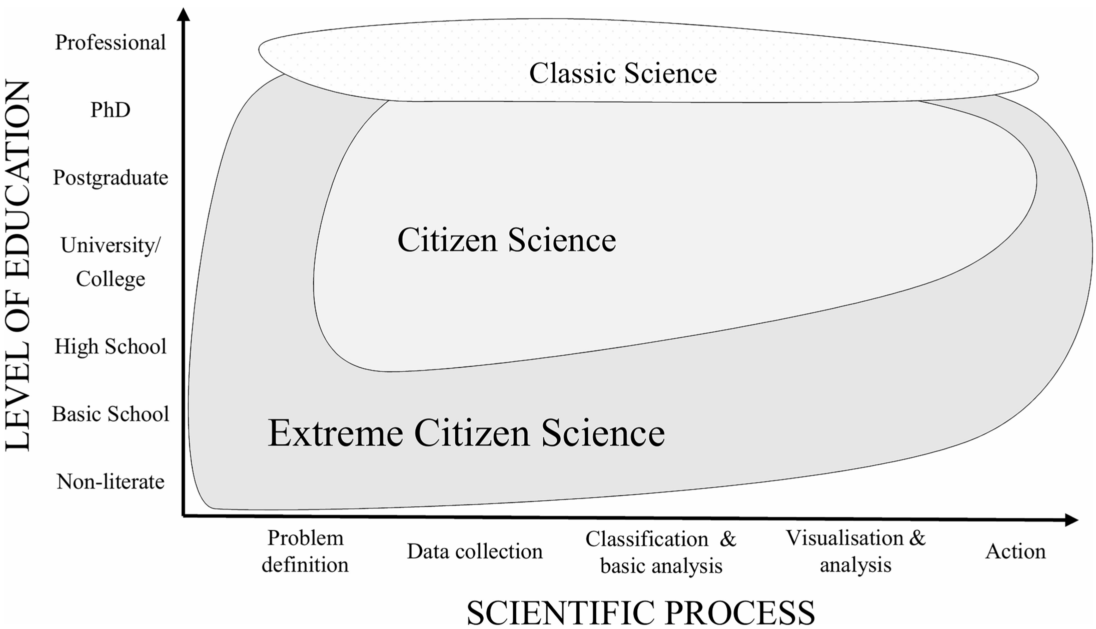


**FIGURE 1 |** Positioning Extreme Citizen Science (ECS) within the scope of citizen science.

instruments for scientific research, and their ubiquitous use among most human populations makes them a most promising tool for popularising scientific activity. However, to ensure that local users, such as the Congolese hunter-gatherers we first collaborated with, are able to use smartphones to address whatever issues they identify, we have iteratively adapted interfaces for a smartphone application aimed at scientific data collection. Since existing applications (e.g., Open Data Kit) assume literacy, so UCL's Extreme Citizen Science (ExCiteS) research group developed Sapelli, an open-source mobile data collection and sharing platform designed with a particular focus on including non-literate users with little or no prior experience of Information and Communication Technology (ICT)— "non-literate" is a non-judgemental statement of fact; it differs from "illiterate" which could imply someone has tried to become literate but failed.

The Sapelli platform plays a central role in facilitating the main ECS objective—which is to develop theories, tools, and methodologies to enable any community, anywhere, to engage in local citizen science research, mostly using a process of participatory mapping and inventory. From our research collaborations in the Congo Basin, the Amazon Basin and in other case studies (https://uclexcites.blog/; Skarlatidou and Haklay, 2021) maps have proved to be an accessible format for non-literate people to visualise and analyse the data they collected using Sapelli, and an efficient and appropriate form of communication between groups of different power and means (Lewis, 2012b). The density of information compressed into maps makes evidence quick to access and visually analyse, without the restrictions of linear, logical sequential representations more common in textual documentation that tend to be as often ignored by busy senior managers and decision-makers as they are by non-literate people (Lewis and Nkuintchu, 2012). By sidestepping the limitations of text, such maps provide an alternative medium for understanding the problem and opening up a discussion that avoids many of the barriers to participation facing local and indigenous communities in places such as Central Africa. Such maps can become a medium of empowerment and protest for communities to assert their rights to resources and territories (Peluso, 2005; Lewis and Nkuintchu, 2012; Özden-Schilling, 2016, 2019). In this way, ECS can support local citizen scientists to address for themselves the questions that they initially posed (Haklay and Francis, 2018).

In this paper, we introduce the stages of the ECS methodology, based on the last 13 years of field experiences of participatory design centred on the user (**Figure 2**). This paper focuses on the deployment of Sapelli as a tool grounded in a methodology which relies on two pillars: the socio-cultural and the socio-technological. The former pillar promotes problem definition carefully adapted to the socio-cultural and environmental context of the people that are engaged in the process through meetings and discussions to identify the foci of work (Stage 1), to explore potential negative and positive consequences to elaborate the Free, Prior, and Informed Consent (FPIC) process (Stage 2). The socio-technological pillar incorporates the participatory icon design and interface evaluation of Sapelli (Stage 3), together with the Community Protocol (CP) that organises the structures and needs of the community in order to collect data and to conduct the research (Stage 4). This approach enables communities to collaboratively create a Sapelli project that is widely understood, easy to use, and which meets the needs of local people. The final stage brings together both pillars to organise appropriate ways to analyse and visualise the collected data and eventually to act upon it (Stage 5). We will provide details of each stage, with reference

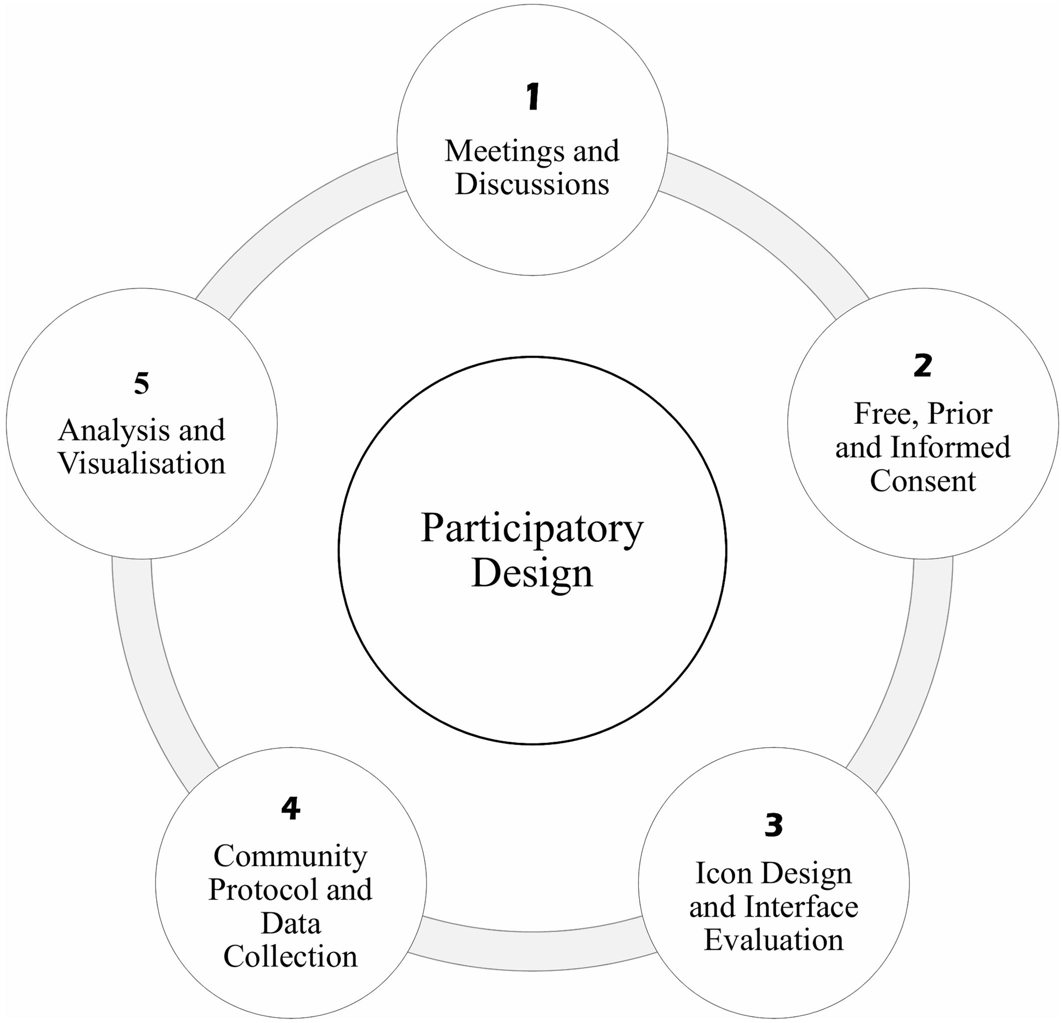


**FIGURE 2 |** Diagram of the different stages of ECS methodology relying on participatory design.

to case studies in Cameroon, Brazil. By focussing primarily on the ECS methodology to implement Sapelli, we hope to assist others who may wish to use the approach described here.

## SAPELLI

### The Origins

The methodology and approach taken in ECS evolved out of Lewis' environmental justice and participatory mapping work supporting non-literate indigenous hunter-gatherers in the Congo Basin to better represent themselves and their interests to powerful outsiders such as timber companies and conservation organisations. These outsiders were given rights over indigenous peoples' and local communities' (IPLCs) lands and resources by national elites without the consent of the hunter-gatherers (Lewis, 2012b, 2020). To facilitate the highly ecologically literate Congolese hunter-gatherers to map their key resources in 2005 Lewis designed icon-driven software for a rugged handheld computer-GPS unit to overcome their non-literacy. Later, in Cameroon, together with Nkuintchua, Lewis developed an early version of the ECS methodology for working with IPLCs based on FPIC, a project co-design process and an advocacy strategy to support IPLCs to act on their findings. This approach and the device were used successfully in negotiations with multinational timber companies to protect key resources from damage during logging, and also to document illegal logging activities (Lewis, 2007, 2012b; Lewis and Nkuintchu, 2012). In 2009, Haklay introduced Lewis to citizen science, and applied his experience in this domain to guide the development of "Extreme Citizen Science" (ECS) and the Sapelli suit of tools using much cheaper and widely accessible smartphones.

### Community Data Sovereignty

The approach we take towards data sovereignty in ECS projects recognises the potential for harm that can be caused by extractivist approaches to data collection by outsiders, and the subsequent misuse of information provided by indigenous peoples or local communities, particularly in white settler society contexts such as New Zealand, Australia, and North America (Kukutai and Taylor, 2016; Lovett et al., 2019). As a consequence, we recognise the importance of ensuring that participants from the indigenous groups and other local communities with whom we collaborate retain full control of the data that they facilitate collecting. This is made more complex in our situation because many of our collaborators have little or no knowledge about the way data can travel and be appropriated for use in ways that those who created the data would deem unacceptable. In such contexts the significance of working with a trusted gatekeeper cannot be under emphasised. During the discussions to develop the CP (Stage 4), the community is supported by their trusted gatekeepers and the ECS facilitators to plan the most effective ways of using the data to achieve community objectives. As this often requires sharing data with outsiders, this is clearly discussed and the acceptable organisations, individuals and modalities for doing so are noted down in the CP, as well as which types of data can be shared. The community will often nominate a trusted gatekeeper to keep them informed about how their data is being used if they cannot verify this themselves (e.g., in the context of wildlife law enforcement). Additionally, sometimes new actors request access to the data. In these cases the trusted gatekeeper or other person acceptable to the community goes to ask permission for the new use or change of use. Only if the community gives consent will the data be used in these new ways. The GeoKey server that ECS has developed was designed to facilitate this level of control and protection (Stage 5). The most significant problem we have faced is that any changes to access or following up on requests for access can sometimes take months to agree because of the remoteness and mobility of communities, and lack of communication infrastructure.

## Stage 1: Meeting and Discussions

The ECS methodology is based on the understanding that IPLCs know themselves and their local area best. In this regard, being introduced by a trusted gatekeeper and working with local people in their communities rather than convening workshops in regional centres or cities is prioritised to tackle local issues. The role of professional scientists is to support the process of building a Sapelli project by listening and understanding what IPLCs identify as the challenges they face, and then supporting them to focus on issues that they can address using Sapelli. Applying the iterative and participatory design process ensures that the project is centred on the needs identified by participants and informed by their understanding and knowledge of local ecosystems and their experience within them. Sapelli translates local knowledge into datasets that can be visualised and analysed through maps.

Adapting Sapelli to local needs and cultural practices is one challenge of the ECS methodology, as bringing groups with different backgrounds and cultures to work together requires sensitivity and care. Professional scientists and local communities do not necessarily understand environments in the same way. They do not organise themselves in the same way, nor have the same patterns of value and trust. The collaboration of local communities with newcomers, such as professional scientists, can exacerbate existing tensions related to indigeneity, ethnicity, and gender, or provoke new ones. For instance, dominant groups in Central Africa may feel challenged by the attention indigenous groups get and the issues they document. It can also generate conflict when the causes of environmental damage are profit building for dominant groups. Regular meetings and discussions with participating communities and their allies, in conjunction with the Free, Prior and Informed Consent (FPIC) process (Stage 2) and CP (Stage 3), help negotiate such risks by developing strategies to address them, so improving mutual understanding and trust, and more clearly defining roles and responsibilities. These discussions are an integral part of the ECS methodology (**Figure 2**).

Often after discussion with a third party facilitator, such as an anthropologist, local community group, NGO or a locally active conservation organisation, an ECS facilitator arrives to begin the ECS process. Initial meetings and discussions between the local community and the professional scientists aim to explore challenges identified by the local community that ECS can address. The visit of the professional scientists to a community should be announced some days prior to the meeting, to both the community and relevant local authorities. It is crucial for initial meetings to be facilitated by someone that is a trusted gatekeeper of the community to ensure as much trust and confidence as possible. During the initial meeting, the professional scientists carefully introduce themselves and the purpose of their visit. We have found that an open-ended discussion on issues facing the local community is the best way to proceed to identify potential areas in which collaboration might be possible. If issues emerge that can be meaningfully addressed using ECS the professional scientists lead a more analytical discussion to identify what types of indicators the community uses to measure the degree of the problem, how such indicators are known and shared, and which actors are implicated in the issues raised. With this information it is possible to assess the feasibility of an ECS project to address the issues raised, what risks the project may entail, and what desirable resolution would be like (Fryer-Moreira and Lewis, 2021).

This discussion lays the foundations for collaboratively developing the ECS methodology. It reveals both the challenges that the community wants to address and the reasons why individuals want to resolve them. Through such a consultative and deliberative process, the community highlights what issues it is concerned about. Characteristics through which the community makes sense of its environment might include customary laws and rights, their Traditional Ecological Knowledge (TEK; Berkes, 1999), cultural and spiritual values, social and ecological norms, but also traditional management practices of their territorial resources. All these characteristics are thoroughly discussed in the community with an emphasis on exploring the ways local understandings can conjoin with ECS whilst maintaining the community's ontological order to avoid these "being reduced to fit within western concepts"(Reid and Sieber, 2019, p. 216). As far as possible, strategies to assure participatory parity by addressing any power imbalances are employed when carrying out this deliberation (by consulting different groups simultaneously, or creating multiple break out groups to enable all to express themselves) in order to create a socially accepted frame of reference (Lewis and Nkuintchu, 2012).

This is a crucial condition for community engagement as this shared frame will also become an interpretive framework to help solve issues that prevent the project from flourishing. In our experience, the problems selected by communities are related to their environment and cultural identity. With guidance from the ECS team as to what is realistic, the community is invited to specify at least one of the challenges raised and begin to discuss how it can be addressed using the resources and capacities of the community combined with local partners and the ECS approach. This problem definition marks the start of a local citizen science project.

## Stage 2: Free, Prior, and Informed Consent

Addressing such a challenge will unsurprisingly impact the lives and livelihoods of the IPLCs concerned by this problem. The FPIC process assumes that these impacts, which could be positive or negative, need to be understood by the community before consent can be requested (Office of the United Nations High Commissioner for Human Rights (OHCHR), 2005). Lewis (2012a) describes in detail how to implement FPIC in the field. He warns us about the different meanings that the concept of consent can imply. In Central Africa for example, consent emerges from a long-term ongoing negotiated relationship based on mutual trust. In other words, consent is a social construction of on-going mutual satisfaction that can be broken if one party ceases to respect their obligations. Although different, such agreements can be documented (using video, photographs, and paper) to formally recognise them as equivalent to a written contract signed by both parties.

In a public FPIC process, community and professional scientists explore and discuss all the potentialities, positives and negatives, that their collaboration might engender. Careful attention to mitigation strategies for negative potentialities must be discussed together with ways to enhance positive outcomes. Once the community has weighed the pros and cons and considered mitigation strategies, it can choose to accept, renegotiate, or refuse to participate in the project. Nonetheless, far from being only a validation, the consent of the community must be negotiated in respect of three points: free, prior, and informed (Lewis et al., 2008). Being able to approve, negotiate or refuse a citizen science project before it commences, without pressure or duress, is key to ensure that the community is "free" and "prior" in its choice to participate. Throughout the ECS project, the community has the right to say "no" and to renegotiate or withdraw their consent. If the community withdraws its consent, their decision is respected and if they request that their data contribution be deleted this is done since they own the data. In our experience such undesirable outcomes are avoided if the community is fully informed; meaning that they understand both positive and negative potentialities and have discussed realistic mitigation and enhancement strategies. A free choice means a well-informed choice (Schlosberg, 2007). For instance, collecting data on illegal poaching may be beneficial for the community, but it also involves risks that poachers may realise the community is monitoring them (Brofeldt et al., 2018; Theilade et al., 2021). Together with participants, the ECS team works out strategies to address such potentialities. In this case, the solution was to create personalised pass symbols to prevent access to the Sapelli project by unauthorised people. Informed consent also requires verification that all stakeholders, including potentially marginalised members of the community, have properly understood information despite linguistic differences, literacy levels, and cultural interpretation (Lewis et al., 2008; Lewis and Nkuintchu, 2012). Finally, the overall FPIC negotiation process must happen before the community could be affected by any possible consequences of the implementation of an ECS project. The earlier the FPIC process is negotiated, the stronger it becomes.

In contexts where IPLCs may be non-literate, it is still vital that the FPIC process is synthesised in a form that thoroughly registers all the outputs of the negotiated points. Although this is necessarily a document—formalised in the "Community Protocol"—it becomes a reference point for the cooperation between the community and the professional scientists. If necessary or appropriate, it can also be used to explain the work to local authorities. This document is returned to throughout the project, and updated, or in some cases, adjusted, as different types of information come to light.

## Stage 3: Icon Design and Interface Evaluation

The socio-technological pillar of the ECS method consists of the material extension of the socio-cultural pillar. It relies on the meticulous design of Sapelli based on participatory design (**Figure 2**). The users and their needs remain at the centre of the design process (Sharp et al., 2019; Skarlatidou and Haklay, 2021). The role of the professional scientist consists in translating the user's data needs based on their broader socio-cultural and environmental problem definition and local knowledge to support the community to co-design and co-create appropriate data collection interfaces.

Sapelli is an open-source project that facilitates data collection across language or literacy barriers through highly configurable icon-driven user interfaces. It is designed to be used beyond conventional western utilisation to enable people with no or limited literacy to use smartphones and tablets to collect, share, and analyse data (Lewis, 2007, 2012b). Sapelli is available on the Google Play Store or GitHub repositories. All the information needed to build a Sapelli project that is accessible to any user and adapted to their specific requirements are available on the website: www.sapelli.org, but developing a Sapelli project requires basic computer skills. Sapelli is used in a variety of projects, mostly related to environmental monitoring (see https://uclexcites.blog/; Skarlatidou and Haklay, 2021 for details). It enables communities, regardless of social and geographical background, to map their environment and document any problems or threats they face. With Sapelli people can, for instance, not only report environmental crime, geo-tag valuable resources, monitor agricultural industries and chemicals, prepare land claims, but also survey transport users, navigate complex legal systems, or report wheelchair accessibility. As a result, Sapelli can enable any community to develop a project and engage in citizen science on almost any topic.

Participatory icon and decision-tree design enables communities to collaboratively create a bespoke Sapelli project that addresses their issues. The output is a mobile data-collection tool that reflects local needs and desires, set up on accessible digital platforms with customised icons and voice commands. The first step involves the drawing of the pictogram-based decision tree for Sapelli. Guided by the community participants, the professional scientists help to define the specific data types that need to be collected to address the problem. When the community relies on outside agencies to enforce the law, or act on the data the community collects, then these outside agencies also need to participate in the discussion of what data should be collected to ensure that they can be used as evidence to support the community's objectives. For instance, if the community wants to address illegal poaching, data might include dead animals, cartridge cases or campfires, but also elements such as hidden stashes of ivory. The community, with its rich contextual understanding and local knowledge, is best placed to enumerate the key data points they can collect (Stevens et al., 2014). They are then invited to create drawings on A4 paper, sometimes simply on the ground. Sometimes photographs are taken and turned into icons using graphics software, or simply drawn by members of the scientific team. The drawings are then digitised and tested on the community for accuracy before they become part of the Sapelli interface. This icon testing is done by the professional scientists holding up A4 images and asking the community to tell them what the image means. If the image provokes diverse responses, it needs further work. Only once an image consistently evokes the correct response from participants is it ready to incorporate into the Sapelli design (Fryer-Moreira and Lewis, 2021).

Icon design continues by deciding how icons should be organised in the hierarchical "decision-tree" structure on which Sapelli is based, so that it makes intuitive sense to participants. Although based on a hierarchical structure such as those commonly used in conventional computing applications to organise information, such structures seem to be understandable by non-literate local and indigenous people. Nevertheless, organising data in a hierarchical structure may not always be intuitive and decisions concerning this structure need to be explored together with the community and adapted to their associations. For instance, should the cartridge cases be included in a different category to poacher's campfires in the decision tree, or rather put at the same level (Vitos et al., 2017)? Answering such a question necessitates input from the community as well as further testing of different icon configurations to ensure they are intuitive to users and well-understood.

Finally, the newly designed Sapelli project needs field testing to evaluate whether there are usability issues which need to be addressed. Traditional usability studies rely heavily on observing how people use an interface while collecting feedback to improve the interface (Dumas and Redish, 1999). To do so in this context, the scientific team goes out on data collecting expeditions with different user groups. In many of the communities that we have worked with men and women have different foci when involved in their normal daily activities, so team members divide up to each accompany a different group as they walk in the local area collecting data (Lewis and Nkuintchu, 2012), or occasionally using different Sapelli configurations in controlled usability testing experiments (Vitos et al., 2017). While walking, the professional scientist discusses with the participants their experience of using the project, and if participants have difficulties, confusions or discover that items they wished to record were not available as options in the decision-tree, this is all noted. In return the team discusses the issues with participants and collectively decides how to address them. This often requires corrections to be made to the Sapelli project. Once the changes are complete the same field-testing process is applied again until participants are satisfied that the project addresses all their needs and expectations. In developing Sapelli, the scientific team conducted additional usability experiments to test assumptions built into the technology, to identify barriers that pose difficulty to users and so improve interaction and the overall user-friendliness of the application (Pejovic and Skarlatidou, 2020; Skarlatidou et al., 2020). Once the final prototype is approved by the community, the users can start to organise to collect data.

## Stage 4: Community Protocol and Data Collection

Once the Sapelli project is ready to collect data the process to define who will collect the data, on what terms, when, and with which equipment must be carefully organised. Once data is collected how will it be verified and by whom? Once data is approved where will it be stored and who will get to see it? Here the FPIC discussions that sought ways to minimise the potential for negative outcomes and to enhance the positive ones are an important source of guidance. The CP seeks to pre-empt as many issues as possible from becoming problems by discussing them publicly and formalising the way the community manages them, thereby aiming to ensure the ECS project has the best chance of achieving the expectations of participants and is sustainable. As in the FPIC process and Sapelli design, the CP is a negotiation ensuring that the community and its decisions are at the centre of the process (Fryer-Moreira and Lewis, 2021).

The CP codifies participants' expectations of the project. It defines the responsibility of individuals as well as the timeframe of data collection and use. With the help of the professional scientists, the community decides by whom, when and how data will be collected, and its quality checked. With whom will they share their data? What are their designated partners allowed to do with the data? Who is responsible for the equipment—keeping phones in good order and batteries charged? What steps will be taken to minimise the risks involved when collecting data? The discussion should focus on three main areas that will support the overall objectives: the technical support, the logistical support, and the data sharing protocols. The technical support should be guided by questions such as what equipment is needed? What are the charging facilities? What is the level of connectivity for data transmission? In situations with little technical infrastructure how will this be assured (memory cards, secure wireless/relay transmission)? When, by whom and where? What happens if a phone breaks or is lost? Questions relating to sensitive issues such as what remuneration participants might receive must be transparently discussed and collectively decided upon in order to reduce the potential for misunderstandings and jealousy later. Finally, the CP clearly recognises that the community own their own data and so they must define who they allow access to the data and on what terms, if elements of it can be shared and on what basis, who will host the data and who is permitted access to it. Due to the infrastructural challenges that can make communication difficult or slow, and the lack of literacy among the majority of the indigenous groups we work with, they can choose to delegate certain responsibilities relating to their data to trusted others.

As in the FPIC process, the CP can be synthesised into a form reflecting the output of the negotiation process. It summarises all the practices, procedures and rules developed by a local community to govern their interaction with Sapelli in their environment and with other people such as government officials, conservationists, logging companies, local community-based organisations, the professional scientists, and any other groups concerned by the project.

## Stage 5: Analysis and Visualisation

The final stage brings together the socio-cultural and socio-technological pillars to consider appropriate ways to validate, share and act upon the data that are gathered. Our research has shown that non-literate people do understand maps of their environment with little or no guidance, especially aerial or hi-resolution space imagery (Altenbuchner, 2018). Unsurprisingly, once they have collected data, participants wish to visualise it. Not being able to instantly view the collected data was considered to be a major frustration for participants, which can demotivate them from collecting further data using Sapelli (Comandulli, 2021). While addressing this is the current focus of the UCL ExCiteS group's further development work, currently the professional scientists or organisations supporting participating communities must share the collected information back with participants. This visualisation on a map is the last step of the scientific process as the participant will be able to validate and analyse the data collected, begin to formulate an answer to their research question, and decide how to act upon it.

### Geokey Server and Community Maps

The data collected with Sapelli Collector can be transmitted to the GeoKey server and then visualised in the mobile-friendly Community Maps web map (see www.sapelli.org; https://geokey.org.uk/; https://communitymaps.org.uk/; Ellul et al., 2009 for details). GeoKey is an open data infrastructure for community mapping that provides opportunities for participatory mapping (Roick et al., 2016). This platform serves as a connecting point between data collection and data visualisation and provides the functionality to edit and comment existing data and add new contributions using points, lines, polygons, text, the Sapelli Project icons, and media files.

As noted above, technological and knowledge disparities mean that the responsibility for ensuring that the information is protected and shared under the agreed terms of the CP only resides with the researchers or field workers who established the project with the community. Data, and especially sensitive data, must be protected and used for carefully. In cases where the data is only used in the field and where data is extracted from the mobile phones in the form of files, data can be managed by the field team. In cases where the information is stored on a remote server such as the GeoKey server, there are several issues that need to be considered. While the encryption of an individual record is not yet possible, the database that stores the information is set on an encrypted drive, and uses a whole database encryption. Finally, a password is used to protect the GeoKey server that is linked to the Sapelli project, and only authorised users can access the data.

Though Community Maps was created with a deliberately simple design to support community mapping in different situations and it plays a key role in enhancing collaboration between groups with different backgrounds and education, the participants in the case studies described here and others do not visualise and analyse regularly the data collected in Community Maps due to, among other, the need of fast internet speed, email registration (if the data is password protected) or literacy barriers. This highlights the technological gap that the ECS methodology aims to address. That is, the need for a visualisation tool (see below) that, on the one hand allows for the validation and analysis of the data collected in real time, regardless of connectivity, and the participant's level of literacy, technical skills and previous experience in interacting with maps. On the other hand, the tool needs to allow for data sharing between members of the same or other communities and stakeholders when access to the internet is an option. Whilst internet access in rural areas in developing countries is increasing (International Telecommunication Union (ITU), 2020), factors such as internet speed to load online maps or Earth Observation (EO) imagery, transmit media files, the cost of being connected, or the storage capacity of the devices (offline use) must be taken into account when implementing Geospatial and Information and Communication Technologies (Geo-ICTs) in such contexts.

Similarly, the volume of freely available high spatial and temporal resolution EO data is increasing exponentially, and this brings opportunities for improving the quality of hybrid base maps (satellite or aerial imagery and thematic maps) which provide not only critical contextual information to analyse the data collected in visualisation tools (Altenbuchner, 2018), but also critical awareness of human impacts on the Earth's surface as changes can now be seen from above, sometimes in near-real time, as never before. The positive impacts of emerging synergies between citizen science and Digital Earth are widely acknowledged (Brovelli et al., 2020), but it is worth reiterating that the democratisation of EO data use is not a reality. It is important to note that, monitoring land use and land cover changes at near-real time using manual image interpretation methods often requires access to recent and very high spatial resolution (i.e., pixel size less than 1 $m^2$), however, such imagery is currently not freely available, especially in non-urban areas in developing countries.

### Sapelli Viewer

Current research efforts focus on the development of a "Sapelli viewer," an application that aims to address the gaps identified above and enhance the appropriateness of the system in order to meet the needs of the communities. The challenges are significant, and expectations must be managed accordingly, especially considering the limitations of long-term research (software) projects to address short-term local needs. Sapelli viewer is designed to allow participants without technical literacy to view the data that they are collecting (**Figure 3**). The final version of Sapelli will bring the data collector functionality together with the visualisation functionality in a single smartphone application. Similarly to the data collection tool, the design, development, implementation, and evaluation of Sapelli viewer relies on an iterative, participatory design process. Eventually Sapelli viewer will support end-users, not only to view and validate the data they collect, but also to explore the data by running more advanced analysis functionalities such as viewing changes over time.

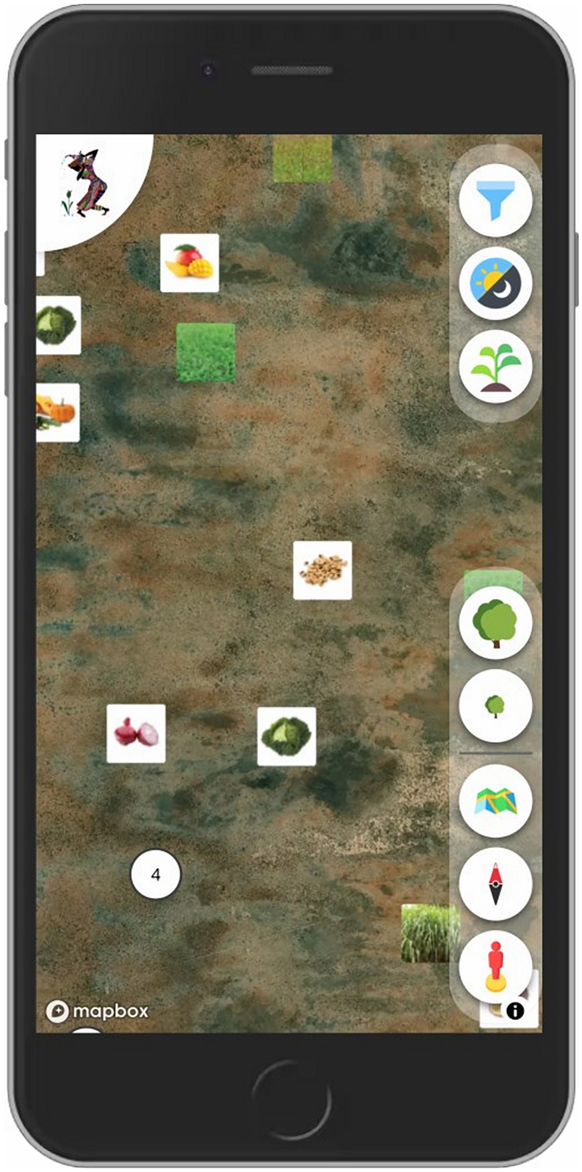


**FIGURE 3 |** Sapelli viewer (prototype with basic viewing functionality).

## TWO CASE STUDIES

### Meeting, Discussions, and FPIC Process in Cameroon

In comparison to the academic landscape when Linda Tuhiwai Smith's *Decolonising Methodologies* was first published in 1999 (Smith, 1999), the rights of communities involved in research projects or other forms of interventions is a subject that is now receiving a significant amount of attention (Tilley, 2017; Kouritzin and Nakagawa, 2018; Brittain et al., 2020). Those who are most vulnerable to negative outcomes of such work are often indigenous and local communities, and several international mechanisms serve to provide protection and best practice, particularly the United Nations Declaration on the Rights of Indigenous Peoples (UNDRIP). The key foundation of UNDRIP is the FPIC process, intended to ensure that communities have the opportunity to consider and either accept or deny proposals that will affect them (United Nations, 2007). Implementing the process of FPIC is not a simple matter of box ticking, but a purposely long, ongoing, and open discussion (Lewis, 2012a). The process does, unfortunately, get abused (see, for example, Clarke, 2019) which is perhaps no surprise given that UNDRIP is not legally binding (though other mechanisms which support FPIC such as the Convention on Biological Diversity and International Labour Organisation Convention are) and it can be at odds with the interests of extractive industries (Franco, 2014) and settler-dominated governments such as the United States, Canada, New Zealand, and Australia who voted against the adoption of UNDRIP.

In Cameroon, indigenous Baka communities are rarely consulted in interventions that will affect their lives and their forest (Pyhälä, 2012). The emphasis on extracting wealth from Cameroon's rainforests and wildlife, often to the detriment of Baka and other local communities' territories, resources, health, and wellbeing continues to accelerate despite increasing awareness of this. Their marginalisation from local, national and international elites' decision-making processes, and their continued disregard by international development organisations reveals the widespread discrimination they face and that FPIC methodologies are rarely applied (Lewis, 2020).

Since August 2016, the ECS group has been carrying out citizen science initiatives alongside indigenous Baka hunter-gatherer and local Bulu farming communities in the south-eastern forested region of Cameroon in collaboration with the Zoological Society of London (Hoyte, 2020) and the World Wide Fund for Nature (WWF). Twenty-two communities around two key areas in the South and East provinces of Cameroon were consulted on their use of the forest and their associated concerns. This formed the beginning of the FPIC process, following the methodology described in Lewis (2012a) and Lewis and Nkuintchu (2012), the project was not pre-designed or imposed upon communities, but rather time was spent understanding local concerns and building trust. Researchers, rather than community members, had to adapt to local decision-making processes, such as allowing the space and time for Baka egalitarian structures of collective discussion to take their course. The project was introduced in communities where anger over illegal wildlife trade or exclusionist conservation was evident and community members expressed the wish to be involved in addressing such issues, totalling 13 communities out of the 22 consulted, and engaging with roughly 78 active community members.

Community input was continuously encouraged, and as Sapelli software was co-designed over time, community members were consulted on why certain aspects were important and what the function was. This culminated in a broad range of socio-environmental attributes for which data would be collected, from wild fruiting trees to poachers' camps, to births and deaths in the village and the documentation of forest spirits. A key focus was on ensuring that those involved understood both the potential benefits and risks of involvement. In such a corrupt context as Cameroon, it is common that envisaged benefits simply do not materialise and discussing this possibility in an open way avoids raising unrealistic expectations. Similarly, risks of safely managing expensive technology (one smartphone per community), collecting data on sensitive matters amongst other risks must be explored honestly and mitigation measures established together. Although the FPIC process continues throughout the life of the initiative, an FPIC agreement was signed or recorded which detailed these complexities as well as the right of community members to change or leave the initiative at any time. Direct impact, on reducing the wildlife trade in particular, is hard to quantify, partly due to a lack of quantitative data in relation to the trade in Central Africa in general. However, testimonies from law enforcement staff attest to the direct contribution of citizen data to inform local forestry authorities, law enforcement patrols and international agents (TRAFFIC, Interpol) on the types of activities, frequencies and parties involved in poaching and trafficking for the illegal wildlife trade. It is used to guide the Ministry of Forestry (MINFOF) enforcement officers on the ground, increasing teams from 6 to 8 members or extending their duration. Some MINFOF control posts have been relocated to better tackle traffickers and camping, and patrolling materials for mobile staff have been improved upon. These actions have had tangible results: seizures and arrests have increased due to discrete and precise information supplied through the local community networks. Between 12/2017 and 08/2020, 36 arrest incidents, sometimes of multiple perpetrators, and 19 seizures without arrests were recorded. Communities themselves, through an evaluation methodology known as Most Significant Change, have testified to the reduction in wildlife crime in their localities and the empowering effects of involvement: "What we could not openly speak about, we can now report."

## Icon Design, Interface Evaluation and Community Protocol in Brazil

The communication between researchers or practitioners and local people is not as straightforward as most conservation or development initiatives assume it to be. Cultural or language barriers often create challenges to projects, even when the objective is to support local communities themselves. To mitigate this during the implementation of Sapelli it is vital to allow people sufficient time and information to choose the best strategies, icons and decision tree that best represents their own reality. This case study from the Western Border of the Pantanal wetland, Brazil, illustrates this well.

Between the 1990s and early 2000s several traditional fishery communities in the region were displaced from their original settlements due to the creation of strictly protected areas in the region (Chiaravalloti, 2019). Conservation managers accused them of overfishing local fish stock (Franco et al., 2013).

Supported by a local development human rights NGO, local fishers decided that it would be important to present their understanding of how they manage resources in the region and the boundaries of their traditional territory. Thus, Sapelli was employed to support local people to record their fishing strategies and the boundaries of their community territory in a scientifically valid way. Between January and July 2014, the ECS was adapted to local people's needs and between August 2014 and February 2015 two families of fishermen collected data. Four smartphones were brought to the local communities and people were trained how to use it, since most of them did not have previous experience with smartphones.

However, although the goal of the project was very clear, and the lead researcher had long experience working with local people, the first prototype created for them to record the data was not understood by local people. Participants found it challenging to navigate across several screens to record a single item in a specific geographic location. Thus, a new version of Sapelli was co-developed which included a simplified decision-tree, reducing the steps before reaching the end of a branch of the decision tree.

After reaching community consensus on the data collection process in the new Sapelli project, another major interaction barrier emerged. The first version of Sapelli was built using pictograms with caricatured images of the monitoring target (fish and crabs). This was a mistake, as the ecological knowledge of the fishers was very detailed, and they complained that the pictograms were too imprecise (Lewis, 2012b; Nyadzi et al., 2020). However, local fishers thought that the pictograms were too imprecise to accurately represent the fish or bait they were seeing. So they asked to have pictograms that precisely represented the key identificatory features of the actual species they sought to monitor. The pictograms were then replaced with scientific illustrations of the two most common fish (Pacu—*Piaractus mesopotamicus* and Pintado—*Pseudoplatystoma corruscans*) and two most common bait fish (Tuvira—*Gymnotus* sp. and Caranguejo—*Dilocarcinus pagei*) in the Pantanal (Chiaravalloti, 2021).

The last challenge was related to the lack of infrastructure in the region. The community is located in an isolated area of the Pantanal wetland where there is no electricity nor phone and internet connection. Therefore, instead of programming the software to send the data through wireless connection, an intermediary had to, every 20 days, bring a laptop to the community, download the data from the phones, return to the office, up-load the data onto a mapping platform, print out the maps, and return the data to local people for verification and approval.

Although the whole process of adapting the software, returning, and verifying the data, and explaining the results to local people was time-consuming, fishers felt their territory was well represented on the maps. Supported by local NGOs, the results were presented to the Federal Prosecutors' Office in Brazil, who validated the claims the fishers had made using Sapelli data. The maps they had created from collected data were so persuasive that the Federal Prosecutor demanded that the protected area managers respect the boundaries of the fishers' territories as represented on the maps they had made. After 4 years of negotiation, local fishers gained official tenure rights to a large part of their territory (2,000 $km^2$). Although it does not fully meet their needs, it was an important victory in terms of community empowerment and ensuring sustainable livelihoods for them.

## INSIGHTS FROM THE CASE STUDIES

The strategy of ECS is based on the principle that the local community, with appropriate support when needed, is best placed to lead the process of solving the challenges it faces. To get the most out of this process, regular communication between stakeholders must remain at the core of the citizen science activity. In ECS, participatory design assumes that reciprocal recognition and status equality between the professional and the non-professional scientists enable them to build a flourishing and resilient long-term cooperation. The methodology of ECS deployment is therefore open-ended and deliberately leaves ample space for co-design, co-creation, local leadership, and capacity building. We believe that this approach is adapted to give all people, including non-literate people, access to science and the capacity to take action on issues that they are concerned about.

However, the ECS methodology has its limitations. It should be clear from our different case studies that each methodological stage is heavily influenced by the specific context. Local conditions are constitutive parts of the ECS methodology which is designed to be flexible enough to adapt to these variables. Thus, the ECS methodology is first and foremost explorative, experimental, and cumulative. To implement Sapelli in the field, professional scientists have to face uncertainty in terms of what the community and the context will require of them and avoid "railroading" the process to their conceived goal. They need to deal with slow starts, unexpected changes, expect setbacks and deal with the slow process of building trusted relationships.

One important difficulty that we have experienced is a result of combining a project that is fundamentally research-centred with instigating direct action on the ground. Whilst implementing Sapelli projects comes with many challenges these are integral to the research and interesting to document and eventually work to address. However, the very nature of Sapelli is to be deeply embedded in the concerns and priorities of communities, and to resolve these often requires action on the part of authorities that have little interest in attending to community concerns. Nkuintchua developed a specific advocacy methodology to address this (see Lewis and Nkuintchu, 2012) that includes peer-to-peer meetings between participating communities to develop shared messaging and engagement strategies with official representatives. When conducting meetings where community representatives present their data, we invite line managers or bosses to meetings with officials. When sensitive data such as criminal activities are being presented it is necessary to incorporate external oversight into meetings. This is most effectively achieved by inviting funders and other influential individuals to attend to ensure conversations remain constructive, positive, and collaborative.

Expectations for the technology we experimented with also presented problems. People expect gadgets and software to work. When things malfunction and a "quick fix" is not possible due to a lack of resources (most often access to a software developer), external collaborators and community members can get quickly frustrated. The expectations of community members and in-country partners, who may often presume that the technology is faultless have to be managed appropriately from the outset.

Developing a fully functional project requires considerable commitment in time, effort, and relative costs (e.g., the cost of smartphones and access to the mobile network, and the cost of the installation and use of GeoKey). These elements cannot be quantified since they depend so much on the context the collaborating communities find themselves in. The work of listening to the issues they identify and co-designing a Sapelli project, then working through the CP as described here can be achieved in a relatively short time depending on the context - sometimes in just a few days. However, the relationship is ongoing and there will still be a need for regular contact with the community to troubleshoot technical issues, adapt software to new scenarios, incorporate new items for data collection, inform them of new requests for access to the data they collected, or of new uses of it that could be to their advantage (e.g., incorporating elements of it onto an online platform) to support. While these are predictable inputs, by far the most time consuming and unpredictable elements have been in identifying partners to support achieving community goals (e.g., the Ministry of Forestry in Cameroon) and the negotiations that this entails.

Our case studies have shown that all ECS experiences have not fully succeeded in the way they were intended. The main limitation of the methodology is the complexity and unpredictability of the networks of relations that professional scientists need to cultivate and maintain to achieve community-defined objectives. In conjunction with close and ongoing relationships with local participating communities, effective working relationships are required with government and enforcement agencies, businesses, conservation, and other locally present organisations, in order that appropriate follow-up actions occur. To promote sustainable collaboration, it is therefore important that professional scientists partner with intermediaries who can provide support and maintain connections with local communities and the other stakeholders when they are absent. Professional scientists must also ensure that the local communities are updated if the ways that the collected information will be used or the implications of such use change after the original FPIC and CP discussions. Due to the power and knowledge differences, it is the responsibility of the professional scientists or whoever participating communities have nominated to act as custodians of the information, to act in good faith, and respect community consent as an ongoing process, and never completed.

Such factors impose limitations on the use of community collected information, but this is in line with an ethical commitment to the participants. Finally, professional scientists must provide regular feedback and have in place the means to share important information with participants in a timely way. The development of Sapelli viewer will contribute greatly to enabling participants to visualise and analyse their data on maps while giving them more autonomy to create dialogues not only with professional scientists but also with other communities and stakeholders.

## CONCLUSION

This article provides an overview of the participatory design process used in Sapelli-based ECS projects in the field. The methodology of ECS starts with a dialogue to identify the needs and concerns of potential participants in their local community. If these concerns might be realistically addressed using ECS, professional scientists work together with local people to design an ECS project and support them to implement it in their community to address issues of local concern. Although potential implementations of the technology and the process have been developed in contexts in which technical and literacy levels are low, the process has also worked well when collaborating with highly educated participants such as wheelchair users in London, or environmental lawyers in Ghana.

We have outlined the five main stages in the design process that can enable people to develop and run a Sapelli project. An active collaboration between professional scientists and local communities through meetings and discussions (Stage 1) addresses the socio-cultural context in which the community is living, and identifies the challenge/s the community wants to address using an ECS approach. The FPIC process (Stage 2) ensures that the community is aware of the possible negative or positive consequences if they decide to participate in the ECS project, and how these can be mitigated or enhanced. This characteristic of open negotiation is extended into the technological design and implementation methodology of the Sapelli project. The Sapelli decision-tree and icons are then designed following people's recommendations through icon design and interface evaluation (Stage 3). The CP thoroughly organises and outlines the data collection and data sharing process by taking into account the material, institutional and environmental constraints (Stage 4). Finally, the collected data are shared with those individuals or organisations that participants have permitted to view it. A visualisation tool named Sapelli viewer, currently under development, will enable people to visualise, validate and analyse their data and eventually develop actions based on these analyses (Stage 5).

In outlining the ECS methodology in this paper, we wish to emphasise that this methodology is open-ended so that others who may wish to use the approach, can adapt or improve it according to their project specificities and local contexts of use [see https://preylang.net/for a very successful adaptation, also described in Brofeldt et al. (2018) and in Theilade et al. (2021)]. Worldwide, there are 1.3 billion forest-dependent people whose territories protect much of the remaining biodiversity on Earth (Sobrevila, 2008; Pretty et al., 2009; Porter-Bolland et al., 2012), a rural population of 3.4 billion and more than 750 million adults, of whom two-thirds are women, who are unable (or choose not to) to read and write (UNESCO, 2015; Macqueen and Mayers, 2020). Sapelli has great potential to be deployed in multiple contexts, and to empower people to explore and tackle the challenges they face locally.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## AUTHOR CONTRIBUTIONS

FM led the publication. MH, JL, AA, MM, RC, and SH contributed to writing and reviewing the manuscript. AS, AV, CC, EN, MV, JA, ML, RF-M, and DA contributed to reviewing the manuscript. All the authors have contributed to the development of Sapelli. All authors have read and agreed to the published version of the manuscript.

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# Perspective: The Power (Dynamics) of Open Data in Citizen Science

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In citizen science, data stewards and data producers are often not the same people. When those who have labored on data collection are not in control of the data, ethical problems could arise from this basic structural feature. In this Perspective, we advance the proposition that stewarding data sets generated by volunteers involves the typical technical decisions in conventional research plus a suite of ethical decisions stemming from the relationship between professionals and volunteers. Differences in power, priorities, values, and vulnerabilities are features of the relationship between professionals and volunteers. Thus, ethical decisions about open data practices in citizen science include, but are not limited to, questions grounded in respect for volunteers: who decides data governance structures, who receives attribution for a data set, which data are accessible and to whom, and whose interests are served by the data use/re-use. We highlight ethical issues that citizen science practitioners should consider when making data governance decisions, particularly with respect to open data.

**Keywords: ethics, volunteer monitoring, data stewardship, data privacy, community science**

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## INTRODUCTION

One aspect of open science involves sharing scientific data broadly, maximizing its power to benefit society through use and re-use in other research. In conventional environmental research, professional scientists generate data and make decisions about stewardship of resulting data sets. In contrast, in research through citizen science, those who generate data are not likely to be those making stewardship decisions about it. Consequently, the loss of volunteer control could lead to greater potential harms to data producers in citizen science from decisions about data use/re-use. Ethical conundrums arise when different parties (scientists and volunteers) have conflicting interests in relation to the data governance. Given the power differentials between scientists and volunteers, and irrespective of whether some parties have legal rights to control access to and use of the data, responsible research requires attention to the interests of all stakeholders (Ballantyne, 2018).

In this Perspective, we adopt the premise that professional scientists should steward data for its maximal use in advancing science via open data practices. We advance the proposition that stewarding data sets generated by volunteers involves the typical technical decisions in conventional research plus a suite of ethical decisions stemming from the relationship between professionals and volunteers. Differences in power, priorities, values, and vulnerabilities are features of the relationship between professionals and volunteers. Thus, ethical decisions about open data practices in citizen science include, but are not limited to, questions grounded in respect for volunteers: who decides data governance structures, who receives attribution for the data set, which data are accessible and to whom, and whose interests are served by the data use/re-use.

In our recent work, supported by the National Science Foundation, we aim to provide practitioner-built tools to identify and facilitate ethical data practices in citizen science. In 2017, we held an interdisciplinary workshop about ethics in citizen science (Lisa M. Rasmussen: NSF SES-1656096, Filling the "Ethics Gap" in Citizen Science Research). The workshop brought together nearly three dozen attendees involved with citizen science, research ethics, and Science and Technology Studies to consider the novel ethical challenges posed by citizen science research. Workshop aims included identifying ethical issues in citizen science, articulating conceptual frameworks for them, and brainstorming possible solutions. The workshop yielded a list of over 40 ethical issues related to the practice of citizen science, many of which were explored in papers in two special collections: one in the journal of the Citizen Science Association, *Citizen Science: Theory and Practice* (Rasmussen and Cooper, 2019), and one in *Narrative Inquiry in Bioethics* (Rasmussen, 2019). Some of the topics related to different aspects of data acquisition and management.

The workshop findings informed a plan for research and facilitation to develop norms, and resources and tools to support those norms, around responsible, trustworthy data practices in citizen science (Caren B. Cooper: NSF CCE-STEM-1835352, *Cultivating Ethical Norms in Citizen Science*). Our aim with the grant is for the field of practitioners to expand their understanding of trustworthy data to include ethical practices related to data acquisition and management. In citizen science, there are unique ethical issues with open data practices. We begin from the assumption that data quality and data ethics are equally important, as both center on actions related to rigorous field methodology by volunteers and appropriate practices by data stewardship, such as attribution, accessibility, confidentiality, and transparency.

Citizen science produces scientific data. Practitioners of citizen science therefore have the same data stewardship obligations as conventional scientists. In addition, however, management decisions about citizen science data may include consideration of a unique set of risks and benefits for volunteers. For example, anonymity in projects, datasets, or contributions is not always possible, and can run counter to desired interests of attribution. Data stewardship in citizen science has a broader scope than in conventional science, including reporting back to volunteers so that they can make meaning of the data, respecting how volunteers want sensitive data to be handled, recognizing contributions in a manner preferred by volunteers, and communicating clearly and transparently with volunteers about the above. We expand on these issues below.

## OPEN DATA DECISIONS

Data governance can be responsive to concerns about protecting sensitive and personally identifiable information, treatment of indigenous knowledge, and intellectual property. Making data open is the act of making data available for others to freely use and re-use. However, the appropriate form that "open data" takes varies with the context of a given citizen science project. The majority of projects identified as citizen science have goals of advancing scientific research, and as such, practitioners should make data open to maximize the scientific value of the data. At the same time, we recognize that some projects have specific, action-oriented goals other than the general advancement of science, such as directly informing policy or social action. Given varied uses of scientific data and interests served, making data open is not always or automatically the most appropriate choice. We emphasize that ethical practices for establishing open data involve decisions about what should, and what should not, be shared, and what restrictions are warranted.

A misperception of "open data" is that posting data to the Web implies making it available for free use. However, the concept of "open data" is much more complex than the seemingly binary decision to make data "open" or "closed." Complexity stems from the numerous motivations for, approaches to, and justifications for making data open in the first place. When making and sharing content, copyright is a traditional mechanism to clarify restrictions on data use/re-use. However, according to US law, copyright applies to "creative works" and thus does not often apply to databases unless there is some creativity in their compilation (Miller et al., 2008; Kristof, 2016). However, there are alternative approaches to data stewardship besides copyright.

In 2010, the Panton Principles launched a guide for open data practices (Molloy, 2011). The Panton Principles recommended public domain licenses via the Open Data Commons Public Domain Dedication and License (PDDL–http://opendatacommons.org/licenses/pddl/1-0/) or Creative Commons Zero (CC0–http://creativecommons.org/publicdomain/zero/1.0/) which waive copyright. Such public domain licenses allow free, unrestricted use of the data for any purpose. While these might be a viable guide for datasets produced by conventional science, licensing in this way does not necessarily provide an open data solution for citizen science if volunteers want attribution. For example, the ODC PDDL and CC0 licenses do not require any attribution; however, one can use CC0 "with attribution appreciated." CC-BY allows free use of the data for any purposes with the requirement of attribution and allows attribution to extend to groups such as members of a citizen science project. Open data practices are further complicated when citizen science databases include photographs and/or open text, each a creative product with potential claim to copyright. Such licenses may not be entirely sufficient for these datasets. Groups that have historically experienced data inequities, exploitation by scientists, and/or intimidation by powerful interests may have heightened concerns about data access, data re-use, and the distribution of benefits. Thus, there can be varied circumstances where volunteers want to restrict data use, rather than adopt free, unrestricted licensing options.

Nevertheless, persistent interest in open data for citizen science has led to nuanced applications of licensing options and exploration of unique challenges that public data archiving presents to the sustainability of long-term citizen science projects (Pearce-Higgins et al., 2018). In light of this complexity, it is essential to recognize that regardless of what approach one takes to make data open, and the benefits and challenges associated with it, the process of making data accessible for third parties to use requires active steps by a data steward (Miller et al., 2008). Next in this Perspective, we highlight ethical issues that citizen science data stewards and practitioners should consider when making data governance decisions, particularly with respect to open data.

## Decision-Makers and Data-Producers

In citizen science, data stewards and data producers are often not the same people. When those who have labored on data collection are not in control of the data, ethical problems could arise from this basic structural feature. Power differentials arise because practitioners may have more education and institutional resources than project volunteers, and when practitioners are the sole data stewards, the power differentials are amplified. Thus, in these cases, data stewards (practitioners) need to properly consider the interests of the data producers (volunteers). For example, a data steward may view sharing geo-located data produced by volunteers as a way to maximize scientific goals, but data producers may view sharing as increasing their risks of physical, economic, or emotional harm. Insofar as datasets are monetizable, some communities may want to retain control over them for the benefit of those who have compiled the data or may be directly affected by it. Alternatively, volunteers may want to ensure that a dataset cannot be used for any commercial purposes (e.g., CC-NC restricts uses to non-commercial purposes).

Few studies have examined volunteer perspectives on the handling of citizen science data. Fox et al. (2019) found that volunteers in a large-scale UK project supported open access in principle but for its practice supported cautionary actions to protect sensitive information and restrict commercial reuse of data. Groom et al. (2017) reviewed the open access nature of biodiversity observation data contributed to GBIF (one of largest biodiversity data repositories). Contrary to what many people assumed, the datasets generated by citizen scientists were actually among the most restrictive in how they could be used. A further study examined the challenges and opportunities presented digital platforms that host citizen science data. In this case, Lynn et al. (2019) described the technology of the CitSci.org platform that allows project managers to choose different data governance options, some of which allow volunteers to make data governance choices themselves. We found no work yet addressing the challenges presented by the involvement of other third-party organizations (e.g., schools, museums) that manage volunteers in citizen science without involvement in making decisions about data stewardship.

## Attribution and Acknowledgment

Attribution is the act of recognizing an individual's or group's contribution and appropriately acknowledging it. There are different forms of attribution, including non-monetary recognition such as authorship, acknowledgment, and citation. Accountability may also be associated with some forms of attribution, and involves an individual or group taking responsibility for some or all of the work. For example, in authorship, one is taking credit for the work and also taking responsibility for its quality and integrity.

In conventional and citizen science, publishing datasets is an old practice modeled after systems for publication of research results. For research papers, there are generally accepted standards for authorship when someone has made a substantial intellectual contribution to a project, or acknowledgment for contributions that are significant but not rising to that level (Brand et al., 2015; International Committee of Medical Journal, 2015). For citizen science papers, mirroring conventional approaches to authorship of papers is probably not meaningful, appropriate, or always possible for volunteers (Ward-Fear et al., 2020). For datasets, we are not aware of widely accepted standards for levels of contribution that warrant authorship or licensing attribution. Given the absence of norms, we encourage the data stewardship practice of licensing a dataset to foster intentional deliberation and decisions related to attribution.

## Data Accessibility

Considerations of data accessibility should address the question, "accessible by whom?" Open data practices generally involve datasets being documented, discoverable, and allowing use by other scientists. In citizen science, however, data accessibility extends beyond engagement by scientists to practices that ensure that the data producers (volunteers) can make meaning of the datasets and use them for their own goals. With origins in environmental health, a standard practice of citizen science practitioners is the provision of "report-backs" to volunteers (Brody et al., 2007). Report-backs typically include personalized summaries of data (e.g., placing the individual contributor's data in context within the project) and/or excellent visualization of the collective data. Although report-backs are an important component of citizen science projects, they can raise privacy concerns if they disclose sensitive or private data to project participants or the public.

An additional consideration of data accessibility is the question, "accessible for what purpose?" Open data practices involve making datasets useable by other scientists for purposes similar to the original collection effort as well as re-use by other scientists for other, perhaps unanticipated, current or future purposes. In a citizen science context, when data producers are not data stewards, they have limited control of data re-use (Ganzevoort et al., 2017). In this light, it is important to note that currently, there is no open data license that can restrict data use in cases where it might harm data producers. Instead, case-by-case assessment to determine the potential for harm would require a closed license. Alternatively, an approach could be built around a framework of ethical principles guiding data use. For example, in considering indigenous data sovereignty, Carroll et al.

(2020) presented a framework that combined FAIR (Findable, Accessible, Interoperable, Reusable) Guiding Principles for scientific data management and stewardship with the CARE (Collective benefit, Authority to control, Responsibility, Ethics) principles for Indigenous Data Governance. This kind of framework could help meet challenges of operationalizing "Open by default" (Stone and Calderon 2019) and give clarity on sensitive data and mechanisms to minimize harms and maximize benefits to data producers.

## Data Confidentiality

Decisions about what data to share rely on considerations about the project's context and the types of other publicly available data. There are numerous instances in citizen science in which confidentiality of volunteer data should have primacy over open data sharing. This might include the collection of sensitive data based on location (e.g., volunteer location or protected species location), the collection of other sensitive data based on the subject of research (e.g., health), the unintentional collection of data from other people (e.g., photographs), or the possibility of combining data sets which could identify volunteers. For example, data collected by volunteers about corporate polluters may, if publicly released, identify and endanger those who have collected it (e.g., Wing, 2002). Additionally, in conjunction with existing data sets such as tax and real estate data or voter lists, new volunteer-collected data sets may enable re-identification of individuals or their locations via data triangulation (Golle, 2006). Even when researchers anonymize environmental health data by removing overt identifiers such as names and addresses, risks to re-identification of participants remain (Boronow et al., 2020).

Nissenbaum's privacy framework (2004), called Privacy 3.0, is helpful for navigating the various contexts and potential concerns that may arise through the data collection and management process more generally. Privacy 3.0 emphasizes the importance of (1) data minimization, (2) user control of personal information disclosure, and (3) contextual integrity (Nissenbaum, 2004, 2010, 2019). The concept of contextual integrity is particularly important; it focuses on understanding the flow of data from the sender to the recipient with attention to the subject matter, information type, and transmission principle (Nissenbaum, 2019). In a citizen science context, this might involve (a) not collecting personal data that should be confidential or (b) ensuring that if personal data must be collected that it remains confidential throughout the data lifecycle (i.e., ensuring that those portions of the dataset never go into open license or public domain). Further, Bowser and Wiggins (2015) have suggested the importance of viewing data privacy as involving a volunteer's right to manage access to their own voluntarily contributed personal data, which includes identified or identifiable information.

In certain types of projects, however, volunteers have no choice in the handling of their data or the protection of their privacy (Cooper et al., 2019). For example, in a sample of projects in which volunteers contributed data that unwittingly contained personally identifiable information, none involved volunteers in data governance decisions, and only half of the projects informed volunteers about data stewardship decisions, mostly related to privacy, liability, and copyright, typically through Terms of Service agreements (Cooper et al., 2019). Furthermore, even the professional scientists do not always play an active role in stewardship decisions of citizen science data, instead leaving decisions to the hosting platforms or institutional IT support (Bowser et al., 2020). Digital platforms that host citizen science projects, however, can enable joint decision making. For example, the platform CitSci.org supports preferences of both project managers and volunteers for customized levels of access to data (Lynn et al., 2019).

## Transparency

The success of science, as well as citizen science, rests on the transparency of its technical and ethical practices. Transparency can be understood as the act of "making implicit and explicit values known or potentially discoverable by providing accessible information about research methods and data" (Elliott, 2017). There are two types of transparency that are especially important for discussing ethical data practices in citizen science. In the first instance, scientifically relevant transparency "refer[s] to efforts designed to assist scientists in achieving their goals, such as promoting new scientific discoveries and maintaining the reliability of scientific research" (Elliott and Resnik, 2019). Meanwhile, socially and ethically relevant transparency is more "focused on providing information that enables decision makers and members of the public to make effective use of scientific research" (Elliott and Resnik, 2019). These two understandings of transparency are not mutually exclusive of one another; they are two sides of the same coin. Both are important to consider when making decisions about how to collect and steward citizen science data in the most effective and ethical manner. In other words, transparency is an overarching obligation that applies to data accessibility, data confidentiality, and volunteer attribution and acknowledgment.

# CONCLUSION AND RECOMMENDATIONS

"Thinking like a scientist" refers to higher order reasoning that distinguishes evidence from opinion and uses formal tools like statistics to minimize biases in human judgements (Kahneman, 2011). Scientific methods often include hypothesis testing that will ideally produce replicable conclusions. A scientific question can result in an agreed upon scientific answer. In contrast, "thinking like an ethicist" often means identifying ethical issues and using ethical frameworks to weigh a variety of options for addressing the issues. An ethical question can result in many ethical answers, each with equal validity. When there are competing values among those with valid interests in a dataset, there can be multiple ethical (and unethical) decisions about data governance (Ballantyne, 2018). Because of the pluralism of moral values, it may be impossible to offer, in the abstract, a set of ethical prescriptions that will be true for all citizen science research. Context matters, and what arises as an ethical issue and appropriate solution in one project might not in another almost-identical project.

Thus, ethical issues in citizen science have many solutions, most often including open data practices. When practitioners opt for open data, they can do so effectively and responsibly by communicating intentions clearly with volunteers. For example, in considering the content of consent statements, Meyer (2018) recommended avoiding promises not to destroy data (which runs counter to expectations of some IRBs), not to share data, to restrict data analysis to the focal topic, and to obtain re-consent for additional sharing. Although Resnik et al. (2015) suggested all data sharing requests should go through the lead investigator of citizen science projects, Meyer (2018) recommended that practitioners can provide maximal access by working with a data repository that provides the desired governance options. Similarly, selection of the appropriate IT platform for the administration of the project should consider whether there are the desired data governance options (e.g., Lynn et al., 2019).

Open data is not a "one-size-fits-all" answer to the challenges of every project. A key variable to consider when deciding on data restrictions is the interests of the volunteer data producers, especially if they are not also part of the data stewardship team, with regard to accessibility, confidentiality, and attribution. Data stewards should listen to data producers, which may dictate more openness, or less, depending on a variety of circumstances. With transparency, practitioners can help data producers make highly informed decisions. Our dual hopes for citizen science are first, that a better understanding of the issues, risks, and stakes in decision making about open data in citizen science may help project leaders navigate these ethical decisions; and second, that by incorporating ethical rigor into data science practices from the outset, work in citizen science will be deeply informed by ethical practice.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## AUTHOR CONTRIBUTIONS

CC lead the compilation, organization, and writing of the paper. LR and EJ helped with the compilation, organization, and writing of the paper. All authors contributed to the article and approved the submitted version.

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METHODS
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# MaDCrow, a Citizen Science Infrastructure to Monitor Water Quality in the Gulf of Trieste (North Adriatic Sea)

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Within the United Nations Sustainable Development 2030 agenda, sustainable growth in the marine and maritime sector needs sea water quality monitoring. This is a very demanding and expensive task which results in the sea being largely undersampled. MaDCrow is a research and development project supported by the European Regional Development Fund, that involves citizens as data collectors while aiming to improve public environmental awareness and participation in scientific research. Its goal is to create an innovative technological infrastructure for real-time acquisition, integration and access of data, thus generating knowledge on sea water quality and marine ecosystem of the Gulf of Trieste. Data acquisition is based on an autonomous and removable device, developed within the project, that can be deployed on any small size sailing boat, recreational vessel, or fishing boat. The device holds low-cost sensors to measure pH, temperature, dissolved oxygen and salinity and the hardware and software to acquire, georeference and transmit the environmental data without interfering with the activities of the boats. In this work we analyze the use, capabilities and advantages of low-cost sensors but also their limitations, comparing, with a special focus on pH, their performances with those of the traditional ones. Applying the paradigm in a highly anthropized area such as the Gulf of Trieste, which is characterized also by a very high spatial and temporal variability of environments, we point out that this new approach allows to monitor sea water quality and highlight local anomalies with a resolution and spatial and temporal coverage that was not achievable with previous procedures, but yet at very low costs. Once received, data are then processed and submitted to a mediation flow that contextualizes and disseminates them for public use on a website. The final products have been customized to reach stakeholders such as tourists, fishermen and policy makers. The availability of information understandable to everyone, while fostering environmental awareness, stimulates, at the same time, involvement and participation of citizen scientists in the initiative. In the future, while committing to enlarge the number of participants, we will extend the analysis also toward other types of sensors.

**Keywords: crowdsourcing, citizen science (CS), sea water quality, infrastructure, environmental awareness, Gulf of Trieste (North Adriatic Sea)**

# INTRODUCTION

Ocean waters cover over 70% of the Earth's surface. They are responsible for more than 50% of the oxygen production on Earth and are fundamental in regulating the overall Earth climate. They have the capacity to absorb and, through the sea currents, distribute around the world, vast amounts of matter, carbon dioxide (CO2) and half of the heat reaching the Earth from the Sun. A large part of the global population lives along the coast. The anthropogenic pressure on coastal areas is heavily increasing so that understanding the effects that this can have on the sea is of paramount importance at multiple scales and for all of us (Halpern et al., 2012).

Within the Ocean Decade Framework[1], ocean science needs to achieve key societal outcomes and a clean, safe, healthy and resilient, sustainably harvested, productive, predictable, and open data-transparent ocean. Understanding the ocean's health is important in order to manage it while harvesting its resources and promoting its protection at the planetary level. The scientific community is deeply committed to the endeavor of monitoring the sea but experiences restrictions in studying the geographic and temporal coverage of phenomena, due to the limited funding of traditional methods based on expensive infrastructures, sensors, logistics and personnel (Lauro et al., 2014).

As often happens, issues can revert to be opportunities when a new approach is devised. This new paradigm can be built outsourcing activities outside the so far closed scope of the scientific community. The exchange of data, information and knowledge between researchers and laypeople can solidly ground the environmental awareness of the latter and improve their will to participate in the project (Nelms et al., 2017; Schleicher and Schmidt, 2020).

The mass media show a general commitment to highlight the problem of climate changes (Michael et al., 2016) but at the same time can give resonance to illusory and misleading views (Boykoff, 2013). This can be confusing and detrimental to the environmental awareness of the general public, which needs instead to be informed correctly in order to act consistently. Undoubtedly, the best way for the public to understand and appreciate science is to participate in it (Silvertown, 2009). Many scientific research projects took the citizen-science turn demonstrating very promising outcomes, as have been reported for example by McKinley et al. (2015); Schleicher and Schmidt (2020), and many other authors. These projects span a wide range of topics: from species observations to air quality measurements to asteroids and comets observation and identification.

## Crowdsourcing Marine Environmental Monitoring

If marine monitoring is very important to understand human impact on the environment, the availability of innovative methods that can improve the spatial and temporal coverage of natural phenomena over what available with traditional methods can be crucial toward the achievement of the United Nations Sustainable Development Goals (SDG) 2030 agenda[2]. Fraisl et al. (2020) conducted a very detailed mapping of all SDG goals, targets and indicators to understand where alternative methods such as crowdsourcing and citizen-science would be beneficial.

Among the firsts to introduce the citizen-science approach in the field of oceanography, Lauro et al. (2014) understood perfectly the opportunity offered by the availability of multiple private vessels, and in particular of sailing yachts or leisure boats that could enhance massively the coverage of an area. Underlying these efforts, important questions were posed such as: can meaningful data be collected with the kind of narrowly focused, low-cost instrumentation that is easily mass produced and deployable [on such types of platforms]? If so, what vessels will carry it, and what personnel will operate it?

Within the field of marine environment monitoring only few initiatives that follow this vision have taken place so far. Among those we can recall Chang et al. (2019), focused on weather data, the freshwaterwatch sampling initiative[3], Bärlocher (2013) that describes the activities of the OpenSeaMap, a project devoted to the production of free-of-charge nautical maps that is mainly maintained by experienced volunteers. Another successful story is OSD, Ocean Sampling Day (Kopf et al., 2015) where worldwide scientists and citizens collected marine samples in a contemporaneous fashion, following the same standardized protocols for assessing marine microbial diversity. Luccio et al. (2020) propose a project where an Internet of Things (IoT) based system is tuned for the marine case [Internet of the Floating Things (IoFT)] building on top of a specific and already existent network of sensors that must be based on the industrial standards NMEA and Signal K. Other initiatives based on low cost solution are Spotter and Trident, from Sofar ocean, a commercial company, or the Smartfin initiative.

## The MaDCrow Project

MaDCrow is a research and development project supported by the European Regional Development Fund - ERDF. Being the result of a regional implementation by the Italian region Friuli Venezia Giulia (North East of Italy), the project has a specific focus on the Gulf of Trieste (Northern Adriatic Sea-Mediterranean Sea), but it can be easily reconfigured and scaled to other possible areas.

A very important aspect of the project is that it aims to support open innovation between public institutions and private companies to stimulate economic activities related to the oceans and seas in the perspective of the Blue Economy. Private companies comprise, in fact, half of the partnership of the project, while the other half is constituted by research institutions, in a synergy between these two worlds that has been very beneficial to both of them.

The MaDCrow project aims at developing methods and technologies to improve geographic and time coverage of

[1] https://www.oceandecade.org/

[2] https://sdgs.un.org/goals

[3] https://freshwaterwatch.thewaterhub.org

environmental marine monitoring involving volunteers that host, on their small vessels or leisure boats, a specific autonomous monitoring system developed within the project. This system is quasi-real time, platform agnostic, self-sufficient, interoperable and based on open technologies. The MaDCrow project aims at demonstrating that this paradigm can be a solution to the aforementioned problems while introducing at the same time the positive outcome of the improvement of the environmental awareness of volunteers and of the public at large. MaDCrow has to be intended as a proof of concept that, at the local levels, relevant stakeholders have joined forces to create a product that can use scientific data and inform citizens, fishermen and managers on the state of the sea. MaDCrow at the moment is not fully complying with the level of accuracy and precision and standardization protocols required by the SDG indicators, while in the future the project wishes to reach those goals thus being fully integrated in the SDG indicator 14.3.1 (*Average marine acidity: pH*). Furthermore, within the project portfolio, we envision future development to tackle explicitly the water-quality and climate risk-management related to harmful algal bloom and ocean acidification. Within this framework, this paper explores the opportunities and limitations of the proposed approach in comparison with the traditional methods, from the point of view of the performances of measurements and the improvement in resolution and spatial and time coverage of the designated area.

# MATERIALS AND EQUIPMENT

## The Infrastructure

The MaDCrow infrastructure consists of several integrated modules that cover all the technological steps from environmental parameters acquisition to data and information access by the end users. As in **Figure 1**, modules can be gathered in three segments and namely: (I) acquisition and transmission (II) processing and mapping, (III) contextualization and end user access.

Modules have been developed independently by the partners of the project leveraging each partner's previous specific experiences and backgrounds. Particular care has been taken to grant seamless integration between modules using robust open standards technologies, in order to allow easy refinements or possible additions of further new modules.

Modularization responds also to the needs of different communities of end users. Raw data, for example, can be used by scientists for data assimilation, model development and maintenance and to integrate them with the data they already have or acquire using traditional methods. On the other hand, it will be very difficult for the general public, or for non-technical communities, to understand the information and knowledge contained at this level. It is necessary, then, to address the needs of end users creating specific products that will reduce complexity through a process of representation (Callender and Cohen, 2006; Diviacco, 2014). This can be implemented by developing different co-existent modules that match the needs of each designated community.

### The Acquisition System

As mentioned before the acquisition system was devised to be hosted on leisure boats or small vessels owned by volunteers/citizen scientists. Following Silvertown (2009) a very important factor to consider in designing acquisition systems to be used within projects where laypeople are involved is the usability of all the tools made available. We decided to keep the system as simple and automatic as possible, and in fact, not considering switching it on and off, essentially no intervention from volunteers is necessary, as the system acquires and transmits data autonomously and continuously.

### Sensors

A fundamental issue to consider planning the choice of sensors is cost. High end multiparametric probes can cost up to several tens of thousands of dollars; considering that the acquisition system has to be deployed on many platforms at the same time, the multiplicative effect that this can have on the budget can be frustrating. To address this problem MaDCrow focused on employing low-cost sensors only. In this perspective there was no need to develop yet another set of probes since the market offers already existing solutions.

An important choice to be made is whether to measure parameters *in situ* or taking samples to be measured on the ship. Byrne (2014) recommends the former while warns that any other practice can strongly affect the values taken. We therefore have chosen to deploy the instruments directly at sea using a frame that aims at maintaining constant, as much as possible, the boundary conditions of measurements. This choice unfortunately introduces other issues. Since the sensors are constantly immersed in seawater, a residue forms on the transducer so that eventually, the sensor may begin to report erratic measurements. In addition to this, bio-fouling further isolates sensors from the environment, adding progressive drift to measurements. Professional probes are equipped with self-cleaning devices that are too expensive and energy consuming to be used in our case. To address such problems, sensors need to be removed from the sea when not used and substituted when degraded in order to carefully clean and recalibrate them at the laboratory.

The specific sensors to be used within MaDCrow have been chosen upon the possibility to correspond to several characteristics, and namely: (i) to be low cost (it was estimated that each sensor should cost at most around a hundred dollars) (ii) to use the same data communication interface (iii) to be robust, lightweight, of small dimension and that can remain submerged in salt water indefinitely; (iv) to provide the information needed to produce values of the marine environment quality indicator defined by the Apparent Oxygen Utilization (AOU) (see section 2.1.10); (v) to provide easy calibration of sensors with dedicated calibration liquids.

At the beginning of the project (2018), after an extensive market research, we selected a set of sensors produced by Atlas Scientific because, at that time, those met all requirements set above. This of course should not be considered an endorsement to any specific model or company. In this work, in fact, it was

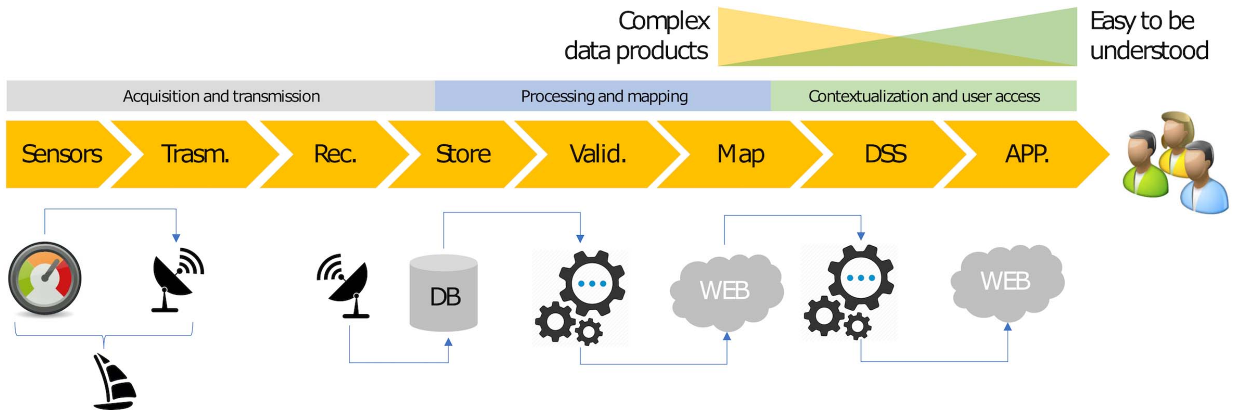


**FIGURE 1 |** The MaDCrow project framework.

our concern to always highlight the limitations of the tools adopted and of the paradigm in general (see the following section "The issue of precision, accuracy, and calibration of low-cost sensors"). Other models from other companies will for sure appear in the future, or possibly have even already appeared meanwhile, that will respond to the needs set above as well as those chosen in this work.

## The Issue of Precision, Accuracy, and Calibration of Low-Cost Sensors

The use of low-cost sensors brings the issue of their precision and accuracy. In **Table 1** we list the nominal values of resolution and accuracy of the sensors chosen for this work, as reported by the manufacturer.

All sensors, except the temperature one, are shipped with a set of reference liquids that allow a quick but rather accurate calibration. Probes have to be immersed in the liquids and the reference value has to be stored in the board that manages the probe itself.

The pH probe has a flexible calibration protocol, which provides three successive calibration levels: single point, two points and three points. Three calibration solutions have been used, with pH 4 (low), 7 (mid), and 10 (high) respectively.

The dissolved oxygen (DO) was calibrated using two reference points, storing the value while the probe is in the air, and using a calibration solution (DO = 0).

Similarly also the conductivity probe was calibrated using a two points procedure, where the two calibration solutions used were respectively 1,413 and 12,880 μS.

**TABLE 1 |** Nominal values of resolution and accuracy of the sensors chosen for this work, as reported by the manufacturer.

| Sensor | u.o.m. | Range | Resolution | Accuracy |
|---|---|---|---|---|
| Temperature | °C | −126 ÷ 1254 | 0.001 | ±0.1 |
| Acidity | pH | 0.001 ÷ 14.00 | 0.001 | ±0.002 |
| Dissolved Oxygen | mg/l | 0.01 ÷ 100 | not specified | ±0.3 |
| Conductivity | μS/cm | 5 ÷ 200000 | variable | ±0.02 |

The temperature probe was calibrated using boiling water, to correctly establish the value of 100°C.

The acquisition boards need a further setting for temperature or salinity compensation. More specifically, pH, DO, and EC sensor boards require temperature compensation (default is 20°C) and DO requires an additional salinity compensation (default is 0 μS for conductivity). This operation is performed periodically and automatically as new measures of temperature and conductivity become available.

A common opinion on low-cost sensors is that their accuracy and precision is low. This is certainly true under laboratory conditions, while at sea the situation can be less clear since other factors might further affect the measurements making low-cost sensors' low performances less relevant. Among those factors we have to keep in mind that the paradigm we are exploring postulates the acquisition of data from mobile platforms. The side effects of this configuration adds to the limitations of low cost sensors affecting further their precision and accuracy. Within this work we were able to study in detail the case of pH probes that is particularly important for SDG indicator 14.3.1. While in future works we plan to study in detail the case of the other types of sensors, since very likely they have a similar behavior to pH sensors, in this study we assumed they behave the same.

The pH measures the degree of acidity or alkalinity of a solution with an adimensional number ranging from 0 to 14, while for sea water it is important to be able to discriminate phenomena within a range between 7.5 and 8.5 (Marion et al., 2011). Following Yang et al. (2014) the accuracy of different types of technologies, corresponding to different ranges of costs, can scale down from ±0.001 to ±0.1. Okazaki et al. (2017) maintained that at sea, where temperature, gas exchange, pressure, and biological processes simultaneously affect seawater, precision and accuracy is not easy to be controlled, so that in these conditions, the gap between low-cost and high-end probes is moved from measurement accuracy and precision more toward repeatability and stability.

A further layer of complication is introduced by the fact that sensors are bound to a moving acquisition platform. Since opportunistic crowdsourcing of voluntary leisure boats is at the very core of the acquisition method, the idea was to avoid interfering with the activities of volunteers, so that within the MaDCrow project no restriction on velocity during acquisition was imposed on volunteers. This can end up in measurements being affected by the motion of the platform hosting the sensors. Specific tests have been made to assess the range of velocities within which measurements can be considered acceptable. These tests took place in a delimited area where measurements done with high-end instrumentation reported reasonably constant value and consisted in a certain number of profiles carried out with a small boat that mounted the MaDCrow acquisition system. Within each profile, velocity was kept 'ideally' constant while it was changed from one test to the other. We say that the velocity was kept 'ideally' constant since controlling the platform motion can be challenging. Operating the engine can be rather arbitrary and other factors, such as currents, waves and ship motion can further make measurements unclear. As mentioned above, the MaDCrow system allows to associate each measurement with its GPS position and speed so that during the analysis it was possible to gather data upon GPS speed. Notwithstanding the fact that tests were performed under ideal weather conditions of no wind and flat sea, it has been very difficult, as a matter of fact, to discriminate velocities with a resolution below 1 km/h.

To understand the dependence of measurements with motion, we can refer to the normalized distribution of seawater pH measurements made with the low-cost sensor in relation to platform speed in **Figure 2**. Each curve corresponds to the distribution of measurements retrieved during a specific test held at constant velocity. Curves are normalized in order to allow comparison between tests with a different number of samples.

For ease of reading, **Figure 2** shows five colored cases that are representative of a specific behavior: blue (0 km/h), green (4 km/h), orange (10 km/h), red (11 km/h) and darker red for velocity values above 11 km/h. It is easy to see how within the range between 0 and 4 km/h, pH measurements peak approximately around a value of 7.7. Within the range between 4 and 10 km/h the peaks move toward a pH value of 7.8, while for values higher that 10 km/h the situation quickly changes, and the pH measurements show a trend that exceeds values of 8. At the same time also the dispersion of measurements shows a quite distinctive trend in the graph of **Figure 2**, and namely that higher velocities show reducing peaks and more dispersed measurements.

Following Urbini et al. (2020), the North Adriatic Sea, due, probably to river discharges, shows pH values that decrease from West (8.4) to East (8.15), with pH measurements decreasing from the sea surface to the bottom, while, in detail, in the area of the Gulf of Trieste, in winter, pH values are higher (8.2) while in summer they are lower (7.9). During the velocity tests made with low-cost sensors, we measured a reference value with a top-end pH probe system. This provided a value of 7.9. **Figure 3** shows the average, the median and the standard deviation of all sensed raw pH measurements as a function of velocity. Low-cost sensors raw data acquired within the tests tend to have an almost constant drift of approximately −0.2 units compared to the reference values, up to the velocity of 10–11 km/h, when it starts to change steeply. This regular trend is even more clear considering the median value instead of the average of pH measurements. Following Okazaki et al. (2017) and considering the intrinsic limitations of low-cost sensors this behavior seems reasonable, while the degradation after 11 km/h could be related to different fluid flow status and could be important in order to plan the future development of new shapes for the sensor case. This behavior suggests that when the velocity of the platform remains below 10 km/h data acquired with low-cost sensors are consistent and could possibly be bulk corrected using professional high-end probes as reference measurements. Data acquired when velocity exceeds 10 km/h need corrections that are not easy to define so that within MaDCrow they are flagged out and do not enter the following steps of processing.

## Acquisition Hardware

The control board for the whole MaDCrow acquisition system is based on an Arduino Pro Mini 5V/16MHz. A switching regulator provides stable power at 5V DC to every component, using a 12V lead-battery as main power source. The Arduino microcontroller communicates with the sensors, processes and redirects the data through RS232 up to the GPS and communication device (**Figure 4**). Every unit is endowed with the acquisition board, additional boards for the electric insulation (needed to avoid interferences among the probes), BNC waterproof cables and the actual sensors.

The boards require 5V DC powering and are able to communicate through I2C protocol with a control board. The control software performs a periodic reading with each sensor board, followed by a period of sleep mode, in order to reduce consumption.

With respect to factory presets, the sensor boards require a setup at the laboratory, before being ready to be used at sea: the I2C protocol must be activated (the default is RS232) and a calibration procedure must be performed, by means of reference samples and lab measures.

## Transmission and Storage

After the acquisition by the control board, data are sent every 10 s through a simple unidirectional serial protocol to the transmission device, connected by RS232. Data transmission is based on a dual SIM industrial modem unit with 2/3/4G GSM technology. The availability of a dual SIM unit is a key feature for seas or body waters that cross several countries, such as the North Adriatic Sea, where three countries (with several GSM providers) share a relatively small sea region.

The transmission system adopted by MaDCrow is based on a high-gain GSM antenna that guarantees an open GPRS socket in case of long distances. The internal firmware selects automatically the proper GSM provider over 2, 3, or 4G technology, so that the board unit can rely on different types of communication technologies. In addition, the specific modem device chosen offers multiple I/O connectivity (1Wire, RS 232 and SD card reader) for future further development.

The on-board unit is equipped also with a GPS and GLONASS satellite navigation device and sends data every 10 s or 10 m or 15° bearing movement, according to an adaptive path algorithm. This approach aims to gather sensor measurements independently

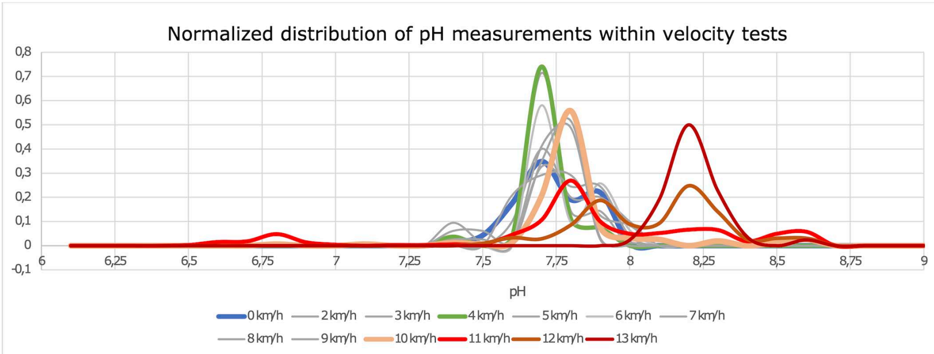


**FIGURE 2 |** Normalized distribution of seawater pH measurements in relation to platform speed. Velocities from 0 to 13 km/h are plotted. For ease of reading some of them are colored in order to highlight the trend: blue for the 0 km/h curve, green (4 km/h), orange (10 km/h), red (11 km/h) and in dark red the curves corresponding to velocities above 11 km/h. The graph shows that lower velocities exhibit peaks at lower pH values, while increasing the speed, the distribution of pH measurements moves toward higher values.

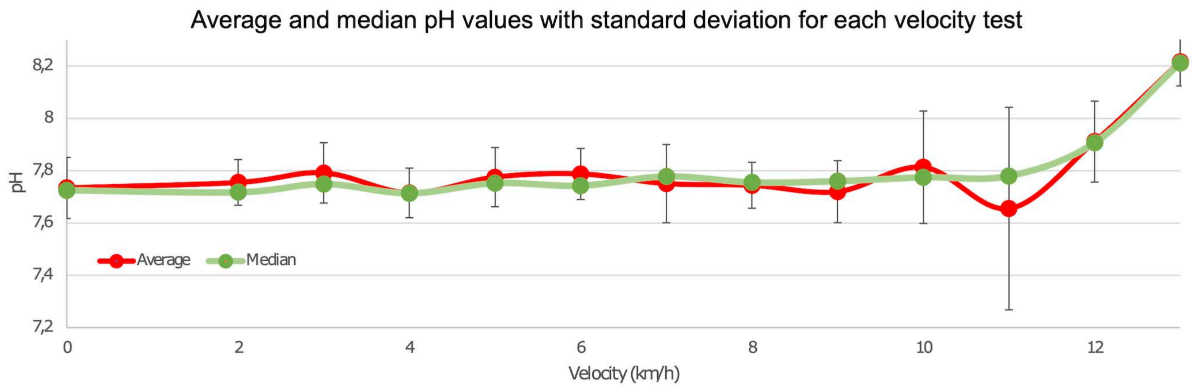


**FIGURE 3 |** Average, median, and standard deviation of all sensed raw pH measurement as a function of velocity.

from the vessel status, in order to maximize geo-referenced environmental data acquisition.

When the system insists in an area that is not covered by the mobile phone network, it can store up to 16,000 measurements that later can be sent onshore when the network is reached again.

The communication server is separated from the processing server and is accessed remotely, using secure authentication and by means of a set of customized Rest-API that transfer data in JSON format (**Figure 5**).

## Power Consumption

In order to estimate the average power consumption and the autonomy of the battery during the testing process, we separated two modules, and namely the sensor circuit on one side and the transmission system on the other.

The sensor circuit has two modes (**Figure 6**): active and sleep. In the active period (sensing and processing) we measured an average current of 76 mA. During the sleep period, we measured a value of approximately 60 mA. As active and sleep periods are approximately the same the average current was (76 mA + 60 mA/2) = 68 mA. The transmission, then, consumes alone 182 mA which makes the whole system consume in total 250 mA. When available, the acquisition system can be powered by the vessel's electric supply, using for example the cigarette lighter or other means. When this is not available the system can be operated on batteries only. Using a standard 12V 9Ah motorcycle battery the energy consumption of the whole system is 3Wh, which guarantees 36 h uptime. In order to extend this period, we studied and tested different renewable energy generation methods such as solar energy, wind power and water turbines. Using renewable energy, we keep the system independent from the boat/sailboat power supply system while using sources that are inexhaustible, clean and sustainable.

We tested a 100 W solar panel connected to a solar charger controller and a 12V 9Ah battery. This configuration allowed us to fully charge the battery on a sunny day so that in these conditions the system can run indefinitely. Of course, in case of reduced exposure to solar radiation, as often happens during the winter season, this cannot be fully guaranteed. A more powerful set of solar panels and batteries should be used in this case, which, on the other hand, can create deployment issues and could be perceived by the volunteers as too invasive.

We also studied the possibility of using wind generators. Several commercial solutions tailored for leisure boats are

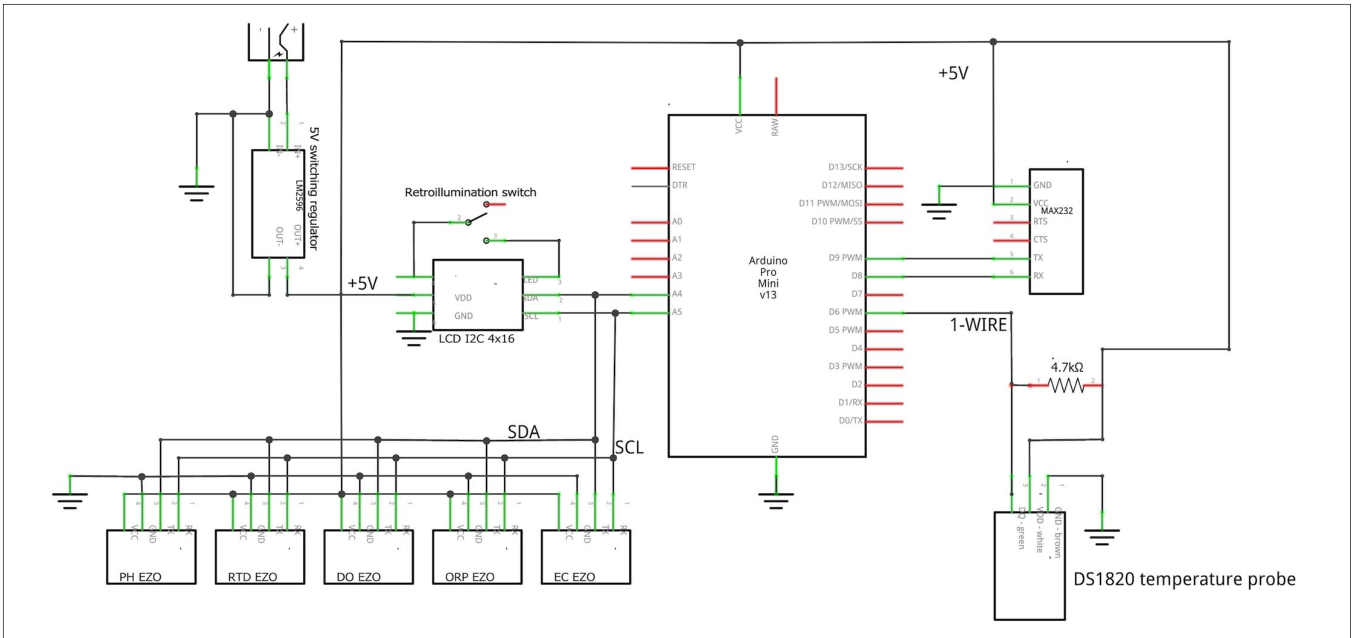


**FIGURE 4 |** Circuit diagram of the acquisition system.

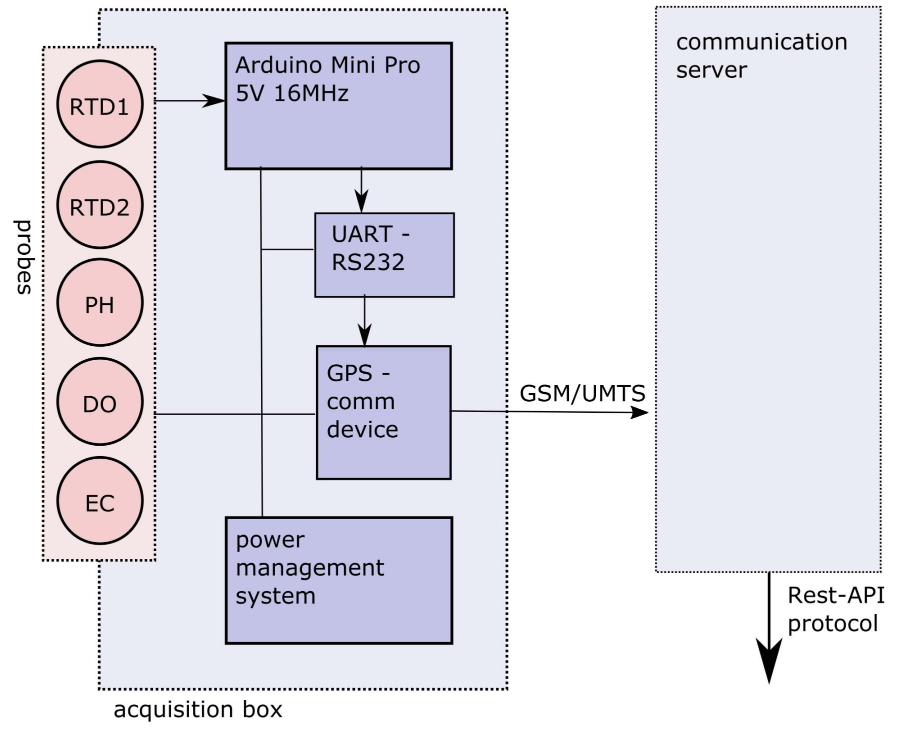


**FIGURE 5 |** Dataflow of the acquisition process.

available but with a higher cost compared to solar systems. In general wind generators are complementary to solar panels. In fact, in wintertime, they will keep on generating power even on cloudy days. They are operative also when the ship is docked/anchored, and they are also largely maintenance-free. On the downside, the relationship between wind speed and the energy these generators can produce is cubic, so power decreases exponentially if the wind regime is not sufficient.

We also analyzed the chance of improving power supply using water turbines and hydro generators designed for boats

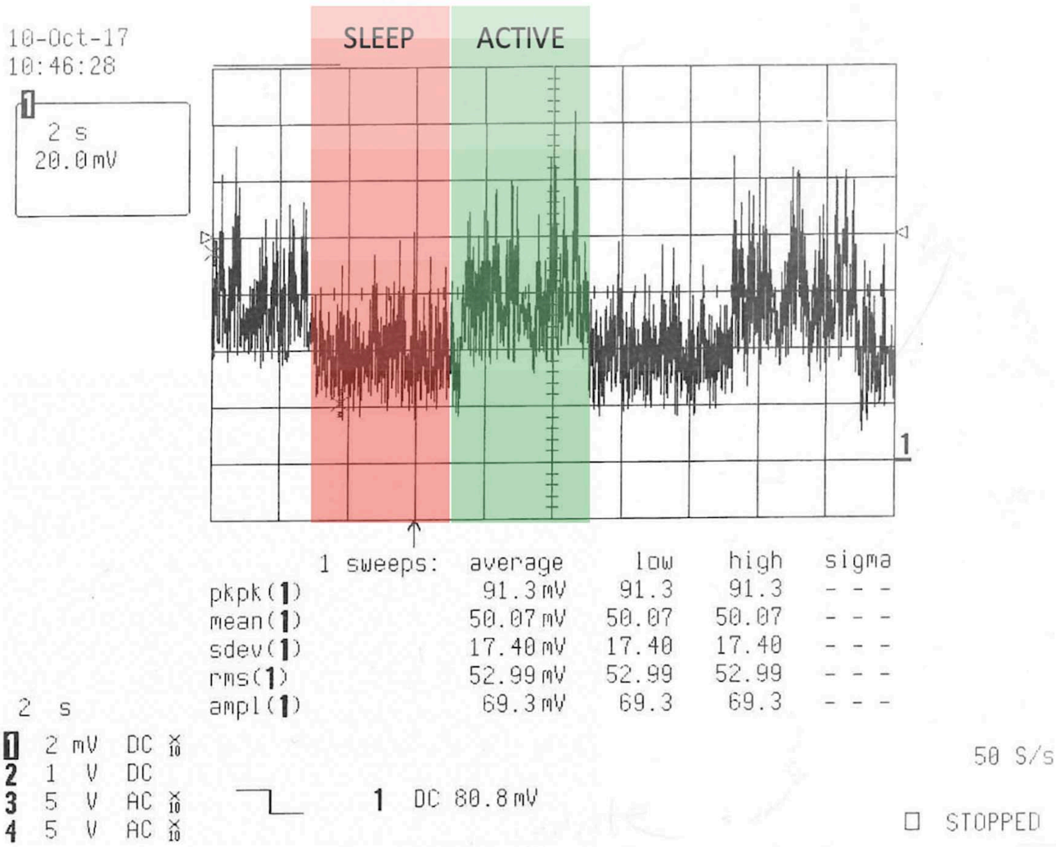


**FIGURE 6 |** Power consumption of the MaDCrow acquisition and transmission system in sleep and active mode.

and sailboats. This technology is very attractive because it can charge the batteries during all the time the boat is sailing, even in wintertime, without wind or daylight. Unfortunately, these generators are rather expensive in comparison with solar panels and wind turbines, they need high speed for high power output, and in addition, of course, they cannot produce energy while the boat is docked.

Summing up when electric supply is available from the boat, this solution is preferable. When this is not the case, considering that since a large number of platforms has to be employed costs have to be reduced at minimum, the best solution is to use solar panels, or in case the single vessel can bear the costs complement these with wind generators or water turbines.

## Hardware Case and Deployment at Sea

The sensor case (**Figure 7**) has been designed taking into account these fundamental requirements: waterproofness, impact resistance, flexibility of use, ease of installation and attractive design.

To deal with these requirements, the developed case consists of two sections, an upper one, which contains the electronics for data transmission and batteries, and a lower one, which houses the sensors and enters directly into the water. Two straps, placed in the upper part, and two lateral steel eyelets, allow the fixing of the MaDCrow device case on a wide range of boats. Sensors are deployed at approximately 50 cm depth, which is a tradeoff resulting after testing several configurations where higher depths imposed too much tension on the assembly, while more shallower


**FIGURE 7 |** The MaDCrow acquisition device and case: the lower segment contains sensors and is immersed; the upper segment contains all the electronics.

ones were too much influenced by the pitch and roll of the ship. The fixed and rather shallow depth of the sensor deployment of course implies further limitations on the possible information collected within the proposed paradigm.

### Processing

Within the processing phase data are retrieved from the communication server and stored into a relational database (**Figure 8**). After a set of processing steps specifically developed within the project, products are made available through an interactive web interface and through machine-to-machine web services.

The server was implemented in Linux (Red Hat Enterprise), a Postgres + PostGIS relational database, an Apache/Tomcat web server, a GeoServer GIS, and some PHP + HTML + CSS + Javascript code. The so-called "LAPP" stack solution provides reliability, scalability and is totally open-source. The engine of the system is a collection of PHP scripts, scheduled with crontab, which harvest the data from the communication server, perform all the required data processing and store the products into the database. The PostGIS extensions of Postgres database allow to perform complex geographical queries, to deal with projection and reference systems and to store processed data into database geometrical features such as points, lines or polylines.

### Visualization and Web Services

MaDCrow web-based data access relies on GeoServer software. This is a web GIS, based on Tomcat, capable of connecting to the Postgres + PostGIS database where crowdsourced data are stored, that allows to manage the geographical representation of data and maps and eventually to provide several web services. This allows an easy integration with web interfaces like OpenLayers or Cesium (for an interactive geographical view based on Javascript libraries) and with other automated systems, such as the Decision Support System (DSS) developed within the project.

The MaDCrow system makes use of standard web services defined by the OGC (Open Geospatial Consortium). WMS (Web Map Service) dynamically generates georeferenced maps, both vectorial (SVG) and raster (PNG, JPG, TIF, GeoTIFF). WFS (Web Feature Service) is defined as an XML protocol for geographical data exchange, based on GML (Geography Markup Language – ISO 19136). GeoJSon is an open-source format, based on a Javascript Open Notation (RFC 79146) and describing properties and geographical objects.

A pilot platform for visualization, with query and mapping capabilities, has been developed, based on open source Javascript library OpenLayers (**Figure 9**).

### From Data to Knowledge to Participation: Contextualization and End User Access to Knowledge via DSS

Participation of the general public, not only to increase the number of volunteers, but also to improve environmental awareness is at the very core of the project. We are convinced that, in this perspective, involvement must be based on a reward mechanism where the needs of many possible communities should be addressed by a production chain of knowledge focusing, at this stage of the project, on replying to easy to be understood sentences. After analyzing the outcomes of a web-based questionnaire submitted to the stakeholders, three use cases, have been identified: (1) "Let's go to the beach!", (2) "Vitality of the sea," (3) "Be careful at sea!". The first one gives information about the conditions of a specific area in terms of pleasantness of going to the beach and swim, the second one describes the status of the water in order to assess if fishes or mussels are under a stress, and the third one gives information about a potential oil spill in the sea. This, somehow, mirrors the above-mentioned identification of the main economic activities in the Gulf of Trieste (tourism, aquaculture, and marine transport).

Temperature, salinity, pH, DO data collected by MaDCrow are integrated with external sources and the Apparent Oxygen Utilization (AOU) indicator (Broecker and Peng, 1982; Ito et al., 2004) within a Decision Supporting System (DSS). The AOU is the difference between the measured DO concentration and its equilibrium saturation concentration in water with the same physical and chemical properties (as defined in the Biological and Chemical Oceanography Data Management Office[4]). This derived concept is influenced by physics and chemistry and by biology (see **Supplementary Materials**). The external sources used in the DSS are the ARPA environmental agency and other international bodies that provide forecast models based on real data such as the United States National Oceanic and Atmospheric Administration (NOAA).

The output of the DSS is a set of Key Performance Indicator (KPI) that can be used to deliver to stakeholders direct replies to the three questions mentioned above. For each scenario, the system provides an indication on the opportunity to make this choice in a given area, providing an indication with three values, green if positive, red if negative, yellow if the conditions are not totally negative but should be carefully considered (**Figure 10**).

Within the "Let's go to the beach!" scenario the DSS integrates MaDCrow crowdsourced data together with other parameters such as chlorophyll concentration, *Ostreopsis ovata* (harmful microalga, that blooms in the summer months and produce a powerful toxin), coliforms abundances (harmful bacteria that are discharged by the wastewater systems), local weather conditions (air temperature and wind) and the AOU. In the "Vitality of the sea" scenario, MaDCrow temperature, salinity, oxygen and pH and AOU are used, together with chlorophyll concentration and *Ostreopsis ovata* abundances. For the "Be careful at sea!" scenario all MaDCrow temperature, salinity, oxygen, pH and AOU data are used.

## METHODS

## Study Area

To test the proposed approach, we deployed the developed system in a specific area of the Gulf of Trieste that can roughly

[4]https://www.bco-dmo.org/parameter/527499

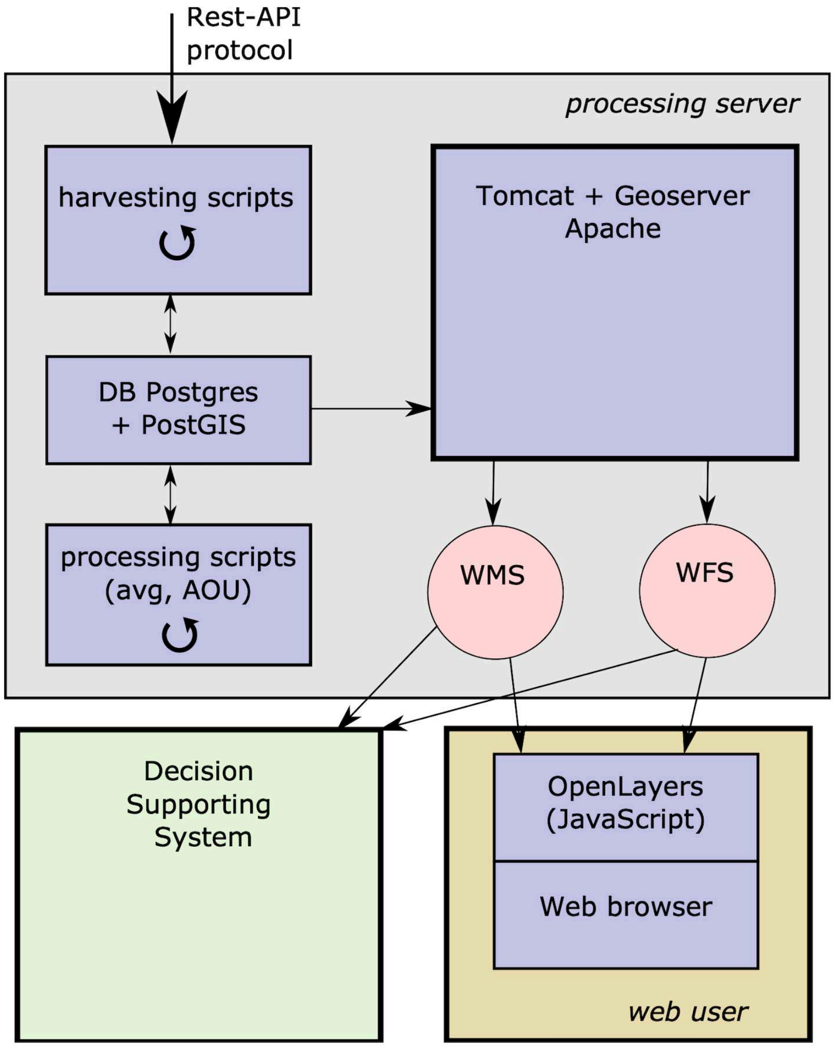


**FIGURE 8 |** Architecture of the MaDCrow processing server and the web front-end.

be associated with the bay of Panzano, that corresponds to the coastal area between the river outlet of the Isonzo river and the Natural Marine Reserve of Miramare (**Figure 11**). The area is densely anthropized with the prominent urban area of the city of Monfalcone and several touristic marinas and resorts that discharge their sewage in the area. The resulting enrichment of water in nutrients (eutrophication) causes structural changes to the ecosystem such as: increased production of algae and aquatic plants, oxygen depletion (hypoxia), general deterioration of water quality, changes in ambient light environment and depletion of fish species (Alexander et al., 2017).

The bay of Panzano is home also of industrial activities such as very important and active shipyards, a papermill and a thermoelectric plant.

All these factors are a threat to the environment, but at the same time endanger also human activities such as fishery and mussel farming.

The shallow and semi-closed area takes to the extremes the peculiarities of the Northern Adriatic Sea where the dynamics of ecosystems are strongly dependent on air, land and sea interactions and prone to fall into worst case scenarios due to climate warming (Riedel et al., 2008). In detail, the study area is characterized by a very high spatial and temporal variability of environments due to the interaction between fresh-water river inputs and saltwater which is often responsible for the formation of strong salinity gradients (25–38 PSU) (Cozzi et al., 2012). River inflows are due mainly to the influence of the Isonzo river discharges. These can be estimated on average between approximately 90 and 120 $m^3/s$ (Comici and Bussani, 2007), with two typical flood periods: one in spring, due to snowmelt and one in autumn due to heavy rainfalls when it can exceed 2500 $m^3/s$ (Sirca et al., 1999; Covelli et al., 2004). Minor influxes are related to the Timavo river, which has a Karstic regime, and re-emerges from several springs with an average influx of approximately 30 $m^3/s$ (Gabrovšek and Peric, 2006). Currents in the Gulf of

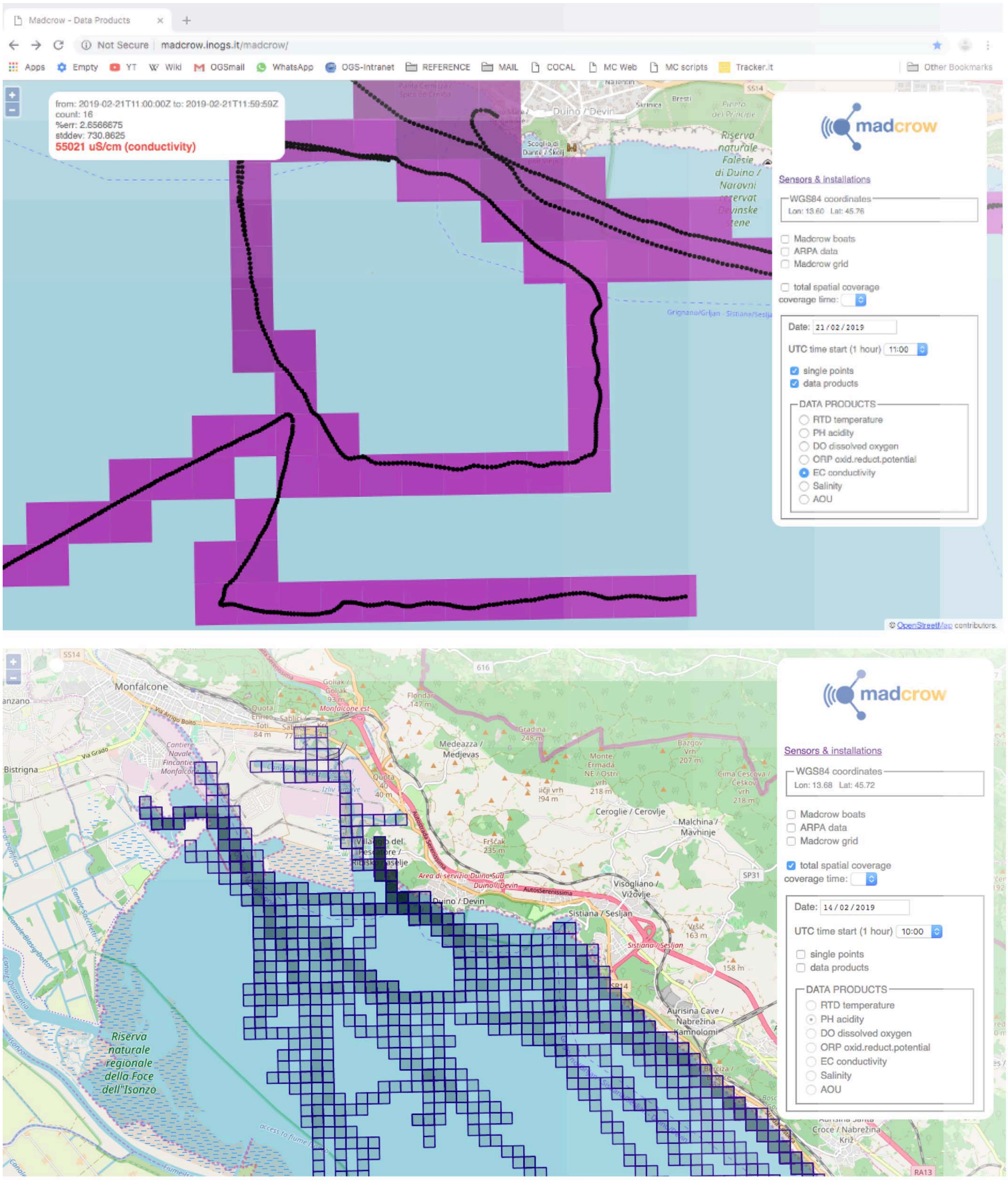


**FIGURE 9 |** Coverage of the processed data and Geographic distribution of a single parameter (Conductivity) as can be seen for the pilot web portal of the MaDCrow Project. The portal allows to retrieve single measurements, aggregate gridded data and details for a single cell.

Trieste can be described through the layered gyre-type circulation pattern composed of a weak (2–3 cm/s) permanent cyclonic (counterclockwise) circulation below 10 m and a wind driven alternating cyclonic/anticyclonic flow in the surface (approx 5 m thick layer) proposed by Stravisi (1983). In the bay of Panzano this model becomes even more complex, dynamic and sensitive to climate change due to the very shallow sea and the proximity with the outlet of the Isonzo river. The whole Gulf of Trieste is often swept in winter by a very strong Bora wind (NNE) characterized by the formation of alternating jets and wakes associated with the coastal orography (Vozila et al., 2019).

Land borne nutrients follows the distribution of the haline fronts, showing complex horizontal and vertical gradients (Cozzi et al., 2012) sustaining productivity of the coastal zones and triggering frequent phytoplankton blooms and hypoxia, especially in late winter and autumn (Cozzi and Giani, 2011),

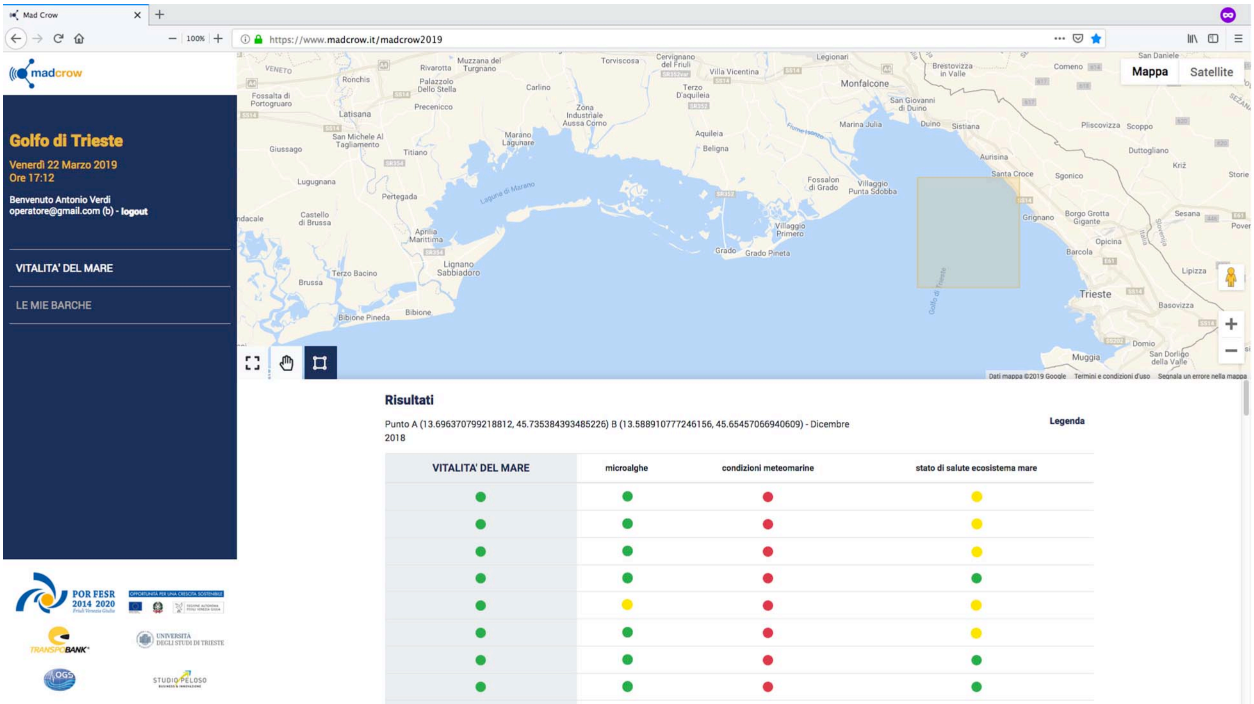


**FIGURE 10 |** DSS web portal. Here data acquired within the MaDCrow project is integrated with information from other sources. To make it understandable and respond to contextualization knowledge is represented using the metaphor of a semaphore.

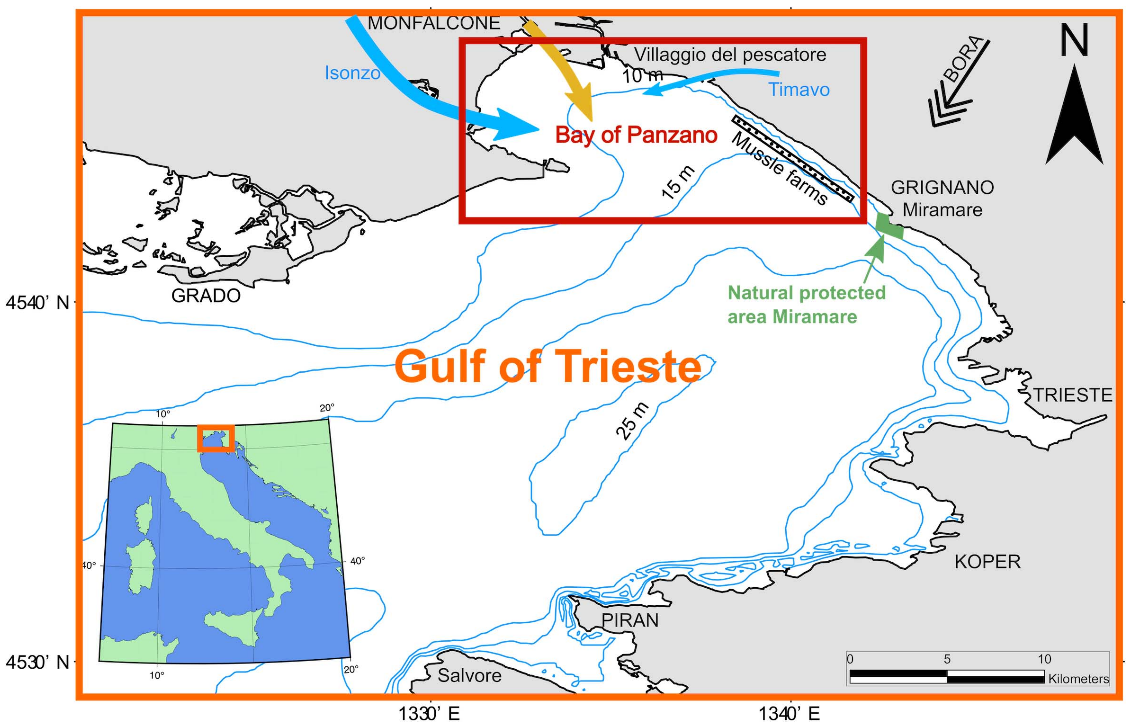


**FIGURE 11 |** The Gulf of Trieste (Northern Adriatic Sea) and the study area: the bay of Panzano.

which can result in negative impacts on tourism, fishery and mussel farms hosted in the area. Following Vidović et al. (2016) long term organic enrichment in this area is witnessed by the changes in the presence of foraminiferal species while Tomašovych et al. (2018) studied hypoxia periods through time that seemingly have not been induced only by human activities. Dynamics and extension of river plumes conditions also the formation of mucilaginous aggregations (Giani et al., 2005). In addition, the Isonzo river is of interest, also because it has been a source of mercury coming from cinnabar mining activity since the sixteenth century (Covelli et al., 2006) in the Slovenian hinterland. The shallow sea of the bay is characterized by sediments that range from pebble enriched sands in the nearshore areas to an increasing pelitic fractions in the foreset beds.

The complexity of the designated area results in a very dynamic environment which calls for high resolution and high spatial and temporal coverage. While this is very difficult and expensive to obtain with traditional methods, considering what said above, the proposed paradigm seems a very promising perspective.

## Environmental Parameters

Monitoring the sea is a very complex and wide research domain. Considering that within MaDCrow data acquisition has to take place within a crowdsourcing paradigm, it was necessary to narrow the range of the possible environmental parameters to acquire, taking great care, at the same time, to avoid hampering scalability and preserving the possibility to apply straightforwardly the system elsewhere. In this sense, the Gulf of Trieste and in detail the Bay of Panzano can be considered representative of many coastal areas where the economic activities, ad possible harms to the sea are centered on industries, tourism, aquaculture and maritime transport but where also there is a high spatial and temporal variability of the environments due to the interaction between river inputs and saltwater. These economic activities do not always coexist without problems so that the participative monitoring model MaDCrow proposes could be very effective also from the point of view of policy makers.

We recognized science and society should aim at a quantum leap strategy in monitoring the sea by measuring in quasi real-time the Environmental Essential Ocean Variables (EOVs, Miloslavich et al., 2018) in accordance with the GOOS (Global Ocean Observing System, Global Ocean Observing System – GOOS) measurements, and in this perspective MaDCrow has the potential to fill the gap of the ongoing monitoring efforts increasing local high resolution of primary variables and associated products both from a spatial and temporal point of view.

Considering all these factors, the choice of the environmental parameters to measure was on temperature, salinity, DO, and pH.

The four parameters can capture the most important physical and chemical properties of seawater. Chlorophyll and turbidity sensors were also considered since they offer information about microalgae and the presence of particles in the sea, but the implementation of sensors oriented toward biology have been delayed until an initial test phase with the first series of sensors have reached sufficient robustness. In this perspective, the choice of the environmental parameters to measure was a tradeoff between the availability and affordability of sensors, the technical integrability of hardware components and the actual scientific targets that were considered. In the detail of the study area (the Bay of Panzano), the scientific target was the assessment of the marine environment status to monitor algal blooms and hypoxia through the AOU indicator that is calculated from crowdsourced data. In this perspective the choice of sensors matched the scientific purpose.

## Data Collection

During 3 days in February 2019 (13, 14, and 20) the designated area was surveyed using three voluntary boats mounting the MaDCrow acquisition device. Data collection for all platforms was simultaneous and lasted during the whole daytime. The three boats were very different; one of them was a Archambault A35 racing boat that acquired data mostly while sailing; another one was an outboard motor inflatable rubber boat, while the third vessel was a Carolina Skiff motorboat. They are generally docked in different marinas and run by different people that were enrolled specifically for the survey. As mentioned above, no obligation was imposed to the owners of the boats except to navigate within the designated area and, considering the limitations highlighted in section "The issue of precision, accuracy and calibration of low-cost sensors," to avoid, if possible, velocities above 13 km/h. The installation of the acquisition device on the rubber boat and motorboat were simple and efficient while we realized that some attention must be paid in the case of the sailing boat, because ship rolling can, during certain sailing maneuvers, project the sensors outside the sea. The coverage of the area was a concern but eventually exceeded expectations. This probably could be due to the different areas of provenance of the boats that forced them to enter the designated area from different directions. We realized that there is a slight prevalence of coverage on the North East part of the designated area. This is easy to explain since that is the more touristic portion of the bay, which demonstrates that some motivational strategies, from gamification to economic rewarding should be considered to extend coverage in less pleasant areas.

## Data Validation

The first step of data processing is data validation. Values that fall outside an acceptable interval must be dropped (for instance a water temperature of 50°C). In order to mitigate the effect of random spikes, the time series undergo a smoothing process. In this we tested several methods and the moving median proved to be the most robust and effective method, as displayed in **Figure 12**, where the blue line is the original time series, and the red line represents the filtered values.

## Statistics

After the validation, the measurements are a set of different scalar values for each measured parameter, marked with a timestamp (in UTC), latitude and longitude (based on GPS standard, WGS84). The database is populated by measurements acquired by all the

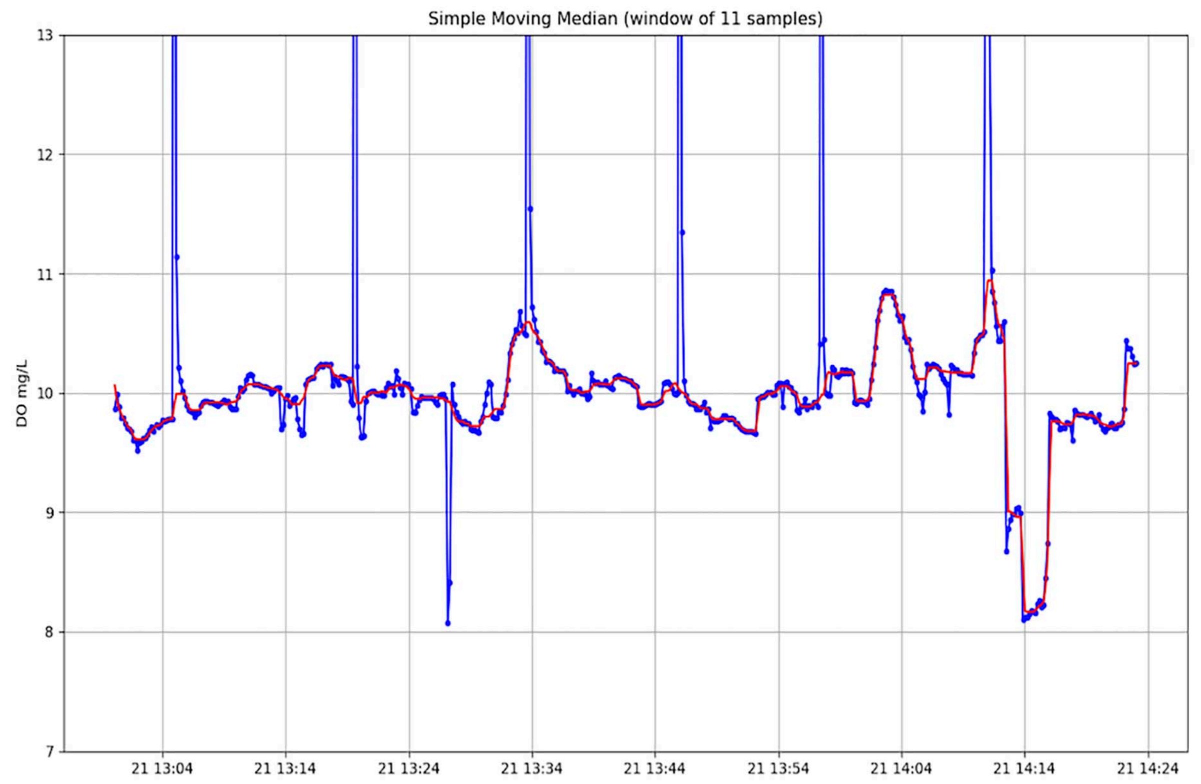


**FIGURE 12 |** Data quality control, validation, and filtering.

available vessels and the objective of this processing step is to statistically aggregate these data (**Figure 13**).

We have chosen a geographical reference system tuned for the North-East Adriatic Sea, based on the Universal Transverse Mercator projection UTM 33N (EPSG:32633) with a regular square grid with side length of 200 m. Considering time intervals of one UTC hour (e.g., from 13:00:00 to 14:00:00), we may define our datacube as the subset of measured values within one square cell and within one specific hour. All values within a datacube are aggregated in order to generate processed data products on a cell-by-cell basis and namely: the mean and median value, the number of samples, the standard deviation and the estimated percent error. These aggregated data (primary products) are then stored into the database and made available through the web interfaces.

Further processing of primary products generates "secondary products" such as salinity (in pss, a function of temperature, pressure and electric conductivity) and the AOU environmental quality indicator.

## RESULTS AND DISCUSSION

A very important factor to consider in order to understand the importance of the use of crowdsourced data is how they relate to the available data acquired with traditional methods, how the former and the latter can address the scientific questions that rise in the specific environment and how they match the needs of the end users. The relation between traditional and crowdsourced data can change depending on the different environment. In the case of wide oceanic areas with slowly changing parameters, for example, the resolution and coverage needed will be much lower than that required in dynamic coastal and shallow water environments. While there is no limitation in the use of low-cost sensors in oceanic environments, the advantages of the low-cost approach in terms of logistics, costs and increase in resolution and coverage become less evident. Tuning the integration of the two approaches on the specific environment under study, potentially can result in great improvements from proceeding separately.

We will here consider the case of the study area starting from what data is currently available, what is missing and how the crowdsourcing approach can not only fill gaps but also increase dramatically spatial and temporal coverage and resolution.

### Data Sources

Currently, environmental data, within the bay of Panzano, can be obtained essentially from the Territorial Environmental Protection Agencies (ARPA-FVG) and the Copernicus data services. Other possible sources of observations are the oceanographic buoys located in the Gulf of Trieste that are rather distant from the study area and the Emodnet services which cover the Gulf with a single cell and therefore cannot have the needed resolution to account for the high variability of the environment of the bay.

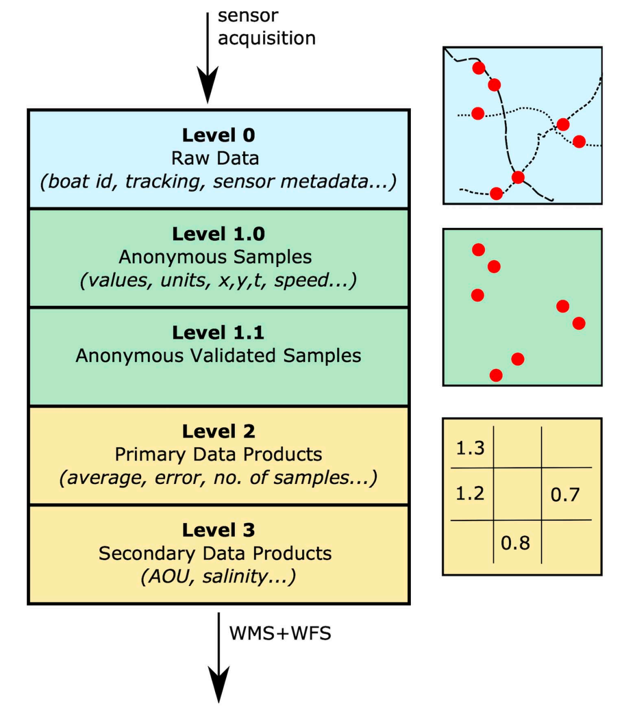


**FIGURE 13 |** Production workflow of the MaDCrow project. From level 0 to level 3 raw data is transformed into statistically validated environmental quality indicators such as the Apparent Oxygen Utilization (AOU).

The FVG regional environmental agency of ARPA-FVG[5] monthly monitors 28 marine historical stations, 13 stations that have been defined according to the MSFD and 19 transitional water stations. Three are the sampling depths (surface, intermediate and deep) where temperature, salinity, pH, oxygen saturation, chlorophyll, PAR (photosynthetically active radiations) are measured. *In situ* values are spatially interpolated between sampling stations, while monthly acquisitions leave large gaps between observations.

The Copernicus Marine Service, Ocean Products service (Escudier et al., 2020) offers daily averaged data products generated by a numerical system composed of an hydrodynamic model, supplied by the Nucleus for European Modelling of the Ocean (NEMO) and a variational data assimilation scheme (OceanVAR) for temperature and salinity vertical profiles and satellite Sea Level Anomaly along track data. The resolution of the data is approximately 4 km by 4 km.

## Data Analysis

Comparison of the resolution and coverage obtainable from crowdsourced data and traditional methods available in the study area can be seen in **Figure 14**.

**Figure 14A** reports on the distribution of temperature collected during the survey mentioned in section "Data collection." It shows superimposed the available datasets, and namely (i) the high resolution (200 m × 200 m) measurements obtained using 3 crowdsourcing boats; (ii) the Copernicus model (Mediterranean Sea Physics Reanalysis) with a lower resolution 4 km × 4 km grid; (iii) the network of ARPA observation stations (the black triangles in **Figure 14**) that in the study area comprises only point measurements acquired monthly, that need to be later inter/extrapolates in the area. In addition, unfortunately no data is available from this source in the designated period of the test survey.

During the 3 days, the routes of the three MaDCrow boats covered almost randomly the area of interest since no constraint was imposed on their activities. Notwithstanding this, they reconstructed a very detailed, although of course not complete, distribution of measurements in the area. A larger number of volunteers could have covered almost all the area, but it is difficult to estimate the ideal number of boats needed because, as mentioned above, if no constraint is imposed on volunteers, they tend to avoid unpleasant areas. With a more systematic approach, instead, we estimate that already with less than five boats it could be possible to cover in great detail the whole area.

From the comparison of the different datasets in **Figure 14A** it is possible to see the large improvement in resolution and coverage provided by the crowdsourced dataset, which allows to highlight the influences of the varying regime and extension of freshwater plumes and how they relate with saltwater masses, of the depth of the seafloor, and the effects due to the presence of the small marinas. The values from Copernicus and crowdsourcing are rather similar in the open sea areas with differences approximately below the unit Celsius degree while they diverge significantly in the highly dynamic areas.

**Figure 14B** shows the distribution of salinity using Copernicus and crowdsourced data. There is a very good correlation between the two datasets in open sea areas while the crowdsourced dataset is very successful in highlighting the local variations due to river inflows or marinas. This is very important because as mentioned before land borne nutrients follow the distribution of the haline fronts.

Referring to **Figures 14C,D**, unfortunately we have to highlight that Copernicus service does not provide data for pH and DO, so we can only map the positions of ARPA station, that unfortunately has no coverage in the time period of the survey.

MaDCrow ideally has the potential to increase the temporal and spatial resolution of the data available with traditional methods in a study area considering the scenario of a fleet of citizen scientists sailing the area for fishing and bathing activities or just enjoying the breeze. We recognize that as humans we tend to be very active during the daylight and the holidays. Nevertheless, data will be generated at unprecedented spatial and temporal resolution and once integrated within larger databases (e.g., Emodnet and Copernicus) will deepen our knowledge and understanding of temperature, salinity, DO and pH dynamics in this area.

## LESSON LEARNED

The MaDCrow project has been devised to develop mainly the technologies that could support crowdsourcing/citizen science

[5]http://www.arpa.fvg.it/cms/tema/acqua/

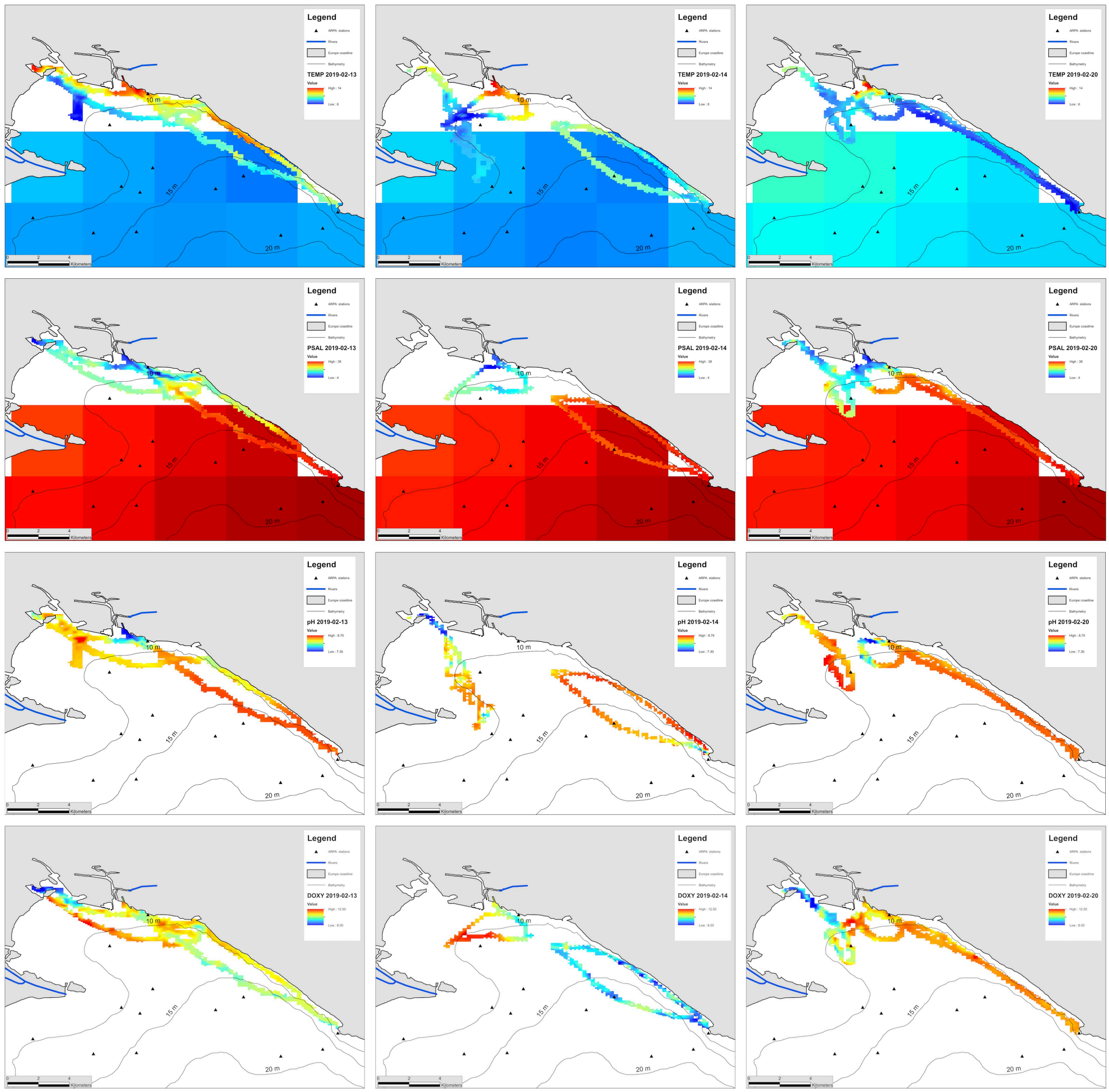


**FIGURE 14 |** Spatial distribution of the four environmental parameters (Temperature, Salinity, pH, Dissolved Oxygen) considered in the MaDCrow project from three data sources (i) the crowdsourced dataset with a resolution of 200 m by 200 m grid (ii) the Copernicus model with a resolution of 4 km by 4k m grid (iii) the positions of the ARPA stations whose measurements are taken monthly and have to be inter/extrapolated geographically and in time. **(A,B)** Shows the three datasets superimposed highlighting the improvement of the resolution and coverage of the crowdsourced data. **(C,D)** Shows only the crowdsourced data since no data is available from the other sources.

initiatives in marine environmental data acquisition and access. Following EU codes for Technology Readiness Level (TRL) MaDCrow was planned and funded to produce a result that corresponds to level 6 – Technology demonstrated in a relevant environment. We were able to go well beyond this goal and are currently working on the preparation of a full-scale crowdsourcing/citizen science initiative that will be entirely based on the outcomes of MaDCrow.

During the development of the project we have been able to identify several issues at different levels and namely: scientific, technical, and participative. We have been able to tackle most of them, while several are still under scrutiny.

From a scientific point of view, we were able to address the main goal of the MaDCrow project, that was to demonstrate that the acquisition of data within a crowdsourcing paradigm allows effectively to cover large areas and ranges of time with small investments. Besides this we have been able also to address other non-trivial questions such as 'what is the real value of crowdsourced data?,' 'How does the lack of accuracy and precision of low cost sensors affect results?' and 'How can we address this issue?'; questions that are in line with those posed by Lauro et al. (2014) and that have been mentioned in section "The infrastructure" of this work, regarding which, it is possible to say, yes; low cost instrumentation can produce meaningful data and can be easily deployed on a large range of types of boats where almost anyone can operate them. We have seen that the comparison between low-cost sensors and high-end probes cannot be straightforwardly extended from the laboratory to the sea. In the latter case, in fact, stability and replicability of the measurements can be themselves an issue, so that intrinsic precision and accuracy starts to be less relevant. As a matter of fact, considering the deployment device we have developed and the specific sensors we have used, we carefully analyzed the behavior of the MaDCrow system in comparison with the traditional methods. If the former is mounted on a marine platform moving at velocities below 12 km/h (which is often the case for leisure or small boats) we demonstrated that the sensor drift is almost constant and therefore crowdsourced measurements can be corrected using reference values acquired with traditional methods. In this perspective it is possible to extend the quality of local measurements obtained with high end instrumentation to the areas covered by means of crowdsourcing methods only. At the same, time, since the spatial distribution of crowdsourced data preserves its high spatial resolution and even most importantly, values does not result from an intra/extrapolation of sparse points but from an actual measurement, crowdsourced data are able to highlight features that would be overlooked in the case of undersampled data acquired with traditional methods.

On a technical level we have demonstrated that the entire workflow from data acquisition to data access through web-based portal and services is feasible and can be developed using open-source hardware, programming languages and software solutions only. At this level an issue that could be relevant is the power consumption of the acquisition and transmission device. When an external power supply line is not available, we demonstrated that an easy solution can be achieved using 100 W solar panels coupled to 12 V batteries. This set up of course requires space onboard that is not always easy to find and is, therefore, a solution that needs to be agreed upon with the boat owners. Alternative solutions have been explored that having some advantages over solar power, impose higher costs; a perspective which is against the philosophy of the project.

Although MaDCrow was mainly aiming at developing solutions at technical and scientific levels we studied carefully also the participative aspects of the initiative. This will be extensively reported in a related publication (Diviacco et al., 2021), while we would like here to highlight what is the rationale behind our choices. The importance of considering openly the goals of participants and stakeholders in these types of projects has been pinpointed by several authors such as for example Bruyere and Rappe (2007) and Ellwood et al. (2017) with a specific focus on public awareness of environmental issues, where people contribute both because the environment has an intrinsic value and because they want to learn and gain knowledge.

If learning and knowledge is therefore central in the perspective of volunteering to initiatives such as MaDCrow and ultimately in environmental awareness (the other main goal of the project) it is of paramount importance to be able to reach the public with messages that can be easily understandable. Raw data (complex products in **Figure 2**) are useful for scientists but cannot be used directly to address laypeople. They need to be translated into easy to be read products (**Figure 2**). To convey these messages, we identified some questions that can be linked to the main economic activities and interests of the area of the Gulf of Trieste (tourism, aquaculture, and maritime transportation) and built a DSS that integrates Crowdsourced data, information from external sources and expert's knowledge in order that each community of end users will then find easy to understand answers for their needs. We estimate that the availability of these end user-oriented products besides nurturing environmental awareness in the general public will also stimulate participation in the project through identification with the processes of knowledge creation. We think this is of paramount importance since a very unfortunate phenomenon that can be easily identified in contemporary society is the detachment between science and people, which can give rise to unmotivated and deplorable habits, such as propagating news and views that are not based upon scientific research.

## THE WAY AHEAD

The MaDCrow project has been able to reply to many questions and to address many issues. Some results are still to be fine-tuned while others are still open.

The main weakness MaDCrow has to address as soon as possible is to extend the fleet of participating volunteer vessels. As mentioned above, the project aimed mainly at developing the technologies behind the infrastructure, leaving the actual implementation to a specific second round. As a matter of fact, only a restricted fleet of three testing vessels took part in the acquisitions done so far, while reaching a critical mass of platforms is important for several reasons.

From a scientific perspective, of course, the availability of a larger fleet will allow to cover larger areas and improve statistics.

From a development point of view, we would have the possibility to better test the scalability of the infrastructure in terms of robustness and needs of resources, to test the processing module with larger datasets, to further test the behavior of sensors in different conditions and to improve the design of the acquisition device frame. Regarding this latter topic, while so far, the frame we used to deploy the acquisition system at sea revealed to be efficient on several classes of vessels we highlighted that on motorboats its design should be revisited. As already mentioned, we'd be very interested in studying a different shape and other means to physically attach it to the hull of the boat in order to reduce turbulence and possibly improve the range of velocities within which data can be considered acceptable.

From a participative perspective, we think that reaching a critical mass of volunteers could be very important. Following Maund et al. (2020), in fact, individuals are more motivated to engage into large-scale citizen science projects, while

Sutherland et al. (2015) maintains that if initiatives fail to engage or retain enough contributors, they are unlikely to achieve good results.

We are currently planning to implement a full scale MaDCrow initiative, and to address the extension of the fleet of voluntary platforms following multiple paths. The first one will be to use the current restricted fleet and the data that has been acquired to demonstrate the possibilities of the initiative to the larger public. In this sense we already started to promote MaDCrow in the broadcast media, at local, regional and national level. We were also successful in gaining visibility on national newspapers and planned a dense outreach program aiming at science fairs, schools, public talks, lectures and discussions. Unfortunately, the Covid 19 outbreak heavily reduced the possibility to follow this specific direction, which demonstrated to be very efficient.

Another path we are following, is to enroll volunteers within a commercial perspective. This is in line with the expectations of the ERDF framework to develop business, competences and jobs in the perspective of the blue economy. The idea behind this path is essentially an extension of the mechanism to reach end users through simplified and tailored data products, and consists in identifying specific classes of users, tune the infrastructure to solve their specific needs, while involving them in the acquisition of raw data that will become an asset of the project.

The data collected and their subsequent reprocessing represent the heart of the project, but the success of the MaDCrow model will depend on the way in which information that is truly relevant to end users will be identified and then disseminated, exploiting a disruptive network effect.

## DATA AVAILABILITY STATEMENT

All data acquired and used within the MaDCrow project can be freely accessed through the web based portal http://madcrow.inogs.it/madcrow and through the OGC compliant WMS/WFS web services it offers at the following URLs: http://madcrow.inogs.it/geoserver/wms and http://madcrow.inogs.it/geoserver/madcrow/ows.

## AUTHOR CONTRIBUTIONS

PD led, organized, and wrote most of the manuscript. AN and LG were responsible for data transmission. MI was responsible and wrote the parts related to data processing and web mapping. RC was responsible and wrote the part related to power supply and together with AP developed and wrote on hardware development. MB gathered and mapped all data available in the study area. AB was responsible for IT system management. MN was responsible and wrote together with PD the part regarding the DSS development. AM developed and wrote the business oriented part. FM was responsible and wrote together with PD the parts related to the biological and oceanographic phenomena and processes. All the authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2021.619898/full#supplementary-material

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METHODS
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# The Reef Check Mediterranean Underwater Coastal Environment Monitoring Protocol

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Since 2001, trained snorkelers, freedivers, and scuba diver volunteers (collectively called EcoDivers) have been recording data on the distribution, abundance, and bathymetric range of 43 selected key marine species along the Mediterranean Sea coasts using the Reef Check Mediterranean Underwater Coastal Environment Monitoring (RCMed U-CEM) protocol. The taxa, including algae, invertebrates, and fishes, were selected by a combination of criteria, including ease of identification and being a key indicator of shifts in the Mediterranean subtidal habitats due to local pressures and climate change. The dataset collected using the RCMed U-CEM protocol is openly accessible across different platforms and allows for various uses. It has proven to be useful for several purposes, such as monitoring the ecological status of Mediterranean coastal environments, assessing the effects of human impacts and management interventions, as well as complementing scientific papers on species distribution and abundance, distribution modeling, and historical series. Also, the commitment of volunteers promotes marine stewardship and environmental awareness in marine conservation. Here, we describe the RCMed U-CEM protocol from training volunteers to recording, delivering, and sharing data, including the quality assurance and control (QA/QC) procedures.

**Keywords: marine citizen science, indicator species, marine protected areas, coastal zone management, monitoring, climate change, human impacts, Mediterranean Sea**

## INTRODUCTION

Community-based environmental monitoring is a participatory approach engaging volunteers through citizen science (CS) programs to enhance the ability of decision-makers and non-government organizations to monitor and manage natural resources, track endangered species, and protect biodiversity (Conrad and Hilchey, 2011; Chandler et al., 2017). Therefore, community-based monitoring engages citizen scientists and other stakeholders in the ecosystem-based management of natural heritage, not only aiming to increase the chance of obtaining biodiversity data for conservation purposes but also to raise public awareness and support for environmental protection (Keough and Blahna, 2006; Freiwald et al., 2018; Alexander et al., 2019). Marine citizen science (MCS) may provide a valuable contribution to community-based monitoring in marine environments, given the vastness of the world's oceans and coastlines and the diversity of their habitats, communities, and species (Thiel et al., 2014; Garcia-Soto et al., 2017). Involving millions of people worldwide, MCS programs are becoming increasingly important to conservation science not only by providing monitoring of biodiversity, ecosystem services, and functions but also by influencing and improving the management of marine protected areas and fishery resources (Freiwald et al., 2018). Despite a worldwide increase in program number and extent of MCS (Thiel et al., 2014), the collected information is rarely used for institutional monitoring programs or to inform decision-making processes in marine conservation (Conrad and Hilchey, 2011). This disconnect is partly due to persisting skepticism about the reliability of data collected from volunteers (Burgess et al., 2017) and a co-creation approach in the supply and demand of environmental monitoring data that is still not well-integrated in CS processes (Bonney et al., 2015). However, many studies demonstrate that well-trained citizens can provide valuable data on marine environmental issues and that suitable protocols for volunteer projects can provide results consistent with the methods used by the professional researchers (e.g., Holt et al., 2013; Forrester et al., 2015; Done et al., 2017). Still, there are limits to accessing the MCS data (Thiel et al., 2014), which are not always well-organized and readily available according to the FAIR (findable, accessible, interoperable, and reusable) data principles (*sensu* Wilkinson et al., 2016).

Here, we describe a well-established MCS protocol i.e., the Reef Check Mediterranean Underwater Coastal Environment Monitoring (RCMed U-CEM) protocol, which is refined and applied since 2001 by trained snorkelers, freedivers, and scuba diver volunteers (hereafter called as EcoDivers) to collect data on the occurrence, distribution, abundance, and bathymetric range of selected key marine species along the Mediterranean Sea coasts. The obtained dataset is openly accessible across different platforms and allows for various uses, such as complementing scientific papers on the species distribution and abundance, aiding distribution modeling, and comparing historical series (Lucrezi et al., 2018 and references therein). The protocol is implemented, and the data are maintained by the non-profit organization Reef Check Italia onlus, collaborating with the other European Reef Check organizations, members of the worldwide Reef Check Foundation, and within the Reef Check Mediterranean Sea network.

## METHODS

Reef Check Mediterranean Underwater Coastal Environment Monitoring (RCMed U-CEM) protocol is intended to collect data on the abundance, and geographical and bathymetric distribution of selected taxa. It requires trained participants (certified EcoDivers) to collect standardized data and send it to the online database. The data are then processed and made available on the various open access sharing platforms.

### Selected Taxa

The 43 target taxa were selected by scientists from a combination of two or more criteria, including ease of identification, inclusion in the international lists of protected species, being sensitive to human impacts, and the effects of climate change occurring in the Mediterranean subtidal habitats (**Table 1**). Morphologically and ecologically similar species have been included at the genus level or higher taxa (Cerrano et al., 2017). The selected taxa embrace a broad taxonomic range, from algae to invertebrates and vertebrates. Most of them are sessile or sedentary with a limited home range; therefore, they cannot escape the local human disturbances and changes in environmental conditions. In terms of both resistance and resilience of local populations, their sensitivities to pressures were assessed and employed to develop the *MedSens* biotic index (see Supplementary materials in Turicchia et al., 2021a).

### Participants Training

The trained volunteers are involved in the program. Their training is verified before being certified as EcoDivers. Once certified, they can independently apply the RCMed U-CEM protocol. Although they are often passionate naturalists, diving experts, and sometimes marine biologists, participants are not required to have any particular level of scientific background. Of course, they must be sufficiently skilled in snorkeling, freediving, or scuba diving, depending on how the protocol will be applied. Training is based not only on protocol explanation but also on raising awareness of the usefulness and importance of the data collected for the conservation of the Mediterranean Sea's coastal marine habitats. The course syllabus includes knowledge about main marine habitats, field identification of target species, and their ecological role. It also covers a range of geographic localization methods using nautical charts, conspicuous points, and satellite global positioning system (GPS) devices. Training materials encompass an illustrated protocol manual and benefit from a multi-language website[1]. Teaching methods include the initial lesson, class discussion, full hands-on demonstration, data entry, and final debriefing. Trainers are generally marine biologists, diving instructors, or both, with proven communication skills and experience in applying the protocol. Individual learning assessments are based on an online questionnaire (implemented on the QuestBase platform[2]), allowing immediate feedback on the ability of the participants to provide the data correctly. Certified EcoDivers are assigned a unique identification code to be used for data entry. They also sign a privacy agreement, compliant with the European general data protection regulation, which allows sharing the collected data on their behalf but leaves each one responsible for the quality of the data they provided.

### Survey Method

The surveyed sites are freely chosen by EcoDivers and localized using GPS receivers, nautical charts, or conspicuous points (e.g., mooring buoys in marine protected areas). Geographic coordinates (WGS84) are recorded with $\pm$ 6 arc-seconds (i.e., 185 m in latitude) accuracy, the usual distance range explored by divers. Before going snorkeling or diving, each EcoDiver has to

[1]https://www.reefcheckmed.org
[2]https://www.questbase.com

**TABLE 1 |** The selected taxa, the criteria that they meet, and their main features.

| Taxon | Class | Habitus | Typical habitats | Depth range (m) | Protection | Habitat forming | Human exploitation | Non-indigenous species | Sensitive to | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | divers | pollution | habitat loss | climate changes |
| *Caulerpa cylindracea* | Ulvophyceae | S | Rocky bottom | 1–40 | | ✓ | | ✓ | | | | |
| *Caulerpa taxifolia* | Ulvophyceae | S | Rocky bottom | 1–40 | | ✓ | | ✓ | | | | |
| *Ircinia* spp. and other Keratosa | Demospongiae | S | Coralligenous | 1–200 | P2 (*) | ✓ | | | | | | |
| *Axinella* spp. | Demospongiae | S | Coralligenous | 5–200 | P2 B2 (*) | ✓ | | | | | | |
| *Aplysina* spp. | Demospongiae | S | Rocky bottom, cave | 2–100 | P2 B2 (**) | ✓ | | | | | | |
| *Geodia cydonium* | Demospongiae | S | Rocky bottom, detritic | 5–100 | P2 | | | | | | ✓ | |
| *Tethya* spp. | Demospongiae | S | Rocky bottom, detritic | 1–30 | P2 (**) | | | | | | ✓ | |
| *Corallium rubrum* | Anthozoa | S | Coralligenous, cave | 15–1000 | P3 B3 H5 | ✓ | ✓ | | ✓ | | | ✓ |
| *Paramuricea clavata* | Anthozoa | S | Coralligenous | 15–150 | | ✓ | | | ✓ | | | ✓ |
| *Eunicella cavolini* | Anthozoa | S | Coralligenous | 5–200 | | ✓ | | | ✓ | | | ✓ |
| *Eunicella singularis* | Anthozoa | S | Coralligenous | 5–100 | | | | | ✓ | | | ✓ |
| *Eunicella verrucosa* | Anthozoa | S | Soft bottom | 15–120 | | | | | ✓ | | | |
| *Maasella edwardsii* | Anthozoa | S | Rocky bottom | 2–30 | | | | | | | | ✓ |
| *Cornularia cornucopiae* and other Stolonifera | Anthozoa | S | Rocky bottom | 1–20 | | | | | | | ✓ | |
| *Parazoanthus axinellae* | Anthozoa | S | Rocky bottom | 1–150 | | | | | | | | ✓ |
| *Epizoanthus* spp. | Anthozoa | S | Rocky bottom, artificial reef | 1–50 | | | | | | | | ✓ |
| *Savalia savaglia* | Anthozoa | S | Coralligenous | 10–200 | P2 B2 | ✓ | | | ✓ | | ✓ | ✓ |
| *Cladocora caespitosa* | Anthozoa | S | Coralligenous | 1–40 | C2 | ✓ | | | | ✓ | | ✓ |
| *Astroides calycularis* | Anthozoa | S | Rocky bottom | 1–40 | P2 B2 C2 | ✓ | | | | | | |
| *Balanophyllia europaea* | Anthozoa | S | Rocky bottom | 0–40 | C2 | | | | | | | ✓ |
| *Leptopsammia pruvoti* | Anthozoa | S | Coralligenous | 5–100 | C2 | ✓ | | | ✓ | | | |
| *Patella ferruginea* | Gastropoda | M | Rocky shore | 0–1 | P2 B2 H4 | | ✓ | | | | | |
| *Rapana venosa* | Gastropoda | M | Rocky bottom, artificial reef | 0–15 | | | | ✓ | | | | |
| *Pinna nobilis* | Bivalvia | S | Sea grasses, detritic | 2–40 | P2 H4 | | ✓ | | ✓ | | ✓ | |
| *Arca noae* | Bivalvia | S | Rocky bottom | 1–60 | | | ✓ | | | | | ✓ |
| *Pecten jacobaeus* | Bivalvia | M | Soft bottom | 20–200 | | | ✓ | | | | | |
| *Mimachlamys varia* and other Pectinidae | Bivalvia | S | Rocky bottom | 5–100 | | | ✓ | | | | | |
| *Palinurus elephas* | Malacostraca | M | Coralligenous, cave | 5–150 | P3 B3 | | ✓ | | | | | |
| *Homarus gammarus* | Malacostraca | M | Coralligenous, cave | 5–150 | P3 B3 | | ✓ | | | | | |
| *Scyllarides latus* | Malacostraca | M | Rocky bottom, cave | 4–100 | P3 B3 H5 | | ✓ | | | | | |

*(Continued)*

**TABLE 1** | Continued

| Taxon | Class | Habitus | Typical habitats | Depth range (m) | Protection | Habitat forming | Human exploitation | Non-indigenous species | Sensitive to divers | Sensitive to pollution | Sensitive to habitat loss | Sensitive to climate changes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Paracentrotus lividus* | Echinoidea | M | Rocky bottom | 0–30 | P3 B3 | ✓ | ✓ | | | | | |
| *Centrostephanus longispinus* | Echinoidea | M | Rocky bottom | 10–200 | P2 B2 H4 | | | | | ✓ | | ✓ |
| *Ophidiaster ophidianus* | Asteroidea | M | Rocky bottom | 1–100 | P2 B2 | | | | | ✓ | | ✓ |
| *Microcosmus* spp. and other similar Pyuridae | Ascidiacea | S | Rocky bottom | 3–100 | | | ✓ | | | | | ✓ |
| *Polycitor adriaticus* | Ascidiacea | S | Rocky bottom, detritic | 2–50 | | ✓ | | | | | | |
| *Aplidium tabarquensis* | Ascidiacea | S | Rocky bottom, detritic | 3–50 | | ✓ | | | | | | |
| *Aplidium conicum* | Ascidiacea | S | Rocky bottom, detritic | 3–50 | | ✓ | | | | ✓ | | |
| *Hippocampus* spp. | Actinopterygii | SW | Sea grasses | 2–40 | P2 B2 C2 (**) | | ✓ | | | | ✓ | ✓ |
| *Conger conger* | Actinopterygii | SW | Rocky bottom, wreck | 1–1000 | | | ✓ | | | | | |
| *Sciaena umbra* | Actinopterygii | SW | Rocky bottom | 5–200 | P3 B3 | | ✓ | | | | | |
| *Chromis chromis* | Actinopterygii | SW | Rocky bottom | 2–40 | | | | | | ✓ | | |
| *Diplodus* spp. | Actinopterygii | SW | Rocky bottom | 1–100 | | | ✓ | | | ✓ | ✓ | |
| *Trisopterus minutus* | Actinopterygii | SW | Rocky bottom, detritic | 15–200 | | | ✓ | | ✓ | ✓ | ✓ | |
| | | | | | Tot.: | 16 | 16 | 3 | 9 | 7 | 8 | 15 |

*Habitus: S, sessile; M, motile; SW, free-swimming. Protection status: B2-3, 1979 Bern Convention on the conservation of European wildlife and natural habitats, annex 2-3; P2-3, 1995 Protocol concerning Mediterranean specially protected areas and biological diversity (after Barcelona 1976), annex 2-3; H4-5, 1992 European Habitats Directive (92/43/EEC) on the conservation of natural habitats and of wild fauna and flora, annex 4-5; C2, 1973 CITES Washington Convention on international trade in endangered species of wild fauna and flora, annex 2. (*) one or more protected species belong to this genus, (**) the two Mediterranean species belong to this genus are protected (modified from* Cerrano et al., 2017*).*

**TABLE 2 |** Numerical and descriptive abundance classes used to record the abundance of the target species observed during the survey.

| Class | Numerical range | Descriptive class | Web GIS legend |
|---|---|---|---|
| 0 | 0 individuals | Absent | × |
| 1 | 1 individual | One specimen | |
| 2 | 2 individuals | Some scattered specimens | |
| 3 | 3–5 individuals | Several scattered specimens | |
| 4 | 6–10 individuals | A crowded area | |
| 5 | 11–50 individuals | Some crowded areas | |
| 6 | >50 individuals | Several crowded areas | |

*The color scale used in the legend of the Web GIS application is reported.*

**TABLE 3 |** List of prevailing habitats considered.

| Habitat |
|---|
| Coastal rocks |
| Offshore rocks |
| Rocky cliff |
| Posidonia meadow |
| Posidonia and sandy bottom |
| Posidonia and rocky bottom |
| Cave |
| Metal wreck |
| Sandy bottom |
| Muddy bottom |
| Breakwaters, ports and artificial reefs |
| River mouth |
| Coastal lagoon |

choose one or more of the 43 taxa included in the protocol as search targets, according to the expected habitat typology, survey depth, and personal motivations.

EcoDivers can make independent observations along random swim (Hill and Wilkinson, 2004; also called "roving visual census," *sensu* Rassweiler et al., 2020). They record the presence/absence of the species and their abundance (using numerical or descriptive classes according to the countability of organisms; see definition in **Table 2**) and depth range of the searched taxa. Prevailing habitat (chosen from a list; **Table 3**), estimated underwater visibility, and the presence/abundance of gas bubbles leaching from the seabed are also recorded. Not encountered but actively searched taxa are reported as absent. No data are provided for not searched taxa. The time dedicated to actively search target species (at least 10 minutes) must be recorded. A preset underwater slate, with target species drawings and available with different species selections and languages, helps in the identification and recording tasks (**Figures 1**, **2**).

## Data Entry

Recorded observations, including absence, site name, geographic coordinates, date and time, underwater visibility, survey depth range (min and max), and observation effort in terms of dedicated time, are uploaded to the online database through an internet form[3] or a dedicated multilanguage app for Android smartphones ("Reef Check Med" app) connected to the online database (**Figure 3**).

Geographic coordinates can be entered either in decimal degrees, degrees and decimal minutes, or degrees, minutes, and seconds, specifying east or west. Users of the smartphone app can benefit from the built-in GPS, remembering to use it near the surveyed site. The website and the app also provide EcoDivers with an online satellite map to retrieve geographic coordinates based on conspicuous points. Finally, the smartphone app also allows to store and review data, even offline, before submitting them to the online database. Additional notes on the characteristics of the site or the presence of anomalous situations such as mortality/disease events of marine organisms, presence of waste, or abandoned fishing nets, can be provided at the end of the form.

## Data Quality Assurance and Control

Citizen science reliability is a major issue in the acceptance and actual use of data collected by citizen scientists. As such, proper data quality assurance (QA) and data quality control (QC) are essential steps. For the RCMed U-CEM protocol, QA is mainly based on the quality and learning verification of the initial training and the personal responsibility for the provided data. At the end of each training session, a test is carried out to verify the level of competence of each volunteer in the data collection. Only volunteers who provide at least 70% correct answers can be qualified as EcoDivers.

In April 2015, a field test was carried out to verify the ability of the method to discriminate species assemblages among close sites with similar habitats and the ability of the trained volunteers to collect suitable data for this purpose. Ten EcoDivers were divided into three training levels: two participants belonged to the category "professional scientist and trainer" (i.e., marine biologists who are also trainers of EcoDivers), four to "professional scientist" (i.e., marine biologists trained as EcoDiver), and four to "citizen scientist" (i.e., EcoDivers without any academic training in marine sciences). Two dive sites were randomly selected at Gallinara Island, an islet in the Ligurian Sea (NW Mediterranean Sea). At each site, participants independently recorded the presence, abundance, and depth distribution of 20 target taxa selected among the ones in the RCMed U-CEM protocol, along a predefined belt-transect of $100 \times 6$ m. The dive profile varied from 3 to 30 m in depth. Each participant recorded the data by applying the RCMed U-CEM protocol, except for the constrained path, and entered them into the online database. Afterward, records were extracted from the database, and multivariate species assemblage data were analyzed using principal coordinate analysis (PCoA) based on Bray–Curtis similarities without any transformations. Differences in species assemblage structures (i.e., the combination of species found and their abundance)

[3]https://www.reefcheckmed.org/english/underwater-monitoring-protocol/upload-your-data/.

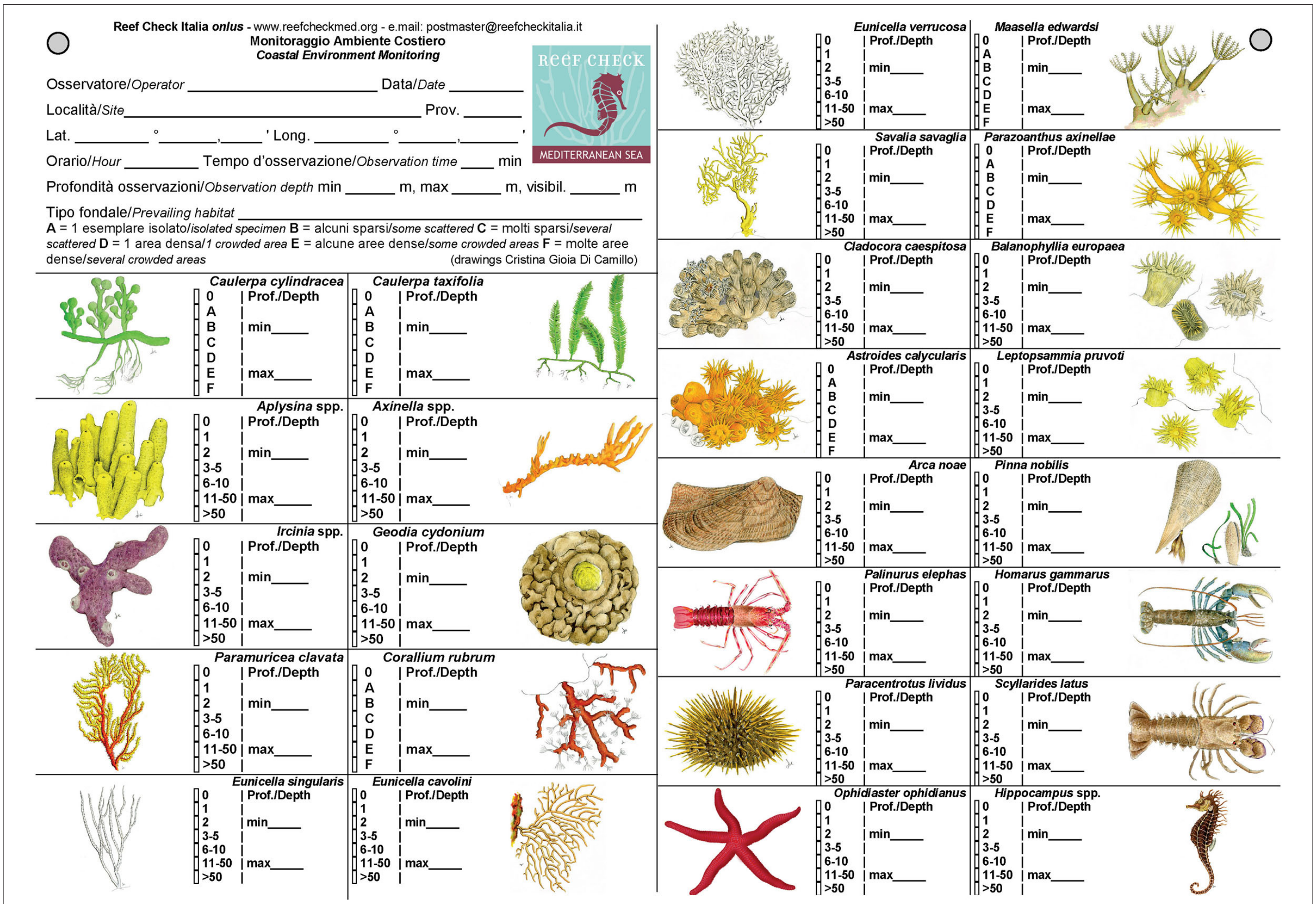


**FIGURE 1 |** Example of front and back of an underwater slate preset to record data according to the RCMed U-CEM protocol (Italian–English version with a subset of the most common target species on rocky bottoms).

between the two sites (random factor) and resulting from the observation carried out by participants having three different training levels (fixed factor) were assessed by a two-way crossed permutational non-parametric multivariate ANOVA (PERMANOVA, $\alpha = 0.05$; Anderson and ter Braak, 2003) under the hypothesis that the assemblage structures differed between sites and these differences were similarly detected independently by the training levels of the observers. The test assesses if there are no assemblage structure differences between the two sites, differences among the assemblage structures detected by the operators with different training levels, or a combination of these two factors (training level and site). The analyses were performed using the software PRIMER v. 6 (Anderson et al., 2008). Patterns of similarities among the observed assemblages are shown in the PCoA ordination plot (**Figure 4**). In this plot, the distances among the points are inversely proportional to the level of measured similarity in the corresponding assemblage structures. The first two axes of the PCoA explained 34.8% and 28.9% of the total variation. The ordination plot shows some degrees of separation of the points from the two sites but not among the observer training levels. The PERMANOVA test confirmed the pattern showing a significant difference ($p < 0.01$) in assemblage structure only between sites and not among training levels (**Table 4**). Even if some minor differences among the single operators were obtained, these represent a random effect related to the accuracy of the method, as occurs in any visual census. However, the method appeared robust enough to distinguish the assemblages between sites with similar habitats, a few 100 m apart. This case study shows that the absence of effects of the training level indicates that the trained citizen scientists can provide the same results as the professional scientists.

As data are sent to the online database, EcoDivers can see their survey counter increasing. That represents an important feedback that allows everyone to verify that the system has accepted the data submission. Moreover, it provides immediate public recognition for the volunteers' work. However, the collected data are not made public immediately but only after undergoing the quality control (QC).

The user interface is designed in such a way to facilitate data entry; however, typos in manual entry are difficult to

**FIGURE 2 |** Scuba diver recording data close to a rocky bottom.

prevent. For this purpose, both web and app data entry forms are equipped with automatic checks that prevent oversights and common errors. Some fields are mandatory; some are preset (all species are initially set to "not considered") or contain limits in the values that can be entered (for example, for geographic coordinates). Yet, this cannot completely avoid all possible errors. Post-entry QC is based on automatic procedures (e.g., consistency among survey and observation depth ranges, check for the possible exchange of the max and min depths) and manual checks (e.g., matching between the site name and geographic coordinates). Automatic algorithms are applied during data extraction from the online database using specific queries and procedures implemented in R (R Core Team, 2019), ending with the automatic creation of shapefiles (ESRI, 1998; Stabler, 2013). The shapefiles are closely inspected by the Reef Check Med operators and then validated. In the case of inconsistencies that cannot be resolved uniquely by the operators, the EcoDivers who provided the data are contacted by email to ask for further information. If the problem cannot be solved, the indicated data are definitively discarded.

An online interactive peer review represents a further step in the QC of the data. To this end, as soon as the data are published online, EcoDivers are informed and invited to check the data in their favorite areas and report any possible doubts or inconsistencies through an online form. Based on their reports, the data are then re-analyzed and, where possible, the errors are fixed in the subsequent data publication.

## Open Access to Online Data

Data that has passed the QC are made public through the various platforms. The most updated data are made freely available on a web-based geographic information system (Web GIS) built-up using the QGIS Cloud free platform[4] This platform allows the visualization of all data on the Bing Aerial basemap (**Figure 5**). The user can choose to visualize the survey points, displayed as yellow dots, or the data inherent single target species distribution and abundance, displayed as dots colored according to an abundance scale or as a black cross in case of species not found (**Table 2**). With the pointer, it is possible to query the data stored for each point, including geographic coordinates in decimal degrees, survey date and depth, and the EcoDiver's name, according to their informed consent. The QGIS Cloud platform provides users with a full-screen version and a smartphone version. Moreover, being the platform an Open Geospatial Consortium compliant web services allows the display of the maps *via* the Web Map Service (WMS) or downloading the data *via* the web feature service (WFS). Data are distributed under the international Creative Common license (CC BY 4.0), which allows for free sharing and adaptation, giving appropriate credit to the Reef Check Mediterranean network.

Following the FAIR principles, a Darwin Core (Wieczorek et al., 2012) compliant version of the whole dataset is available at the Biology data portal of the European Marine Observation and Data Network (EMODnet; Miguez et al., 2019) and redistributed under the Ocean Biodiversity Information System (OBIS) networks (including EurOBIS, MedOBIS; Costello and Vanden Berghe, 2006 and references therein), the European infrastructure on biodiversity and ecosystem research (LifeWatch; Basset and Los, 2012), and the Global Biodiversity Information Facility (GBIF; Flemons et al., 2007).

# RESULTING DATA AND THEIR APPLICATIONS

As of December 2020, the dataset consisted of 50,255 records (including absence records) unevenly distributed among 43 taxa in the Mediterranean Sea collected in 4,898 single survey events from 2001 and carried out by 692 EcoDivers (Ponti et al., 2021; Turicchia et al., 2021b). The data comes from Croatia, France, Greece, Italy, Spain, and Tunisia, covering part of the following ecoregions (*sensu* Spalding et al., 2007): Western Mediterranean (52.3% of the surveys), Adriatic Sea (42.2%), Ionian Sea (4.9%), Alboran Sea (0.2%), Aegean Sea (0.2%), and Tunisian Plateau/Gulf of Sidra (0.2%). The possibility to focus on a few target species during the underwater surveys ensures a higher accuracy of the data collection: EcoDivers select the species based on confidence (thereby reducing identification errors), personal interest (increasing satisfaction), or because some species are more charismatic than others (KrŽelj et al., 2020). Although never assessed, a reduced number of species to consider may reduce psychological stress during the surveys; however, this generates skewed distribution efforts among the searched taxa and surveyed coastal habitats. Indeed, the most-searched taxa are common species like seabreams (*Diplodus* spp.) and the edible sea urchin (*Paracentrotus lividus*), the noble pen shell (*Pinna nobilis*), the red coral (*Corallium rubrum*), and sea fans (*Paramuricea clavata* and *Eunicella cavolini*). Less conspicuous but highly concerning species, such as invasive algae in the genus

[4]https://www.reefcheckmed.org/english/underwater-monitoring-protocol/webgis-map/.

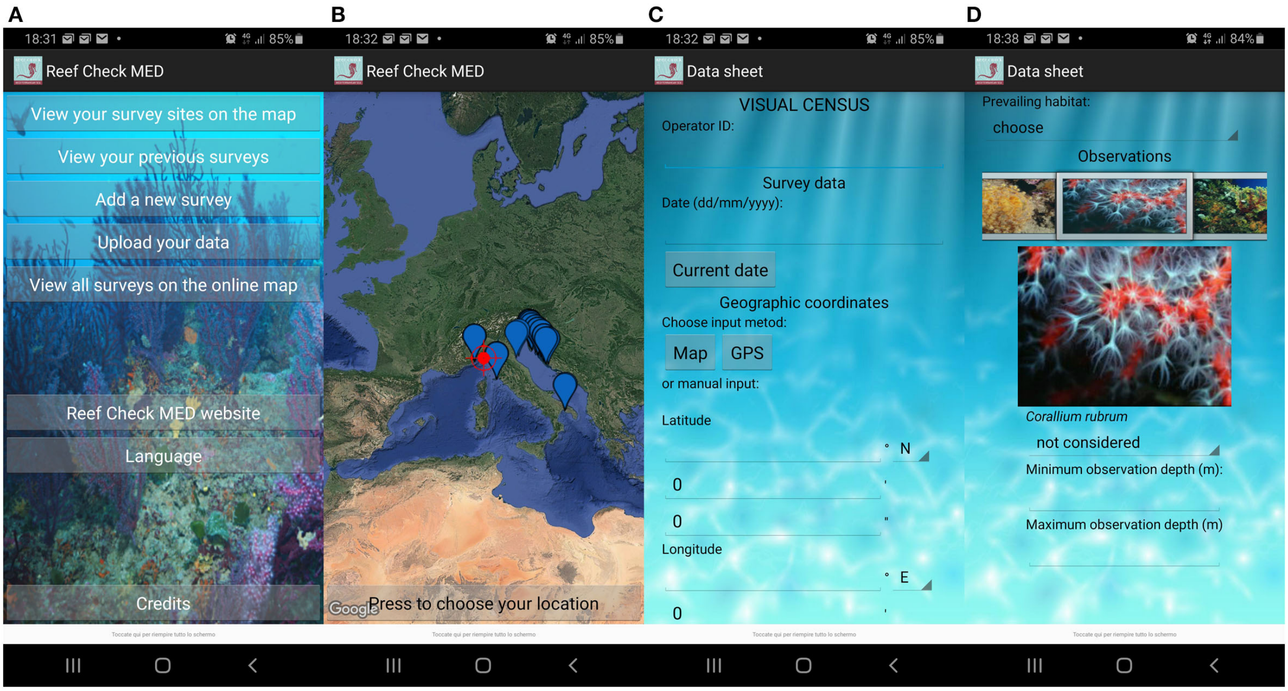


**FIGURE 3 |** Android smartphone app screenshots: **(A)** main menu; **(B)** maps with previously investigated sites; **(C)** initial part of the data entry form; and **(D)** final part of the data entry form.

*Caulerpa*, are also frequently surveyed (**Figure 6A**). As expected, the most investigated habitats are those most attractive to divers, namely, rocky coasts, cliffs, and wrecks (**Figure 6B**).

Over the years the dataset has been successfully used to complement studies on the spatial and the temporal distribution of key marine species such as the habitat-forming corals in the central-eastern Mediterranean (Özalp and Alparslan, 2016; Di Camillo et al., 2018), the pink sea-fan *Eunicella verrucosa* (Chimienti, 2020), as well as of rare and/or endangered species like the gold coral *Savalia savaglia* (Giusti et al., 2015), the zooxanthellate soft coral *Maasella edwardsii* (Özalp and Ateş, 2015), and the sponge *Geodia cydonium* (Turicchia et al., 2013). These data can also help in tracking mass mortality events and assess the possible effects of climate change (Pairaud et al., 2014; Ponti et al., 2018; Turicchia et al., 2018; Garrabou et al., 2019) and the invasion of the non-indigenous species *Caulerpa taxifolia* and *Caulerpa cylindracea* (Montefalcone et al., 2015; Cerrano et al., 2017). Moreover, the dataset can be used in assessing the protected and sensitive species richness within the marine protected areas (Turicchia et al., 2015, 2016; Cerrano et al., 2017), and in offering an effective monitoring tool for the Mediterranean subtidal rocky coastal habitats through the *MedSens* biotic index (Turicchia et al., 2021a).

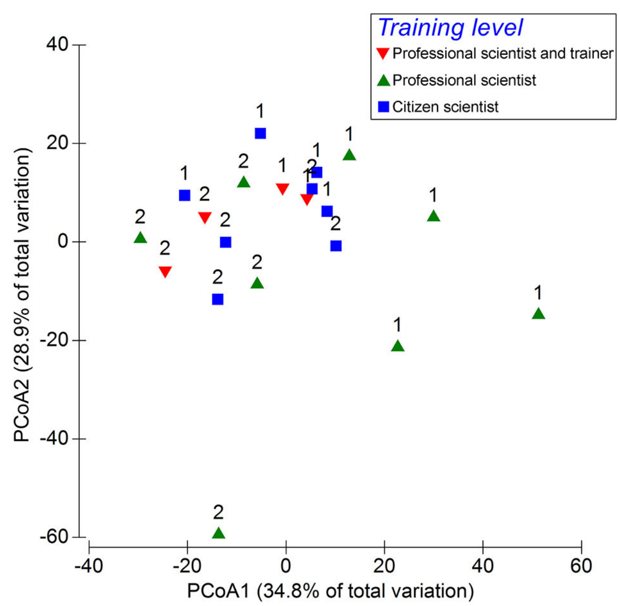


**FIGURE 4 |** Principal coordinate analysis (PCoA) ordination plot based on Bray–Curtis similarities comparing species assemblages detected by scuba divers with different training levels along the same pathway at two sites (Sites 1 and 2 are indicated by numbers) at Gallinara Island (Ligurian Sea). The training level is indicated with symbols and colors.

## DISCUSSION

The RCMed U-CEM protocol integrates the Reef Check family of protocols, which already includes those for the California coasts (Gillett et al., 2012) and tropical coral reefs around the world (Hodgson, 2001) extending its range to the Mediterranean

**TABLE 4 |** Permutational non-parametric multivariate ANOVA (PERMANOVA) test on differences among training levels (Tl, 3 levels, fixed) and between sites (Si, 2 levels, fixed) and their interactions (Tl × Si) (Bray–Curtis similarities abundance data).

| Source | df | SS | MS | Pseudo-F | P (perm) | Unique perms | P (MC) |
|---|---|---|---|---|---|---|---|
| Training level (Tl) | 2 | 3280 | 1639.9 | 1.544 | 0.2865 | 180 | 0.3049 |
| Site (Si) | 1 | 3429 | 3429.2 | 3.977 | 0.0045 | 9959 | |
| Tl × Si | 2 | 2125 | 1062.3 | 1.232 | 0.3213 | 9940 | |
| Res | 14 | 12072 | 862.3 | | | | |
| Total | 19 | 20999 | | | | | |

*When less than 1000 unique permutations were available, the asymptotic Monte Carlo (MC) p-value was used instead of the permutational (perm) one.*

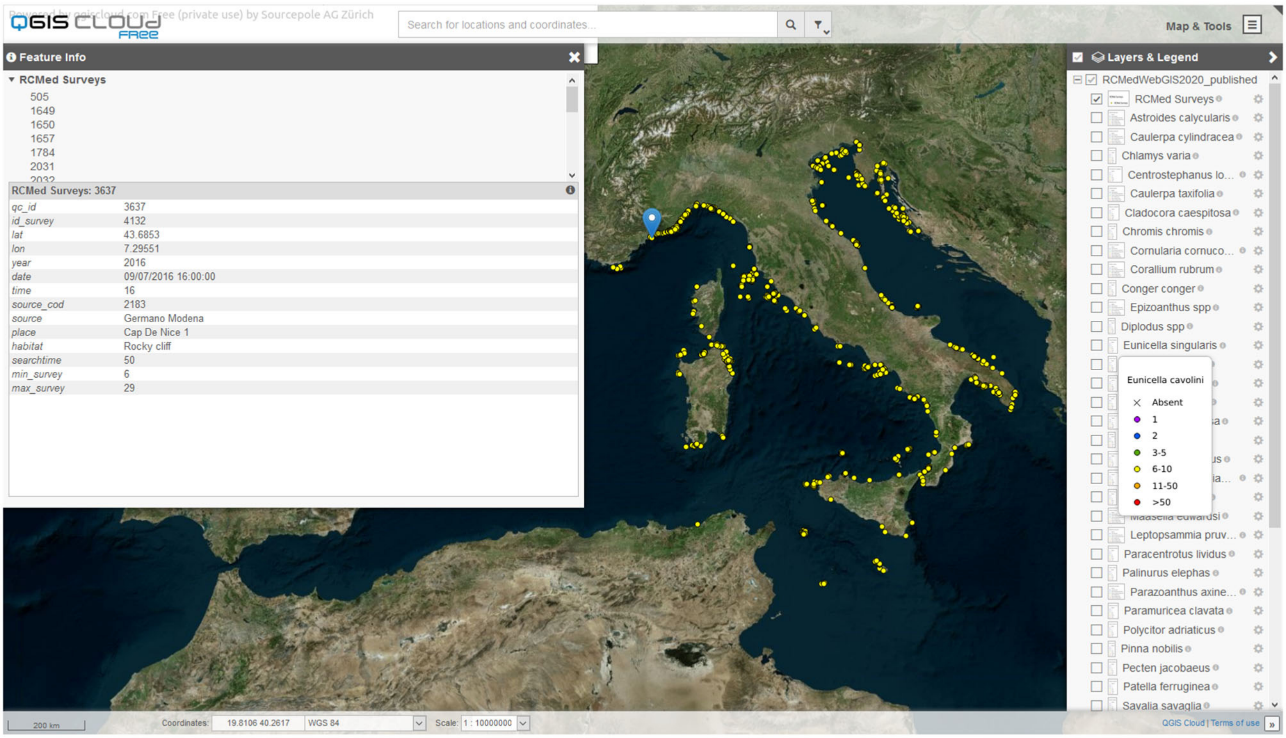


**FIGURE 5 |** Web GIS screenshot shows some data interrogation options: on the left, the data of a single survey and on the right, the list of species layers that can be activated with the relative symbol legends, which display the abundance classes (see **Table 2**).

Sea. These standard protocols aim to report the presence and the abundance of key species and to assess and monitor over time the ecological status of the investigated sites based on the relative abundance of selected indicator species. They are optimized for the habitats and operating conditions for which they are intended. In tropical reefs and California, standard transects are made in shallow waters under the supervision of a scientist and/or a team leader, while in the Mediterranean, volunteers independently apply a roving visual census that allows them to explore from shallow to deep habitats (see further comparisons in **Table 5**). RCMed U-CEM is not the only protocol that can be adopted by snorkelers and divers to report marine species in the Mediterranean Sea; however, the aims and methods applied differ widely. Among those listed by Earp and Liconti (2020), the most popular and internationally applied alternatives in the Mediterranean Sea are: REEF, Sea Watchers, and iNaturalist. Their main features are summarized in **Table 5** for comparison. REEF, started in 1993 with the fish visual census in the tropical western Atlantic, was one of the forerunners in involving volunteer divers (Pattengill-Semmens and Semmens, 2003). Over the years, the protocol has been extended to various regions of the world, and since 2014, it also includes the Eastern Atlantic and the Mediterranean Sea. As RCMed U-CEM, REEF is based on roving visual census carried out by trained volunteers. While the main focus of REEF's program is marine fish, they also survey selected invertebrates and algae in the temperate water regions. In addition to the different lists of considered species, the major difference between the two protocols lies in the less explicit and not always precise location of the sites (based on hierarchical area

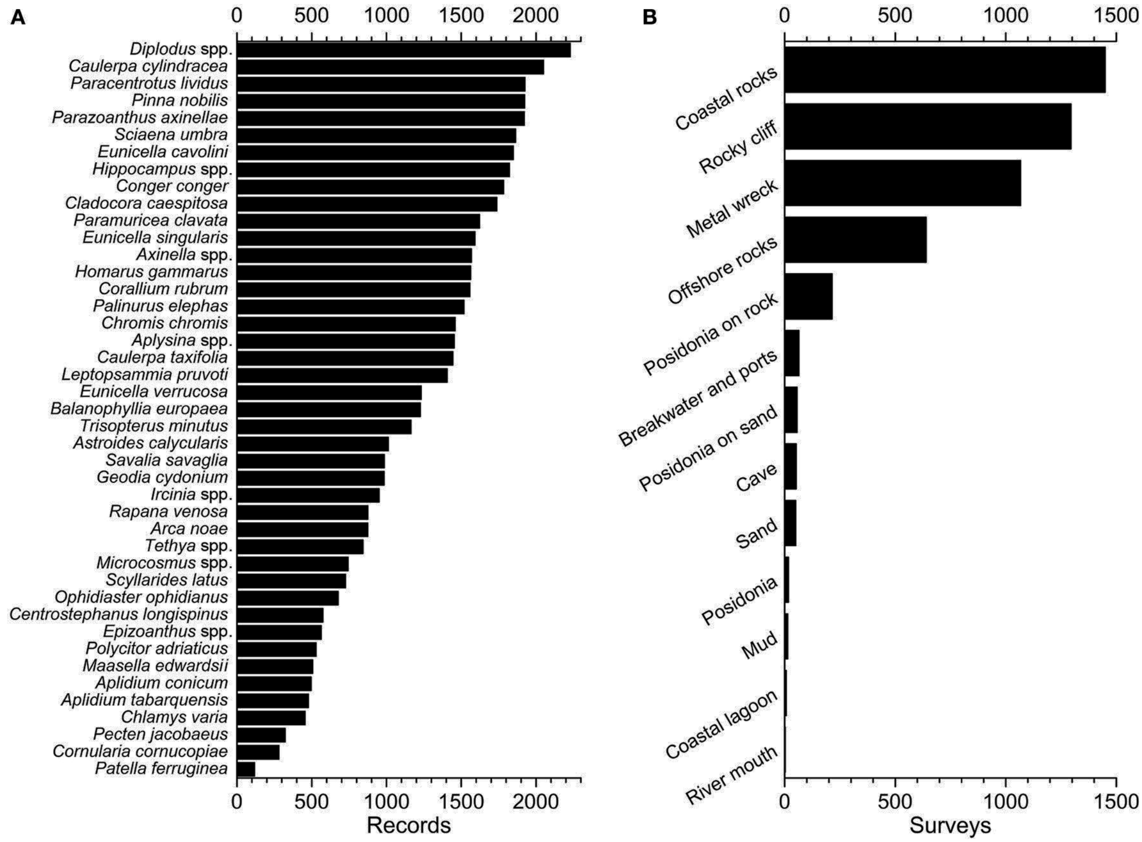


**FIGURE 6 |** Dataset contents (last access October 18th, 2020): **(A)** number of records (including absences) for each target species and **(B)** number of surveys carried out at each habitat.

codes and not geographic coordinates), the lack of information on the bathymetric distribution of species, and the reduced findability, accessibility, and interoperability of the REEF data. Sea Watchers, launched in Spain in 2009 as "Observadores del Mar," includes several thematic sub-projects (e.g., massive mortalities of corals, death of pen shells, alien fishes, invasive algae, decapod crustaceans, sharks and rays, and zooxanthellate scleractinian; see Mariani et al., 2018); they are based on visual observations supplemented by photographs that are sent to experts for identification and analysis. Involved experts assess and archive the observations, possibly integrating with additional information interactively requested to the participants. Data collected from some sub-projects are already distributed by EMODnet or other data portals. iNaturalist, which began in 2008, is the widest social network of nature enthusiasts that share and cross-validate photographic observations and it is one of the more FAIR initiatives worldwide (Bowser et al., 2014). Unfortunately, despite initiatives on marine organisms are multiplying within it (Reef Check Italia has launched two calls for contributions on Mediterranean nudibranchs and corals), most of the collected data concerns terrestrial species. In addition, many of the marine species' records lack important additional data such as observation depth or surveyed habitat. Notably, except for RCMed U-CEM, none of the other initiatives mentioned here for the Mediterranean Sea provide information on the absence of key species, a "dark diversity" (*sensu* Partel et al., 2011) usually neglected but potentially very useful in assessing biological integrity, ecological status, and the effects of global changes.

The application of the RCMed U-CEM protocol may generate a range of direct societal impacts, including a higher public awareness of environmental threats and the involvement of stakeholders (e.g., tourists, divers, and diving centers) in the monitoring and conservation of coastal marine environments (Turicchia et al., 2021a). Therefore, it may enhance the collaboration between coastal management authorities, stakeholders, and researchers, increasing the acceptability of management decisions and enabling more participatory conservation tactics (Markantonatou et al., 2013; de Francesco et al., 2017; Lucrezi et al., 2018).

To obtain and distribute reliable and scientifically sound data, RCMed U-CEM protocol was designed to minimize taxonomic and geolocation errors. However, taxonomic and spatial biases, recognized as major issues in CS projects and biodiversity databases, remain intrinsically unavoidable for this

**TABLE 5 |** Selected protocols comparison.

| Protocol name | Reef check med (RCMed-UCEM) | Reef check tropical | Reef check california | REEF | Sea watchers | iNaturalist |
|---|---|---|---|---|---|---|
| **Maintainer organization** | Reef Check Italia onlus | Reef Check Foundation | Reef Check Foundation | Reef Environmental Education Foundation | Instituto de Ciencias del Mar (CSIC) | California Academy of Sciences and National Geographic Society |
| **Web site** | www.reefcheckmed.org | www.reefcheck.org | www.reefcheck.org/california-program/ | www.reef.org | https://www.observadoresdelmar.es/ | www.inaturalist.org |
| **Starting year** | 2001 | 1997 | 2005 | 1993 (Mediterranean 2014) | 2009 | 2008 |
| **Geographical scope** | Mediterranean Sea | Worldwide tropical | California | Worldwide | Mediterranean Sea | Worldwide |
| **Habitats** | Intertidal and subtidal coastal sea bottoms | Coral reefs | Subtidal rocky shores | Subtidal coastal sea bottoms | Intertidal and subtidal coastal sea bottoms | Any |
| **Training program** | With learning verification | With learning verification | With learning verification | With learning verification | Depending by sub-project | None |
| **Geolocalization** | Geographic coordinates | Geographic coordinates | Geographic coordinates | Proprietary area codes | Geographic coordinates | Geographic coordinates |
| **Data collecting methods** | Visual census | Visual census | Visual census | Visual census | Visual census/Photograph | Photograph |
| **Investigated area definition** | Random swim | Transect | Transect | Random swim | Random swim | Random swim |
| **Sampling effort measure** | Sampling time | Fixed area | Fixed area | Sampling time | Depending by sub-project | None |
| **Selected target species** | Yes | Yes | Yes | Yes | Yes | No |
| **Quantitative/qualitative data** | Quantitative | Quantitative | Quantitative | Quantitative | Depending by sub-project | Qualitative |
| **Species absence recording** | Yes | Yes | Yes | No | No | No |
| **Survey depth** | Recorded | Fixed depth | Fixed depth | Recorded | Optional | Optional |
| **Species depth distribution** | Recorded | Fixed depth | Fixed depth | Not recorded | Optional | Optional |
| **Habitat type recording** | Recorded | Coral reefs | Subtidal rocky shores | Recorded | Optional | Optional |
| **Data findability** | Proprietary WebGIS EMODnet/OBIS/GBIF | Proprietary WebGIS | Proprietary WebGIS | Online proprietary archive | Proprietary WebGIS or repository | Proprietary WebGIS OBIS/GBIF |
| **Data accessibility** | Open access | Open access | Open access | Partially open access /On request | Partially open access /On request | Open access |
| **Data interoperability** | EMODnet/OBIS/GBIF | None | None | None | EMODnet/OBIS/GBIF | OBIS/GBIF |
| **Data reusability** | CC-BY 4.0 | Not declared | Not declared | Not declared | Part CC-BY-NC-SA 4.0 | CC-BY 4.0 |
| **Data providers** | Acknowledged | Anonymous | Anonymous | Anonymous | Acknowledged | Acknowledged |
| **Data entering** | Smartphone app/website form | Email | Email | Website form | Email/website form | Smartphone app/website form |
| **QA/QC procedures** | Training verification /Data check | Training verification /Data check | Training verification /Data check | Training verification /Data check | Expert photo validation | Expert photo validation |

and most CS initiatives (Beck et al., 2014; Troudet et al., 2017). New technologies may help improve the protocol and reduce the possibility of common errors. For example, the widespread use of the smartphone app has already reduced localization errors, thanks to the integrated GPS. The increasing adoption of waterproof cases for smartphones and tablets suggests the possibility of entering data directly during the in-water activity and collecting photos to verify the species identification later using a specifically preconfigured app (Max and Gualdesi, 2013). Advances in image analysis and deep learning algorithms coupled with photo databases can support the development of apps for identifying marine species, as has been the case for identifying plants and terrestrial animals (e.g., the app Seek by iNaturalist; see Waldchen and Mader, 2018 for a review about automatic terrestrial plant identification), and this technology could be implemented on the Reef Check Med app and possibly used directly underwater.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

## AUTHOR CONTRIBUTIONS

MP conceived the early version of the protocol, which was refined together with CC, GR, CGDC, and ET. MP and ET wrote the first draft of the manuscript. All authors contributed to and approved the final version of the manuscript.

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# Citizen Science for Quantification of Insect Abundance on Windshields of Cars Across Two Continents

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The abundance and the diversity of insects in Europe have declined considerably during recent decades, while it remains unclear whether similar changes may also have occurred elsewhere. Here we used citizen science for quantifying the abundance of flying insects on windshields of cars across Europe and to a smaller extent in China. We used the abundance of insects killed against windshields of cars during 3,530 transects for a total distance of 83,019 km made by 50 observers as estimates of insect abundance. A total of 124,606 insects were recorded, or approximately 1.5 insect per km. The abundance of insects killed against windshields was highly repeatable among days for the same locality, showing consistent estimates of abundance. The main determinants of insect abundance were features of cars (driving speed and car model that can be considered noise of no biological significance), local weather (temperature, cloud cover and wind speed) and variation across the season and the day. We tested for differences in the abundance of flying insects killed on windshields of cars predicting and finding (1) a reduction in insect abundance in areas with ionizing radiation at Chernobyl compared to uncontaminated control sites in the neighborhood, (2) a reduction in the abundance of flying insects in Western compared to Eastern Europe, (3) a reduction in the abundance of flying insects killed on windshields from southern to northern Europe compared to latitudinal samples of insects from southern to northern China, and (4) a difference in abundance of insects killed on windshields of cars in Spain with a significant interaction between Spain and Denmark. Thus a number of abiotic and biotic factors accounted for temporal and spatial heterogeneity in abundance of insects, providing a useful tool for monitoring and studying determinants of spatial and temporal patterns of insect abundance. This also implies that our estimate of insect abundance may be relevant for the study of competition and for interactions at higher trophic levels.

**Keywords: birds, changes in abundance of flying insect, Chernobyl, citizen science, windshields**

## INTRODUCTION

Surveys of insects have shown recent reductions in abundance by as much as 80%, even in nature reserves (Hallmann et al., 2017; Møller, 2020). These changes have been attributed to climate change, altered farming practice, changed land-use and underlying associated factors (Vogel, 2017). While some studies have documented large reductions in abundance of insects (Hallmann et al., 2017; Møller, 2020; Nyffeler and Bonte, 2020), others have shown smaller declines or no declines at all (Conrad et al., 2002, 2006; Shortall et al., 2009; Fox et al., 2014). This raises questions about the generality of these patterns, but also the underlying mechanisms accounting for such effects. In other words, which factors account for such effects, and which taxa differ in reductions of abundance?

Biodiversity and abundance generally show latitudinal gradients although the causes of such differences among taxa are poorly known (e.g., Rohde, 1992; Møller, 2020). A number of hypotheses has been proposed to account for such gradients, including differences in life history, in particular generation time, and differences in the relative importance of interspecific interactions. Thus, we investigated the predictors that potentially account for reductions in abundance of insects.

A decrease in the abundance of insects in recent decades makes it important to identify the factors that account for such spatial and temporal patterns (Hallmann et al., 2017; Møller, 2020). Several not mutually exclusive factors may cause reductions in insect abundance (Taylor, 1974; Pomfret et al., 2000; Poulin et al., 2010; Nocera et al., 2012). Changes in agricultural land-use and increased use of pesticides (Pomfret et al., 2000; Poulin et al., 2010; Hallmann et al., 2014) appear to have reduced the abundance of insects, and, therefore, also the abundance of insectivorous birds because the latter rely on flying insects as food (Hallmann et al., 2017; Vogel, 2017; Møller, 2019). Here we tested for effects of climate, and its spatial and temporal heterogeneity, on insect abundance using surveys of insects on cars as a method for the quantification of flying insects.

Many monitoring programs following the abundance of living beings at local, national and international scales have been conducted since the 1960s. They are currently financed by national and international census programs to provide extensive and reliable monitoring data (Blondel et al., 1970; Møller, 1983; Bibby et al., 2005; Voříšek et al., 2010). Such surveys mainly monitor birds nationally and across continents such as North America and the European Union. Similar programs exist for spiders (Nyffeler and Bonte, 2020), butterflies, mammals and many other organisms (see the monitoring programs run by Museum National Histoire Naturel, Paris, France as an example). Survey sites are assumed to be randomly located and their locations geographically unbiased, although that is rarely tested explicitly. We are unaware of such explicit tests, and, therefore, we performed such tests. Surveys of birds and other living beings rely on the assumption that findings are consistent among days and hence provide repeatable findings. Such repeatability is required for tests of consistency across taxa and trophic levels. Here we provide such repeatability tests for insect counts obtained from the abundance of flying insects killed on the windshield of cars in an attempt to assess the assumption that survey sites provide repeatable findings.

We used extensive transects with cars to quantify the number of insects killed against windshields (Møller, 2013, 2019, 2020). This method has previously been verified as providing reliable information from cross-validations using three different methods [sweep-nets (Møller, 1987, 2001, 2019, 2020), sticky traps (Teglhøj, 2017) and feeding rates of nestling barn swallows *Hirundo rustica* (Møller, 2013)].

Citizen science has only rarely been used to quantify the abundance of flying insects, and the abundance of prey for flying insects. This method was first utilized by Møller (2013), who showed a decline in wind speed during 1997–2011 at Kraghede (Denmark) during July, but not during the months April-August. These studies showed that the abundance of insects on windscreens was highly repeatable, as was the duration of the pre-laying period of the second brood. Years with adverse weather had lower abundance of insects before laying and lower breeding success decreasing with wind speed. The number of insects sampled was repeatable among sampling events. There was also a high repeatability when relating insect abundance measured with sweep-nets and insects on windscreens. Finally feeding rates of barn swallows were highly repeatable when comparing abundance of insects with abundance on car windscreens (Møller, 2013).

The abundance of insects depended on ambient temperature, time of day and the interaction between temperature and time of day (Møller, 2019; **Figure 1**). A more extensive study by Møller (2019) showed a reduction by more than 80% in the abundance of insects on windscreens between 1997 and 2017. Because aerial insectivorous birds almost exclusively rely on flying insects for food, we should expect that the number of breeding pairs increased with increasing abundance of insects. That was indeed the case for barn swallows, sand martins and house martins (Møller, 2019; **Figure 2**).

This simple so-called "splatometer" method described above relies on insects killed on the windscreen of cars. The Royal Society for Protection of Birds adopted this method first in 2004. A total of 324,814 insects were recorded on the windscreens of cars participating in the project, or on average 1 killed insect per 5 miles, or one insect per 8.045 km. A repeat of the project in 2019 revealed 1 insect per 10 miles or 16,090 km, or 0.125 insects per km. However, we note that this study statistically speaking only had two observations (a mean value in 2004 and another in 2019) making it difficult to draw any conclusions. Surveys of flying insects by Kent Wildlife Trust, Kent, United Kingdom under the direction of Dr. Paul Tinsley-Marshall, were performed in 2019. This innovative citizen science project using "splatometer" tests found 50% fewer insects in 2019 than in 2004. In Kent there were 50% fewer insects in 2019 with a value of 0.2 insects per mile in 2004 to 0.1 insects per mile in 2019, or 0.063 insects per km. The decline by 50% could be due to different causes including changes in pesticide use, altered morphology of windscreens of cars or changes in habitats between pairs of observation points in time. Finally, age of cars contributed to explain the abundance of killed insects with more recent car models being associated with more killed insects.

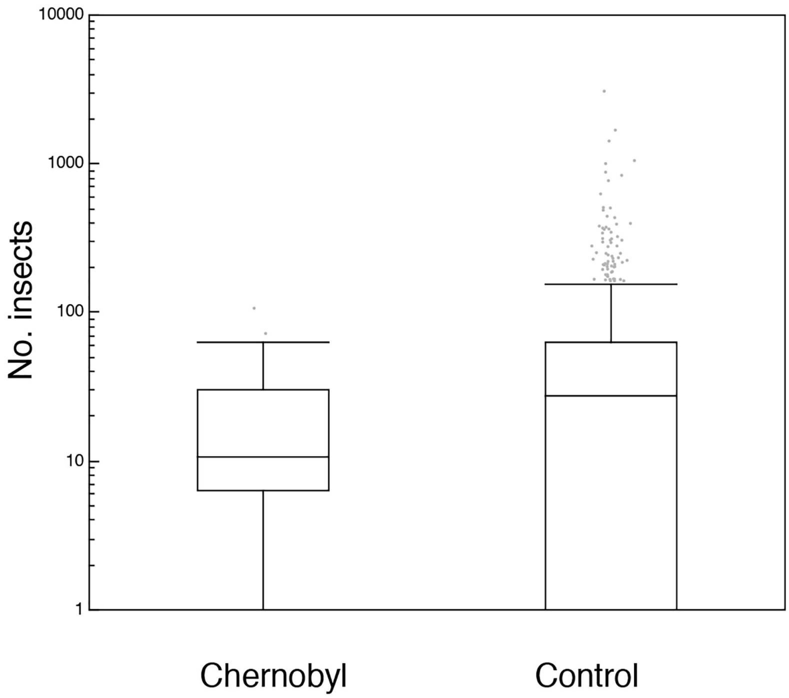


**FIGURE 1 |** Box plots of the number of insect sampled with a car in Chernobyl and in uncontaminated control areas in Europe. The box plots show median, quartiles, 5- and 95-percentiles and extreme values. Observations are jittered to make all observations visible.

The hypothesis to be tested was that environmental conditions affected the size of insect populations. We did so by testing eight biologically meaningful predictions. First, we tested whether the abundance of insects is related to features of cars such as driving speed, car model and windscreen size and shape, which may differ in angle and area. Second, we tested whether insect abundance is related to local weather as reflected by temperature, cloud cover and wind speed that are all known to have an impact on insect abundance. Third, we tested whether insect abundance increased during spring and during the day as expected from timing of emergence of insects. Fourth, we tested whether insect abundance is reduced in Chernobyl compared to uncontaminated control sites nearby, since numerous organisms show reduced population density under radiation exposure (Møller and Mousseau, 2009, 2018; Bezrukov et al., 2015). Fifth, whether there was a higher density of insects in Eastern than in Western Europe due to less intensive agriculture in eastern Europe (Tucker and Heath, 1994; Donald et al., 2001; Schimmelfenning and Sedelmeier, 2005; Reif et al., 2011). Sixth, whether there are fewer insects in Europe than at comparable latitudinal sampling transects in China. Seventh, we tested if there was a reduction in insect abundance between 1997 and 2018 in study sites Denmark and in Spain. These two areas with multiple study sites were chosen because they provide estimates of insect abundance used for food by insectivorous birds from 1997 to 2018 (Møller, 2019). Eighth, whether there was an increase in insect abundance with increasing longitude because climatic conditions during the breeding season deteriorate toward the east.

## MATERIALS AND METHODS

### Paired Designs

Heterogeneous field data are often difficult to analyze due to the many factors affecting the conclusions. We attempted to match paired samples whenever possible because differences between such pairs will tend to be similar in most respects.

### Study Sites

This study is part of a citizen science project (Crain et al., 2014) on the determinants of the abundance of insects using the windshield of cars as a sampling device (Møller, 2013, 2019, 2020). The criteria used for inclusion of participants in this study are similar to the criteria for inclusion of participants among ornithologists in national or European, Asian or North American bird census programs. The only criterion was that participants are knowledgeable naturalists.

Study sites were chosen by participants following requests for participation from amateurs who had previously expressed interest in this project (**Figure 3**). Participants were not asked to drive more than they usually did for their profession and their spare time interests. Thus, study sites were located where participants lived. We asked more than 1,000 amateurs in the ornithology literature for participation, and all interested persons were asked to make contact through a web site with information in Danish and English (insect.count.dk).

Eastern and Western European countries were categorized with Eastern countries being those belonging to the former

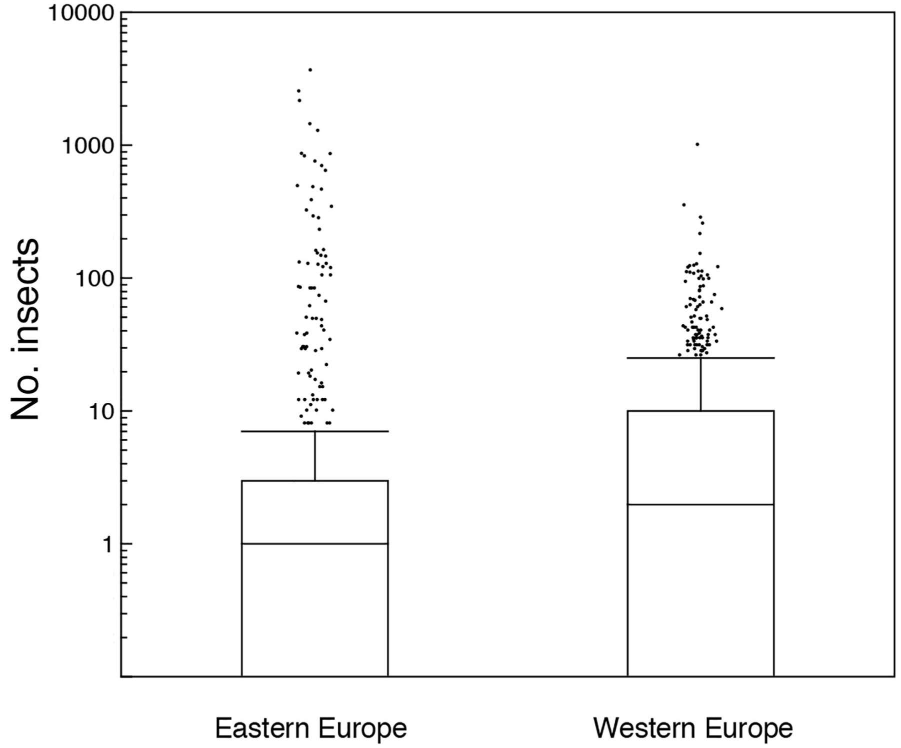


**FIGURE 2 |** Box plots of the number of insect sampled with a car in Eastern and Western Europe. The box plots show median, quartiles, 5- and 95-percentiles and extreme values. Observations are jittered to make observations visible.

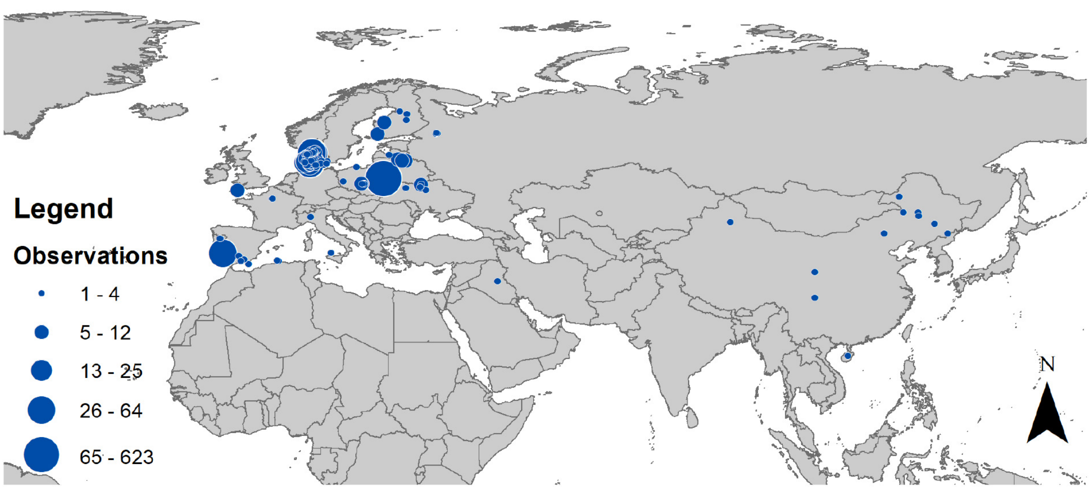


**FIGURE 3 |** Map of the distribution of sampling sites for insects with cars in Europe and Asia. The size of circles is proportional to the number of samples. The map was created using ArcGIS 10.1 (ESRI, 2012).

communist countries and Western European countries constituting the remainder. This categorization is similar to what has been used in previous studies of the reasons for differences in population trends of birds between Eastern and Western Europe (Reif et al., 2011).

Our study sites in China covered a large number of transects along a latitudinal gradient from Hainan in the south to Xinjiang and Inner Mongolia in the north. The latitudinal gradient was located along localities that were part of a latitudinal study of the brood parasitic common cuckoo *Cuculus canorus* in China. This gradient in China was compared with a similar gradient in Europe.

We surveyed birds in Chernobyl along roads within the Chernobyl Exclusion Zone where we have conducted research during 1991–2019. Ambient radiation at Chernobyl has a patchy distribution that ranges by more than a factor 50,000 with contaminated and clean sites often being separated by distances of just a few hundred meters. We conducted insect transects in Chernobyl using a categorization of level of ionizing radiation more or less than 0.10 μSv/h as the ambient ionizing radiation level. This criterion has been used previously in other studies that we have conducted (Møller and Mousseau, 2009, 2018; Bezrukov et al., 2015). We obtained radiation estimates from our measurements and cross-validated these with measurements by the Ministry of Emergencies.

We measured α, β, and γ radiation at ground level directly at each transect using a handheld dosimeter (Model: Inspector, SE International, Inc., Summertown, TN, United States). We measured levels several (2–3) times at each site and averaged the measurements. Our data were validated with correlation against data from the governmental measurements published by Shestopalov (1996), estimated as the midpoint of the ranges published. This analysis revealed a strong positive relationship (linear regression on log–log transformed data), suggesting that our estimates of radiation provided the same ranking of levels of radiation as did published estimates. The measurements by the Ministry of Emergencies were obtained by repeated standardized measurement of radiation at the ground level in a large number of different localities in Ukraine.

Radiation levels vary considerably at very short geographical distances due to heterogeneity in the deposition of radiation after the Chernobyl accident (Shestopalov, 1996). Our measurements at the transects ranged from 0.10 to 135.89 μSv/h.

## Web Site and Web Site Contents

A web site named insect.count.dk was established on February 1 2018 with information on the project in Danish and English, its purpose, a contact email address and a dedicated excel data sheet for entering data.

We published an article in the Danish popular bird journal *Fugle* & *Natur* with a circulation of more than 16,000 on May 1 2018.

We asked national natural history or ornithology web sites for participants. These sites included web sites for citizen scientists in Finland, Belgium and Spain.

At the start of surveys the participants were asked to clean the windshield to ensure that no insects were present at the start of a transect. The data sheet requested information on locality, GPS coordinates as latitude and longitude for the start location, date, month, time of day, temperature (°C), wind (Beaufort units), precipitation (mm rain), cloud cover (in units of 0.125) (thus all weather information was recorded locally), number of insects counted on the windshield upon arrival, distance driven (km), speed of car (km/h), windshield area (height and width in cm) and car model.

Participants were only asked to survey insects when driving on roads that they would otherwise have driven for other purposes including their profession and for spare time activities. Hence participants were not asked to make detours in order to participate. There were no restrictions on the number of times that a survey of a given transect could be made nor to the landscapes and habitats along the roads. Surveys were made February–October 2018–2020.

## Statistical Analyses

First, we visually inspected the distributions of the data for and deviations from normality or other frequency distributions such as binomial or poisson distributions depending on the distribution of data. Second, analyses of insect data and information on car features, climate and spatial and temporal variation were made using Generalized Linear Models (GLM). Third, data were inspected for goodness of fit to ensure that distributions did not deviate from normality. All statistical models, covariates, distributions of data link functions and fixed effects are reported in **Supplementary Table 1**. Fourth, we calculated repeatabilities and the associated SE using the equations in Becker (1984), Falconer and Mackay (1996), and Bell et al. (2009). The significance level was set to 0.05.

There was no evidence of collinearity between variables as revealed by variance inflation factors all being less than 5 (McClave and Sincich, 2003). All analyses were made using JMP (SAS, 2012).

# RESULTS

## Summary Statistics for Insects

A total of 50 observers participated in the study with the number of transects per observer ranging from 1 to 963 transects, mean (SE) = 71.265 transects per observer (25,237). The total number of transects was 3,530 with a mean (SE) number of insects of 35.289 insects per transect (SE = 5.883), or in total 124,567 insects. Transects were 1.0–1,125 km long, with a mean (SE) = 23.518 km (0.778), or in total 83.01 km. Thus, there was between 0 and 420.333 insects per km, on average 1.329 insects per km, SE = 0.249. Transects were made between February 3 and October 6, mean June 23, SE = 0.8 days.

Nine factors explained variation in the abundance of insects accounting for 52% of the variance (**Table 1**). Features of cars could affect the abundance of insects killed on windshields. The number of insects should increase with faster driving speed. If cars drive faster, there should be more insects killed as we actually observed here [Test 1; **Supplementary Table 1**; LR = 8.049, $df = 1$, $p = 0.0046$, estimate (SE) = 0.00062 (0.00022), 95% CI = 0.00019, 0.0010]. There were also significant differences among car models in number of insects killed on windshields. If windshields differ in angle and other properties for different models of cars, we should expect such variation to be eliminated by inclusion of car brand as a random factor.

## Spatial Consistency in Estimates of Insect Abundance

It is an underlying assumption of surveys of all living beings that such surveys provide consistent and reliable information on abundance and diversity of organisms. We tested for consistency in abundance of insects with $\log_{10}$-transformed number of insects as response variable and locality as predictor variable for the 3,530

**TABLE 1 |** Generalized Linear Mixed Model (GLMM) of the abundance of insects in relation to wind speed, temperature, date, distance, longitude, latitude, Chernobyl, Western or Eastern Europe and China or Europe.

| | Estimate | SE | *t* | *p* |
|---|---|---|---|---|
| Intercept | – 1.295 | 0.148 | – 8.73 | < 0.0001 |
| China | 1.002 | 0.094 | 10.67 | < 0.0001 |
| W Europe | – 0.059 | 0.019 | – 3.20 | 0.0014 |
| Chernobyl | – 0.469 | 0.031 | – 15.33 | < 0.001 |
| Latitude | – 0.016 | 0.002 | – 7.17 | < 0.0001 |
| Longitude | 0.022 | 0.002 | 11.67 | < 0.0001 |
| Distance | 0.814 | 0.017 | 46.59 | < 0.0001 |
| Date | – 0.0012 | 0.00012 | – 6.47 | < 0.0001 |
| Temperature | – 0.017 | 0.0016 | – 10.33 | < 0.0001 |
| Wind | – 0.051 | 0.0050 | – 10.12 | < 0.0001 |

*The random effects of locality and car model were excluded. The table includes estimates (SE), t- and p-value. The model has the statistics F = 408.105, df = 9, 3322, $r^2$ = 0.52, p < 0.0001.*

transects with two or more estimates for all 724 localities in a standard least squares regression. The model had the statistics $F = 14.086$, $df = 722, 2806$, $r^2 = 0.71$, $p < 0.0001$, repeatability $R$ (SE) = 0.727 (0.008). In a second model we predicted $\log_{10}$-transformed number of insects as response variable and locality, longitude, distance, date, temperature and wind as predictors. The model had the statistics $F = 15.864$, df = 674, 2660, $r^2 = 0.750$, $p < 0.0001$. This model had as repeatability for abundance of insects of 0.739 (0.008). These repeatabilities for localities were highly consistent showing that the abundance of insects was very similar within localities among days.

## Weather and Abundance of Insects

Insects are ectothermic and higher ambient temperatures should thus advance phenology [Test 2; LR = 5.759, $df = 1$, $p < 0.0001$, estimate (SE) = –0.005 (0.0002), 95% CI = –0.0083, 0.0008 mm]. Higher wind speed reduced the abundance of insects [Test 3; LR = 26.501, $df = 1$, $p < 0.0001$, estimate (SE) = –0.034 (0.007), 95% CI = –0.047, –0.021]. More extensive cloud cover should reduce temperature and hence reduce the abundance of insects as observed in the present study [test 4; LR = 26.306, $df = 1$, $p < 0.0001$, estimate (SE) = –0.177 (0.034), 95% CI = 0.245, 0.110].

## Temporal Trends in the Abundance of Insects

Insect abundance should increase in spring as temperature increased. There was a significant positive relationship between date and insect abundance when controlling for windshield area, car model, speed, cloud cover, wind, temperature, time, distance and latitude (Test 5; **Table 1**).

We should expect more insects around noon than early in the morning or late in the evening when it is colder. There was a significant positive linear relationship between time of day when controlling for windshield area, car model, speed cloud cover, wind, temperature, time, distance and latitude [Test 6; LR = 8.130, $df = 1$, $p = 0.0044$, estimate (SE) = 0.005 (0.002), 95% CI = 0.0014 0.0075], and there was also a significant quadratic effect as predicted [Test 7; LR = 7.995, $df = 1$, $p$ 0.0047, estimate (SE) = – 2.741 10–6 (9.687 10–6), 95% CI = –4.54 10–6, –8.418 10–6].

## Spatial Abundance of Insects in Chernobyl and Eastern Europe

There were significantly fewer insects in contaminated areas at Chernobyl with more insects per km driven than in control areas in Eastern Europe (**Figure 2**; Test 8; **Table 1**). A number of other variables were controlled statistically in this analysis (**Supplementary Table 1**). There were more insects in Eastern than in Western Europe (**Figure 4**; Test 9; **Table 1**).

We predicted a latitudinal trend in the abundance of insects in both countries because of latitudinal differences in productivity (Møller, 2020). There was a significant latitudinal increase in the abundance of insects (Test 10; **Table 1**). That was also the case separately for the abundance of insects in Europe (Test 11; **Table 1**). There was significantly more insects in China than in Europe independent of latitude (**Figure 5**; Test 12; **Table 1**). Finally, there was an increase in the abundance of insects with longitude (**Table 1**).

## Temporal Trends in Abundance of Insects

Insect abundance was larger at Badajoz, Spain than at Kraghede, Denmark (**Figure 5** and **Table 2**). However, there was no significant difference in insect abundance between 1997 and 2018 (**Figure 5** and **Table 2**). In contrast, there was a significant interaction between country and year (**Table 2**). The variance in abundance of insects was larger in Spain than in Denmark

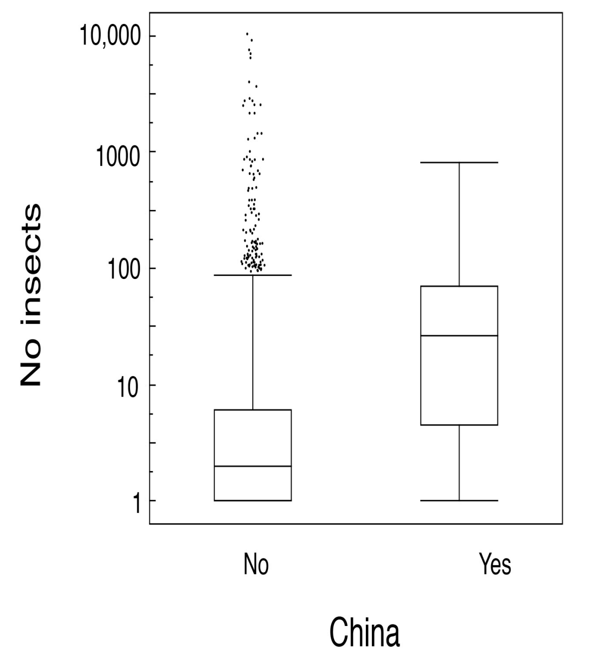


**FIGURE 4 |** Box plots of the number of insects sampled with a car in China and Europe. The box plots show median, quartiles, 5- and 95-percentiles and extreme values. Observations are jittered to make observations visible.

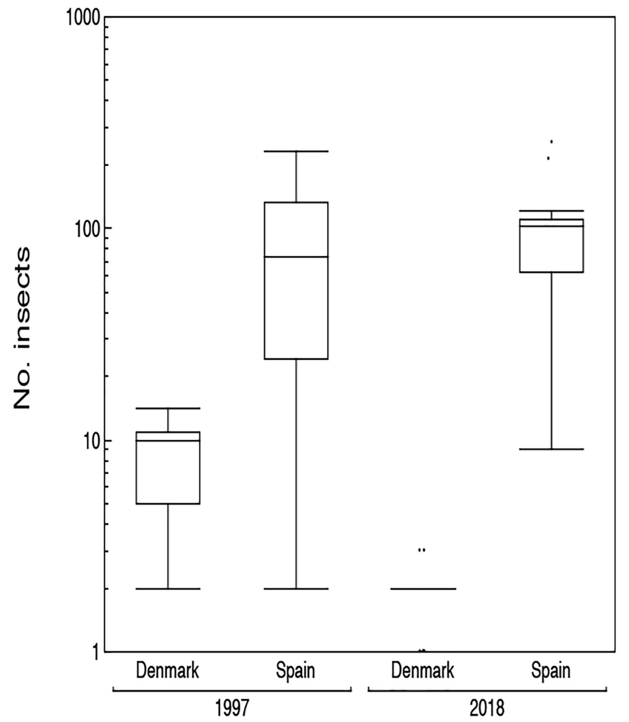


**FIGURE 5 |** Box plots of the number of insects sampled with a car for Denmark and Spain in 1997 and 2018. The box plots show median, quartiles, 5- and 95-percentiles and extreme values. Observations are jittered to make them visible.

**TABLE 2 |** Generalized Linear Model (GLM) of number of insects in relation to country (Spain or Denmark), year (1997 or 2018) and country by year interaction in a model with normally distributed data and an identity link function.

| Term | LR | *p* | Estimate | SE | Lower CL | Upper CL |
|---|---|---|---|---|---|---|
| Country | 161.852 | < 0.0001 | – 0.544 | 0.030 | – 0.604 | – 0.484 |
| Year | 0.056 | 0.813 | – 0.0007 | 0.0029 | – 0.0064 | 0.005 |
| Country*year | 45.248 | < 0.0001 | – 0.021 | 0.0029 | – 0.027 | – 0.016 |

*The table reports likelihood ratio statistics, p-values, estimate, SE and 95% confidence intervals.*

(**Table 2**). The abundance of insects was 32% smaller in Denmark than in Spain, and 40% smaller in 2008 than in 1997 as shown by the interaction profiler. These results suggest that there was a in abundance of insects in Denmark, while there was no such decline in Spain.

## DISCUSSION

The present study was based on extensive surveys of almost 124,500 km roads for a total of almost 35,500 flying insects mainly across Europe and China. Previous studies in Denmark have cross-validated abundance estimates of insects using a number of different methods to show high consistency between samples with sweep-nets, sticky plates and feeding rates of barn swallow chicks by parent birds (Møller, 2013, 2019, 2020). We documented a highly consistent repeatability among days, implying that insect surveys provided reliable information on the abundance of insects.

We identified nine factors that accounted for variation in abundance of insects. First, locality accounted for variation in abundance of insects. Second, car model accounted for variation in insect abundance. Third, temperature accounted for insect abundance. Fourth, insect abundance decreased with wind speed. Fifth, insect abundance declined with date. Sixth, insect abundance was lower at Chernobyl than in non-contaminated sites surrounding Chernobyl. Seventh, insect abundance decreased with latitude. Eight, insect abundance increased with longitude. Ninth, there were more insects in China than in Europe. Tenth, there were more insect in Eastern than in Western Europe.

The abundance of insects differed between the two study sites in Spain and Denmark, but not between 1997 and 2018 as revealed by the interaction between year and country. The repeatability of insect abundance within localities among days was high at 0.727 and 0.739, which is highly consistent (Bell et al., 2009). This indicates that the surveys were highly repeatable as required for consistent and reliable surveys of any living being.

The patterns that we have described here addresses a range of ecological questions that we have investigated. While scientific questions may suffer from publication bias (Møller and Jennions, 2002), we have reported all our findings in the present study. After the present paper was preliminarily accepted, we had an additional study accepted reporting reductions in insect abundance when pesticide use, fertilizer use and land-use were entered as predictor variables (Møller et al., 2021).

Extensive insect surveys have shown recent reductions in abundance of insects by as much as 80% during just a few decades, even in nature reserves in Germany where insects are not exterminated (Hallmann et al., 2017; Møller, 2019, 2020). These changes in abundance of insects have been attributed to altered farming practice, altered land-use and the altered underlying factors (Vogel, 2017). While some studies have documented such large reductions in abundance of insect (Hallmann et al., 2017; Tinsley-Marshall, 2019), others have shown smaller declines (Conrad et al., 2002, 2006; Shortall et al., 2009; Fox et al., 2014; Møller, 2020). This raises questions about the generality of these changes, but also the underlying mechanisms accounting for variation in insect abundance.

There is good reason to expect that insect abundance has declined since the 1960s. Among the citizen science participants in this project, 10 drivers reported that when they were driving a car in the 1960s and 1970s, they encountered so many insects that they had to make several stops during a trip of 100 km in order to clean the windshield (Hallmann et al., 2017; Tinsley-Marshall, 2019). Many participants in this project reported that they subjectively had judged that the number of insects was considerably reduced in 2018 compared to previous years due to an unusual warm and dry summer (Meteorologisk Institut, 2018). The present study recorded repeated surveys in 1997 and 2018 at the same two roads in Spain and Denmark showing a 40% decline in Denmark, but no uniform decline at the site in Spain between 1997 and 2018. The reason for the lack of decline in Spain may derive from insect abundance already having declined in 1997 due to more intense agriculture in Spain than in Denmark.

Two pieces of evidence suggest that insect abundance was negatively impacted by human perturbation of environmental conditions. The abundance of insects was reduced by two thirds in Chernobyl compared to uncontaminated control areas. This implies that the abundance of insects has been reduced across more than 50,000 km$^2$ in Ukraine, Belarus and Russia (Møller and Mousseau, 2009, 2018; Bezrukov et al., 2015). Second, we documented differences in insect abundance between Western and Eastern Europe as revealed by similar changes during recent decades when extensive farming became predominant in Western, but subsequently also in Eastern Europe (Tucker and Heath, 1994; Donald et al., 2001; Schimmelfenning and Sedelmeier, 2005).

Factors other than agriculture and associated land-use and crops may account for the observations reported here. The present study identified clear correlations between insect abundance and temperature, cloud cover and wind speed. These effects may apply to short-term weather conditions that affect the flight activity of insects, or they may be attributed to climate change (IPCC, 2007a; Hurrell and Trenberth, 2019). It is likely that insect abundance may change in response to both factors. Møller (2013) has already reported extensive data on insect abundance based on windshield surveys during 1997–2012 as described in this paper. While temperatures during summer have increased in large parts of the temperate zone and at higher latitudes, there has been a decrease in cloud cover and wind speed (IPCC, 2007b; Hurrell and Trenberth, 2019), and thus in the main study sites investigated here (Møller, 2013). Such changes in temperature, wind speed and cloud cover should increase the abundance of insects, as shown with insect abundance increasing with temperature and decreasing with wind speed and cloud cover in two study sites in Denmark and Spain in 1997 and 2018.

A number of hypotheses have been proposed to account for latitudinal gradients (e.g., Rohde, 1992; Møller, 2020). We investigated the extent to which latitude and taxa were associated with a reduction in abundance of insects. China had consistently higher abundance of insects in China than in Europe. The reason for such differences in latitudinal trends in the abundance of insects between continents remains to be identified.

In conclusion, the abundance of flying insects provides a relative estimate of the abundance of food for a range of other organisms. Here we have shown that features of vehicles, weather, climate, spatial and temporal variation and the effects of ionizing radiation may contribute independently to estimates of the abundance of flying insects and hence the abundance of food for offspring and parent birds (Møller, 2019). We hypothesize that variation in the abundance of insects will predict the abundance of insectivorous birds as already reported (Møller, 2019).

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

AM conceived and designed the experiments, and analyzed the data. AM, DC, EF-J, JE, KL, WL, and WW performed the experiments, and wrote and edited the manuscript. All authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2021.657178/full#supplementary-material

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METHODS
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# Evaluating the Fitness for Use of Citizen Science Data for Wildlife Monitoring

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Contributory citizen science programs focused on ecological monitoring can produce fine-grained and expansive data sets across spatial and temporal scales. With this data collection potential, citizen scientists can significantly impact the ability to monitor ecological patterns. However, scientists still harbor skepticism about using citizen science data in their work, generally due to doubts about data quality. Numerous peer-reviewed articles have addressed data quality in citizen science. Yet, many of these methods are not useable by third-party scientists (scientists who are not directly involved in the citizen science program). In addition, these methods generally capture internal data quality rather than a dataset's potential to be used for a specific purpose. Assessing data fitness for use represents a promising approach to evaluating data accuracy and quality for different applications and contexts. In this article, we employ a Spatial, Temporal, Aptness, and Application (STAAq) assessment approach to assess data fitness for use of citizen science datasets. We tested the STAAq assessment approach through a case study examining the distribution of caribou in Denali National Park and Preserve. Three different datasets were used in the test, Map of Life data (a global scale citizen science mobile application for recording species observations), Ride Observe and Record data (a program sponsored by the park staff where incentivized volunteers observe species in the park), and conventionally collected radio collar data. The STAAq assessment showed that the Map of Life and Ride Observe and Record program data are fit for monitoring caribou distribution in the park. This data fitness for use approach is a promising way to assess the external quality of a dataset and its fitness to address particular research or monitoring questions. This type of assessment may help citizen science skeptics see the value and potential of citizen science collected data and encourage the use of citizen science data by more scientists.

**Keywords: volunteered geographic information, data fitness, data quality, ecological monitoring, citizen science**

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## INTRODUCTION

Contributory citizen science programs focused on ecological monitoring are generally initiated by scientists, researchers, or resource managers. In these types of citizen science programs, volunteers typically assist scientists with data collection or analysis (see Shirk et al., 2012 for a typology framework of citizen science projects). Ecological monitoring focused citizen science programs can collectively produce finer grained and more expansive data sets over regional and global scales and collect data more frequently, covering long temporal extents (Theobald et al., 2015). With these data collection abilities, citizen scientists can significantly impact the ability to monitor ecological patterns (Dickinson et al., 2010; Magurran et al., 2010; Andelman, 2011; Jetz et al., 2012; Ballard et al., 2017; Kress et al., 2018). These more temporally and spatially expansive datasets can support longitudinal surveys and help identify climate change signals, particularly species distribution changes (Champion et al., 2018; Pecl et al., 2019). Nevertheless, scientists still harbor skepticism about using citizen science data in their work, generally due to doubts about data quality (Bonter and Cooper, 2012; Riesch and Potter, 2014; Burgess et al., 2017; Golumbic et al., 2017). They are concerned that individuals from the public lack the necessary skills to identify species or collect data in a rigorous manner (Burgess et al., 2017).

Despite concerns over citizen science data quality, the number of contributory citizen science programs focused on collecting data for ecological modeling is growing. This is due in part to advances in mobile technology. Smartphones as data collection devices have helped increase the number of volunteers contributing to a diverse range of citizen science initiatives at various spatial scales (Roy et al., 2012; Luna et al., 2018). Some app-based programs have a global focus and amass large observation datasets for any researcher to use for monitoring purposes; these apps. include iNaturalist, eBird, and Map of Life, among others. eBird, in particular, is a prominent data source for monitoring the effects of climate change on birds (Hurlbert and Liang, 2012; Cooper et al., 2014; Callaghan and Gawlik, 2015; Walker and Taylor, 2017). eBird, developed by the Cornell Lab of Ornithology, serves as a birding guide and citizen science data collection tool; over 1 billion bird sightings have been contributed as of 2021[1]. The Map of Life (MOL) mobile application developed at Yale University is a citizen science offshoot of the online species distribution platform of the same name (Jetz et al., 2012). The app serves as a simple field guide for tens of thousands of species (flora and fauna) worldwide. It also allows users to record species observations and contribute important data for research and conservation, and it has over 50,000 downloads since its launch in 2016[2]

The managers of these global scale app-based programs would like to see more third-party scientists (those who are not directly affiliated with the program) taking advantage of these data to address their own research and monitoring objectives. Scientists, however, have various concerns with using citizen science collected data in their work; Burgess et al. (2017) provides a comprehensive overview of these concerns over data quality, including accuracy and reliability. A common concern found by Burgess et al. (2017) is data accuracy, specifically concerns about how a program accounts for the volunteers' data collection skills and the adequacy of volunteer training- or lack thereof. Furthermore, much of the data collected through app-based citizen science programs are considered opportunistic data- "observations of species collected without standardized field protocol and explicit sampling design" (Van Strien et al., 2013). While logistically opportunistic data is more manageable for volunteers to collect than strategic sampling, opportunistic citizen science data may not be reliable for monitoring distribution trends over time. This is because opportunistic citizen science data may suffer from changes in observation bias, reporting bias, and geographical bias. However, Van Strien et al. (2013) compared opportunistic citizen science data to strategic samples monitoring data and found similar distribution trends.

Numerous peer-reviewed articles have looked at the quality of citizen science data. Some have adapted or developed frameworks and methods for validating data, assessing data quality, and accounting for bias (Cohn, 2008; Wiggins et al., 2011; Toogood, 2013). Wiggins et al. (2011) provides a review of data validation methods. The authors surveyed 52 citizen science projects about how they validate data. Many of them reported using a combination of methods, including expert review and additional documentation of observations. Expert review means project team members or other subject matter experts validating data before it is accepted into the database. Further documentation of observations could include asking citizen scientists to provide photos, filling out article datasets, submitting observations digitally, or filling out additional dataset fields about how the observation was made.

Other methods found in the literature include increasing the number of participants contributing data (such as Linus' Law) and data quality assessments based on data quality indicators (Haklay, 2010; Comber et al., 2013; Senaratne et al., 2016). Linus' Law originated in open-source software development and refers to the process of measuring the quality of the citizen science data, in particular citizen science data that includes spatial information (also called volunteered geographic information (Goodchild, 2009). Linus' Law considers the number of peers who have reviewed or edited its content (Elwood et al., 2012). In the case of citizen science data, Linus' Law refers to the notion that with a large number of data contributors, the biases or inaccuracies made by a few of those contributors will be quieted.

A thorough assessment of citizen science data, based on quality indicators, is also used to improve and examine data quality. Senaratne et al. (2016) identified 17 quality measures and indicators for spatial citizen science data (also called Volunteer Geographic Information or VGI). These indicators include standard measures of quality, position accuracy, topological consistency, thematic accuracy, completeness, and temporal accuracy. They found that these standard data quality measures alone are not enough to assess VGI quality. Thus, additional indicators like reputation, trust, credibility, vagueness, experience, and local knowledge are also used in the VGI literature (Senaratne et al., 2016).

Many of these methods are meant to be done for internal quality checks. Internal quality, generally reported in the metadata (data about the data), is the intrinsic characteristics of the data as determined by the producer of the data (Gervais et al., 2009). External data quality looks at how data fit the user's needs (Juran et al., 1974; Devillers and Bédard, 2007;

[1] https://eBird.org
[2] https://mol.org

Gervais et al., 2009). More externally focused data assessments that third-party scientists can use may make more of them amiable to using citizen science data in their work.

An analysis of data fitness for use offers a way to address these ongoing concerns of data quality by providing a way for scientists and researchers to do a data quality assessment for their specific research needs after they obtain data (Dickinson et al., 2010; Parker et al., 2012; Crall et al., 2015). A data fitness for use assessment does not provide a blanket assessment of data quality; however, it assesses whether these data could be used for a specific application within a given area (Juran et al., 1974; Chrisman, 1991; Veregin, 1999; Devillers and Bédard, 2007). Providing scientists with the ability to test the fitness of the data for their specific research needs offers the potential to standardize the use of citizen science data in knowledge production.

Additionally, using data fitness as a metric for data quality is a way to reduce the uncertainty of using a specific dataset. These data are not only judged on what it can be fit for but also the limitations and uncertainty (Veregin, 1999). While the citizen science data quality literature does not explicitly showcase a data fitness for use approach, some articles discussing data quality suggest that assessing citizen science data for specific use cases will increase the utility of the data (Dickinson et al., 2010).

Senaratne et al. (2016) concluded that a systematic framework needed to be developed that provides methods and measures to evaluate the fitness volunteer collected data. Furthermore, Haklay (2013) also indicates that something like a data fitness approach for citizen science data would ensure collected data can answer the scientific questions being posed. Kosmala et al. (2016) also determines that each citizen-science dataset should be judged individually, based on the project design and application, and not assumed to be substandard simply because volunteers generated it. The authors also note that data fitness allows scientists to assess if a possible bias in a particular dataset is an issue for their specific research question.

There are various models of a data fitness assessment. Some depend on metadata to assess data fitness, and others run datasets through a series of fitness indicator checks. Pôças et al. (2014) created an assessment called EQDaM, external quality of spatial data from metadata. The metadata for each dataset was used to compare different quality indicators, where the users choose these indicators. The indicators include: spatial, temporal, topology, lineage, precision, accessibility, and legitimacy. A metadata-focused assessment may not be appropriate for citizen science data. The lack of incompleteness of metadata is a known issue in citizen science. While programs are improving their efforts with the help of resources like the Citizen Science Associations Data and Metadata Working Groups PPSR Core Standards[3], many citizen datasets do not have reliable metadata for a fitness assessment (Grira et al., 2010).

Another way to assess data fitness is through different indicator checks. Wentz and Shimizu (2018) compared data sets through a framework based on quality indicators with the DaFFU assessment. The DaFFU assessment compares fitness based on the accuracy, agreement, and aptness of the datasets. Instead of relying on metadata like Pôças et al. (2014) and Wentz and Shimizu (2018) identified specific data characteristics that were compared through spatial analysis created a fitness assessment based on the mathematical framework of multiple criteria decision making. The DaFFU method selects "the best data set from multiple options using a select set of user criteria." The DaFFU assessment is robust and can easily be modified for other applications. The assessment is applicable to any modeling with a statistical performance output. This type of assessment allows users to compare datasets (collected conventionally or by volunteers) to determine which datasets (or combination of datasets) may be best for the specific research or objective. This ability to compare volunteer collected data to conventionally collected data is suggested as a more comprehensive way to assess citizen science data (Kremen et al., 2011; Holt et al., 2013; Cooper et al., 2014; Theobald et al., 2015).

The comparison of datasets allows scientists to see how citizen science data may be integrated (or mashed-up) with other data they use. Hybrid/mash-up datasets are another method to assess and improve citizen science data quality. Hybrid datasets involve integrating the citizen science data with conventionally collected data (Elwood et al., 2012; Parker et al., 2012; Upton et al., 2015). Combined datasets (e.g., data mash-ups, hybrid datasets, or cross-validation) allow researchers to test out the accuracy or combine the datasets to fill in gaps (Batty et al., 2010; Connors et al., 2012; Parker et al., 2012; Abdulkarim et al., 2014; Bruce et al., 2014; Upton et al., 2015).

Wentz and Shimizu (2018) suggest that an adaption of their assessment would be appropriate for citizen science/VGI data. The use of user criteria instead of metadata makes this type of data fitness assessment more amiable to citizen science collected data. This article presents an application of the DaFFU assessment presented in Wentz and Shimizu (2018) called, The Spatial, Temporal, Aptness, and Application (STAAq) assessment. This assessment was developed to address data fitness of ecological monitoring citizen science data specifically but can be used for other data types. The STAAq assessment adapts the DaFFU assessment by adding a temporal component and additional elements of assessing spatial resolution. Understanding the temporal and spatial resolution of species observation data set is important for examining bias in the data and its fitness to monitor species that may have seasonal distribution changes or varying spatial ranges. The spatial resolution may also affect the performance of different ecological models (Guisan et al., 2007).

To test the STAAq assessment, we used it for a case study with various datasets collected in Denali National Park and Preserve. We used the assessment to compare the fitness of data from a global app-based citizen science program (Map of Life) with two other species occurrence datasets managed by the park service. We wanted to determine if these datasets are fit to monitor caribou (*Rangifer tarandus*) distribution in the park. After running each dataset through the STAAq assessment components, we ranked the results to compare the datasets and how well each performed in assessing spatial scale, temporal scale, aptness, and application. The results of this assessment quantify

[3]https://core.citizenscience.org/docs/

how fit each dataset is for monitoring caribou distribution in the park. More broadly, this assessment shows how quantifying the fitness of citizen science data can make volunteer collected data more usable and trustworthy for researchers monitoring ecosystems for climate change signs.

# METHODS

## The Spatial, Temporal, Aptness, and Application Assessment

The STAAq assessment modifies and adds additional assessment components to Wentz and Shimizu's (2018) DaFFU assessment, including spatial and temporal scale; these additions make the idea of data fitness more applicable to citizen science data. Like similar assessments, the STAAq assessment ranks each dataset according to its performance in the Spatial, Temporal, Aptness, and Application components. These rankings are averaged to create an overall ranking of the datasets (q). **Table 1** shows each of the four components in the STAAq assessment. The number of elements (j) that is assessed by the particular component. The datasets (q) are evaluated through STAAq, and then these rankings can be weighted individually then are averaged to give the overall ranking for each dataset in each component. Weighting the ranking from each component allows the assessment to account for components that may be more important than others for specific research questions. In **Table 1**, weights are represented by the symbol (w).

The Spatial component (S) (**Figure 1**) assesses two elements: spatial resolution and spatial extent. These elements are evaluated to determine each dataset's rank. The datasets are assessed on how well they perform at different standards of the spatial scale elements. Depending on the geographic scale and scope of a research question, different resolutions may be desired in a dataset. For example, if a research question is focused on a small area, data with a finer spatial resolution may be desired. Spatial resolution refers to the minimum cell size of the raster data or a measurement of error in the case of point data (Goodchild, 2011). Spatial resolution is assessed through examining these data per a specific cell size or measurement of error. Spatial extent refers to the spatial scope of these data or the area size represented in these data (Goodchild, 2011). The spatial extent can be determined by calculating the convex hull around the set of data points.

The Temporal component (T) (**Figure 2**) is determined by assessing the performance of each dataset with three different elements (j) of temporal scale, event, temporal resolution, and temporal extent. Temporal aspects of data are important for species observation data in particular. Temporal aspects of the data can show the season it was collected, the time of day, and how long the datasets have been collected. Event refers to the time at which the event was observed (Guptill and Morrison, 2013). Temporal resolution, also referred to as temporal consistency, is the frequency at which the dataset is collected (Guptill and Morrison, 2013). Temporal extent, or temporal transaction, relates to the data collection's length or how much time the dataset covers (Guptill and Morrison, 2013). The datasets are ranked based on how they perform with each of the elements. For example, if a dataset spanning multiple years is desired, the dataset with a more extensive temporal extent is higher.

Aptness (A1) determines the uniqueness (U) of the datasets (**Figure 3**). To determine aptness, these data must be in raster format. Aptness is calculated cell by cell to determine how unique each dataset is. In some cases, uniqueness is a desired quality in the datasets, while it is not in other cases. For example, the Aptness component can identify outliers in a dataset not found in other datasets. Outliers may be desired, a researcher may want to know if there is something other datasets are missing, or outliers may not be desired because these outliers may be errors. **Figure 3** Aptness (A1) Component modified from Shimizu (2014) shows the process of determining aptness. R1, R2, and RQ represent sample raster data for each of the datasets (Q). Each cell in the raster is given a value. The raster layers are then added together to create R. The original raster layers for each dataset are multiplied by R to create R1R, R2R, and RQR. Then cell by cell agreement, c, is determined between the datasets.

c = 0 none of the datasets have an attribute assigned to that cell.

c = 1 one dataset assigned an attribute to that cell.

**TABLE 1** | STAAq assessment.

| Component | Formula | Description | Definition |
|---|---|---|---|
| Spatial Scale | $S_q = w_1 \frac{s_1+s_2+s_j}{j}$ | Spatial Scale = $S_q$<br>$S_j$ = rank of elements<br>j = number of elements | The spatial scale component assess the dataset's spatial resolution and extent |
| Temporal Scale | $T_q = w_2 \frac{t_1+t_2+t_j}{j}$ | Temporal Scale = $T_q$<br>$t_j$ = rank of elements | The temporal scale component assesses the following elements: observation time, temporal resolution, and temporal extent |
| Aptness | $A_{1q} = w_3 \cdot a_{1q}$ | Aptness = $A_{1q}$<br>a = the uniqueness of the dataset | Aptness refers to the context in which these data are used. Aptness in the ranking order depends on what level of errors the decision-makers are willing to accept (Wentz Shimizu 2018) |
| Application | $A_{2q} = w_4 \frac{a2_1+a2_2+a2_j}{j}$ | Application = $A_{2q}$<br>$a_{1j}$ = rank of elements for the datasets | Refers to how accurate these data are geographically and categorically. It can be examined through how well these data address different accuracy components |
| $STAA_Q$ | $STAAq = w_1 \sum X_{iQ}$ | Average of all the ranks of all components (X) for each data set. Rank of 1 is considered best | The dataset that is most fit for use is ranked 1 |

c = 2 two datasets assigned an attribute to that cell.

c = Q all datasets assigned an attribute to that cell.

In the case of aptness, c = 1 shows which dataset is unique. The process of "cell by cell" agreement results in a new raster layer (RQA1); the layer RQR is divided by this new layer to calculate the percent of uniqueness (U) of the dataset. Then it must be determined if omission or commission is preferred. Is the uniqueness of a dataset a desired quality or not?

e = 1 when error of commission is preferred.

e = 0 when error of omission is preferred.

Finally, the datasets are ranked in either ascending or descending order, depending on the value of e.

The Application (A2) component is concerned with the product of a model (**Figure 4**). The elements of the Application component vary with the models being assessed. For example, Wentz and Shimizu (2018) use the Application component

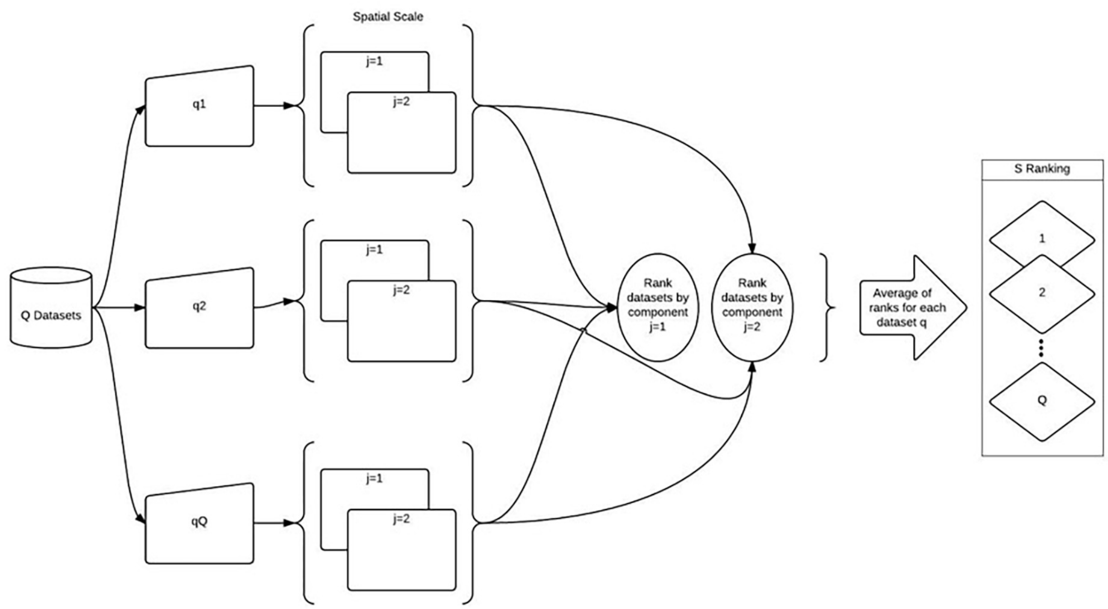


**FIGURE 1 |** Spatial Scale (S) component, adapted from Shimizu (2014).

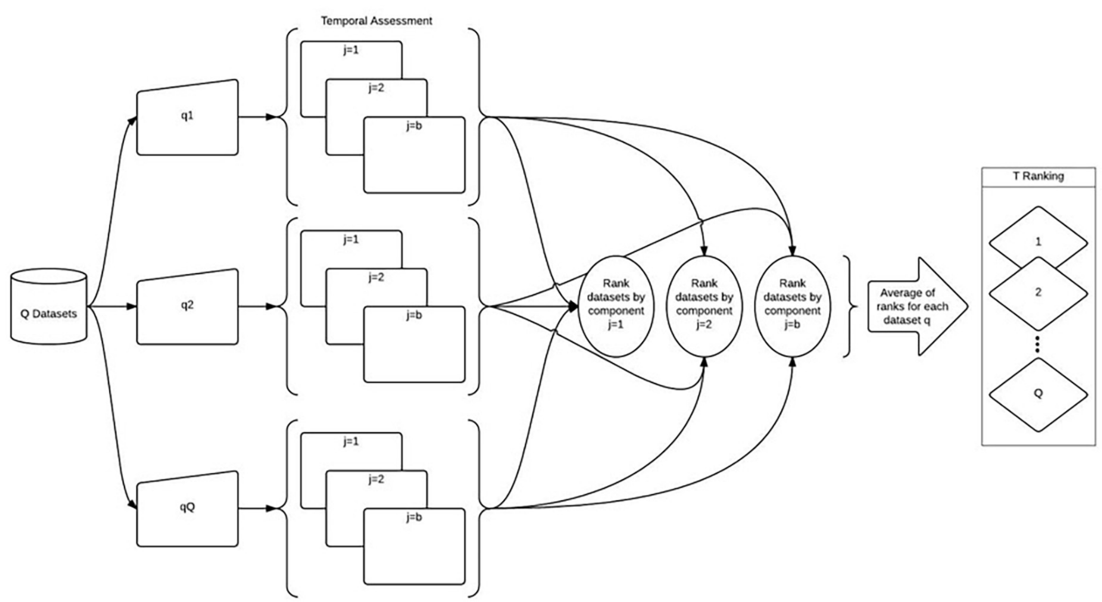


**FIGURE 2 |** Temporal Scale (T) component, adapted from Shimizu (2014).

(called Accuracy component in Wentz and Shimizu, 2018) to determine how accurately a model calculates the total nitrogen removal and nitrogen load a watershed. The model that is used in this component is specific to the research question. In **Figure 4** Application (A2) component applied from Shimizu (2014), the datasets are represented by q1, q2, and qQ.

The datasets' overall ranking was determined by averaging each component (Roszkowska, 2013). The resulting fractional ranks were then ranked to provide a final ranking of the datasets. We then examine the average ranking to compare datasets in terms of fitness for use. Weights can be applied to each component before averaging the ranks if desired. The elements

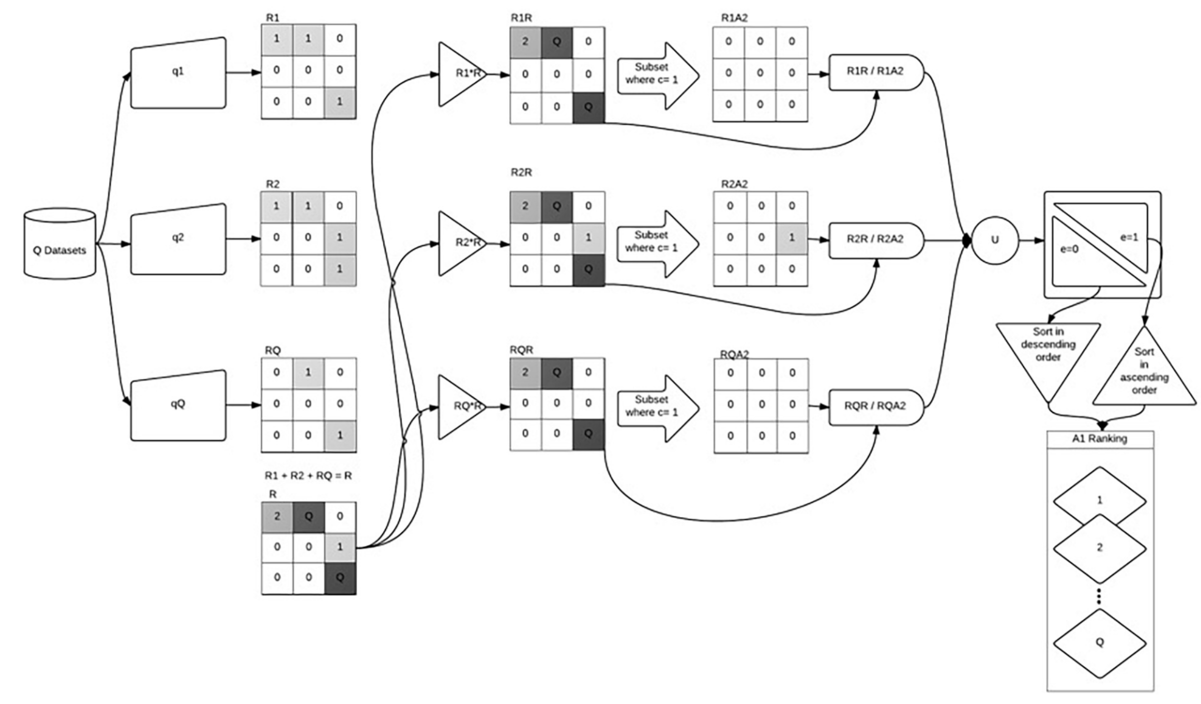


**FIGURE 3 |** Aptness (A1) component, adapted from Shimizu (2014).

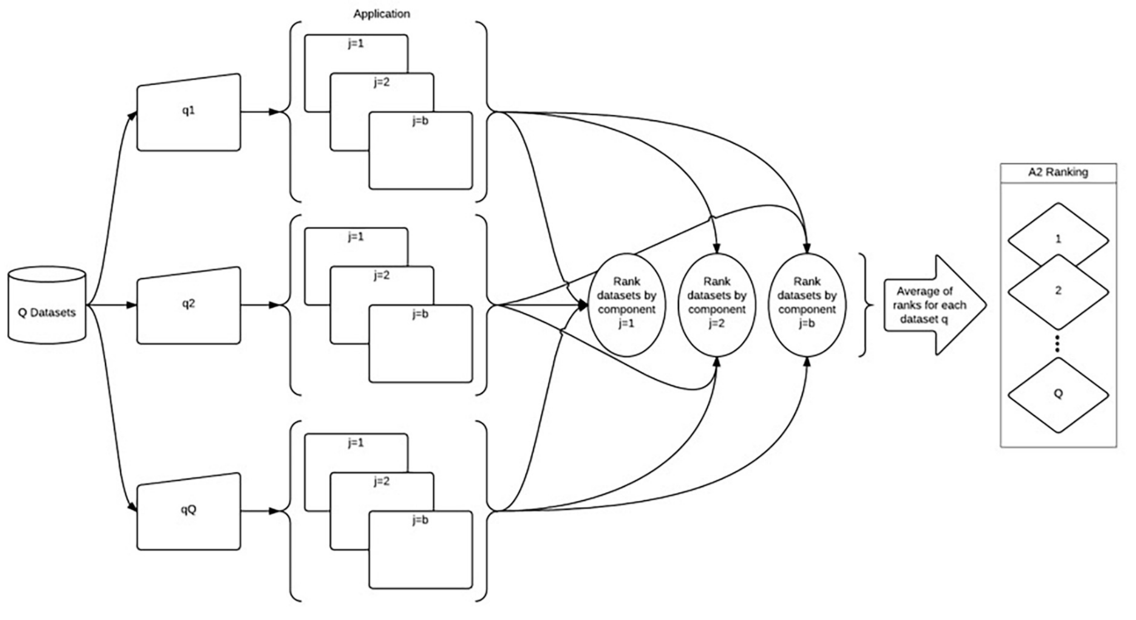


**FIGURE 4 |** Application (A2) component, adapted from Shimizu (2014).

and components of the assessment can be modified or weighted to fit the user's needs; assessment results can be included within the metadata for each dataset and provide an example of what these data fit for. A vital aspect of this assessment is that it can be used when a conventionally collected dataset is unavailable or only one dataset exists. Additionally, the assessment can be used to partially perform a data fitness assessment.

This fitness for use assessment is relevant for volunteer collected data and can be used with many other types of data and models. Other typologies of citizen science programs can use the data fitness for use framework. In this article, we focused on adapting a method to work with the data collected by a contributory style citizen science program focused on ecological monitoring. Elements of the assessment can be adapted to fit

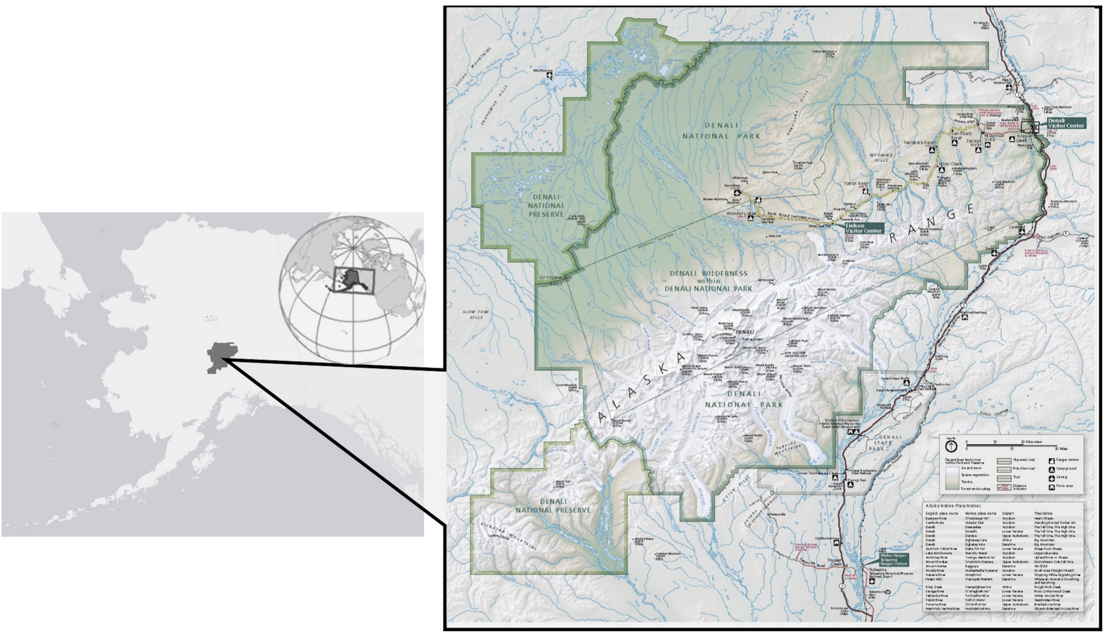


**FIGURE 5 |** Denali National Park and Preserve (Park Map obtained from https://www.nps.gov/carto/).

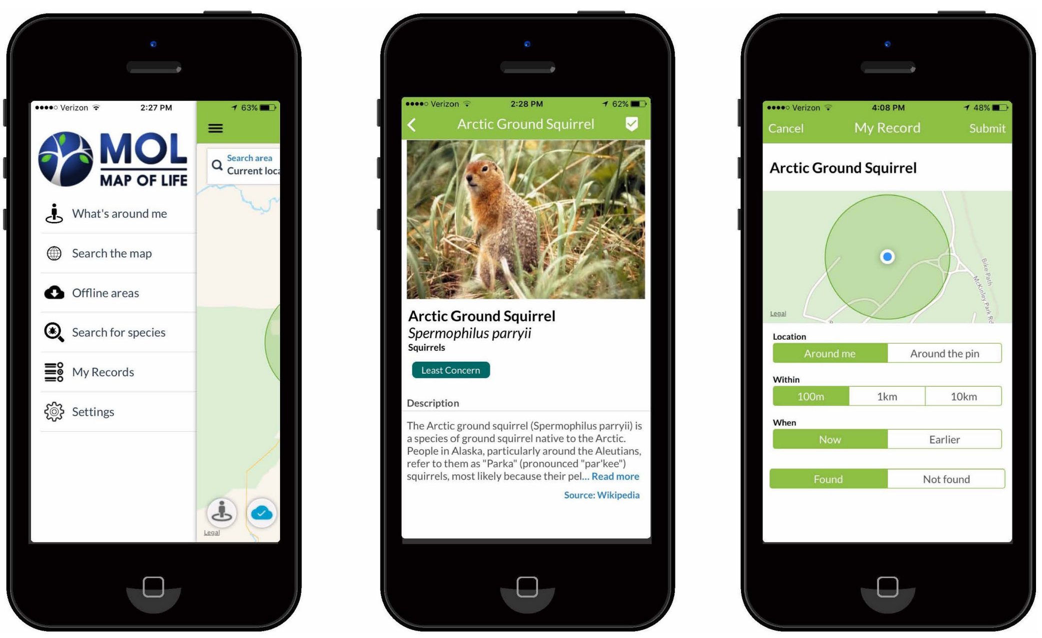


**FIGURE 6 |** Map of life mobile application: home page, species information page, and record observation page.

other citizen science programs, such as a more collaborative program, incorporating traditional knowledge with scientific data. Additionally, this fitness for use assessment was developed with citizen science data in mind and used citizen science data. However, we recognize that this assessment can be applied to conventionally collected data.

## Denali National Park and Preserve as a Case Study

We tested the STAAq assessment with a case study in Denali National Park and Preserve (**Figure 5**). We chose Denali as a case study because the park is interested in using citizen science collected data to support their ecological monitoring efforts, mainly monitoring the status and trends of selected environmental and resource "vital signs" such as vegetation composition, temperatures, species occurrence data, and visitor use (Sadoti et al., 2018; Brodie et al., 2019). In Denali specifically, vegetation changes due to rising temperatures affect caribou habitat in the park, especially in popular visitor areas (Joly, 2011). Thus, Denali is keen to monitor the changes in habitat in the park area and how they may affect the visitor experience. For this test of the assessment, we chose to focus on caribou monitoring and caribou occurrence data because of the abundance of data in the three datasets we compared for the test. We also chose it because the park actively impacts and monitors the needs of the Denali caribou herd. We wanted to showcase the potential of the STAAq assessment on data that scientists are using for wildlife monitoring. The results of this test of the assessment were not intended to be directly used by the park staff for caribou monitoring but rather be an example of how the STAAq assessment works and how it may perform with observation data collected through a citizen science mobile-application program.

The three datasets include volunteer collected data from the Map of Life mobile application (MOL), volunteer collected data from the Ride Observe and Record Program (ROAR), and radio-collar data from the National Park Service. The Map of Life mobile phone-based application developed at Yale University-allows volunteers to record the precise location of their wildlife observations while touring the park with their phone's internal GPS to capture spatial data (**Figure 6**). The data used in this case study was collected in 2016; we retrieved from the Map of Life server on September 30, 2016. These data include the wildlife observation's geographic coordinates, taxonomic information for the species, a time stamp, and a unique observer ID. In 2016 MOL volunteers recorded 1,200 wildlife and plant observations in Denali; 343 observations were caribou observations. The MOL volunteers are untrained and mainly tourists visiting Denali for the first time. The mobile application and data collection protocol are managed by the team at Yale University. The team did include specific information pages for areas where a user can download a species list. Thus, users in the Denali area were prompted to download a local species list and see a Denali-specific information page with some park-specific information, such as animal safety warnings. The species list includes species photos and detailed species information such as range maps.

Trained and incentivized local volunteers collect ROAR program data (some are park employees or students at the local high school and other community members). Volunteers ride the shuttle buses in the park and record species observation data using a GPS-enabled device to record: species location, time of observation, and species behavior. This program is managed and facilitated by park officials. These data used in this case study were also recorded during the summer of 2016. The radio collar caribou data were recorded through NPS wildlife population surveys and were recorded at various time spans over the last 25 years. Both male and female caribou are collared; they are captured and collared when they are calves (Adams, 2017). These data include location and time.

Park officials currently use ROAR data and radio-collar data for wildlife monitoring. They showed interest in seeing how citizen science collected species observation data through an established mobile application (such as MOL) could support Denali's habitat monitoring efforts, especially in the high visitor use areas. Using an existing global-based app. means the park can benefit from the data collected and promote the use of the app.

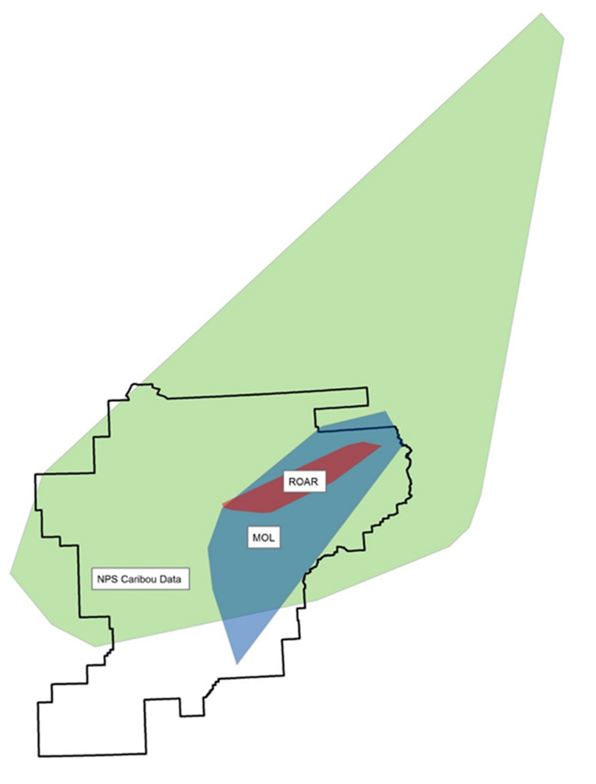


**FIGURE 7 |** Spatial extent, convex hull for each dataset (the black outline represents the Denali Park boundary).

**TABLE 2 |** Spatial extent, percentage of the desired extent covered, and rankings.

| Dataset | Extent coverage (%) | Rank (1 is best) |
|---|---|---|
| MOL | 24.9 | 2 |
| ROAR | 4.46 | 3 |
| NPS | 76.7 | 1 |

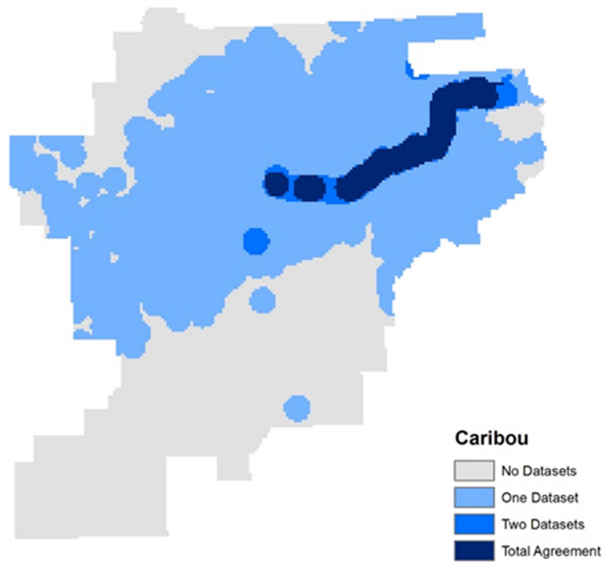


**FIGURE 8 |** Aptness Component results, areas of dark blue show agreement amongst the three datasets.

but does not need to manage another citizen science program. There were concerns over data quality and bias in the data. Thus, we felt this was a good test of the STAAq assessment to show how a researcher who does not control the data collection protocol can perform a data quality assessment to determine if these data are fit for their purposes.

## RESULTS

To test STAAq, we assessed each of the three datasets' performance with each of the STAAq assessment components. The Spatial component of the STAAq assessment allows the examination of the spatial extent and resolution of the data. The desired spatial resolution is high-resolution caribou data for the Denali case study, reflecting the point data's measurement error. Such data were collected with various techniques: GPS collar and mobile phone GPS systems. The resulting points have some error associated with them; the error amount is considered the spatial resolution. The dataset with the highest spatial resolution thus had the least amount of location error. For the spatial extent element of the Spatial component, the desired spatial extent is the park's boundary. The percentage of the dataset area that falls within the park boundary was calculated to determine which datasets more closely matched the desired extent. In the STAAq assessment, each dataset is ranked in each element. The overall ranking for the Spatial component was determined by averaging the datasets' rankings in each element.

For the spatial extent, the dataset, which most closely matches the desired extent- the park boundary in this case study- is given a rank of 1. **Figure 7** and **Table 2** show the results from the spatial extent analysis. The NPS caribou dataset covers 76.7% of the park area and thus received a rank of 1 (**Table 2**). The MOL data received a rank of 2, and the ROAR data was third because these data extent covered the least amount of the park. The extent that covers the park area the most is preferred because the data would be used to monitor the caribou distribution in the entire national park. The NPS dataset received a rank of 1 for the spatial resolution element because these data were collected at high resolution, with fewer errors. The NPS radio collar dataset's resolution is mainly due to the data collection methods of radio collars directly on the caribou. In contrast, the other two datasets were collected through GPS locations on tablets or smartphones, recording the volunteer's location observing the caribou, not the actual caribou.

The Temporal component includes the analysis of the datasets' temporal event, resolution, and extent. To monitor caribou distribution in the park, observations made at any time of day throughout the year on a weekly (or more frequent) basis are acceptable. The desired temporal extent is the last 5 years: June 2012 to September 2016. For the temporal event analysis, the MOL and ROAR data received a ranking of 1 because both were


**FIGURE 9 |** Aptness component results for each dataset. Gray areas are where no datasets have data, blue are areas of agreement, and red areas are unique. **(A,B)**, and **(C)** show where each dataset is in the agreement with the others. **(A)** The MOL data; the areas in blue are where the MOL data are in agreement with the other two datasets and the areas in red show where the MOL data are unique and had observations where the other two datasets do not. **(B)** The ROAR data; the ROAR data are mostly in agreement with the other two datasets. **(C)** The NPS radio collar collected data and it is the dataset with the most unique points.

**TABLE 3 |** Aptness Component Rankings.

| Dataset | Uniqueness (%) | Total agreement (%) | Rank for aptness |
|---|---|---|---|
| ROAR | 0.41 | 83.31 | 1 |
| MOL | 16.5 | 69.21 | 2 |
| NPS | 90.9 | 6.98 | 3 |

recently collected. The radio collar data was also collected year-round but not within the last 5 years, so this dataset received a rank of 3. For the temporal resolution analysis, the MOL and ROAR datasets were ranked 1 because the data were collected almost daily (multiple observations were made on collection days). Since the NPS data were collected with radio collars, each caribou's location was only collected twice a month; thus, this dataset received a ranking of 3.

For the temporal extent analysis, the NPS data has the largest temporal extent and therefore received a rank of 1. The MOL and ROAR datasets only contain one summer season (2016) of data and are tied at a rank of 2. To obtain an overall ranking for the Temporal component, each dataset's rankings for the temporal elements were averaged then ranked to create the final Temporal component rankings. The MOL and ROAR datasets are tied at a rank of 1; while these datasets did not match the desired temporal extent, they were acceptable for the desired temporal events and temporal resolution.

The Aptness component compares the datasets to each other and determines the spatial uniqueness of the datasets. Uniqueness is not the desired data quality for this case study, so the more similar dataset is ranked higher. The ROAR data are almost in total agreement with the other two datasets for the Aptness component, meaning that much of these data in the ROAR dataset is also reflected in the other two datasets (**Figures 8**, **9** and **Table 3**). Since the error of omission is preferred, the ROAR dataset is given a rank of 1.

The Application (A2) component is concerned with the model's product, which in this case, we used Species Distribution Models (SDM). However, the STAAq assessment can be used with other models; in the Wentz and Shimizu (2018) DaFFU assessment, they used nitrogen models and ranked the data based on the outputs of the nitrogen models. We chose to use SMDs in this test of the assessment because they are ecological models that use species presence data and environmental variables to predict species distribution (Franklin, 2013), also many citizen science projects are applied to conservation biology and ecological assessments. The species occurrence points are subject to a set of constraints based on the environmental variables (Phillips et al., 2006). Environmental variables include climate, land/ground cover, and elevation. This project used the Maxent software package with the maximum entropy models and the species' distribution. The available data drove this project to use Maxent, which only requires presence and ecological data for the study area (Phillips et al., 2006; Franklin, 2013).

The SDM created with the datasets is depicted in **Figure 10**. The resulting maps show areas with a high probability of caribou (warmer colors) and areas with a low probability of presence (cold colors). The large blue area in the middle of the park is the location of the Alaska Range and Denali; we do not expect to find caribou near 20,000 feet elevation. With the MOL data, the area to the northeast of the park (where many of the observation points were collected) has many areas with a high probability of occurrence. These areas are of known caribou habitat. The SDM output using the ROAR data are similar to the MOL data since both datasets were collected on and around the park road area (**Figure 10**). The model using ROAR data did outperform the model using MOL data by a small margin. The SDM model using the NPS dataset performed worse than the other two models.

The ROAR dataset had the highest AUC and received a rank of 1 (**Table 4**). The differences in variable contributions, seen in **Table 4**, may be caused by the datasets' spatial extent; since the MOL and ROAR data are clustered around the park road, the model may be relying on variation in each of the environmental variables in that area. Land cover is essential for caribou habitat since caribou generally prefer open tundra and are not often found lingering in dense boreal forest areas.

Each dataset was assigned a final STAAq ranking, which is the average of the four component rankings. The highest-ranking is 1; this indicates the dataset that is the fittest for use. The ROAR program data was ranked 1, the Map of Life data came in second in this test, and the radio collar data was third (**Table 5**). This shows that volunteer collected data may be more fit than authoritative datasets when fitness for use is considered depending on the specific use case.

## DISCUSSION

The STAAq assessment was tested to characterize data fitness for use in citizen science data. Citizen science data are typically not looked at for external data fitness but rather an internal assessment of data quality or accuracy. The STAAq assessment shows data fitness for a specific application and provides a third-party scientist or researcher the ability to assess data fitness for their particular needs. This type of assessment uses fitness indicators instead of metadata like other assessments such as Pôças et al. (2014). Citizen science data often have incomplete or missing metadata.

The STAAq assessment is relevant to evaluating data in the context of intended use. It assesses these data's usability for that specific purpose by comparing these data to data from other datasets. We tested the assessment in a case study examining which of three datasets would be most fit to use in monitoring or caribou distribution in Denali National Park and Preserve. The assessment's initial step is to clarify the desired data quality elements for the particular use case. This, in itself, is a valuable exercise. The assessment proved flexible and adaptable yet straightforward to implement. We were able to quantify how each dataset performed in the assessment in the same way, even though the datasets were collected differently, covered different spatial and temporal extents, and had different spatial and temporal resolutions.

For this case study, we expected the NPS radio collar data to outperform the volunteer datasets, not because these data

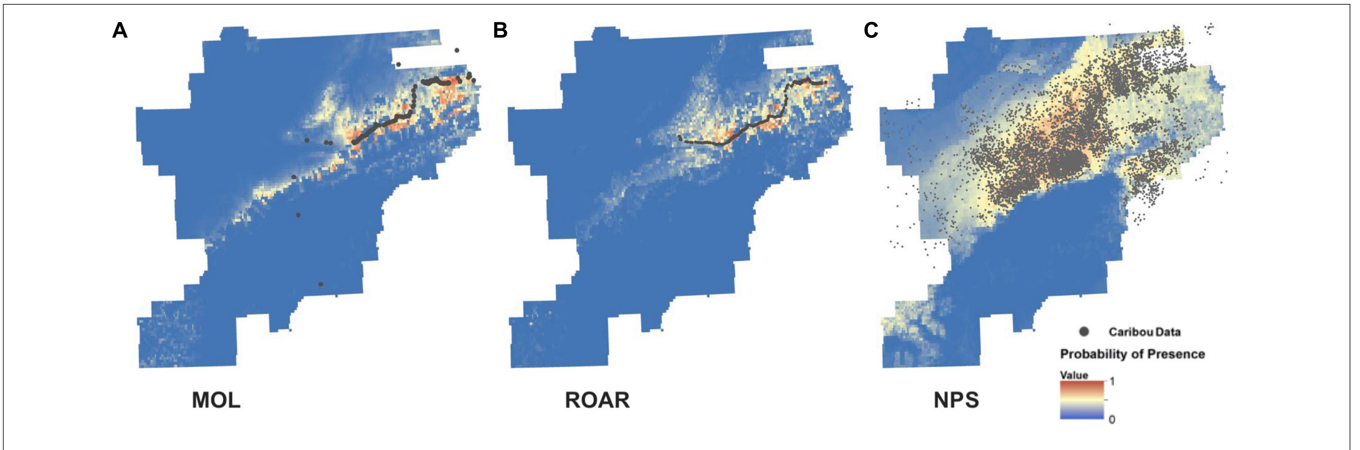


**FIGURE 10 |** SDM made with caribou data. **(A)** The distribution of the MOL collected caribou data. **(B)** The ROAR data. **(C)** The NPS radio collar collected data. Areas of warmer colors have a higher probability of caribou presence.

are authoritative, but because the data covers a greater spatial and temporal extent. However, these data did not meet other desired data quality elements. We also thought the spatial bias of the MOL and ROAR data being collected near the park road might hinder its performance in the Application component. In Denali, this assessment shows that volunteer collected observation data was more fit for use than radio collar data for ecological modeling. This outcome of the assessment shows us that volunteer collected data from both the ROAR program and MOL is a viable and usable data source for caribou monitoring. The next step for biologists in Denali is to use the STAAq assessment to compare data for other species they monitor, such as bears, wolves, moose, and Dall sheep. It is also possible to combine the MOL and ROAR data and see how a hybrid dataset performs compared to the other datasets.

Employing and testing this assessment did pose some challenges and revealed some improvements and refinements that could be made. For the Spatial component, elements may be added. For example, an element related to the clustering of data in a given area, would be useful if the research question focused on a smaller area or multiple smaller area in a given region.

**TABLE 4 |** SDM results.

| Dataset | AUC | Variables which contributed the most | Variables which contributed least |
|---|---|---|---|
| MOL | 0.961 | Elevation and land cover | Summer temperature |
| ROAR | 0.979 | Elevation and fall precipitation | Spring precipitation |
| NPS | 0.804 | Winter and fall precipitation | Winter temperature and slope |

**TABLE 5 |** Overall rankings.

| Dataset (q) | S (Spatial) | T (Temporal) | A1 (Aptness) | A2 (Application) | Rank |
|---|---|---|---|---|---|
| MOL | 2 | 2 | 1 | 2 | 2 |
| ROAR | 1 | 2 | 2 | 1 | 1 |
| NPS | 1 | 2 | 3 | 3 | 3 |

The Aptness component is the only component that requires other datasets for comparison, and it only performs a binary assessment – whether data for a particular attribute is present or not. It would be interesting to expand this assessment to be able to test the magnitude of the attributes. Also, it would be interesting to use the aptness components for vector data in addition to raster data. For this test of the STAAq assessment we choose to use SDMs for the Application component. Other types of models can be used in this component. We recognize the criticism of the use of AUC to evaluate SDMs (Lobo et al., 2008). The use of AUC in this test was to to compare models of the same species (similar to El-Gabbas and Dormann, 2018).

This fitness for use assessment is relevant for volunteer collected data and can be used with many other types of data and models. The elements and components of the assessment can be modified or weighted to fit the user's needs. The STAAq assessment results can be included within the metadata for each dataset and provide an example of what these data are fit for. A vital aspect of this assessment is that it can be used when an authoritative dataset is unavailable or only one dataset exists. It can be used to partially perform a data fitness assessment.

Future directions for researching data fitness for use in citizen science include refining the STAAq assessment process, comparing this assessment technique to other data quality evaluation methods, and applying it to different types of citizen science programs. The impetus of this assessment was to determine data fitness for data collected in a contributory style citizen science program through a mobile application. The STAAq assessment should be further adapted and refined to possibly be used to assess data quality in other types of citizen science programs, such as collaborative programs and programs that may include local and indigenous knowledge with their data. The assessment could be used to assess the potential for a citizen science dataset to be combined with a conventionally collected dataset and determine the fitness for the hybridized dataset. As noted earlier in this article, hybrid datasets can fill in gaps and create a more comprehensive and complete dataset (Batty et al., 2010; Connors et al., 2012; Parker et al., 2012; Abdulkarim et al., 2014; Bruce et al., 2014; Upton et al., 2015). The assessment should be tested with standalone datasets to determine how the assessment can evaluate fitness for use when there are no conventionally collected datasets for comparison. Further development of this assessment could include automatization, web interface components, and possibly a simplified GUI (Graphical User Interface) to allow researchers to examine data fitness easily.

## CONCLUSION

Mobile technology creates opportunities for citizen science programs to collect more ecological data covering more temporal and spatial extents (Jepson and Ladle, 2015). These data can be vital for ecological monitoring; however, without adequate data quality assessments, these data may go unused by scientists (Coleman et al., 2009; Boulos et al., 2011; Dickinson et al., 2012; Hart et al., 2012; Roy et al., 2012; Devisch and Veestraeten, 2013; Starr et al., 2014).

Various data quality assessments have been presented in the citizen science literature; however, these mainly focus on internal data quality and do not allow third-party scientists to assess external data fitness. An easy-to-implement data fitness for use assessment may encourage more scientists and researchers to utilize these ever-growing volunteer collected datasets for their own research and monitoring purposes (Wentz and Shimizu, 2018). This article presented and tested a promising method for assessing citizen science data based on its fitness for a particular purpose. This assessment stresses that not all data are created equal, and different datasets may be appropriate (or deemed adequate) for various purposes. Getting the scientific community to trust citizen science data is a fundamental challenge (Burgess et al., 2017). By developing easy-to-implement external data quality methods such as this data fitness for use assessment, citizen science data will become more accepted by the scientific community and more widely used for ecological monitoring. Data fitness assessments, like STAAq, can help make decisions on using different datasets for different models and analyses.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

HF performed data analysis and supported the interpretation of the data analysis. LG and EW advised the study. EW initiated the development of the data fitness assessment. All authors contributed to the article and approved the submitted version.

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# The Reef Check Med Dataset on Key Mediterranean Marine Species 2001–2020

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## BACKGROUND

Mediterranean marine coastal habitats have been and continue to be threatened by human-related pressures, such as resource over-exploitation, pollution, habitat loss and fragmentation, and the invasion of non-native species (Airoldi and Beck, 2007; Micheli et al., 2013). These pressures are exacerbated by disturbances associated with global climate change, which have led to major shifts in marine ecosystems, impacting their resilience and ability to provide goods and services (Ponti et al., 2014; Garrabou et al., 2019). Ecological shifts in marine benthic communities are difficult to recognize because of the scarcity of: findable, accessible, interoperable, and reusable quantitative data (FAIR data principles; Wilkinson et al., 2016), which could serve as a baseline. The situation is impaired further by a lack of long-term monitoring capability at a regional scale. To be successful, marine coastal habitat conservation requires ecosystem-based management approaches that give ample consideration to the spatial and temporal distribution of key species over broad scales (Foley et al., 2010). It is evident that, easily accessible, reliable, and accurate data are essential to successfully monitor marine ecosystem health providing the knowledge needed to address the threats to coastal marine habitats, develop policies and regulations to protect vulnerable areas, understand trends, and forecast future changes (Martín Míguez et al., 2019). However, data obtained from scientific investigations and institutional monitoring programs, albeit very accurate, are generally too scarce and fragmented to be used effectively for spatial planning (Hochachka et al., 2012). This is particularly true for subtidal marine environments, as making sufficient repeated observations and measurements requires a large effort. As a solution, volunteers—citizen scientists—trained in the use of specifically developed monitoring protocols can help fill the gap in high-quality data acquisition, by performing monitoring over broad spatial and temporal scales.

Since 2001, volunteer certified trained snorkelers, freedivers, and scuba divers (hereafter EcoDivers) have collected data for selected key marine species, recording their occurrence, distribution, abundance, and bathymetric range along the Mediterranean Sea coasts, using the Reef Check Mediterranean Underwater Coastal Environment Monitoring (RCMed U-CEM) protocol (Turicchia et al., 2021b). Here, we describe the resulting dataset, the "Reef Check Med dataset on key Mediterranean marine species 2001–2020" (RCMed_2001–2020; Ponti et al., 2021), which is hosted by the European Marine Observation and Data Network (EMODnet; Martín Míguez et al., 2019) open repository. The organization and consistency of the data, the standards adopted, and how they can be accessed and used are also reported. The dataset is maintained by the non-profit organization Reef Check

Italia (RCI), collaborating with the other European Reef Check organizations, members of the worldwide Reef Check Foundation, and within the Reef Check Mediterranean Sea network[1].

## METHODS

Abundance data for target species were collected according to the RCMed U-CEM protocol developed by RCI for a Citizen Science (CS) initiative that aims to monitor the ecological status of the Mediterranean marine coastal habitats. For this protocol, 43 taxa were selected based on two or more criteria, including ease of identification, being included in the international lists of protected species, being sensitive to human impacts, and being key indicators of the shift that Mediterranean coastal habitats can undergo under local pressures and climate change. Morphologically and ecologically similar species have been included at the genus or higher taxa level (Cerrano et al., 2017). Before going diving or snorkeling, each trained EcoDiver chooses one or more taxa, among the 43 included in the protocol (**Table 1**), to actively search for, according to the type of habitat typology, survey depth, and personal interests. EcoDivers make independent observations along random swims (as defined in Hill and Wilkinson, 2004) and upload their records to the online database using the specific smartphone app or the Internet form. Not encountered but actively searched taxa are reported as absent. No data is provided for not searched taxa. New data are made publicly available following quality assurance and control (QA/QC) procedures. Data that do not meet the standards of the QA/QC procedures are discarded. The detailed monitoring protocol and methodology used to collect and record the data, including species selection, participant training and QA/QC procedures, is described in Turicchia et al. (2021b). EcoDiver personal data are managed in accordance with the European general data protection regulation (GDPR), which allows sharing the collected data on their behalf but leaves each one responsible for the quality of the data they provided. No ethical approval was obtained regarding plants and animals because the protocol does not provide for collecting or manipulating organisms, but only visual observations into the wild.

## DATASET STRUCTURE

The RCMed_2001–2020 dataset is fully compliant with the EMODnet biology standards (Martín Míguez et al., 2019). The taxonomic guideline used is based on the World Register of Marine Species (WoRMS; Vandepitte et al., 2015), the authoritative and comprehensive global list of marine organisms' names. Biotic and abiotic measurements are reported using the controlled thesaurus from the Natural Environment Research Council (NERC; http://vocab.nerc.ac.uk) Vocabulary Server maintained by the British Oceanographic Data Center (BODC), and the Darwin Core Archive (DwC-A), an internationally recognized biodiversity informatics standardized data system intended to facilitate information sharing on biological diversity. This ensures interoperability and maximizes reusability, by providing a core standard (Wieczorek et al., 2012).

Following the EMODnet biology standards, data are organized in three tables: the DwC Event Core table stores information on the survey events, the DwC Occurrence extension table stores occurrence details, while the DwC Measurement or Facts extension (eMoF) table contains quantitative and additional information collected during survey events and species occurrences. The metadata records are based on ISO19115 standards.

### DwC Event Core Table

Individual survey events correspond to single dives or swims, carried out independently by single EcoDivers inspecting the seabed at a specific time and place to collect data on single or multiple species. Several EcoDivers can investigate the same place simultaneously, but each provides an independent survey event. Each survey has a unique ID (*eventID*, including a progressive number, automatically attributed at the time of data entry) and is characterized by: the survey date (*eventDate*, in the format YYYY-MM-DD, conforms to the ISO 8601 1:2019); geographical coordinates in decimal degrees (*decimalLatitude*, *decimalLongitude*) based consistently on the same geodetic datum (*geodeticDatum* = WGS84; i.e., EPSG:4326); and with an accuracy (*coordinateUncertaintyInMeters*) of 200 m, as provided by the adopted protocol. Minimum (*minimumDepthInMeters*) and maximum (*maximumDepthInMeters*) depths represent the bathymetrical range of the survey and are expressed in meters. The *verbatimLocality* field contains textual information on the survey site (i.e., the site's local name and municipality).

The prevailing *habitat* surveyed is identified according to the following categories (when available, the corresponding European Nature Information System marine habitat classification, EUNIS v2019[2], is shown in parentheses):

- Coastal rocks (MA153, MA154, MA255, MB151, MB251, MC151, MC251, MD15, MD25)
- Offshore rocks (MC151, MC251, MD15, MD25)
- Rocky cliff (MC151, MC251, MD15, MD25)
- Posidonia (MB252)
- Posidonia and sand (MB252)
- Posidonia and rock
- Cave (MC152)
- Metal wreck
- Sand (MA452, MB254, MB551, MB552, MB553, MC35, MC55, MD35)
- Mud (MB651, MC451, MC65)
- Breakwaters and ports
- River mouth (MA353, MA553)
- Coastal lagoon (MB152, MB253, MB554)

All records also report the codified institution name providing data (*institutionCode* = RCI), the name of the dataset (*datasetName* = Reef Check Med - key Mediterranean marine

[1] www.reefcheckmed.org

[2] Permalink to this version https://www.eea.europa.eu/ds_resolveuid/6d0484fd0078483ca73bec230574b34e.

**TABLE 1 |** List of taxa recorded in the dataset and corresponding Life Sciences Identifier (LSID).

| scientificName | identificationQualifier | scientificNameID |
|---|---|---|
| *Aplidium conicum* | | urn:lsid:marinespecies.org:taxname:103641 |
| *Aplidium tabarquensis* | | urn:lsid:marinespecies.org:taxname:103667 |
| *Aplysina* | spp. | urn:lsid:marinespecies.org:taxname:131975 |
| *Arca noae* | | urn:lsid:marinespecies.org:taxname:138788 |
| *Astroides calycularis* | | urn:lsid:marinespecies.org:taxname:135178 |
| *Axinella* | spp. | urn:lsid:marinespecies.org:taxname:131774 |
| *Balanophyllia europaea* | | urn:lsid:marinespecies.org:taxname:1451203 |
| *Caulerpa cylindracea* | | urn:lsid:marinespecies.org:taxname:660621 |
| *Caulerpa taxifolia* | | urn:lsid:marinespecies.org:taxname:144476 |
| *Centrostephanus longispinus* | | urn:lsid:marinespecies.org:taxname:124331 |
| *Chromis chromis* | | urn:lsid:marinespecies.org:taxname:127000 |
| *Cladocora caespitosa* | | urn:lsid:marinespecies.org:taxname:135146 |
| *Conger conger* | | urn:lsid:marinespecies.org:taxname:126285 |
| *Corallium rubrum* | | urn:lsid:marinespecies.org:taxname:125416 |
| *Diplodus* | spp. | urn:lsid:marinespecies.org:taxname:126076 |
| *Epizoanthus* | spp. | urn:lsid:marinespecies.org:taxname:100790 |
| *Eunicella cavolini* | | urn:lsid:marinespecies.org:taxname:125361 |
| *Eunicella singularis* | | urn:lsid:marinespecies.org:taxname:125365 |
| *Eunicella verrucosa* | | urn:lsid:marinespecies.org:taxname:125366 |
| *Geodia cydonium* | | urn:lsid:marinespecies.org:taxname:134025 |
| *Hippocampus* | spp. | urn:lsid:marinespecies.org:taxname:126224 |
| *Homarus gammarus* | | urn:lsid:marinespecies.org:taxname:107253 |
| Keratosa | | urn:lsid:marinespecies.org:taxname:366651 |
| *Leptopsammia pruvoti* | | urn:lsid:marinespecies.org:taxname:135193 |
| *Maasella edwardsii* | | urn:lsid:marinespecies.org:taxname:125420 |
| *Ophidiaster ophidianus* | | urn:lsid:marinespecies.org:taxname:124101 |
| *Palinurus elephas* | | urn:lsid:marinespecies.org:taxname:107703 |
| *Paracentrotus lividus* | | urn:lsid:marinespecies.org:taxname:124316 |
| *Paramuricea clavata* | | urn:lsid:marinespecies.org:taxname:125387 |
| *Parazoanthus axinellae* | | urn:lsid:marinespecies.org:taxname:101055 |
| *Patella ferruginea* | | urn:lsid:marinespecies.org:taxname:140679 |
| *Pecten jacobaeus* | | urn:lsid:marinespecies.org:taxname:394429 |
| Pectinidae | | urn:lsid:marinespecies.org:taxname:213 |
| *Pinna nobilis* | | urn:lsid:marinespecies.org:taxname:140780 |
| *Polycitor adriaticus* | | urn:lsid:marinespecies.org:taxname:103625 |
| Pyuridae | | urn:lsid:marinespecies.org:taxname:103449 |
| *Rapana venosa* | | urn:lsid:marinespecies.org:taxname:140416 |
| *Savalia savaglia* | | urn:lsid:marinespecies.org:taxname:383014 |
| *Sciaena umbra* | | urn:lsid:marinespecies.org:taxname:127010 |
| *Scyllarides latus* | | urn:lsid:marinespecies.org:taxname:107708 |
| Stolonifera | | urn:lsid:marinespecies.org:taxname:1368 |
| *Tethya* | spp. | urn:lsid:marinespecies.org:taxname:132077 |
| *Trisopterus minutus* | | urn:lsid:marinespecies.org:taxname:126446 |

species 2001–2020), and the protocol name (*samplingProtocol* = RCMed U-CEM protocol).

## DwC Occurrence Extension Table

The DwC Occurrence extension table stores details on species occurrence linked to the individual survey events (*eventID*). Each record has a unique numeric identifier (*occurenceID*), attributed in post-processing after the QA/QC procedures, and is related to a single taxon that was searched for during the survey. Taxa are identified by their scientific name at the lowest possible taxonomic level (*scientificName*), with the indication of multiple species (spp.) belonging to the same genus when appropriate (*identificationQualifier*), and the corresponding Life Sciences Identifier (LSID), a consistent globally unique identifier based on the AphiaID (Vandepitte et al., 2015) from the World Register of Marine Species (stored in the field *scientificNameID*). Each record reports whether the species searched for during the survey was found or not (*occurrenceStatus* = present or absent). As explicitly indicated, all records are based on an on-site visual census (*basisOfRecord* = HumanObservation) carried out by an EcoDiver identified by name and unique certification number (*identifiedBy*).

## DwC Measurement or Facts Extension (eMoF) Table

The DwC eMoF table contains additional quantitative information on species occurrences and events. Records are linked to every single occurrence (*occurenceID*) and to the individual survey events (*eventID*) to which they belong. Four types of measurement (*measurementType*) are stored:

- "Abundance category of a biological entity specified elsewhere" for each occurrence;
- "Depth minimum of biological entity specified elsewhere on the bed by epibenthic sampling" (in meters) for each occurrence;
- "Depth maximum of biological entity specified elsewhere on the bed by epibenthic sampling" (in meters) for each occurrence;
- "Sample duration" (in minutes) for each survey event.

Measurement type and units refer to the NERC vocabulary, as indicated in the appropriate fields (*measurementTypeID*, *measurementUnitID*). Corresponding values are stored in the *measurementValue* and *measurementUnit* fields. Abundance categories are identified by a ranking number, using numerical or descriptive classes according to the countability of the taxa/organisms searched for (in brackets the corresponding descriptive categories):

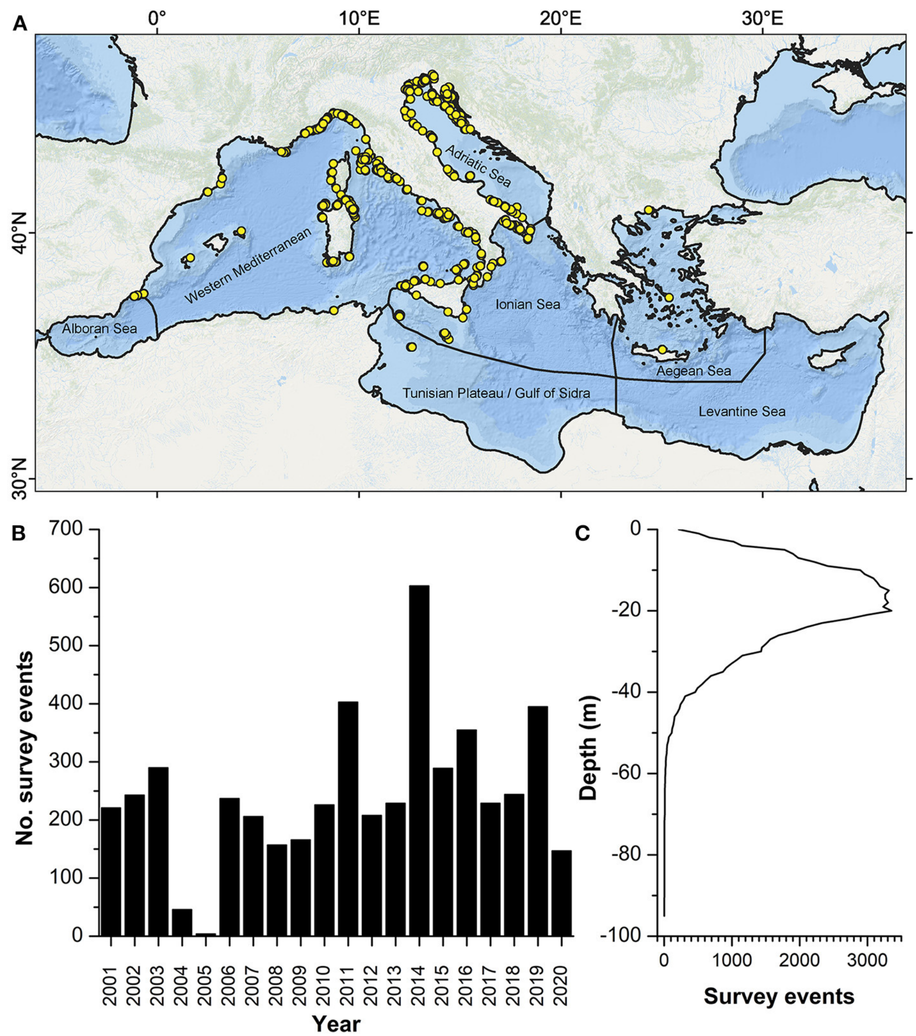


**FIGURE 1 |** Summary of the survey events included in the RCMed_2001–2020 dataset: **(A)** geographic distribution of all recorded survey events (yellow dots) within the Mediterranean ecoregions, defined according to Spalding et al. (2007) (Mercator projection); **(B)** temporal distribution; **(C)** depth distribution.

- Category 0: 0 specimens (absent)
- Category 1: 1 specimen (isolated specimen)
- Category 2: 2 specimens (some scattered specimens)
- Category 3: 3–5 specimens (several scattered specimens)
- Category 4: 6–10 specimens (a crowded area)
- Category 5: 11–50 specimens (some crowded areas)
- Category 6: > 50 specimens (several crowded areas)

## DATA SEARCH, UPDATES, AND USE

The RCMed_2001–2020 dataset is distributed under the international Creative Common license (CC BY 4.0), which guarantees transparency on the origin of the data and allows for free sharing and adaptation, giving appropriate credit to the Reef Check Mediterranean network. It can be directly accessed from the EMODnet Biology Portal[3] that offers different services, including the data catalog, a data download toolbox with a step-wise filtering approach, a map viewer, the atlas of marine life data, and a web feature service (WFS), compliant with the Open Geospatial Consortium (OGC) standards for direct integration in geographic information systems (Martín Míguez et al., 2019). Thanks to the interoperability of the network (Tanhua et al., 2019), the dataset is redistributed under the Ocean Biodiversity Information System (OBIS) networks (including EurOBIS, MedOBIS; Costello and Vanden Berghe, 2006 and references therein), the European infrastructure on biodiversity and ecosystem research (LifeWatch; Basset and Los, 2012), and the Global Biodiversity Information Facility (GBIF; Flemons et al., 2007). Periodic submissions of newly acquired data to EMODnet are expected.

## DATASET CONTENTS AND APPLICATIONS

The RCMed_2001–2020 dataset consists of 50,255 observations unevenly distributed among 43 key taxa in the Mediterranean Sea recorded in 4,898 individual survey events, carried out by 692 EcoDivers from 2001 to 2020. The data comes from Croatia, France, Greece, Italy, Spain, and Tunisia, covering parts of the following ecoregions (*sensu* Spalding et al., 2007): Western Mediterranean (52.3% of the surveys), Adriatic Sea (42.2%), Ionian Sea (4.9%), Alboran Sea (0.2%), Aegean Sea (0.2%), and Tunisian Plateau/Gulf of Sidra (0.1%; **Figure 1A**). After an initial period of protocol development in the Adriatic Sea (2001–2003, originally called "Adriatic Underwater Watching Project") with 200–300 surveys carried out per year, there was a reduction in the number of surveys the following two years. After this, the number of surveys per year has varied from 150 to 600, with the minimum value in 2020. This is likely related to the COVID-19 pandemic lockdown (**Figure 1B**). While $\sim$ 97% of observations took place in the recreational diving depth range (0–40 m), the maximum depth reached during surveys was 95 m (**Figure 1C**). The spatial and temporal distribution of the data is affected by the volunteers' willingness, habits and preferences applying the RCMed U-CEM protocol. However, spatial and temporal biases are recognized as major issues in CS projects and biodiversity databases, remaining intrinsically unavoidable for this and most other CS initiatives (Beck et al., 2014).

The United Nations Decade of Ocean Science for Sustainable Development (2021–2030) asks for an urgent improvement in marine conservation actions worldwide. Similarly, the EU Biodiversity Strategy for 2030 includes among its main tasks an enhanced focus on Natura 2000 species and habitats and a Nature Restoration Plan of degraded ecosystems across the EU, addressing the key drivers of biodiversity loss. Without a detailed census and mapping of the distribution and abundances of target species, it is impossible to address these objectives effectively. Marine Citizen Science is a promising and powerful tool to enhance engagement in marine conservation worldwide and increase ocean observation capability ensuring long-term monitoring whenever appropriate protocols are applied. In these regards, the application of the RCMed_2001–2020 dataset ranges from: monitoring the ecological status of Mediterranean coastal environments to assessing the effects of human impacts and management interventions (Turicchia et al., 2021a); raising public awareness; and involving people in marine conservation (Lucrezi et al., 2018 and references therein). Moreover, the dataset has been used to complement scientific papers on species distribution and abundance, distribution modeling, and comparing historical data series (Cerrano et al., 2017; Ponti et al., 2018; Turicchia et al., 2018). A list of applications and publications obtained by applying the protocol and using this data is kept up to date on the Reef Check Med website, and authors are encouraged to report their outcomes.

## DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: EMODnet Biology data portal, https://doi.org/10.14284/468.

## AUTHOR CONTRIBUTIONS

MP conceived the database of Reef Check Med Dataset—key Mediterranean marine species 2001–2020. ET and MP wrote the first draft of the manuscript. All authors contributed to and approved the final version of the manuscript.

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[3]https://www.emodnet-biology.eu/data-catalog?module=dataset&dasid=6454

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# Adopt a Pixel 3 km: A Multiscale Data Set Linking Remotely Sensed Land Cover Imagery With Field Based Citizen Science Observation

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## INTRODUCTION

Public participation is critical to the mission of Earth system science. Citizen science provides a personally meaningful way for the public to engage with the dynamic changes taking place on our planet, and to participate in scientific data collection and analysis at scales that are not otherwise feasible. An unexpected contribution of citizen science emerged during the 2020 COVID-19 pandemic, when we deployed an existing mobile app to engage spatially distributed students in co-creating and testing a citizen science project in lieu of a residential research internship program.

Global Learning and Observations to Benefit the Environment (GLOBE) is an international science and education program established in 1995, connecting students, teachers, and scientists in monitoring changes in the Earth system (Rock et al., 1997; Finarelli, 1998; Means, 1998; Berglund, 1999; Butler and MacGregor, 2003; Muller et al., 2015; Nugent, 2018). GLOBE participants from 126 countries, using more than 50 scientific protocols, have collected more than 200 million data environmental observations for use by scientists and students in research.

GLOBE recently expanded its mission to support citizen scientists at large and launched the GLOBE Observer[1] (GO) mobile application (Amos et al., 2020) to increase the spatial and temporal coverage of GLOBE data. Using four tools on the GO platform, citizen scientists report *in-situ*, ground-based observations of clouds, land cover, mosquito habitats, and/or tree height. GLOBE citizen science data complement remotely sensed data obtained from sensors on NASA's suite of airborne and spaceborne observing platforms (Amos et al., 2020). Citizen scientists are encouraged to make coincident observations using more than one GO tool, for instance, using the Land Cover and the Mosquito Habitat Mapper tools at the same site. Associating data from multiple tools increases its usefulness for a wider range of projects.

Building on the GLOBE mission to promote student and citizen science research, the Adopt a Pixel 3 km (Adopt a Pixel) framework was created to take advantage of the personal connection and familiarity citizen scientists have with their local landscapes. Adopt a Pixel applies a nested sampling framework to GO-obtained data, thus enabling quantitative and statistical analysis.

We piloted the Adopt a Pixel project with 74 high school research interns in summer 2020 as part of the STEM Enhancement in Earth Sciences summer research internship experience, hosted by Texas Space Grant and the University of Texas, Austin. The 2020 pandemic necessitated all internships to be conducted virtually. Interns were scattered across the continental U.S.

[1] https://observer.globe.gov

and in two locations overseas. Because "safer at home" orders were in place in many areas, the project could not require students to participate in field data collection, as in previous summers, but all participants could examine and analyze very high-resolution satellite imagery. These logistical conditions contributed to our project's structure, research design, and resulting dataset. Participants selected a local study site of interest and applied their own knowledge to develop and analyze a robust 9 $km^2$ land cover data set. We provided 8 weeks of virtual research training support to participants, including "Meet Up and Do Science" coworking webinars, peer discussions, lectures, and mentor relationships with NASA scientists.

Ground-based observations of environmental data are critical to the interpretation and downscaling of satellite products, but more *in-situ* observations are needed, especially in regions where variable conditions are pronounced or where rapid change is occurring (Moorthy et al., 2020; World Health Organization, 2020). *In-situ* validation of land-use and land-cover (LULC) products plays an important role in improving the accuracy of models employing remotely sensed data and map products for practical management purposes (Eriksen et al., 2018).

This project contributes to the ecosystem of citizen science initiatives documenting land cover, land use, and landscape change through photo data collection and/or analysis of remotely sensed aerial or space imagery. The ecosystem includes such projects as Geo-Wiki (Fritz et al., 2009), VIEW-IT (Clark and Aide, 2011), FieldScope (Switzer et al., 2012), LACO-Wiki (See et al., 2015), Field Photo Library (Xiao et al., 2011), and the Degree Confluence Project (Qian et al., 2020). These projects have enabled participating volunteers to produce data at an unprecedented rate (Muller et al., 2015) and play a critical role in obtaining the velocity, volume, and variety of data needed to continuously monitor our changing planet. Opportunistically collected data can be especially informative at large spatial scales. Projects employing Geo-Wiki data provide examples of robust outcomes arising from citizen science data (Fritz et al., 2015, 2017; See et al., 2015). Both the observers and the environmental features or phenomena of interest are not distributed evenly across space and time, and not all observations are equally valuable scientifically (Callaghan et al., 2019). Our approach enables citizen scientists, who are using GO, to access systematically collected data and conduct robust analyses of smaller, site-based data sets.

All GLOBE data are openly accessible and readily downloadable as CSV files using either the Advanced Data Analysis Tool or an API through the GLOBE website.[2] Descriptions of GLOBE metadata and data quality assurance procedures are detailed in Amos and Andersen (2019) and Global Learning to Benefit the Environment (GLOBE) (2019). Data quality assurance parameters for the GLOBE Observer tools used in this project are presented in Amos et al. (2020).

[2]https://www.globe.gov/globe-data

# METHODS

## Geographic Area

For this dataset, each citizen scientist identified the center of a 9 $km^2$ Area of Interest (AOI) that they could access (**Figure 1**). This resulted in 49 AOIs unevenly distributed across the United States, Puerto Rico, and Germany.

## Very High-Resolution Satellite Image Derived Land Cover Data

The center latitude and longitude of each AOI was uploaded to a project on Collect Earth Online (CEO), an open-source, cloud-based satellite image viewing and interpretation system (Saah et al., 2019). This platform ensures that there is "consistency in locating, interpreting and labeling reference data plots for use in classifying and monitoring land cover/land use change," (Saah et al., 2019). Using the provided sampling tools, each AOI had Primary Sample Units ($n = 36$), each with dimensions of $100 \times 100$ m, systematically located with a 500 m spacing on a grid to minimize spatial autocorrelation at moderate resolution (Buchhorn et al., 2020). Each of these Primary Sample Units then had a systematic dot grid overlaid with 10 m spacing ($n = 121$).

These secondary 2 m circular sample units were subsequently labeled using a slightly modified land cover classification protocol (**Table 1**) (Becker et al., 1998). Previous studies have shown that citizen scientists who collected land cover reference data using this protocol, "are at least as accurate as that collected by professionals," (Becker et al., 1998).

Summarizing these secondary sample units allows calculation of the fractional and overall land cover for the Primary Sample Unit and the AOI. The selected very high-resolution imagery for interpretation was sourced as the MapBox Global Satellite Basemap[3] that is provided in a cloud-free color-corrected and sharpened 3-band imagery for the visible wavelengths of red, green, blue (RGB) derived from various sources with reported ground resolution of 50 cm.

Citizen scientists were aided in understanding their Primary Sample Units through the customizable GeoDash feature on the CEO platform (Markert et al., 2017). Both a Normalized Difference Vegetation Index (NDVI) and a Normalized Difference Water Index (NDWI) timeseries for each Primary Sample Unit were calculated from MODIS data and presented in the GeoDash (Geo, 1996; Didan, 2015).

Across the 49 AOIs based on the very high-resolution satellite imagery, the team labeled 1764 Primary Sample Units that had a representation on average of 33% tree canopy cover, 19.5% impervious surface cover, 16.3% grass cover, 16.5% building cover, 6% cultivated vegetation cover, 2% shrub cover, 1% river/stream flowing water cover, 1% lake or ponded water cover, and less than 1% for the categories of treated water (pools, containers) or irrigation ditches.

### Ground Reference Land Cover Data

Within each of the 49 AOIs, oblique ground photos were collected using the GO Land Cover protocol (Kohl et al.,

[3]https://www.mapbox.com/maps/satellite

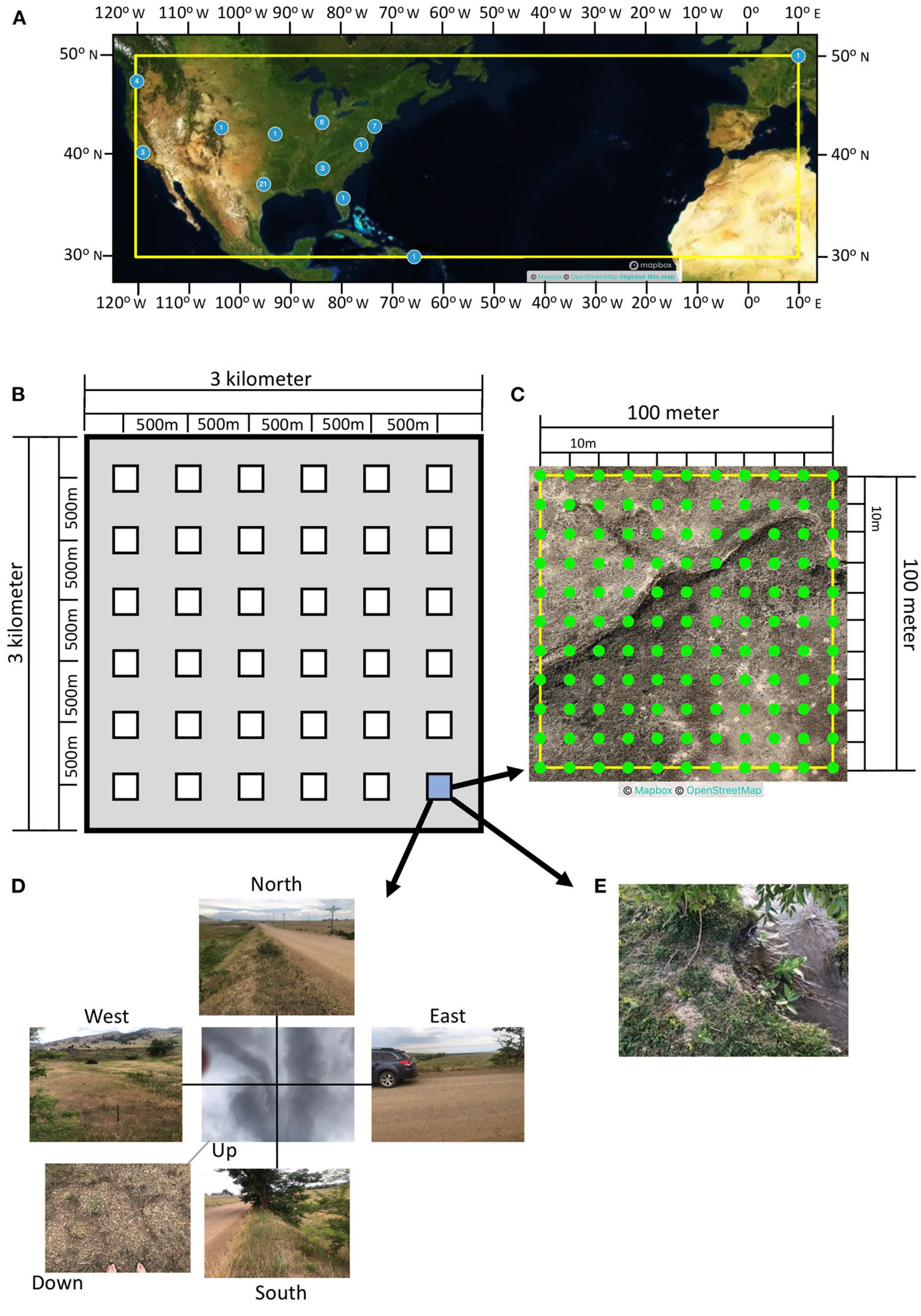


**FIGURE 1 |** The research design collected reference samples at multiple scales. **(A)** Geographic location of the 49 Areas of Interest. **(B)** Within each Areas of Interest, defined as a 3 × 3 km area, there are 36 Primary Sample Units spaced on a systematic grid 500 m apart. **(C)** Each Primary Sample Unit is a 100 × 100 m area: very high resolution satellite imagery is characterized using a dot grid with equal spacing of 10 m. This results in a total of 121 samples which allows calculation of fractional land cover estimates. **(D)** Ground reference images are collected within the Area of Interest using the GLOBE Observer Land Cover tool. **(E)** Mosquito habitat data is collected using GLOBE Observer Mosquito Habitat Mapper within each Area of Interest whenever present.

2021). These ground images provide a corroborating data source for land cover labeling in this dataset. The date and time of observation and the geolocation as obtained by the GPS receiver/location services built into the user's mobile device is collected by the GO app. The user answers a series of yes/no prompts to describe the surface conditions (potential reflectivity) at the site. Land cover is documented though 6 directional photos. For each cardinal direction (north, east,

**TABLE 1 |** Overview of land cover element attributes used in the three different citizen science tools.

| Harmonized land cover | Satellite imagery (Collect Earth Online) | GLOBE observer land cover (primary \| distinction) | GLOBE observer mosquito habitat mapper |
|---|---|---|---|
| Vegetation \| Trees | Trees—Canopy Cover | Trees | Tree holes |
| Vegetation \| Shrubs | Shrubs/bushes | Shrubs | Plant clumps |
| Vegetation \| Herbaceous | Grasses | Herbaceous | Plant clumps |
| Vegetation \| Cultivated | Cultivated vegetation | Cultivated | Plant clumps |
| | | | Water tank |
| | | | Animal trough |
| | | | Irrigation ditches |
| Vegetation \| Wetlands | – | Wetlands \| Freshwater riverine | Lake/Pond/Swamp |
| | | Wetlands \| Freshwater lacustrine | |
| Unvegetated \| Barren | Bare ground | Barren | – |
| Unvegetated \| Urban | Building Impervious Surface | Urban \| Residential | Ditch |
| | | Urban \| Commercial | Puddle |
| | | Urban \| Roads | Cistern/Well |
| | | Urban \| Other | Water storage container |
| | | | Architectural feature |
| | | | Culvert/Bridge/Road |
| Unvegetated \| Water | Water \| treated pool | Open Water \| Freshwater | Still \| Lake/Pond/Swamp |
| | Water \| lake/pond | | |
| | | | Flowing \| Still-water found next to river or stream |
| | Water \| rivers/stream | | |
| | Water \| irrigation | | |
| Unknown | – | – | Container \| Natural |
| | | | Container \| Artificial |
| Missing data | Shadow | – | – |

south, west), users are instructed to orient their camera to capture an image focused on the nearest 50 m. Upward and downward/images are collected to document atmospheric conditions/canopy cover and ground cover, respectively. Along with text field notes, citizen scientists have the option to label land cover elements and estimate the percentage they observe in the field for each directional image. These data are then submitted over the internet to the GLOBE database for archiving and eventual retrieval.

Across the AOIs, there were 8,312 ground images collected using the GO Land Cover protocol at 1,047 locations. Only 39% of these locations were classified in the field using this tool. The viewsheds corresponding to field classified images show a dominance of building cover (26%), followed by impervious surface cover (25%), tree canopy cover (22%), herbaceous vegetation (19%), barren land (4%), open water (1%), and shrub cover (1%).

## Data Advantages, Limitations, and Challenges

This Adopt a Pixel dataset has the advantage of being part of the GLOBE data ecosystem. Since 1995 GLOBE citizen scientists have contributed more than 200 million environmental measurements to the GLOBE database. Adopt a Pixel data is readily associated with these environmental observations, collected using more than 50+ scientist-developed research protocols. Together, these data contribute to the examination of diachronic landscape evolution resulting from large scale processes such as urbanization, globalization, and climate change (Kennedy et al., 2015).

GO enables a citizen scientist to collect coincident data using more than one tool: atmospheric conditions (Clouds), canopy height (Trees), still or stagnant pools of water (Mosquito Habitat Mapper), and land use and vegetation cover (Land Cover). We developed the nested Adopt a Pixel 3 km project with an eye toward future applications of land cover data to projects that employ more than one of the GO tools. For instance, land cover variables are critically important to include in predictive mosquito vector borne disease risk models because mosquito species have specific habitat preferences and microhabitat requirements, including plant height and density, both of which are captured in *in-situ* ground photos. Vegetation-dependent associations have been identified in numerous studies (see systematic review by Sallam et al., 2017). However, the field research that documents spatial patterns in mosquito habitats (oviposition sites) and uses these data to inform the interpretation of mosquito breeding sites from satellite imagery is still nascent. In a recent publication, Lorenz et al. (2020) called for scientists to test mosquito habitat and distribution models using freely available satellite imagery, such as Landsat 8.

From an initial 79 submitted AOIs, a filter for completeness was applied to select those that included the 36 labeled Primary Sample Units and had associated GO Land Cover photos, resulting in the 49 AOIs presented here. During data collection activities and subsequent review of the satellite image classifications, we identified context-dependent errors in the categorical assignment of specific thematic attributes by the citizen scientist team. We adjusted the definitions used by the volunteers to provide clearer definitions of irrigated fields vs. cultivated lawns vs. open rangeland, and manually fixed these errors. In a future iteration of this seasonal project, we intend to expand our work to systematically identify bias and residual errors in land cover classification by the citizen scientists. To improve the quality of this data set, we are working on adding inter-rater reliability statistics on Adopt a Pixel 3 km data and assign a reliability index to land cover classifications which will facilitate an independent dataset update with appropriate documentation. These data are available to be employed training computer-vision algorithms that will verify the accuracy of citizen scientist classifications (Xing et al., 2018; Ceccaroni et al., 2019; McClure et al., 2020).

Spatial accuracy is problematic for many citizen science programs that rely on the built-in GPS receiver of a user's personal mobile device. A recent study of horizonal positional error exhibited in geolocations identified using an iPhone 6 averaged between 7 and 13 m (Merry and Bettinger, 2019). The GO Land Cover tool provides an estimate of accuracy to the user, and they are asked to refresh their GPS reading until they obtain the lowest error reading (3–65 m). This step introduces potential human error: if the GPS receiver is not refreshed, the reported geolocation will have greater positional error. We plan to document such errors systematically in the next season and explore the potential of the Adopt a Pixel data to quantify positional error for citizen science data obtained through GO.

One of the analytical challenges associated with opportunistic data sets relates to the unique and inherent spatial and temporal biases that pose statistical and data informatics challenges for the end user (Muller et al., 2015). A variety of techniques and statistical procedures can be applied to improve or characterize the reliability of opportunistic data (Isaac et al., 2014; Lukyanenko et al., 2016, 2020; Aceves-Bueno et al., 2017). One of the most common approaches is through models comparing opportunistic data with an embedded data set that employs a structured sampling design (Giraud et al., 2016). Such a model-based approach has been used with land cover data to meet conditions necessary to reduce errors and obtain useful outcomes from data collected opportunistically (Stehman et al., 2018; Henckel et al., 2020). However, the Adopt a Pixel data set was collected using a systematic sampling design to overcome some of the biases and analytical limitations associated with opportunistic data sets.

There is a concern that rapidly expanding access to personal mobile devices is resulting in "a fragmented landscape where there are a large, and increasing, number of citizen science type projects collecting data which are often highly specific to those projects." (Higgens et al., 2016). While Adopt a Pixel supports research using data specific to the GLOBE Program, it can also contribute to broad scale mapping science initiatives such as the Land Change Monitoring, Assessment, and Projection project (LCMAP) (Brown et al., 2020; Pengra et al., 2020), the scale of which requires the use of all available data.

In this pilot project, citizen scientists examined satellite imagery coupled with their *in-situ* LULC observations and classified the images using Collect Earth Online (CEO), an open source, web-based tool designed for systematic LULC data analysis. Adopt a Pixel contributes to describing GO Land Cover data in a way that will improve the ability of interested scientists to assess the quality and fitness-for-use of GO data in their research. As we continue to find ways to evaluate and document the quality of GO data, we expect to see increasing scientific and societal applications of the data in research.

## DATA ACCESS

The Adopt a Pixel 3 km data, along with its metadata description, is hosted in the openly accessible Earth System Data Exploration Portal, at https://geospatial.strategies.org/pages/publication-data (accessed October 06, 2021). This portal hosts curated data sets and associated metadata derived from citizen science data reported using GLOBE Observer. Additional functionalities provided in the portal include ready to use source data, dashboards, and data processing scripts.

## DATA AVAILABILITY STATEMENT

These data were obtained from the GLOBE Program. Curated data sets on which this article is based, as well as the Python code employed in quality assurance and metadata descriptions are available at https://geospatial.strategies.org/pages/publication-data (Nelson et al., 2021).

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All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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