Smartphones for citizen science water quality monitoring in developing regions

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INFORMATION

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ABSTRACT

Among many other efforts, high spatial and temporal resolution water quality monitoring data are required to help mitigating the ongoing global freshwater crisis. Citizen science is said to have a high potential to contribute valuable water quality monitoring data, while at the same time offering a range of qualitative benefits such as generation of a social fabric, environmental education, and improved relationships between citizenry and authorities. The potential of citizen science is elevated by integration with technology, especially smartphones, which allow for easy data capture and information sharing among a range of other powerful features.

As part of the CGIAR Initiative on Digital Innovation, we aimed to test some of the most prominent smartphone applications (apps) to investigate their scalability to developing regions for monitoring the Sustainable Development Goal (SDG) target 6.3.2 indicator water quality parameters or other key water quality metrics. We used southern Africa as a case study, since it characterises numerous key challenges to citizen science water quality monitoring using smartphones in developing regions. We evaluated five smartphone apps that are plug-and-play, assessing both their quantitative accuracy as well as their qualitative suitability to a southern African context. We found that the Hydrocolor and EyeOnWater apps showed theoretical promise but would not be useful for typical citizen science monitoring of streams, river, and dams from the banks of those water bodies given their requirement for deep water. The MQuant® StripScan App was not useful given that the reference cards required to use the app could not be sourced and that the app did not function to read the Mquant® nitrate test strips. The Nutrient App showed some promise but has ceased being supported, illustrating the critical importance of designing and developing tools with sustainable financing and maintenance in mind (as well as the need for funders to support key tools so they remain freely accessible) so that the great efforts that go into research and development are not ultimately wasted. The Aquality app was fairly user friendly, intuitive, and accessible for free via the Play Store and the Apple App Store. The development and support team were helpful and responsive, with ongoing research and development regarding the app showing good potential for upscaled functionality and implementation in the future. However, we found that there were significant qualitative and quantitative issues with the app that should be investigated further and addressed to ensure the app is suitable for global use, especially in the context of developing regions. These included that i) the material requirements for the app (i.e., a reference card mailed directly from Deltares in the Netherlands and Hach© nitrate test strips) were difficult to source in South Africa (which is likely to be the case in many other countries), ii) each test carried a significant financial cost (USD 2 - 5 per test), and iii) the guidelines of the app, especially concerning the appropriate lighting requirements, left considerable room for novice user error or lack of standardisation. Concerns over the standardisation and accuracy of the data were supported by the fact that we found little to no correlation

between the estimated nitrate concentrations in surface water samples calculated by the app compared to accredited laboratory measurements of the same water samples.

Overall, we suggest that though our data were limited, they provide evidence that the data generated by real citizen scientists using such app around the world need to be carefully validated before they can be trusted. The reality is that doubt over standardisation and validity of results could prove a serious barrier to use of the data for management and policy interventions. More broadly, we identified a need for digital innovations within citizen science to remain human-centric and not become extractive, treating citizen scientists simply as data collection units. The massive potential for a nexus between digital innovation and citizen science will only be realised if we specifically cater towards the human part of the equation and if researchers and developers remain mindful of technicist assumptions about the utility, understandability, and validity of innovative technologies in different contexts.

INTRODUCTION

The need for freshwater monitoring

There is a global environmental crisis disproportionately affecting freshwater systems (Lynch et al. 2023; Ottoni et al. 2023; Robinson 2023; Tickner et al. 2020; WWF 2020). Freshwater ecosystems, though only making up <2% of the surface of the earth, support approximately 12% of all species on earth, including humans (Abramovitz 1995; Carrizo et al. 2017). The drivers of the present day freshwater crisis are established, although they are increasingly being aggravated by further anthropogenic pressures (Albert et al. 2021; Darwall et al. 2018; Dudgeon 2019; Flitcroft et al. 2019; Reid et al. 2019; Wang, M. et al. 2024). It is now estimated that the upstream water sources that supply about 82% of people are under threat of degradation (Green et al. 2015).

To address the pervasive threats posed by degrading freshwater systems, global collaboration towards achieving the Sustainable Development Goals (SDGs) has taken on a particular focus on SDG 6 "clean water and sanitation for all" (Capdevila et al. 2020; Gemeda et al. 2021; Hegarty et al. 2021; Quinlivan et al. 2020a; 2020b; White et al. 2020). The focus is based on the simple fact that healthy freshwater underpins all life (Njue et al. 2019). Achieving SDG 6 through improving freshwater resource management and conservation requires large scale, fine spatial and temporal resolution, credible monitoring data (Arthington 2021; Behmel et al. 2016; McKinley et al. 2017; Tickner et al. 2020).

Conventional water resource monitoring is valuable but requires constant expert involvement as well as specialist equipment, making it expensive in both time and money. Consequently, conventional monitoring efforts are frequently cut due to financial and time constraints (Jan et al. 2021; Silva et al. 2022; Zainurin et al. 2022), leading to the data becoming uncoordinated, outdated, and only available at course spatial and temporal scales (Arndt et al. 2022; König et al. 2021; Njue et al. 2019; O'Grady et al. 2021; Wu et al. 2022). These limitations hinder the influence these data can have on management or policy, especially at fine-scale resolutions (O'Grady et al. 2021; Ouma et al. 2018).

Modern technology has shown great potential to augment or innovate with conventional monitoring. However, there remain significant challenges. Remote monitoring installations can suffer from, among others, bio-fouling, power supply and internet connectivity issues, difficulties with maintenance, as well as data and physical security issues (Jan et al. 2021; Manjakkal et al. 2021; Rahim et al. 2017). This means that various technologies are precluded, especially in developing and rural settings, because of challenges primarily related to cost, but also limitations with, for example, commercial accessibility and potential for vandalism or theft (Adu-Manu et al. 2017; Chandra Kishore et al. 2022; Zulkifli et al. 2018).

It is also becoming increasingly clear that conventional 'top-down' methods are often ineffective in mobilising the urgent management and monitoring changes needed to address the freshwater crisis (Buytaert et al. 2014; De Filippo et al. 2021; Jordan and Cassidy 2022; Paul et al. 2018). In response, there have been global calls for integrated water resource management that employs holistic multi-tier stakeholder engagement (Behmel et al. 2016; De Filippo et al. 2021; Pastor et al. 2019). Citizen science (also discussed under various other terms such as participatory science or community-based monitoring) is a potential tool for answering this call (de Sherbinin et al. 2021). Citizen science can fill critical data and knowledge gaps and work towards achieving the SDGs via the involvement of the public and stakeholders in the scientific process at various levels (Amador-Castro et al. 2024; Bishop et al. 2020; Capdevila et al. 2020; Collins et al. 2023; Corburn 2022; Dörler et al. 2021; Elias et al. 2023; Fraisl et al. 2020; 2023; Fritz et al. 2019; Hegarty et al. 2021; Kelly-Quinn et al. 2023; Kirschke et al. 2022; 2023; McKinley et al. 2017; Moczek et al. 2021; Poisson et al. 2020; Queiruga-Dios et al. 2020; Quinlivan et al. 2020b; Ramírez et al. 2023; UNEP 2018; Wu et al. 2023).

Citizens can be involved in the scientific research process in numerous ways at various levels. This can include data collection, study design, or even analysis, reporting, and stakeholder engagement (Buytaert et al. 2014, Schölvinck et al. 2022; Graham, P. M. and Taylor 2018). The benefits of citizen science for monitoring are perhaps most obvious in the collection of large volumes of data at fine spatial and temporal resolutions. However, there are a range of benefits of citizen science beyond simply quantitative data capture including the capture of qualitative data such as indigenous knowledge and community-based insights usually missed by conventional data collection (Bishop et al. 2020; Hegarty et al. 2021; Paul et al. 2018). Through involvement of citizens in the scientific process, citizen science enables a sense of agency to develop in members of the public (Conrad and Hilchey 2011; Corburn 2022; De Filippo et al. 2021; Jalbert and Kinchy 2016; McKinley et al. 2017). This can be especially important for traditionally marginalised and disaffected communities who often struggle to enter public discourse, yet are among the most impacted by environmental, water, and sanitation issues (UN Habitat and WHO 2018; WHO and UNICEF 2021). Citizen science also elevates public awareness, and, depending on the tools and methods used, has significant potential to improve scientific literacy, instil a sense of environmental stewardship and ownership, become a potent mechanism for environmental education, and even aid in establishing discourse between communities and authorities (Bonney et al. 2009; Carlson and Cohen 2018; Dörler et al. 2021; Jönsson et al. 2024; Queiruga-Dios et al. 2020). The involvement of citizens, at all levels, in water issues and risks can enable a 'social fabric' to develop that helps connect citizens with the authorities and other leaders responsible for water related service delivery. This social fabric of connected people is much needed where citizens are disconnected with the responsible authorities.

Despite the clear potential of citizen science, it is still broadly viewed with scepticism, with widespread doubt over the rigor and validity of the data (Bonney et al. 2014; Cook et al. 2021). The mistrust originates from, among others, a general lack of belief in the scientific understanding of the participants, the potential introduction of bias, and the potential for inadequate training, effort in standardisation, and verification protocols (Hadj-Hammou et al. 2017; Kolok et al. 2011). These concerns have validity and must be addressed for citizen science to gain the credibility required for it to be integrated in the science-management-policy pathways.

DIGITAL INNOVATION WITH SMARTPHONES AND CITIZEN SCIENCE

With the rapid innovation and adoption of new technologies and recognition of the potential of citizen science, it is increasingly clear that a combination of accessible technology and citizen science could prove potent for addressing the monitoring requirements for meeting the SDGs. The goals of the CGIAR Initiative on Digital Innovation are particularly well-suited to engaging with this potential synergy with regards to achieving SDG 6.3.2 'proportion of bodies of water with good ambient water quality' and SDG 6b 'procedures for participation of local communities in water and sanitation management'.

The potential integration between modern, accessible technology and citizen science is perhaps most clear with smartphones. Most of the adult population of the world owns or has access to a smartphone (approximately 80-90% of the population) and possesses the digital literacy required to use it and engage with new software and tools made available via smartphones (Buytaert et al. 2014; 2016; Fabio et al. 2022; Graham, E. A. et al. 2011; Njue et al. 2019; Ouma et al. 2018; Rahim et al. 2017). Smartphones themselves are powerful tools for inclusion in the scientific process, since they are the focus of some of the most fast-paced, inventive, and cutting-edge innovations in technology. They have become handheld, easy-to-use supercomputers that have good battery life, the ability to connect to the internet, local and cloud-based data storage, as well as a built-in range of abilities, possibly including accurate Global Positioning Systems (GPS), accelerometers, gyroscopes, and high-pixel cameras (Aitkenhead et al. 2014; Chandra Kishore et al. 2022; Dutta 2019; Kwon and Park 2017).

With these capabilities, smartphones can allow citizen scientists to easily and quickly gather high volumes of data that are comprehensive, standardized, and uploaded and backed up in real-time to cloud-based storage that can be automated for efficient data handling (Graham, E. A. et al. 2011; Park et al. 2020). This process enables verification, validation, summarisation, and visualization processes to be built in and automated to enhance data transfer and reporting (Adu-Manu et al. 2017; O'Grady et al. 2021; Paul et al. 2018; Poisson et al. 2020). The data transfer and associated reporting feedback can also be designed to function, at least partially, in a two-way manner. Data can be summarised and visualised for the citizen scientists contributing towards the database, with avenues for 'gamification' to reward and incentivise citizen scientists for their involvement (Buytaert et al. 2014; Geetha and Gouthami 2016; Graham, E. A. et al. 2011; Njue et al. 2019).

Smartphones possess the possibility to improve the involvement of citizen scientists in scientific research through improving education and training, providing feedback and intuitive data collection. They can also support reporting frameworks, the upscaling the standardisation and comprehensiveness of the data collected, as well as showing strong potential for helping citizen science make great strides towards achieving the SDGs. This is particularly important in rural and developing areas, where there is an under-representation of diverse and traditionally marginalised groups in scientific data collection (Bishop et al. 2020; Buytaert et al. 2016; Fraisl et al. 2020; Jönsson et al. 2024; Silva et al. 2022; Thornhill et al. 2019; Walker et al. 2020). Water quality monitoring data have thus far primarily come from the developed west and global north, given developing regions often lack the resources required to gather, analyse, and manage data (Bishop et al. 2020; Capdevila et al. 2020; Paepae et al. 2021; Quinlivan et al. 2020a; 2020b). Southern Africa is a good example of these obstacles to water quality monitoring, which will need to be overcome if the global south and other developing regions can begin to meaningfully engage citizens and contribute valuable data (Graham, P. M. and Taylor 2018; Hulbert et al. 2019; Weingart and Meyer 2021).

VALIDATION OF SMARTPHONE-ASSISTED CITIZEN SCIENCE WATER QUALITY MONITORING IN SOUTHERN AFRICA

The need to implement citizen science monitoring initiatives must be tempered with sensible determination of which data collection tools are realistically deployable. In southern Africa the challenges to integrate smartphones into citizen science and use them for monitoring are likely to be different to those that might be encountered in western Europe or northern America (Benyei et al. 2023; Hulbert et al. 2019; Pocock et al. 2019; Weingart and Meyer 2021). Not all smartphone-based or assisted citizen science water quality monitoring tools, developed in the differing contexts of the global north will be applicable in a southern African context.

As part of research within the CGIAR Initiative on Digital Innovation, we explored what pre-existing smartphone-based or smartphone-assisted water quality monitoring citizen science tools might be suitable for use in southern Africa. The selection of the tools that were tested was based on a set of criteria determined a priori to be of importance in a southern African situation: Is the tool low-cost (requiring minimal input costs beyond having a smartphone), easy-to-use (accessible to people from diverse backgrounds and educational levels), easily scalable (easy to disseminate and implement among diverse communities and stakeholders), available (free to acquire and commercially available to all), and best suited to citizen science rural and developing areas (where mobile data signal and storage space on simply smartphones might be limited and offline capabilities will be required)?

Based on these criteria, the first filter applied to potential tools was that they should be applications (apps) or protocols that are observation only (app-based with no additional technology or materials required and limited to no data interpretation) and / or plug-and-play (off-the-shelf, cheap kits or sensors that can be combined with smartphone apps or capabilities for data collection and analysis) (Aitkenhead et al. 2014; Rahim et al. 2017).

A further refinement stemmed from the fact that monitoring all water quality parameters (i.e., physical, chemical, and biological) is not possible (Okpara et al. 2022; Paepae et al. 2021). Therefore, the parameters to monitor should be those widely applicable to the most people and available freshwater bodies. Where possible these should be standardised and easy to capture across geographic and social contexts. The SDG 6.3.2. indicator uses a water quality index that integrates basic core water quality parameters; oxygen, salinity, nitrogen, phosphorus and acidification (Quinlivan et al. 2020a; UN Water 2018; Wu et al. 2022). Algae, temperature, and turbidity / clarity (and by proxy, total suspended solids; TSS) are also important water quality parameters that can be easily and cost-effectively monitored through citizen science (Castilla et al. 2015; Dahlgren et al. 2004; Graham, P. M. et al. 2024; Ho et al. 2020).

Ultimately, the scope was refined to minimum cost, smartphone-based or assisted citizen science technologies that are directly aimed at measuring or recording this set of key water quality parameters. Technologies which do not meet these requirements are currently precluded from scalable implementation in a southern African context. For instance, some smartphone-based tools require expensive investments in auxiliary sensors or modules which are prohibitively expensive for citizen scientists in developing regions (Abegaz et al. 2018; Njue et al. 2019). Moreover, many of the recently developed smartphone-assisted tools for water quality monitoring are not commercially available or easy and affordable to manufacture or maintain in southern Africa, ruling them out for easy implementation and upscaling.

Through surveys of the literature and other sources (see Pattinson et al. 2023), the **Hydrocolor** (Leeuw 2014; Leeuw and Boss 2018), **EyeOnWater**[1] (formerly Citclops; NIOZ and MARIS B.V.), **Deltares Aquality app**[2] (Deltares, Netherlands), **The Nutrient App** (Push Interactions, Inc., developed by the University of Saskatchewan and Global Water Futures Project (GWF) with the support of Environment and Climate Change Canada[3]) (Costa et al. 2020), and **The MQuant® StripScan App** (Merck KGaA, Darmstadt, Germany) were isolated for trials in southern Africa. This list was not exhaustive; some potentially useful options may exist that were not tested. Validation aimed to assess data collection accuracy, accessibility, ease of use, cost, and the feasibility to contribute to pathways from data collection, citizen mobilisation and decision-making. We aimed to test the accuracy and utility of these apps for monitoring the water quality of streams and rivers in a southern African context.

METHODS

Study area

Data were collected from 27 sample sites on streams, rivers, and a dam (Henley dam) in the mSunduzi and uMngeni River catchments within the Pietermaritzburg region of Kwa-Zulu Natal (KZN), South Africa (Figure 1; Table 1). The sample sites were spread across a range of human impacts within the system, as well as across stream and river sizes, compositions, and conditions.

The uMngeni (also known as the Mgeni, Mngeni, or Umgeni) River catchment is fairly large (~4432 km2) receives 400 – 1500 mm of rain annually and contains a broad mixture of anthropogenic impacts along its length (DWAF 2002; DWS 2019). In the sample region, the main impact upstream of

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[1] https://www.eyeonwater.org/

[2] https://www.deltares.nl/en/software/nitrate-app/

[3] https://gwf.usask.ca/projects-facilities/nutrient-app.php#Overview

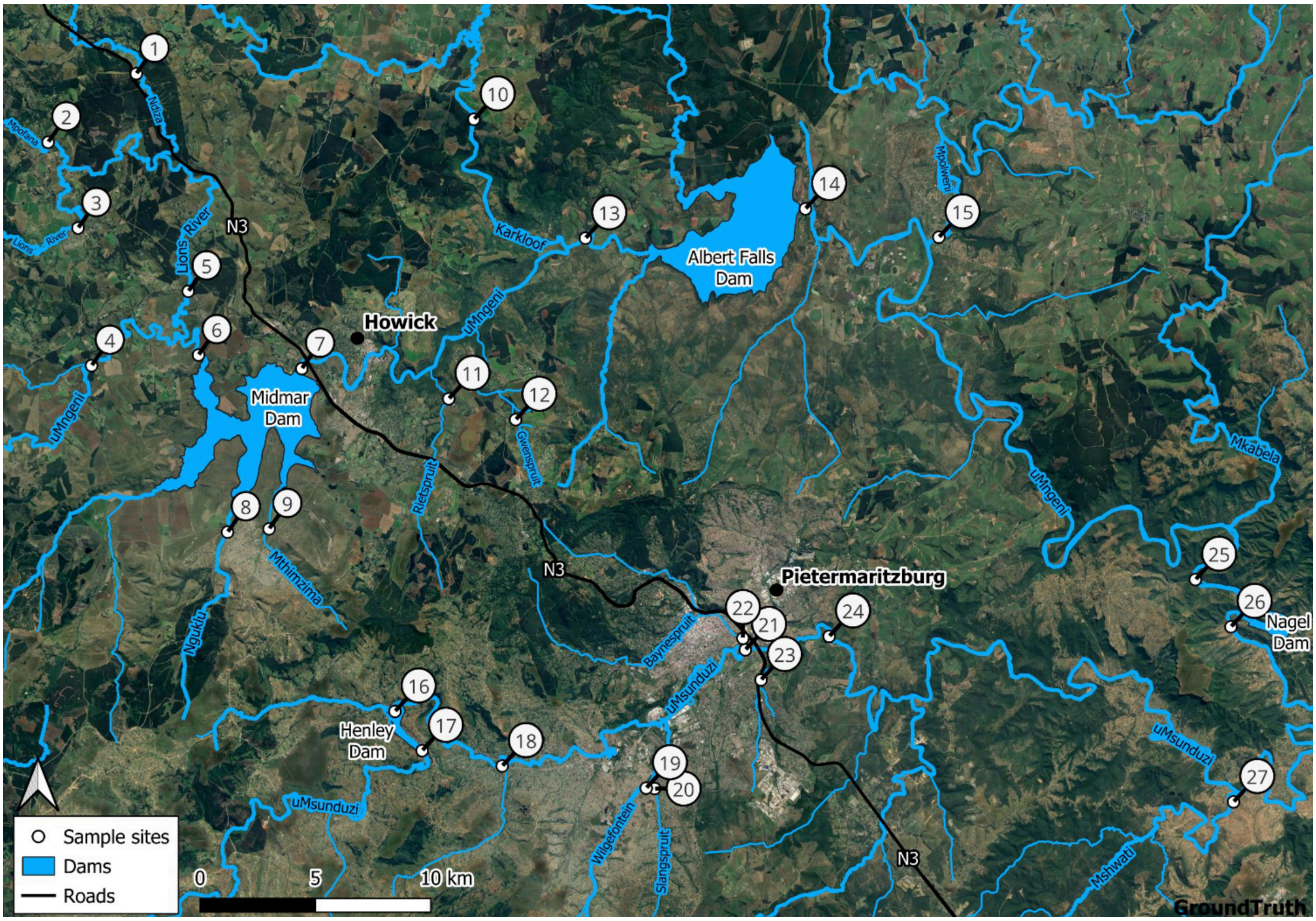

Figure 1. Map of sample sites showing major dams, rivers, and towns in the catchment.

Midmar dam is agricultural run-off, containing agricultural waste and nutrient pollution (Baker et al. 2015). Downstream of Midmar dam there are additional impacts from the impoundments (including the smaller Nagle dam, upstream of the confluence with the uMsunduzi), including alterations to flow regimes, sedimentation, and nutrient loading.

The uMsunduzi (also known as the Dusi, Duzi and Umsunduzi) River catchment is smaller (~ 900km2) than the uMngeni, receives 600 – 1200 mm or rain annually, and flows into the uMngeni upstream of Inanda dam (Gericke et al. 2004). The uMsunduzi river upstream of Pietermaritzburg comes under pressure primarily from agriculture, with some input from largely rural communities (Agunbiade and Moodley 2016). It passes through and supplies Henley dam before flowing through the Pietermaritzburg city centre where it comes under severe pressure from industrial and domestic waste. The river also absorbs the ouflow from the Darvill WWTW which services most of the catchment area, processing approximately 75 million litres per day and discharging into the uMsunduzi downstream of the city (Adeyinka et al. 2019; Agunbiade and Moodley 2016; Baker et al. 2015; Matongo et al. 2015).

The dams in the region all serve as critical sources of water for irrigation and domestic use (Gumbi et al. 2017; Hart and Wragg 2009). Midmar dam on the uMngeni River was constructed in 1965 and today supplies water to over 700 000 people in the Pietermaritzburg district. Midmar has a gross capacity of 177 million m3 (Agunbiade and Moodley 2016). Downstream of Midmar the uMngeni then flows through Albert Falls dam, established in 1976, with a gross capacity of 289 million m3 (Agunbiade and Moodley 2016). Continuing eastwards, the uMngeni then flows into the Nagle dam, constructed in 1950 with a gross capacity of 39.3 million m3. Finally, after the confluence with the uMsunduzi, the uMngeni flows through Inanda dam, founded in 1989 with a gross capacity of 245 million m3. Inanda dam forms the main water supply to the city of Durban, on South Africa's east coast. Henley dam is a relatively small impoundment on the uMsunduzi, with a gross capacity of 1.07 million m3. Its importance is in its location surrounded by settlements, and upstream of the city of Pietermaritzburg.

Stream and river data were collected on sections that were at least 1 meter (m) wide to give adequate space for sampling. Sampling was done on sunny days to standardise weather conditions during data collection. Sampling was restricted to sites near bridges or public roads for logistic ease and safety. The samples were also taken by a person situated safely on the bank of the stream or river. These parameters were selected as those representing places where citizen scientists would be comfortable and have access for sampling.

Smartphone data collection

Data were collected between 25/01/2024 and 22/02/2024 (Table 1). The smartphone apps were operated by freshwater ecological professionals. Although they were professional scientists, they were novice users who were given no guidance except the instructions (text guidelines and videos where available) provided within the apps for their use to best simulate the conditions of a citizen scientist attempting to use the apps. We specifically aimed to test the functionality and accuracy of the apps in the context of how they might be used by citizen scientists in regions like southern Africa. Therefore, we only took single samples (as opposed to replicate samples to generate averages) and sent the data collectors to the field to use the apps given only the information available in the apps and via the supporting documentation given on the associated websites. Data were collected exclusively on clear, sunny days between 08h00 and 16h30, following Al-Ghifari et al. (2021). Smartphone data were collected using a X7a smartphone which has a 50 megapixel HD (F1.8) main camera and a Samsung Galaxy A70 which has a 32 megapixel (F1.7) with PDAF main camera. Due to various constraints, not all the data were collected at all sites (Table 1).

Hydrocolor and EyeOnWater

Hydrocolor (Leeuw 2014; Leeuw and Boss 2018) and EyeOnWater[4] measure water colour, reflectance, and turbidity (Al-Ghifari et al. 2021; Ayeni and Odume 2020; Burggraaff et al. 2022; Malthus et al. 2020). Instructions on how to use each app are provided in the app.

Deltares Aquality App

The Deltares Aquality app automates the reading of a Hach© nitrate strip (0-50 mg/L) based on a calibrated, specific Deltares reference card (Topping and Kolok 2021). The nitrate-nitrogen (NO3-N) and nitrate (N = NO3-N x 4.4268) results are displayed real-time to the user on the phone, with the option to upload the results to the Delta Data Viewer[5] (Sohrabi et al. 2022). The app was used according to the instructions given in the app and in the online ‘tips and tricks’ guidelines[6]. The Aquality app can also capture electrical conductivity data but only through use of a relatively expensive (USD 500) meter for measuring electrical conductivity, so that utility is not explored in the context of citizen science in southern Africa. Anecdotally, we found that different ambient light (not in direct sunlight, but different forms of shade and inside versus outside) significantly altered the readings. In communication with the app developers, they recommended that the app is used in ‘good’ lighting, but not direct sunlight. Therefore, we took measurements in ‘indoor’ shade, either inside a building or within the cabin of a vehicle, but with natural light illuminating the strip and reference card.

The Nutrient App

The Nutrient App determines nitrate and phosphate concentrations in water based on automated analysis Hach© nitrate test strips (0-50 mg l1) and API phosphate test kits (0-10 mg l1) (Costa et al. 2020). The results are stored on a server hosted and managed by the University of Saskatchewan. User measurements can be viewed directly in the Nutrient app or on the Nutrient App webpage[7]. Protocols for use of the app are accessible via the app, or on the official app's webpage instructions. The ability of the app to read nitrate test strips was not tested.

MQuant® StripScan

The MQuant® StripScan app (Merck KGaA, Darmstadt, Germany) by Sigma-Aldritch uses Merck test strips for various water quality parameters in conjunction with the required reference card made by Merck. The app is marketed as capable of determining Ammonium (0-400 mg l1), Ascorbic Acid (0-2000 mg l1), Nitrate (0-500 mg l1), Nitrite (0.1-3 g l-1), pH (0-14 pH units), Peracetic Acid (5-50 mg l1), Peroxide (0-25 mg l1), Sulfate (<200 or >1600 mg l1), Sulfite (0-400 mg l1), and Total Hardness (>6 or >31 °e) based on various MQuant® test strips. The MQuant® test strips are advertised as available along with all necessary reagents required for sample pre-treatment studies (Jain et al. 2020). For the purposes of this study, the ability of the app to measure nitrate and pH by reading test strips was explored. Guidelines for use of the app are provided via an online video. The results are stored on a server hosted and managed by Merck and users can view their measurements in the app.

The procedural guidelines for use of each of the test strips was either supplied with the strips or outlined within the apps. Guidelines were followed as closely as possible for sampling and interpretation.

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[4] https://www.eyeonwater.org/

[5] https://v-web002.deltares.nl/fewsprojectviewer/projectviewer/

[6] https://publicwiki.deltares.nl/pages/viewpage.action?pageId=127634730

[7] https://gwf.usask.ca/projects-facilities/nutrient-app.php

Table 1. Table indicating the sample site details, sampling dates, and the data captured at each site

		GPS coordinates			Laboratory				Clarity Tube	In-situ (YSI Handheld Meter)			Apps	
Site no.	Site name	Latitude	Longitude	Sample date	Nitrate	Suspended Solids at 105°C	Total Phosphorus	Orthophosphate	Water Clarity	Dissolved Oxygen (DO)	pH	Temperature	Aquality (Nitrate)	Nutrient App (Phosphate)
1	Ndiza	-29.37810	30.12845	25/01/2024	X	X	X	X	X	X	X	X	X	X
2	Mpofana	-29.40480	30.08892	25/01/2024	X	X	X	X	X	X	X	X	X	X
3	Lions River	-29.43820	30.10234	25/01/2024	X	X	X	X	X	X	X	X	X	X
4	uMngeni River Upstream of Midmar Confluence	-29.49180	30.10839	25/01/2024	X	X	X	X	X	X	X	X	X	X
5	Lions River Upstream of uMngeni Midmar Confluence	-29.46290	30.15175	25/01/2024	X	X	X	X	X	X	X	X	X	X
6	uMngeni Inflow to Midmar	-29.48770	30.15632	25/01/2024	X	X	X	X	X	X	X	X	X	X
7	Midmar Outflow	-29.49300	30.20260	25/01/2024	X	X	X	X	X	X	X	X	X	X
8	Nguklu Upstream Midmar	-29.55660	30.16934	25/01/2024	X	X	X	X	X	X	X	X	X	X
9	Mthinzima Upstream of Midmar	-29.55540	30.18795	25/01/2024	X	X	X	X	X	X	X	X	X	X
10	Karkloof Falls	-29.39590	30.27979	06/02/2024	X	X	X	X	X	X	X	X		
11	Rietspruit	-29.50470	30.26849	22/02/2024	X	X	X	X	X	X	X	X	X	X
12	Gwenspruit	-29.50250	30.29125	22/02/2024	X	X	X	X	X	X	X	X	X	X
13	uMngeni Upstream Albert Falls Dam	-29.44220	30.32975	06/02/2024	X	X	X	X	X	X	X	X		
14	uMngeni Downstream Albert Falls Dam	-29.43080	30.42831	06/02/2024	X	X	X	X	X	X	X	X	X	X
15	Mpolweni Upstream of the uMngeni Confluence	-29.44180	30.48814	06/02/2024	X	X	X	X	X	X	X	X	X	
16	Henley Dam	-29.62630	30.24437	21/02/2024	X	X	X	X	X	X	X	X	X	X
17	Upstream Henley Dam	-29.64160	30.25656	21/02/2024	X	X	X	X	X	X	X	X	X	X
18	Downstream Henley Dam	-29.64760	30.29243	21/02/2024	X	X	X	X	X	X	X	X	X	X
19	Wilgefontein	-29.65590	30.35938	21/02/2024	X	X	X	X	X	X	X	X	X	X
20	Slangspruit	-29.65630	30.36073	21/02/2024	X	X	X	X	X	X	X	X	X	X
21	Duzi Upstream of Baynespruit Confluence	-29.60020	30.40134	07/02/2024	X	X	X	X	X	X	X	X		
22	Baynespruit Upstream Duzi Confluence	-29.59970	30.40159	07/02/2024	X	X	X	X	X	X	X	X		
23	Blackborough Spruit Downstream Dump	-29.60760	30.42299	07/02/2024	X	X	X	X	X	X	X	X		
24	Darville Outflow into Duzi	-29.59720	30.43899	07/02/2024	X	X	X	X	X	X	X	X		
25	Upstream Nagle Dam	-29.57510	30.60313	22/02/2024	X	X	X	X	X	X	X	X	X	X
26	Downstream Nagel Dam	-29.59350	30.61905	22/02/2024	X	X	X	X	X	X	X	X	X	X
27	Mshwati Upstream of the Duzi	-29.65870	30.61917	22/02/2024	X	X	X	X	X	X	X	X	X	

In-situ measurements, manual water sampling, processing, and handling

When data smartphone app data were captured, we also captured in-situ water quality parameters and water clarity data. The in-situ water quality parameters were temperature, pH, and dissolved oxygen (DO), measured by a YSI 556 MPS handheld multiparameter (YSI Incorporated, Yellow Springs, OH, USA; calibrated according to factory recommendations prior to use), at 20 cm depth. Water clarity was collected using a clarity tube (Graham, P. M. et al. 2024). Three replicates of clarity tube readings were collected, with the replicates averaged for a single reading per site.

Water samples were taken at approximately 20 cm below the surface at each of the sites. These samples were immediately stored in a cooled, darkened container and transported for storage at 5 °C before being sent for analysis within 24 hours. Water samples were analysed by Talbot Laboratories (Facility Accreditation Number: T0122; Pietermaritzburg, KZN, South Africa), a laboratory accredited in accordance with the International Standard ISO/IEC 17025:2005 by the South African National Accreditation System (SANAS). Laboratory analyses were for total suspended solid (TSS), nitrate (NO3-), orthophosphate, and total phosphate (i.e., orthophosphate, condensed phosphate, and organic phosphate).

Data analysis

The suitability of the apps was assessed qualitatively based on their availability, accessibility, functionality requirements, cost, and ease-of-use in the field. Assessment was carried out by three professional freshwater ecologists. The data collected by the smartphone apps were modelled as a function of the in-situ and laboratory water quality results to assess goodness-of-fit and visualise correlations. Specifically, we tested how well 1) the Aquality app's estimate of nitrate concentration correlates to the nitrate and TSS concentrations determined by laboratory analyses and in-situ measured DO, 2) the Nutrient app's estimations of phosphate correlated to the orthophosphate, total phosphate, and TSS concentrations determined by laboratory analyses and in-situ measured DO, and 3) if the nitrate and phosphate measurements by the apps correlated to clarity. We also tested for other relationships between water quality variables. This included testing the correlation between a) in-situ measurements of DO and laboratory measured concentrations of nitrate and phosphate, b) laboratory measured concentrations of nitrate and phosphate, and c) laboratory measured concentrations of TSS and clarity as measured by a clarity tube.

RESULTS

Qualitative assessment of app suitability in southern Africa

Hydrocolor and EyeOnWater apps

Most of the sites visited for testing in this study, including the sites at impoundments, the riverbed or bottom was visible from the bank where the measurements were being collected. Therefore, the Hydrocolor and EyeOnWater apps were ruled out for monitoring in the context of this study (especially monitoring streams and rivers), since both cannot be used where the bottom is visible. These apps should be explored further for monitoring specifically from boats on larger rivers and dams.

MQuant® StripScan app

The MQuant® StripScan app was ruled out based on two factors. Firstly, despite repeated efforts, we were unable to attain the necessary reference card to make use of the app for pH measurements. According to the reviews for the app on the Google Play store, the inability to source appropriate reference cards appears to be a pervasive problem. Secondly, the reference card supplied with the Merck nitrate test strips did not work with the app, which was tested on four different devices.

Aquality app

The Deltares Aquality app (available for free via the Play Store and the Apple App Store) required reference cards from Deltares which were supplied for free (including shipping costs), arriving approximately 2 weeks after being ordered. The app also required Hach© nitrate test strips, which were difficult to source and took approximately 2 months to ship from the USA, ultimately costing approximately R32,0 (~USD 2) per test strip. In the field, the app functionality was intermittent; we encountered issues with overheating, and an inability of the app to read strips under some lighting conditions. We found that the app only intermittently read the strips in direct or bright adjacent sunlight and that the lighting did significantly affect the readings. We also found that the instructions for use need to be much clearer to standardise measurements (especially concerning people unfamiliar with scientific standardisation practices), since it only recommends 'good' lighting, without specifying what constitutes 'good'.

The Nutrient App

The Nutrient App required API Phosphate Water Test Kits, which are readily available in South Africa for approximately R6 (~USD 0,32) and ship within a week of order. The Nutrient App can also measure nitrate using Hach© test strips. The guidelines for use of the test kit are detailed in both a guideline document and in instructional videos. The app was generally easy to use but needs to be updated to make colour card calibration instructions clear and concise for general users.

However, at this time the app is not available on the Play Store or App Store and does not connect to an active server for data storage and viewing, since it is not being actively maintained. Therefore, the app had to be downloaded via a third-party as a .apk file, which is not sustainable for upscaling. The results of the phosphate measurements of the app were still analysed, though the lack of maintenance rules it out as a potential option going forward.

Both the Aquality app and Nutrient App were somewhat extractive in their results. It is not clear to the user what the measurements mean. A nitrate or phosphate score is essentially arbitrary, without clear information on whether the concentration estimated indicates a problem with pollution or not.

Quantitative accuracy of app readings and correlations with other water quality parameters

Aquality app

The estimates of nitrate concentration according to the Aquality app (n = 21) showed no strong correlation between laboratory measured nitrate (r2 = 0.25), laboratory measure TSS (r2 = 0.01), or water clarity measured by clarity tubes (r2 = 0.00; Figure 2).

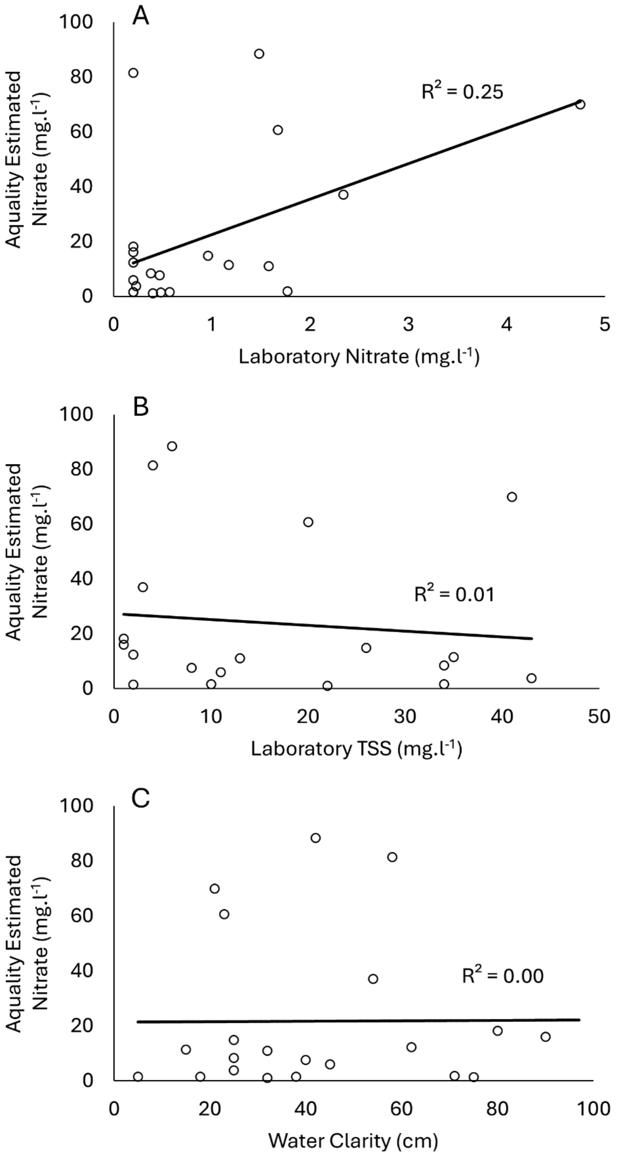

Figure 2. Nitrate (N) concentration in surface water samples as estimated by the Aquality app plotted as a function of, A) the laboratory measured concentration of N, B) the laboratory measured concentration of TSS, and C) water clarity as measured by a clarity tube. Linear regression lines are shown with the r2 indicated as a measure of goodness-of-fit.

The Nutrient App

There were also no strong correlations between phosphate as estimated by the Nutrient App (n = 19) and laboratory measured orthophosphate (r2 = 0.05), total phosphate (r2 = 0.01), TSS (r2 = 0.06), or water clarity as measured by clarity tubes (r2 = 0.02; Figure 3).

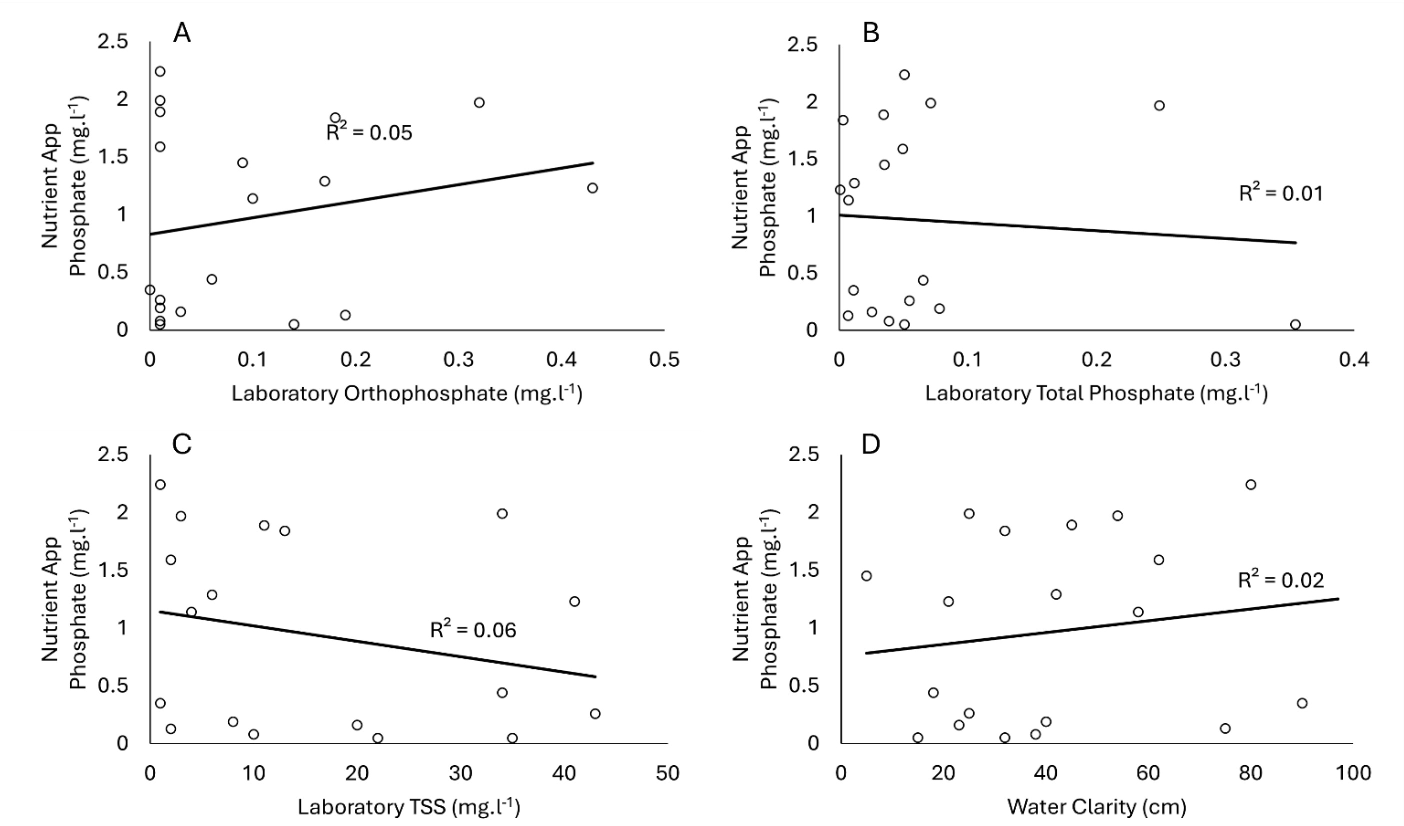

Figure 3. Phosphate (P) concentration in surface water samples as estimated by the Nutrient App plotted as a function of, A) the laboratory measured concentration of orthophosphate, B) the laboratory measured concentration of total P, C) the laboratory measured concentration of TSS, and D) water clarity as measured by a clarity tube. Linear regression lines are shown with the r2 indicated as a measure of goodness-of-fit.

Other water quality correlations

There were no strong correlations between DO and either laboratory measured nitrate (n = 27; r2 = 0.01) or orthophosphate (n = 27; r2 = 0.01; Figure 4). However, there were strong correlations between laboratory measured concentrations of nitrate and phosphate (n = 27; r2 = 0.66) and between the laboratory measured concentration of TSS and water clarity from clarity tubes (n = 27; r2 = 0.67; Figure 5).

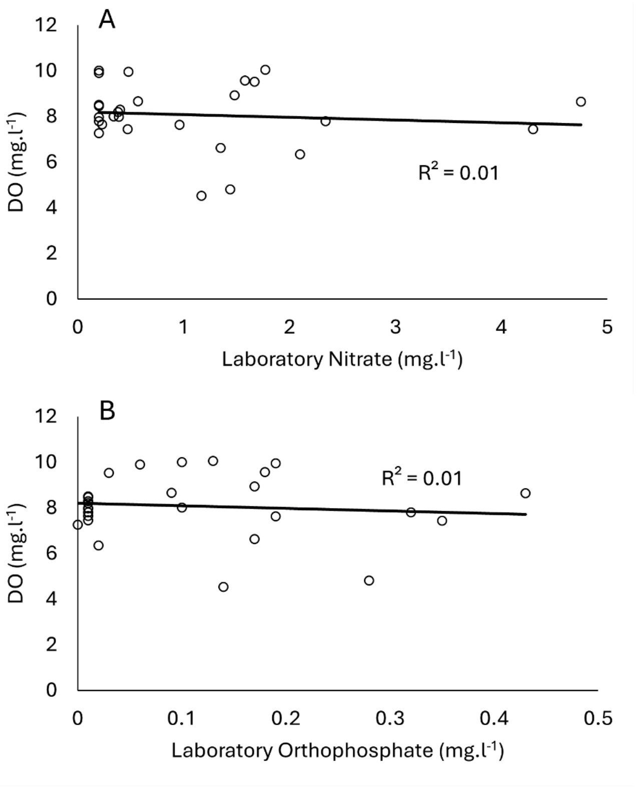

Figure 4. The concentration of DO (measured in-situ) plotted as a function of laboratory measured concentrations of A) nitrate (N), and B) orthophosphate in surface water samples. Linear regression lines are shown with the r2 indicated as a measure of goodness-of-fit.

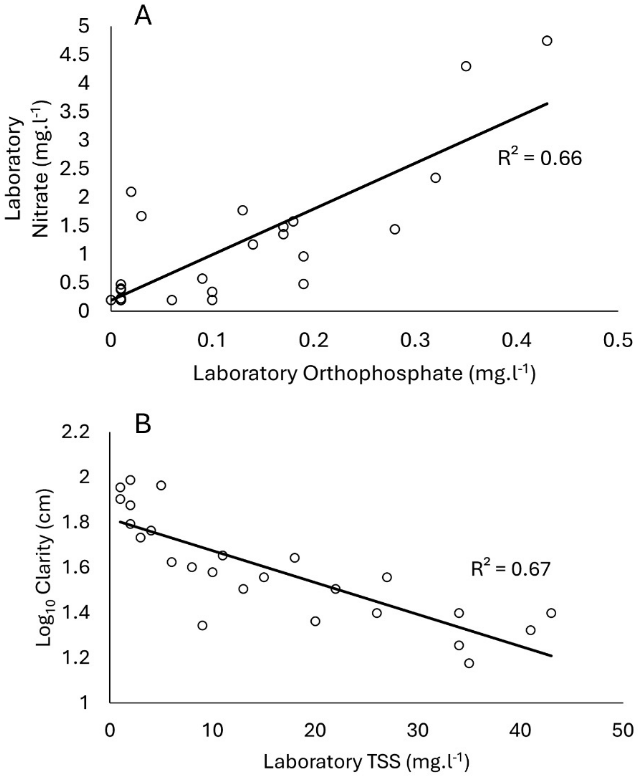

Figure 5. Plots of A) the laboratory measured concentration of nitrate (N) as a function of the laboratory measured concentration of orthophosphate, and B) the log10 transformed water clarity as a function of the laboratory measured concentration of TSS, for surface water samples. Linear regression lines are shown with the r2 indicated as a measure of goodness-of-fit.

DISCUSSION

The need to fill the data gaps in water quality monitoring worldwide is well-known. Many studies have come out over the past decade advocating for the investigating the use of citizen science for contributing meaningful water quality data (Amador-Castro et al. 2024; Babiso et al. 2023; Collins et al. 2023; Kelly-Quinn et al. 2023; Ramírez et al. 2023; de Sherbinin et al. 2021; Wu et al. 2023). This study investigated the utility of some of the most prominent smartphone-based citizen science water quality monitoring tools for water resource monitoring in southern Africa as a case study for the utility of such options in similar developing regions.

We investigated five smartphone apps. This narrow selection was based on a prior more thorough investigation of citizen science water quality monitoring options that evaluated and discussed numerous possibilities and existing technologies (Pattinson et al. 2023). Three were ruled out of use for citizen science monitoring of streams, rivers, and dams (specifically monitoring from the banks of waterbodies, with use on boats notwithstanding). The Hydrocolor and EyeOnWater apps cannot be used where the bottom of a water body is visible, which precludes their use in most instances where a citizen scientist will be measuring a stream, river, or dam from the bank. These apps warrant further investigation for monitoring via boats (Al-Ghifari et al. 2021; Ayeni and Odume 2020; Burggraaff et al. 2022; Leeuw 2014; Leeuw and Boss 2018; Malthus et al. 2020). The MQuant® StripScan app was ruled out based on an inability to procure the required reference cards as well as the fact that the app failed to read the reference card supplied for the nitrate test strip, even when attempted on four different devices. The Aquality app and the Nutrient App were tested for data collection in field by novice users.

The Aquality app

Qualitatively, we found several challenges to using the app in the field. Different lighting conditions noticeably affected the results, and it was unclear what the best lighting conditions should be or how to keep lighting conditions between samples at different locations at different times of day standardised. Anecdotally, we found that the nitrate concentrations estimated by the app could be up to 10x different based on being in bright sunlight (with the app sometimes failing to read at all in bright ambient light) versus shade, indicating the strong potential effects of lighting conditions on readings. This corroborates the findings of Topping and Kolok (2021), who also concluded that the app was prone to inaccuracy and imprecision when used by novel users in the field likely primarily based on variation in lighting conditions. We recommend that in the case where these types of apps are developed, the developers create more detailed guidelines and instructional videos (ideally understandable in multiple languages) to ensure that data are collected as consistently as possible by different users.

It is also worth noting that it was difficult and expensive to source the Hach© test strips in South Africa, which caused long delays in field testing (sourcing strips took over 2 months). Individual citizen scientists having to request a single reference card for the app for shipment globally might be a strong hindrance to citizen uptake, similar to sourcing the Hach© test strips. For such an app to really become feasible for globally upscaled use, their would ideally need to be an in-country supplier of both the test strips and the reference cards. Alternatively, organisations involved in monitoring could source the requisite materials and distribute them to specific projects.

The difficulty in sourcing the Hach© strips in southern Africa, paired with the cost of approximately R32,0 (USD 2) per strip, may prove prohibitive for using the Aquality app for a majority of potential citizen scientists in regions such as southern Africa (Benyei et al. 2023; Jönsson et al. 2024; Weingart and Meyer 2021). When contacted, the developers also recommended that getting three measurements and taking the average might generate more accurate results, but using three strips would then take the cost of a single reading to nearly R100,0 (USD 5). To put this into context, the monthly social grant paid to 19.7 million people in South Africa is R350,08 (USD 19), so weekly measurements in replicates to get an average would cost more than what a third of the population earns in an entire month from the social relief grant. This is not a flaw in the design of the app or a criticism, it is simply an observation on the limited accessibility of tools such as this that require ongoing input costs in the context of the socio-economic landscape of developing regions.

Quantitatively, the nitrate estimations, based on single measurements by novice users, from the Aquality app showed little to no correlation with laboratory measured nitrate concentrations, TSS, or water clarity in the surface water samples. We suspect this may reflect the variability introduced by variable lighting conditions in the field. The inaccuracy of the estimates may also arise from the conditions of the surface water tested in our study, which may differ from the laboratory or field based validations performed to develop the tool. The sediment load of the water tested can also affect the reading, so stream and river conditions in southern Africa that are often carrying high sediment loads may also reduce the utility of the app. In communication with the developers, they suggested filtering the water samples prior to testing in the case that the sediment load is high. It may be an interesting avenue for further research to determine the effects of filtering on the nitrate readings in both the app and paired laboratory tested samples.

Importantly, we had relatively few measurements that we specifically captured from diverse river conditions with varying levels of human impact. Several of the locations are known to have severe wastewater pollution issues, which may introduce variability in surface water conditions not encountered in the app development. Moreover, we used the apps as they are currently designed and following the guidelines as written to specifically test how they operate under the conditions they might be currently used by citizen scientists. However, it may prove useful to do more intensive study of the effect of different lighting conditions with multiple replicates of each measurement to get a better handle on precision and accuracy in different locations. Therefore, while we found no relationship between single app readings by novice users and the laboratory concentrations, our data are not conclusive and do not invalidate the calibrations used to develop the app. It is possible that a more consistent relationship may exist at specific sites, that more data would begin to show a clearer relationship, or that more stringently following the set of testing protocols used to develop the app measurement algorithm would lead to higher accuracy. Each of these are possibilities would be worth exploring and building into the apps use guidelines were appropriate.

Cumulatively, the qualitative lack of a correlation between the nitrate estimates from the app and the laboratory measured concentrations does raise the need for validation of the data collected by real, in-field citizen scientists using the app under different circumstances and in different locations. Our data are simply an indication that further validation and investigation are required. If the lack of a relationship here is replicated elsewhere with more intensive study, it will be a serious cause for concern for the utility of the app for water quality monitoring.

The positives of the app are that it is fairly intuitive and provides a neat data visualisation interface for seeing one's own data among all submissions globally. The Deltares Aquality support team for the app was also highly supportive and responsive, providing many reference cards for the app quickly when requested and information to follow up on all queries.

The Nutrient App

From a qualitative perspective, the Nutrient App was easy to use and comes with comprehensive training materials in both text and video format. The phosphate tests are also ~6x cheaper than the nitrate tests, which makes them far more accessible to citizen scientists. However, the app appears to no longer be maintained. The app does not connect to the online server database to upload, store, and visualise data on the global map, and is no longer available on the Google Play store. Like the Aquality app, we also found little to no correlation between the phosphate estimated by the Nutrient App and the laboratory measurements. In combination, these factors essentially rule out the Nutrient App as a potential option for citizen science water quality monitoring until the app is revitalised and validated for accuracy and precision when used by citizen scientists worldwide.

The current unmaintained status of the app is another example of how critical it is to build in a model for sustainability and maintenance support financing when developing tools and databases for citizen science. Without a framework in place for who will keep the technology running and up to date, as well as who will fund that maintenance or ongoing development, large time and money investments in promising tools and initiatives can end up stalling or being completely abandoned (Hulbert et al. 2019). This has already been the case for several promising initiatives, such as the Creek Watch app which helped people monitor various aspects of streams and rivers but was eventually discontinued (Kim et al. 2011). We encourage researchers and developers to co-engage with funding partners to develop a plan for the longevity of project outcomes so that tremendous efforts are not wasted. The onus is also not just on the researchers and developers. The case of the Nutrient App demonstrates the need for funding agencies to implement funding models that allow for financial support beyond short-term project completion dates.

Other water quality parameter correlations

The fact that we found no relationship between DO and laboratory measured concentration of nitrate or phosphate is understadable given that the relation between these parameters is complex, with them all interacting via various biological and physico-chemical processes (Liu et al. 2021; Ouma et al. 2020). A clear inverse relationship might be expected in cases of eutrophication, where algal blooms emerge in response to high nutrient loads and reduce DO (Akinnawo 2023; Wang, J. and Zhang 2020). However, at concentrations too low to elicit these blooms, the relationship is not always expected to be clear.

There was a strong correlation between the laboratory measured concentrations of nitrate and phosphate which was expected given that they often enter into freshwater systems together from agricultural run-off and wastewater (Akinnawo 2023; Frazar et al. 2019; Velusamy et al. 2021). This is a useful correlation to note where only nitrate or phosphate, but not both, can be measured within a freshwater system, since it suggests that indication of high levels of one will correspond to high levels of the other. In the case of the Aquality app, which does not measure phosphate, the nitrate measurements can be assumed to generally correlate to suspected high phosphate levels as well.

The correlation between TSS and water clarity was expected since it is well-established worldwide and has recently been validated in southern Africa (Graham, P. M. et al. 2024). The goodness-of-fit (r2 = 0.67) was similar to that found in previous studies, reiterating the usefulness of clarity tubes for generating citizen science estimates of TSS (Dahlgren et al. 2004; Graham, P. M. et al. 2024; Johnson et al. 2018; Kilroy and Biggs 2002).

CONCLUSIONS

There is a need to engage with citizen science to assist in meeting the SDG targets. The progress over the last decade, in particular, is promising, but the need for citizen science to be validated for its intended purpose remains paramount if citizen science data are going to be useful for reporting, management, and policy. After an investigation of several smartphone citizen science water quality monitoring apps, the only app that showed promise for further investigation in southern African streams, rivers, and dams was the Deltares Aquality app. The app is user friendly, fairly intuitive, and aims to contribute vital water quality data towards a global, open-source database. The development and support team are engaged, with the app showing real promise to help citizens engage with water resource monitoring. However, we found several issues with the cost of use and difficulty in procuring the required materials that may for significant barriers to implementation in the developing world, reinforcing the imbalance in where and by whom citizen science data are collected (Benyei et al. 2023; Capdevila et al. 2020; Harrisberg 2021; Jönsson et al. 2024; Lepheana et al. 2021; Pateman et al. 2021; Quinlivan et al. 2020b; Walker et al. 2020). Moreover, we found a concerning lack of a correlation between the nitrate estimates from the app, being used by novice users, and the concentrations of nitrate measured by an accredited laboratory. Again, we emphasise that this is based on relatively little data from only two users taking single measurements, but it certainly raises the need for the app's accuracy and precision to be validated for use in different contexts for the data to be trusted and useful. We recommend more targeted exploration of the validity of the app results when used by real citizen scientists in developing regions, and also recommend that more detailed guidelines are established specifically on the lighting conditions required so that results are standardised and comparable. Further explorations should increase the number of samples tested in replicate, test for site and season-specific relationships, and test for the effects of sedimentation and lighting.

Lastly, we will note that both the Aquality and Nutrient apps were primarily extractive (a trait shared by many such innovations), treating the citizen scientist performing the tests and using the apps as simple data collectors, without sufficient intuitive feedback on what the results mean or how they might be used in future. The potential for engagement with the citizen scientist and the sense of agency they might develop appears overlooked. Citizen science can be powerful vehicle for generating public awareness and empowerment, facilitating environmental education, increasing scientific literacy and environmental accountability, and creating relationships between the public and the authorities (Bonney et al. 2009; Capdevila et al. 2020; Carlson and Cohen 2018; Dörler et al. 2021; De Filippo et al. 2021; Queiruga-Dios et al. 2020). However, these benefits are accrued or maximised through active co-engagement with citizen scientists. The apps can make participation easy (Alender 2016; Scott and Frost 2017) but lack sufficient feedback to sustain input and foster the multiple benefits citizen science can elicit. A user, discovering that they generate an estimated nitrate concentration of, for example, 9.1 mg l-1 is not likely to find that this fact is intuitively meaningful. Is that normal, or indicative of pollution, one may ask? If it is indicative of pollution, what are the potential sources, and what can one do about it? Are the levels dangerous? Even simple feedback to the user on the meaning of their readings can go a long way to ensuring public buy-in and repeat engagement (Alender 2016). More complex feedback via gamification or information on how the data are being used in scientific research can be useful for engaging people and getting them to keep monitoring and contributing data (Ighalo et al. 2021; Khakpour and Colomo-Palacios 2021; Lowry et al. 2019; Lukyanenko et al. 2020; Morschheuser et al. 2017; Scott and Frost 2017). The vast majority of citizen science data (>80%) are contributed by a minority of people who become actively engaged and continually contribute data (August et al. 2020). Therefore, it is absolutely critical to consider the human participation and motivation element when designing citizen science tools to ensure that people are motivated to continuously engage. Feedback is crucial so that their levels of understanding and commitment to the citizen science can grow and develop. Citizen scientists can be demotivated if it is unclear as to what their data means or how those data will be used (Capdevila et al. 2020; Conrad and Hilchey 2011; Dörler et al. 2021; Rahnema 2020). We recommend that citizen science initiatives and tools specifically develop feedback mechanisms to maximise the benefit to the citizen scientists, rather than simply using them as data collection points. This will not only benefit the citizen scientists but will also work to build trust and increase the uptake and longevity of initiatives and tools whilst addressing potential technicist assumptions regarding utility and engagement.

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