Citizen meets social science: predicting volunteer involvement in a global freshwater monitoring experiment

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Abstract: FreshWater Watch is a global citizen science project that seeks to advance the understanding and stewardship of freshwater ecosystems across the globe through analysis of their physical and chemical properties by volunteers. To date, literature concerning citizen science has mainly focused on its potential to generate unprecedented volumes of data. In this paper, we focus instead on the data relating to the volunteer experience and ask key questions about volunteer engagement with the project. For example, we ask what factors influence: a) volunteer data submission following a training event and b) the number of water quality samples volunteers subsequently submit. We used a binomial model to identify the factors that influence the retention of volunteers after training. In addition, we used a generalized linear model (GLM) to examine the factors that affected the number of samples each citizen scientist submitted. In line with other citizen science projects, most people trained did not submit any data, and 1% of participants contributed 47% of the data. We found that the statistically significant factors associated with submission of data after training were: whether training was given on how to upload data, the number of volunteers that attended the training, whether the volunteer was assigned to a research team, the outside temperature, and the average engagement of others in the training group. The statistically significant factors associated with the quantity of data submitted were: the length of time volunteers were active in the project, whether training took place as part of a paid work day, the difficulty of the sampling procedure, how socially involved volunteers were in the project, average sampling group size, and engagement with online learning modules. Based on our results, we suggest that intrinsic motivation may be important for predicting volunteer retention after training and the number of samples collected subsequently. We suggest that, to maximize the contribution of citizen science to our understanding of the world around us, there is an urgent need to better understand the factors that drive volunteer retention and engagement.
Key words: citizen science, volunteer engagement, participation, training, freshwater monitoring

Citizen science brings together scientists and volunteers, who then collaborate to generate knowledge about real-world issues (Bonney et al. 2009). The ability of citizen science to generate data that contribute to our understanding of the environment over broad temporal and spatial scales that transcend national (North American Lake Management Society 2017), cultural (Braschler 2009), and in the case of Zooniverse, planetary (Raddick et al. 2013) bound-

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aries is now widely recognized (Silvertown 2009, Thornhill et al. 2016). However, the social elements that drive participation, and underpin these projects, remain relatively underexplored (Geoghegan et al. 2016). A review of 888 papers including the term 'citizen science' in 2015 found that only 3% covered motivations of participants (Follett and Strezov 2015). Since then, more studies have explored motivations of participants, usually through questionnaires. These studies have found that some of the important motivators are a desire to contribute to science, to help the environment (e.g., Hobbs and White 2012, Raddick et al. 2013, Alender 2016, Domroese and Johnson 2017), or to learn (e.g., Domroese and Johnson 2017). In addition, some studies (such as Domroese and Johnson 2017) have found that social factors, such as a desire to participate with family or friends, are much less important motivators for most participants. Some of the factors associated with sustained participation, aside from ensuring motivations are met, include giving timely feedback, good communication, providing opportunities for social interaction, and rewarding participants (West and Pateman 2016). As the involvement of volunteers in traditional scientific pursuits becomes more commonplace, it is imperative that the social factors that encourage continued participation are better understood. This understanding will lead to longer-term and more fulfilling volunteer engagement with science (Wright et al. 2015), as well as higher quality datasets.

FreshWater Watch (FWW) is a citizen science project that was established in 2012 as part of the HSBC Bank's Water Program (HWP). The goal of FWW is to identify causes behind the loss of freshwater quality and to promote freshwater sustainability (HSBC 2016). Within the HWP, the Earthwatch Institute and their partners trained more than 8000 volunteers to use standardized water quality methods, with additional information collected depending on the locally important research question (Fig. 1). This global-local approach has resulted in a suite of published research (e.g., Castilla et al. 2015, Cunha et al. 2016, Loiselle et al. 2017) and local impacts such as the identification of point pollution sources and contributions to management plans (Earthwatch Institute 2017). However, as with many other citizen science projects, few attempts have been made to consider the factors that affect volunteer participation.

The supply of freshwater is widely recognized as an ecosystem service crucial to human existence, but freshwater systems are among the most degraded ecosystems on earth, principally because of human activities (Dudgeon et al. 2006, Vörösmarty et al. 2010). The need to protect, maintain, and enhance the provision and quality of freshwater is widely acknowledged (Millenium Ecosystem Assessment 2005, Griggs et al. 2013). Further, it is likely that the dominant pressures facing freshwater today will intensify rather than diminish, given the combined effects of population growth and climate change.

Our understanding of the global extent of water quality deterioration is limited by a lack of freely available data, an absence of standardized sampling techniques, and inconsistent monitoring across spatial and temporal scales (Revenga et al. 2005), even though water quality monitoring at the regional scale can be intensive. At present, water quality data produced by citizen science programs have been recommended as a complement to nutrient data collected by governments across London, UK (Hadj-Hammou et al. 2017) and for assessing post-ecological restoration success (Huddart et al. 2016, Yardi et al. 2019 *this issue*), suggesting that citizen science could be part of a solution to the global monitoring challenge. However, an understanding of which factors drive engagement or disengagement with citizen science

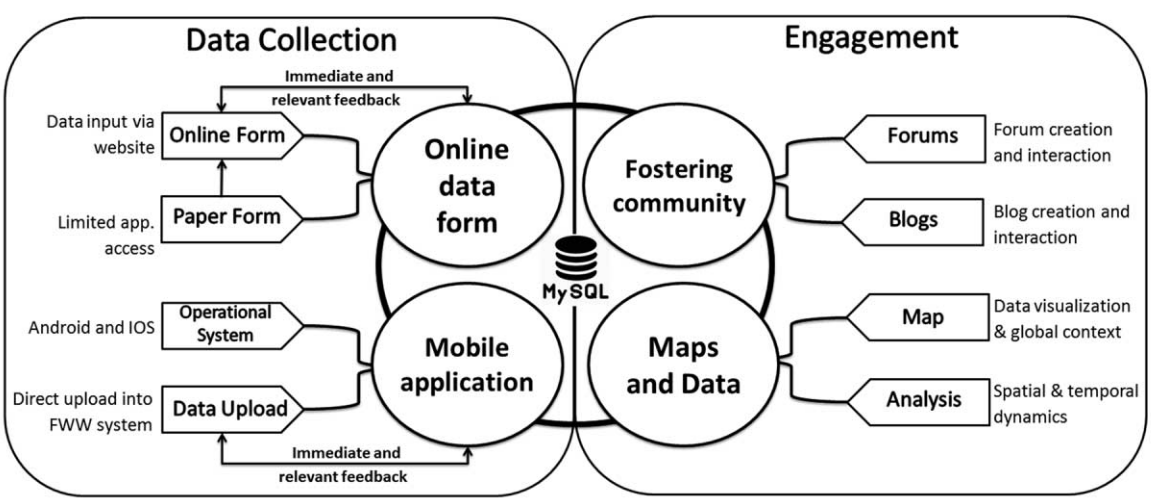

Figure 1. Schematic of the FreshWater Watch project for engagement and scientific data collection.

projects is needed so that projects can develop effective engagement strategies that maximize participation (Geoghegan et al. 2016).

Important and under-studied questions about volunteers include: how do people engage with a project over time and what influences their participation? These questions are important because recruiting volunteers and training them is often time-consuming and expensive (West and Pateman 2016). Maintaining volunteer engagement in citizen science initiatives is known to be challenging because retention is often low and the majority of data is typically generated by few participants (Worthington et al. 2012, Lakeman-Fraser et al. 2016). We, therefore, used FWW engagement data to identify which factors predict: a) whether people went on to submit records post training, and b) their subsequent sampling effort. We include factors specific to the training, the sampling protocol, social interaction through the FWW online platform, and the nature of the sampled environments. This level of detail is unusual, because access to such information generated by citizen science projects is rarely accessible (West et al. 2016).

METHODS

We used data on the participation of 7413 FWW citizen scientists from 13 countries who were trained to participate in the HWP. Participants used a standardized FWW method with the addition of 1 of 25 protocols that varied in the technologies used, site selection procedures, sampling regularity, and degree of coordination (see Loiselle et al. 2016 and Thornhill et al. 2018 for further details). Participants were recruited through an internal promotion campaign within the HSBC bank. We focused on participants who were trained between 10 September 2012 and 29 November 2016, with the 1st sample submitted 14 November 2012 and the last on 25 May 2017. Consequently, all study participants had the opportunity to take part in FWW for at least 6 months after their initial training. We included sampling period in our model of participant contribution because of the variation in time that volunteers spent in the project. Staff members and principal investigators were removed from the dataset to avoid sampling bias, and because our interest was in the volunteers. A range of explanatory variables was used in the model of participant retention and participant data contribution (see below). We selected these variables from a limited set of data available from across all FWW sites globally and included variables that describe the types of support given during training, social factors, sampling context (e.g., water quality and difficulty), and others. The country in which sampling and training took place was not included in the model due to high covariance with a number of other variables that were specific to the locally important question being investigated. All analyses were done in R (version 3.3.2; R Project for Statistical Computing, Vienna, Austria) and we used the package *effects* to visualize model coefficients (Fox 2003, Fox and Hong 2009). This study was developed during the Freshwater and Citizen Science Research Hackathon, Oxford (25th to 27th May 2017). The hackathon (or Research Derby) is an intensive, collaborative event, during which all attendees provided critique and refinement to a range of research ideas based around a theme (Favaro et al. 2013).

Training factors that correlate with participant retention

Prior to gathering and submitting data, all FWW participants took part in a 1-d training event (406 training events in total), which included introductions to key ecosystem concepts and freshwater issues, as well as practical sessions that demonstrated how to follow the chosen sampling protocol. Social factors, such as the number of people at each training session, varied among locations. We assessed which factors predicted whether training participants moved from trainee to active sampler (i.e., a participant who submits a sample to FWW) with a binomial model where the successful transition (from trainee to sampler) was the binary response variable. We selected explanatory variables that characterized the amount of support and training provided on training day, the engagement of the other attendees, and the weather on training day. Thus, we included the variables: transport provision to the training day (*Transport Provided*), training to upload data to the FWW platform (*Upload training*), the number of attendees on the training day (*Attendees*), whether the training was on a paid work day (*Work Day*), whether the participant was assigned to a research team (*Team*), average air temperature on the training day (*Temp*), and average rainfall (*Rainfall*) on the training day (Kemp et al. 2012; see Table S1). We also included the average (mean) number of points subsequently earned on the FWW platform by the training day participants (*Team points*). This variable related to the gamified aspect of the FWW platform where participants gained points (0–50 per activity) through sampling, blogging, completion of learning modules, and presenting to external audiences. Points could differ for each activity depending on special events or promotions (e.g., taking part in a water blitz).

We tested explanatory variables for collinearity, and some correlations were found (max $r = 0.52$), but these were unimportant according to variance inflation factors calculated after the analysis (Fox and Weisberg 2011). All covariates were, therefore, included in our model. The variable *Team points* was natural log-transformed to lessen the effect of 3 outliers with very large values. No other variable was transformed.

Factors that correlate with participant contribution to data collection

We used the subset of volunteers who uploaded ≥1 water quality sample ($n = 1510$) to identify factors that predict the amount of data a volunteer will submit. Here, the response variable was the natural log of the number of samples submitted. For this model, we chose explanatory variables that characterized the level of engagement with the project outside of sampling, the attractiveness of the site in terms of water quality, and elements of the training received. In particular, we included the variables: the number of days elapsed between training and last sample date (*Sampling period*) to account for variation attributable to the time involved in the project. The other variables considered were: (*Work day*, as above), the median number of people recorded as taking part in each sample (*Attendees*), the number of learning modules completed on the FWW platform (*Learning*), observed water quality related to the presence of point discharges and water discoloration (e.g., brown water or algal blooms) (*WQO*), water quality related to catchment intensification (e.g., cropland or impermeable surfaces; Latham et al. 2014) (*WQC*), and measured nutrient status (*WQM*). In addition to these variables, we added 2 metrics that were derived from 2 sets of variables. First, we created a score based upon the difficulty of the local sampling protocol (*Difficulty*). This metric used axis scores from a principal component analysis (PCA) on the time required to complete sampling, equipment bulkiness, the equipment complexity, and the amount of processing needed (e.g., writing labels, posting samples, etc.). These variables are highly correlated, and as a result the 1st PCA axis accounted for 94% of the variation. The 2nd composite metric was a communication category based on the participants' social interactions on the FWW platform (*Communication*). This metric captures the involvement of a participant in social elements of the project and is the sum of blogs written, comments made on blogs or forums, invitations sent to work colleagues to get involved, the number of shares via social media, and presentations made to non-FWW audiences. To account for the amount of time a participant had been involved with the project, each component of *Communication* was converted to a weekly rate and normalized between 0 and 1, before all components were summed to get the total communication score. The resulting metric is highly skewed, so the score was used to place participants into 3 categories (see Table S1). We then used a GLM to test the effects of these covariates on the natural log number of samples collected. Based on examination of residual plots, the use of the natural log number of samples resulted in a better model fit than when we fit the non-transformed data to Poisson or negative binomial models.

RESULTS

Approximately ⅔ of all FWW participants were trained as part of 25 local HWP projects between September 2012 and May 2017. Over 20% (1510) of the 7413 participants contributed at least 1 sample, whereas more than ½ (57.9%) engaged in some way with the FWW platform (e.g., by blogging or completing quizzes). Just 3 (<1%) of all training events (n = 406) resulted in no further participation, either through interactions with the platform or taking samples. Sixty-five super-users each submitted more than 20 samples. Taking 20 samples is equivalent to sampling 5 sites on a quarterly basis for 1 y or sampling 1 site quarterly for 5 y. The top 1% of contributors collected 47% of the samples, which reflects the long tail observed in the number of samples contributed per user (Fig. 2).

Training factors that correlate with participant retention

Of the variables included in the binomial model to predict volunteer transition from trainee to sampler (Table 1, Fig. 3A–E), 5 were significant. However, the model explained a small amount of the overall deviance (10%), so there are almost certainly other important drivers of participant retention, which we did not record. The retention rate was positively associated with participants receiving training to upload data (*Upload training*, Fig. 3A), assigning participants to a research team for the sampling (*Team*, Fig. 3B), and with the average number of points scored by fellow training day participants (*Team points*; Fig. 3E). Negative associations included the number of people that attended the training event (*Attendees*, Fig. 3C) and the temperature (i.e., transition success declined with increasing temperature; *Temp*, Fig. 3D). Removing outliers with high values of *Team points* did not affect the results.

Factors that correlate with participant contribution to data collection

After removing people who submitted no data after training, we looked for covariates that explained variation in the number of samples collected by 1510 FWW participants. We found 6 statistically significant variables (*Work day*, *Communication*, *Sampling period*, *Attendees*, *Difficulty*, and *Learning*) based on the general linear model (Table 2,

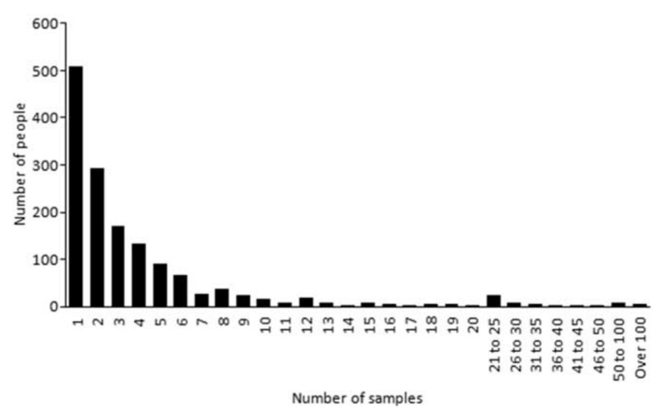

Figure 2. Frequency distribution of the number of samples collected by FreshWater Watch participants (n = 1510).

Table 1. Results of an analysis of factors associated with participant retention after training events in the FreshWater Watch project. The 5 significant variables are in bold; SE = standard error; *Temp* = temperature.

Variable	Estimate	SE	*z*-value	Pr(>|*z*|)
(Intercept)	−0.564	0.145	−3.88	<0.001
Work day	0.086	0.099	0.87	0.38
Transport provided	−0.089	0.081	−1.10	0.27
Upload training	**0.638**	**0.075**	**8.45**	**<0.001**
Attendees	**−0.032**	**0.005**	**−6.87**	**<0.001**
Team points	**0.335**	**0.017**	**20.30**	**<0.001**
Team	**1.282**	**0.109**	**11.81**	**<0.001**
Temp	**−0.021**	**0.005**	**−4.10**	**<0.001**
Rain	−0.14007	0.104687	−1.34	0.18

Fig. 4A–F). Participants submitted more samples if they were involved in the project for longer, undertook more difficult sampling, communicated more online about the project, or completed more learning modules on FWW. Participants submitted fewer samples if they attended a paid training day (rather than attending on their own time), and if they went sampling in larger groups. However, the model explained a small amount of the overall deviance (15%).

DISCUSSION

Volunteer retention

Our statistical model of participant retention indicates that volunteer involvement depends on aspects of the training received and the extent of project management and coordination. Practical elements of training, such as receiving hands-on training on uploading data or being assigned to a research team, lowered the barriers to ongoing involvement

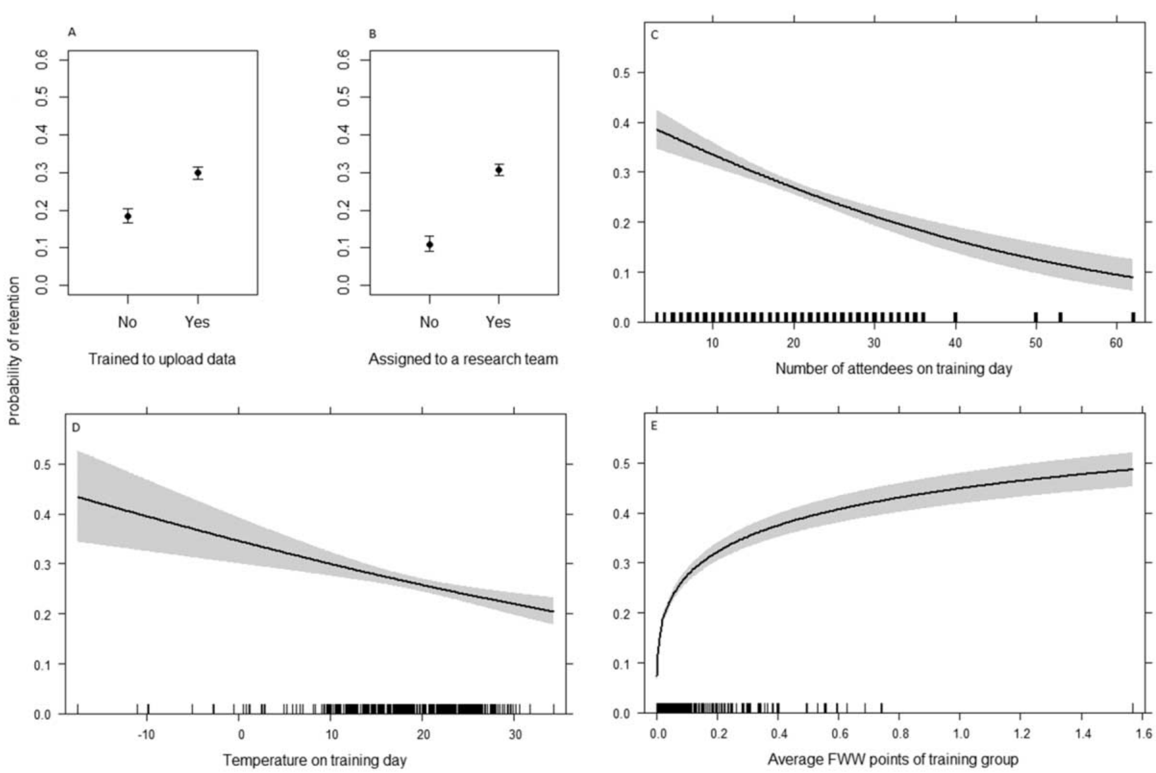

Figure 3. Response plots of significant associations between covariates and the probability of participant retention post-training: *Upload training* (A), *Team* (B), *Attendees* (C), *Temp* (D), and *Team points* (E). Estimates are given with 95% confidence intervals. Rug identifies distribution of data.

Table 2. Results of an analysis of factors associated with the number of samples submitted by participants in the FreshWater Watch project. The model intercept and 6 significant variables are in bold. SE = standard error; *WQC* = water quality related to catchment intensification; *WQO* = observed water quality; *WQM* =

Variable	Estimate	SE	*t*-value	Pr(>|*t*|)
(Intercept)	**7.37E–01**	**1.64E–01**	**4.495**	**<0.01**
Sampling period	**6.14E–04**	**8.25E–05**	**7.438**	**<0.01**
Work day	**−4.22E–01**	**6.60E–02**	**−6.391**	**<0.01**
Attendees	**−1.43E–02**	**5.69E–03**	**−2.518**	**0.01**
Difficulty	**5.26E–02**	**1.65E–02**	**3.19**	**<0.01**
Communication	**3.88E–01**	**4.19E–02**	**9.263**	**<0.01**
Learning	**9.25E+00**	**3.07E+00**	**3.013**	**<0.01**
Team	−9.88E–02	8.05E–02	−1.228	0.21983
WQC	3.46E–04	2.19E–02	0.016	0.98739
WQO	−3.34E–02	2.26E–02	−1.475	0.1405
WQM	2.17E–02	2.21E–02	0.981	0.32676

in the project and led to greater volunteer retention. Being part of a small training group also led to greater volunteer retention. The positive influence of working as part of a team that we observed here reflects the success realized through the practice of Team Based Learning (TBL; Parmelee and Michaelsen 2010). Within FWW, the structured, interactive, and outcome-oriented design of the training day fits recommendations for the successful implementation of TBL (Parmelee and Michaelsen 2010), which could be undermined where, for example, group sizes exceed single figures (Michaelsen et al. 2004, Willett et al. 2011). In addition, the result we found here, that there is a positive effect of gaining a full hands-on experience that includes both FWW sampling practice (delivered as standard) as well as data upload, agrees with a study of volunteer participation in the Monarch Larva Monitoring Project that suggested hands-on practice is probably the optimum way to develop accurate data collection strategies (Oberhauser and Prysby 2008). Similarly, Krasny and Bonney (2005) identify a number of case studies that employ hands-on approaches to enrich environmental education.

Being a member of a training group whose members went on to be more active in the FWW project also predicted higher retention. This association may have emerged if training with engaged peers leads to others becoming more engaged (Alender 2016, Laut et al. 2017). Alternatively, people predisposed to engage with the project because of their personal motivations may have been more likely to attend training events with like-minded people. The positive influence of peers suggests the possibility of a shift to a more sustainable form of citizen science that would require less top-down coordination and instill greater ownership of the project in its participants (Wildschut 2017).

The negative effect of increasing temperature requires further analysis but could be driven by the few training events carried out at very low temperature (see data distribution indicated by the ‘rug’; Fig. 3D). Trainees that attend events in spite of adverse conditions may be more intrinsically motivated and may form stronger team bonds.

Participant contributions

The factors that were correlated with the number of samples a participant submitted suggest that intrinsic motivation or personal ideology may be important. Intrinsic motivations are internal personal rewards, such as a desire to aid in conserving wildlife, or the enjoyment gained from engaging with science (Geoghegan et al. 2016). People who undertook more difficult sampling, attended a training event on their own time (i.e., at a weekend), and sampled in small groups were more likely to submit large numbers of samples and, therefore, were probably intrinsically motivated. However, further research involving participant surveys will be needed to confirm this. Intrinsic motivations have been shown to increase the quantity of data contributed by citizen scientists (Stewart and Gosain 2006, Nov et al. 2014). Users who submitted many samples were also more likely to engage with the website by, for example, writing blogs or completing online learning. This correlation suggests that those users that engage with the website are not a different set of users to those who submit data.

Contrary to other studies regarding citizen science (e.g., Devictor et al. 2010, Pocock et al. 2014), we found little evidence to suggest that complex tasks (relative to the range of tasks within this study) deterred participation. Instead, higher technical complexity was correlated with higher levels of data generation. Higher levels of complexity in FWW may allow volunteers to gain a deeper understanding of freshwater systems, thus, providing intellectual stimulation over a longer period of time as suggested by several authors (Cooper et al. 2007, Tweddle et al. 2012). However, simplifying volunteer tasks serves other purposes, such as main-

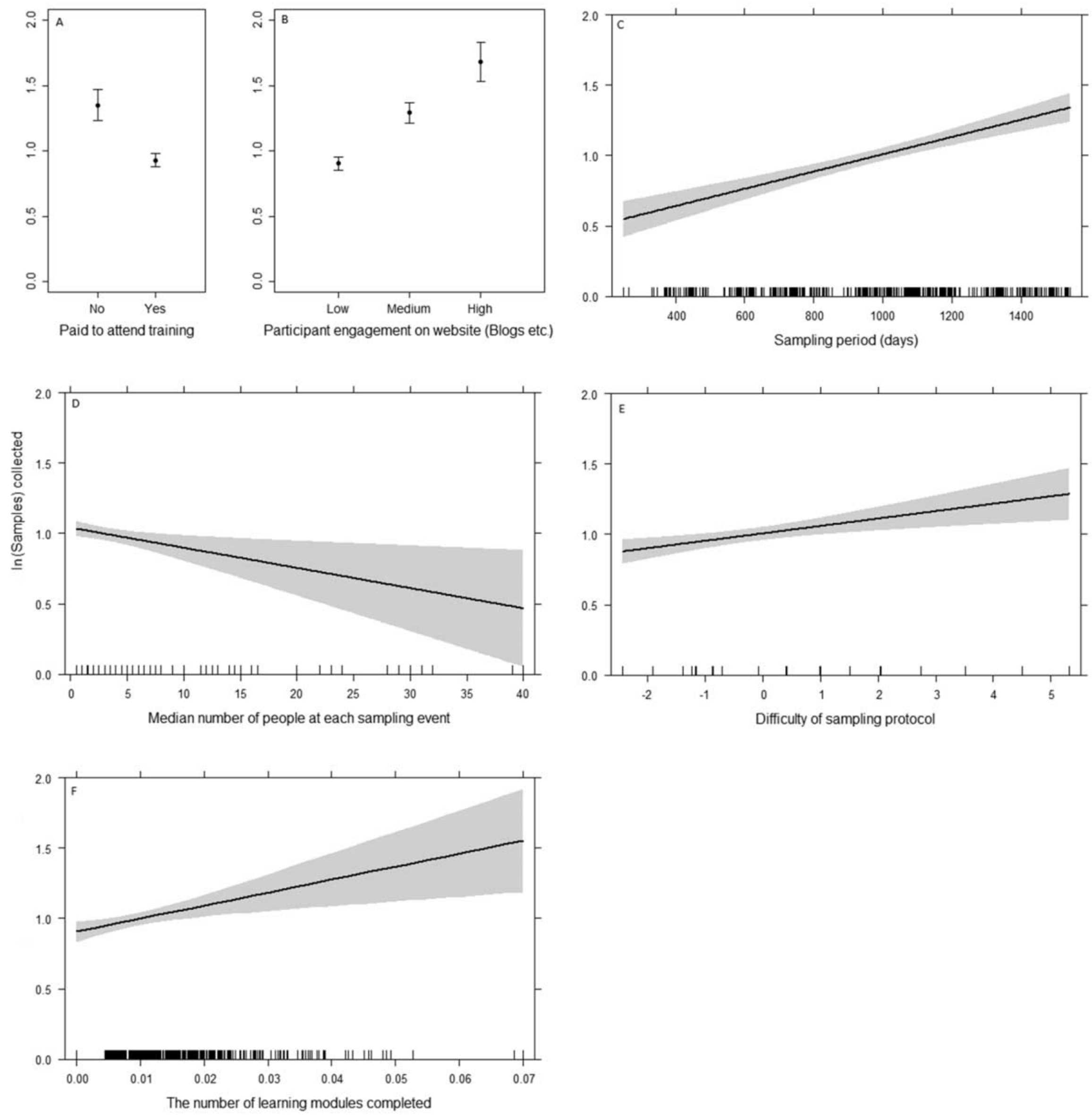

Figure 4. Response plots of significant associations between covariates and the natural log of the number of samples a participant contributes: *Work day* (A), *Communication* (B), *Sampling period* (C), *Attendees* (D), *Difficulty* (E), and *Learning* (F). Estimates are given with 95% confidence intervals. Rug identifies the distribution of data.

taining data quality and potentially exposing volunteers to fewer health and safety concerns (Iannone et al. 2012, Pocock et al. 2014).

The FWW platform is gamified to recognize participant achievements and promote friendly competition by including elements such as leaderboards and points awarded for science (i.e., sampling), communication (e.g., blogs), and skills (learning). The effect of gamification upon volunteer involvement cannot be differentiated from intrinsic or extrinsic motivations in the present study. However, the expectation that gamification is always positive is unrealistic, and it may appeal more to particular groups, such as millennials (Bowser et al. 2013). The effect of gamification on volunteer engagement is challenging to generalize when participants react both positively and negatively (Eveleigh et al. 2013, Massung et al. 2013). Thus, while gamification is probably 1 in a set of components designed to attract and sustain participation, further research is required (Greenhill et al. 2014).

The long tail of participation

We found that a small percentage of volunteers, 1%, contributed 47% of the data. This observation fits with the 'long tail of participation' that is often found in citizen science projects and other schemes where people upload data (e.g., Boakes et al. 2016). A study of participation in the Zooniverse crowdsourcing citizen science platform, for example, found that the top 10% of contributors did 79% of the work (Sauermann and Franzoni 2015), compared with 89% across FWW. Differences in the tail occurred across different FWW project locations (e.g., Toronto; Scott and Frost 2017) where 50% of the samples were collected by 5% of participants.

The majority of volunteers trained (80%) did not participate in water quality monitoring beyond their training event. Most citizen science projects do not publish figures about the amount of data collected. One exception is Evolution MegaLab, where only 38% of >6000 registrations submitted data (Worthington et al. 2012). Another exception is the Open Air Laboratory (OPAL) project, where around 10% of survey packs distributed to volunteers are returned with data (Lakeman-Fraser et al. 2016). Of the participants who did submit FWW samples, 508 submitted only 1 sample (34%), which is comparable to participation in Galaxy Zoo (crowdsourcing classification of images), where only 27% of users return to the project after their 1st time on the site (Sauermann and Franzoni 2015). FWW, therefore, does not seem to be exceptional in its low rate of volunteer retention when compared to other citizen science initiatives.

Other projects report higher levels of data submission than FWW. For example, SoundCitizen, a water sampling project in Puget Sound, USA, had 60% of samples returned in the 1st year (Kimball et al. 2009). This difference may reflect the recruitment channel, because SoundCitizen invited local members of the public to apply for an online kit, whereas FWW participants under the HWP were corporate volunteers that could train as part of their work duties. Higher rates of return may also be expected if projects have clear regulatory buy-in and endorsement. For example, the Angler's Riverfly Monitoring Initiative engages with >2000 active volunteers that monitor biological quality on a monthly basis, and has an agreement with the Environment Agency (UK) such that when the monitoring scores are low enough the cause is investigated by officials (Huddart et al. 2016, Brooks et al. 2019 *this issue*).

Implications for project design

Measham and Barnett (2008) found that if volunteer motivations for participating in environmental volunteering projects are met, they are more likely to stay engaged. If motivations are not fulfilled and volunteers leave, however, new people need to be recruited and trained to maintain the quantity of data being submitted, which can be time-consuming and expensive (West and Pateman 2016). Volunteer participation is highly variable, and our models explain only a relatively small amount of the variation seen in our dataset. Still, we propose the following recommendations in relation to volunteer training and long-term engagement.

Training For citizen science projects that require training sessions for participants, we recommend the following:

1. Assign participants to teams (e.g., research or monitoring) and provide opportunities for them to form a social network after the training day.
2. Deliver training sessions to groups of ≤10 individuals. If necessary, break down larger attendances into subgroups to encourage peer-to-peer interaction.
3. Ensure training covers different methods of uploading data collected by citizen scientists and give trainees an opportunity to practice data entry.
4. Try to balance attendance at training days between participants with higher and lower levels of intrinsic motivation. Balance may be achieved by gathering information during training registration or initial expressions of interest.

Volunteer involvement To increase the likelihood of greater quantity of data generated by project participants, we recommend the following:

1. Make space within the project for social interactions to occur, as this may increase the sustainability of the citizen science project, with lower levels of volunteer drop-out.
2. Include complex tasks (as well as simple) that may stimulate highly motivated participants and encourage them to participate for longer periods of time.
3. Identify which participants are contributing the bulk of the data and ensure their resource needs are met and that opportunities exist for higher levels of engagement with the project.
4. Build in opportunities for participants to learn about the topic through quizzes or other learning resources.

Conclusions

We conclude that factors associated with training and sampling, both practical and social, significantly affected the retention of citizen scientists and their contribution to the FreshWater Watch (FWW) project. We have identified several practical considerations to any individual or organization embarking upon a new project. Our results transcend FWW, and emphasize the need for the organizers of citizen science projects to invest time in identifying which volunteers contribute to the effort, how they stay involved with the project, and why they stay involved. Identifying these factors will make it possible to engage more effectively with participants and to lay the foundations for sustainable citizen science that provides both the data necessary for research and fulfillment for its participants. In addition, a deeper understanding these factors will lead to more cost-effective recruitment and training, and a better return on investment.

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LITERATURE CITED

Alender, B. 2016. Understanding volunteer motivations to participate in citizen science projects: a deeper look at water quality monitoring. Journal of Science Communication 15:1–19.

Boakes, E. H., G. Gliozzo, V. Seymour, M. Harvey, C. Smith, D. B. Roy, and M. Haklay. 2016. Patterns of contribution to citizen science biodiversity projects increase understanding of volunteers' recording behaviour. Scientific Reports 6:33051.

Bonney, R., C. B. Cooper, J. Dickinson, S. Kelling, T. Phillips, K. V. Rosenberg, and J. Shirk. 2009. Citizen science: a developing tool for expanding science knowledge and scientific literacy. BioScience 59:977–984.

Bowser, A., D. Hansen, Y. He, C. Boston, M. Reid, L. Gunnell, and J. Preece. 2013. Using gamification to inspire new citizen science volunteers. Pages 18–25 *in* L. E. Nacke (editor). Proceedings of the First International Conference on Gameful Design, Research, and Applications – Gamification '13. ACM Press, New York.

Braschler, B. 2009. Successfully implementing a citizen-scientist approach to insect monitoring in a resource-poor country. BioScience 59:103–104.

Brooks, S. J., B. Fitch, J. Davy-Bowker, and S. A. Codesal. 2019. Anglers' Riverfly Monitoring Initiative (ARMI): a UK-wide citizen science project for water quality assessment. Freshwater Science 38:270–280.

Castilla, E. P., D. G. F. Cunha, F. W. F. Lee, S. Loiselle, K. C. Ho, and C. Hall. 2015. Quantification of phytoplankton bloom dynamics by citizen scientists in urban and peri-urban environments. Environmental Monitoring and Assessment 187:690.

Cooper, C. B., J. Dickinson, T. Phillips, and R. Bonney. 2007. Citizen science as a tool for conservation in residential ecosystems. Ecology and Society 12:1–11.

Cunha, D. G. F., J. Fernandes Marques, J. Cristina de Resende, P. Bortoletto de Falco, C. Melina de Souza, and S. Loiselle. 2016. Citizen science participation in research in the environmental sciences: key factors related to projects' success and longevity. Anais da Academia Brasileira de Ciências 89:2229–2245.

Devictor, V., R. J. Whittaker, and C. Beltrame. 2010. Beyond scarcity: citizen science programmes as useful tools for conservation biogeography. Diversity and Distributions 16:354–362.

Domroese, M. C., and E. A. Johnson. 2017. Why watch bees? Motivations of citizen science volunteers in the Great Pollinator Project. Biological Conservation. 208: 40–47.

Dudgeon, D., A. H. Arthington, M. O. Gessner, Z.-I. Kawabata, D. J. Knowler, C. Lévêque, R. J. Naiman, A.H. Prieur-Richard, D. Soto, M. L. J. Stiassny, and C. A. Sullivan. 2006. Freshwater biodiversity: importance, threats, status and conservation challenges. Biological Reviews of the Cambridge Philosophical Society 81:163–82.

Earthwatch Institute. 2017. Water: our precious resource. A report on the impact of five years of FreshWater Watch. Earthwatch, Oxford, UK. (Available from: https://www.thewaterhub.org/sites/thewaterhub/files/doc/EW_FreshWaterWatch_WEB.pdf)

Eveleigh, A., C. Jennett, S. Lynn, and A. L. Cox. 2013. "I want to be a captain! I want to be a captain!" Pages 79–82 *in* L. E. Nacke (editor). Proceedings of the First International Conference on Gameful Design, Research, and Applications – Gamification '13. ACM Press, New York.

Favaro, B., D. C. Braun, and the Earth2Ocean Research Derby. 2013. The "Research Derby": a pressure cooker for creative and collaborative science. Ideas in Ecology and Evolution 66:40–46.

Follett, R., and V. Strezov. 2015. An analysis of citizen science based research: usage and publication patterns. PLoS ONE 10:e0143687.

Fox, J. 2003. Effect displays in R for generalised linear models. Journal of Statistical Software 8:1–27.

Fox, J., and J. Hong. 2009. Effect displays in R for multinomial and proportional-odds logit models: Extensions to the effects package. Journal of Statistical Software 32:1–24.

Fox, J., and S. Weisberg. 2011. An R companion to applied regression. SAGE Publications, Los Angeles, California.

Geoghegan, H., A. Dyke, R. Pateman, S. West, and G. Everett. 2016. Understanding motivations for citizen science. Final report on behalf of UK Environmental Observation Framework. (Available from: http://www.ukeof.org.uk/resources/citizen-science-resources/MotivationsforCSREPORTFINALMay2016.pdf)

Greenhill, A., K. Holmes, C. Lintott, B. Simmons, K. Masters, J. Cox, and G. Graham. 2014. Playing with science: gamised aspects of gamification found on the Online Citizen Science Project – Zooniverse. Pages 15–24 *in* P. Dickinson (editor). GAME-ON 2014, 15th International Conference on Intelligent Games and Simulation. EUROSIS-ETI, University of Lincoln, Lincoln, UK.

Griggs, D., M. Stafford-Smith, O. Gaffney, J. Rockström, M. C. Öhman, P. Shyamsundar, W. Steffen, G. Glaser, N. Kanie, and I. Noble. 2013. Policy: sustainable development goals for people and planet. Nature 495:305–307.

Hadj-Hammou, J., Loiselle, S., Ophof, D. and Thornhill, I., 2017. Getting the full picture: Assessing the complementarity of citizen science and agency monitoring data. PloS ONE 12: e0188507.

Hobbs, S. J. and P. C. L. White. 2012. Motivations and barriers in relation to community participation in biodiversity recording. Journal of Nature Conservation, 20:364–373.

HSBC. 2016. The HSBC Water Programme. London, UK. (Available from: https://www.thewaterhub.org/)

Huddart, J. E. A., M. S. A. Thompson, G. Woodward, and S. J. Brooks. 2016. Citizen science: from detecting pollution to evaluating ecological restoration. WIREs Water 3:287–300.

Iannone, B. V., L. G. Umek, D. H. Wise, and L. Heneghan. 2012. A simple, safe, and effective sampling technique for investigating earthworm communities in woodland soils: implications for citizen science. Natural Areas Journal 32:283–292.

Kemp, M. U., E. Emiel van Loon, J. Shamoun-Baranes, and W. Bouten. 2012. RNCEP: global weather and climate data at your fingertips. Methods in Ecology and Evolution 3:65–70.

Kimball, B., A. Myers-Pigg, T. Clay, J. Neibauer, and R. Keil. 2009. SoundCitizen: students and citizens conducting environmental science together. Pages 1–4 *in* Proceedings from the NAAEE Research Symposium, Portland, Oregon, October 7–10.

Krasny, M. E., and R. Bonney. 2005. Environmental education through citizen science and participatory action research. Pages 292–320 *in* E. A. Johnson and M. J. Mappin (editors). Environmental education and advocacy: changing perspectives of ecology and education. Cambridge University Press, Cambridge, UK.

Lakeman-Fraser, P., L. Gosling, A. J. Moffat, S. E. West, R. Fradera, L. Davies, M. A. Ayamba, and R. van der Wal. 2016. To have your citizen science cake and eat it? Delivering research and outreach through Open Air Laboratories (OPAL). BMC Ecology 16:S16.

Latham, J., R. Cumani, I. Rosati, and M. Bloise. 2014. FAO Global Land Cover (GLC-SHARE) Beta-Release 1.0 Database. (Available from: http://www.fao.org/geonetwork/srv/en/main.home?uuid=ba4526fd-cdbf-4028-a1bd-5a559c4bff38)

Laut, J., F. Cappa, O. Nov, and M. Porfiri. 2017. Increasing citizen science contribution using a virtual peer. Journal of the Association for Information Science and Technology 68:583–593.

Loiselle, S., D. Gasparini Fernandes Cunha, S. Shupe, E. Valiente, L. Rocha, E. Heasley, P. P. Belmont, and A. Baruch. 2016. Micro and macroscale drivers of nutrient concentrations in urban streams in South, Central and North America. PLoS ONE 11: e0162684.

Loiselle, S. A., E. Turak, I. Thornhill, and P. C. Frost (editors). 2017. Citizen science providing insights into freshwater ecosystem dynamics (Special issue). Science of The Total Environment. (Available from: https://www.sciencedirect.com/journal/science-of-the-total-environment/special-issue/10LXJ6J513J)

Massung, E., D. Coyle, K. F. Cater, M. Jay, and C. Preist. 2013. Using crowdsourcing to support pro-environmental community activism. Pages 371–380 *in* S. Bødker, S. Brewster, P. Baudisch, M Beaudouin-Lafon, and W. Mackay (editors) Proceedings of the 31st Annual CHI Conference on Human Factors in Computing Systems.

Measham, T. G., and G. B. Barnett. 2008. Environmental volunteering: motivations, modes and outcomes. Australian Geographer 39:537–552.

Michaelsen, L. K., A. B. Knight, and L. D. Fink. 2004. Team-based learning: a transformative use of small groups in college teaching. Stylus Publishing, Sterling, Virginia.

Millenium Ecosystem Assessment. 2005. Ecosystems and human well-being: a framework for assessment. Island Press, Washington, DC.

North American Lake Management Society. 2017. The Secchi dip-in. (Available from: http://www.secchidipin.org)

Nov, O., O. Arazy, D. Anderson, N. Podsakoff, and P. Freytag. 2014. Scientists@Home: What drives the quantity and quality of online citizen science participation? PLoS ONE 9:e90375.

Oberhauser, K. S., and M. D. Prysby. 2008. Citizen science: creating a research army for conservation. American Entomologist 54:97–99.

Parmelee, D. X., and L. K. Michaelsen. 2010. Twelve tips for doing effective Team-Based Learning (TBL). Medical Teacher 32:118–122.

Pocock, M. J. O., D. S. Chapman, L. J. Sheppard, and H. E. Roy. 2014. Choosing and using citizen science: a guide to when and how to use citizen science to monitor biodiversity and the environment. NERC/Centre for Ecology and Hydrology, Wallingford, UK. (Available from: https://www.ceh.ac.uk/sites/default/files/sepa_choosingandusingcitizenscience_interactive_4web_final_amended-blue1.pdf)

Raddick, M. J., G. Bracey, P. L. Gay, C. J. Lintott, C. Cardamone, P. Murray, K. Schawinski, A. S. Szalay, and J. Vandenberg. 2013. Galaxy Zoo: motivations of citizen scientists. Astronomy Education Review, *in press*.

Revenga, C., I. Campbell, R. Abell, P. de Villiers, and M. Bryer. 2005. Prospects for monitoring freshwater ecosystems towards the 2010 targets. Philosophical Transactions of the Royal Society of London Series B: Biological Sciences 360:397–413.

Sauermann, H., and C. Franzoni. 2015. Crowd science user contribution patterns and their implications. Proceedings of the National Academy of Sciences 112:679–684.

Scott, A. B., and P. C. Frost. 2017. Monitoring water quality in Toronto's urban stormwater ponds: Assessing participation rates and data quality of water sampling by citizen scientists in the FreshWater Watch. Science of the Total Environment 592:738–744.

Silvertown, J. 2009. A new dawn for citizen science. Trends in Ecology and Evolution 24:467–71.

Stewart, K. J., and S. Gosain. 2006. The impact of ideology on effectiveness in open source software development teams. MIS Quarterly 30:291–314.

Thornhill, I., A. Chautard, and S. Loiselle. 2018. Monitoring biological and chemical trends in temperate still waters using citizen science. Water 10:839.

Thornhill, I., S. Loiselle, K. Lind, and D. Ophof. 2016. The citizen science opportunity for researchers and agencies. BioScience 66:720–721.

Tweddle, J., L. D. Robinson, M. J. O. Pocock, and H. E. Roy. 2012. Guide to citizen science: developing, implementing and evaluating citizen science to study biodiversity and the environment in the UK. (Available from: http://www.nhm.ac.uk/content/dam/nhmwww/take-part/Citizenscience/citizen-science-guide.pdf)

Vörösmarty, C. J., P. B. McIntyre, M. O. Gessner, D. Dudgeon, A. Prusevich, P. Green, S. Glidden, S. E. Bunn, C. A. Sullivan, C. R. Liermann, and P. M. Davies. 2010. Global threats to human water security and river biodiversity. Nature 468:334–334.

West, S., and R. Pateman. 2016. Recruiting and retaining participants in citizen science: what can be learned from the volunteering literature? Citizen Science: Theory and Practice 1(2):15.

West, S., R. Pateman, and A. Dyke. 2016. Data submission in citizen science projects report for DEFRA (Project number PH0475). (Available from: https://www.york.ac.uk/media/sei/documents

/publications/projectreports/West-Pateman-Dyke-DEFRA-Data-Submission-in-Citizen-Science-Projects.pdf)

Wildschut, D. 2017. The need for citizen science in the transition to a sustainable peer-to-peer-society. Futures 91:46–52.

Willett, L. R., G. C. Rosevear, and S. Kim. 2011. A trial of team-based versus small-group learning for second-year medical students: does the size of the small group make a difference? Teaching and Learning in Medicine 23:28–30.

Worthington, J. P., J. Silvertown, L. Cook, R. Cameron, M. Dodd, R. M. Greenwood, K. McConway, and P. Skelton. 2012. Evolution MegaLab: a case study in citizen science methods. Methods in Ecology and Evolution 3:303–309.

Wright, D. R., L. G. Underhill, M. Keene, and A. T. Knight. 2015. Understanding the motivations and satisfactions of volunteers to improve the effectiveness of citizen science programs. Society and Natural Resources 28:1013–1029.

Yardi, K. D., Bharucha, E., and Girade, S. 2019. Post-restoration monitoring of water quality and avifaunal diversity of Pashan Lake, Pune, India using a citizen science approach. Freshwater Science 38:332–341.