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Participatory science for coastal water quality: freshwater plume mapping and volunteer retention in a randomized informational intervention†

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Among the biggest threats to coastal water quality are freshwater discharges. It is difficult to predict the spatial extent of freshwater plumes at marine beaches because processes governing mass transport in the surf zone are complex. Participatory science approaches could facilitate collecting shoreline data, although volunteer sampling campaigns can be challenged by data quality and volunteer retention. The goals of this study were to (1) work with volunteers to estimate safe swimming distances at beaches that receive polluted discharges, and (2) test whether informational feedback to volunteers increased retention. Forty-six volunteers participated over 12 weeks in 2019 by collecting 1452 salinity measurements at beaches near the mouths of two Central California freshwater discharges and completing participation surveys. These measurements resulted in 145 distinct estimates of safe swimming distances (D_{90}), spanning a range of environmental conditions during rainy and dry periods. Median D_{90}s were 150 and 100 m at San Pedro Creek south and north, and 490 and 330 m at San Lorenzo River west and east, respectively. D_{90} was significantly associated with adjacent freshwater discharge rate at both discharges and tide level at one discharge. On average, the odds of volunteers conducting sampling decreased by 4% (95% CI: 1%, 7%) with each successive week. A randomized intervention providing repeated data feedback *via* email to volunteers did not affect their retention in the study.

Environmental significance

Runoff from land can carry high concentrations of contaminants, including pathogens, nutrients, and trace organic chemicals to coastal waters. This research investigated the factors that control the shoreline extent of runoff plumes and found that discharge rate of the runoff source, as well as tide level at one beach, were associated with plume extents. A unique aspect of this study is that sampling was performed by local volunteers. Utilizing a randomized control experiment, we found that volunteers who received project results during the study were not more likely to stay active in the study than other volunteers. This work contributes to understanding factors that affect coastal water quality, as well as best practices for engaging volunteers in environmental science projects.

Introduction

Forty-four percent of the world's population resides within 150 km of a coastline, and eight of the world's ten largest cities are coastal.[1] Shoreline and coastal waters are valuable natural resources that provide numerous cultural, economic, and ecological benefits.[2,3] Despite the economic and cultural importance of clean coastal waters, human impacts on water quality along the world's coastlines threaten ecosystem and human health.[4,5]

Among the biggest threats to coastal water quality are small-scale (flow rate on the order of 10 m^3 s^{-1} or less) freshwater discharges from rivers, streams, tidal outlets, and storm drains.[6] These are common along US coastlines[7] and often contain urban and agricultural runoff,[8] feces from wildlife,[9,10] and wastewater treatment plant effluent, as well as septage[11] or raw sewage when treatment systems perform poorly or are overwhelmed.[12,13] Incoming waves affect the mixing and transport of these freshwater discharges by opposing the freshwater jet's cross-shore momentum, rapidly mixing the water column, and driving an alongshore current in the direction of the waves' shoreline approach.[14,15] At wave-dominated beaches, much of

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the freshwater plume from these small-scale discharges may be entrained in the surf zone, the region between the shoreline and the wave breaker line.[16] This freshwater can remain trapped near the shoreline, where it spreads in the alongshore direction along with any pollutants it contains.[15–17] A surf zone tracer study conducted at two tidal outlets in Southern California found that the alongshore flux of surf zone water was 50–300 times greater than the cross-shore flux.[17] This is important for beach water quality because it means that freshwater pollutants may spread considerable distances along the shoreline, increasing beachgoers' pollutant exposure.

It is difficult to predict the spatial extent of freshwater plumes along the shoreline using analytical models because the processes governing mass transport in the surf zone are numerous and complex.[14,17–22] One empirical method to estimate the length scale of freshwater plumes in the surf zone is to use salinity as a naturally occurring tracer. This approach is advantageous because salinity measurements are analytically simple to make. However, to capture the variability in the freshwater plume extent at a beach, many measurements must be made across space (to estimate spatial variation in freshwater content) and time (to span the range of physical conditions present at a beach). Additionally, measurement must be undertaken by hand, since sensor deployment in the surf zone may be impeded by waves and tides, permitting requirements, and beachgoers, particularly if deployment across multiple days is required.

Working with local community members to gather frequent samples could help meet these sampling requirements. In recent years, participatory science (also "citizen science") has grown increasingly popular among academics and practitioners for gathering environmental data.[23,24] Volunteer-based participatory science offers the potential benefits of gathering many observations in a cost-effective way,[23,25,26] enhancing public scientific knowledge and skills,[27] and elevating the perceived value of the issue or environment under study.[28] Two primary challenges for participatory science are data quality and volunteer retention. To mitigate potential data quality problems, methods and protocols must be appropriate for volunteer skill levels and the logistical challenges of numerous participants independently contributing data.[29] Quality control (QC) measures specific to the protocols used by volunteers must also be developed to ensure that data are of adequate quality for their intended purpose.

Data quality concerns are common to all scientific studies. In contrast, volunteer retention is a unique and important challenge for participatory science.[30–32] Retaining volunteers in longitudinal studies is particularly difficult, and poor retention can threaten a study's success.[30] Therefore, understanding how specific aspects of project design or management affect sustained volunteer participation could improve outcomes for participatory science studies. Indeed, a growing number of studies has sought to understand drivers of volunteer participation and retention.[33–41] The use of cross-sectional or observational designs, however, has precluded any participatory environmental science study from inferring causality between project or volunteer characteristics and volunteer retention. The present study seeks to test the effect of providing motivationally-targeted feedback to volunteers in a scientific study using a managed experimental design.

The basis for this experimental treatment, which aims to enhance learning-oriented benefits of volunteering by regularly presenting volunteers with data collected during the study, is a framework for understanding volunteer retention from the field of functional psychology. This framework posits that volunteer participation is more likely sustained when specific motivations for volunteering align with perceived benefits of participating. Motivations alone, divorced from corresponding perceived benefits, are insufficient to sustain volunteer participation.[42,43] Randomized experiments assessing the impact of motivationally-targeted communication materials on volunteer participation have been conducted in the human services sector[44] and in a massive online participatory physics study.[45] The present study is the first known participatory environmental science study to test the effect of informational feedback on sustaining participation with an experimental design.

This study sought to address knowledge gaps in beach water quality (WQ) and participatory science (PS) research by investigating the following four questions: WQ1: How far along the shoreline are two polluted freshwater discharges at popular beaches likely to have meaningful public health impacts? WQ2: How does variation in environmental conditions at these sites affect these alongshore extents? PS1: How much is volunteer retention increased by regularly presenting to volunteers the data that they collect? PS2: To what extent is this effect moderated by motivations for volunteering? This study provides data to inform safe swimming distances from discharges at recreational beaches, a systematic framework for assessing volunteer data quality that may be adapted to other studies, and insight into best practices for sustaining volunteer engagement in participatory environmental science.

Methods

Study sites

Study sites (Fig. 1) were located at the receiving beaches for two freshwater discharges in California, USA. San Pedro Creek in Pacifica (37.596560°, −122.505785°), which discharges to Pacifica State Beach, and San Lorenzo River, which discharges to Main and Seabright Beaches in Santa Cruz (36.963278°, −122.012892°), were selected because they frequently contain unsafe levels of fecal indicator bacteria[46–49] and pathogens,[8,50] discharge to popular recreational beaches, and differ in scale.[8] Both discharges are located in watersheds that experience distinct wet and dry seasons, with most precipitation typically falling from November to March.[51] The shoreline on each side of each discharge was considered a sampling site. These four sites are referred to as San Pedro Creek south (meaning the shoreline to the south of San Pedro Creek's mouth), San Pedro Creek north, San Lorenzo River west, and San Lorenzo River east (Fig. 1).

Volunteer recruitment and communication

Volunteers were recruited online and in-person from nearby communities (see ESI†) and were required to attend one of

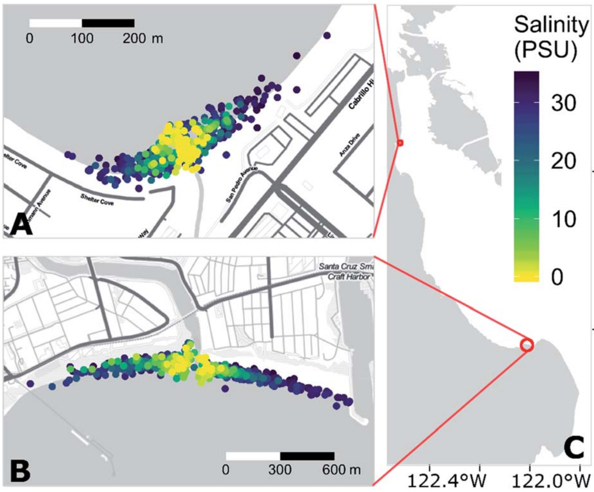

Fig. 1 All salinity measurements that passed QC at (A) San Pedro Creek and (B) San Lorenzo River. Note that apparent differences in distance from the water reflect the dynamic location of the land–water interface, which is influenced by tides. (C) Depicts the California coast spanning from San Francisco in the north to Monterrey Bay in the south.

several in-person trainings. Following training, all communication with volunteers was *via* email, until after the project's end date when all volunteers were invited to results presentations. Volunteers were required to be at least 18 years of age and were not compensated for their participation in this study. This study was approved by Stanford University's Institutional Review Board (protocol IRB-37740).

Field sampling

Volunteers were assigned to sample at one sampling site and conducted field sampling between February and May 2019. All volunteers received a kit of sampling supplies with a detailed sampling protocol (see ESI†), as well as one 90 minute in-person training held in a classroom setting. The training included background information on beach water quality, an overview of project goals, and detailed step-by-step instructions for performing field sampling and project logistics. Volunteers were asked to conduct sampling once per week for twelve weeks. During each sampling event, volunteers were asked to collect samples in ankle deep water, on an incoming wave, at a minimum of five points along the shoreline. Volunteers recorded the salinity of each sample using a low-cost analog refractometer (Agriculture Solutions, Dual Scale Refractometer). The measurements made during a sampling event are collectively referred to as a salinity profile. Other relevant meta-data were also recorded (see ESI†). Volunteers were asked to select locations that spanned a full range of salinity values, from the salinity at the mouth of the discharge (as low as 0 PSU) to background marine salinity of 34 PSU. Volunteers then recorded the GPS coordinates of each location using a smartphone app (Save Location GPS, Rayo Infotech).

Data were recorded, and GPS coordinates were transcribed on paper data sheets. Following each sampling event, volunteers deposited a data sheet along with one of the water samples for which they recorded salinity at an adjacent drop-off point hosted by a local establishment. Project staff collected samples each week and returned them to the lab for validation of salinity measurement accuracy and data digitization. To prevent data digitization errors, all data sheets were digitized twice by different project staff, and mismatches were identified and corrected.

Refractometer QC

An experiment to determine a threshold for acceptable refractometer accuracy among volunteers, incorporating both variability due to field conditions and differences across refractometers, was conducted as follows. One trained project staff member made five measurements with each of ten refractometers in the field, mimicking the salinity profiles requested of volunteers. Accuracy of these fifty measurements was determined by comparing them to measurements made in the lab using a digital Sonde probe (YSI-30), and the acceptable accuracy threshold was set at the level of error containing 95 percent of measurements, equal to ±2.3 PSU. Further investigation of refractometer accuracy and repeatability is described in the ESI.†

Volunteer data QC criteria

To ensure that data collected by volunteers were sufficiently accurate to produce scientifically defensible estimates of 90 percent dilution distances (D_{90}s), we implemented a strict QC procedure. The QC framework was divided into three conceptual categories: (1) completeness, the requirement that data collection tasks were completed sufficiently for data to be interpretable; (2) reasonableness, the requirement that data were plausible; and (3) usefulness, the requirement that the data collected could be used to answer the scientific questions of this study. Each category was operationalized by multiple criteria (Table 1). For example, measurement accuracy is one criterion under the reasonableness category. Salinity accuracy was determined by using a digital salinity probe (YSI, Model 30, Yellow Springs, Ohio) to measure the salinity of volunteers' submitted samples, representing about 20 percent of all recorded measurements. If a volunteer's measurement of a submitted sample had error exceeding 2.3 PSU, all measurements recorded by that volunteer on that day were discarded.

D_{90} estimation

After QC, refractometer instrument bias was corrected to increase salinity measurement accuracy (see ESI†). Salinity was transformed to freshness, defined as $f = (\mathrm{sal}_{\mathrm{bg}} - \mathrm{sal}_{\mathrm{meas}})/\mathrm{sal}_{\mathrm{bg}}$, where f is freshness, $\mathrm{sal}_{\mathrm{bg}}$ is background coastal salinity (34.5 PSU was used, based on measurements made by staff at field sites during low discharge flow conditions), and $\mathrm{sal}_{\mathrm{meas}}$ is the measured salinity. Salinity values below 0 were assigned 0 PSU and above 34.5 assigned 34.5 PSU to ensure that freshness was bounded by [0, 1]. Note that measured values above 37 or below −3 PSU were discarded (Table 1).

Table 1 Volunteer data QC criteria. Criteria are presented in the order in which they were applied to the data

Category	Criterion	Description	Data discarded if failed
Completeness	Calibration performed	Calibration measurement recorded	Entire salinity profile
Reasonableness	Validated sample accurate	Volunteer measurement within interval [validation measurement $\pm$2.3 PSU]	Entire salinity profile
Completeness	GPS coords fully transcribed	GPS coordinates must have 6 digits following decimal	Single data point
Reasonableness	Salinity range reasonable	Salinity reasonable given acceptable refractometer error of $\pm$2.3 PSU: within [−3, 37] PSU	Single data point
Reasonableness	GPS coords on target beach	Coords lie within reasonable beach polygon	Single data point
Reasonableness	GPS coords on shoreline	Shoreline approximated by quadratic fit to all data points; coords must fall within 3 standard deviations of quadratic fit	Single data point
Usefulness	Sufficient number of points per profile	Minimum of 4 points per profile pass quality control criteria; necessary to fit exponential function	Entire salinity profile
Usefulness	Sufficient spatial coverage	Sufficient distance along shoreline and sufficient salinity range measured to accurately estimate D_{90}. see ESI for details	Entire salinity profile

To compute shoreline distances from GPS-labeled sampling locations, several intermediate approximations were made (see ESI†). Then, nonlinear regression was used to estimate how freshness decayed with alongshore distance from each discharge datum. A two-parameter exponential decay model was fit to each freshness profile:

$$f_{ij} = k_{1j}\exp(-k_{2j}d_{ij}) + \varepsilon_{ij} \quad \varepsilon_j \sim N(0, \sigma_j^{\,2}).$$

where f = freshness (dimensionless) of the i^{th} point in the j^{th} freshness profile; d = distance from discharge (m); k_1 = best fit freshness at discharge mouth (dimensionless); k_2 = spatial decay rate of freshness (m^{-1}); ε = regression residual (dimensionless). Non-linear regression of freshness values was used rather than linear regression on log-transformed data because freshness residuals were normal and additive on the untransformed scale.[52]

Finally, D_{90}, the alongshore distance from the creek or river at which freshwater was diluted by 90 percent, was estimated for each freshness profile by setting each f_j to 0.1 and solving for d_j. Ninety percent was used because fecal indicator bacteria (FIB) levels in San Pedro Creek and San Lorenzo River from 2016 to 2018 were frequently greater than the CA single sample criterion used to protect public health, but rarely exceeded ten times the criterion, indicating that 90 percent dilution is typically sufficient to reduce FIB to levels considered safe in individual samples (Fig. S2†).

Associations between D_{90} and hydrodynamic variables

Linear associations between D_{90} and tide level, flow rate, and alongshore current were investigated. Verified six-minute tide level data were obtained from NOAA (San Francisco Station, 9414290) with mean lower low water datum.[53] Fifteen-minute flow rates of San Lorenzo River were retrieved from a USGS gage near the river mouth.[54] Hourly flow rates of San Pedro Creek were predicted from weekly flow measurements (handheld flow meter, FP101, Global Water) and hourly precipitation data using random forest regression (see ESI†). Alongshore velocity was estimated using an equation proposed by Inman *et al.*,[14] which is a function of surf zone wave height and angle (output from the Coastal Data Information Program model[55]), beach slope (for San Lorenzo River, calculated in QGIS using a USGS digital elevation model;[56] for San Pedro Creek, taken from Wong *et al.*[16]), and bottom drag (taken from Inman *et al.*[14]) (see ESI†). Velocity estimates were z-standardized and interpreted as relative values.

To evaluate associations between D_{90} and hydrodynamic variables, linear ordinary least squares regression was used. One model was estimated for each of the two discharges (San Pedro Creek and San Lorenzo River). Models were specified as:

$$\sqrt{D_{90}} = \beta_0 + \beta_1 \times \text{tide} + \beta_2 \times \log_{10}(\text{discharge}) + \beta_3 \times Z_{\text{current}} + \varepsilon$$
$$\varepsilon \sim N\left(0,\ \sigma^2\right)$$

where tide is tide level (relative to mean lower low water) at the time of sampling, discharge is volumetric flow rate at the time of sampling, and Z_{current} is the z-standardized alongshore current velocity at the time of sampling. D_{90} was square-root transformed to reduce heteroscedasticity in the residuals. Variance inflation factors were used to check for multicollinearity. Wilcoxon rank sum tests were used to test several hypotheses regarding whether excluding the D_{90}s that failed certain QC criteria biased D_{90} statistics. Specifically, D_{90} estimates that were excluded due to insufficient spatial coverage of samples (Fig. S7†) were compared to other D_{90}s with respect to magnitude and correlations with hydrodynamic variables.

Throughout this paper, an alpha level of 0.05 was used to determine statistical significance.

Randomized informational feedback

All participants received twice-monthly emails with recommendations for resolving common data collection issues observed by project staff or reported by volunteers. To test whether increasing scientific feedback to volunteers affected sampling effort, emails sent to one half of volunteers also prominently featured a link to access a report of data collected over the previous two weeks ("data reports"). Treatment condition (receive or not receive links to data reports) was randomly assigned after stratifying the volunteers by gender and sampling location. Data reports included plots and descriptions of aggregated salinity data collected by volunteers, along with discharge flow data and FIB measurements (see ESI†). Emails were sent with Mail Chimp; click data were retrieved to determine the number of data reports viewed by each volunteer.

Volunteer survey overview

Three online surveys were administered to each volunteer over the course of the project (see ESI†). Prior to commencing sampling, volunteers were administered a pre-project survey, which included one battery of items based on the Volunteer Functions Inventory[43] to gauge volunteer motivations for participating, and a battery of items to gauge expected obstacles to participating (see data analysis: motivations and obstacles). A mid-project survey was administered during weeks 6–7 of sampling, and a post-project survey was administered immediately following conclusion of field sampling. Both mid and post surveys asked participants about sampling and participation problems they had experienced, and repeated questions from the Volunteer Functions Inventory to gauge perceived benefits of participating up to that point. All surveys were conducted *via* the Qualtrics online platform (see ESI†). Links to surveys were emailed to participants, and up to four follow-up emails were sent to volunteers to encourage survey completion.

Survey constructs and analysis: motivations, benefits, and obstacles

We evaluated six motivations for and corresponding benefits of volunteering in this project: learning-, values-, social-, career-, recreation-, and child-oriented. The first four were proposed by Clary *et al.*,[43] and we added the last two after administering an open-ended survey during a pilot version of this project in 2017. Motivational constructs were defined in terms of volunteers' perception of opportunities offered by volunteering with the project, as follows. Learning-oriented motivation is the perception that volunteering with this project offers opportunities to learn or exercise knowledge or skills. Values-oriented motivation is the perception that volunteering with this project offers opportunities to contribute to an issue the volunteer is concerned about. Social-oriented motivation is the perception that volunteering with this project offers opportunities to develop social relationships. Career-oriented motivation is the perception that volunteering with this project offers opportunities to develop one's career. Recreation-oriented motivation is the perception that volunteering with this project offers opportunities to engage in an enjoyable activity. Child-oriented motivation is the perception that volunteering with this project offers opportunities to participate in an activity with one's children.

Corresponding benefit constructs were measured in the mid- and post-project surveys, and differed from motivation constructs in that they addressed retrospective, rather than prospective, project experience. Benefit constructs were defined similarly to motivation constructs. For example, learning-oriented benefits are the perception that volunteering with this project offered opportunities to learn or exercise knowledge or skills.

Construct indicators, each corresponding to one survey item, permitted integer responses from 1 to 5, corresponding to 'strongly disagree' to 'strongly agree' with 3 as 'neither agree nor disagree'. Three indicators operationalized each of the learning-, values-, and social-oriented motivational constructs, while one indicator operationalized each of the career, recreational, and child-oriented motivations (Table S1† lists individual indicators). This design was used to constrain the length of the survey while including other crucial survey items. Learning- and values-oriented motivational constructs were prioritized because they were expected to be common among volunteers, based on pilot surveys conducted in 2017, and because volunteers of either orientation were theorized to plausibly respond positively to the informational intervention. The social-oriented construct was prioritized to serve as a control: we theorized that volunteers with social-oriented motivations would be unaffected by the intervention. Confirmatory factor analysis could not be performed on the motivational constructs due to statistical concerns (see ESI†). To determine a volunteer's primary motivation, a score was calculated for each motivation as either the average response value (for constructs with multiple indicators) or the response value (for constructs with a single indicator). A volunteer was classified as learning oriented if their learning score was greater than 3 and at least as high as all other motivation scores.

Obstacles to participating were surveyed and defined as the logistical, financial, or physiological hindrances that make participation more effortful. These hindrances included low time availability (indicated by self-reported employment status), high travel time to project site (volunteers' self-reported estimates), having to pay for parking at field sites (self-reported), and physical difficulty of performing sampling tasks (self-reported). Surveyed obstacles and scoring details are provided in Table S2 and Fig. S4.†

Analysis of volunteer retention

The null hypothesis corresponding to research question PS1 was that receiving data reports was not associated with retention (referred to as the "information hypothesis"). Since receiving data reports was a randomly assigned condition, this association was interpreted as being causal. The null hypothesis corresponding to PS2 was that retention of volunteers who received data reports and whose motivations were learning-oriented was equal to retention of other volunteers (referred to as the "motivation hypothesis"). Since motivation type was not a randomly assigned condition, this association was not interpreted as being causal.

Generalized Estimating Equations (GEE) models with logit links were fit to test each of these two hypotheses. In both models, the binary outcome was whether a volunteer conducted sampling on a given day. Each of the 45 volunteers that completed the pre-project survey and attended training was included over the 85 day duration of their sampling campaign.[44] An exchangeable correlation structure with robust standard errors was used to account for repeated observations of each volunteer. Predictors for the information hypothesis model were obstacles score, treatment group (coded 0/1 for control/treatment), time (in days, coded 0 for training day to 84), and a treatment group by time interaction. Predictors for the motivation hypothesis model were obstacles score, target group (to be distinguished from a true treatment group, coded 0/1 for other volunteers/volunteers who received data reports and were learning motivated), time (in days), and a target group by time interaction. The coefficient estimate of the treatment (or target) group by time interaction term in each model tests the corresponding hypothesis regarding retention. Exponentiating this coefficient yields an odds ratio, describing how the odds of conducting sampling for volunteers in the treatment (target) group change over time compared to the control group, *i.e.*, volunteer retention. Obstacles score was included to control for factors expected to impact retention that were not accounted for in the randomized treatment assignment, including age- and access-related factors. Participant age was correlated with obstacles score (Pearson's $r = -0.57$; 95% CI = -0.74, -0.34; Fig. S5†), so age was excluded from regression models.

Results

Salinity measurements

1452 salinity measurements were submitted by 36 participants between Feb 2 and May 4, 2019. Sampling occurred on 55 and 73 out of 92 possible days at San Pedro Creek and San Lorenzo River, respectively. Forty-five percent of measurements did not meet the QC criteria for the analysis of D_{90} (Fig. S6†). The criterion most commonly failed was accuracy (17 percent of all measurements), followed by failing to sample a sufficiently long beach extent to estimate D_{90} ("sufficient spatial coverage", 11 percent) and failing to perform calibration (7 percent). Grouping discarded data by QC category revealed that 10 percent of measurements were discarded due to insufficient completeness, 21 percent due to insufficient reasonableness, and 14 percent due to insufficient usefulness with respect to the specific analysis aims of this study. After QC, 804 observations across the four study beaches, constituting 145 salinity profiles, were used to estimate D_{90} values. D_{90}s excluded due to insufficient spatial coverage tended to be longer than included D_{90}s (p < 0.05, Fig. S7†) at San Pedro south, San Lorenzo west, and San Lorenzo east. At San Pedro south, excluded D_{90}s were associated with higher discharge rates. At San Lorenzo west, excluded D_{90}s were associated with higher discharge rates and higher tide levels. San Lorenzo east showed no associations between data exclusion due to spatial coverage and hydrodynamic variables. At San Pedro north, no D_{90}s failed the sufficient spatial coverage criterion.

Distance to 90 percent dilution

Exponential decay models fit freshness profiles well, judged by residual standard deviations for each profile (example fits in Fig. S8†). Median (minimum, maximum) residual standard deviation across profiles was 0.07 (0.00, 0.36) in units of freshness. Thirty-five, thirty-nine, twenty-seven, and forty-four D_{90}s were estimated and passed QC criteria at San Pedro Creek south, San Pedro Creek north, San Lorenzo River west, and San Lorenzo River east, respectively (Fig. 2). The median (25th, 75th percentiles) D_{90}s were 150 (100, 180) m at San Pedro Creek south, 100 (70, 180) m at San Pedro Creek north, 490 (320, 720) m at San Lorenzo River west, and 330 (210, 520) m at San Lorenzo River east.

During sampling events that passed QC, discharge ranged from 5.9×10^{-2} to 1.4×10^{0} m^3 s^{-1} with a mean of 3.8×10^{-1} m^3 s^{-1} in San Pedro Creek, and from 2.7×10^{0} to 1.6×10^{2} m^3 s^{-1} with a mean of 1.7×10^{1} m^3 s^{-1} in San Lorenzo River. Alongshore current velocities were northward for all 74 D_{90}s at San Pedro Creek and eastward for all 71 profiles at San Lorenzo River. For linear regression modeling, alongshore current velocities were coded such that the direction of the corresponding D_{90} with respect to the discharge mouth is positive. The mean (range) velocity magnitude was 1.8 (0.6, 3.0) m s^{-1} in Pacifica, and 1.9 (0.7, 3.2) m s^{-1} in Santa Cruz. These values exceeded ranges previously reported for similar conditions by up to an order of magnitude.[16,17] Thus, velocities were interpreted as relative values.

Linear regression models of D_{90} incorporating discharge rate, alongshore current, and tide level were estimated for each

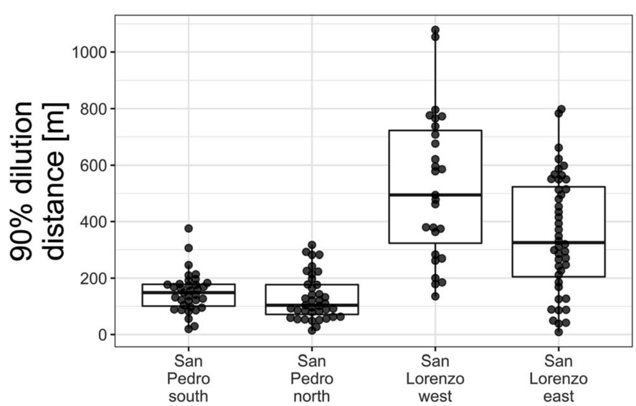

Fig. 2 Boxplots representing distributions of D_{90} distances at each beach. Boxplot centerlines are medians, bottoms and tops of boxes are 25th and 75th percentiles, and whiskers extend to the furthest data point within a distance of 1.5× interquartile range from the 25th and 75th percentiles, respectively. Individual points are displaced horizontally to aid visualization.

of the two discharges. The model for San Pedro Creek explained about one-third of the variation ($R^2 = 0.38$) in D_{90} (Table S3†). The model for San Lorenzo River explained about one-tenth of the variation in D_{90} (adj. $R^2 = 0.11$). At San Pedro Creek, a 10-fold increase in discharge ($m^3\ s^{-1}$) was significantly associated with a 16 m (95% CI: 6, 30 m) increase in D_{90}. A 1 m increase in tide level was significantly associated with a 4 m (1, 10 m) decrease in D_{90}. Alongshore current velocity was not statistically associated with D_{90}.

At San Lorenzo River, a 10-fold increase in discharge was significantly associated with a 19 m (0, 17 m) increase in D_{90}. Tide level was not statistically associated with D_{90}. A 1-standard deviation increase in alongshore current velocity was statistically associated with a 2 m (0, 9 m) decrease in D_{90}.

Due to the perfect collinearity between alongshore current velocity direction and discharge side (north/south at San Pedro Creek, east/west at San Lorenzo River), dummy variables for discharge side were not included in the model. This correlation made it impossible to use regression to distinguish the effects of alongshore current direction on D_{90} from effects of other features specific to each side of a discharge, such as discharge mouth or coastal morphology. Variance inflation factors for reported model variables were approximately 1, indicating that multi-collinearity was not a problem in these models.

Volunteer participation and data report viewing rates

Of over 60 people who expressed interest in volunteering by completing a preliminary survey, 46 people attended a training and were given sampling kits. Of those 46, 45 completed the pre-project survey, 31 completed the mid-project survey, and 29 completed the post-project survey. Thirty-six volunteers completed sampling at least once. Participation trends are shown Fig. 3 and S9,† and participation rates and the number of data reports viewed by each volunteer are shown in Fig. S10.† Volunteers who received links to data reports conducted an average of 5.7 ($\sigma = 4.5$) out of 12 requested sampling events, and volunteers who did not receive links conducted an average of 5.6 (4.4) sampling events. Volunteers who received data report links viewed an average of 2.2 ($\sigma = 2.1$) of the 6 data reports, and the number of reports viewed was significantly, positively associated with participation rate (Spearman's $\rho = 0.51$, $p = 0.02$). Note that this correlation does not indicate a causal relationship between receiving data reports and participation.

Effect of data reports on volunteer retention

Data from 45 volunteers who completed the pre-project survey were included in the model testing the information hypothesis. Among the 21 volunteers who received data reports, median (range) age category was 35–44 (18–24, 65–74) years. Fifteen were female, and 6 were male. Among the 24 volunteers who did not receive data reports, median age was 35–44 (18–24, 75–84) years. Twenty were female, and 4 were male. Aggregating across treatment groups, the odds of volunteers conducting sampling decreased by 4 percent (OR = 0.96, 95% CI: [0.93, 0.99]) with each successive week. The information hypothesis model (Table S4†), described in Methods, indicates that a 1-unit increase in composite obstacles score was associated with a 37 percent reduction (OR = 0.63, [0.46, 0.86]) in the odds of conducting sampling. A one unit increase in obstacles scores is equal to any combination of obstacles scores in Table S2† that sums to 1. For each passing week, the odds of conducting sampling among the control group declined by 4 percent, though this was not statistically significant. Furthermore, the interaction between time and treatment was not statistically significant, indicating that receiving links to data reports did not alter retention.

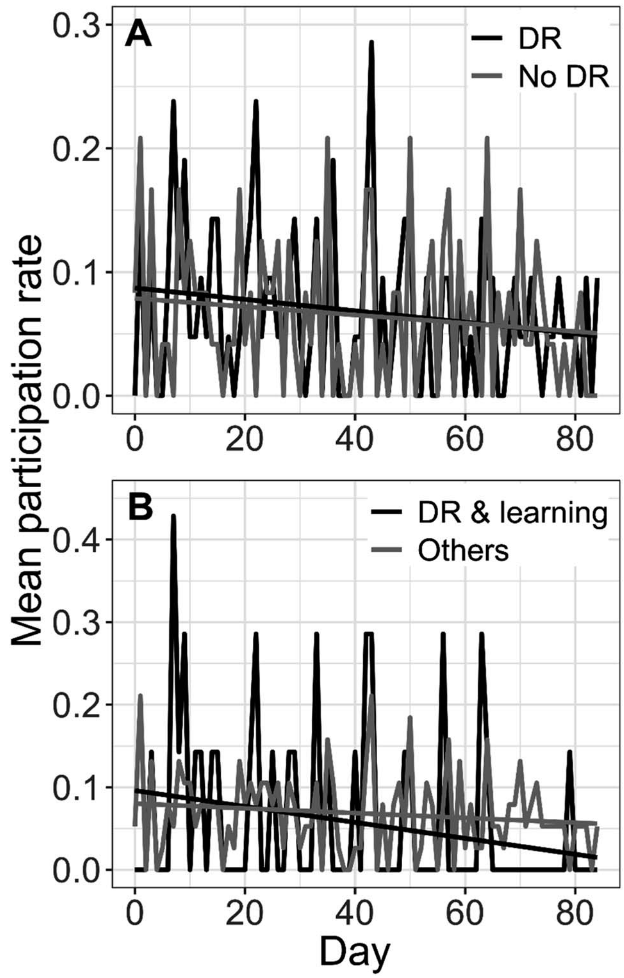

Fig. 3 Mean participation rate by study day. Mean participation rate is the number of volunteers out of 45 total who sampled on a given day. Volunteers conducted sampling over an 85 day window. Volunteers are disaggregated by (A) treatment group for the informational hypothesis and (B) target group for the motivational hypothesis. "DR" means received links to data reports; "learning" means volunteers who were learning oriented. Trend lines are linear fits.

Association between data reports and retention for learning-oriented volunteers

Of 45 volunteers, 7 received data reports and were learning-oriented. Characteristics of these volunteers are presented in Table S5.† The motivation hypothesis model (Table S4†) indicates that, adjusting for obstacles to participation, learning-oriented volunteers who received data reports had statistically significantly lower retention than other volunteers (*i.e.* volunteers who either did not receive data reports or who received data reports but were not learning motivated). Specifically, for each one week increase in time, the odds of conducting sampling among learning-oriented volunteers who received data reports dropped 10 percent compared to other volunteers (OR = 0.90, [0.83, 0.98]). This result is driven by the fall in participation after day 60 among learning-oriented volunteers who received data reports, as retention prior to day 60 is not statistically different between target and control groups (Fig. 3).

Discussion

Safe swimming distances from freshwater discharges to two marine beaches were identified through participatory science

Median safe swimming distances (D_{90}s) were 130 m at San Pedro Creek and 380 m at San Lorenzo River. San Mateo County, where San Pedro Creek is located, currently encourages beachgoers to remain at least 300 ft (90 m) from a flowing creek or storm drain when making water contact. This distance corresponds to the 30th percentile of D_{90}s measured at San Pedro Creek in this study. To be more health protective, San Mateo County could consider increasing the recommended swimming distance to 130 m (420 ft) or 180 m (580 ft), which would be sufficiently far to result in 90 percent dilution of San Pedro Creek water in approximately half or three quarters, respectively, of days in winter and spring. We did not measure FIB in our study since high levels of fecal contamination have been extensively documented at both sites,[8,57] resulting in both sites currently being listed on the US Clean Water Act 303(d) list.[48,49] Measuring salinity, rather than FIB, is advantageous because it allows the spatial impact from freshwater discharges to be isolated from other nearby FIB sources. Efforts similar to those described in this paper could be undertaken with volunteers at other beaches to refine beach management and protect beachgoers from exposure to pollutant-laden runoff.

Freshwater discharge rate was positively associated with D_{90} at both discharge sites

In fact, the effect size was similar at both sites, despite site-specific differences in beach and coastline morphology and wave action. Furthermore, the intercepts of the two models, which correspond to the estimated average D_{90} with a 0 m tide (mean lower low), 1 $m^3\ s^{-1}$ discharge rate, and mean alongshore velocity, were nearly identical, reinforcing the idea that the spatial impact of freshwater is similar at both sites. This suggests that the estimated effects of discharge rate on D_{90} may be generalizable to other ocean-exposed marine beaches.

Lower tides were associated with longer D_{90}s at San Pedro Creek

The intertidal zone at San Pedro Creek is rocky and slopes downward. At low tides, the creek spreads along the beach, reducing the momentum with which it meets the surf zone.[16] This lower momentum may result in greater wave trapping of freshwater against the shoreline, where salinity measurements for this study were made.[16] At San Lorenzo River, where tide level was not associated with D_{90}, the tidally-influenced interaction between the river mouth and marine water is more complex. For example, the San Lorenzo River mouth morphology can be highly tidally influenced, with increasing mouth curvature and width at high tide, and exposed sand bars at low tide forming following heavy rains. Thus, potential impacts of tide level on D_{90} may not be captured by this simple linear model.

Alongshore current effects on D_{90} could not be distinguished from other beach-specific effects

The estimated negative effect of alongshore current on D_{90} at San Lorenzo River contradicted expectations. Wave-driven alongshore currents in the surf zone are expected to have a positive effect on D_{90} by bending the freshwater jet in the current's direction.[16] However, larger alongshore currents may also have resulted in strong rip currents which can eject water from the surf zone.[14] Further study, including *in situ* current measurements, is required to understand the effects of alongshore currents on freshwater mixing and transport in the surf zone at these sites.

Although QC resulted in discarding nearly half of collected data, remaining data were sufficient in quantity and quality to address the study's research questions

A common concern in participatory science is that measurements made by volunteers may be of poor quality.[31,58] Many studies cite data quality concerns, asserting that volunteer-made measurements are inferior in accuracy or precision to measurements made by trained scientists.[59–63] However, studies often do not clearly define reasonable criteria for data quality acceptability specific to the methods utilized by volunteers, and recent review articles point out that data quality inferiority assertions are frequently supported by weak evidence or biased assumptions.[63,64] Although acceptable data quality will be specific to each project's methods and objectives, there is a lack of systematic data quality evaluation present in the participatory science literature. This study sought to rigorously assess volunteer-collected data quality by thoroughly assessing the accuracy of the instruments used by volunteers, implementing sampling procedures that reduce these instruments' inaccuracies, and defining accuracy criteria specific to these instruments under field conditions so that instrument accuracy and volunteer-associated errors were not confounded. Although our QC criteria resulted in discarding 45 percent of all measurements, the remaining data were of high quality and sufficient in number to investigate the stated water quality research questions. The QC constructs of data completeness, reasonableness, and usefulness proposed in this study are sufficiently broad that they could be applied to other studies and operationalized with project-specific QC criteria. QC failures in each of these three categories can be ameliorated by improving sampling protocols and providing feedback to volunteers about how to make data more complete, reasonable, and useful.

Volunteer retention did not differ between volunteers who received data reports and those who did not

Previous findings from survey-based analyses indicate that it is highly important to volunteers that results from their work are shared with them.[34] Experimental findings from this study do not support the proposition that regularly sharing results with volunteers *via* a link in an email affects retention. This may be due to data reports not providing additional learning-oriented benefits beyond those experienced by all participants through other project experiences, such as training and sampling. This hypothesis is supported by responses in mid- and post-project surveys indicating that learning-oriented benefits of participating were high (>4 out of 5) for both treatment and control groups. Furthermore, volunteers who received data reports did not report experiencing learning-oriented benefits different from other volunteers in either survey (Wilcoxon rank sum, $p > 0.05$). Note that a randomized experimental design enables us to distinguish the positive correlation between viewing data reports and participation rates among volunteers in the treatment group from the null causal effect of receiving data reports.

Volunteers who were learning-oriented and received data reports had lower retention than other volunteers

A second, explicitly functional psychological hypothesis was also tested to determine whether volunteer motivations moderated the effect of the informational intervention. Specifically, since the informational intervention was designed to increase learning-oriented benefits of volunteering *via* increased access to study data, it was hypothesized that learning-oriented volunteers would be most positively affected. Model results, however, indicated the opposite: learning-oriented volunteers who received the informational intervention had statistically lower retention than other volunteers. Since learning-oriented volunteers who received data reports did not report a statistically significant difference in learning-oriented benefits compared to other volunteers in either mid- or post-project survey, this finding is not easily explained by the functional psychology framework used in this paper.

Several *post hoc* explorations were undertaken to better understand the reduced retention of learning-oriented volunteers. First, we hypothesized that, by providing evidence to volunteers that the data they collected were being quickly processed and used by project staff, data reports may have enhanced volunteers' perception that they were contributing to a worthwhile project. This perception would correspond to an increase in perceived values-oriented benefits relative to learning-oriented benefits. To test whether the intervention affected retention of values-oriented volunteers, the motivation regression model was fit for values-oriented volunteers. Model results did not indicate that the intervention statistically affected retention of values-oriented volunteers compared to other volunteers.

Second, we surmised that learning-oriented volunteers may have had lower retention than other volunteers, regardless of receiving data reports. However, our modeling suggested that, ignoring treatment condition, learning-oriented volunteers did not differ from other volunteers in terms of retention. Thus, no evidence was found that lower retention for learning-oriented volunteers who received data reports was driven by lower retention among all learning-oriented volunteers.

Finally, it is possible, although counter to expectations, that learning-oriented volunteers perceived the data reports particularly negatively, driving down their retention. In the final survey, volunteers who received data reports were asked whether data reports had a positive impact on their volunteering experience. Unfortunately, an insufficient number of people responded to the final survey to partition respondents by motivational orientation. Thus, the hypothesis that learning-oriented volunteers perceived data reports more negatively than others could not be tested.

These *post hoc* analyses did not explain the finding that learning-oriented volunteers who received data reports, intended to be a learning-oriented benefit, had lower retention than other volunteers. Together, these *post hoc* analyses and the survey responses regarding learning-oriented benefits suggest that receiving data reports had little impact on the perceived benefits of volunteering. Given this finding and the small number of volunteers who were learning oriented and received data reports, the association between learning-oriented volunteers who received data reports and retention may be attributable to unmeasured factors or be spurious.

It also worth noting that although we classified volunteers as learning oriented or not, many volunteers had multiple motivational orientations. We defined a motivational orientation as a motivation with a score greater than three and at least as high as all other motivation scores, which is aligns with previous work.[43,44] Under this definition, thirty-one volunteers had a single motivational orientation, while fourteen volunteers had more than one motivational orientation (Table S6†), which supports Clary and Snyder's finding that volunteers are often multiply motivated.[42] In this study, the values orientation was most common among volunteers with single motivational orientations (seventeen of thirty-one) and among volunteers with multiple orientations, followed by the enjoyment and then the learning orientation. Future participatory environmental science studies should consider strategies for increasing retention that explicitly target values-oriented motivations, potentially in conjunction with enjoyment or learning motivations.

Participation rates did not differ between the 2019 study described in this paper and a 2017 pilot study

In contrast to the 2019 study, the pilot study was designed to have minimal contact and feedback between volunteers and project staff. No in-person training was conducted, and no project update emails were sent during the project unless volunteers explicitly asked for input. Sampling protocols were very similar, occurred at the same sites during the same season, and the volunteers ($n = 53$), although all different individuals, were recruited by the same means from the same population of local NGOs and beachgoers. Interestingly, average participation rates did not statistically differ between the pilot study and the study presented in this manuscript (Fig. S11†), despite the increased time required of project staff in the 2019 study to provide training and data reports.

Conclusions

This study presents a novel framework for estimating safe swimming distances at beaches and is the first participatory environmental science study to experimentally test strategies for increasing volunteer retention. The empirical estimates of freshwater plume extents presented in this work will be useful for future surf zone circulation studies. They also provide scientific grounding for guidance provided to swimmers by beach managers about safe swimming distances from freshwater discharges. This work shows that by implementing thorough data quality control measures, volunteers using low-cost instruments can implement complex sampling schemes to collect water quality data in the surf zone, which is a complex, data-poor environment. Furthermore, although receiving project feedback is commonly cited as motivating to volunteers, results from this study's experimental intervention suggest that managers of participatory science projects should not rely on disseminating project data *via* email to promote retention.

Disclosures

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Conflicts of interest

The authors declare no competing financial interest.

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