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Supporting Information for

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

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Sampling protocol. See file "FieldProtocol_SanPedroCreekNorth.pdf"

Example data sheet. See file "FieldDataSheet_SanPedroCreek.pdf"

Example data report. See files "DataReport_SanLorenzo_20190322.pdf" and "DataReport_SanPedroCreek_20190407.pdf"

Surveys. See files "Survey_Pre-project.docx", "Survey_Mid-project_DataReport.docx", "Survey_Mid-project_noDataReport.docx", "Survey_Post-project_DataReport.docx", and "Survey_Post-project_noDataReport.docx

Refractometer QC. Since low-cost refractometers were relied upon for scientific data collection, extensive effort was made to understand and reduce sources of measurement error. First, preliminary field and lab testing by project staff indicated that refractometer accuracy was sensitive to ambient temperature, with accuracy varying approximately linearly with temperature (data not shown). To correct for this temperature dependence, volunteers were asked to calibrate refractometers immediately before their first measurement and measure the salinity of the calibration solution again following their last measurement of each sampling event. These two calibration points were regressed against elapsed sampling time to determine a linear calibration equation over time for each salinity profile. This equation was used to correct each salinity measurement for time-changing accuracy error, assuming equal time intervals between samples and a linear change in calibration offset. Calibration solutions were made from filtered, autoclaved seawater, diluted with deionized water to 17 PSU, the midpoint of the expected surf zone salinity range.

Second, a controlled laboratory study was conducted with a group of volunteers (undergraduate students recruited separately from the main study) to mimic the level of familiarity with refractometers expected by volunteers and understand inter-volunteer and inter-refractometer variability. Forty-nine volunteers made 426 measurements with twenty calibrated refractometers at three different levels of salinity from fresh to marine (0, 17, and 34 PSU). Data were analyzed using linear mixed model regression, specifying salinity as the dependent variable, salinity level as a categorical fixed effect, and refractometer and operator (i.e., volunteer) as random intercepts, with operator nested under refractometer. Results indicated that the measurement variance associated with differences across refractometers was 3.5 times larger than that associated with differences across volunteers.

Refractometer instrument bias correction. After QC, refractometer instrument bias was corrected to increase salinity measurement accuracy. A linear regression of all refractometer measurements that passed QC against digital salinity probe measurements revealed regression intercept not equal to zero and slope not equal to one. Refractometer measurements were accordingly adjusted for this estimated mean instrument bias. Note that mean instrument bias did not penalize volunteer measurements in the QC accuracy check because the acceptable accuracy threshold (+/- 2.3 PSU) was determined using identical refractometers under similar field conditions.

Random forest regression to estimate hourly San Pedro Creek flow rates. San Pedro Creek flow is not gauged. Therefore, project staff made in situ measurements with a handheld flow meter (FP101, Global Water). Measurements were made once per week during the 2019 study. To estimate creek flow at the time of each sampling event conducted by a volunteer, hourly flow estimates were predicted from a model of measured flow regressed against precipitation variables. To capture non-linear responses of flow to precipitation (rather than use linear interpolation), random forest regression, growing 1000 trees and sampling 6 of 28 precipitation variables at each split, was used (Figure S1). Since only 12 flow measurements were made during the 2019 study, these data were augmented with other flow measurements made by our research group in previous studies: 13 measurements made during the 2017 pilot study (from February to May); and 9 measurements made at approximately twice-monthly intervals during winter 2018-2019. A total of 28 precipitation variables were used as model features, comprising daily cumulative precipitation for each of the preceding 14 days from each of the two nearest Local Climatological Data stations (Half Moon Bay Airport and San Francisco Airport,[1] which are approximately equidistant from San Pedro Creek). Median cross-validation root mean squared error of this model was 0.18 m^3/s.

Alongshore velocity equation from Inman, 1971:[2]

$$v_l = \frac{c_4}{c_f} * \mathrm{u}_m * \tan(\beta) \sin(\alpha_b) cos(\alpha_b)$$

where v_l is the alongshore velocity (m/s); $c_4 = 5\pi/8$; c_f is the bottom drag coefficient, estimated by Inman as 0.02; β is the beach slope; α_b is the incident wave angle, [-π/2 rad, π/2 rad]; u_m is the maximum horizontal component of the orbital velocity at the waves' breakpoint (m/s), equal to $\frac{1}{2}\gamma(gh_b)^{1/2}$, where γ is the ratio of wave height to depth, assumed to be 0.78 (Komar and Inman, 1970[3]), g is gravitational acceleration = 9.81 m/s^2, and h_b is the significant wave breaker height (m).

Calculating shoreline distances from GPS coordinates. To compute shoreline distances from GPS-labeled sampling locations, several intermediate approximations were made. Figure S3 depicts this procedure used for San Lorenzo River. First, line segments parallel to each discharge (river or creek) were constructed to define datums from which to measure distance along the shoreline. San Lorenzo River is sufficiently wide that volunteers sampled the mouth of the discharge from the River's edge, rather than the River's midline. Thus, distinct lines were used to define each side of the River, depicted in Figure S3 as a red line for San Lorenzo River west and an orange line for San Lorenzo River east. San Pedro Creek is sufficiently small that volunteers were often able to sample the Creek mouth at its midpoint. Thus, a single line was used to define the Creek centerline. Equations of these datum lines were calculated from pairs of points measured in QGIS using satellite images courtesy of Planet Labs, Inc. and Google Earth (Figure S3).

Second, to prevent noise in GPS coordinates and sampling locations (depicted as blue circles) from inflating cumulative distances from the datums described above, coordinates of each sample were projected onto linear fit lines (depicted as a dark blue line), one for each profile. Orthogonal regression was used to minimize residuals in both longitude and latitude, and straight lines fit profiles well (data not shown; median Pearson r = 0.92, 90% of r > 0.52).

Shoreline distance from the discharge was then computed as the distance from the datum along the fit line to each projected point (depicted as yellow dashes crossing the blue fit line).

Volunteer recruitment and training. Volunteers were recruited by contacting local environmental and volunteer organizations, state and local agencies, posting on Stanford social media platforms and an environmental job board, and via in-person recruiting at study beaches. Volunteers were referred to a project website with more detailed project information, including a recruitment video and a signup form. In-person trainings instructed volunteers about the scientific objectives of the project, sampling procedures, and project logistics. Project staff did not conduct sampling alongside volunteers.

Post-project results and debriefing with volunteers. Volunteers were invited to attend results presentations approximately two months after completing the post-project survey. Four presentations (two in each city) at venues near the study sites and two online presentations were given. During these presentations, volunteers were debriefed about analyses conducted with their survey responses, as well as planned presentations to government stakeholders.

Survey items not described in main text. Volunteers who were assigned to receive data reports were also asked if they were aware that data reports had been emailed to them, and how many of them they had looked at. In addition, the post-project survey included an item asking volunteers what effect reviewing data reports had on their volunteering experience. Finally, the pre and post surveys included a battery of items to gauge place attachment,[58] which is not discussed further in this manuscript.

Motivational constructs. Motivational constructs were defined in terms of volunteers' perception of opportunities offered by volunteering with the project. 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.

Survey confirmatory factor analysis. Confirmatory factor analysis (CFA) could not be performed on these data of learning, values, and social items, to confirm that survey items operationalized these constructs as intended because distributional assumptions of the procedure were violated by highly non-normal response distributions. Although ordinal CFA remove some of the distributional assumptions, and the quantity of data gathered in our surveys was insufficient to perform ordinal CFA (data not shown).

QC criterion to determine sufficient spatial coverage of data points along the shoreline. D_{90} distances were estimated from nonlinear regression fits between freshness values and shoreline distance. Often, volunteers sampled a sufficient distance along the shoreline that their sampling locations spanned the estimated D_{90} distance. However, for some salinity profiles, especially at San Lorenzo River, the estimated D_{90} was beyond the range of distances sampled by a volunteer (Figure S7). Extrapolating D_{90} estimates beyond the spatial domain covered by measurements increases uncertainty in D_{90} estimates. Thus, a QC criterion describing an acceptable amount of distance extrapolation for D_{90} estimates was defined. This acceptable amount of extrapolation was defined as the distance extrapolation factor (DEF, i.e., the ratio of the estimated D_{90} to the farthest measured distance) associated with 20% relative error (DEF_{20}) in D_{90} estimates, and was calculated to be 2.43. The algorithm for determining DEF_{20} was: 1) For each salinity profile and D_{90} estimate, compute the DEF. 2) Subset the data to include only profiles for which DEF ≤ 1 (i.e., no extrapolation required). 3) Define the D_{90} of each of these profiles as 'true D90' because they required no distance extrapolation. 4) For each of these profiles, remove the salinity measurement corresponding to the most distant point. Call this a truncated profile. 5) For each truncated profile, re-estimate D_{90}. 6) For each truncated profile, compute the DEF and the relative accuracy of the D_{90} estimate. 7) Repeat 4-6 for each truncated profile until the number of remaining points in that profile is < 4, at which point nonlinear regression cannot reliably be performed. 8) Finally, plot all the computed DEFs against the corresponding (absolute value) relative accuracy of D_{90} estimates. Use linear regression to estimate the DEF at which the relative accuracy is 20%.

Tables

Table S1. Motivation and benefit constructs and indicators. Each indicator was an individual survey item, which permitted integer responses from 1 to 5, corresponding to 'strongly disagree' to 'strongly agree' with 3 as 'neither agree nor disagree'. These items were randomized within a survey block of motivations or benefits. See the survey files for contextual language used to present these items.

Construct	Definition	Indicators
Motivations		
Learning-oriented motivation	The perception that volunteering with this project offers opportunities to learn or exercise knowledge or skills	1. I am interested in learning techniques used to analyze water quality data. 2. I want to gain a better understanding of coastal water quality issues. 3. I want to learn about making water quality measurements through direct, hands-on experience.
Values-oriented motivation	The perception that volunteering with this project offers opportunities to contribute to an issue the volunteer is concerned about	1. I am concerned about poor water quality at X beach. 2. I feel it is important to protect coastal water quality. 3. I want to contribute to a worthy cause.
Social-oriented motivation	The perception that volunteering with this project offers opportunities to develop social relationships	1. Participating will provide an opportunity to spend time with people I care about. 2. Participating will allow me to meet people with similar interests to mine. 3. Participating will provide social time.
Career-oriented motivation	The perception that volunteering with this project offers opportunities to develop one's career	1. Volunteering with this project will look good on my resume.
Recreation-oriented motivation	The perception that volunteering with this project offers opportunities to engage in an enjoyable activity	1. Participating in this project sounds enjoyable to me.
Child-oriented motivation	The perception that volunteering with this project offers opportunities to participate in an activity with one's children	1. Participating in the project seems like a good activity to do with my children.
Benefits		

Learning-oriented benefit	The perception that volunteering with this project offered opportunities to learn or exercise knowledge or skills	1. By participating in this project, I have gained a better understanding of beach water quality issues. 2. By participating in this project, I have gained skills in making water quality measurements. 3. By participating in this project, I have learned something new about how rivers and creeks impact beach water quality.
Values-oriented benefit	The perception that volunteering with this project offered opportunities to contribute to an issue the volunteer is concerned about	1. By participating in this project, I feel I have done something for a cause I believe in. 2. By participating in this project, I have contributed to a worthwhile effort. 3. By participating in this project, I have contributed to protecting coastal water quality.
Social-oriented benefit	The perception that volunteering with this project offered opportunities to develop social relationships	1. Participating in this project has been an opportunity to spend time with people I care about. 2. Participating in this project has enabled me to meet people with interests similar to mine. 3. Participating in this project has provided social time.
Career-oriented benefit	The perception that volunteering with this project offered opportunities to develop one's career	1. Volunteering with this project has strengthened my professional resume.
Recreation-oriented benefit	The perception that volunteering with this project offered opportunities to engage in an enjoyable activity	1. Participating in this project has been enjoyable.
Child-oriented benefit	The perception that volunteering with this project offered opportunities to participate in an activity with one's children	1. Participating in this project has been a good activity to do with my children.

Table S2. Survey items for and scoring of obstacles to participating. Scoring was based on conversations with volunteers and the authors' extensive experience sampling at the sampling sites. Scores were intended to be comparable across each of the four obstacle types, with higher scores indicating greater obstacles. Each volunteer's score is the sum of their scored responses for each of the four obstacles types. Responses from the pre-project survey for expected obstacles were utilized because the pre-project survey had the highest completion rate.

Obstacle indicator	**Obstacle construct**	**Survey item**	**Possible responses**	**Score**
Expect to have to pay to park	Financial obstacle	Do you think that you will have to pay for parking when you go to the beach to conduct sampling for this project?	Yes, usually or always	0.5
			Yes, sometimes	0.3
			No	0
Travel time for sampling	Logistical obstacle	Each time you go sampling, about how much time will you spend traveling to and from [sampling site] that you would not otherwise spend traveling to and from [sampling site]?	1 hour or more	1
			45-59 minutes	0.9
			30-44 minutes	0.7
			15-29 minutes	0.5
			0-14 minutes	0
Time unavailable due to employment obligations	Time obstacle	Which of the following best describes your employment status?	Employed, working 40 or more hours per week	1
			Employed, working 20-39 hours per week	0.7
			Student	0.7
			Employed, working 1-19 hours per week	0.5
			Stay-at-home parent	0.5
			Not employed and looking for work	0.2
			Not employed and not looking for work	0
			Not able to work	0
			Retired	0
Expected physical difficulty of sampling	Physical obstacle	Collecting water samples will require you to wade in water up to your ankles or knees. How physically challenging do you think that will be for you?	Very challenging	1
			Moderately challenging	0.7
			Mildly challenging	0.3
			Not challenging at all	0

Table S3. Linear regression estimates of associations between D_{90} and tide level, discharge, and longshore velocity. Longshore velocity is coded such that the direction of the corresponding D_{90} is positive. Note that confidence intervals for statistically significant associations may appear to include 0 due to rounding. CI is 95% confidence interval.

	San Pedro Creek		**San Lorenzo River**	
Parameter (units)	*Estimate (CI)*	*p-value*	*Estimate (CI)*	*p-value*
Intercept (m)	243 (199, 292)	<0.001	248 (114, 432)	<0.001
Tide level (m)	-4 (-10, -1)	<0.001	-1.0 (-15, 2)	0.42
Discharge, log10 (m^3 /s)	16 (6, 30)	<0.001	19 (0, 72)	0.05
Longshore velocity, standardized (-)	0 (-1, 0)	0.28	-2.0 (-9, 0)	0.05
Observations	74		71	
R^2	0.11		0.38	

Table S4. Regression results testing volunteer retention. Interaction terms in each model test the corresponding hypothesis. 'Received data reports' is a dummy variable coded 1 (0) for volunteers who received (did not receive) data reports. 'Received data reports & Learning motivated' is the corresponding dummy variable for the motivation model. An odds ratio of 1 indicates no effect. Dashes indicate coefficients that were not estimated for a given model. CI is 95% confidence interval.

	Information hypothesis		**Motivation hypothesis**	
Predictor	*Odds ratio (CI)*	*p-value*	*Odds ratio (CI)*	*p-value*
Intercept	0.13 (0.09, 0.17)	<0.001	0.12 (0.09, 0.17)	<0.001
Obstacles	0.63 (0.46, 0.86)	0.00	0.71 (0.51, 0.99)	0.04
Time (weeks)	0.96 (0.92, 1.01)	0.08	0.97 (0.94, 1.00)	0.06
Received data reports	1.46 (0.92, 2.32)	0.11	-	-
Received data reports & Learning motivated	-	-	1.60 (0.97, 2.64)	0.07
(Time) X (Received data reports)	0.99 (0.93, 1.05)	0.70	-	-
(Time) X (Received data reports & Learning motivated)	-	-	0.90 (0.83, 0.98)	0.01
Num. clusters (volunteers)	45		45	
Cluster size (days)	85		85	

Table S5. Volunteer characteristics in information and motivation regression models. The same 45 volunteers are included in both models. The number in each cell represents the number of volunteers in that category.

		Information hypothesis		**Motivation hypothesis**	
		Data reports	*No data reports*	*Data reports & Learning-oriented*	*Others*
Gender	Female	15	20	5	30
	Male	6	4	2	8
Age	18-24	4	4	3	5
	25-34	3	4	0	7
	35-44	6	7	1	12
	45-54	5	1	3	3
	55-64	2	4	0	6
	65-74	1	3	0	4
	75-84	0	1	0	1
	85+	0	0	0	0
Sampling site	San Pedro south	4	4	0	8
	San Pedro north	5	5	4	6
	San Lorenzo west	5	6	0	11
	San Lorenzo east	7	9	3	13
No. volunteers		21	24	7	38

Table S6. Distribution of volunteer motivational orientations. A motivational orientation was defined as a motivation with a score greater than 3 and at least as high as all other motivation scores. Since all volunteers had at least one motivation score greater than 3, the column 'Motivation selection count' is equivalent to the number of motivational orientations present in the data set. For example, 31 volunteers had a single top-scoring motivation, and 5 of those were children oriented, while 17 were values oriented. In contrast, 14 volunteers had more than one top-scoring motivation, and hence more than one motivational orientation.

No. motivations volunteer ranked as most important	No. volunteers	Motivation	Motivation selection count
1	31	children	5
		enjoy	4
		learning	5
		values	17
2	7	children	1
		enjoy	5
		social	1
		learning	3
		values	4
3	5	children	2
		enjoy	5
		learning	3
		values	5
4	2	career	1
		children	1
		enjoy	1
		social	1
		learning	2
		values	2

Figures

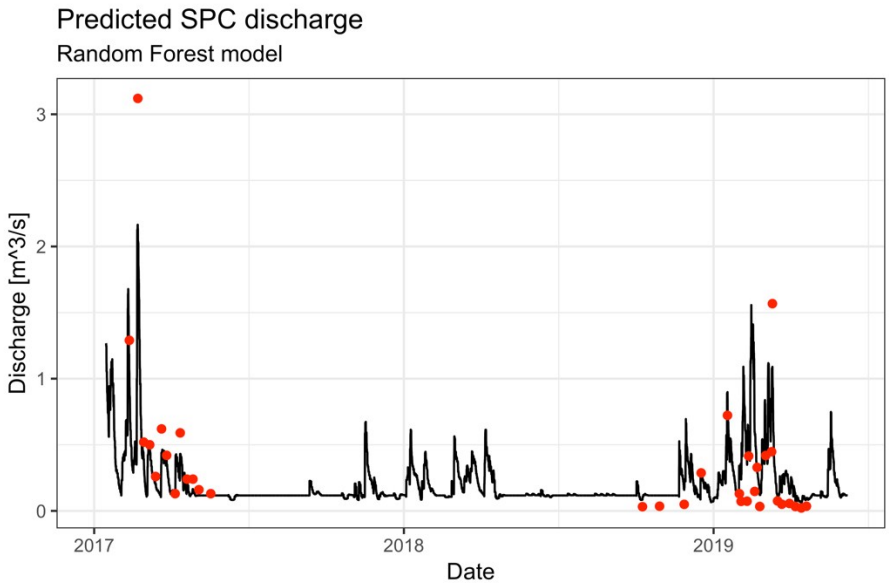

Figure S1. Prediction of hourly San Pedro Creek discharge rates. Red points are measured values. The black line indicates predicted values. Median cross-validation root mean squared error of this model was 0.18 m^3/s.

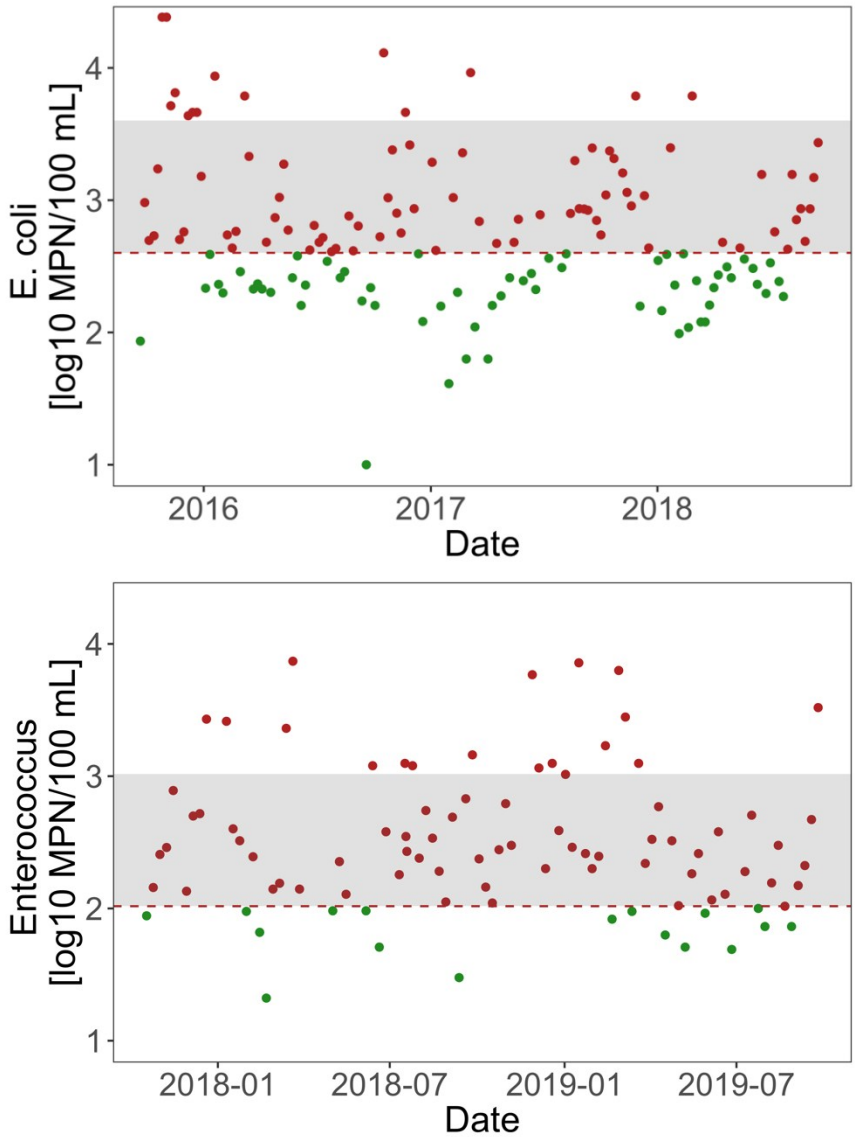

Figure S2. Historical FIB levels at the mouths of San Pedro Creek (top) and San Lorenzo River (bottom). The red dashed line indicates the single sample maximum used by California of 400 MPN / 100 ml for *E. coli* or 104 MPN/100 ml for *Enterococcus*. Red (green) points indicate concentrations that (do not) exceed this threshold. The gray, shaded regions depict concentrations that, if diluted by 90% (i.e., at the D_{90} location), would fall below the concentration threshold. Source: San Mateo County Department of Public Health and Santa Cruz County Department of Environmental Health.

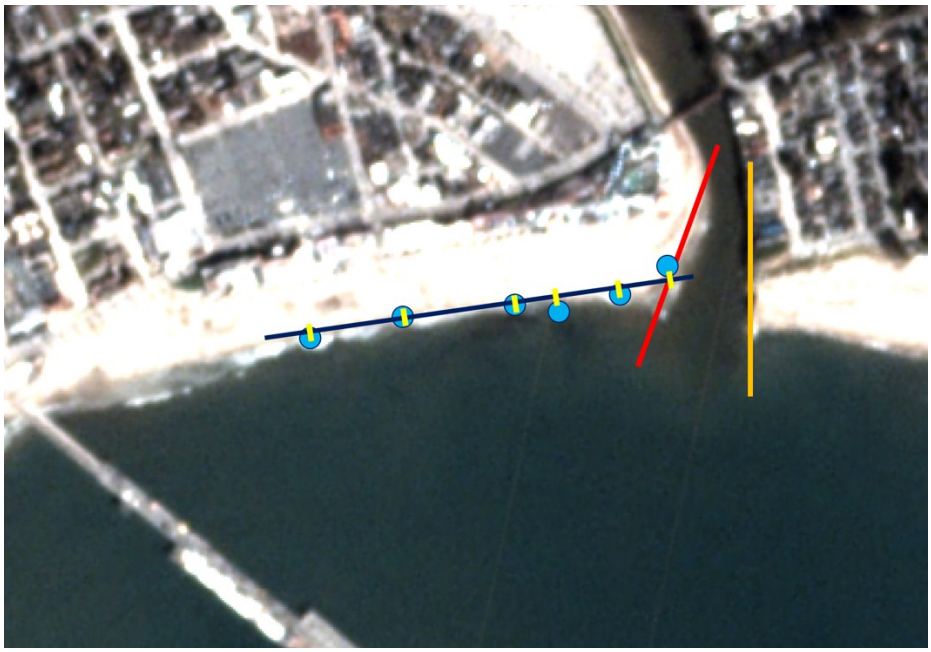

Figure S3. Calculating shoreline distances from GPS coordinates. Satellite image courtesy of Planet Labs, Inc.

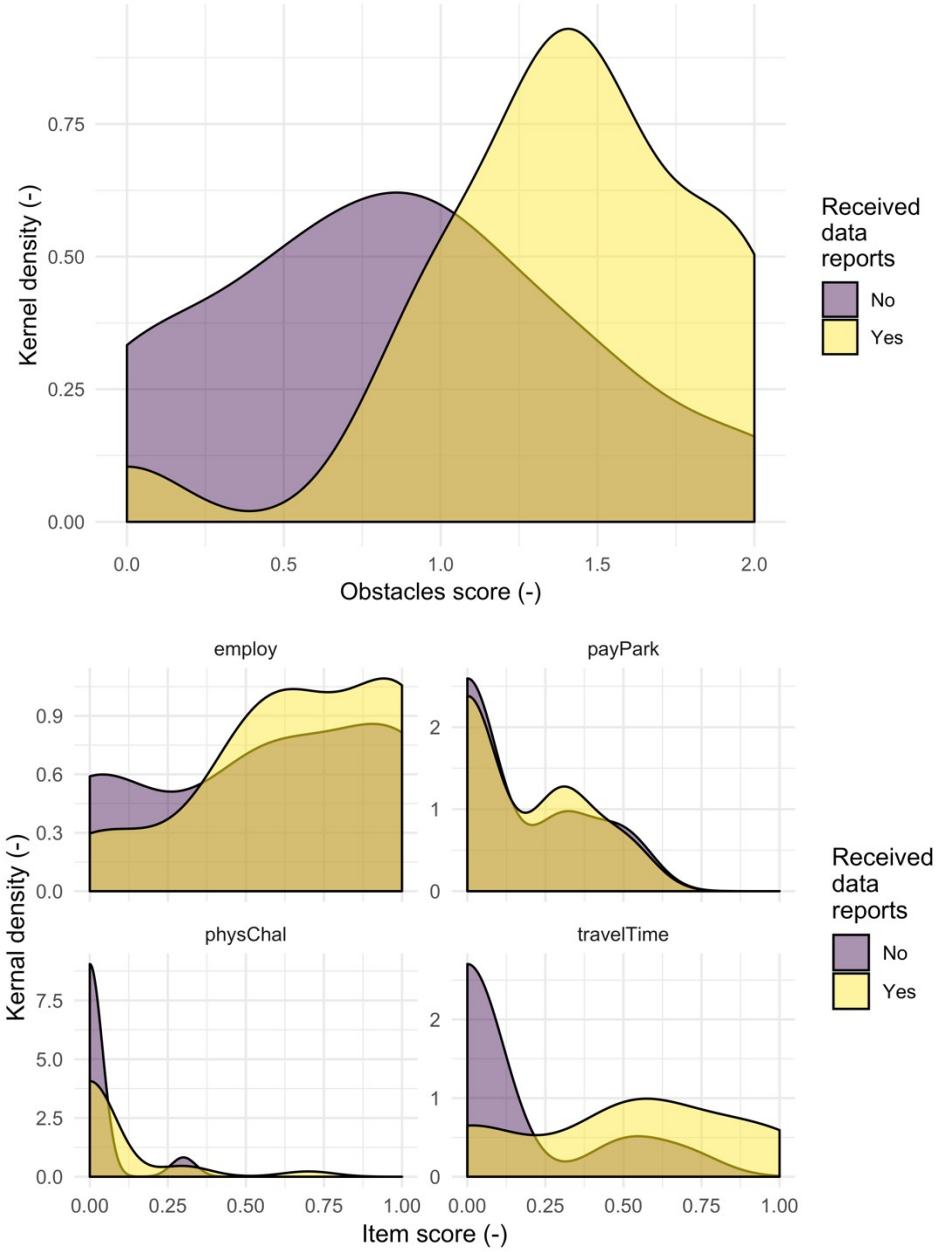

Figure S4. Obstacles to participating reported by volunteers. Higher scores indicate greater obstacles. Top figure: obstacle score distributions. Bottom figure: Individual obstacle item distributions (employment, paying to park, physical challenges, and travel time), the 4 components of obstacle scores. Yellow denotes the treatment group (volunteers who received data reports); purple denotes the control group (volunteers who did not). A kernel density plot is a smoothed version of a histogram (the default estimation procedure and bandwidth from the R package 'ggplot2' were used).

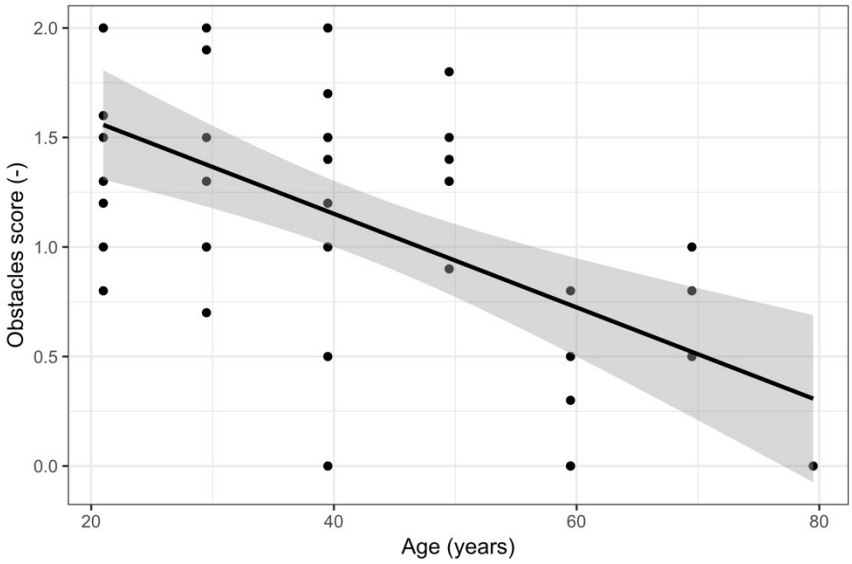

Figure S5. Participant obstacles scores against age. Obstacles scores and age were negatively correlated (Pearson's r = -0.57; 95% CI = -0.74, -0.34). Note that age was reported categorically, and the midpoint of each category is depicted here. Categories were 18-24, 25-34, 35-44, …, 75-84, >84.

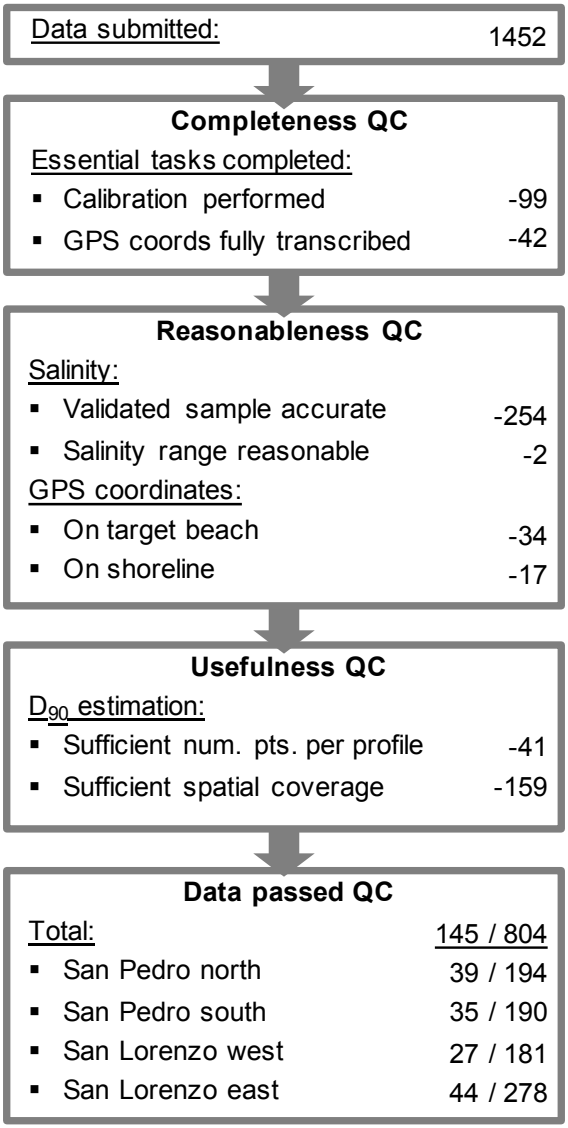

Figure S6. QC flow chart. Negative numbers indicate the number of measurements discarded due to each QC criterion. Numbers in the bottom box indicate the number of salinity profiles that passed QC, represented as the number of salinity profiles, followed by a slash, followed by the corresponding number of individual salinity measurements. Note that the number of data points discarded by each criterion depends on the order in which criteria were applied.

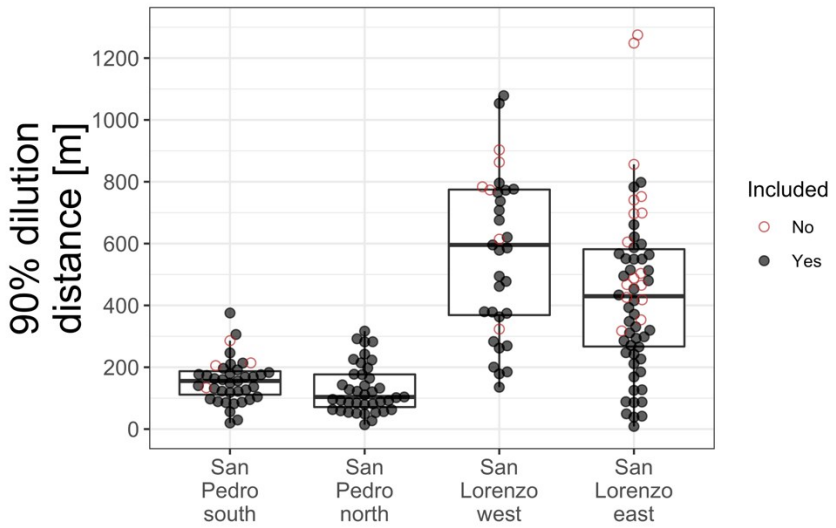

Figure S7. D_{90}s that failed the 'sufficient spatial coverage' criterion. D_{90}s that failed are depicted with unfilled, red circles. The uncertainty in these D_{90} estimates was deemed unacceptably high due to the extrapolation required beyond the spatial range spanned by measurements. These D_{90}s were excluded from the final statistics and linear models. 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.

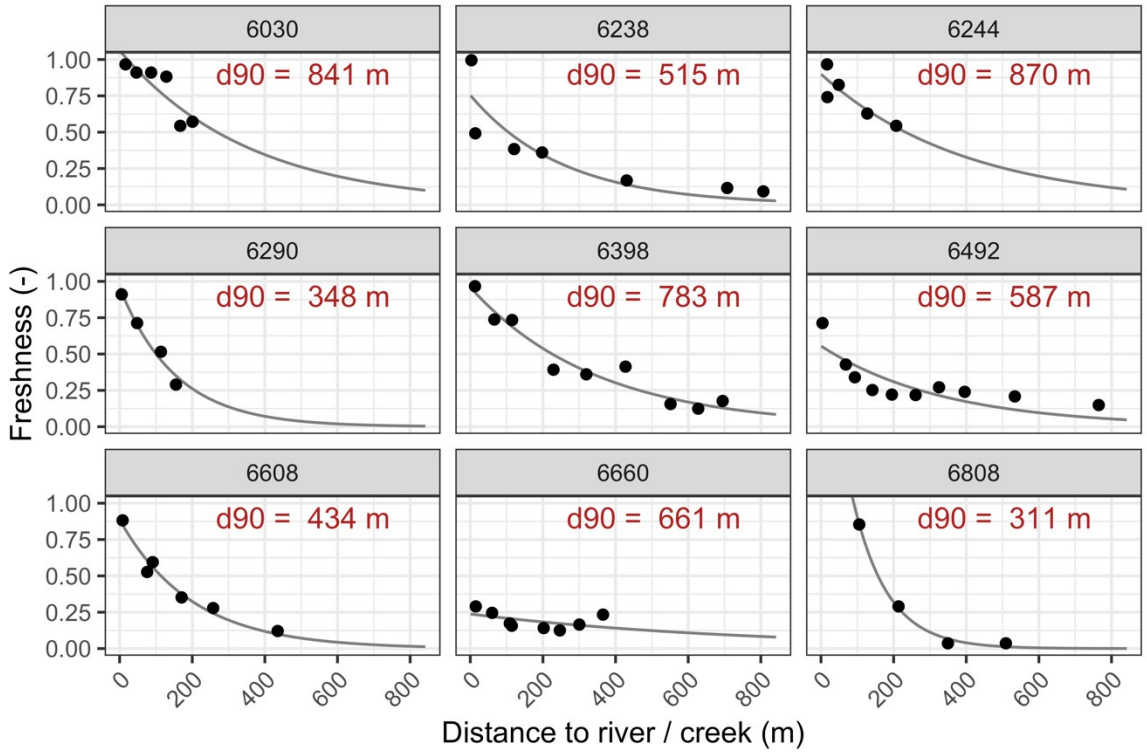

Figure S8. Example of 9 individual salinity profiles used for estimating D_{90} at San Lorenzo River. Each profile represents measurements collected by an individual in one sampling event. The y-axis shows freshness from 0 (marine water) to 1 (fresh water). The x-axis shows the shoreline distance from the mouth of the river. Numbers in gray boxes are sample IDs. Fit lines are exponential decay functions used to estimate D_{90}, described in Methods. Note that D_{90} estimates for 6030 and 6244 were not included in final D_{90} statistics because they failed the 'sufficient spatial coverage' QC criterion.

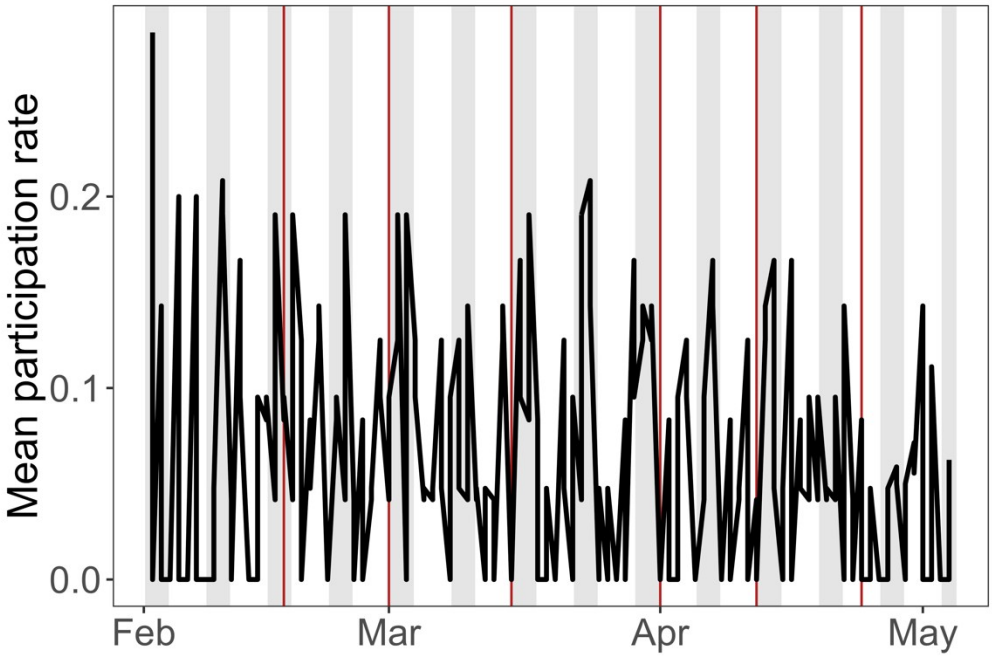

Figure S9. Mean participation rate by calendar day. Mean participation rate is the number of volunteers out of 45 total who sampled on a given day. Gray shaded regions indicate weekends (Saturdays and Sundays). Red vertical lines indicate days on which project emails, including data reports, were sent to volunteers. Note that each volunteer conducted sampling over an 85-day window, and that all volunteers started and finished within one week of each other.

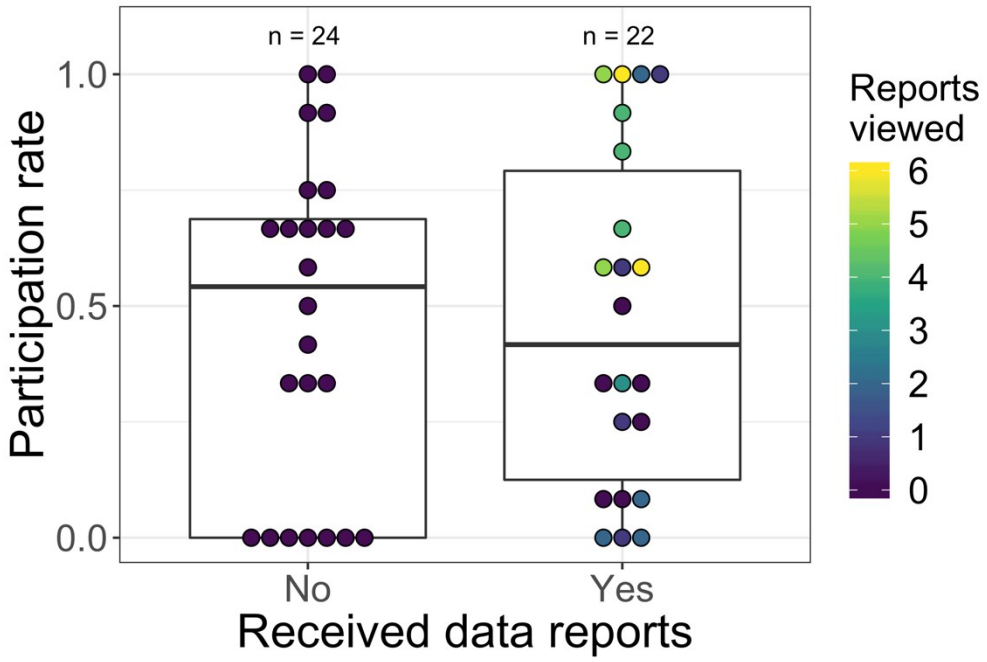

Figure S10. Participation rates for each volunteer, disaggregated by treatment group. A participation rate of 1 indicates that a volunteer sampled 12 times, which was the number of samples requested from each volunteer. Colors indicate the number of data reports viewed by each volunteer, measured by clicks on emailed links to online data reports. Six reports were sent during this 12-wk project. 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 $\times$ interquartile range from the 25th and 75th percentiles, respectively. Individual points are displaced horizontally to aid visualization.

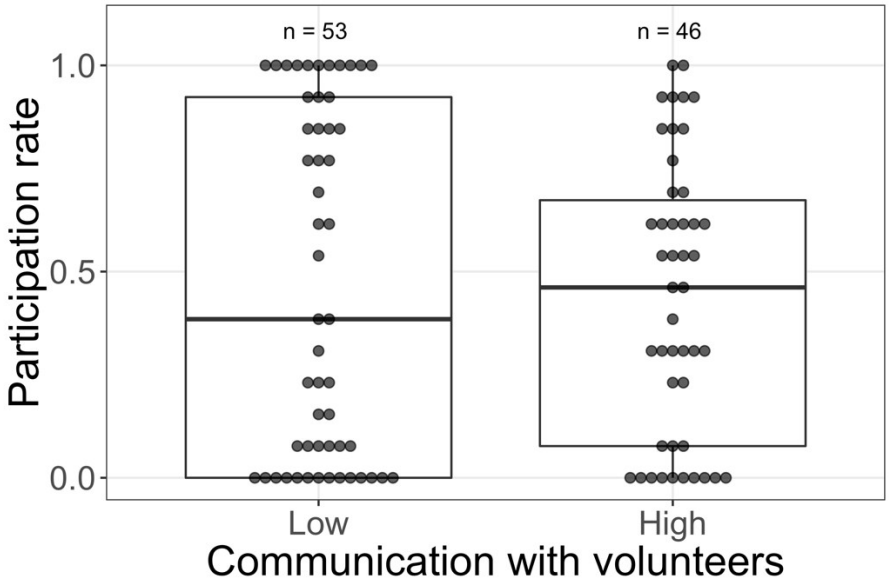

Figure S11. Participation rates in 2017 pilot study and 2019 study described in this paper. As described in Discussion, project staff communicated minimally with volunteers in the 2017 pilot study (the 'low' communication condition). In 2019, volunteers received an in-person training and regularly email communication from project staff, updating them on project status and data quality issues ('high' communication). 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 $\times$ interquartile range from the 25th and 75th percentiles, respectively. Individual points are displaced horizontally to aid visualization.

References

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