Modeling Exposure to Fecal Contamination in Drinking Water due to Multiple Water Source Use

Sean W. Daly* and Angela R. Harris*

ABSTRACT: The Joint Monitoring Programme estimated that 71% of people globally had access to “safely managed” drinking water in 2017. However, typical data collection practices focus only on a household’s primary water source, yet some households in low- and middle-income countries (LMICs) engage in multiple water source use, including supplementing improved water supplies with unimproved water throughout the year. Monte Carlo simulations and previously published data were used to simulate exposure to fecal contamination (as measured by E. coli) along a range of supplemental unimproved source use rates (e.g., 0–100% improved water use, with the remainder made up with unimproved water). The model results revealed a statistically significant increase in annual exposure to E. coli when individuals supplement their improved water with unimproved water just 2 days annually. Additionally, our analysis identified scenarios—realistic for the data set study setting—where supplementing with unimproved water counterintuitively decreases exposure to E. coli. These results highlight the need for evaluating the temporal dynamics in water quality and availability of drinking water sources in LMICs as well as capturing the use of multiple water sources for monitoring global access to safe drinking water.

KEYWORDS: multiple water source use, supplemental unimproved source use, fecal contamination, Monte Carlo simulations, drinking water quality, low- and middle-income countries

INTRODUCTION

Inadequate water, sanitation, and hygiene (WASH) were estimated to have caused 829,000 diarrheal disease deaths in 2016, representing 60% of all diarrheal deaths, including 5.3% of all deaths in children under 5 years of age.1 WASH-associated diseases are predominately caused by enteric pathogens, such as rotavirus, Cryptosporidium, enterotoxigenic Escherichia coli, and Shigella.2 Ensuring “safe and affordable drinking water” and “adequate and equitable sanitation and hygiene” are critical to reducing these disease burdens and are global targets in the Sustainable Development Goals (SDGs).3 The Joint Monitoring Programme (JMP) 2017 Update and SDG Baselines report 93% of the global population as having access to improved or higher quality drinking water.4 Improved water sources are those likely to be protected from fecal contamination, such as boreholes and piped supplies, while unimproved sources are not protected, such as unprotected wells and surface water.5

Interventions to provide new water sources or improve drinking water quality are common strategies to reduce disease associated with inadequate WASH conditions; however, their effectiveness varies significantly between reports and geographies.6,7 Pickering et al. compared the effectiveness of WASH interventions in various geographies, including Bangladesh, Kenya, and Zimbabwe. They found WASH interventions to be ineffective in all settings at improving child growth and found that WASH interventions reduced diarrhea in some contexts but not in others.8 Clasen et al. found that common environmental interventions, including providing improved water sources, were generally not effective at reducing diarrheal disease. They did find that improving the microbial quality of water at the point of use, via methods such as disinfection and filtration, had some effectiveness at preventing diarrhea.9 However, there are challenges with ensuring consistent, long-term point-of-use water treatment in intervention participants, as adherence to the intervention product often declines over time.10 The investment into intervention programs and targeting of populations to intervene is often informed by monitoring efforts, such as the JMP, which, particularly for monitoring access to “safe” drinking water, exhibits notable limitations.

Current global drinking water monitoring statistics are primarily informed by household surveys, asking households to describe their primary source of drinking water.11 However, a recent systematic review revealed that households across low- and middle-income countries (LMICs) practice multiple water source use (MWSU).12 Households may use multiple drinking water sources for various reasons, including seasonal changes in availability, insufficiencies in supply or breakdown, aesthetics,

Received: August 25, 2021
Revised: February 16, 2022
Accepted: February 17, 2022
Published: March 3, 2022

https://doi.org/10.1021/acs.est.1c05683
Environ. Sci. Technol. 2022, 56, 3419−3429
financial cost, and physical distance to source.⁶ Daly et al. also found that, in some cases, households in LMICs supplement an improved primary water source with unimproved water throughout the year, a practice referred to as ‘supplemental unimproved source use’ (SUSU).⁵ As unimproved sources of water are more likely to be contaminated with fecal contamination than improved sources,⁦ the practice of SUSU provides the potential for unmonitored exposure to unsafe drinking water. Even in high-income countries, generally with more reliable water supplies, SUSU has been reported.⁴⁵ Prior studies have not explored how varying levels of SUSU may influence exposure, nor has the impact of SUSU on intervention effectiveness and noncompliance with WHO water quality standards been investigated. Rigorously evaluating the potential increase in exposure to fecal contamination due to SUSU could standards been investigated. Rigorously evaluating the potential increase in exposure to fecal contamination due to SUSU could provide explanations for recent evaluations of intervention success and provide justification for including SUSU in global monitoring strategies.

This study estimated the exposure to fecal contamination via drinking water due to the practice of SUSU. We conducted an ingestion exposure assessment using Monte Carlo simulations and published data to model the varying exposures to fecal contamination (as E. coli) across a range of SUSU rates (i.e., fraction of the year relying on improved versus unimproved sources). The model was developed using suggested distributions for ingestion from the U.S. Environmental Protection Agency (EPA)⁴⁷ and a published data set of water quality from Tanzanian sources,⁵¹ but can be altered to fit other scenarios or location-specific data, as we also demonstrate.

## METHODS

### Estimating Exposure via Drinking Water

In order to estimate the potential exposure to E. coli in drinking water due to the use of multiple sources, a scenario assessment was conducted. An exposure scenario is an estimate of exposure of humans to hazards in their environment, where certain assumptions or inferences are made to define a scenario where exposure may occur.⁴⁸ The following ingestion exposure equation represents a scenario where an individual is exposed to a contaminant through ingestion of the contaminant in water:

\[
E_{\text{ing}} = (C_{\text{ing}}) \times (IR)
\]

(1)

where \(E_{\text{ing}}\) is the ingestion exposure (organism per time), \(C_{\text{ing}}\) is the concentration of the ingested chemical/substance in water (organism per volume of water), and IR is the ingestion of the water (volume per time). Equation 1 represents one exposure to one hazard source with one concentration, one ingestion rate, and one exposure estimate. In order to represent a person’s exposure to E. coli from consuming water from improved and unimproved drinking water sources over the course of a year, the ingestion equation was modified to the following:

\[
E = \sum_{k=1}^{365} (C_i \times IR_i \times S_i) + (C_u \times IR_u \times (1 - S_i))
\]

(2)

where \(E\) is the annual exposure to E. coli [colony forming unit (CFU) E. coli/year] determined by the summation of daily ingestion exposure; \(C_i\) and \(C_u\) are the concentration of E. coli in the improved and unimproved water sources, respectively (CFU E. coli/mL), \(IR_i\) is the ingestion rate of drinking water in a given day of the year (mL/day), and \(S_i\) is a binary categorical variable which represents whether an improved or unimproved source is used for a given day. The \(S_i\) variable is determined by probability, based on the specified MWSSU scenario (i.e., fraction of the year using an improved water source ranging from 0–100%). The assignment of \(S_i\) reflects the probability that a simulated individual uses an improved source \((S_i = 1)\) or an unimproved source \((S_i = 0)\) on a given day. Within this simulation framework, a person is randomly assigned one improved and one unimproved source that they access over the year and does not switch between an improved and unimproved source within a given day.

### Modeling Exposure in a Population

Monte Carlo simulations, created using R version 4.0.5, were used to generate the distribution of exposures that a simulated population may experience, accounting for the variability in source water quality, water ingestion rates, and water source usages described below. As part of the simulation, eq 2 is used to estimate the yearly exposure for an individual that is randomly assigned one improved and one unimproved source, each representing a source sampled in Tanzania with its own unique log-normal distribution for E. coli concentrations. Each simulated day, a simulated individual is assigned a concentration from their specific water sources’ quality distributions, ingestion rate, and source used (improved or unimproved). The concentrations of E. coli in drinking water, \(C_i\) and \(C_u\), were pulled from concentration distributions from data collected by Matwewe et al., who reported temporal variability in source water quality \((N = 331\) total sources) in 9 sampling rounds over 20 months in Tanzania. Each simulated E. coli concentration was first subjected to a binary “probability of detection” based on the number of nondetect (ND) measurements for a source. Then, if the simulated E. coli concentration for a day was assigned as “detected,” an E. coli concentration was calculated from that source’s log-normal distribution for detected samples. To account for the temporal variability of water quality in this analysis, only water sources sampled three or more times over the sampling rounds were included, totaling 1364 individual water source measurements. Water quality data for the improved source types of piped supplies (piped to house and public taps, \(N = 436\) measurements from 87 unique sources), boreholes (electric, hand, and rope pump, \(N = 463\) measurements from 73 unique sources), protected dug wells \((N = 279\) measurements from 43 unique sources), and protected springs \((N = 7\) measurements from 1 unique source) and the unimproved source type of unprotected dug wells \((N = 179\) measurements from 38 unique sources) were used. The water ingestion rate \((IR)\) was drawn from a natural-log-normal distribution \((\text{mean} = 7.487, \text{standard deviation} = 0.405)\) of drinking water IRs suggested by the U.S. EPA for exposure assessments. The rate of improved water use, \(S_i\), is a binary variable determined by probability along a range of 0–100% improved water use. Each day \((k)\), a new \(S_i\) value is calculated. When \(S_i\) is assigned a value of 1, the simulated individual collects water from their improved source, with the E. coli concentration taken from the improved source’s distribution. When \(S_i\) is assigned a value of 0, the simulated individual collects water from their unimproved source, with the E. coli concentration taken from the unimproved source’s distribution. Additional information on each input variable (i.e., distribution type and parameters) is available in Table S11. The Monte Carlo simulation estimates a distribution in yearly exposure to E. coli from drinking for a population of 5000 individuals. Larger simulations of 10,000 individuals yielded no statistically significant differences, and observed trends remained the same. Within the simulation, to
measure the daily compliance with WHO drinking water quality standards (0 CFU E. coli per 100 mL), the fraction of the year being exposed to water above the WHO standard was recorded. Distributions are then created for scenarios where the probability of using an improved source of water each day ranges from 0 to 100%, in increments of 5%. In addition, the resolution between 90 and 100% improved water use was increased by increments of 0.5%. This framework allows for modeling exposure related to varying levels of SUSU practices.

Data Preparation and Analysis. For simulated individuals whose total annual exposure was 0 CFU E. coli, their annual exposure was replaced with 0.5 CFU E. coli to allow for log-transformation and calculating the geometric mean. Statistical significance of comparisons between improved source usage rates was determined by conducting an analysis of variance (ANOVA) Tukey post hoc test. This analysis compares the exposure estimates for all improved water source usage rates (i.e., comparing 0 and 5%, 0 and 10%, etc.) and was also done for the higher resolution data between 90 and 100% improved water use rates. Significance was measured at an \( \alpha = 0.05 \) significance level.

The influence of ND data was evaluated using five approaches: “substitute zero,” “substitute half-limit,” “substitute full-limit,” “combined,” and “Poisson log-normal.” The first three “substitute” approaches follow the approach outlined above, where a “probability of detection” for a simulated water sample was used to calculate whether E. coli concentrations were pulled from the source’s log-normal distribution for non-zero values, or if an ND was assigned, either 0, 0.5, or 1.0 (limit of detection) CFU E. coli per 100 mL. For the “combined” approach, a single distribution (no “probability of detection”) was created using all of a source’s data, with NDs replaced with 0.5 to allow for necessary log-transformation prior to establishing the distribution. Finally, the “Poisson log-normal” approach addresses ND data by using a Poisson distribution which includes random sampling error for log-normally distributed data.

Sensitivity Analyses. Sensitivity analyses were conducted via established methods to determine the sensitivity of the model output (per capita annual exposure to E. coli via drinking water) to variation in input parameter values. A baseline annual exposure estimate was calculated with all inputs to eq 2 (Ir, Ci, Ck, and Si) set to the median (p50) values of their distributions. As the Ci and Ck inputs come from multiple distributions representing multiple water sources sampled by Matwewe et al., the percentile values were taken from the distribution of all the water source measurements within each water source category (i.e., improved and unimproved). Then, the annual exposure output was calculated with each input individually set to their 25th percentile (p25), then their 75th percentile (p75), with the other inputs fixed at their 50th percentile. The ratios between the output values for each of these three settings were calculated (i.e., p50:p25, p75:p50, and p75:p25), with ratios close to 1 representing low sensitivity, ratios less than 1 representing a negative influence over the output, and ratios greater than 1 representing a positive influence over the output. The rank-order of the strength of each input’s influence over the output was determined by calculating the absolute value of the logarithm of the p75:p25 ratio, with larger numbers suggesting stronger influence.

Model sensitivity related to the E. coli concentrations in the source water was further evaluated with an extreme scenario analysis. Using the same Monte Carlo simulation framework, the exposure output’s sensitivity to the mean and standard deviation of the water quality of improved and unimproved sources (Ci and Ck) was investigated. Sixteen models were created to represent the most extreme scenarios, by creating combinations among the least and most contaminated improved water sources, the most and least contaminated unimproved water sources, and the lowest and highest standard deviations of water quality for improved and unimproved sources. All of the values for “extreme” means and standard deviations were taken from primary data collected by Matwewe et al. in Tanzania. The lowest mean contamination for both improved water and unimproved water sources was used to calculate whether E. coli concentrations were pulled from the source’s log-normal distribution for non-zero values, or if an ND was assigned, either 0, 0.5, or 1.0 (limit of detection) CFU E. coli per 100 mL.
unimproved water was 0 CFU E. coli, meaning no detection. The highest mean contamination was 430 CFU E. coli/100 mL for an improved source and $1.68 \times 10^4$ CFU E. coli/100 mL for an unimproved source. The lowest standard deviation for both improved water and unimproved water was 0 CFU E. coli/100 mL. The highest standard deviation for improved sources (486 CFU E. coli/100 mL) was larger than the highest standard deviation for unimproved sources (58 CFU E. coli/100 mL). As it is unrealistic for a contaminated source to exhibit zero variation in the magnitude of contamination, when a scenario called for a source with the most contaminated mean E. coli and the lowest standard deviation, the lowest standard deviation for a source that had at least one detection was used (1.0 CFU E. coli/100 mL and 1.2 CFU E. coli/100 mL for improved and unimproved sources, respectively).

**RESULTS**

**Comparing Improved Water Source Usage Rates: Annual Exposure.** The results of the model simulation for estimating annual E. coli exposure for varying levels of SUSU are shown in Figure 1. There was a statistically significant ($p < 0.05$, ANOVA with Tukey post hoc test) increase in exposure when the simulated population went from 100 to 99.5% improved water use (see Figure S12). This represents an increase in annual exposure for individuals using unimproved water approximately 2 days per year, compared to those who solely use improved water throughout the year. From 0 to 85% improved water use, the interquartile ranges (IQRs) of the exposure estimates overlap, and the mean annual exposure ranges from $4.90 \times 10^4$ to $8.51 \times 10^4$ CFU E. coli/year. While two estimated means may be statistically significantly different from one another based on the ANOVA test (such as exposure between 80 and 85% improved water use), the changes in the IQR of exposure estimates are minimal until improved water use reaches approximately 90% of the year. For 95 and 100% improved water use, the IQRs do not overlap and significant differences occur in the estimated means (ANOVA with Tukey post hoc test, $p < 0.001$), with the mean annual exposure at 95 and 100% improved water use being $3.55 \times 10^5$ and $9.77 \times 10^5$ CFU E. coli, respectively.

**Comparing Improved Water Source Usage Rates: Noncompliance with WHO Drinking Water Quality Standard.** The model reporting the fraction of the year drinking water out of compliance with the WHO standard for drinking water quality of 0 E. coli/100 mL exhibits a different trend compared to the yearly exposure to E. coli (see Figure 2). A negative linear relationship is observed between improved water source use and the fraction the year simulated individuals consumed water that is out of compliance with WHO standards. There is a statistically significant increase in noncompliance rate for each 5% decrease in improved water use (ANOVA, Tukey post hoc test, $p < 0.05$), except for between 70 and 75% improved water use. The mean noncompliance rate ranges from 92% of the year for 0% improved water source use to 42% of the year for improved water source use 100% of the time. These values represent the mean probability, taken from sources sampled in Tanzania by Matwewe et al., that an unimproved and improved source will be contaminated (CFU E. coli detected in 100 mL sample), respectively. For varying fractions of improved water source use (5–95% improved water use), the fraction of the year out of compliance aligns with the mean probability of contamination in the improved and unimproved sources studied by Matwewe et al., weighted by the fraction of time used.

**Comparing Improved Water Source Usage Rates by Improved Water Source Type.** Matwewe et al. sampled four types of improved water sources: piped supplies, boreholes, protected dug wells, and protected springs. We used the same Monte Carlo framework to analyze potential differences in exposure between users of the different improved water source types, with protected springs excluded due to data limitations (i.e., only 1 protected spring was sampled three times or greater). Protected dug wells contained the highest average concentration of E. coli, yielding statistically significantly (ANOVA, Tukey post hoc test, $p < 0.05$) higher annual

---

*Figure 2. Fraction of the year the mean individual consumes water out of compliance with the World Health Organization standard for drinking water quality (0 E. coli/100 mL) by improved water source use rate (N = 5000 for each rate). The center line of the boxplot represents the median exposures, with the box encapsulating the interquartile range (IQR) between the 25th and 75th percentiles. The upper and lower lines of each boxplot represent the values 1.5 times the IQR above the 75th percentile and 1.5 times the IQR below the 25th percentile. Points outside this range are considered outliers and are illustrated individually. The x-axis indicates the annual rate of improved water use (%). The y-axis indicates the fraction of the year that simulated individuals are out of compliance with the World Health Organization standard.*
exposure than piped supplies and boreholes at and beyond 30% and 80% improved water source use, respectively. Piped supplies contained the lowest average concentration of \( E. coli \), yielding statistically significantly lower annual exposure compared to boreholes at 15% improved water source use and beyond (see Figure S14). The trends related to the fraction of the year that simulated individuals were drinking water out of compliance with the WHO standard for drinking water quality were influenced by the type of improved water source used (see Figure S15). At just 5% improved water source use, protected dug wells yielded statistically significantly (ANOVA, Tukey post hoc test, \( p < 0.05 \)) higher noncompliance rates compared to

**Figure 3.** Annual exposure to \( E. coli \) per capita by improved water source use rate (\( N = 5000 \) for each scenario) for each extreme scenario analysis model, with the 5th, 25th, 50th, 75th, and 95th percentiles illustrated. The least and most contaminated sources correspond to the water sources with the lowest and highest mean \( E. coli \) values for both improved and unimproved sources. The low and high “SD” correspond to the lowest and highest standard deviations for water quality distributions for both improved and unimproved sources, respectively. The \( x \)-axis for each sub-figure indicates the annual rate of improved water use (%). For any value below 100% improved water use along the \( x \)-axis, the remainder is made up with unimproved water, simulating supplemental unimproved source use (SUSU). The \( y \)-axis for each sub-figure indicates the annual exposure (CFU \( E. coli \) per year), with an ND level at 0.5. Plot #1, illustrating exposure from uncontaminated improved and unimproved sources, yields no annual exposure to \( E. coli \), but is replaced with the ND level of 0.5 CFU \( E. coli \) to allow for illustration on the log-scale. The extreme scenarios with a positive relationship between improved water source use rate and annual exposure to \( E. coli \) are highlighted in gray.
both piped supplies and borehole sources. For 15% improved water source use and beyond, boreholes yielded higher noncompliance rates compared to piped supplies. These trends are driven by the differences in quality and variability observed between the different improved water source types.

**ND Data.** Figures 1 and 2 illustrate the results for the “substitute zero” for handling ND data. Comparing all five approaches at 100% improved water use, where ND data are most prevalent, each yielded mean annual E. coli exposure estimates that were statistically significantly different from one another, with the exception of comparing the “substitute zero” and “Poisson log-normal” approaches. The estimated mean annual exposure (upper, lower 95% confidence interval; CFU E. coli per year) at 100% improved water use for the “substitute zero” approach was lower than that for the “Poisson log-normal” approach. The results for handling ND data were comparable to those for handling ND data in the extreme scenario analysis model, where ND data were most prevalent.
zero,” “substitute half-limit,” “substitute full-limit,” “combined,” and “Poisson log-normal” approaches were 1.05 (1.16, 0.94) × 10^4, 3.05 (3.24, 2.88) × 10^4, 3.77 (3.98, 3.57) × 10^4, 2.53 (2.68, 2.39) × 10^4, and 9.66 (9.84, 9.49) × 10^3 CFU E. coli, respectively. Despite significant differences in the magnitude of exposure—although within the same order of magnitude—the trends between the improved water use rate and annual exposure remained similar across the five approaches. A statistically significant increase in annual exposure to E. coli was observed, in all approaches, between 100% improved water use and just 99.5% improved water use.

**Sensitivity Analysis.** The results of the sensitivity analysis (reported as absolute values of the logarithm of each p75:p25 ratio) reveal that the input factors from most to least influential over the annual exposure output are the E. coli concentration in unimproved water (C_u) (1.17), improved water source use rate (S_i) (0.48), IR (IR_f) (0.24), and E. coli concentration in improved water (C_i) (0.01). Both the IR and E. coli concentration in unimproved water had a positive influence over the exposure output, while the improved water use rate had a negative influence over the exposure output. The exposure model was not sensitive to the E. coli concentration in improved water, likely due to the limited variation in water quality in improved source waters (e.g., p75 for C_i is 2.5, while p75 for C_u is 757.5). More details of the sensitivity analysis are presented in Table S11.

**Extreme Scenario Analysis.** The results of evaluating theoretical extreme scenarios of water quality for improved and unimproved sources revealed more generalizable findings regarding MWSU. The 16 scenarios evaluating the highest and lowest means and standard deviations for improved and unimproved source water concentrations reveal that the means and standard deviations of the E. coli contamination in a water source greatly influence the impact that SUSU has on annual exposure to E. coli and noncompliance rates.

Some scenarios yield an expected negative relationship between improved water use and yearly exposure (scenarios 5, 7, 9, 11, 13, 14, and 15; no gray highlight in Figure 3), and other scenarios yield a counterintuitive positive trend between improved water use and yearly exposure (scenarios 2, 3, 4, 6, 8, 10, 12, and 16; highlighted in gray in Figure 3). All but one of these counterintuitive models occur when the improved source has a high standard deviation, with the exception occurring when the improved source had the highest mean and lowest standard deviation and the unimproved source had the lowest mean and lowest standard deviation of water quality (scenario #3). Notably, when both the improved and unimproved sources are of the highest mean contamination (430 and 1.68 × 10^4, respectively) and highest variability in contamination (standard deviations of 486 and 58, respectively), the relationship between improved water use and exposure is positive (scenario #16). It is also important to note that, in some scenarios where simulated individuals are using the least contaminated improved source and the most contaminated unimproved source, the relationship between improved water use and exposure can be positive (scenario #10). The means and standard deviations for E. coli concentration in both the improved and unimproved sources influence the relationship between improved water use and annual exposure. For example, in scenario 6, increasing just the improved water’s standard deviation compared to scenario 5 (i.e., means remain the same) causes the trend to reverse and using unimproved water no longer increases annual exposure. In scenario 16, increasing just the improved water’s mean contamination compared to scenario 14 (i.e., standard deviations remain the same) causes the trend to reverse as well. Supplementing improved water with unimproved water sources does not always increase exposure to fecal contamination. Instead, the magnitude and variability of contamination in both the improved and unimproved source types influence whether SUSU results in increased exposure to fecal contamination.

In these extreme scenarios, different trends are found between improved water use rates and portion of the year drinking water was out of compliance with WHO standards. Changing the magnitude of the mean contamination and the standard deviation of the source water quality distribution affected both the annual exposure to E. coli and the noncompliance rate, but their trends did not always agree. Comparing scenarios #7 and #8 in Figure 4, the trend in the noncompliance rate is positive, meaning that as the rate of improved water use increases, the noncompliance rate increases as well. However, the annual exposure estimates, displayed in Figure 3, show an opposite trend. When the improved water source’s standard deviation is low (scenario #7), the relationship between annual exposure to E. coli and the rate of improved water use is slightly negative, but when the standard deviation is high (scenario #8), the relationship is positive. This suggests that, depending on the mean contamination of a water source and the variability of the contamination, the influence that SUSU has on the annual exposure and the noncompliance rate of users may not always agree.

**DISCUSSION**

Our study rigorously evaluates the relationship between SUSU and annual exposure to E. coli based on water quality measurements of sources in Tanzania, and our simulations of possible water source combinations suggest that SUSU is likely to increase annual exposure to E. coli via drinking and noncompliance rates with WHO standards. The portion of the Tanzanian population with access to improved drinking water has been increasing, with 57% of the population having access to improved or higher quality water in 2017. However, some of the population surveyed by Matwake et al. use alternative drinking water sources seasonally, and there is further evidence of individuals in Tanzania using multiple sources of water, which, based on our simulations, would likely cause these individuals to lose the benefits of improved water access.

Based on a variety of pairings of improved and unimproved water sources, this model estimates that engaging in SUSU for just 2 days per year (~99.5%) is more likely to increase a user’s annual exposure to E. coli, rather than reducing or not influencing exposure. Thus, it is important to understand SUSU in the community in order to properly classify access to safe drinking water, as Hunter et al. estimated that just a few days per year of consuming contaminated water may significantly reduce or negate positive health benefits from improved water. While estimating health risks associated with the fecal indicator bacteria E. coli are challenging, estimates on exposure simply to human feces can also be made. Forsythe (2010) estimated an average of approximately 10^6–10^7 CFU fecal coliform per gram of human feces, and if we consider E. coli and fecal coliform to be comparable, our model would suggest that dropping from 100% improved water use over a year to 95% improved water use could increase an individual’s annual consumption of human feces from approximately 9.33 mg to approximately 314 mg. There is evidence that households in various LMICs often use...
unimproved water sources even when they have access to improved water, suggesting that SUSU could be an explanation for the limited impact of some WASH intervention efforts.\textsuperscript{11,39}

We also explored the conditions under which SUSU may not result in increased exposure to contamination via drinking water. Contrary to the expected impact of SUSU, our simulations of theoretical (but plausible) extreme scenarios reveal that under certain source water quality scenarios, increasing the fraction of annual water consumed from an unimproved source may not increase an individual’s exposure to fecal contamination. Even in scenarios where an improved source has low average contamination and an unimproved source has high average contamination, supplementing with unimproved water may not increase exposure to fecal contamination over the course of a year if the improved source exhibits high variability (see Figure 3, scenario 10). It may seem intuitive that two sources with the same average contamination would yield the same annual exposure; however, the temporal variability of a source can significantly increase the resulting annual exposure, as it is a summation of daily drinking exposure events. Even when the improved source, on average, is 0 CFU \textit{E. coli} per 100 mL, but subject to high variability (scenarios 2, 6, 10), supplementing with unimproved water may not increase exposure. It is important to capture variability for characterizing water quality, and infrequently sampling of a source (e.g., once or twice per year) introduces uncertainty surrounding resulting exposure estimates. Depending on the mean contamination and the variability in water quality in both the improved and unimproved sources an individual accesses, SUSU may or may not impact their annual exposure to \textit{E. coli} or their noncompliance rate with WHO standards. With some residents of the study area reporting that they did not always have water access to meet their needs,\textsuperscript{31} it is possible that, under the right conditions, SUSU may not increase exposure to fecal contamination. As seen in Figure 3, when an improved source is more variable than the unimproved, supplemental source, or when they are of comparable average contamination and variability in contamination, SUSU may not increase exposure to \textit{E. coli}. Given that improved sources in LMIC settings do not always meet water quality standards, it could be the case that having a supplemental source could increase resilience to scarcity, without increasing exposure to unsafe drinking water. This highlights the importance of characterizing the water quality of all sources a household uses, including the temporal variability in source quality.

There is some evidence of extreme temporal variability in source water quality in LMICs,\textsuperscript{17,26,28,31} however, it is not a well-studied aspect of safe water access. There is evidence that seasonal changes can influence source water quality.\textsuperscript{26,28,31} Kostyla et al. found seasonal variability in source water quality in various geographies, with a significant trend for greater contamination of boreholes and piped supplies during the rainy season compared to the dry season.\textsuperscript{22} This would suggest that sampling a source in both rainy and dry seasons would help capture the variability in quality. Levy et al. found source quality variable at short time increments, with variability of \textit{E. coli} concentrations in drinking water sources of up to 158 and 251 CFU \textit{E. coli} on a daily and hourly basis, respectively.\textsuperscript{28} Further, Taylor et al. explored how variability in a system’s water quality relates to sampling frequency in order to confidently characterize water quality. Taylor et al. demonstrated that, as the water quality in a piped system becomes more variable, the required sampling frequency may be up to 10 times the frequency suggested by the WHO Guidelines for Drinking Water Quality to achieve the same confidence level in the estimate of a system’s water quality.\textsuperscript{46} Accurate characterization of water quality, including temporal variability in quality, is essential to capture drinking water risks, particularly when considering risks associated with source switching behaviors.

The concern of variability in quality extends beyond the point of collection at a water source, as household water storage is common in LMICs.\textsuperscript{1} Water quality often deteriorates between collection and use, and water in household storage containers is often contaminated.\textsuperscript{17,15,17,32} The practice of SUSU can exacerbate this issue, as there is evidence in some settings of households mixing water they access from both improved and unimproved sources in household storage containers.\textsuperscript{34,35,44} This could limit the effectiveness of point-of-use water treatments, such as chlorine,\textsuperscript{31} and negate most if all of the benefits of improved water access. It may also be the case that the water becomes further contaminated during transport and in-home storage; thus, even water from improved sources could exhibit high levels of fecal contamination at the point of consumption.\textsuperscript{17,38,54} It is critical to ensure that improved water sources are always available and desirable for their users and always remain of high microbial quality throughout the year (i.e., low variability in quality, no post-supply contamination of water), as even infrequent introduction of contamination can negatively impact the health of users.\textsuperscript{19}

Understanding how water sources vary in quality over time and how and why individuals and households engage in potentially risky behaviors like SUSU is critical to reaching the JMP target 6.1 of “achieving...access to safe and affordable drinking water for all”.\textsuperscript{50} As MWSU and SUSU are currently not regularly monitored, there is limited understanding on how and why these practices occur, but there are some insights in the literature. Seasonality and water source insufficiencies are prominent reasons for households using multiple sources of drinking water.\textsuperscript{8} There are reports that up to 91% of surveyed households in the Marshall Islands and Solomon Islands,\textsuperscript{29} 29% of surveyed households in Tanzania, and 50% in Uganda\textsuperscript{37} switched drinking water sources in the dry and rainy season, with some households switching between improved and unimproved water seasonally. In sub-Saharan Africa, Foster et al. estimated that approximately 25% of handpump water sources are nonfunctional at any point.\textsuperscript{13} The WHO and UNICEF estimated in 2000 that half of piped water systems in Asia and one-third of piped water supplies in Africa and Latin America are intermittently functioning.\textsuperscript{50} Insufficiencies or breakdown in water supplies has been cited to influence the use of multiple drinking water sources in Ecuador,\textsuperscript{42} Nigeria,\textsuperscript{1,35} and in India,\textsuperscript{2} among other countries. There is also evidence in various LMICs that households switch water sources for reasons unrelated to availability. There are reports in Ghana\textsuperscript{21} and Nigeria\textsuperscript{26} of households switching sources for their perceived, not actual, quality. Aesthetics (i.e., taste or odor) has influenced users to switch away from available water sources in Ghana\textsuperscript{21} and in Mexico.\textsuperscript{10} Factors such as distance to source, collection time, financial cost, and social influences can also affect household water source decisions.\textsuperscript{33,43} Ensuring that primary water supplies are resilient enough to prevent breakdown, insufficient supply, or seasonal unavailability is key to avoid unmonitored MWSU and SUSU and the potential exposure related to these behaviors; however, ensuring safe sources are desirable and used when available is equally important.
Given the nature of the simulations developed in this work, insights should be considered alongside some limitations. The simulations used ingestion rate distributions that were developed based on studies conducted within the United States. The U.S. EPA does recommend these data for exposure assessments, but it is likely that individuals in different climates and cultures ingest different volumes of water. However, the model sought to explore relative differences in exposure based on changes in water source selection, so the uncertainty of ingestion is not believed to bias the trends observed. Additionally, the use of water source quality data from a study conducted in Tanzania yields insights specific to that study area. Although water source E. coli concentrations can vary drastically from region to region, the concentrations observed by Matwewe et al. are not atypical for regions still struggling with safe drinking water access. While these estimates are context-specific, evaluating the theoretical extreme scenarios did increase our ability to generalize these results to identify conditions under which SUSU would represent increases in exposure to fecal contamination.

While methods for handling ND data did not impact the general relationship between improved water use and exposure to E. coli, the presence of ND data introduces uncertainty into the model framework. The “Poisson log-normal” and “substitute zero” approach yielded lower estimates compared to the other approaches, which is expected for substitution methods, which tend to right-skew estimates by universally inserting non-zero values for ND data. Approaches which involve substituting half or the full detection limit are often considered a “worst-case scenario” approach, as they incorrectly assume that all ND measurements are a positive measurement at or below the detection limit, overestimating conclusions. The “combined” approach also overestimates exposure, as combining detect and ND values into one distribution reduces or removes the possibility for “accurate” ND measurements in a simulation. As a data set has fewer ND measurements, simple methods such as substituting half the detection limit will introduce less bias into the overall estimate, and there is evidence that statistical approaches such as the “Poisson log-normal” approach can reduce error associated with ND data. Interestingly, our unique “zero substitution” approach did not yield a significant difference compared to the “Poisson log-normal” method, which is considered to address the weaknesses of the common substitution approaches. Separating ND data from the detected measurements allows for including ND measurements in the exposure estimate as well as avoids skewing the concentration distribution by mixing ND and detect measurements into a single distribution. In order to reduce uncertainty surrounding ND measurements in environmental data, more sophisticated methods than substituting non-zero values for ND measurements are recommended, such as the Poisson log-normal approach, separating detect and ND data to avoid skewing distributions, or other statistical methods.

Increasing the volume of the sample processed for evaluating water quality would increase the limit of detection and also reduce uncertainty associated with NDs. As more of the global population gain access to improved and higher quality drinking water sources, which are likely to yield more measurements below detection limits due to being of higher quality, handling ND data will continue to be a pressing concern for evaluating environmental contamination data.

This model did not estimate direct health outcomes in the form of risk, only exposure to E. coli, a fecal indicator bacterium. E. coli does not necessarily cause negative health outcomes; instead, it is used as a proxy indicator for fecal contamination and potential enteric pathogens. Prior work modeling exposure to fecal contamination has also elected to model exposure to E. coli rather than reporting the resulting health risks. Estimating health risks from exposure rates to E. coli requires assumptions related to correlations between pathogen and E. coli concentrations. These assumptions introduce uncertainty in the risk estimates, and correlations between pathogen and fecal indicator bacteria concentrations in surface water or ground-water (common drinking water sources) are varied and less consistent than correlations between these organisms in sewage. Nonetheless, there is evidence that exposure to E. coli is associated with negative health outcomes, including a reported 54% higher probability of diarrhea for those exposed to E. coli in their drinking water compared to those not exposed, which does suggest that the increased exposure to E. coli in our model could yield increased disease outcomes. Our analysis that shows water quality noncompliance rates may be more insightful for decisions related to health, as this standard is designed to protect human health. Infectious dose also varies between pathogens, with some being infectious at the quantity of tens of organisms and others infectious at hundreds of thousands of organisms, and more extensive data on pathogen-specific concentrations in drinking water sources are needed in order to more reliably estimate health risks.

This work has identified potential gaps in understanding the reality of global safe water access, as well as unmonitored routes of exposure to fecal contamination in drinking water. The results of this model suggest that SUSU, a behavior not captured in typical monitoring methods and statistics, can increase human exposure to fecal contamination via drinking water. Our analysis of extreme water quality scenarios also reveals that supplementing improved water sources with unimproved water sources may not always result in increased exposure to fecal contamination. However, given the generally lower microbial quality of unimproved water sources, it is the more likely scenario that SUSU would yield higher annual exposure to E. coli via drinking water. It is recommended that water source quality be better characterized, including temporal sampling of the source to capture variability in water quality. This improved characterization would then allow for a better assessment of exposures given different water source use patterns. However, at the very least, impact evaluations and global monitoring efforts should capture all of the sources a household relies on in order to accurately assess “compliance” to water interventions and to capture risks associated with water access. We strongly recommend that SUSU does not remain an unmonitored behavior and it is included in future monitoring efforts for characterizing water access in order to ensure safe drinking water access for all, as outlined in the SDGs.

## ASSOCIATED CONTENT

* Supporting Information*

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c05683.

Exposure model input parameters; Monte Carlo model framework diagram; annual exposure to E. coli per capita by improved water source use; sample size increased to 10,000 individuals; annual exposure to E. coli per capita by improved water source use; between 90–100% in increments of 0.5%; results of ANOVA with Tukey post
hoch test; annual exposure to E. coli per capita by improved water source use; comparison between three improved water source types; fraction of the year out of compliance with WHO standard for drinking water quality; comparison between three improved water source types; and results of sensitivity analysis (PDF)

■ AUTHOR INFORMATION

Corresponding Authors
Sean W. Daly — Department of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, North Carolina 27695, United States; Email: swdaly@ncsu.edu
Angela R. Harris — Department of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, North Carolina 27695, United States; orcid.org/0000-0001-8639-8539; Email: aharris5@ncsu.edu

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.1c05683

Notes
The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

We recognize Dr. Dan Harris and Dr. Natalie Nelson for offering their statistical and coding expertise in organizing the model framework. We thank Dr. Jacqueline Thomas and Matwew et al. for providing their raw data set to us to use in our simulations. We would like to thank the North Carolina State University Office of Information Technology for allowing us to use their High-Performance Computing services to conduct our simulations.

■ REFERENCES

(1) Adeniji-Oloukoi, G.; Urmilla, B.; Vadi, M. Households’ coping strategies for climate variability related water shortages in Oke-Ogun region, Nigeria. Environ. Dev. 2013, 5, 23–38.
(2) Anthony, J. Drinking water for the third world: Problems and prospects in a medium-sized city. J. Am. Plan. Assoc. 2007, 73, 223–237.
(3) Bain, R.; Cronk, R.; Wright, J.; Yang, H.; Slaymaker, T.; Bartram, J. Fecal Contamination of Drinking Water in Low- and Middle-Income Countries: A Systematic Review and Meta-Analysis. PLoS Med. 2014, 11, No. e1001644.
(4) Bivins, A. W.; Sumner, T.; Kumpel, E.; Howard, G.; Cumming, O.; Sanogo, D.; Onwuchekwa, U.; Manna, B.; Ramamurthy, T.; Kanungo, T. H.; Panchalingam, S.; Wu, Y.; Sow, S. O.; Sur, D.; Breiman, R. F.; Sommerfelt, H.; Robins-Browne, R. M.; Levine, M. M. Burden and Aetiology of Diarrhoeal Disease in Infants and Young Children in Developing Countries (the Global Enteric Multicenter Study, GEMS): a Systematic Review. Sci. Total Environ. 2015, 514, 333–343.
(5) Chik, A. H. S.; Schmidt, P. J.; Emelko, M. B. Learning something from nothing: the critical importance of rethinking microbial nondetects. Front. Microbiol. 2018, 9, 2304.
(6) Clasen, T.; Schmidt, W. P.; Rabie, T.; Roberts, I.; Cairncross, S. Interventions to improve water quality for preventing diarrhoea: systematic review and meta-analysis. BMJ 2007, 334, 782.
(7) Clasen, T. F.; Bastable, A. Faecal contamination of drinking water during collection and household storage: the need to extend protection to the point of use. J. Water Health 2003, 1, 109–115.
(8) Daly, S. W.; Lowe, J.; Hornsby, G. M.; Harris, A. R. Multiple water source use in low- and middle-income countries: a systematic review. J. Water Health 2021, 19, 370–392.
(9) Elliott, M.; MacDonald, M. C.; Chan, T.; Kearton, A.; Shields, K. F.; Bartram, J. K.; Hadwen, W. L. Multiple Household Water Sources and Their Use in Remote Communities With Evidence From Pacific Island Countries. Water Resour. Res. 2017, 53, 9106–9117.
(10) Espinosa-Garcia, A. C.; Diaz-Avalos, C.; Gonzalez-Villarreal, F. J.; Val-Segura, R.; Malvaez-Orozco, V.; Mazarri-Hiriart, M. Drinking Water Quality in a Mexico City University Community: Perception and Preferences. EcoHealth 2015, 12, 88–97.
(11) Fewtrell, L.; Kaufmann, R. B.; Kay, D.; Enanoria, W.; Haller, L.; Colford, J. M., Jr. Water, sanitation, and hygiene interventions to reduce diarrhoea in less developed countries: a systematic review and meta-analysis. Lancet Infect. Dis. 2005, 5, 42–52.
(12) Forsythe, S. J. The microbiology of safe food. John Wiley & Sons, (2010), 46–50.
(13) Foster, T.; Furey, S.; Banks, B.; Willetts, J. Functionality of handpump water supplies: a review of data from sub-Saharan Africa and the Asia-Pacific region. Int. J. Water Resour. Dev. 2020, 36, 855–869.
(14) Gruber, J. S.; Ercumen, A.; Colford, J. M. Coliform bacteria as indicators of diarrheal risk in household drinking water: systematic review and meta-analysis. PLoS One 2014, 9, No. e107429.
(15) Gyundy, S. W.; Wright, J. A.; Conroy, B.; Du Preez, M.; Genthe, B.; Moyo, S.; Mutisi, C.; Ndamba, J.; Potgieter, N. Contamination of drinking water between source and point-of-use in rural households of South Africa and Zimbabwe: Implications for Monitoring the Millennium Development Goal for Water. Water Pract. Technol. 2006, 1, 1–9.
(16) Gwimbi, P.; George, M.; Ramphalile, M. Bacterial contamination of drinking water sources in rural villages of Mohale Basin, Lesotho: exposures through neighbourhood sanitation and hygiene practices. Environ. Health Prev. Med. 2019, 24, 33.
(17) Harris, A. R.; Davis, J.; Boehm, A. B. Mechanisms of post-supply contamination of drinking water in Bagamoyo, Tanzania. J. Water Health 2013, 11, 543–554.
(18) Helsel, D. R. More than obvious: better methods for interpreting nondetect data. Environ. Technol. 2005, 39, 419A–423A.
(19) Hunter, P. R.; Zmirou-Navier, D.; Hartemann, P. Estimating the impact on health of poor reliability of drinking water interventions in developing countries. Sci. Total Environ. 2009, 407, 2621–2624.
(20) Julian, T. R.; Canales, R. A.; Leckie, J. O.; Boehm, A. B. A model of exposure to rotavirus from nondietary ingestion iterated by simulated intermittent contacts. Risk Anal. 2009, 29, 617–632.
(21) Kosinski, K. C.; Kulinkina, A. V.; Abrah, A. F. A.; Adjei, M. N.; Breen, K. M.; Chaudhry, H. M.; Nevin, P. E.; Warner, S. H.; Tendulkar, S. A. A mixed-methods approach to understanding water use and water infrastructure in a schistosomiasis-endemic community: case study of Asamama, Ghana. BMC Public Health 2016, 16, 322.
(22) Kostyla, C.; Bain, R.; Cronk, R.; Bartram, J. Seasonal variation of fecal contamination in drinking water sources in developing countries: a systematic review. Sci. Total Environ. 2015, 514, 333–343.
(23) Kothary, M. H.; Babu, U. S. Infective dose of foodborne pathogens in volunteers: a review. J. Food Saf. 2001, 21, 49–68.
(24) Kotloff, K. L.; Nataro, J. P.; Blackwelder, W. C.; Nasrin, D.; Farag, T. H.; Panchalingam, S.; Wu, Y.; Sow, S. O.; Sur, D.; Breiman, R. F.; Faruque, A. S. G.; Zaidi, A. K. M.; Saha, D.; Alonso, P. L.; Tamboura, B.; Sanogo, D.; Onwuchekwa, U.; Manna, B.; Ramamurthy, T.; Kanungo, S.; Ochieng, J. B.; Omoro, R.; Oundo, J. O.; Hossain, A.; Das, S. K.; Ahmed, S.; Qureshi, S.; Quadri, F.; Adegbola, R. A.; Antonio, M.; Hossain, M. J.; Akinsola, A.; Mandomando, I.;楠pam, T.; Acicio, S.; Biswas, K.; O’Reilly, C. E.; Mintz, E. D.; Berkeley, L. Y.; Mühsen, K.; Sommerfelt, H.; Robins-Browne, R. M.; Levine, M. B. Burden and aetiology of diarrhoeal disease in infants and young children in developing countries (the Global Enteric Multicenter Study, GEMS): a prospective, case-control study. Lancet 2013, 382, 209–222.
(25) Krometis, L. A.; Patton, H.; Wozniak, A.; Savar, E. Water Scavenging from roadside springs in Appalachia. J. Contemp. Water Res. Educ. 2019, 166, 46–56.
(26) Kumpel, E.; Cock-Esteb, A.; Duret, M.; de Waal, D.; Khusz, R. Seasonal variation in drinking and domestic water sources and quality in Port Harcourt, Nigeria. Am. J. Trop. Med. Hyg. 2017, 96, 437–445.
(27) Kwong, L. H.; Ercumen, A.; Pickering, A. J.; Arsenault, J. E.; Islami, M.; Parvez, S. M.; Unicomib, L.; Rahman, M.; Davis, J.; Lubiy S. P. Ingestion of Fecal Bacteria along Multiple Pathways by Young Children in Rural Bangladesh Participating in a Cluster-Randomized Trial of Water, Sanitation, and Hygiene Interventions (WASH Benefits). Environ. Sci. Technol. 2020, 54, 13828–13838.
(28) Levy, K.; Hubbard, A. E.; Nelson, K. L.; Eisenberg, J. N. S. Drivers of water quality variability in northern coastal Ecuador. *Environ. Sci. Technol.* 2009, 43, 1788–1797.

(29) Luby, S. P.; Keswick, B. H.; Hoekstra, R. M.; Mendoza, C.; Chiller, T. M. Difficulties in bringing point-of-use water treatment to scale in rural Guatemala. *Am. J. Trop. Med. Hyg.* 2008, 78, 382–387.

(30) Mattioli, M. C. M.; Davis, J.; Boehm, A. B. Hand-to-mouth contacts result in greater ingestion of feces than dietary water consumption in Tanzania: a quantitative fecal exposure assessment model. *Environ. Sci. Technol.* 2015, 49, 1912–1920.

(31) Matewewe, F., Boniphace, A., Mrimi, E., Guo, D., Lwetoijera, W., Johnson, F., Thomas, J. Determining the effectiveness of water, sanitation and hygiene interventions to reduce health vulnerability to climate change in Tanzania. Final report on 30th April to World Health Organization, Geneva, Switzerland, 2018.

(32) McGuinness, S. L.; O’Toole, J.; Barker, S. F.; Forbes, A. B.; Boving, T. B.; Giryan, A.; Patil, K.; D’Souza, F.; Vhaval, R.; Cheng, A. C.; Leder, K. Household Water Storage Management, Hygiene Practices, and Associated Drinking Water Quality in Rural India. *Environ. Sci. Technol.* 2020, 54, 4963–4973.

(33) Nauges, C.; Whittington, D. Estimation of water demand in developing countries: An overview. *World Bank Res. Obs.* 2010, 25, 263–294.

(34) Ngasala, T. M.; Gasteyer, S. P.; Masten, S. J.; Phanikumar, M. S. Linking Cross Contamination of Domestic Water with Storage Practices at the Point of Use in Urban Areas of Dar es Salaam, Tanzania. *J. Environ. Eng. (New York)* 2019, 145, No. 04019017.

(35) Onabolu, B.; Jimoh, O. D.; Igboro, S. B.; Sridhar, M. K. C.; Onyilo, G.; Gege, A.; Ilya, R. Source to point of use drinking water changes and knowledge, attitude and practices in Katsina State, Northern Nigeria. *Phys. Chem. Earth* 2011, 36, 1189–1196.

(36) Payment, P.; Locas, A. Pathogens in water: value and limits of contamination between source and point-of-use. *Environ. Sci. Technol.* 2011, 49, 4–11.

(37) Pearson, A. L.; Zwickle, A.; Namanya, J.; Rzotkiewicz, A.; Mwita, E. Seasonal shifts in primary water source type: a comparison of largely pastoral communities in Uganda and Tanzania. *Int. J. Environ. Res. Public Health* 2016, 13, 169.

(38) Pickering, A. J.; Davis, J.; Walters, S. P.; Horak, H. M.; Keymer, D. P.; Mush, D.; Strickfaden, R.; Chynoweth, J. S.; Liu, J.; Blum, A.; Rogers, K.; Boehm, A. B. Hands, water, and health: fecal contamination in Tanzanian communities with improved, non-networked water supplies. *Environ. Sci. Technol.* 2010, 44, 3267–3272.

(39) Pickering, A. J.; Null, C.; Winch, P. J.; Mangwadu, G.; Arnold, B. F.; Prendergast, A. J.; Njenga, S. M.; Rahman, M.; Ntouzini, R.; Benjamin-Chung, J.; Stewart, C. P.; Huda, T. M. N.; Moulton, L. H.; Colford, J. M., Jr.; Luby, S. P.; Humphrey, J. H. The WASH Benefits and SHINE trials: interpretation of WASH intervention effects on linear growth and diarrhoea. *Lancet Glob. Health* 2019, 7, e1139–e1146.

(40) Pripús-Ustún, A.; Wolf, J.; Bartram, J.; Claesen, T.; Cumming, O.; Freeman, M. C.; Gordon, B.; Hunter, P. R.; Medlicott, K.; Johnston, R. Burden of disease from inadequate water, sanitation and hygiene for selected adverse health outcomes: An updated analysis with a focus on low- and middle-income countries. *Int. J. Hyg. Environ. Health* 2019, 222, 765–777.

(41) Quick, R. E.; Venczel, L. V.; Bean, N. H.; Highsmith, A. K.; de Hannover, E. H.; Espada, A.; Damiani, E.; Gonzalez, O.; Mintz, E. D.; Tauxe, R. V. Narrow-mouthed water storage vessels and in situ chlorination in a Bolivian community: a simple method to improve drinking water quality. *Am. J. Trop. Med. Hyg.* 1996, 54, 511–516.

(42) Fernanda Reyes, M. F. R.; Trifunović, N.; Sharma, S.; d’Ozouville, N.; Kennedy, M. Quantification of urban water demand in the Island of Santa Cruz (Galápagos Archipelago). *Desalin. Water Treat* 2017, 64, 1–11.

(43) Rodrigues Peres, M.; Ebdon, J.; Purnell, S.; Taylor, H. Potential microbial transmission pathways in rural communities using multiple alternative water sources in semi-arid Brazil. *Int. J. Hyg. Environ. Health* 2020, 224, No. 113431.