Sanitary inspection characteristics, precipitation, and microbial water quality - A three-country study of rural boreholes in Sub-Saharan Africa

Syed Anjerul Islam[1¶], Argaw Ambelu[2], Zakariah Seidu[3], Ryan D. Cronk[1&], and Michael B. Fisher[1¥*]

[1]The Water Institute at UNC, Department of Environmental Science and Engineering, Gillings School of Global Public Health, The University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, United States of America

[2]Ethiopian Institute of Water Resources, Addis Ababa University, Addis Ababa, Ethiopia

[3]Department of Biochemistry, University of Development Studies, Nyankpala Campus, Nyankpala, Ghana

*Corresponding author

E-mail: mbfisher@gmail.com (MBF); sislam@unc.edu (SAI)

Author Contributions:

¶ - Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing- Original draft, review and editing

&- Formal analysis, Resources, Supervision, Writing- review and editing.

¥ - Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing- review and editing

ABSTRACT

Microbial contamination of drinking water contributes to a substantive and preventable burden of enteric disease that disproportionately impacts infants and children. The World Health Organization (WHO) has published guidance on water safety and water quality monitoring, including sanitary inspection (SI) of water systems to detect and manage hazards such as fecal contamination. Sanitary inspection is a low-cost, on-site risk assessment tool for water supply systems based on observable risk factors (RFs) associated with potential hazards or defects. While water quality sampling and analysis methods are well characterized, SI as a tool for risk management in drinking water systems is under-studied. We used SI and water quality data from 966 rural boreholes in Ethiopia, Ghana, and Burkina Faso and merged these with remote-sensing rainfall estimates based on household location. Logistic regressions (binary and ordinal) were used to characterize associations of total SI risk score, as well as individual risk factors (RFs), and classes of RFs (i.e., “Source,” “Transport,” and “Barrier” risks) with fecal indicator bacteria (FIB) occurrence as the outcome, controlling for estimated cumulative rainfall (over the past 1-15 days before sampling). We found associations ($P<0.05$, OR: 3.5, 95% CI 1.05-11.66) between SI scores and *E. coli* risk categories controlling for fifteen-day cumulative rainfall. Furthermore, risk factors in the “barrier” category, such as the presence and adequacy of fencing around boreholes, concrete pads, and walls extending below the ground, were associated with the *E. coli* risk category. When examining individual RFs in the regression models, the presence of human excreta 10 m from the source (OR: 2.53), absence of cement floor (OR: 0.16), handpumps that were loosely attached at the base (OR:1.57), adequate fencing to keep animals out (OR: 0.57) and the presence of stagnant water (OR:1.39) were significantly associated with microbial contamination. Incorporating precipitation into models improved model fit characteristics (improved Pseudo R squared and AIC value); specifically, accounting for cumulative rainfall during the fifteen days before sampling improved model fit (increased pseudo-R^2 from 0.035 to 0.05) for *E. coli* contamination. These findings can inform the design, construction, maintenance, and monitoring of boreholes and prompt timely remediation of critical hazards in such systems, potentially enhancing water safety.

Keywords: Sanitary inspection; rainfall; precipitation; coliform; coli; microbial; bacteria; contamination; water quality; water safety; heath; SDG; environmental health; microbiology

Introduction

An estimated 2.2 billion people worldwide and 69% of households in Sub-Saharan Africa (SSA) lack safely managed drinking water (*Progress on Household Drinking Water, Sanitation and Hygiene 2000-2022: Special Focus on Gender | JMP*, 2023). Even when households rely on "improved water sources," there is no guarantee that water is free from fecal contamination (R. Bain, Cronk, Wright, et al., 2014; Brown et al., 2013) . It is estimated that more than one billion individuals worldwide use water from improved sources that are microbially contaminated and two billion lack safely managed water (R. Bain, Cronk, Hossain, et al., 2014; Onda et al., 2012; *Progress on Household Drinking Water, Sanitation and Hygiene 2000-2022: Special Focus on Gender | JMP*, 2023; Roy et al., 2016). According to the WHO/UNICEF Joint Monitoring

Programme for Water Supply, Sanitation and Hygiene (JMP), boreholes are classified as improved water sources (World Health Organization & United Nations Children's Fund (UNICEF), 2006), and approximately 200 million people in SSA depend on boreholes for drinking water (Danert, 2022). In SSA, rural drinking water systems generally have poorer water quality than urban ones (R. E. S. Bain, Wright, Christenson, et al., 2014). Rural systems may also be smaller in scale than urban systems in many SSA settings, and are more likely to be community-managed (Harvey & Reed, 2007) (although multi-village supply schemes managed by rural utilities are increasingly prevalent in Ethiopia).

Sanitary inspections (SIs) are useful for monitoring and managing water systems. Sanitary inspections are observational checklists that help managers assess the overall risk of contamination in a water system by identifying 1) potential contamination sources, such as inadequate sanitation facilities (i.e., open defecation, absence of toilet facilities, presence of unimproved toilet facilities, etc), waste disposal practices, or nearby sources of pollution, as well as 2) deficiencies in the sanitary seals/barriers/protections designed to protect improved sources from such contamination sources, and 3) transport mechanisms/vehicles such as stagnant/ponded water, leaking pipes, etc. (*Guidelines for Drinking-Water Quality*, 2022). They can be readily implemented using standardized forms developed by the WHO (World Health Organization) and adapted by others. These checklists consist of a series of yes/no questions indicating the presence or absence of sanitary risk factors (RFs). Risk factors help identify vulnerabilities in the water source and guide interventions to improve water quality and safety. While SIs cannot provide unambiguous quantitative data on exposures or risks, they can be a valuable and cost-effective tool for prioritizing interventions and reducing the risk of waterborne disease, especially in resource-limited settings (Cronin et al., 2006).

It is understood that SI scores are intended to be interpreted in combination with microbial data and not as a substitute for fecal indicator measurements. It is reasonable to expect that SI scores would be associated with measures of fecal contamination occurrence in water systems. However, published comparisons of sanitary survey data with microbial water quality measures have produced mixed results (Cronin et al., 2006; Ercumen et al., 2017; Howard et al., 2003; E. Kelly et al., 2021; E. R. Kelly et al., 2020; Misati et al., 2017; Mushi et al., 2012; Parker et al., 2010). A study on shallow tubewells in rural Bangladesh found no association between composite or overall sanitary risk score and water quality (Ercumen et al., 2017). Conversely, a study of protected springs in Uganda and a study of wells in Tanzania found associations between sanitary risk score and microbial water quality (Howard et al., 2003; Mushi et al., 2012). If the lack of associations between these variables in some studies and the inconsistency of findings among different studies cannot be explained, such findings may tend to weaken the strength of evidence for SIs as water safety management tools, even though the tested association is not specifically what SIs are designed to do (E. R. Kelly et al., 2020).

One factor with some potential to explain the differences among studies is rainfall, as theprevious studies did not systematically account for precipitation as a potential covariate or modifier of the relationship between sanitary inspection scores and microbial water quality. Previous studies in Bangladesh and Tanzania on rainfall (in the absence of SI data) found that water samples collected following heavy rainfall events positively correlates with microbial water contamination (Guo et al., 2019; Nijhawan & Howard, 2022; Wu et al., 2016), and the effect is strong for cumulative precipitation measures (Engström et al., 2015; Ercumen et al., 2015; Powers et al., 2023). Research in Bangladesh found significant associations between *E. coli* in wells and heavy rainfall occurring within the 7, 15, and 30 days before sampling (Wu et al., 2016). Likewise, a study in Tanzania indicated that heavy rainfall within 14 days of sample collection better predicted *E. coli* levels in wells (Guo et al., 2019). Therefore, a study incorporating rainfall may be able to parse the relationship between SI scores and microbial indicators and evaluate the relative importance of different RFs and RF categories.

This study used data from 966 rural boreholes in three African nations (Ghana, Ethiopia, and Burkina Faso) to explore the relationship between sanitary inspections and microbial water quality, accounting for rainfall. In addition, specific SI risk categories and factors strongly associated with microbial contamination were identified. In our analysis, rainfall events were included as either present or absent and as cumulative over various integration periods, known as "lag times," ranging from 1 day up to 15 days before sampling. This was done to determine the most effective precipitation lag times associated with microbial contamination. We hypothesized that integrating prior precipitation with SI data would allow for the prediction of water safety, as indicated by *E. coli* counts in water.

Methods

Study Design

A retrospective analysis was conducted using SI and microbial water quality data previously collected from 1251 boreholes in three African countries: Ethiopia, Ghana, and Burkina Faso. Water quality data were available for 966 boreholes (water quality samples and data could only be collected from systems that were functional on the day of the visit). Among these systems, most (n=958) had manual pumps, and the rest (n=8) were mechanized. International non-governmental organizations (NGOs) World Vision, WaterAid, Living Water, CARE, and Helvetas collaborated in collecting the data between 2014 and 2016. Enumerators conducted sanitary inspections in each country, collected and analyzed water quality samples, and recorded GPS coordinates, system details and images, and other relevant site and water system characteristics. More detailed study design and data collection procedures for each country are provided in Appendices 1 and 2.

Figure 1: Map of sampling locations in each study area (Ghana, Ethiopia, and Burkina Faso) on the map using triangles (an ArcGIS-created map). Shapefiles obtained from GADM (gadm.org).

Field Data Collection

Ethiopia:

NGO partners had worked in 222 kebeles (the smallest administrative units) in Ethiopia between 2011 and 2017. For this study, 88 kebeles were randomly selected (44 from the 'experimental' arm where water, sanitation, and hygiene (WaSH) program activities had been implemented, and 44 from the 'comparison' arm where WaSH programs had not yet been implemented). Data collection occurred from May 18 to July 16, 2015, using Samsung DUOS smartphones equipped with the Akvo FLOW (Akvo Foundation, Amsterdam, The Netherlands) platform. This data collection period spanned the transition from dry to rainy seasons. Additional details on data collection are presented in Appendix 1.

Ghana:

NGO partners implemented WaSH programs in 296 communities in Ghana. Two hundred sixteen of these communities were randomly selected for this study, comprising four districts in the Northeastern region of Ghana. Data were collected on Android-operated mobile phones between April and November 2014 using the mobile survey tool Akvo FLOW V 1.6 (Akvo Foundation, Amsterdam, The Netherlands). Details of the data collection have been previously reported (Fisher et al., 2020) and are also summarized in Appendix 2.

Burkina Faso:

In Burkina Faso, NGO partners implemented a water program in 401 villages across six regions from 2003 to 2015. Data were collected from 95 randomly selected villages between September 15, 2015, and January 9, 2016. The data were recorded on the mWater mobile application (New York, USA) utilizing Motorola XT 1021 phones. Additional data collection details are provided in Appendix 3.

Water Quality Sample Collection and Analysis

Water quality samples were collected and analyzed according to the protocols detailed in Supplemental Information file S1. Samples were collected from rural boreholes using sterile

100-mL Whirl-Pak Thio bags (Nasco, Ft Atkinson, WI) labeled with unique barcodes. Samples were analyzed for *E. coli* concentration (most probable number (MPN) per 100 mL) using the Compartment Bag Test (CBT) method (Aquagenx LLC, Chapel Hill, NC, USA) according to the manufacturer's specifications. Briefly, 100-mL samples were transferred to CBTs within 30 minutes of collection and stored at 4 C until enumerators returned from the field, then incubated at ambient temperature for 24 +/-2 hours for mean daily ambient temperature >30 C and 48 +/- 2 hours for mean daily ambient temp 25–30- C per the manufacturer's guidelines (Brown et al., 2011; E. Kelly et al., 2021; Stauber et al., 2014). Mean daily ambient temperatures were above 25 C in all study settings during data collection periods. *E. coli* count was recorded as *E. coli* MPN/100 mL.

For quality control, field blanks and duplicates were collected randomly and analyzed identically to other samples, comprising 5-10% of all samples. Briefly, a random subset of 5-10% of systems were selected to collect field blanks and/or duplicates. For blanks, a bottle of packaged drinking water from a reliable local brand (typically the top brand in the country) was opened near the water source or system being sampled, and a 100-mL 'field blank' sample was collected alongside the typical experimental field sample being collected at that system. For field duplicates, the experimental field sample to be obtained was simply collected in duplicate. Field blanks and duplicates were labeled using unique barcodes and treated identically to experimental samples concerning collection, transport, and analysis. Because of barcodes, enumerators were ostensibly blinded to the sample type (experimental, duplicate, or blank) being processed and analyzed after leaving the sample collection location.

Sanitary Inspection

Sanitary inspection data were collected using an 18-question SI form (Appendix 4) adapted from published examples (Bartram, 1996; Water & Team, 2006). Sanitary risk factors were divided into three categories, namely "Source," "Transport," and "Barrier" risks, as described previously (E. Kelly et al., 2021)(Figure 2). Risk factors in the "Source" category include potential origins or reservoirs of contamination. "Transport" risks denote potential pathways through which pathogens could contaminate water sources, while "Barrier" risk factors define engineered and/or natural barriers to the intrusion of microbial contamination.

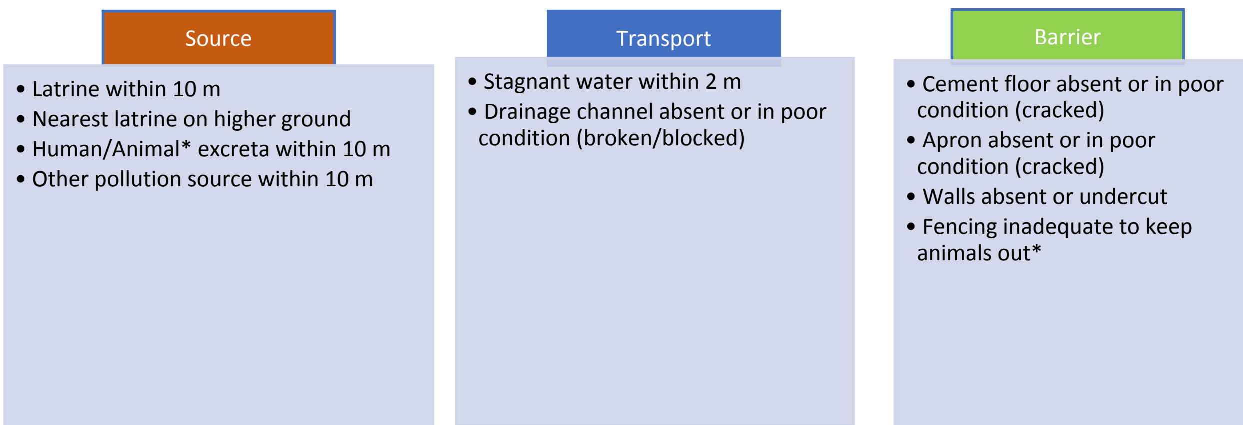

Figure 2 : Theoretical framework to assess sanitary inspection adapted from Kelly et al. 2021 (E. Kelly et al., 2021). (*these items are linked and do not fit neatly into a single category)

The sanitary risk scores were calculated for each borehole observation and disaggregated (source, transport, and barrier). Each risk category was equally weighed and scored items so that '0' denoted that the state of the given item was expected to correspond to lower risk, while '1' indicated that the state was likely to correspond to higher risk. Table S1 presented disaggregated risk factors and indicated each state's scoring convention (0 or 1). To calculate the risk score for a given borehole, the states of all risk factors (0 or 1) were summed and divided by the total number of applicable factors to obtain a composite risk score between 0 and 1, with 1 representing the greatest risk and 0 lowest risk (Appendices 3 and 4).

Imputed precipitation and water table depth estimates

Rainfall

Satellite rainfall estimates with 0.05-degree resolution were obtained from the University of California, Santa Barbara's Climate Hazards Center InfraRed Precipitation with Station (CHIRPS) website Funk et al., 2014). For each included borehole, the closest rainfall gauge station was located, and rainfall in mm were integrated over one-, two-, three-, seven-, 10-, and 15-day periods prior to the date of the site visit (sanitary inspection and water quality sample collection).

Water Table Depth

Annual groundwater depth data for boreholes were estimated from a continuous global map of groundwater depths. This map was generated by Fan et al. based on a groundwater model incorporating more than 100,000 direct well measurements from government archives and published articles (Fan et al., 2013) and (Fan et al., 2017). The groundwater depth corresponding to the closest point from the Fan et al. dataset was used for each borehole site.

Statistical Analysis

Summary statistics were calculated for all water systems by country and overall. Hypothesis testing was done using one-way analysis of variance (ANOVA) and logistic regression. Briefly, ANOVA was used to compare microbial data across the three countries. Logistic regression models explored associations between sanitary inspection scores and microbial data while controlling for precipitation and covariates (country, groundwater depth, etc.).

E. coli MPN values were tabulated, and binary (presence/absence) and categorical (microbial risk category) variables were constructed from numeric MPN data for statistical analysis. Briefly: a binary variable was created and coded based on "presence" (≥ 1 MPN/100 mL) or "absence (< 1 MPN/100 mL) of *E. coli*. A categorical variable was created and coded according to WHO microbial risk categories (World Health Organization, 2011): conformity (<1 MPN/ 100 mL), low-risk (1<= MPN/100 mL < 10), intermediate-risk (10<=MPN/100 mL<100), or high-risk (MPN/100 mL>=100). *E. coli* presence/absence was then modeled using binary logistic regression, while the WHO health risk category (conformity/low/medium/high risk) was modeled using ordered logistic regression. In both types of regression models, independent variables included sanitary risk scores (overall, disaggregated by risk category, or disaggregated by individual risk factor), precipitation (binary or cumulative [mm] over one, two, three, seven, or 15-day periods), estimated water table depth (meters), and country (Figure 3). Various combinations of sanitary risk and precipitation were assessed in our models to determine the most effective model estimates. Pseudo R-squared values were used to evaluate model fit for binary logistic regressions (Menard, 2000); the Akaike Information Criterion (AIC) value was used to assess fit for ordered logistic regressions (Chakrabarti & Ghosh, 2011).

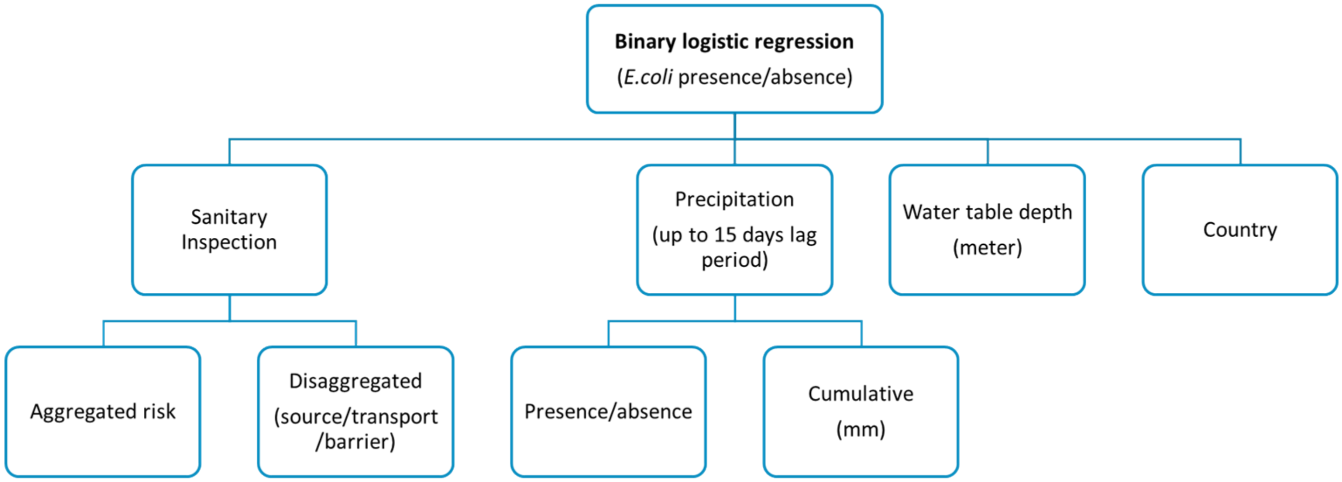

Figure 3: Conceptual diagram of a binary logistic regression model with all independent variables (sanitary inspection, precipitation, annual water table depth, and country) and the dependent variable (E. coli presence/absence). The independent variables remained the same for ordered logistic regression, but the dependent variables would be E. coli *as WHO risk category (conformity/low/intermediate/high risk).*

Software

The Python programming language (version 3.11.4, Python Software Foundation, 2022. https://www.python.org/) was used to run the regression models (binary and ordered logistic), implementing a package called STATSMODELS of version 0.13.1 (statsmodels.org). ArcGIS Pro from Esri (Sources: Esri, DeLorme, HERE, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), Swiss topo, MapmyIndia, and the GIS User Community) was used to extract and merge rainfall data with other variables and to produce maps of study data.

Ethics

No human subjects' data are included in this retrospective analysis of environmental monitoring data from communal water systems. Ethical review for this retrospective analysis was undertaken by the University of North Carolina Institutional Review Board (IRB study number 21-0592). The current study uses environmental monitoring data from prior fieldwork in Burkina Faso, Ghana, and Ethiopia. Ethical approval for that prior fieldwork, on which this retrospective study is based, was granted by the University of North Carolina Institutional Review Board (IRB study numbers: 14–0386; 15-1021; 15-1607). Approval was also obtained from the applicable Health ministry in each country.

Results

E. coli occurrence

Most borehole water samples, totaling 665 (69%), showed no detectable *E. coli* contamination in a 100 mL sample (Figure 4, Table 1). The highest proportion of borehole samples with detectable contamination was in Ethiopia and the lowest in Burkina Faso (Figure 4), and differences among countries were significant by one-way ANOVA ($p<0.05$). The average and geometric mean of *E. coli* MPN concentrations were 31 MPN/100 mL (standard deviation [SD]= 31) and 15 MPN/100 mL (SD = 31), respectively. Overall, the mean annual water table depth was 20 m, the mean 15-day cumulative precipitation (CP-15) was 53 mm, and an average of 36% of systems had reportedly failed in the past year (Table 1, Appendix 6).

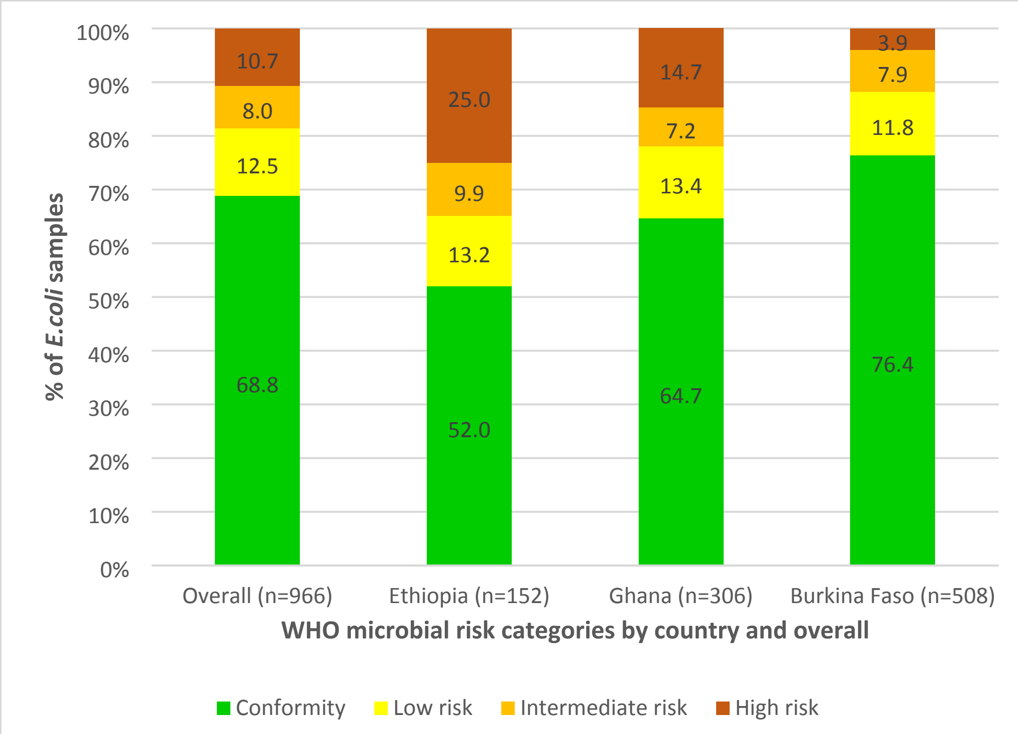

Figure 4 : WHO microbial risk categories for water quality samples from study boreholes

Table 1. Water system characteristics by country

Variable	Overall	Ethiopia	Burkina Faso	Ghana
# boreholes	1251	183	593	475
Functional on day of visit	78.4%	80.3%	89.7%	63.6%
boreholes w/ handpump	1235	176	593	466
Mechanized boreholes	16	7	0	9
*Hand-dug [n]	16.5% [775]	64.5% [183]	1.7% [592]	No data
*Water table depth (SD) [n]	19.8 (27.8) [1251]	14.5 (14.9) [183]	16.6 (12.5) [593]	25.9 (41.2) [475]
*CP-15 (mm) (SD) [n]	52.6 (42.4) [1251]	60.0 (26.5) [183]	42.2 (43.7) [593]	62.8 (42.8) [475]
**E. coli* MPN (SD) [n]	13.0 (31) [966]	27.5 (43) [152]	6.3 (20.7) [508]	17.1 (35.5) [306]
**E. coli* risk cat [n]	[966]	[152]	[508]	[306]
conformity	68.8%	51.7%	76.4%	64.7%
low-risk	12.5%	13.2%	11.8%	13.4%
intermediate risk	8.0%	9.9%	7.9%	7.2%
high risk	12.5%	25.0%	3.9%	14.7%
*Flow rate in L/min (SD) [n]	14.7 (7.3) [981]	4.43(2.9) [147]	15.8 (6.2) [532]	17.9 (6.2) [302]
*Failure in last year (Yes) [n]	36.0% [1035]	30.1% [176]	52.0% [592]	No data
*Source continuous (Yes) [n]	75.3% [1241]	80.6% [180]	81.9% [592]	64.8% [469]
*Seasonality (Yes) [n]	7.4% [1212]	6.8% [177]	4.0% [580]	12.1% [455]
*Conductivity in uS (SD) [n]	468 (447) [980]	348 (317) [154]	317 (230) [520]	785 (595) [306]
*pH (SD) [n]	6.8 (0.9) [978]	7.4 (1.0) [153]	6.4 (0.5) [516]	7.3 (0.8) [309]

* denotes values that are significantly different ($p<0.05$) among countries by one-way ANOVA

Determinants of microbial contamination

Significant associations (P<0.05) were observed between rainfall events and *E. coli* contamination using both binary and ordinal logistic regressions; effect sizes were greater, and model fits were better for longer vs. shorter rainfall integration periods (Appendix 7). Cumulative precipitation using a fifteen-day integration period (CP-15) was more strongly associated with microbial contamination than binary precipitation variables or cumulative precipitation variables using shorter integration periods, and regression results presented in the main findings were therefore based on CP-15 (Appendix 8 – Appendix 11). No significant association was found between microbial contamination and water table depth. Consequently, this variable was not reported in the main results. Binary regression models achieved slightly better fit (greater R^2) values than ordinal logistic regression models, but neither model explained a large proportion of the variability in the dependent variable (Appendix 7).

Aggregated Sanitary Risk

For both binary and ordered logistic regression models, a significant association (p<0.05) between overall sanitary risk score and microbial contamination was found when 15 days' cumulative precipitation was included in a simple model controlling for the country (Table 2). Odds ratios for overall sanitary risk score were 3.49 and 4.33 for binary and ordinal logistic regression, respectively, indicating that systems with the highest vs. lowest possible risk scores were, in theory, 3-4 times more likely to have any detectable *E. coli* in 100 mL (binary model) or to have *E. coli* MPN values corresponding to a higher vs lower risk category (ordinal model). Associations between overall SI score and *E. coli* occurrence measures were positive and significant across the various cumulative precipitation integration periods (one day to fifteen days) studied (Appendix 10). CP-15 was also significantly associated with *E. coli* occurrence measures across binary and ordinal logistic regression models (as were CP measures using shorter integration periods). However, the effect size was modest (OR: 1.007, 95% CI 1.004-1.01), implying that a system receiving the mean CP-15 of 53 mm over 15 days would have roughly 37% greater odds of *E. coli* occurrence than a system receiving no precipitation over the same interval (Appendix 6).

Table 2: Logistic Regression results of aggregated sanitary risk scores with cumulative precipitation of 15 days

Model	Variables	Odds Ratio	P-value	95% CI
Binary logistic	Overall sanitary risk score	4.03*	0.24	1.20, 13.5
	Cumulative rainfall in mm (15 days)	1.007*	0.000	1.004, 1.010
Ordered logistic	Overall sanitary risk score	4.09*	0.020	1.25, 13.4
	Cumulative rainfall in mm (15 days)	1.007*	0.000	1.004, 1.010

Disaggregated Sanitary Risk

When sanitary risk was broken down into source, transport, and barrier components, the barrier risk component was the only one significantly associated with *E. coli* occurrence in ordered logistic regression models (OR: 2.55, 95% CI 1.14-5.69, Table 3). This result was consistent across all precipitation integration periods (Appendix 11). For binary logistic regression, barrier failure was associated with decreased *E. coli* occurrence (OR: 0.42, CI -0.18-0.98).

Table 3: Logistic Regression results with disaggregated sanitary risk score with 15 days of cumulative precipitation

Model	**Variables**	**Odds Ratio**	**P-value**	**95% CI**
Binary logistic	Source risk	1.38	0.624	0.37, 5.15
	Transport risk	2.64*	0.001	1.52, 4.57
	Barrier risk	0.42*	0.044	0.18, 0.98
	Cumulative rainfall in mm (15 days)	1.005*	0.002	1.002, 1.009
Ordered logistic	Source risk	1.11	0.874	0.31, 4.04
	Transport risk	1.09	0.731	0.65, 1.86
	Barrier risk	2.55*	0.022	1.14, 5.69
	Cumulative rainfall in mm (15 days)	1.007*	0.000	1.004, 1.01

Individual Risk factors

In binary and ordinal logistic regressions, several individual risk factors were significantly associated with E. *coli* occurrence. Four were significant in both models: drainage channel filled with water; inadequate fencing to keep animals out; visible cracks in concrete pad/floor; and absence of concrete walls extending below the ground surface (Table 4). Detailed results can be found in Appendix 12. The direction of the effects for each of these risk factors was similar for binary and ordinal logistic regression. Odds ratios (ORs) were generally >1 for risk factors structured such that an affirmative response corresponds to greater risk (e.g., “Are there visible cracks on the cement floor around the water point?”), while ORs were <1 for risk factors structured so that a negative response indicates greater risk. At least one risk factor in each category (transport, source, and barrier risk) was significant in each model.

Table 4: Logistic Regression results of individual risk factors with cumulative precipitation of 15 days

#	Sanitary Survey	Risk Disaggregation	Response indicating risk	OR (Binary Logistic)	OR (Ordinal Logistic)
9	Is the drainage channel filled with stagnant water?	Transport	Yes	1.58	1.52
10	Is there fencing around the installation inadequate to keep animals out?	Source	No	0.63	0.55
11	Does the water point have a cement floor?	Barrier	No		0.36
12	Are there visible cracks on the cement floor around the water point?	Barrier	Yes	1.43	1.42
13	Are there signs of leaks in the mains pipes feeding this system?	Barrier	No		
14	Are pipes exposed within 10 m of this waterpoint?	Barrier	No		
15	Are there any cracks in the walls of the water point?	Barrier	Yes		
16	Do the walls not extended below the surface of the ground at all points?	Barrier	No	0.377	0.467
17	Are the above-ground parts loose at the point of attachment to base?	Barrier	No		
18	Is the base of the water source inadequately sealed so that water can enter?	Barrier	Yes		0.715

Discussion

This cross-sectional study investigated the correlation between sanitary inspections and microbial water quality data from 966 boreholes across three SSA countries. When controlling for rainfall, the sanitary inspection risk score and barrier failure were associated with *E. coli* occurrence. Precipitation was significantly associated with *E. coli* contamination, and longer rainfall integration periods produced stronger associations. Furthermore, when statistical models were applied at individual risk factors level, several adapted SI risk factors were significantly associated with *E. coli* occurrence. Ordinal logistic regression models outperformed binary logistic regression models for understanding *E. coli* occurrence in drinking water concerning rainfall and sanitary risk factors. However, neither model explained a large proportion of the variability in the dependent variable.

The observed strong and statistically robust association between sanitary inspection and microbial contamination findings was consistent with previous studies from Uganda (Howard et al., 2003) and Tanzania (Mushi et al., 2012). However, these previous studies did not account for precipitation. When precipitation was included in regressions, model fits improved (AIC values decreased, Appendix 7). Irrespective of precipitation lag time from the sampling day, the ordinal logistic regression model indicated a significant association between overall sanitary inspection score and WHO *E. coli* risk categories. Given the impact of controlling for rainfall, the case can be made that sanitary inspection scores provide useful indicators of water system vulnerability to contamination, particularly during wet weather events, rather than acting as a direct proxy for contamination. The case can also be made that, since model fit improved with the addition of rainfall, the failure of some prior studies to report associations between sanitary inspection scores and *E. coli* occurrence may be related to the lack of inclusion of a rainfall variable.

When sub-categorized by sanitary risk factors, barrier failure demonstrated consistent and significant associations (OR>2.4) with microbial contamination. Similar findings were observed in (E. Kelly et al., 2021), indicating barrier failure best predicted microbial contamination.

Previous studies also observed an association between the structural integrity of the wellhead (absence or cracked platform, apron failure) and water quality (Cronin et al., 2006; Ercumen et al., 2017; Parker et al., 2010). To the extent that this relationship corresponds to broader microbial risk, identifying and proactively addressing barrier deficiencies could reduce borehole susceptibility to microbial contamination during wet weather conditions and potentially improve user outcomes.

In our analysis of individual risk factors, we observed that some risk factors were more influential than others despite being given equal weight. Stagnant water in drainage channels (transport risk), cracks in concrete pads/floors (barrier risk), inadequate fencing (source risk), and lack of adequate walls preventing undercutting or intrusion of water below concrete pads/floors (barrier risk) were among the risk factors significantly associated with water contamination. Similarly, two other studies found that inadequate fencing was a significant factor contributing to microbial contamination (Howard et al., 2003; Parker et al., 2010). It is plausible that each of the significant individual risk factors plays a role in preventing contamination, and monitoring and rehabilitation efforts may aim to prioritize some of these factors.

Our study revealed that prior precipitation events influenced the ability of sanitary inspection to predict microbial water quality, consistent with the findings of a previous study (E. Kelly et al., 2021) and consistent with work indicating that heavy rainfall after a prolonged drought can cause "first flush" contaminant spikes in rural water sources if the wellhead is not adequately protected (Powers et al., 2023). Future work may define relevant thresholds for classifying precipitation as sufficiently heavy to cause such events. Understanding these relationships can strengthen microbial monitoring and data analysis in the context of varying precipitation. Likewise, the understanding that routine monitoring may often miss high-risk periods following intense precipitation may help contextualize monitoring results and account for previously under-recognized limitations.

Limitations

This study was built on cross-sectional data, and therefore did not capture trends or variations in *E. coli* occurrence over time, which can be important in water safety risk estimation (Harris et al., 2023; Kostyla et al., 2015). Rainfall data were estimated based on remote sensing data (CHIRPS) with limited resolution. CHIRPS covers the globe and is freely accessible, making it suitable for studies requiring remote rainfall data. However, the average distance from a water sample to the closest rain gauge station in this study was 20 km. This degree of indirectness and imprecision in the rainfall data limits the ability of the current study to precisely characterize and control the effects of prior rainfall. Another notable limitation was the use of a sanitary risk scoring algorithm that applies equal weights to all risk factors: while this approach replicated standard practice in the field, future studies may explore other weighting approaches to better reflect the relative importance of risk factors.

Another limitation of the current study was the limited inclusion of data on local topography and on-site hygiene practices (limited in our study to noting whether nearby latrines are uphill), which were also essential factors when considering the influence of precipitation (Engström et al., 2015). Finally, the current study did not control for the age of the borehole, a variable reported to be associated with water quality in prior studies (Ercumen et al., 2017). Water infrastructure deteriorates as it ages and may impact below-ground barrier factors in ways not easily captured by a visual sanitary inspection of the above-ground system. While primary data were not collected with a sole focus on describing and refining sanitary inspection studies, they provide considerable valuable evidence for that purpose. Further work that addresses the above limitations could meaningfully build upon the results of this study.

Implications

The finding that sanitary risk score in general, and barrier risk score in particular, were significantly associated with borehole vulnerability to microbial contamination during/following rainfall events in the study settings had several implications for small water system construction, monitoring, and management, as well as potential implications for policy and practice. Most notably, unless further work contradicts the present findings, sanitary inspections are as relevant as ever in meaningfully assessing the safety/vulnerability of rural boreholes. They should continue to be included in monitoring programs and water safety plans covering such systems. Incorporating the results of SI into the risk management process of water safety plans (WSP) would help water utilities and regulatory authorities identify areas for improvement and potential mitigation measures to enhance drinking water supply safety. The finding that barrier risk factors such as the presence and adequacy of concrete pads and walls extending below the ground, as well as factors such as adequate fencing, are strongly associated with safely managed water also suggests that these elements should continue to be included in the specifications, design, and construction of new rural boreholes. SI should continue to receive close attention while monitoring, maintaining, and rehabilitating existing systems. Where defects in these SI risk factors are detected in monitoring, prompt repair of these items may help improve microbial water quality, especially at the beginning of rainy seasons/wet weather.

While the finding that "Barrier" risks were strongly associated with water system vulnerability was worth acting upon, that did not necessarily mean that "Source" and "Transport" risks, which were not associated with *E. coli* occurrence in our models, should be seriously deprioritized *per se*. It may be the case that these risk categories were less important to the safe management of rural boreholes than implied by previously proposed mechanistic models (E. Kelly et al., 2021). However, it is also possible (and perhaps more likely) that the risks associated with the "Source" and "Transport" categories may be more difficult to adequately capture using current SI observation protocols and risk scores than those making up the "Barrier" category. This latter hypothesis seems credible since almost anyone can readily observe the presence/absence of a wall or a concrete pad, and these items are, in fact, difficult for a trained observer to miss; by contrast, the presence of human or animal feces deposited several meters away under vegetation before the last rainstorm could be almost impossible for a trained enumerator to detect by a rapid visual inspection alone. Additional limitations include using binary risk factor scoring algorithms, which may miss important distinctions in the intensity of the presented and detected risk factors.

Finally, the findings that including rainfall in regression models improved their performance confirms what WHO and others have long specified: that sanitary inspections were intended to detect and prioritize the *VULNERABILITY* of water systems to fecal contamination during/after weather events and *NOT* to *PREDICT* or *REPLACE* testing for fecal indicator bacteria occurrence. A longer integration period of precipitation would increase the likelihood of *E. coli* contamination. Ongoing monitoring, management, and planning of rural boreholes should continue to leverage sanitary inspections and microbial water quality testing wherever feasible and appropriate, especially during wet weather events. Further studies may explore how both can be reviewed and refined to support progress more efficiently and effectively on safely managed water in new and existing systems.

Conclusions

Sanitary inspection, rainfall monitoring/estimation, and water quality analysis are valuable tools for assessing water source vulnerability and safety. They can be potent tools for driving and maintaining progress on safely managed water when used together. This study aims to inform the design, implementation, management, and monitoring of community-managed rural water systems in SSA. Specifically, this work suggests that while all aspects of safe water management should continue to be prioritized, ensuring the presence, adequacy, and maintenance of essential barrier factors such as adequate and undamaged impervious pads and walls extending below the surface of the ground, as well as factors such as adequate fencing and adequately functioning drainage channels, may be particularly effective in the study setting. Further work can generate evidence on quantifying these and other measures' relative effectiveness and efficiency in ensuring water safety in existing boreholes and exploring approaches to refine and improve methods and protocols for collecting and analyzing sanitary inspection data. Both sanitary inspection and water quality testing of new and existing boreholes should continue to be conducted and prioritized wherever appropriate and feasible, especially during wet weather events. Together, these tools can provide better evidence for advancing progress on safely managed water than either tool alone.

Financial Disclosure Statement

This work was supported in part by the Conrad N. Hilton Foundation, which supported initial field data collection (Project ID: "Monitoring, Evaluation and Learning for WASH"), as well as by the World Health Organization, which supported in part the secondary data analysis included in this study (Project ID: "Review of Sanitary Inspections for Drinking water"). We gratefully acknowledge in-kind support from students and staff at the Water Institute at UNC, which supported in part the secondary data analysis included in this study. The funders played no role in the analysis or writing of this manuscript nor in the decision to publish. The authors declare that they have no competing interests that could be perceived to bias this work.

Acknowledgements

In addition to the listed authors, many other students, advisors, colleagues, and collaborators supported this work, and it could not have been completed without their generous efforts. Thanks, especially to Bansaga Sage, Hermann Kambou, and many others for logistical support during field data collection, as well as to Matthew Dinwiddie for support with rainfall data acquisition and merging.

REFERENCES

Bain, R., Cronk, R., Hossain, R., Bonjour, S., Onda, K., Wright, J., Yang, H., Slaymaker, T., Hunter, P., Prüss-Ustün, A., & Bartram, J. (2014). Global assessment of exposure to faecal contamination through drinking water based on a systematic review. *Tropical Medicine & International Health*, *19*(8), 917–927. https://doi.org/10.1111/tmi.12334

Bain, R., Cronk, R., Wright, J., Yang, H., Slaymaker, T., & Bartram, J. (2014). Fecal Contamination of Drinking-Water in Low- and Middle-Income Countries: A Systematic Review and Meta-Analysis. *PLOS Medicine*, *11*(5), e1001644. https://doi.org/10.1371/journal.pmed.1001644

Bain, R. E. S., Wright, J. A., Christenson, E., & Bartram, J. K. (2014). Rural:urban inequalities in post 2015 targets and indicators for drinking-water. *The Science of the Total Environment*, *490*, 509–513. https://doi.org/10.1016/j.scitotenv.2014.05.007

Bartram, J. (1996). *Optimising the Monitoring and Assessment of Rural Water Supplies (PhD , University of Surrey, 1996)*.

Brown, J., Hien, V. T., McMahan, L., Jenkins, M. W., Thie, L., Liang, K., Printy, E., & Sobsey, M. D. (2013). Relative benefits of on-plot water supply over other “improved” sources in rural Vietnam. *Tropical Medicine & International Health: TM & IH*, *18*(1), 65–74. https://doi.org/10.1111/tmi.12010

Brown, J., Stauber, C., Murphy, J. l., Khan, A., Mu, T., Elliott, M., & Sobsey, M. d. (2011). Ambient-temperature incubation for the field detection of Escherichia coli in drinking water. *Journal of Applied Microbiology*, *110*(4), 915–923. https://doi.org/10.1111/j.1365-2672.2011.04940.x

Chakrabarti, A., & Ghosh, J. K. (2011). AIC, BIC and Recent Advances in Model Selection. In P. S. Bandyopadhyay & M. R. Forster (Eds.), *Philosophy of Statistics* (Vol. 7, pp. 583–605). North-Holland. https://doi.org/10.1016/B978-0-444-51862-0.50018-6

Cronin, A. A., Breslin, N., Gibson, J., & Pedley, S. (2006). Monitoring source and domestic water quality in parallel with sanitary risk identification in northern Mozambique to prioritise protection interventions. *Journal of Water and Health*, *4*(3), 333–345. https://doi.org/10.2166/wh.2006.029

Danert, D. K. (2022). *Report III: Handpump standards, quality and supply chains with Zambia case study*.

Engström, E., Balfors, B., Mörtberg, U., Thunvik, R., Gaily, T., & Mangold, M. (2015). Prevalence of microbiological contaminants in groundwater sources and risk factor assessment in Juba, South Sudan. *Science of The Total Environment*, *515–516*, 181–187. https://doi.org/10.1016/j.scitotenv.2015.02.023

Ercumen, A., Naser, A. M., Arnold, B. F., Unicomb, L., Colford, J. M., & Luby, S. P. (2017). Can Sanitary Inspection Surveys Predict Risk of Microbiological Contamination of Groundwater Sources? Evidence from Shallow Tubewells in Rural Bangladesh. *The American Journal of Tropical Medicine and Hygiene*, *96*(3), 561–568. https://doi.org/10.4269/ajtmh.16-0489

Ercumen, A., Naser, A. M., Unicomb, L., Arnold, B. F., Colford, J. M., & Luby, S. P. (2015). Effects of source- versus household contamination of tubewell water on child diarrhea in rural Bangladesh: A randomized controlled trial. *PloS One*, *10*(3), e0121907. https://doi.org/10.1371/journal.pone.0121907

Fan, Y., Li, H., & Miguez-Macho, G. (2013). Global Patterns of Groundwater Table Depth. *Science*, *339*(6122), 940–943.

Fan, Y., Miguez-Macho, G., Jobbágy, E. G., Jackson, R. B., & Otero-Casal, C. (2017). Hydrologic regulation of plant rooting depth. *Proceedings of the National Academy of Sciences*, *114*(40), 10572–10577. https://doi.org/10.1073/pnas.1712381114

Fisher, M. B., Danquah, L., Seidu, Z., Fechter, A. N., Saga, B., Bartram, J. K., Liang, K. M., & Ramaswamy, R. (2020). WaSH CQI: Applying continuous quality improvement methods to water service delivery in four districts of rural northern Ghana. *PLOS ONE*, *15*(7), e0233679. https://doi.org/10.1371/journal.pone.0233679

Guidelines for drinking-water quality: Fourth edition incorporating the first and second addenda. (2022). https://www.who.int/publications-detail-redirect/9789240045064

Guo, D., Thomas, J., Lazaro, A., Mahundo, C., Lwetoijera, D., Mrimi, E., Matwewe, F., & Johnson, F. (2019). Understanding the Impacts of Short-Term Climate Variability on Drinking Water Source Quality: Observations From Three Distinct Climatic Regions in Tanzania. *GeoHealth*, *3*(4), 84–103. https://doi.org/10.1029/2018GH000180

Harris, A. R., Daly, S. W., Pickering, A. J., Mrisho, M., Harris, M., & Davis, J. (2023). Safe Today, Unsafe Tomorrow: Tanzanian Households Experience Variability in Drinking Water Quality. *Environmental Science & Technology*, *57*(45), 17481–17489. https://doi.org/10.1021/acs.est.3c05275

Harvey, P. A., & Reed, R. A. (2007). Community-managed water supplies in Africa: Sustainable or dispensable? *Community Development Journal*, *42*(3), 365–378. https://doi.org/10.1093/cdj/bsl001

Howard, G., Pedley, S., Barrett, M., Nalubega, M., & Johal, K. (2003). Risk factors contributing to microbiological contamination of shallow groundwater in Kampala, Uganda. *Water Research*, *37*(14), 3421–3429. https://doi.org/10.1016/S0043-1354(03)00235-5

Kelly, E., Cronk, R., Fisher, M., & Bartram, J. (2021). Sanitary inspection, microbial water quality analysis, and water safety in handpumps in rural sub-Saharan Africa. *Npj Clean Water*, *4*(1), 1–7. https://doi.org/10.1038/s41545-020-00093-z

Kelly, E. R., Cronk, R., Kumpel, E., Howard, G., & Bartram, J. (2020). How we assess water safety: A critical review of sanitary inspection and water quality analysis. *Science of The Total Environment*, *718*, 137237. https://doi.org/10.1016/j.scitotenv.2020.137237

Kostyla, C., Bain, R., Cronk, R., & Bartram, J. (2015). Seasonal variation of fecal contamination in drinking water sources in developing countries: A systematic review. *Science of The Total Environment*, *514*, 333–343. https://doi.org/10.1016/j.scitotenv.2015.01.018

Menard, S. (2000). Coefficients of Determination for Multiple Logistic Regression Analysis. *The American Statistician*, *54*(1), 17–24. https://doi.org/10.1080/00031305.2000.10474502

Misati, A. G., Ogendi, G., Peletz, R., Khush, R., & Kumpel, E. (2017). Can Sanitary Surveys Replace Water Quality Testing? Evidence from Kisii, Kenya. *International Journal of Environmental Research and Public Health*, *14*(2), Article 2. https://doi.org/10.3390/ijerph14020152

Mushi, D., Byamukama, D., Kirschner, A. K. T., Mach, R. L., Brunner, K., & Farnleitner, A. H. (2012). Sanitary inspection of wells using risk-of-contamination scoring indicates a high predictive ability for bacterial faecal pollution in the peri-urban tropical lowlands of Dar es Salaam, Tanzania. *Journal of Water and Health*, *10*(2), 236–243. https://doi.org/10.2166/wh.2012.117

Nijhawan, A., & Howard, G. (2022). Associations between climate variables and water quality in low- and middle-income countries: A scoping review. *Water Research*, *210*, 117996. https://doi.org/10.1016/j.watres.2021.117996

Onda, K., LoBuglio, J., & Bartram, J. (2012). Global Access to Safe Water: Accounting for Water Quality and the Resulting Impact on MDG Progress. *International Journal of Environmental Research and Public Health*, *9*(3), 880–894. https://doi.org/10.3390/ijerph9030880

Parker, A. H., Youlten, R., Dillon, M., Nussbaumer, T., Carter, R. C., Tyrrel, S. F., & Webster, J. (2010). An assessment of microbiological water quality of six water source categories in north-east Uganda. *Journal of Water and Health*, *8*(3), 550–560. https://doi.org/10.2166/wh.2010.128

Powers, J. E., Mureithi, M., Mboya, J., Campolo, J., Swarthout, J. M., Pajka, J., Null, C., & Pickering, A. J. (2023). Effects of High Temperature and Heavy Precipitation on Drinking Water Quality and Child Hand Contamination Levels in Rural Kenya. *Environmental Science & Technology*, *57*(17), 6975–6988. https://doi.org/10.1021/acs.est.2c07284

Progress on household drinking water, sanitation and hygiene 2000-2022: Special focus on gender | JMP. (2023, July). https://washdata.org/reports/jmp-2023-wash-households

Roy, B., Vilane, B. R., & Dlamini, T. (2016). An Assessment of Groundwater Pollution from On-Site Sanitation in Malkerns, Swaziland. *Journal of Agricultural Science and Engineering*, *2*, 11–17.

Stauber, C., Miller, C., Cantrell, B., & Kroell, K. (2014). Evaluation of the compartment bag test for the detection of Escherichia coli in water. *Journal of Microbiological Methods*, *99*, 66–70. https://doi.org/10.1016/j.mimet.2014.02.008

Water, W. H. O., & Team, S. and H. (2006). *Guidelines for drinking-water quality [electronic resource]: Incorporating first addendum. Vol. 1, Recommendations*. World Health Organization. https://iris.who.int/handle/10665/43428

World Health Organization. (2011). *Guidelines for drinking-water quality*. https://iris.who.int/handle/10665/44584

World Health Organization & United Nations Children's Fund (UNICEF). (2006). *Core questions on drinking water and sanitation for household surveys*. 24.

Wu, J., Yunus, M., Islam, Md. S., & Emch, M. (2016). Influence of Climate Extremes and Land Use on Fecal Contamination of Shallow Tubewells in Bangladesh. *Environmental Science & Technology*, *50*(5), 2669–2676. https://doi.org/10.1021/acs.est.5b05193

Supplemental Information

Appendix 1. Study design and data collection in Ethiopia

Appendix 2. Study design and data collection in Ghana

Appendix 3. Study design and data collection in Burkina Faso

Appendix 4. Table of adapted sanitary inspection questions with subcategorized risk factors.

Appendix 5: Sanitary risk score calculation

Appendix 6: Table of descriptive data of cumulative rainfall for 15 days lag time and annual water table depth

Appendix 7: Table of regression model fit parameters with and without precipitation

Appendix 8: Table of regression results for aggregated sanitary risk with different binary precipitation(presence/absence) lag time

Appendix 9: Table of regression results for dis-aggregated sanitary risk with different binary precipitation (presence/absence) lag time

Appendix 10: Table of regression results for aggregated sanitary risk with different cumulative precipitation lag time

Appendix 11: Table of regression results for dis-aggregated sanitary risk with different cumulative precipitation lag time

Appendix 12: Table of regression results for individual sanitary risk factors with fifteen days cumulative precipitation

File S1. Indicative field data collection instruments and training materials