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The Association Between Rainfall, Temperature, and Reported Drinking Water Source: A Multi-Country Analysis

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Key Points:

- Access to and reported use of basic drinking water (BDW) is dependent on rainfall and temperature in The Gambia, Mozambique, Pakistan, and Kenya
- Higher temperatures are associated with decreased access to and use of BDW
- Climate change threatens access to safe drinking water in settings where infrastructure is vulnerable to rainfall and temperature

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Climate change may alter access to safe drinking water, with important implications for health. We assessed the relationship between temperature and rainfall and utilization of basic drinking water (BDW) in The Gambia, Mozambique, Pakistan, and Kenya. The outcomes of interest were (a) whether the reported drinking water source used in the past 2 weeks met the World Health Organization definition of BDW and (b) use of a BDW source that was always available. Temperature and precipitation data were compiled from weather stations and satellite data and summarized to account for long- and short-term weather patterns and lags. We utilized random forests and logistic regression to identify key weather variables that predicted outcomes by site and the association between important weather variables and BDW use. Higher temperatures were associated with decreased BDW use at three of four sites and decreased use of BDW that is always available at all four sites. Increasing rainfall, both in the long- and short-term, was associated with increased BDW use in three sites. We found evidence for interactions between household wealth and weather variables at two sites, suggesting lower wealth populations may be more sensitive to weather-driven changes in water access. Changes in temperature and precipitation can alter safe water use in low-resource settings—investigating drivers for these relationships can inform efforts to build climate resilience.

Plain Language Summary This manuscript examines the association between temperature, precipitation and the use of safe drinking water sources in four low and middle-income countries. Climate is known to impact the risk of diarrheal disease, but the potential mechanisms driving this relationship are poorly described. We hypothesized that both short and long-term trends in temperature and precipitation may affect both improved water source availability and usage in low-resource settings. We utilized data from a case-control study on diarrheal disease with data on household water source use and availability. Machine learning was used to identify the most important weather predictors of households using "basic drinking water" (BDW) as defined by the World Health Organization. We found higher temperatures and decreasing rainfall were associated with decreased BDW use overall at three of the four sites. Notably, we also found evidence of resilience to climate impacts linked to safe drinking water availability and household wealth. Our findings have broad-reaching implications for climate resilient infrastructure development and provide critical evidence that increasing prevalence of drought and rising temperatures can lead to use of less-safe water sources.

1. Introduction

Reducing the climate impacts on diarrheal diseases is important, as the burden of diarrheal diseases is high: in 2019, 1.5 million people died from diarrheal disease, with the greatest burden of deaths occurring among children under 5 years of age (Vos et al., 2020). Investments in water, sanitation and hygiene (WASH) have been promoted as a way to build resilience to climate variability and change, based on the idea that provision of reliable and safe drinking water sources will reduce vulnerability to enteric diseases in a future with more extremes of rainfall, high temperature, and drought (IPCC, 2018). This is grounded in two evidence streams. First, there is strong evidence that high temperature, rainfall, and drought increase the risk of diarrheal diseases (Carlton et al., 2016; Levy et al., 2016; Mertens et al., 2019). Growing evidence suggests that rainfall, in particular, may impact diarrheal illness via exposures to pathogens in drinking water (Jagai et al., 2015; Kraay et al., 2020). Second, it is well established that access to safe drinking water can reduce diarrheal diseases: a recent analysis identified unsafe drinking water as the leading environmental risk factor for diarrheal diseases, with approximately 75%

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of diarrhea-related deaths attributed to use of unsafe drinking water (Murray et al., 2020). WASH interventions, including providing improved drinking water systems, are associated with significant improvements in early childhood health, including decreases in diarrheal diseases (Fewtrell et al., 2005).

However, the ways in which temperature and rainfall impact the use and availability of safe drinking water are poorly characterized. We hypothesize that meteorological conditions, such as periods of low rainfall or high temperatures, may lead to decreases in the availability and use of basic drinking water (BDW) sources. Understanding this relationship is important because while there is considerable evidence that rainfall can compromise water quality through fecal contamination (Kostyla et al., 2015; Poulin et al., 2020), less is known about how different weather conditions alter the use of different types of drinking water sources. If people are using more or less safe water sources under different weather conditions, this can alter the impacts of WASH investments on health and climate vulnerability.

Prior work has found evidence of seasonal patterns in drinking water use, but the results are inconsistent. Qualitative research into WASH uptake has frequently identified seasonal factors including temperature, rain, flooding, water scarcity, and seasonal field-work as influencing WASH uptake, desirability and feasibility (Anthonj et al., 2018; Banda et al., 2007; Francis et al., 2015; Gomes et al., 2015; Halvorson et al., 2011; Hoat et al., 2012; Hoque et al., 2004; Simms et al., 2005; Wood et al., 2012). A number of these studies have found evidence that seasonality directly influences water-source choice. For example, in India, treated water is preferred in the rainy season due to perception of decreased water quality following rain (Poulin et al., 2020).

There is also evidence that seasonality influences water availability. In some sites in Ghana, Kenya, and Zambia, less safe water sources were used in the rainy season due to failure of solar-powered pumps (Kelly et al., 2018). Quantitative studies are limited. Several studies indicate preference for surface water sources during the rainy season or after heavy rainfalls, even when groundwater sources were available (Kelly et al., 2018; Thomas et al., 2019; Thomson et al., 2019). Surface water sources are often more convenient and available free of cost but are vulnerable to fecal contamination (Kelly et al., 2018). Rainy season was associated with increased rainwater use in the Pacific (Elliott et al., 2017) and increased surface water usage in East Africa (Pearson et al., 2016; Tucker et al., 2014). Drought, which is happening with greater frequency and severity, can lead to limited water availability (Howard et al., 2016; Watts et al., 2021), and increased contamination (Lal & Konings, 2018). Additionally, season is known to impact the ability of communities to maintain water sources and latrines, with stressors in both rainy and dry seasons (Foster, 2013; Kelly et al., 2018; Whaley & Webster, 2011). Despite substantial qualitative evidence supporting seasonal changes in water source selection, there is limited quantitative research on how changing meteorological conditions affect water source use and access.

In this study, we aim to evaluate how meteorological conditions including high temperature and drought are associated with the use and availability of drinking water sources across four diverse locations in Asia and Africa. Because research on this topic has been limited and the evidence to date is inconsistent, we adopted an analytical framework that allowed us to consider a large set of candidate predictors, describing long- and short-term rainfall and precipitation patterns. This approach is designed to be hypothesis generating, facilitating identification of key predictors for investigation in future studies, while avoiding the perils of multiple hypothesis testing. We used a standard World Health Organization definition of BDW and water that is always available to ensure the generalizability of our findings to global safe water standards. Given the well-recognized role of socio-economic status in access to safe drinking water we included this as a predictor and tested for evidence that socio-economic status modifies the relationship between climate variables and basic water use.

2. Methods

This analysis utilizes data from the Global Enteric Multicenter Study (GEMS) of moderate-to-severe diarrheal disease (MSD) in infants and young children in developing countries (Kotloff et al., 2013) as well as in situ and modeled meteorological data to assess the relationship between weather and the utilization of and access to improved water sources.

Table 1
Description of Drinking Water Use and General Characteristics of the Global Enteric Multicenter Study Sites

	Gambia	Mali	Mozambique	Kenya	India	Bangladesh	Pakistan
Number of participants	**2,598**	4,097	**1,976**	**3,359**	3,582	3,859	**3,096**
Study site characteristics							
Rural/urban	**Rural**	Urban	**Rural**	**Rural**	Urban	Rural	**Urban**
Population at risk	**29,076**	31,768	**15,380**	**21,603**	13,416	25,560	**25,659**
Area (km^2)	**1,084**	16	**500**	**500**	10.5	374	**10**
Outcomes							
Main source of water is an improved water source[a]	**85.0**	99.9	**82.6**	**62.6**	98.6	99.8	**95.2**
More than 30 min wait time for main source of water	**8.6**	2.6	**15.9**	**19.7**	8.4	0.1	**19.3**
Main source of water is always available	**54.2**	94.3	**59.7**	**90.3**	1.0	99.9	**62.4**
Main source of water is basic drinking water[b] (Outcome 1)	**77.4**	97.2	**68.9**	**55.0**	90.5	99.6	**76.4**
Main source of water is basic drinking water that is always available (Outcome 2)	**35.0**	92.3	**41.5**	**46.9**	1.0	99.6	**45.7**
Included in analysis	**Yes**	No	**Yes**	**Yes**	No	No	**Yes**

Note. Countries with sufficient variability (≥10% and ≤90% of observations with Outcome 1 or Outcome 2) in the primary and secondary outcome to be included in analysis, are indicated in bold.

[a]Improved water sources include: Piped water, boreholes or tubewells, protected dug wells, protected springs, rainwater, and packaged or delivered water. [b]Basic drinking water is defined as drinking water from an improved source, where collection time is not more than 30 min.

2.1. Study Population

Household drinking water use behaviors were drawn from GEMS. GEMS was conducted in seven countries (Kenya, Mali, Mozambique, The Gambia, Bangladesh, India, and Pakistan) with moderate-to-high under-five child mortality to study enteric disease epidemiology and has been described at length (Kotloff et al., 2013).

In brief, GEMS was a 3 year (December 2007 to March 2011), prospective, age-stratified, matched case-control study of MSD among children 0–59 months of age belonging to a geographically defined censused population that varied in size from 10 to 1,084 km^2 (Table 1). Cases were systematically enrolled from those seeking care at hospitals and health centers. For each case, one to three controls were randomly selected from a demographic surveillance system to serve as controls. Controls were enrolled within 14 days of the index case and matched to cases by age, gender, and location. Upon enrollment, parents or primary caretakers of cases and controls were administered a detailed survey to assess demographics, household wealth indicators, and water usage. At a follow-up visit 50–90 days after enrollment, water usage questions were asked again but water collection time was collected only at enrollment.

Because cases and controls were enrolled year-round over a 36-month period and asked about water sources, availability and fetching times over the past 2 weeks, this presents a unique opportunity to assess temporal variation in drinking water source use. This analysis includes enrollment data on water source usage, demographics, and wealth indicators from all participating households (both cases and controls). While GEMS participants may not represent a true random sample of the population, both cases and controls were evenly sampled throughout the year and selected based on the date of case-illness and thus any selection bias related to weather variables is assumed to be uniform between cases and controls.

2.2. Basic Water Use

The primary outcome of interest was whether a household's reported main source of drinking water used in the past 2 weeks meets the WHO definition of "BDW" (World Health Organization, 2017). BDW is defined as drinking water from an improved source, provided collection time is not more than 30 min, with improved sources including piped water, boreholes, tubewells, protected dug wells, protected springs, rainwater, and packaged water.

Water source type was assessed with the question "During the last 2 weeks, what was the main source of drinking water for the members of your household?" at enrollment. Only one answer was allowed. Water collection time was collected with the question, "How long does it take to go there [main source of drinking water], get water, and come back?".

As a secondary outcome, we examined the availability of BDW. Water availability was determined from the question, "In the last 2 weeks, how often has this water been available from this main source?" For this outcome, a household was classified as using BDW that is always available if their main water source met the above criteria for BDW and they reported the source was always available. Notably, this definition does not include any measure of drinking water quality. BDW sources have been known to be contaminated at the point of collection and/or point of use with fecal bacteria: a recent meta-analysis indicated that 10% of improved sources may contain over 100 *Escherichia coli* or TTC per 100 ml, well above safe drinking water standards (Bain et al., 2014). Therefore, this data set cannot identify water that is free of unsafe contamination.

We first examined the distribution of each outcome at each site. We restricted our analysis to sites with sufficient variability in both of the outcomes of interest (defined as having between 10% and 90% using BDW and between 10% and 90% using BDW i.e., always available), to improve the validity of random forests (RFs) modeling and improve power in statistical models. Only four sites (The Gambia, Mozambique, Kenya, and Pakistan) met this criterion and were included in this paper (Table 1).

2.3. Meteorological Data

To evaluate the associations between drinking water use and high temperatures, rainfall and drought, we calculated precipitation and temperature for each site. Other environmental conditions such as surface water and soil moisture may impact water use and availability (Fankhauser et al., 2022), however were not included in this analysis as we were interested in the direct associations between drinking water and meteorological variables. Precipitation and temperature variables were generated at the site level, as household location data was not available. Precipitation data come from a gridded product that combines satellite measurements and rain gauges: the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Dinku et al., 2018). Daily precipitation (mm) at a resolution of 0.05° (~5 km) was acquired for the years 2007 through 2011. A daily precipitation record for each study site was calculated by taking the spatial mean across a rectangular area encompassing the northmost, southmost, eastmost, and westmost points of the study site. CHIRPS data have been compared favorably to station data and other gridded satellite-based products in the past (Bai et al., 2018; Luo et al., 2019; Zhang et al., 2022). We compared data for the study period to data from the Tropical Rainfall Measuring Mission and found high correlation ($p < 0.0001$) between the data sources for each site, with correlation for biweekly precipitation ranging from 82% to 93% (Figure S1 in Supporting Information S1).

Temperature data were compiled from weather stations nearest to each study site. NOAA had available weather station data for three of the four study sites (Menne et al., 2018). For the fourth site, Kenya, the nearest weather station with NOAA data available was ~100 Km from the study, so the Kenya Medical Research Institute daily temperature records were used. To account for missing data in the weather station temperature records, data were infilled with temperature data from the 0.25° forcing data set for version 1 of the Global Land Data Assimilation System (GLDAS; Beaudoing & Kato, 2019). The Mozambique site was missing 34% of observations for temperature from the weather stations. GLDAS data was highly correlated with observed temperatures from NOAA ($R^2 = 0.86$) and linear regression was used to obtain a linear transformation equation (temp = 1.03 × (GLDAS-value C°) + 1.45) to fill in missing observed temperatures. Only 4% of the temperature observations from Kenya were missing, and GLDAS data was linearly transformed with the following equation: temp = 0.48 × (GLDAS-value mm) + 13.3 to infill the missing data points. Pakistan and Gambia had excellent observational coverage (<1% of days missing), and so were not infilled.

We posited that BDW use may be associated both with seasonal rainfall and temperature patterns as well as with short-term meteorological events. For example, months-long dry periods may reduce surface water availability and prolonged heat may favor evaporative processes over groundwater recharge. Recent rainfall may favor use of surface water and replenished shallow ground water sources. We also posited that there are likely lags between rainfall, temperature and water use, given the time required for recharge of improved water sources. For this reason, we defined a set of meteorological variables that capture potential long-term and short-term conditions

Table 2
Variables Included in Random Forests Models

Variables	Variable name in RF plot	Variable format	Lag
Rainfall variables			
Mean 2-week precipitation	biweekly_p	Continuous	0
Mean 4-week precipitation	fourweekly_p	Continuous	0
Mean 8-week precipitation	eightweekly_p	Continuous	0
Mean 2-week precipitation, lagged 1 week	biweekp_lag1	Continuous	1 week
Mean 2-week precipitation, lagged 2 weeks	biweekp_lag2	Continuous	2 weeks
Mean 4-week precipitation, lagged 1 week	fourweekp_lag1	Continuous	1 week
Mean 4-week precipitation, lagged 2 weeks	fourweekp_lag2	Continuous	2 weeks
Days since previous rainfall	preraindays	Continuous	0
Maximum 1-day rainfall in previous 2 weeks	max_2	Continuous	0
Maximum 1-day rainfall in previous 4 weeks	max_4	Continuous	0
Number of high precipitation days (over 95th percentile) in previous 2 weeks	sum_high_p	Continuous	0
Temperature variables			
Mean 2-week temperature	biweekly_t	Continuous	0
Mean 4-week temperature	fourweekly_t	Continuous	0
Mean 2-week temperature, lagged 1 week	biweekt_lag1	Continuous	1 week
Mean 2-week temperature, lagged 2 weeks	biweekt_lag2	Continuous	2 weeks
Mean 4-week temperature, lagged 1 week	fourweekt_lag1	Continuous	1 week
Mean 4-week temperature, lagged 2 weeks	fourweekt_lag2	Continuous	2 weeks
Number of high temperature days (over 95th percentile) in previous 2 weeks	sum_high	Continuous	0
Number of low temperature days (below 5th percentile) in previous 2 weeks	sum_low	Continuous	0
Other variables			
Case/control status	Type	Dichotomous	N/A
Maternal education level	educat	Categorical	N/A
Socio-economic index	wealth	Continuous	N/A
Month and year of observation	monthyear	Continuous	N/A

defining temperature and rainfall conditions over two, four and 8-week periods, and also considered lags of zero, one and 2 weeks (Table 2). We selected a broad range of variables to begin, under the assumption that machine learning would aid us in selecting a smaller "best" set of variables.

2.4. Demographic Data

Household socioeconomic status (SES) and maternal education were included as potential predictors of BDW use and access as SES has previously been found to be an important predictor of water access (Gomez et al., 2019; Raihan et al., 2017). An asset-based SES index was calculated for each site using PCA incorporating standard economic indicator variables (Vyas & Kumaranayake, 2006) including household assets, and household population. Distribution of indicators varied substantially between sites, thus some indicators were excluded for some sites due to a lack of variability (either no ownership, or complete saturation of the indicator) at the given site (Table S1 in Supporting Information S1). For each site, we utilized the first principal component which explained the greatest percentage of variance across the population as the wealth index. Each household's wealth index value was derived as a linear transformation using the factor scores from the first principal component as weights as has been described previously (Vyas & Kumaranayake, 2006). Maternal education level was collected in the survey as a 7-level categorical variable with categories: No formal schooling, less than primary, completed primary, completed secondary, post-secondary, religious education only, or unknown. Maternal education level was categorized based on the education distribution by site, these categories were not the same between sites due to differences in the distribution of education level between sites.

Date of survey was included in models to account for other time-dependent changes in water use not captured by weather variables (i.e., political or infrastructural changes that may take place over time). SES, maternal education, and case-status were all examined as potential predictors.

2.5. Analysis

Given the large number of potential predictor variables, and the limited research to date on this topic, we opted to employ an analytical approach to identify key predictors and assess the magnitude and direction of the association between key predictors and the outcome of interest. This has the advantage of allowing us to consider a wide array of candidate predictors, avoids the perils of multiple hypothesis testing, and is intended to narrow the list of key meteorological conditions that could be pursued with more focused causal models in subsequent studies. To this end, we conducted RF machine learning to identify the most important rainfall and temperature variables for predicting the use of (a) BDW or (b) BDW always available by site. A separate RF analysis was run for each outcome and site using the same set of predictor variables. RF models included all rainfall and temperature variables, as well as SES, maternal education level, date, and case/control status. RF requires data to be balanced in respect to the outcome (i.e., approximately equal proportions using BDW as not), and as only a fraction of the population at each site reported using BDW, data was weighted and resampled for each site to achieve balanced data sets for RF. Data was split 70%/30% into training and validation sets: models were constructed using the training data sets and tuned by varying the number of trees created and the number of variables randomly sampled at each stage. Final RF models were selected based on out of bag error rate using the validation data set, and models with the lowest error rate were used to identify most important variables. We used the final RF models to identify the 10 variables with the highest mean decrease in accuracy values for each site and outcome.

We then evaluated the direction and magnitude of association between BDW use and these 10 most important variables for each outcome and site using in logistic regression. We first generated unadjusted estimates of associations between BDW use and each important independent variable using logistic regression. To avoid the assumption of linearity and identify more complex relationships between variables (e.g., thresholds), we categorized all continuous independent variables into quartiles, based on the spread of the data, and ran the unadjusted models using these quartiles as the independent variables. We subsequently modeled the independent variable as continuous when linear relationships were evident. Additionally, when no difference was seen between adjacent categories, we collapsed quartiles into fewer categories. SES was categorized into high (top 25% of population), middle (middle 50% of population), low (lower 25% of population) and modeled as linear when justified. Education level was categorized into three or four groups based on the differences in the types of schooling between sites. Because household wealth was the most important predictor of BDW use at all sites, we adjusted all estimates for household wealth. Estimates were generated separately for each of the top 10 variables at each site. Detailed descriptions of variable specification are provided in Tables S2–S9 in Supporting Information S1.

We constructed multivariate logistic regression models, to identify relationships between exposure variables and BDW use, independent of other important variables. Our primary models estimated the odds ratio for each important variable, adjusted only for wealth. As a sensitivity analysis to adjust for potential confounding due to other meteorological variables, we then constructed a multivariate model including multiple predictors. For these models, variables that were statistically significant at $p \leq 0.1$ in the SES-adjusted models were tested for inclusion. Variables were excluded from the model in order of least significance/effect on other variables, and then retested for inclusion in the final model. If two variables were collinear (variance inflation factor >5), the variable with the greater statistical significance was included, and the other was excluded. As a final sensitivity analysis, we used the multivariate models to test for evidence of effect modification by SES, case status, and education level. Effect modification was tested by including interaction terms in models. We repeated this process for Outcome 2, BDW that is always available. Lastly, we ran a sensitivity analysis to test for any confounding due to other seasonal factors, defining season for each site by calendar month, as describe in Table S10 in Supporting Information S1.

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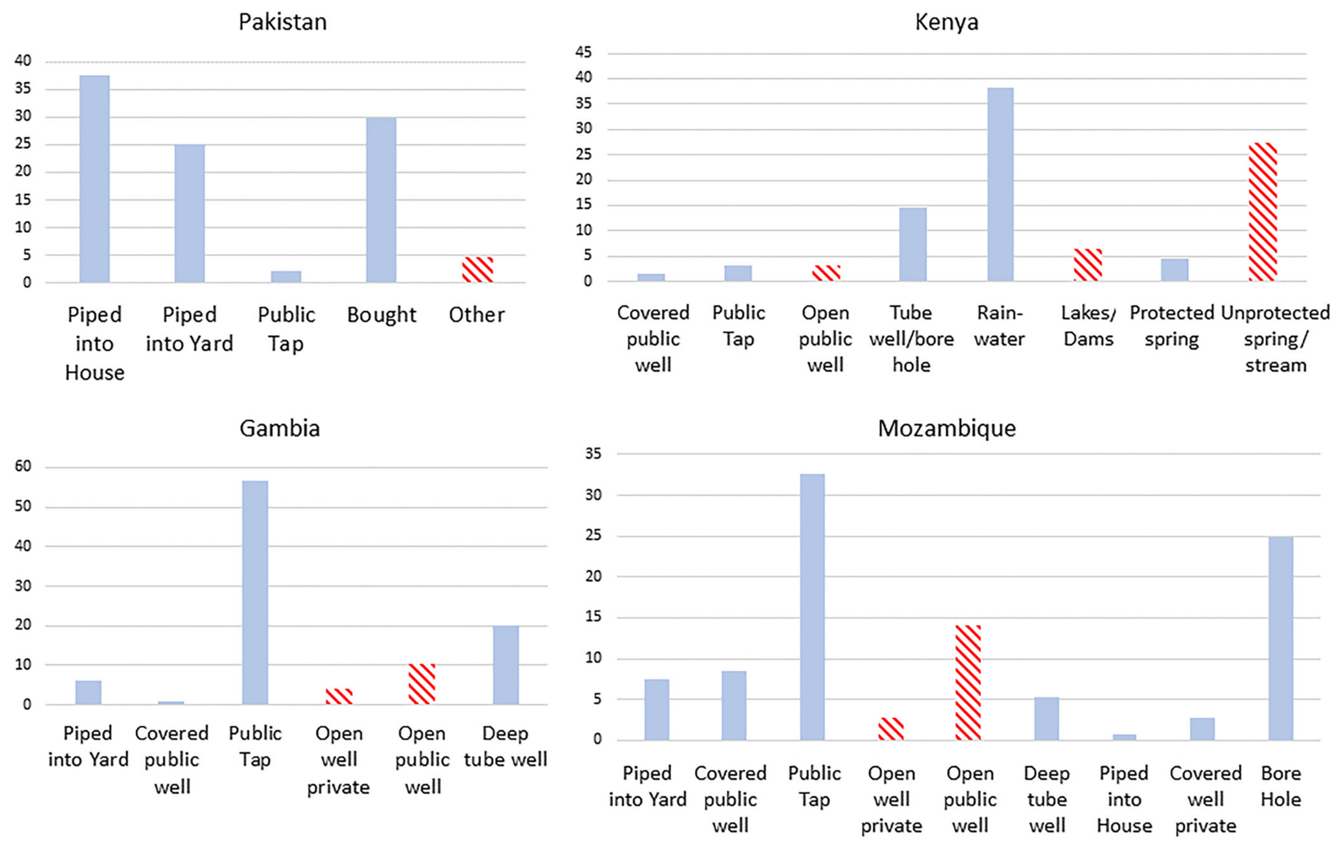

Figure 1. Main sources of water use by site. Sources in blue indicate those categorized as an "improved water source" by the WHO.

3. Results

3.1. BDW Use

Participants reported high use of improved drinking water sources at all sites, ranging from 63% in Kenya to 95% in Pakistan (Figure 1, Table 1). Main sources of drinking water varied by site (Figure 1); participants in Pakistan primarily used improved water sources that were piped (water was piped in from Karachi). In The Gambia, over half of households reported using a public tap for drinking water. Kenya and Mozambique had a wide range of reported water sources, including various wells and taps. Kenya was the only site with significant surface water and rainwater use. The percent of households using BDW (Outcome 1) ranged from 55% in Kenya to 77% in Gambia. Having a main source of water that was always available (Outcome 2) was lowest in The Gambia, with only 35% of participants reporting water was always available, and highest in Kenya (47%).

3.2. Distribution of Rainfall and Temperature Variables

Daily precipitation and temperature over the study period by site are shown in Figure 2. Temperature variability was lowest in Kenya (Figure 2b), with highest temperature variability seen in Pakistan (Figure 2a). Pakistan had very little rainfall compared to the other sites.

3.3. Outcome 1: BDW Use

The best fitting RF model for rainfall and temperature-predictors of BDW use varied widely between sites (Table 3). Models were least predictive of water use outcomes in Kenya, with error rates as high as 19.2% in Kenya. Model fit was best for Outcome 1 in Gambia with 95% of observations in the validation data set predicted correctly.

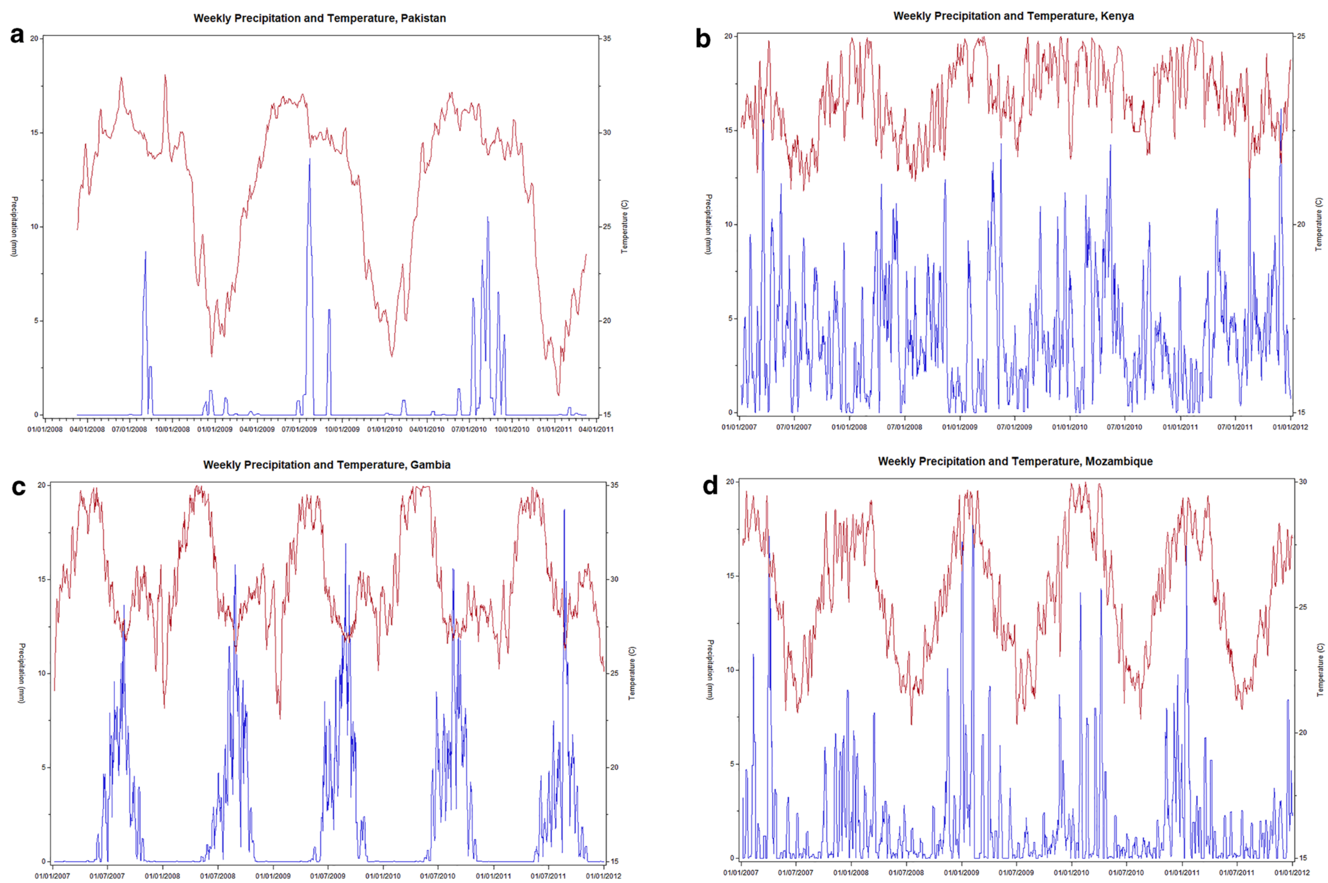

Figure 2. Weekly temperature (red) and precipitation (blue) over the study period, by site. Precipitation data obtained from Climate Hazards Group InfraRed Precipitation with Station data. Temperature data obtained from NOAA weather stations and missing temperature data was infilled from Global Land Data Assimilation System for Kenya and Mozambique.

Most important variables from all RF models are summarized in Table 3. Household wealth was the top predictor of BDW use for all four sites, followed by maternal education. Both temperature and precipitation variables ranked in the top 10 predictors for all four sites. Mean 2-week temperature over the previous 2 weeks with no, 1- or 2-week lags was important in all RF models, as was mean 4-week temperature with a 1- and 2-week lag. The most frequently selected precipitation measure was the number of days since the last rainfall and mean 2-week rainfall lagged by 2 weeks (both selected in models for three of the four sites). Variables describing maximum temperature or high precipitation events including the number of high precipitation days, high temperature days, low temperature days, and the maximum 2- and 4-week precipitation were not in the top 10 most important variables for any site. The variable for date was also not in the top 10 most important variables for any site.

Estimates of the strength and direction of the association between important variables and BDW use, based on logistic regression analysis, are shown in Table 4. Increasing household wealth was associated with increased use of BDW at all sites. Even after adjusting for household wealth, increasing maternal education was associated with increased BDW use in Mozambique, Kenya, and Pakistan. In a sensitivity analysis adjusting for seasonal trends, the direction of associations remained the same across all sites, with a minor decrease in the magnitude of effect in Kenya, and a widening of confidence intervals in Pakistan (Table S10 in Supporting Information S1).

Increasing rainfall, both in the long- and short-term, was associated with increased use of BDW in Mozambique and Kenya and longer dry periods were associated with decreased use of BDW in Pakistan. Increasing temperatures were associated with decreased use of BDW in Mozambique, Kenya, and Pakistan. However, in The Gambia, BDW use increased when mean 2-week temperature with a 2-week lag was above 26.6°C (the 25th percentile value) and no precipitation measure was associated with BDW use, adjusting for household wealth.

Table 3
Top Ten Most Important Predictor Variables of Basic Drinking Water Use (Outcome 1) and Using Basic Drinking Water That Is Always Available (Outcome 2) Identified Using Random Forests Models and Model Parameters by Site and Outcome, Dark Red = 1st Most Important, Light Yellow = 10th Most Important

Variable	The Gambia	The Gambia	Mozambique	Mozambique	Kenya	Kenya	Pakistan	Pakistan
Outcome Modeled	1	2	1	2	1	2	1	2
Demographic variables								
Household wealth	1	1	1	1	1	1	1	1
Maternal education	2	7	2		2	2	2	2
Case/Control				2	4	3	9	8
Temperature variables								
Two-week temp	5	2	8	8	6	7	4	3
Two-week temp, lag1	3	3	9	3	8	9	5	4
Two-week temp, lag2	4	4		4	7	10	6	6
Four-week temp		9					8	7
Four-week temp, lag1	6	10	10		9		10	10
Four-week temp, lag2	7	5	7	5	10	6	7	9
Precipitation variables								
Days since rainfall	8	8	4				3	5
Two-week precip						5		
Two-week precip, lag1	9	6	3	6				
Two-week precip, lag2	10		5		5	4		
Four-week precipitation				10				
Four-week precip, lag1			6	7				
Four-week precip, lag2				9		8		
Eight-week precip					3			
Model Parameters								
Number of trees	250	250	500	250	500	500	250	250
Number of variables tried	15	15	14	11	14	12	15	17
OOB error (%)	4.55	11.86	8.68	10.21	16.93	19.18	7.29	17.82
Validation error (%)	5.00	13.50	9.00	9.95	18.00	21.10	6.80	18.30

Estimates generated using linear exposure variables (when appropriate) were generally consistent with these findings (Tables S2–S5 in Supporting Information S1).

Adjustment for other statistically significant weather and demographic variables had minimal effect on estimates of association in Mozambique or Pakistan (Tables S3 and S5 in Supporting Information S1). In Kenya, after adjustment, education was included in the final model predicting BDW use, and household wealth was not. In Kenya, adjustment did lead to a change in the estimate of association for biweekly temperature with a 2-week lag, but this is assumed to be a result of collinearity between that variable and biweekly temperature with no lag (Table S4 in Supporting Information S1). In Gambia, biweekly temperature with a 2-week lag was the only variable with a strong association with BDW use, so an adjusted model was not constructed (Table S2 in Supporting Information S1). There was no evidence of effect modification by maternal education, household wealth or case status on the relationship between weather variables and BDW use at any of the four sites.

3.4. Outcome 2: Use of BDW That Is Always Available

As with Outcome 1, wealth was the top predictor of using BDW that is always available, however maternal education was no longer the second most important in Gambia and Mozambique. The same temperature and precipitation variables that were important for Outcome 1 were usually important for predicting Outcome 2, but

Table 4
Magnitude and Direction of Associations Between Most Important Variables From Random Forest Analysis and Basic Drinking Water Use (Outcome 1), Adjusted for Wealth, by Site

	The Gambia	Mozambique	Kenya	Pakistan
Variable	$N = 2{,}598$	$N = 1{,}976$	$N = 3{,}359$	$N = 3{,}096$
Demographic variables				
Increasing household wealth	3.38 (2.43, 4.71)	1.61 (1.28, 2.04)	1.19 (1.01, 1.39)	2.62 (2.03, 3.38)
Maternal education[a]		1.67 (1.26, 2.21)	2.90 (2.12, 3.97)	1.68 (1.27, 2.23)
Case (vs. control)			0.74 (0.64, 0.85)	
Temperature variables				
Two-week temperature		0.77 (0.62, 0.96)	0.49 (0.40, 0.59)	0.72 (0.59, 0.89)
Two-week temperature with 1-week lag			0.65 (0.53, 0.79)	0.66 (0.53, 0.81)
Two-week temperature with 2-week lag	1.51 (1.05, 2.19)		0.70 (0.58, 0.85)	0.67 (0.54, 0.82)
Four-week temperature				0.68 (0.55, 0.83)
Four-week temperature with 1-week lag			0.66 (0.57, 0.76)	0.61 (0.49, 0.76)
Four-week temperature with 2-week lag			0.71 (0.61, 0.81)	0.64 (0.51, 0.79)
Precipitation variables				
Previous days since rain				0.71 (0.56, 0.90)
Two-week precipitation				
Two-week precipitation with 1-week lag				
Two-week precipitation with 2-week lag		1.36 (1.10, 1.68)	2.59 (2.12, 3.15)	
Four-week precipitation				
Four-week precipitation with 1-week lag		1.28 (1.03, 1.60)		
Four-week precipitation with 2-week lag,				
Eight-week precipitation			3.95 (3.21, 4.86)	

Note. Associations are odds ratios and 95% confidence intervals comparing the highest quartile/category to the lowest quartile/category of each variable. When, in tests for linearity, no difference was seen between adjacent categories, quartiles were collapsed and we provide ORs comparing the highest to lowest category (detailed descriptions of variable specification are provided in Tables S2–S5 in Supporting Information S1). Models were fit separately for each variable and country, and adjusted for wealth. Colors indicate direction and strength of association: red = decreased basic drinking water use; blue = increased basic drinking water use. Gray indicates association untested because the variable was not identified as an important predictor in random forests. White cells indicate the association was tested but was not statistically significant.

[a]Maternal education was categorized, based on relevant schooling in each region, in three categories in the Gambia, Mozambique and Kenya, and four categories in Pakistan. Estimates compare the highest to lowest maternal education group for each region. Details are provided in Tables S2–S5 in Supporting Information S1.

Kenya and Mozambique both had long-term precipitation variables that were important for Outcome 2 which had not been important at any site for Outcome 1 (Table 3).

Estimates of the strength and direction of the association between weather variables and use of BDW that is always available are shown in Table 5. Increasing wealth was positively associated with Outcome 2 in three of the four sites; a negative association was seen in Gambia. Increasing education level was associated with increased use in Gambia, Kenya, and Pakistan. Households with moderate to severe diarrhea cases were significantly less likely to use BDW which was always available in three sites: Mozambique, Kenya, and Pakistan. Increasing temperature, on both a long and short scale, was consistently associated with decreased use of BDW that was always available at all study sites. The association between precipitation and Outcome 2 varied by site. Increasing long-term (4- and 8-week) precipitation was associated with increased use of always available BDW in Kenya, and longer dry periods were associated with decreased use of always available BDW in Pakistan, however, in contrast to Outcome 1, increasing precipitation was associated with decreased use of BDW that is always available in Gambia and Mozambique.

Adjustment for other important variables had minimal effect on the association between weather variables and use of BDW that was always available in Kenya, Pakistan, and Gambia (Tables S6, S8, and S9 in Supporting

Table 5
Magnitude and Direction of Associations Between Most Important Variables From Random Forest (RF) Analysis and Using Basic Drinking Water Which Is Always Available (Outcome 2), Adjusted for Wealth, by Site

	The Gambia	Mozambique	Kenya	Pakistan
Variable	*N* = 2,598	*N* = 1,976	*N* = 3,359	*N* = 3,096
Demographic variables				
Increasing household wealth	0.46 (0.35, 0.62)	2.24 (1.73, 2.89)	1.24 (1.02, 1.50)	1.84 (1.50, 2.26)
Increasing education levels	1.36 (1.05, 1.77)		2.48 (1.85, 3.32)	1.38 (1.13, 1.70)
Case (vs. control)		0.44 (0.36, 0.54)	0.76 (0.66, 0.87)	0.75 (0.65, 0.87)
Temperature variables				
Two-week temperature	0.51 (0.36, 0.71)	0.77 (0.60, 0.99)	0.51 (0.42, 0.62)	0.87 (0.73, 1.04)
Two-week temperature with 1-week lag	0.73 (0.52, 1.03)	0.78 (0.60, 1.00)	0.67 (0.59, 0.78)	0.73 (0.63, 0.85)
Two-week temperature with 2-week lag	0.66 (0.47, 0.92)	0.81 (0.68, 0.97)	0.73 (0.60, 0.88)	0.67 (0.54, 0.82)
Four-week temperature	0.76 (0.62, 0.93)			0.73 (0.63, 0.85)
Four-week temperature with 1-week lag	0.79 (0.65, 0.96)			0.69 (0.69, 0.80)
Four-week temperature with 2-week lag			0.68 (0.60, 0.79)	0.68 (0.59, 0.79)
Precipitation variables				
Previous weeks since rain				0.72 (0.59, 0.88)[a]
Two-week precipitation			2.77 (2.27, 3.37)	
Two-week precipitation with 1-week lag	0.75 (0.64, 0.88)			
Two-week precipitation with 2-week lag			2.06 (1.70, 2.51)	
Four-week precipitation		0.74 (0.60, 0.91)		
Four-week precipitation with 1-week lag				
Four-week precipitation with 2-week lag		0.79 (0.64, 0.97)	2.29 (1.88, 2.79)	
Eight-week precipitation				

Note. Associations are odds ratios and 95% confidence intervals comparing the highest quartile/category to the lowest quartile/category of each variable. When, in tests for linearity, no difference was seen between adjacent categories, quartiles were collapsed and we provide ORs comparing the highest to lowest category (detailed descriptions of variable specification are provided in Tables S6–S9 in Supporting Information S1). Colors indicate direction and strength of association: red = decreased basic drinking water use; blue = increased basic drinking water use. Gray indicates association untested because the variable was not identified as an important predictor in random forests. White cells indicate the association was tested but was not statistically significant.

[a]Previous weeks since rain recalculated from previous days since rainfall used in RF model.

Information S1). In Mozambique, there was evidence for qualitative interaction between case-status and biweekly temperature with a 2-week lag (Table S7a in Supporting Information S1), such that the decreased use of always available BDW at higher temperatures was only seen among controls. In Pakistan, there was evidence of interaction between SES and case-status and moderate evidence that the association between the number of previous weeks since rain and use of BDW that is always available was most pronounced in the lowest SES group. Among those in the lowest SES category, high severity of drought (>6 weeks since rainfall) is associated with an OR = 0.47 (95% CI: 0.30, 0.74) for use of BDW that is always available, compared to having rainfall in the past week. Gambia similarly had evidence of interaction between education and SES, and the association between mean 2-week temperature and Outcome 2 was most pronounced in those without any formal education, OR = 0.40 (95%CI: 0.23, 0.70). Among those with any formal education, the OR = 1.28 (95%CI: 0.41, 3.96).

4. Discussion

By combining weather data with a large population-based study of diarrheal disease in four countries, we found temperature and precipitation were significantly associated with the availability and use of BDW, however with different directions of association depending on the context. This study capitalized on a large population-level longitudinal data set with thousands of observations per country, capturing a wide temporal and spatial range.

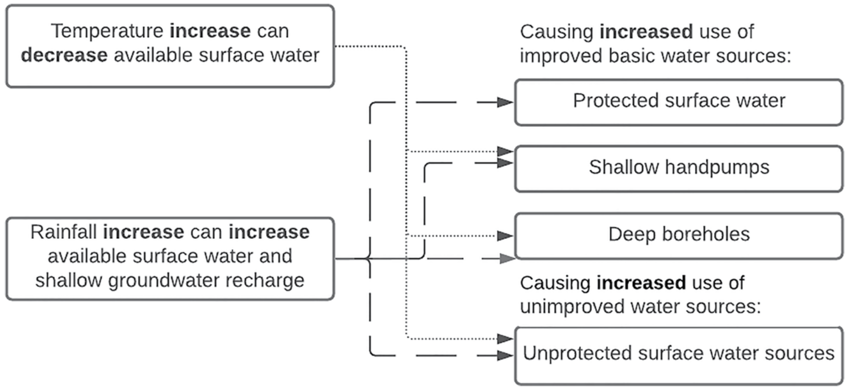

Figure 3. Conceptual model indicating ways in which temperature or rainfall could impact availability and use of water sources.

Patterns in the availability and use of different water sources may be influenced by seasonality and short- and long-term rainfall variability.

In this study, we had four key findings. (a) Across all countries, household SES was by far the most important predictor of increased use of BDW, followed closely in importance by education status. Beyond predicting BDW overall, individuals with low SES were more vulnerable to prolonged dry periods (in Pakistan) or high temperatures (in The Gambia). In three of four locations studied, (b) as temperature increases, BDW use, and use of BDW that is always available decreases and (c) increasing rainfall increased BDW use but did not always increase availability of BDW. Lastly, (d) in The Gambia the association between weather and BDW use did not follow the same patterns in most analyses—suggesting some water systems may be less impacted by weather than others. Notably, The Gambia had the highest BDW use (77%) of sites in our study, was the only location where >50% of the population reported using public tap, and had the lowest spatial resolution. As a result, it is unclear if the unique patterns seen in The Gambia are due to imprecision of our weather estimates or increased resilience to extreme weather.

There are numerous ways climate change may lead to changes in use of and access to BDW sources (Figure 3). In some contexts, increasing temperatures may correlate with decreased surface water retention or shallow groundwater and motivate users toward less safe groundwater sources or less convenient water sources, alternately increasing temperatures may decrease motivation for seeking out safer sources and prompt fallback to more convenient sources of water including groundwater or open wells. Likewise, decreasing rainfall may result in surface water sources drying up, motivating use of other water sources that may or may not be protected. The evidence to date has shown that seasonal and long-term changes in temperature and rainfall can change the mix and convenience of available water sources for communities. A study in Ethiopia identified that water collection times increase during the dry season (Tucker et al., 2014), and a qualitative study of water users and managers in Ghana, Kenya and Zambia reported less time collecting water in the rainy seasons (Kelly et al., 2018). This is consistent with our findings that in three of four sites, BDW use decreased during hot periods and increased during wet periods. However, both our study and the work of others suggest the impact of weather on BDW use and access is context specific. A study in South Africa found some households switch from more contaminated surface water to safer municipal water sources during the dry season (Nguyen et al., 2021). In several recent studies, researchers have examined patterns in use of groundwater boreholes in arid regions of Kenya and Ethiopia and compared these patterns to rainfall trends in the region. In these studies, an inverse relationship between use of electrical borehole pumps as well as handpumps and recent rainfall was observed, as well as overall seasonal trends in decreased groundwater pump use during rainy seasons (Thomas et al., 2019; Thomson et al., 2019). These trends appear to reflect behavioral choices to use surface water sources when available, and do not, generally, reflect an intrinsic hydrologic relationship between rainfall and aquifer recharge. Notably, this behavior has been observed as a risk to professional drinking water services as users may be less willing to pay for improved water sources when unimproved surface water sources are seasonally available (Armstrong et al., 2021). In this study, rainfall was not predictive of BDW at the site with the greatest baseline access to BDW, underscoring the importance of work to understand how the mix of available water sources impacts climate vulnerability.

The significance of household wealth in our analyses underscores the importance of economic development in the use of basic water sources and increasing resilience to climate change. Greater household wealth was associated with increased BDW use at all sites, and BDW availability at three out of four sites. We also found evidence that wealth modified vulnerability to drought and high temperatures, such that less wealthy families had reduced BDW access during these periods. This provides evidence that climate change and poverty can have compounding impacts when it comes to drinking water.

4.1. Limitations

This study has several important limitations. Although we tried to standardize our definition of water sources using the World Health Organization categories of improved water source, the categories are not perfect and do not distinguish between "improved" drinking water sources and water that is free of unsafe contamination. We were unable to measure contamination directly and the water sources were not observed by study staff. Unfortunately, given the data set available, verifying the nature of these water sources was beyond the scope of our analysis. Future studies examining these questions would benefit from testing and observing the water sources. Further, these improved BDW sources include protected surface water sources, and shallow and deep groundwater sources, which have different hydrological and climatic response profiles as well as contamination risk.

There was substantial variation in the size and population density of the study sites we examined by design, including both rural and urban locations, ranging from 10 Km^2 in Pakistan to over 1,000 Km^2 in The Gambia. Weather data—rainfall, in particular, frequently varies over small spatial scales which are imperfectly captured by available meteorological data (Levy et al., 2019). By averaging weather variables over the study sites, we may have introduced misclassification of the weather variables, particularly in the larger sites. Similarly, acute weather events may play a large role in access to and decisions about water-source use. By asking about water-use over the last 2 weeks, we are unable to capture the day-to-day shifts that may occur as a result of acute events. Lastly, we were unable to capture a change in water source use within individual households as a result of weather, as water collection time was only measured at baseline. Comparing main water sources, 90% of households that reported using improved water sources at enrollment reported improved water sources as their main water source at follow-up, and 70% of households reporting using unimproved water sources at enrollment continued to use unimproved sources at follow-up. Future analysis of this data set could be used to examine within-household changes in drinking water source use among households with multiple observations. We did not examine deseasonalized data, while we do not believe the results presented here are purely a result of seasonal trends, it is possible that seasonal trends contributed to our findings.

We utilized a machine learning approach to identify a minimal set of important variables to include in final models. While generally, this approach was successful at identifying clear patterns both across sites and between study aims, there were some non-intuitive findings. For instance, the number of days since the previous rainfall was frequently identified as an important predictor of drinking water use in RF models (in all sites except Kenya), but was not associated with drinking water use in either Gambia or Mozambique after adjustment for confounders in regression models. This is a strength of the combined method we used, as RFs can be used to identify individual important predictors, but does not provide information on the direction or magnitude of the association between variables. While machine learning can be a valuable tool for decreasing the dimensionality of data sets, it is important to recognize its limitations, which is why we used a two-step analysis process involving machine learning for dimension reduction followed by adjusted regression models.

4.2. Conclusions

Despite these limitations, we found strong associations between weather patterns and drinking water source use. These associations have plausible drivers given the intrinsic relationships between the climate variables examined and water availability as well as user preferences for more convenient and/or free water sources. Given the geographic and cultural disparity between the study sites, it is not surprising that there is some diversity in the direction of associations—the conclusion that water use and availability *do* depend on climate is important and lays the groundwork for further studies of mechanisms and implications.

Climate change is anticipated to bring about greater variability in both temperature and rainfall, and low-resource settings are particularly vulnerable to these changes (IPCC, 2021; Watts et al., 2020). The impact of these changes on WASH uptake are expected to be diverse and vary by setting. Increasing prevalence and severity of drought will have obvious consequences in terms of water scarcity and availability and may lead to selection of less-safe water sources, as we saw in Pakistan, but may also lead to increased willingness to utilize improved water sources (Thomas et al., 2019; Thomson et al., 2019). Therefore, any future interventions intended to increase access to and use of safe drinking water should consider the potential impacts of climate on WASH use and availability, and develop infrastructure with these potential mechanisms in mind.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All data used for this research is publicly available. *GEMS data*: WASH variables obtained for GEMS participants obtained from https://l2.clinepidb.org/ce.legacy/app/record/dataset/DS_841a9f5259. Data is available for download on request (Gates Enterics Project, 2018). *CHIRPS data*: precipitation data come the Climate Hazards Group InfraRed Precipitation with Station data (Climate Hazards Center, 2017). Data is available for download without conditions at https://www.chc.ucsb.edu/data/chirps. *Weather Station data*: temperature data used for this study come from Climate Data Online (NOAA, 2022). Data can be downloaded without restrictions at https://www.ncdc.noaa.gov/cdo-web/.

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