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Influence of climate extremes and land use on fecal contamination of shallow tubewells in Bangladesh

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Abstract

Climate extremes in conjunction with some land use practices are expected to have large impacts on water quality. However the impacts of land use and climate change on fecal contamination of groundwater has not been well characterized. This work quantifies the influences of extreme weather events and land use practices on *E. coli* presence and concentration in groundwater from 125 shallow wells, a dominant drinking water resource in rural Bangladesh, monitored over a 17-month period. The results showed that *E. coli* presence was significantly associated with the number of heavy rain days, developed land and areas with more surface water. These variables also had significant impacts on *E. coli* concentration, with risk ratios of 1.38 (95% CI = 1.16, 1.65), 1.07 (95% CI: 1.05, 1.09), and 1.02 (95% CI = 1.01, 1.03), respectively. Significant synergistic effects on *E.coli* presence and concentration were observed when land use and weather variables were combined. The findings suggest that climate extremes and land use practices, particularly urbanization, might promote fecal contamination of shallow well water, thus increasing the risk of diarrheal diseases.

Graphical Abstract

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ASSOCIATED CONTENT

Supporting Information. The additional results of statistical analysis of the land cover and weather variables. This material is available free of charge via the Internet at http://pubs.acs.org.

The authors declare no competing financial interest.

Keywords

E. coli; groundwater; land cover; climate change; extreme weather events; remote sensing

INTRODUCTION

Climate change and land use change are two major types of global environmental change, exerting profound influences on water resources and water quality, as well as human health. Increases in water temperature and climate extremes, e.g. flooding and drought, are expected to deteriorate water quality and lead to many forms of contamination.[1] Land use practices have direct and indirect impacts on water resources and water quality.[2] For example, irrigation directly influences water supply through water withdrawal, and urbanization and agriculture can substantially degrade water quality, contributing to eutrophication and fecal contamination.[3–5] In addition, urbanization increases the demand for groundwater because it is a major drinking water resource in some urban areas.[5, 6] Groundwater is a primary drinking water source in many regions of the world, and plays a central role in sustaining ecosystem and public health, especially in areas with contaminated or limited drinking water resources.[7, 8]

Climate and land use have broad impacts on groundwater resources because they largely determine evapotranspiration and precipitation, thus influencing the recharge of groundwater.[8] In extreme wet weather events, rain-fed recharge may degrade groundwater quality through infiltration of pollutants. Further, climate-driven groundwater quality degradation is often complicated by land use because anthropogenic activities (e.g., industry, urbanization, agriculture) will have chronic effects on pollutant loads.[9] For example, the increases in temperature and evapotranspiration in dry months and extreme rainfall events in the pre-monsoon season from March to May have remarkable influences on ground water supply and quality in Bangladesh.[10, 11]

In Bangladesh, widespread fecal contamination in surface water has led to diarrheal diseases prevalent among its population, especially among children under five.[12, 13] To protect against diarrheal diseases, millions of shallow tubewells (< 140 feet[13]) have been installed in past three decades because they are inexpensive and convenient. These private wells constructed with polyvinyl chloride pipes provide drinking water for over 95% of population in rural areas of Bangladesh.[14] It is generally thought that groundwater is free of microbial contamination. However, recent studies have shown that groundwater is often fecally contaminated and latrines that drain into ponds that are leaching into the water table could be a source of fecal contamination of shallow wells.[15–18] This is concerning because the number of diarrheal disease cases is still high.[13] Bangladesh is one of the countries that is most vulnerable to climate change and climate variablity,[19] which has been linked to the increase in waterborne disease.[20–22] In addition, Bangladesh is experiencing rapid urbanization, resulting in the conversion of rural agricultural areas into urban land uses, which will affect surface and groundwater quality.[23] Therefore, investigating the influences of land use and climate extremes on fecal contamination of groundwater in Bangladesh is important for understanding the risk factors of waterborne diseases and taking pre-emptive adaptation measures to future climate and land use change.

Examining the effects of climate and land use on water resources and water quality has attracted a lot attention, with many studies focused on surface water.[24, 25] Among the few studies on groundwater, the emphasis has been on groundwater resources. It is very rare to find a study that examines the combined effects of climate and land use on groundwater quality. Therefore, this study investigates the independent and combined effects of land use and extreme weather events on fecal contamination of shallow well water, which is expected to be more sensitive to climate change and land use practices than deep groundwater. This work is the first assessment of the influences of land use and extreme weather events on fecal contaminants in groundwater.

METHODS

Study area

Two sites in rural Bangladesh were selected in this study (Figure 1). The first site comprises 6 villages in Matlab upazila, located at nearly 57 km southeast of Dhaka, the capital of Bangladesh. The second site is the village of Char Para in Araihazar upazila, located 25 km east of Dhaka. The household survey of both areas has been conducted in 2008 and 2009, and the detailed information about tubewells and the neighborhood environment was described previously.[15] The hydrogeological features of shallow aquifer in these areas have also been described in literature.[17, 26]

Satellite data and image processing

Land use data in both study areas were obtained by classifying satellite images from Google Earth. The images clipped for Matlab and the village of Char Para areas have spatial resolutions of 2.1 m and 0.33 m, respectively. Both images were acquired in March 2007. The clipped images were georeferenced with a projected coordinate system, WGS (World Geodetic System) 1984- UTM (Universal Transverse Mercator) Zone 46N in ArcGIS 10.1 (ESRI, CA, USA).

USGS land cover classification system[27] was adopted to classify the land cover in both areas. Based on the characteristics of land cover in these areas, land cover was classified into 6 types, which include agriculture (e.g. cropland and rice paddy field), barren land (e.g. transitional area), developed land (also called as urban or built-in, e.g. residential area, road, and commercial area), tree cover, water, and wetland. Since flooding is frequent in Bangladesh and the image was acquired during the dry season, the water areas measured from the satellite image are low lying areas with year-round standing water.

The satellite images were classified with an object-based image analysis (OBIA) method.[28] One of the key steps for this method is image segmentation, which partitions the image into many pieces of objects based on shape, texture, and spectral characteristics of objects. A region growing algorithm was used for image segmentation.[29] The segmented image was classified into multiple spectral/spatial classes (26 classes in Matlab and 28 classes in the village of Char Para) using the ISODATA algorithm,[30] an unsupervised image classified method. These classes were then reclassified into 6 types of land cover according to ground truth information. The overall accuracy for image classification was assessed by comparing the classified image with reference data that includes the points where the true land cover classes are known. For each type of land cover class, over 20 points were randomly selected. The overall accuracy was calculated using the number of correctly classified points divided by the total reference points, which was conducted in ArcGIS 10.1. The classified images were also imported into ArcGIS 10.1 to calculate the percentage of each land cover type around each tubewell. Given that land cover may vary at different spatial scales, two radii, 100 m and 200 m, were chosen. These buffers are appropriate because if a larger buffer is chosen, the land cover around wells sometimes overlaps with many wells, however, if a smaller buffer is chosen, some types of land use may not be included in the buffer.

E. coli and groundwater quality data

Water samples from 92 tubewells in Matlab area and 33 tubewells in the village of Char Para were collected from May 2008 to October 2009 quasi-monthly.[15] In total, over 4000 samples were collected. *E. coli*, an indicator of fecal contaminants, was quantified using the Colilert-18® method with Quanti-Tray 2000® within 8 hours of collection (IDEXX Laboratories, Inc., Westbrook, Maine). The most probable number (MPN) of *E. coli* in 100 mL of water was determined by the number of fluorescence-positive wells of the Quanti-Tray.[15] Besides, total coliforms were enumerated using the same method. Several water quality variables, e.g., pH, Oxidation-Reduction Potential (ORP), dissolved oxygen, specific conductance, and water temperature, were measured on the wells with YSI sensors (YSI, Yellow Springs, Ohio).

Climate data and the definition of climate extremes

Daily precipitation data from January 1, 2001 to December 31, 2010 for Matlab and the village of Char Para were obtained from TRMM (Tropical Rainfall Measuring Mission) online visualization and Analysis System (TOVAS). Since in each area tubewells are very close in space (<3 km), the spatial variability of precipitation among the sites of these tubewells is very small. Therefore, the same rainfall data were used for tubewells in each area. Daily average temperature data in the same period (2001–2010) for Dhaka were obtained from the National Climate Data Center (NCDC), USA (the weather station ID: USAF419230). To define climate extremes, the ten-year (2001–2010) temperature or precipitation data were used as the reference, and 90th percentile of the distribution of the data was calculated as the threshold. If the daily mean temperature was above the threshold, that day was defined as a hot day.[20] A heavy-rain day was defined using a similar approach. After defining climate extremes, the numbers of hot days in the 3, 7, 15 and 30 days preceding a sampling date was calculated, which generated 4 variables, namely, nHD_3, nHD_7, nHD_{15}, and nHD_{30}.[20] Similarly, 4 variables (nHR_3, nHR_7, nHR_{15}, and nHR_{30}) were created to represent the number of heavy-rain days in the 3, 7, 15, and 30 days preceding a sampling date. In addition, 4 variables (mT_3, mT_7, mT_{15}, and mT_{30}) were created to represent the average temperature in the 3, 7, 15 and 30 days preceding sampling and 4 variables (mR_3, mR_7, mR_{15}, and mR_{30}) were created to represent the average rainfall of the 3, 7, 15 and 30 days preceding a sampling date, respectively. In total, 16 weather variables were created. These variables based on different time intervals measure weather conditions and extreme weather events representing their different intensities and the time-lag from a weather event.

Statistical analysis

Logistic regression models and negative binomial regression models were used to examine the relationship between land use and weather variables and *E. coli* data. These two types of models were chosen because the dependent variables, *E. coli* presence and *E. coli* concentration, follow different distributions. The former is binary data, indicating a qualitative measurement of fecal contamination in groundwater, while the later can be regarded as count data, indicating a quantitative measurement of fecal contamination in groundwater. Given that fecal contamination in shallow wells is not well known yet, both measurements are important for understanding the safety of drinking water. The independent variables include 12 land cover variables (the percentages of 6 types of land cover classes in the radii of 100 m and 200 m, respectively), 16 weather variables (the average daily temperature and rainfall, the numbers of heavy rain days and hot days in 3, 7, 15 and 30 days preceding *E. coli* testing), and 3 other factors (population density at the radii of 100 m and 200 m, and total coliforms).

First, logistic regression models were chosen to evaluate the association between *E. coli* presence and these independent variables. For these models, the dependent variable is the presence of *E. coli* in a sample. If *E. coli* was detected in a water sample, the outcome is 1, otherwise, the outcome is 0. According to the independent variables included in the model, 2 types of analyses were conducted: 1) univariable regression; and 2) multivariable analysis with both land cover variables and weather variables. Odds ratios (OR) were calculated to indicate the association between *E. coli* presence and an independent variable. If OR is significantly larger than 1.00 OR>1.00, p<0.05), a positive association was assumed. If OR is significantly less than 1.00 OR<1.00, p<0.05), a negative association was assumed.

Secondly, negative binomial models were used to examine what factors were associated with *E. coli* counts in water samples. In this model, the natural logarithm of the count of *E. coli* in a certain volume of water was the dependent variable. Initially, the concentration of *E. coli* in 100 mL water was assumed to follow a Poisson distribution, of which the mean and the variance are equal. A goodness fit of test revealed that the data did not follow a Poisson distribution well. Then, a negative binomial distribution was assumed because it allows the variance to be larger than the mean. For these models, the dependent variable is the expected number of *E. coli* in a water sample in 1 liter in natural logarithm format. A general mathematical express for a negative binomial regression model is shown below:

$$log(\mu_i)=\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\cdots+\beta_n x_{ni} \quad (1)$$

Where μ is the expected most probable *E. coli* count in 1 liter of water (the unit was converted from MPN/100mL to MPN/L for convenience of analysis), i is the index of a sample, x_1, x_2,…, x_n are the independent variables of the model. Similar to the logistic regression model, 2 types of analyses were conducted based on the independent variables included in the model. The relative risk (RR) was calculated to indicate the association between *E. coli* concentration and an independent variable. If the RR is significantly larger than 1.00 (RR>1.00, p<0.05), a positive association was assumed. If the RR is significantly less than 1.00 (RR<1.00, p<0.05), a negative association was assumed.

Before running these models, multicollinearity among independent variables was examined based on the correlation matrix generated by Pearson correlation analysis and variance inflation factors (VIF). Only one of these highly correlated independent variables (e.g., urban area vs. population density) was included in the model if mulitcollinearity was identified (e.g. r >0.6 or VIF>5).[31] To select best model fit, a general criterion, Akaike's Information criterion (AIC) was adopted, which indicates a better model fit if its value is smaller. The model performance was evaluated by residual diagnostics of the top-ranked model.[31] The model fitting and residual diagnostics were carried out using SAS 9.3 (SAS Institute, Inc., Cary, NC, USA).

RESULTS

Temperature, rainfall and weather extremes

In both areas, the average monthly temperature was relatively low during November 2008 – February 2009 and was the highest in June 2009 (Figure 2C). Hot days were frequently observed from April to June 2009 but not observed from October 2008 to March 2009 (Figure 2D). The highest average monthly precipitation (the sum of daily precipitation for a month divided by the number of days in that month) was observed in July 2009 in both sites, which was 24.68 mm/d and 25.27 mm/d, respectively (Figure 2E). The second highest average monthly precipitation was observed in July 2008 in both sites. During November 2008 – February 2009, very little rainfall was recorded (average monthly precipitation < 2 mm/d). Accordingly, the number of heavy rain days was higher in July 2008 and July and August 2009. However, from November 2008 to February 2009, no heavy rain days were recorded (Figure 2F).

Land use characteristics

The overall accuracies of image classification in the Matlab area and the village of Char Para were 82% and 85%, respectively. In the Matlab area, agriculture is the dominant land use type, accounting for 46% of the area, followed by water, barren land and urban areas (ranged from 10–13%). In the village of Char Para, the major land use types are tree cover and agriculture, which account for 28% and 24% of the area, respectively. The land use components around tubewells are similar to the land use components in the study areas. In Matlab, on average, agriculture was the largest type of land cover class within 100 m of tubewells, followed by tree cover, water, and developed areas. In contrast to Matlab, on average, tree cover is the largest type of land cover class in Char Para within 200 m around tubewells followed by agriculture, developed area and barren land. In Char Para within 100 m around tubewells, tree cover was the largest type of land cover followed by developed land and agriculture (Figure 2G, 2H &Table S1). The percentage of water area decreased as the radius increased in Matlab area.

Presence and concentration of *E. coli* in tubewell water

E. coli was tested in water samples from a total 125 shallow wells from May 2008 to October 2009. In Matlab, the average *E. coli* concentration of the wells monitored was the highest in August 2008 (94 MPN/100mL), followed by November 2008 (86 MPN/100mL) and October, 2009 (74 MPN/100mL). *E. coli* concentration was very low during February – April 2009, which was below 10 MPN/100mL. In the village of Char Para, the average *E. coli* concentration across the wells monitored was very high in October 2008 (193 MPN/100 mL) and June 2009 (109 MPN/100mL), while was very low in February and March, 2009, which was less than 2 MPN/100mL (Figure 2A). With regard to *E. coli* detection rate, in Matlab, *E. coli* was more frequently detected in the samples collected in July and August 2008 (56.52% and 64.14%, respectively), but less frequently detected in March 2009 (17.39%). In the village of Char Para, *E. coli* was more frequently detected in the samples collected in October 2008 (63.64%) and September 2009 (54.55%). *E. coli* was less frequently detected in July 2008 (21.21%) (Figure 2B). Pearson correlation analysis indicated that *E. coli* presence was significantly correlated with the number of heavy rain days in the 7, 15 and 30 days preceding a sampling date ($p<0.05$) and *E. coli* concentration was significantly correlated with the number of hot days in the 7, 15 and 30 days preceding a sampling date ($p<0.05$).

Effects of land use on fecal contamination

The univariable logistic regression model showed that *E.coli* presence had a significant positive association with the percentages of developed area and water area but was negatively associated with the percentage of agricultural area in the 100 m radius. In the 200 m radius around wells, *E. coli* presence only had a significant positive association with the percentage of developed area. The results from the univariable negative binomial regression model showed that *E.coli* concentration had a significant positive association with the percentages of developed area, water and tree cover but a negative association with agriculture in both 100 m and 200 m radius areas (Table S2).

In the multivariable logistic regression models, *E. coli* presence was positively associated with the percentages of developed area (OR=1.03, 95% CI = 1.01–1.04) and water area (OR=1.01, 95% CI =1.00–1.02) in 100 m. In 200 m, *E.coli* presence still had a significant positive association with the percentage of developed area and water area (Table 1). In multivariable negative binomial models, *E. coli* concentration was positively associated with the percentages of developed area and water area for both 100 m and 200 m. For the 200 m radius, the RR values for the percentages of developed area and water were 1.07 (95%CI = 1.05 – 1.09) and 1.02 (95%CI = 1.01 – 1.03), respectively (Table 2).

Effects of weather extremes on fecal contamination

The results from univariable regression models showed that *E. coli* presence was significantly and positively associated with the number of heavy rain days, and also related to the average temperature and rainfall in the 7 day, 15 day and 30 day periods. However, the number of hot days was not significantly associated with *E. coli* presence. *E. coli* concentration was only significantly associated with the number of heavy rain days in the 3 day period, the number of hot days in 7 day and 15 day periods, and the average temperature in the 3 day period (Table S2).

The results from multivariable regression models revealed that the increase in the number of heavy rain days significantly increased the likelihood of the presence of *E. coli* in water samples, for all lag periods including 3 days, 7 days, and 15 days (Table 1). *E. coli* was also likely to be detected if the mean temperature in 7 days or 15 days increased. The association between *E. coli* presence and the number of hot days was not significant. *E. coli* concentration was significantly affected by the number of heavy rain days in 3 days preceding *E. coli* detection. However, when the time period became longer, the increase in the number of heavy rain days did not coincide with significantly increased *E. coli* concentration. Instead, the increase in the number of hot days in 7 days or15 days increased *E. coli* concentration significantly (Table 2).

Combined effects of land use and weather extremes on fecal contamination

The combined effects were equal to the multiplication of individual effects when both land use variables and weather variables were included in multivariable regression models. In the radius of 100 m and 3 days period, because the effects of individual variables (the percentages of developed land and water area, and the number of heavy rain days) on *E. coli* presence are positive (OR>1.00), the combined effect of these variables is larger than the effects of individual variables. For example, the OR value for the combined effect of the percentage of developed area and the number of heavy rain days is 1.19 (=1.03*1.13), which means that the likelihood of the detection of *E. coli* will increase 1.19 times if the percentage of developed area increases by 1% and the number of heavy rain day increases by 1 day in the same time. Similarly, in the radius of 200 m and the time periods of 7 days and 15 days, the combined effects of the percentage of developed area and the number of heavy rain days were stronger than the effects of each individual variables on the presence of *E. coli* (Table 1).

The results from negative binomial models showed *E. coli* concentration had positive associations with land use variables (the percentages of developed area and water area), while the associations with weather variables were either positive or negative. In the radius of 100 m and the 3 day period, the combined effect of the percentage of developed area and the number of heavy rain days (RR= 1.48) was stronger than the effects of any individual variables. It showed that *E. coli* concentration will increase 1.48 times if the percentage of developed area increases by 1% and the number of heavy rain day increases by 1 day during the same time. In the radius of 200 m and 7 days and the 15 day periods, *E. coli* concentration still had positive associations with the percentages of developed area and water area, but its relationship with weather variables was complicated. Since some weather variables (e.g. mean temperature) had negative associations with *E. coli* concentration, the combination of land use variables and weather variables might not have synergistic effects on *E. coli* concentration (Table 2).

Effects of other factors and fecal contamination

The results from univariable logistic regression models showed *E. coli* presence had a significant positive association with the population density in 100 m and total coliforms. According to univariable binomial regression models, *E.coli* concentration was positively associated with the population density in 100 m and 200 m, as well as total coliforms (Table S2).

DISCUSSION

This study highlights the impacts of weather extremes and land use on fecal contamination in groundwater. In this study, we found that the percentages of developed land and depressed areas with year-round standing water, and the number of heavy rain days have synergistic effects on *E.coli* presence and concentration. The findings have implications for identifying sustainable safe drinking water resources and reducing diarrheal diseases, as well as for taking pre-emptive measures to adapt inevitable land use change and climate change, because these land use and weather variables are potential risk factors for fecal contamination of groundwater, a major drinking water resource in Bangladesh, while no attention has been paid to their effects yet.

The impacts of heavy rain on fecal contamination of surface water have been well investigated.[32–35] However, few studies examined its impacts on fecal contamination in groundwater. van Geen et al[15] showed the *E. coli* detection rate in shallow wells in Bangladesh varied following the trend of rainfall and water level. We found that *E.coli* was more likely detected in tubewell water samples if heavy rain days were more frequent preceding *E.coli* detection time. This is understandable because heavy rain can lead to fecal contamination of shallow tubewells through several pathways. First, heavy rain may flush surface contamination from unsanitary latrines into depressed areas holding ponds. In the early wet season, when the water table is low, pond water can rapidly drain into the aquifer.[17] Second, during heavy rain, runoff with fecal bacteria may directly contaminate tubewells if their wellhead is not well protected.[17] In addition, rainwater carrying bacteria may directly enter tubewells. The results from negative binomial models showed that in 3 days preceding *E. coli* detection, *E. coli* concentration would be higher if heavy rain days are more frequent. However, this positive association was not significant if the frequency of heavy rain days were observed in a longer period before *E. coli* detection. This suggested that heavy rain has an acute effect of fecal contamination of shallow wells. A similar phenomenon has been observed in an urban watershed, where heavy storms led to an increase in *E. coli* concentration.[34] The results showed air temperature has a complicated relationship with *E. coli* presence and concentration, which might be explained as follows. First, air temperature does not have a linear relationship with groundwater temperature. It is expected that daily groundwater temperature is less sensitive and less variable to daily air temperature according to our observations on groundwater samples as well as the literature.[36] During hot days, groundwater temperature may slightly increase, which favors the growth of bacteria. On the other hand, water evaporation becomes faster on hot days, which makes small ponds dry and decreases water recharge to groundwater, thus reducing fecal contamination of groundwater.[17]

The results indicate that fecal bacteria are more likely detected from shallow wells in the areas with larger percentages of developed land and water area, which are consistent with the previous findings that increased population, unsanitary latrines and ponds are major sources of fecal contamination of shallow wells in these areas.[37] In land use classification, developed areas are mainly residential areas. Therefore, a larger percentage of developed land around a tubewell suggested larger densities of population and latrines around the tubewell.[15] The Pearson correlation analysis also showed that the percentage of developed land was significantly and positively correlated with population density (Table S3 and Table S4). Studies in rural Bangladesh found that latrine-polluted ponds could be significant sources of fecal contaminants in shallow wells as fecal contaminated surface water recharges to wells in shallow unconfined aquifers,[17] and the number of unsanitary latrines was significantly correlated with *E. coli* concentration in ponds across the spatial-buffer range of 15 to 80 m.[38] Since agricultural area is negatively correlated with developed land, fecal bacteria are less likely to be detected in tubewells surrounded by large agricultural areas. In rural Bangladesh, one of land use practices is to dig holes to build up land. These holes later become ponds used for fish farming or aquaculture and various household practices such as bathing, washing clothes, and dishes.[38] Therefore, this land development increases the percentage of water area, thus increasing the risk of fecal contamination in groundwater. We also find that the percentages of developed land and the number of heavy rain days as well as some other variables have synergistic effects on *E. coli* presence and *E.coli* concentration. For example, the combination of the percentage of developed area and the number of heavy rain days significantly increases *E. coli* concentration with a relative risk of 1.48. This result suggests that if developed land increases 1% and the number of heavy rain days increase in 1 day, the concentration of *E. coli* may increase 1.48 times. The combined effects can still be important for fecal contamination of groundwater even it is not synergistic. Our results, together with others,[17, 37–40] provide useful information for identifying risk factors for fecal contamination of groundwater and finding safe drinking water resources. Bangladesh is extremely vulnerable to climate change.[41] Frequent climate-related hazards, such as floods and cyclones, can seriously damage water supply and sanitation facilities, thus deteriorating groundwater quality. In rural Bangladesh, though the use of sanitary latrines has significantly increased in recent years, nearly half of households still use unsanitary latrines (e.g., pit or ring-slab without water seal).[42] Fecal contaminants are likely transported from unsanitary latrines to nearby ponds during climate extremes, and infiltrate the shallow aquifer or enter groundwater through shallow tubewells that have no platforms to protect them from external contaminated water.[15] Additionally, Bangladesh has experienced rapid urbanization in recent decades, which has resulted in the conversion of rural areas into developed areas. This transformation is expected to aggravate fecal contamination of groundwater, as suggested by results obtained from this study. Therefore, under the changing circumstances of climate and land use, groundwater quality is compromised and unreliable. Monitoring groundwater quality and treating groundwater before drinking are necessary. Finding alternative safe drinking water resources and new technologies to adapt impending climate change and land use change is also crucial.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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ABBREVIATIONS

GIS	Geographic information system
RS	Remote sensing
LULC	land use/land cover
OR	Odds ratio
RR	Relative risk

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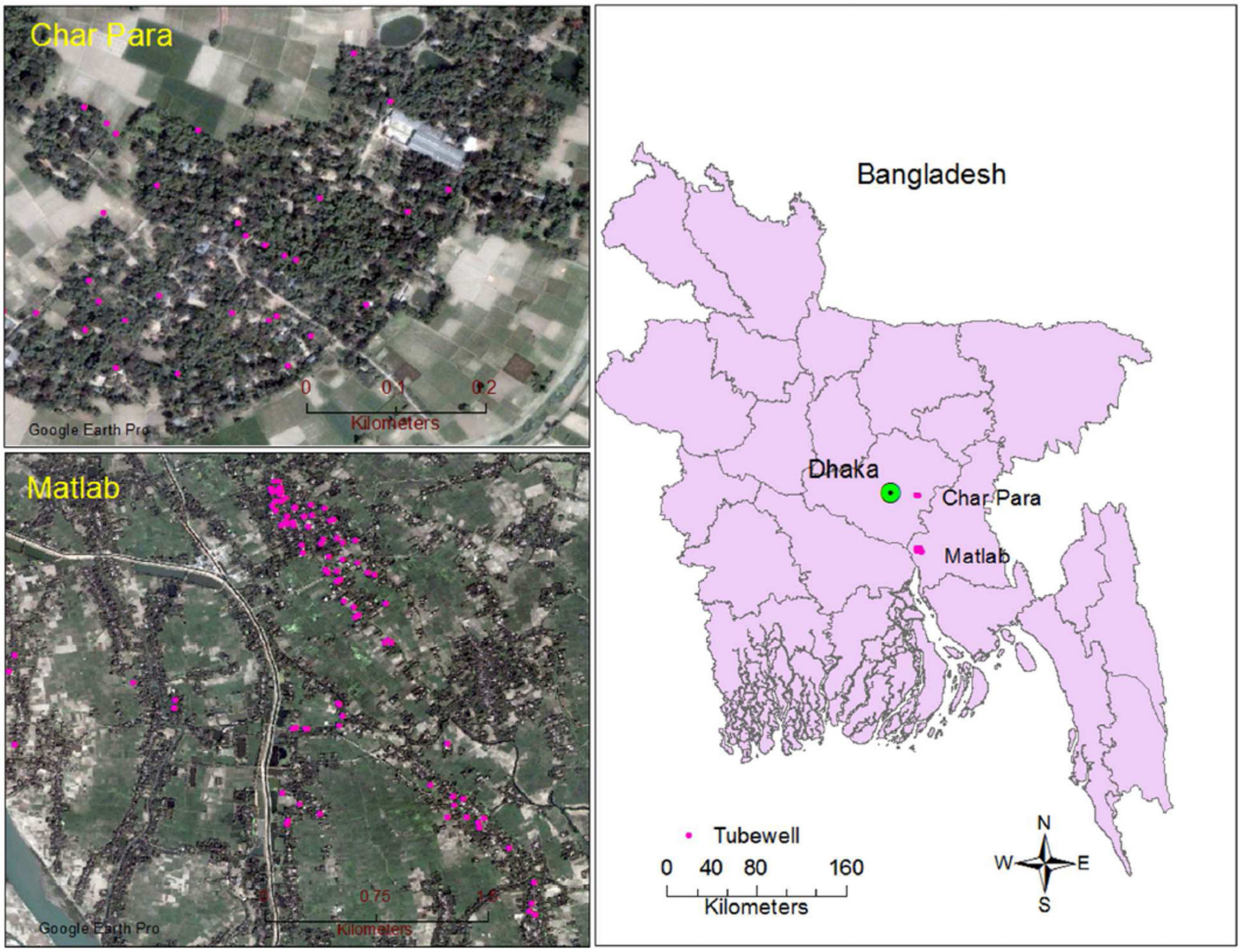

Figure 1.
The locations of tubewells for water sampling in the two study sites (Matlab and the village of Char Para) in Bangladesh

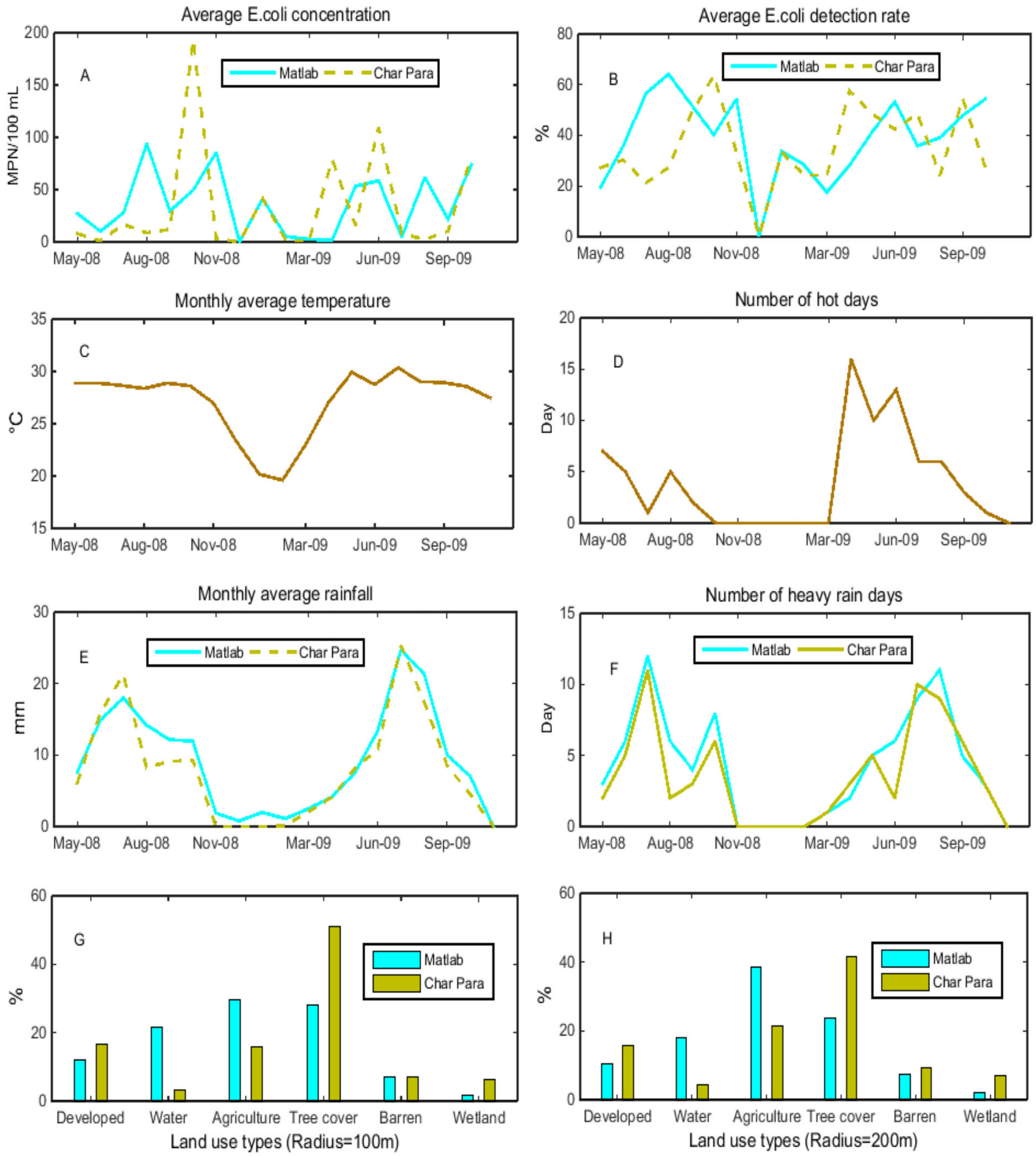

Figure 2.

Characteristics of *E. coli* concentration and detection rate, weather variables and land use variables in two study sites. In the subplot B, the *E. coli* detection rate is the percent of the positive samples in which *E. coli* was detected. In the subplot E, the monthly average rainfall is the accumulation of daily rainfall in a month divided by the number of days in that month.

Table 1

Effects of land use and weather variables on *E. coli* presence analyzed by logistic regression model

	Logistic regression model					
			OR			
	Covariates	β	Point estimate	95% CI		p
3 days	Developed	0.026	1.03	1.01	1.04	<0.001
100 m	Water	0.008	1.01	1.00	1.02	0.034
	nHR_3	0.147	1.16	1.04	1.30	0.010
7 days	Developed	0.027	1.03	1.01	1.04	<0.001
100 m	Water	0.006	1.01	1.00	1.01	0.110
	nHR_7	0.124	1.13	1.06	1.21	<0.001
	mT_7	0.030	1.03	1.01	1.06	0.013
15 days	Developed	0.027	1.03	1.01	1.04	<0.001
100 m	Water	0.007	1.01	1.00	1.02	0.091
	nHR_{15}	0.065	1.07	1.03	1.11	0.002
	mT_{15}	0.038	1.04	1.01	1.07	0.016
3 days	Developed	0.032	1.03	1.02	1.05	<0.001
200 m	Water	0.009	1.01	1.00	1.02	0.083
	nHR_3	0.152	1.16	1.04	1.30	0.008
7 days	Developed	0.034	1.03	1.02	1.05	<0.001
200 m	nHR_7	0.134	1.14	1.07	1.22	<0.001
	mT_7	0.032	1.03	1.01	1.06	0.008
15 days	Developed	0.034	1.03	1.02	1.05	<0.001
200 m	nHR_{15}	0.071	1.07	1.03	1.12	0.001
	mT_{15}	0.039	1.04	1.01	1.07	0.013

Table 2

Effects of land use and weather variables on *E. coli* concentration analyzed by negative binomial regression model

	Negative binomial regression model					
			RR			
	Covariates	β	Point estimate	95% CI		p
3 days	Developed	0.065	1.07	1.05	1.09	<0.001
100 m	Water	0.024	1.02	1.02	1.03	<0.001
	nHR_3	0.324	1.38	1.16	1.65	<0.001
	mT_3	0.093	0.91	0.89	0.93	<0.001
7 days	Developed	0.065	1.07	1.05	1.08	<0.001
100 m	Water	0.016	1.02	1.01	1.02	<0.001
	nHD_7	0.110	1.12	1.04	1.20	0.002
15 days	Developed	0.074	1.08	1.06	1.09	<0.001
100 m	Water	0.020	1.02	1.01	1.03	<0.001
	nHR_{15}	0.018	0.92	0.88	0.97	0.001
	nHD_{15}	0.031	1.03	1.00	1.06	0.055
3 days	Developed	0.053	1.05	1.03	1.08	<0.001
200 m	Water	0.036	1.04	1.03	1.05	<0.001
	nHR_3	0.337	1.40	1.18	1.67	<0.001
	mT_3	0.096	0.91	0.88	0.93	<0.001
7 days	Developed	0.062	1.06	1.04	1.09	<0.001
200 m	Water	0.023	1.02	1.01	1.03	<0.001
	nHD_7	0.115	1.12	1.05	1.20	0.001
15 days	Developed	0.069	1.07	1.05	1.09	<0.001
200 m	Water	0.029	1.03	1.02	1.04	<0.001
	nHR_{15}	0.073	0.93	0.89	0.97	0.002
	nHD_{15}	0.035	1.04	1.00	1.07	0.026