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The joint effect of natural and human-induced environmental factors on surface water quality in the Birim North District of Ghana

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Abstract

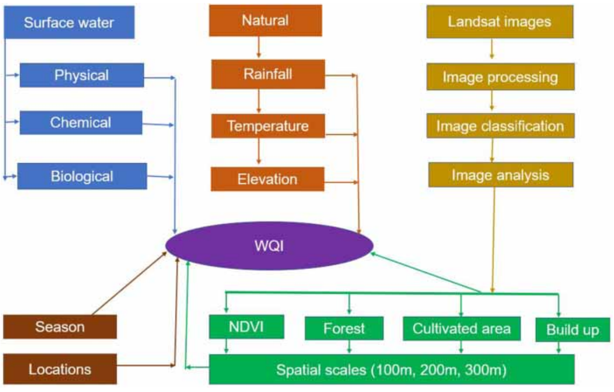
Anthropogenic activities threaten surface water quality across the globe, especially in contexts where monitoring is non-existent or weak. Our understanding of the effect, order and magnitude of natural and human-induced environmental factors on surface water quality is limited. This study assessed the effect, predictive order and magnitude of natural and human-induced environmental variables on surface water quality in the Birim North District of Ghana. Approximately 540 samples were collected from 15 rivers and streams in 2018 and analysed using 31 indicators. Landsat satellite images (2018 and 2019) of the study area were analysed for land use land cover data. The data were fitted to ordinary least squares (OLS) regression model. Season (50%) most accounted for variability in the surface water quality whereas elevation and forest cover accounted for 28% and 21%, respectively. Surface water quality in the Akoase and Nyafoman/Noyem clusters were 30% and 10% respectively better in quality than the Adofokrom/Amenam cluster. The increasing order of magnitude of variables in predicting surface water quality was Buffer, Cultivated area, Built-up, Forest, Rivers and streams cluster, Elevation, and Season. Consequently, management interventions for surface water ecosystems should account for spatio-temporal heterogeneity in the factors that influence surface water quality.

Key words: cumulative, environmental, geo-spatial, modelling, statistics

Highlights

- Determine the effect, order and magnitude of natural and human-induced environmental factors on surface water quality.
- Use of geospatial techniques to assess surface water quality.
- Use of multivariate statistical tools to assess surface water quality.
- Develop composite index of surface water quality.
- Assess how surface water quality varies systematically between wet and dry seasons.

Graphical Abstract



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INTRODUCTION

Assessing surface water quality-environmental relationships is critical globally. In recent years, many developing countries have set the development of safe water resources and reduction of waterborne diseases as their major public health goal (Li & Wu 2019). Lack of safe drinking water currently affects more than a third of the people in the world (Li & Wu 2019). Recreation (swimming in polluted surface water) and irrigation of plants with polluted water exposes humans to chemical toxicants through the skin and food chain, respectively. Bioaccumulation of toxic chemicals by aquatic organisms, including seafood and fish, equally exposes humans to contaminants (Schwarzenbach *et al.* 2010).

Studies and concerns about surface water ecosystems (Armah *et al.* 2010; Bowes *et al.* 2015), their condition and quality (Karikari & Ansa-Asare 2006; McGarvey *et al.* 2008) have increased in recent times. This is largely because surface waters are increasingly threatened by anthropogenic and natural factors (Allan & Castillo 2007).

Processes such as changing land use and land cover (LULC) (Mirzaei *et al.* 2019; You *et al.* 2019; Ekumah *et al.* 2020), surface runoff (Shrestha & Kazama 2006), seasonal variations (Whitehead *et al.* 2009), interflow (Zhang *et al.* 2014) as well as hydrological regimes (Henriques *et al.* 2015) affect river and stream flow and eventually, pollutant levels. In the long run, these processes are likely to cause variations in the structure and function of the aquatic ecosystems (Lindell *et al.* 2010). Intensification in land use and land cover changes increase water temperature (LeBlanc *et al.* 1997) with devastating impacts on the quality of surface water (Fisher *et al.* 2000). Urbanisation and agricultural development are major driving forces in increasing non-point source pollution into surface water (Allan 2004; Tang *et al.* 2005). This deterioration of surface water is expected to worsen, increasing the threat to human health, the environment and sustainable development (Li & Wu 2019). Therefore, abatement efforts are required to gain harmony between human, resources and environment (Li *et al.* 2017). The actions of protecting, restoring and enhancing surface waters demand increasing levels of knowledge about the factors and their interactions thereof influencing their quality, together with cost-efficient modelling techniques.

Although several studies have highlighted the independent effects of human-induced environmental and natural factors on surface water quality, little is known about the joint effect of natural and human-induced environmental factors on surface water quality. Similarly, our knowledge about the order and magnitude of factors that systematically influence water quality of rivers and streams, especially in the gold mining environment, is nascent. Reliable data on surface water quality and variables that influence water quality are of importance to give an in-depth understanding of the order and magnitude of these factors in implementing an effective catchment management strategy for the protection and development of these water bodies. The Birim North District, which is one of the major gold mining hubs in Ghana, has experienced extensive environmental threats (both natural and anthropogenic) during the past decade. The District is characterised by diverse anthropogenic activities (such as agricultural areas consisting of cocoa farming, a large area of plantation, a small area of orange farming, livestock production, small-scale mining) that could largely impact on the quality of the water bodies. Hitherto, besides anecdotal evidence, little has been done to characterise and quantify the combined effect of natural and anthropogenic factors on the sundry water bodies in this geographical area. This study, therefore, sought to assess the joint effect of natural and human-induced environmental factors and their order and magnitude on surface water quality in the Birim North District of Ghana.

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MATERIALS AND METHODS

Study area

The study area, Birim North District, is located within latitude 6.15°N–6.35°N and longitude 0.20°W–1.05°W (Figure 1). It is at the western end of the Eastern Region of Ghana.

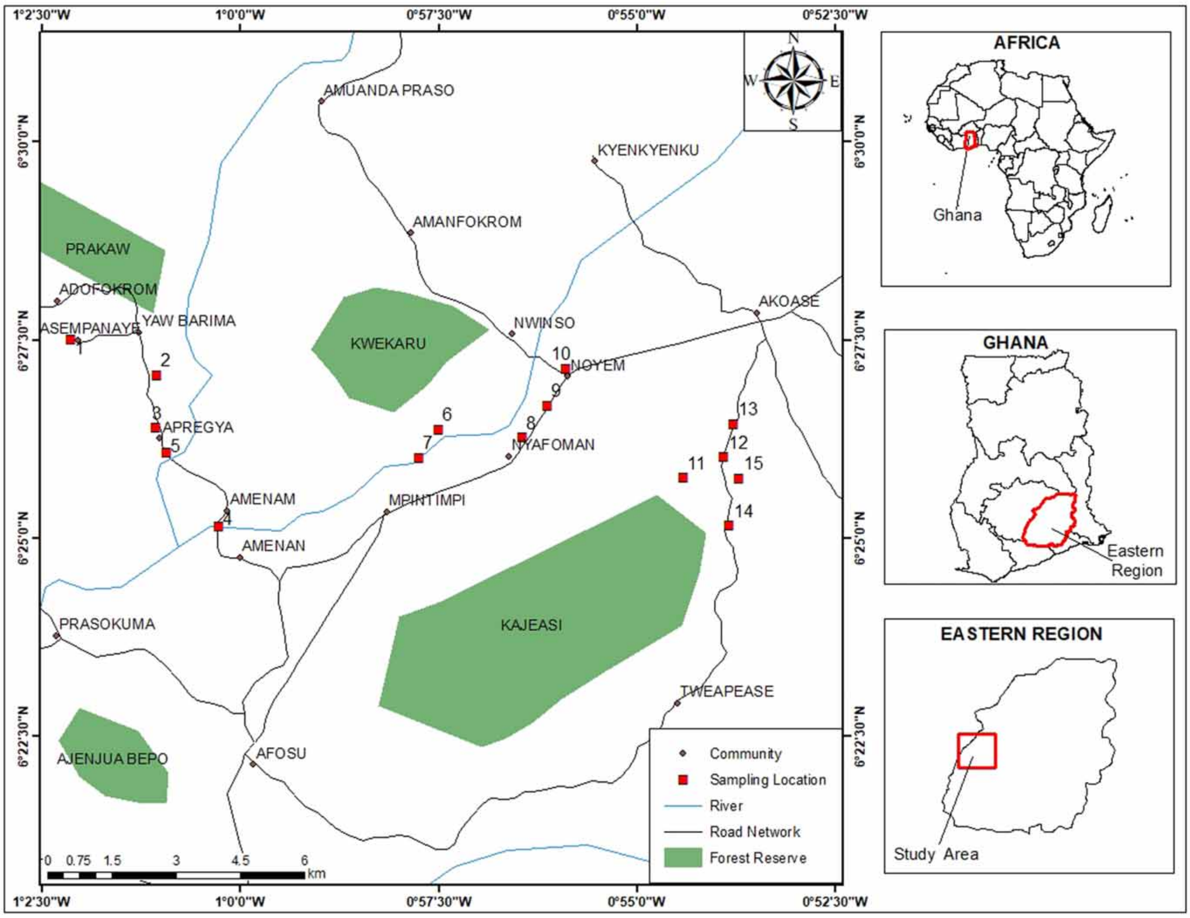

Figure 1 | Map of the study area and sampling locations.

The Birim North District of the Eastern region of Ghana has a land area of approximately 566.48 square km (Ghana Statistical Service (GSS) 2010). The District shares boundaries with Akyemansa District to the south, to the north with Kwahu West Municipal, to the east with Atiwa District and to the west with Asante Akim South. The Birim North District lies within the semi-equatorial climatic zone and experiences a double maxima rainfall pattern (late March to early July and August to late October) with rainfall values between 1,500 mm and 2,000 mm and relative humidity of about 55–59 percent during the year (GSS 2010). Temperatures range between a minimum of 25.1 degrees Celsius and a maximum of 27.9 degrees Celsius. The underlying rock formation is mainly made up of Upper Biriman rocks consisting of predominantly volcanic lava, schist, hyalites and greywacke (GSS 2010). According to the 2010 Population and Housing Census, the district has a population of 78,907 representing 3.0 percent of the region's total population (GSS 2010). The district capital is the New Abirim. The study covered communities in the district including Mpintimpi, Adofokrom, Amenam, Nyafoman, Noyem, Akoase, Prasokuma, Nwinso, Subrinso, Abirim, Afaso, Asempanaye, Yaw Barima, Amanfokrom and Apregya. The study area is drained by several streams and rivers including the Suten, Sakapea, Nwi, Nyanoma, Aprokoma and Asuabena.

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Data collection and laboratory analysis

A total of fifteen surface water sampling points were randomly selected using the Geospatial Modelling Environment (GME), an extension in ArcGIS 10.3 software. Five hundred and forty (540) surface water samples were collected from the fifteen surface water bodies (rivers and streams) in the Birim North District of Ghana from January 2018 to December 2018 with two hundred and seventy (270) samples each collected in the dry and wet seasons. Surface water bodies were repeatedly sampled six times during each season. At each surface water body, eighteen samples were taken during each season (dry and wet seasons) for the whole study period with three replicate samples at every period of sampling. The samples collected for each season were analyzed separately. The sampled surface water locations were labelled from S1 to S15, as described in Table 1.

Table 1 | Sampled surface water locations and their descriptions

Location ID	Location name	Longitude	Latitude	Elevation
S 1	Asuoabena around Asempanaye	−1.036	6.459	200.226
S 2	Asuoabena near pillar P18	−1.018	6.451	179.322
S 3	Tributary of River Pra after Apragya	−1.018	6.440	171.357
S 4	River Nwin near Amenam	−1.005	6.419	164.201
S 5	Pra River at Apragya	−1.016	6.435	173.127
S 6	River Nwin near Nyamebekyere	−0.959	6.440	182.824
S 7	Tributary of Nwin river at Dadekurom	−0.963	6.434	172.729
S 8	Nsuten along main road	−0.941	6.438	185.891
S 9	Nsuten river	−0.936	6.445	185.679
S 10	Aprokroma stream	−0.932	6.452	189.755
S 11	Sakapea stream at Domeabra	−0.907	6.430	206.134
S 12	Nsuten along Domeabra – Nyafoman road	−0.899	6.434	202.741
S 13	Nyanoma along Domeabra – Nyafoman road	−0.897	6.441	207.055
S 14	Nsuten near Odumase	−0.897	6.419	210.342
S 15	Nsuten near Nsiasakuraa	−0.895	6.429	204.747

Surface water quality was studied using thirty-one (31) indicators classified into physical, chemical and biological parameters. Sampling and analytical methods followed the protocols developed by the American Public Health Association (APHA) (1998) and the Australian and New Zealand guidelines for fresh and marine water quality (ANZECC 2000). Sampling bottles were prewashed with detergent and rinsed with 10% hydrochloric acid and double-distilled water prior to sampling. To minimise or eliminate any contaminations that might be introduced in the sampled water at each of the sampling locations, the bottles were rinsed three times with the water to be collected.

Surface water was sampled by gently lowering the sample bottle horizontally into the water with the mouth of the bottle directed upstream, taking reasonable measures to avoid suspended/floating debris. Thus, surface water samples were collected at the subsurface to avoid the colloidal layer as this can influence the concentration of certain parameters. 1,000 mL of water was collected at each location into three blackened, clearly labelled plastic bottles and were kept under ice in an ice chest. This procedure in the long round avoids microbial growth, flocculation and reduces any adsorption on container surfaces that could affect the results (Berg 1992; Armah *et al.* 2010; Keith 2017). The water samples were transported to the environmental laboratory of Envaserv Research

Consult, Accra, for analysis. Physicochemical water quality parameters (conductivity, pH, turbidity, dissolved oxygen and temperature) were measured *in situ* at each sampling location using the Horiba U-53G multi-parameter water quality meter. A Global Positioning System (GPS) device (Garmin Etrex GPS) was used to record the sampling locations.

Reproducibility and recovery studies were carried out. About 1.0 mg/L standard solutions of each trace metal were measured (10 times) using flame Shimadzu model 6401F with respect to the reproducibility studies. The proportion (%) of trace metals recovered in the recovery studies ranged between 92.5 and 99.4% (standard error $\pm$0.005 to 0.570). The standard error is less than 1, which suggests that the analytical methods used for the samples were reproducible (Armah *et al.* 2010). The detection limit of heavy metals except mercury, cadmium, lead and chromium is 0.01 mg/L. The detection limit for mercury, cadmium and chromium is 0.002 mg/L and that of arsenic is 0.001 mg/L; that of lead is 0.005.

Homogenized subsamples were filtered, and acid-digested following the USEPA protocol 2002 (Environmental Monitoring Systems Laboratory 1991) and analyzed for total As, Fe Cd, Mn, Cu, Pb, and Cr using flame atomic absorption spectroscopy (AAS) following USEPA protocol 2007 (Environmental Monitoring Systems Laboratory 1991). Mercury was determined by cold vapour atomic absorption spectrometry. Unprocessed water samples were also analyzed for electrical conductivity and for chloride, sulphate, nitrate, phosphate, alkalinity and cyanide concentrations. Faecal coliform and total coliform bacteria were also determined by the membrane filtration technique.

Generation of water quality index (WQI)

A water quality index of the surface water samples was generated using eleven (11) of the studied water quality parameters (pH, total dissolved solids (TDS), sulphate, conductivity, total suspended solids, sodium, alkalinity, biological oxygen demand, magnesium, turbidity, nitrate) based on theoretical relevance. The average inter-item covariance was 848.3761 with a scale reliability coefficient of 0.7421 between the variables indicating that the index satisfied the condition of reliability. The WQI was calculated using the equation (Armah *et al.* 2012):

$$\mathrm{WQI} = \frac{\Sigma\,(qi.wi)}{\Sigma wi} \tag{1}$$

where wi is the unit weight, and q_i is the water quality rating.

According to Armah *et al.* (2012), for a given water quality indicator, the more harmful it is, the lower its standard and the unit weight (W_I) for the ith parameter (P_I) is assumed to be inversely proportional to its recommended guideline standard S_i ($i = 1, 2, 3 \ldots n$); where n is the number of parameters (11 in this study, i.e. pH, TDS, sulphate, conductivity, total suspended solids (TSS), sodium, alkalinity, biological oxygen demand (BOD), magnesium, turbidity, nitrate).

Except for pH, unit weights for nitrate, sulphate, turbidity, electrical conductivity, TDS, TSS, sodium, alkalinity, BOD and magnesium were calculated as the inverse of their guideline values (Best Applicable International Standards for surface water): 1/50, 1/250, 1/75, 1/1,500, 1/1,000, 1/50, 1/250, 1/150, 1/20, and 1/30, respectively.

Equation (2) shows the relationship between unit weights and the water quality standards (Armah *et al.* 2012):

$$wi = \frac{k}{Si} = \frac{1}{Si} \tag{2}$$

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where wi is the unit weight, Si is the water quality standard and k is the constant of proportionality which is equal to unity.

$$qi = 100\left(\frac{Vi}{Si}\right) \tag{3}$$

For pH, the quality rating qpH can be calculated from Equation (4):

$$qpH = 100\left[\frac{(\mathrm{VpH} \sim 7.0)}{1.5}\right] \tag{4}$$

where VpH is the observed value of pH and the symbol '$\sim$' is essentially the algebraic difference between VpH and 7.0.

The higher the WQI, the more polluted the surface water body. WQI $<$ 100 implies that the water from the surface water is clean and fit for human consumption. Conversely, WQI $>$ 100 implies that the water from the surface water body is polluted and deemed unfit for human consumption without treatment (severely contaminated). Generally, WQI $<$ 50 implies that it is fit for human consumption; WQI $<$ 80 implies that is moderately contaminated, and 80 $<$ WQI $<$ 100 implies that is excessively contaminated (Armah *et al.* 2012).

Landsat satellite image acquisition and classification

Landsat satellite images of the study area for 2018 and 2019 were downloaded from the United States Geological Survey Earth Resources Observation and Science Data Centre (http://www.usgs.gov). Table 2 shows the description of the various land use-land cover types adopted in the study.

Table 2 | Land use land cover classification scheme

Land use- Land cover type	Description
Forest	Vegetated lands that are not cultivated such as grassland, shrubs, forest and other natural vegetation
Cultivated area	Areas used for farming and degraded lands
Built-up	Areas used for residential lands and bare lands
Water	All surface water bodies including rivers and streams

Lu *et al.* (2012) suggest that in land use land cover classification, selection of sufficient number of training and test samples cannot be underestimated. Existing topographic maps and Google Earth images of the study area were used as reference data for the classification of the Landsat satellite images. With the help of field GPS coordinates of the study area, training samples were collected. The satellite images were pre-processed by stacking the individual bands and projected into the Universal Transverse Mercator (UTM) projection system (zone: 30N, datum: WGS84). Maximum Likelihood Classifier of Supervised Classification method was employed to classify the Landsat satellite images in ENVI 5.3. Maximum Likelihood Classifier (Ahmad & Quegan 2012) considers the variability of the various classes and assigns pixels to class of highest probability.

In the spatial study, the environmental variables (forest, cultivated area, and built-up data) were computed at buffer zones of 100 m, 200 m and 300 m around sampled locations. Additionally, the temporal study considered the seasonal variation within the study area, hence resulting in two different temporal periods, dry season and wet season. The surface water bodies were grouped into three

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clusters based on their spatial distribution in the study area to assess which cluster will have better quality.

Measures

Outcome variable

The outcome variable considered in this study is the WQI generated from the analysis of surface water samples in the Birim North District of Ghana.

Predictor variables

The variables chosen and model specification method for this study were based on theoretical relevance, parsimony and sequential regression analysis.

Studies have revealed that surface water quality is influenced by climatic seasonal variation and LULC (Rothwell *et al.* 2010; Wang *et al.* 2013). LULC types such as agriculture (Evans *et al.* 2014), mining site (Armah *et al.* 2010) and built-up areas (Carroll *et al.* 2013) are important factors affecting surface water quality. Where there are considerable variations in precipitation and temperature, constituent concentrations alter due to flow regimes (Pratt & Chang 2012). Seasonal regimes, therefore, need to be accounted for when studying particulate and other pollutants' concentrations to account for dilution and runoff (Tsegaye *et al.* 2006; Kang *et al.* 2010). Hence, to better explore and evaluate surface water quality, spatio-temporal assessment is recommended (Gu *et al.* 2019; Xu *et al.* 2019).

The catchment area of a water body is equally important regarding surface water quality assessment (Pratt & Chang 2012). Activities that are likely to affect surface water quality are not necessarily determined by proximity because an area can be close to a water body but might not drain into it. On the other hand, distant activity might influence the surface water quality if it is located within the drainage area of the water body.

The predictors considered for this study were season (wet and dry), elevation, forest cover, cultivated land, buffer (spatial scales considered around surface water catchments), and river group (group of rivers at the study area).

Data processing and statistical analysis

The data were entered and cleaned in Microsoft Excel 2010 and imported into Stata 13 MP (StataCorp, College Station, TX, USA) for statistical analysis. The analytical methods employed on the data were a combination of descriptive and inferential statistics. The relationships between water quality index (WQI) and predictor variables were determined using ordinary least squares (OLS) regression. The use of OLS in data analysis is appropriate when the dependent variable is a continuous value, normally distributed and has a linear relationship with the independent variables (McClendon 1994). Confidence interval (CI) of 95% and 0.05 level of statistical significance were employed in this study.

Results

The descriptive statistics of all water samples during the study, as well as the significant differences and relationship between water quality index and the predictor variables (season, elevation, forest, built-up, cultivated land buffer and river clusters), are presented in this section.

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Descriptive statistics

The elements of descriptive statistics (measures of central tendency, dispersion, and distribution) of surface water samples for the study period included mean, standard deviation, minimum and maximum values, skewness, and kurtosis as shown in Table 3.

Table 3 | Descriptive statistics of water quality parameters

Parameter	Mean	Std. deviation	Skewness	Kurtosis	Minimum	Maximum
pH	6.582	0.572	−0.517	1.064	4.450	7.890
Conductivity (μS/cm)	118.361	79.308	2.426	7.111	24.000	443.000
Alkalinity (mg/L)	75.800	63.783	1.304	0.459	10.000	246.000
Turbidity (NTU)	125.238	203.443	2.357	4.060	4.000	753.000
Total dissolved solids (mg/L)	77.979	49.682	2.057	5.150	16.000	270.000
Total suspended solids (mg/L)	99.811	162.342	2.453	4.687	1.000	625.000
Dissolved oxygen (mg/L)	3.600	3.561	0.134	−1.866	0.040	8.750
Biological oxygen demand (mg/L)	26.401	23.238	0.366	−1.616	2.660	64.900
Total hardness (mg/L)	72.161	85.888	4.181	18.430	8.000	503.000
True colour (mg/L Pt.co)	255.161	370.633	3.482	14.125	1.000	2,003.000
Apparent colour (mg/L Pt.co)	1,495.461	2,184.070	2.711	6.877	48.000	9,902.000
Chloride (mg/L)	7.482	3.940	1.279	1.724	1.900	21.200
Nitrate (mg/L)	2.548	1.237	0.257	−0.501	0.280	6.020
Sulphate (mg/L)	23.859	38.935	2.435	5.868	0.010	181.000
Sodium (mg/L)	11.883	12.553	4.778	22.764	1.300	79.500
Calcium (mg/L)	116.388	102.085	0.311	−1.499	0.010	312.450
Magnesium (mg/L)	5.074	4.025	0.043	−1.340	0.010	13.000
Potassium (mg/L)	5.149	3.388	1.813	3.291	0.680	18.000
Total phosphate (mg/L)	1.539	1.494	1.184	0.954	0.100	7.650
Total coliform (cfu/100 ml)	122.922	265.192	4.939	28.899	1.000	1,999
Faecal coliform (cfu/100 ml)	20.272	20.949	1.035	0.660	0.000	83
Arsenic (mg/L)	0.084	0.091	1.196	0.635	0.001	0.367
Iron (mg/L)	1.240	1.229	1.370	1.444	0.020	4.987
Manganese (mg/L)	0.225	0.266	1.051	0.305	0.001	0.992
Copper (mg/L)	0.993	1.296	1.038	−0.364	0.002	4.230
Chromium (mg/L)	0.475	0.741	2.128	5.353	0.002	3.800
Lead (mg/L)	0.053	0.172	3.985	15.379	0.002	0.945
Nickel (mg/L)	0.131	0.345	4.203	20.114	0.002	2.300
Zinc (mg/L)	0.121	0.139	2.062	3.359	0.010	0.600
Mercury (mg/L)	0.002	0.000	–	–	0.002	0.002
Cadmium (mg/L)	0.002	0.000	–	–	0.002	0.002

From Table 3, all measured parameters are right-skewed except pH. However, the distribution of data was variable. Fourteen of the parameters had a platykurtic distribution (pH, alkalinity, dissolved oxygen, biological oxygen demand, chloride, nitrate, calcium, magnesium, total phosphate, faecal coliform, arsenic, iron, copper, manganese) while fifteen had a leptokurtic distribution (conductivity, turbidity, total dissolved solids, total hardness, true colour, apparent colour, sulphate, sodium, potassium, total coliform, chromium, lead, nickel, and zinc).

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The mean pH value for all water samples was 6.582. Minimum and maximum values of 4.450 and 7.890 were recorded. The minimum and maximum conductivity values measured were 24 μS/cm and 443 μS/cm, respectively. The mean values of conductivity, alkalinity, turbidity, TDS, and TSS levels were 118.361 μS/cm, 78.8 mg/L, 125.238 NTU, 77.979 mg/L and 99.811 mg/L respectively. Mercury, cadmium, lead and arsenic concentration had approximately similar mean values for all samples (ranging between 0.002 mg/L and 0.084 mg/L).

The recorded levels of the surface water parameters varied across seasons and locations. In the dry season samples, minimum and maximum pH values of 5.94 and 7.89 were recorded at locations S6 and S3, respectively. Conductivity ranged from 38 μS/cm at location S10 to 443 μS/cm at location S13. Location S10 and S13 recorded the minimum and maximum alkalinity levels of 19 mg/l and 246 mg/L respectively. The minimum turbidity of 9.8 NTU was recorded at location S9 with the maximum of 753 NTU occurring at location S3. Location S3 recorded the highest TSS of 625 mg/L while locations S4 and S9 recorded the minimum of 1 mg/l. The dissolved oxygen (DO) level was very low during the dry season and it ranged from 0.040 mg/L at location S15 to 0.260 mg/L at location S5. BOD, on the other hand, ranged from 13.2 mg/L at location S10 to 64.9 mg/L at location S4. Apparent colour ranged from 48 TCU (S9) to 9902 TCU (S7). Two locations, S4 and S14, recorded the minimum nitrate levels of 0.7 mg/L while the maximum concentration of 6.02 mg/L was recorded at S15 and S5. Likewise, observed sulphate levels ranged from 0.010 mg/L (S5, S10, and S15) to 181 mg/L (S3, S13) while the levels of calcium ranged from 0.01 mg/L (locations S3, S8 and S13) to 40 mg/L (locations S4 and S14). All sampled locations recorded the presence of total coliform. The maximum total coliform count of 1,999 cfu/100 ml was obtained at location S14 with the minimum of 1 cfu/100 ml recorded at 8 locations – S2, S3, S5, S7, S8, S10, S12, S15. Faecal coliform was not recorded in all samples. Six locations (S7, S11, S12, S13, S14, and S15) did not record faecal coliform while the maximum faecal coliform load of 83 cfu/100 ml was recorded at location S1. Iron levels were low and ranged from 0.02 mg/L at locations S1, S4, S8, S11, S13 and S14 to 1.88 mg/L at S3. The maximum nickel level of 2.3 mg/L was recorded at location S3 with the minimum level of 0.01 mg/L at locations S5, S10 and S15. Locations S1 and S3 respectively recorded the minimum (0.03 mg/L) and maximum (3.8 mg/L) levels of chromium. Two locations (S4 and S14) recorded the highest copper level of 4.23 mg/L while the lowest level of 0.36 mg/L was recorded at locations S3 and S13.

In respect to the wet season samples, minimum and maximum pH values of 4.45 and 7.0 were measured at locations S2 and S12, respectively. Conductivity ranged from 24 μS/cm at S3 and S13 to 296 μS/cm at S4 and S9. The minimum (10 mg/L) and maximum (78 mg/L) readings for alkalinity level were found at locations S15 and S4, respectively. Turbidity levels ranged from 4.0 NTU at location S6 to 82 NTU at two locations (S2 and S12). Three locations (S1, S11 and S14) recorded the minimum TSS levels of 3 mg/L to a maximum of 147 mg/L at locations S5 and S10. Dissolved oxygen levels ranged from 3.36 mg/L at locations S14 and S4 to 8.75 mg/L at locations S14 and S4. The minimum BOD levels of 2.66 mg/L occurred at locations S8 and S3 while the maximum (7.3 mg/L) was found at locations S7 and S13. Apparent colour ranged from 147 TCU at locations S4, S9 to 2167 TCU at locations S7 and S2. Two locations (S3 and S13) recorded the minimum nitrate levels of 0.277 mg/L while locations S5 and S10 recorded the maximum levels of 4.786 mg/L. Sulphate levels ranged from 0.398 mg/L (location S6) to 7.966 mg/L (location S1) while calcium levels ranged from 120.24 mg/L at location S10 to 312.45 mg/L at location S11. All sampled locations recorded the presence of total coliform. The maximum total coliform count of 130 cfu/100 ml occurred at locations S3 and S13 while the minimum of 13 cfu/100 ml occurred at locations S4 and S9. Faecal coliform was equally recorded in all samples, unlike as observed in the dry season. The maximum faecal coliform load of 74 cfu/100 ml was recorded at locations S1 and S11 while the minimum load of 9 cfu/100 ml occurred at locations S4 and S14. Iron concentration ranged from 0.214 mg/L (locations S1 and S6) to 4.987 mg/L (locations S4 and S9).

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Multivariate statistics

The influence of the independent variables on WQI was assessed using OLS at the multivariate level. Table 4 shows the coefficient, robust standard errors, beta coefficient and probability values associated with WQI and the predictor variables considered in this study.

Table 4 | Linear regression model showing the relationship between WQI and environmental variables

WQI	Coef.	Robust SE	*P*-value	Beta
Season (ref. dry season)				
Wet season	−151.042	10.856	0.000	−0.503
Elevation	−2.817	0.572	0.000	−0.276
Forest	8.748	1.701	0.000	0.213
Scale (ref. 100 m)				
200 m	6.613	13.433	0.623	0.021
300 m	8.953	13.405	0.504	0.028
Built-up	1.519	1.229	0.217	0.169
Cultivated area	1.142	1.007	0.257	0.150
River cluster (ref. Adofokrom/Amenam)				
Nyafoman/Noyem	32.471	15.431	0.036	0.102
Akoase	95.298	19.375	0.000	0.299

The R-squared value obtained for the model is 0.714 ($P < 0.001$), implying that about 71.4% of the variance in the dependent variable, WQI, was accounted for by the predictor variables in the regression model. From the model output (Table 4), seasonal variations (dry to wet) are significantly associated with a change in the WQI ($P < 0.001$). Similarly, change in elevation, forest, and location of surface water (river group) were significantly associated with a change in the WQI ($P < 0.05$). The magnitude of the predictors on WQI in increasing order was as follows: Buffer < Cultivated area < Built-up < Forest < River group < Elevation < Season. Season and elevation were inversely related to WQI. On the contrary, forest, buffer, built-up, cultivated land and river group were directly proportional to WQI.

From Table 4, the quality of the surface water bodies decreased in the wet season compared to the dry season by approximately fifty percent (50%) ($P < 0.001$). Also, the results indicate that an increase in forest cover gives a better WQI ($P < 0.001$). The surface water group (river group) varied systematically with the WQI ($P < 0.05$).

DISCUSSION

This study assessed the joint effect of natural and human-induced environmental variables on surface water quality. The linear regression model output showed that season, elevation, forest, and river cluster are significant predictors of surface water quality. Among all the predictors, season had the greatest influence on WQI unlike buffer zone, which had the least influence on WQI.

Seasonal variation, which affects river and stream flow as found in this study, is paramount and should be considered in evaluating surface water quality–environment relationships in the study area. This finding, therefore, suggests that the anthropogenic human activities (including land-use types) and natural factors and processes are highly dependent on season (dry and wet). This makes it the most important predictor in investigating surface water quality-environment relationships.

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Pratt & Chang (2012) equally found that seasonal variation influences the concentration of water quality parameters. It is extensively proven that seasonal variability in surface water quality is the result of interactions between many processes caused by variations in climate (Araoye 2009). Surface run-off and groundwater discharge are major sources of pollutants of surface water bodies that are highly influenced by seasonal variation and dominant during the wet season. Surface run-off is observed when infiltration is limited by low soil permeability or its saturation causing water to flow over the landscape surfaces, increasing discharge in the receiving surface water bodies during the wet season (Winter 2001; Dosskey *et al.* 2010). Surface run-off carries along with it soil sediments and chemical contaminants, which are deposited into surface water bodies. The deposition of soil sediments and chemical contaminants affect the chemical, physical and biological make-up of surface water bodies, therefore influencing surface water quality (Bechmann 2014).

Elevation affects surface water. From the model output, the quality of the surface water bodies' improves (lesser WQI values) with increasing elevation. Hence, water bodies at higher elevation are of better quality compared with those at a lower elevation. Higher elevation water bodies receive lesser runoff and also experience lower anthropogenic activities. These findings support the works of Pratt & Chang (2012), who found that elevation and slope had a greater influence on surface water quality. Surface run-off usually flows down steep slopes into rivers and streams (You *et al.* 2019).

The third most important variable that predicts the surface water quality was forest cover. The study found that an increase in forest cover increases the quality of surface water. A higher proportion of forest around a surface water catchment indicates less anthropogenic activities and hence fewer potential sources of pollution. Forest sustains water quality by reducing soil erosion as well as filtering other pollutants that could easily get into the water body (You *et al.* 2019). Furthermore, densely growing vegetation in a forest can absorb and concentrate pollutants like nitrogen and phosphorus. Again, microbial communities in surface litters, debris and organically enriched soil can help in efficient degradation of pollutants that impair surface water quality (Allan *et al.* 1997; Ahearn *et al.* 2005; Nielsen *et al.* 2012). The findings are equally consistent with the study by Allan *et al.* (1997), who found that an increase in forested land cover resulted in dramatic declines in runoff and nutrient yields hence influencing the quality of the stream water bodies.

Cultivated land and built-up areas were not found to influence surface water quality. In contrast to the findings, studies have shown that farmland (Chen & Lu 2014) and built-up areas (Morrice *et al.* 2008) have a high influence on water quality. The disparity between those studies and the current study can be attributed to the intensity and closeness of the various land-use types around the surface water bodies.

The last significant variable that predicted the quality of the surface water is the location of the water body. The rivers and streams cluster informs the impact of anthropogenic and natural factors and processes; hence, in this study, the location attribute of the water bodies helps predict the quality. The anthropogenic and natural factors vary across the surface water bodies. The higher the intensity of this process, the poorer the quality of the water.

Study limitations

The study considered surface water bodies in the Birim North District of Ghana and, hence, this makes it impossible to generalize the findings for the whole country. Moreover, the study made use of OLS model, which although it is a flexible method, may not be flexible enough to handle non-linear relationships (Venables & Ripley 2002; Wood & Augustin 2002), as the processes and factors influencing surface water quality are complex (Varanka & Hjort 2016). Again, some LULC classes such as built-up and bare land were classified together as one class because the resolution of the satellite images (30 m) was not high enough to enable the separation of these LULC types. Ashiagbor *et al.* (2019) in their study also classified the two LULC types in one class. Precipitation and

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temperature as natural variables are known in the literature to influence surface water quality. These variables were measured in this study; however, they were dropped because there was little variability in their distributions with respect to the studied surface water bodies' locations and, further, they had limited explanatory power when they were originally added in the regression model. NDVI around the surface water catchments was calculated at the 100 m, 200 m and 300 m buffers. NDVI was automatically dropped in the regression model because of multicollinearity (i.e. NDVI and forest cover).

CONCLUSION

An ordinary least squares regression model was employed to assess the natural and anthropogenic factors that influence the quality of surface water bodies in the Birim North District of Ghana. It can be concluded that season, elevation, forest cover and location of surface water body should be considered in evaluating surface water quality-environment relationships. Season had the greatest effect on surface water quality compared to the other variables and predicted approximately 50% of the variance in the dependent variable (WQI). Approximately 12% and 8% was accounted for by elevation and forest cover respectively. The study equally reveals a better surface water quality in the Akoase cluster compared with the reference group (Adofokrom/Amenam) cluster by approximately 30%. The study confirmed that rivers' and streams' quality are interlinked with several processes and factors such as seasonal variation, elevation, and forest cover among others. It is therefore recommended that management interventions for surface water quality should be targeted temporally and spatially to the key areas that are necessary from both practical and economic perspectives.

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