Water Quality Investigation in Brunei Darussalam: Investigation of the Influence of Climate Change

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Abstract

The majority of Brunei's drinking water is sourced from river water. Increases in population, and industrialization are putting more and more pressure on water resources not only in Brunei but worldwide. The management of water resources under a changing climate is of key importance. The goal of this study was to investigate if current water quality changes in Brunei can be related to climatic change**.** The study investigated time series data from water quality parameters as well as rainfall data measured over a three-year period. The time series data was analysed using auto-correlation and partial auto-correlation functions. The results showed changes in climate evident from a decrease in precipitation and increase in rainfall intensity. These changes can be correlated with changes in water quality in particular a rise in aluminium concentrations. The highest correlation was observed between turbidity and colour, with a Pearson correlation coefficient greater than 0.8. The results from cross correlation showed that pH values tend to be low before the occurrence of rainfall, due to a dropping of water levels and the likely exposure of acid sulphate soils. Low pH values were correlated with higher aluminium concentrations which have been rising consistently throughout the observation period. The rise in aluminium concentration is correlated with a rise in abstraction from the river during the time period which underlines the importance of water management in a changing climate.

Keywords

Brunei, Aluminium, Water Quality, pH, Rainfall, Climate Change

Introduction

Brunei Darussalam on the island of Borneo has a tropical climate. Rainfall shows a seasonal pattern with two maxima and two minima. The first maximum occurs during the period October to January with December being the wettest month and the second maximum from May to July with May generally being the wettest month. The least amount of rainfall occurs in February and the second minimum period occurs during June to August. The average rainfall from 2014 to 2017 was 2676 mm (BMD, 2017) measured at Brunei International Airport.

Most of Brunei's water resources come from surface water and less than 1% from groundwater providing a safe yield of 17.3 million m^3/year used for oil and gas and local bottled water industries (FAO, 2011). Brunei's water consumption is with 350 l/d per person among the highest in South East Asia (Department of Water Services 2018).

Brunei is relatively unexplored with regards to additional water resources such as groundwater. However increases in population, industrialization as well as emerging contaminants are putting more and more pressure on water resources. Possible complex contamination scenarios resulting from this may require a range of remediation and assessment measures (Gödeke. et al. 2003, 2006, 2008a; Schirmer et al. 2006). However, natural occurring microbial processes can break down even recalcitrant contaminants (e.g. Gödeke. et al. 2008b).

Rainfall events have shown to be influencing water quality and human health from increased surface runoff (Setty et al., 2018), stressing the importance of water safety management plans. Climate change prediction for Brunei Darussalam based on different climate models predict a rise in mean annual temperature as well as a decrease in annual precipitation, however with greater rainfall intensities, a trend that has been confirmed by various studies in other regions (NRC 2002; Semenov and Bengtsson 2002; Karl and Trenberth 2003; Groisman et al. 2004; Kharin and Zwiers 2005).. Changes in the rainfall intensity and rainfall pH are another indicator of the anthropogenic effects of climate change (Vet et al. 2014, Häder and Barnes 2019). Recent research has shown that the frequency of extreme precipitation increases extensively under global warming (Myhre et al. 2019), which can affect the turbidity of the water (Lee et al. 2015). Research has shown that pH values for Brunei in rain have been measured to be well below 5 with regional pH values below 4.6 at urban centres in Malaysia (Radojevic and Lim 1995, Vet et al. 2014). Usually, climate change is predicted to have a negative effect on water quality (Mimikou et al. 2000, Salerno et al. 2018). The effects of climate change can already be experienced today in Brunei as the annual average temperature increased by 0.6 degrees over the time period from 1970 to 2014 (BMD 2016).

The management of water resources in a changing climate requires that all stakeholders such as government, research, operators and public work together. The goal of this study was to investigate if current water quality changes can be related to climatic change. As the changes were expected to be small, high quality data over several years was required. Furthermore, the aim was to investigate whether seasonality could be identified in the water quality data, e.g. between wet or dry seasons.

This paper investigates water quality data from the Layong water treatment plant in Brunei Darussalam together with daily rainfall data over a three-year period (2014-2016, BMD 2017). In 2018 samples were taken again to confirm trends. A previous study compiled all available Brunei water quality data and put it into a Microsoft Access Database (Yusri et al. 2018). Time series data mining of large data sets has become increasingly important in water quality research (Deng and Wang, 2017, Yang and Moyer, 2020). An Auto-Regressive Integrated Moving Average (ARIMA) model (Shahwan and Odening, 2007; Ömer Faruk, 2010; Tizro, et al., 2014) can be applied for time series analysis for forecasting purposes. However, for our study, forecasting based on time series data was not the aim.

Changes in water quality for a selected number of available water quality parameters (aluminium, chloride, pH, turbidity and colour) are investigated in detail and their changes are put into the context of climate change. These parameters have been routinely monitored at the raw water intake of the Layong treatment plant which takes water from the Tutong River for drinking water purposes (Figure 1).

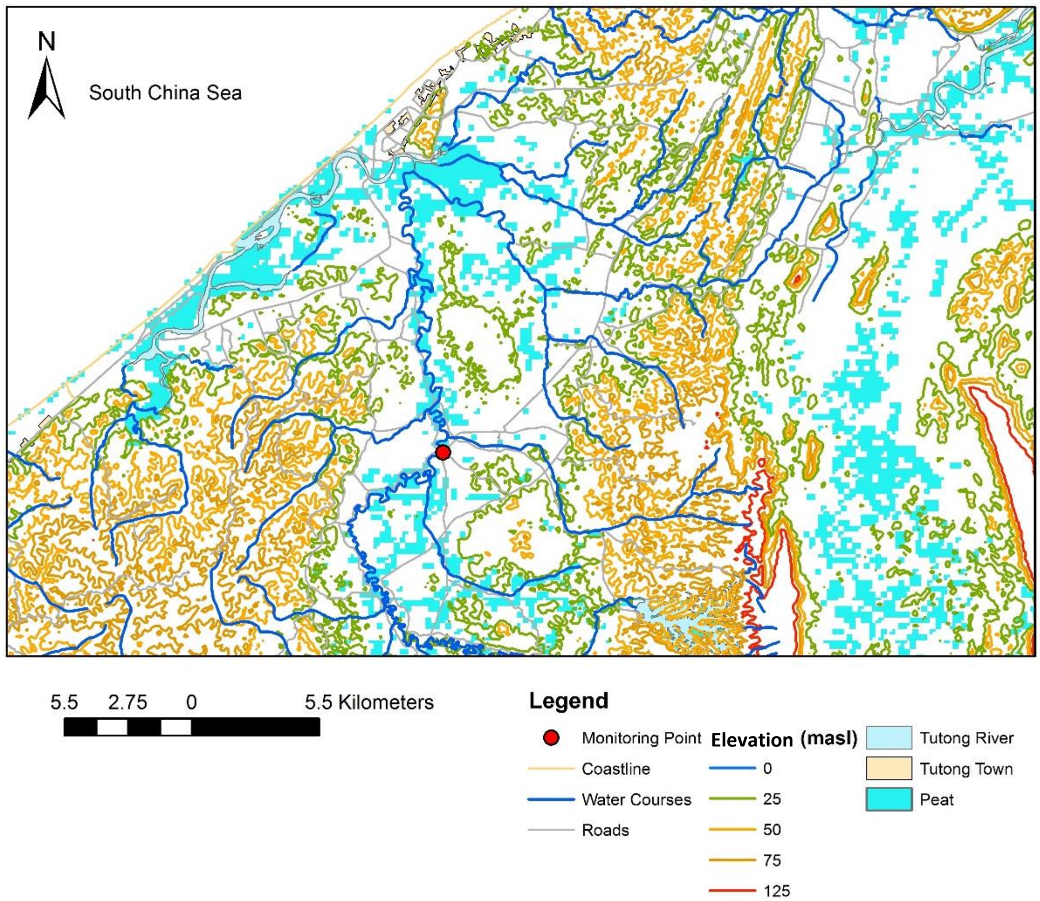

Figure 1: Location of monitoring site at Layong, Brunei Darussalam with distribution of peat after Gumbricht et al. 2017

The treatment plant is located away from any urban centres (around 6 km upstream (south) of the town of Tutong) and agricultural areas and influence from industrial or agricultural activities during this time period are thus regarded minimal. The abstraction history of the treatment plant which is a major source of drinking water supply for Brunei is shown in Figure 2. It can be seen that abstraction has been increasing in 2016. Brunei's population growth is around 1.6 % per year.

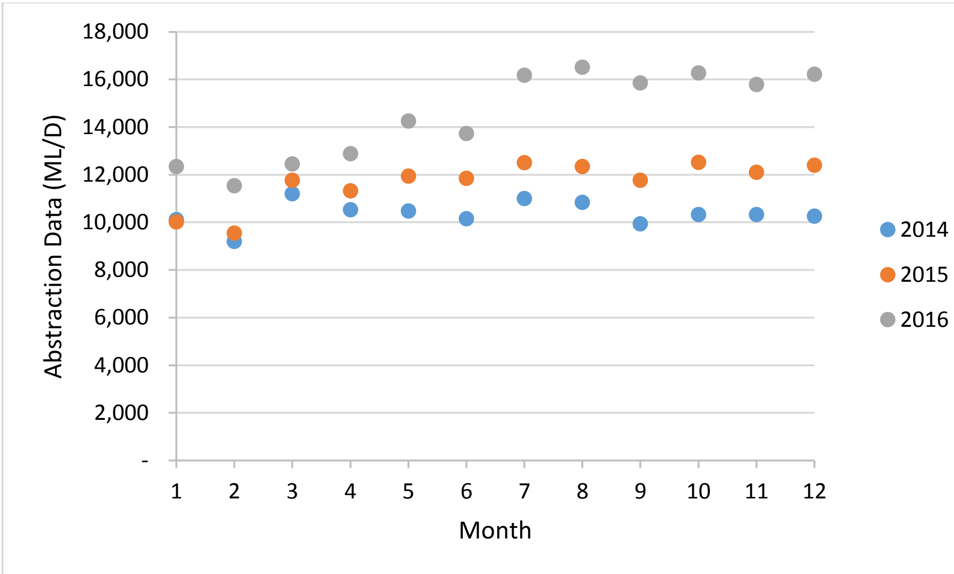

Figure 2: Abstraction data of river Tutong for the years 2014 to 2016 at the Layong water treatment plant

However recently Brunei experienced water quality concerns with the tap water showing slight discolouration, possibly indicating an increased content of particulate matter in the water. This has boosted local demand for household water filters as well as the bottled water industry.

Changes of water quality due to climate change have been mostly investigated through isolated studies, e.g. of rivers or lakes in high-income countries, often with a small number of variables. In addition, even though some studies extend over as many as 80 years, most of them are short term (Gejl et al., 2019). With regards to lakes and reservoirs, the most frequently reported change in water quality is more intense eutrophication as well as algal blooms at higher temperatures, or shorter hydraulic retention times and higher nutrient loads resulting from increased storm runoff (Cisneros et al., 2014). Increased runoff can result in greater loads of salts, faecal coliforms, pathogens, and heavy metals (Pednekar et al., 2005; Paerl et al., 2006; Tibby and Tiller, 2007; Boxall et al., 2009). In some cases there are associated impacts on health. For instance hospital admissions for gastrointestinal illness in elderly people increased by 10% when turbidity increased in the raw water of a drinking water plant even when treated using conventional procedures (Schwartz et al., 2000). While some studies indicate that turbidity cannot be used to calculate Total Dissolved Solids (TDS), recent studies showed a clear and strong linear correlation between TDS and turbidity in river water (Low et al. 2011, Metcalf and Eddy 2014). Greater runoff, instead of diluting pollution, swept more pollutants from the soil into watercourses (Boxall et al., 2009; Loos et al., 2009; Benítez-Gilabert et al., 2010; Gascuel-Odoux et al., 2010; Howden et al., 2010; Saarinen et al., 2010; Tetzlaff et al., 2010; Macleod et al., 2012). For rivers, all reported impacts on water quality due to climate change were detrimental.

Materials and Methods

Daily rainfall from Benutan dam 10 km southeast of Layong including 1 h rainfall intensity data (2014-2016) was obtained from the Department of Water Services as well as the Brunei Meteorological Department (BMD). Water quality data of pH, colour, turbidity, aluminium ir chloride from the Tutong river for the same three year time period were measured twice daily (8 am and 2 pm) using the following methods: pH was measured according to APHA 4500H (APHA 1992) using a membrane electrode. Colour was measured according to APHA 2120 B using a Lovibond Nessleriser. Turbidity was measured according to APHA 2130 B using the Nephelometric method (Hach 2100N). Aluminium was measured using a spectrophotometric method with a Palintest 7100 photometer. Chloride was measured using argentometric method via titration applying a silver nitrate solution. Selected samples were shipped to Switzerland for trace element analysis at the Eawag laboratories. The samples were acidified with HNO_3 to dissolve precipitates and then diluted 1:20 to a final HNO_3 concentrations of 0.7% HNO_3 for ICP-MS measurements. In addition selected peat groundwater samples collected in 4 ml sample vials were taken in February 2018 using a PVC bailer from a pre-installed slotted liner with a screen interval of 20 cm augered at a depth of around 1 m.

To analyse the three-year time series data as well as identify meaningful trends or relationships between the parameters, the following steps were undertaken using the IBM Statistical Package for Social Sciences (SPSS) Software Version 21 (IBM 2012).

The 8am and 2pm data was averaged to get a daily average of the time series. As daily values fluctuate drastically, calculations were made based on the average of daily values of every two weeks to smoothen out the data. We refer to this as the bimonthly data. Using different statistical process control charts and other charts for analysis, we identified any significantly high or low measurements.

Firstly, boxplots of raw and bimonthly data for the three years were created. This is to study the median and interquartile ranges of the different parameters, and to identify any anomalies in the data.

The XBAR and R charts are control charts generally used to determine whether a system is predictable and stable. The XBAR chart plots each measurement as a subgroup of a specific number of points over a one-year period to detect changes, in this case, detecting possible changes happening at the same time over the different years. Each subgroup in this study contains the three-year average of the average of two weeks' worth of daily observations. Using the XBAR chart, we study the general trends of the various water quality parameters over a one-year cycle. Time-ordered data is usually considered a good basis for forming subgroups due to detectable causes that can occur over time (Montgomery, 2009). The opportunity for differences between subgroups will be maximised if such causes are present.

The R chart shows how the range of average values changes over a one-year cycle with each point representing the range value. This allows us to identify the time periods where changes are high across the three years. We also examine the upper and lower control limit to study the stability of the data and to identify if there are causes of variation affecting the mean. The general mean value is indicated by the centre line.

The values for the XBAR chart are calculated based on m samples, each with n observations on a particular characteristic. Usually, n is small, e.g. 4, 5, or 6. Let $\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_m$ be the average of each sample, where each sample is constructed from rational subgroups. Then $\bar{\bar{x}}$ would be used as the center line on the chart. In this study, m is three, for the three years and n is 24 where each subgroup contains two weeks of daily data.

$$\bar{\bar{x}} = \frac{\bar{x}_1 + \bar{x}_2 + \cdots + \bar{x}_m}{m} \qquad (1)$$

To calculate the control limits, the range method is used. If $x_1, x_2, \ldots, x_n$ is a sample of size n, then the range of the sample is the difference between the largest and smallest observations; that is, $R = x_{max} - x_{min}$. Let $R_1, R_2, \ldots, R_m$ be the ranges of the m samples. The average range is

$$\bar{R} = \frac{R_1 + R_2 + \cdots + R_m}{m} \qquad (2)$$

The control limits (CL) of the XBAR chart are as follows with the constant A_2 specified according to various sample sizes (Montgomery, 2009).

$$CL = \bar{\bar{x}} \tag{3}$$

$$UCL = \bar{\bar{x}} + A_2\bar{R} \tag{4}$$

$$LCL = \bar{\bar{x}} - A_2\bar{R} \tag{5}$$

with UCL as the upper control limit and LCL as the lower control limit.

The control limits for the R Chart are as follows:

$$CL = \bar{R} \tag{6}$$

$$UCL = D_4\bar{R} \tag{7}$$

$$LCL = D_3\bar{R} \tag{8}$$

The constants D_3 and D_4 are chosen based on various values of n in Appendix Table VI of Montgomery (2009). Process variability may be examined by plotting sample range R values on a control chart.

In order to identify trends, stacked area charts are drawn to visually study how much differences there are between the three years through the difference in height of two graphs at each vertical section. We can also study the trends in the stacked area charts of more than one parameter.

For our time series analysis, we used autocorrelation function plots (ACF) and partial correlation function plots (PACF) in order to identify whether there are serial dependencies or seasonal patterns within each time series.

An ACF plot is used to determine the correlation between a time series with its past values up to and including the lag unit and not used to determine correlation between two different variables. It tells us how a time series is correlated with itself at different lags. In an ACF plot, the x-axis represents the number of lags while the y-axis determining the correlation coefficient.

A PACF plot shows the amount of autocorrelation at lag k that is not explained by lower order autocorrelations. Thus a PACF graph shows the resulting correlation at lag k of the residuals which remains after removing the effects of any correlation already explained by the earlier lags. To determine whether parent autocorrelations are zero after lag q, the Bartlett's approximation is used which is provided by SPSS. Pearson's correlation function was used to study the correlations between the different water quality and climate parameters. In addition, cross-correlation function was applied to find correlations between any two stationary time series x and y, described below as in (Derrick and Thomas, 2004). In Lehmann and Rode (2001), cross-correlation is applied to detect any relationship between the time series of different water quality parameters. In this study, we apply cross-correlations to detect relationships between time series of water quality and climate parameters (rainfall). One way to calculate cross-correlation is as follows:

$$\rho_{xy}(l) = \frac{\sum_{i=0}^{N-1}(x_i-\bar{x})*(y_{i-l}-\bar{y})}{\sqrt{\sum_{i=0}^{N-1}(x_i-\bar{x})^2}\sqrt{\sum_{i=0}^{N-1}(y_{i-l}-\bar{y})^2}} \quad (9)$$

Where l denotes lag, x_i and y_i are data points at time point i from time series x and y respectively.

Results and Discussion

The results from the descriptive statistics are presented in Figure 3. pH values range from below 4 to well over 6 with a median of around 5. The colour according to Hazen (1892), which is generally a useful indicator of the amount of humic substances present in the water (Hongve and Akesson 1996) show an median value of around 400. Turbidity values show a particular large range with values ranging from just above 0 to 150 N.T.U units. Aluminium values range from around 0 to around 0.15. Chloride values are generally below 8.5 mg/l with a median of slightly above 7.5 mg/l. Rainfall has a median of around 8 mm per event, with minimum and maximum values of 0 to greater than 20 mm per event.

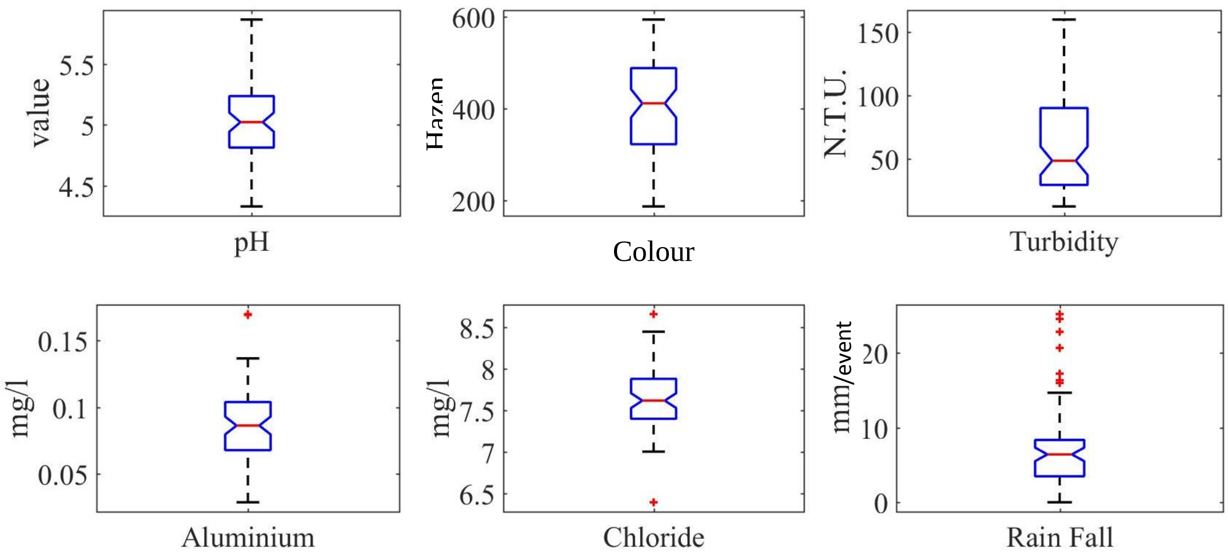

Figure 3: Boxplots of analysed parameters for the three year time period (2014 to 2016)

The results from the XBAR and R – charts (Supplementary Figures 1 and 2), showed that the values are varying across the average range and mostly fall within the confidence limits. The aluminium values in particular showed higher values at the end of each year possibly indicating the influence of increased rainfall and deposition during the wet season. It is assumed that aluminium is mobilised from sediments, e.g. aluminium silicates. Aluminium becomes more soluble at lower pH. Thus a lowering of pH values mobilises aluminium which can then be transported into rivers during rainfall events.

The X-Bar and R control charts also indicated a slightly rising trend for turbidity with higher values towards the end of the year again likely due to increased rainfall which showed an increasing trend towards the end of the year.

While the amount of rainfall dropped significantly between 2016 and 2014 with 2829 mm in 2014 and 2158 mm in 2016 the rainfall intensities clearly increased year by year. Analysis of the 1 hour rainfall intensities showed that the 1 h maximum rainfall intensities for these years increased from 56.8 mm to around 67 mm in 2016 (Table 1). It can be seen from Table 1 that rainfall intensities showed a continuous increase in line with climate change predictions (e.g. Hasan et al. 2016).

Table 1: Recorded maximum 1 hour rainfall intensities for the years 2014 to 2016

Year	**Observed maximum 1 hour rainfall intensities (mm)**
2014	56.8
2015	61.6
2016	66.7

The stacked area charts clearly show a rising trend in aluminium concentrations in the water which is obvious in the wet season in particular (October to January). It is attributed to the higher rainfall in particular high rainfall intensity events during this time period (Figure 4-8).

The rise in aluminium however is attributed to the overall drop in rainfall and increasing rainfall intensities over the years, which leads to acidification due to the presence and exposure of acid sulphate soils in Brunei (Grealish and Fitzpatrick 2013, Marshall et al. 2019). Rivers and unconfined aquifers are vulnerable to acidification e.g. as discharge of sulphuric acid into river systems and increased aluminium loading (Osaki and Tsuji 2015, de Meyer et al. 2017). This increased acidity can yield higher metal leaching which can be carried into rivers and streams in particular during high intensity rainfall events. In order to investigate the influence of river water abstraction (Figure 2) on aluminium concentration in the raw water a correlation between aluminium and river water abstraction was performed on the monthly abstraction and monthly average aluminium concentrations. A correlation coefficient of 0.72 was obtained which indicated that higher abstraction is correlated with higher aluminium concentrations.

In 2018 another sampling campaign was started in order to confirm the rising trend. It becomes obvious that the rising trend in aluminium concentrations has continued (Figure 4). In addition analysis of trace metals were conducted in order to investigate if other metals were also displaying elevated concentrations compared to drinking water guidelines. (Table 2).

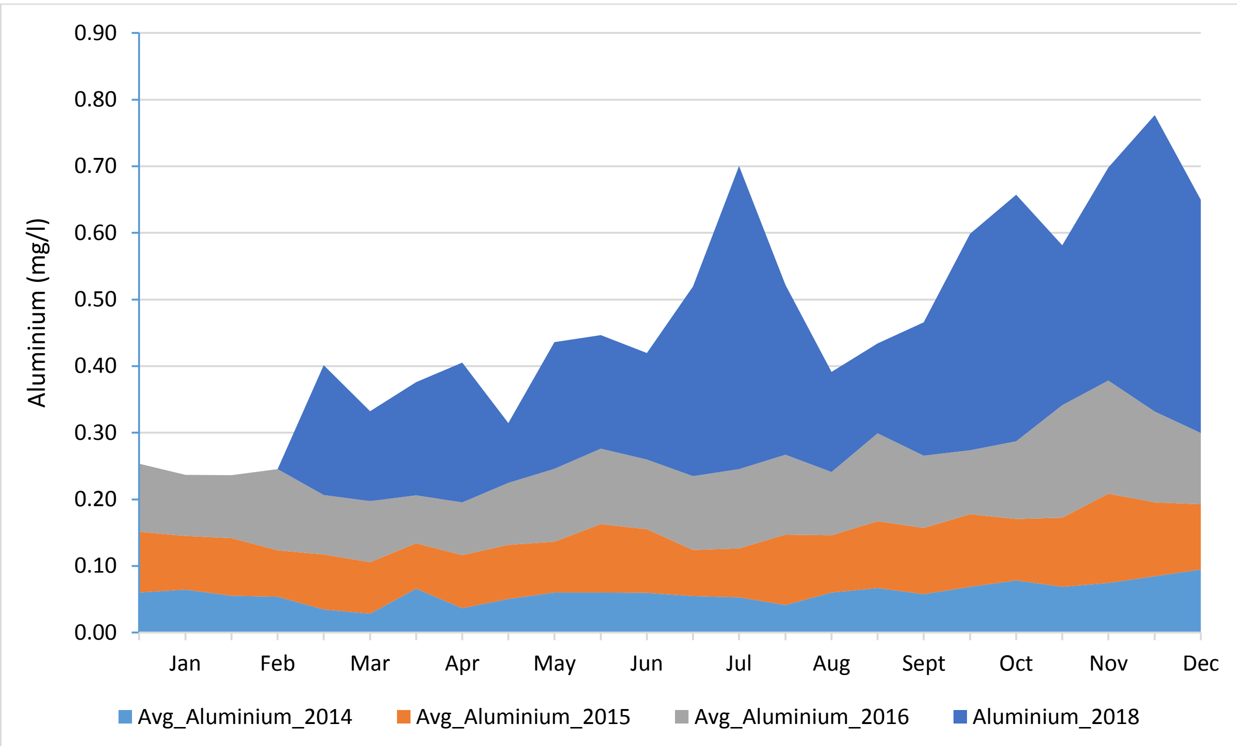

Figure 4: Stacked area graph for aluminium for the years 2014 to 2016 and 2018

Aluminium can be toxic to aquatic life and is a gill toxicant to adult fish, causing both ionoregulatory and respiratory effects (Gensemer and Playle, 1999). The chronic value, intended to protect against significant toxicity in long-term exposures, is 87μg · L–1 Al. The toxicity of aluminium is reduced with humic substances as the aluminium can form complexes with humic substances (Gensemer and Playle, 1999).

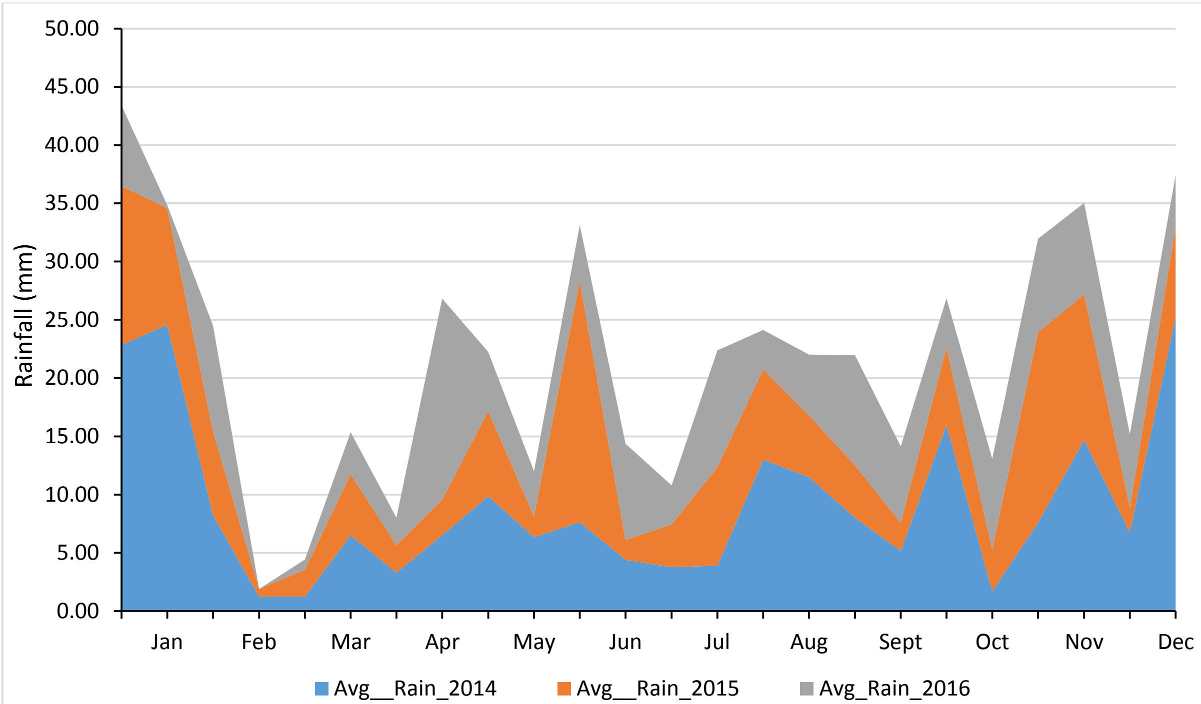

Figure 5: Stacked area chart for rainfall for the years 2014 to 2016

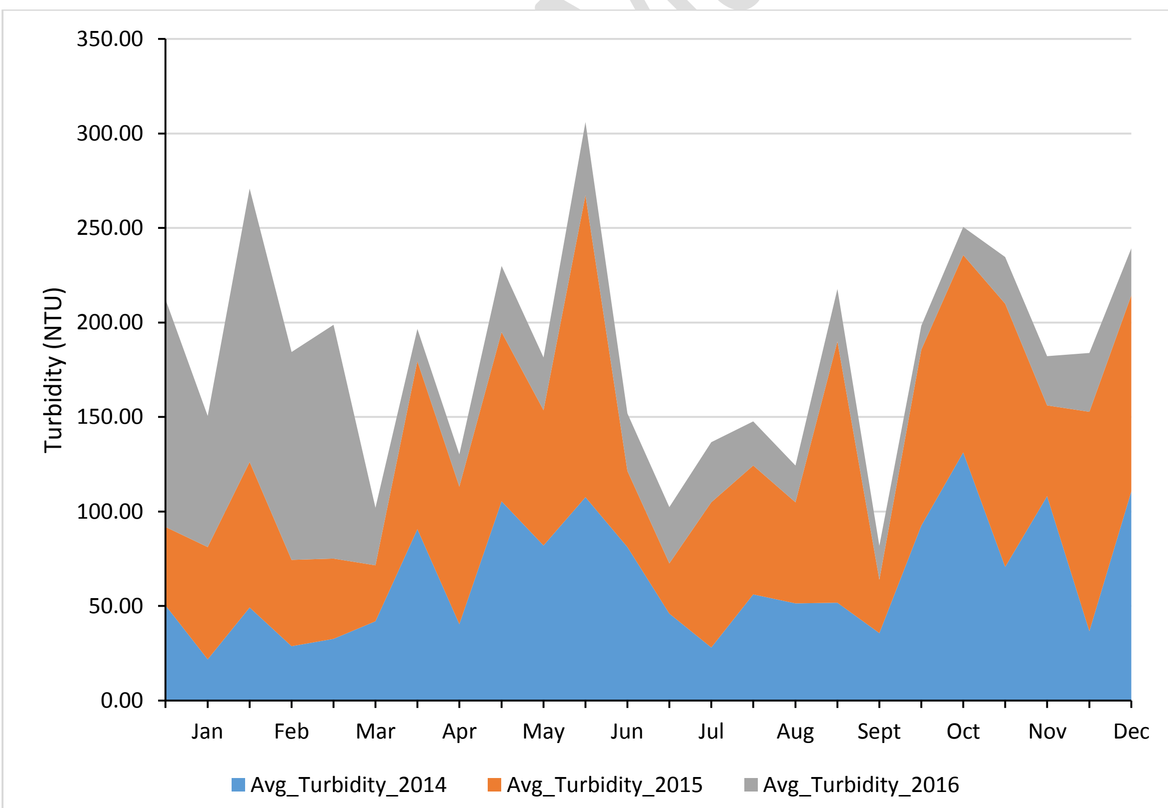

Figure 6: Stacked area chart for turbidity for the years 2014 to 2016

It can be seen that turbidity values were highly variable following a similar pattern of peaks and troughs as can be seen from the rainfall stacked area graph.

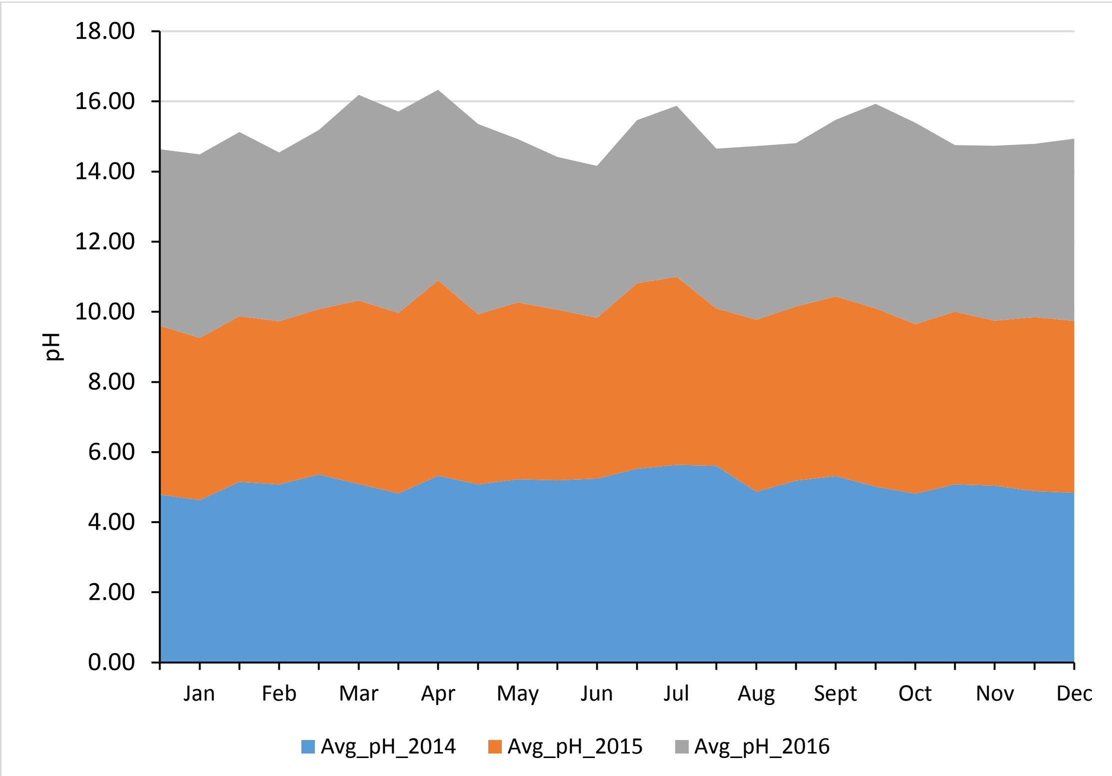

Figure 7: Stacked area chart for pH for the years 2014 to 2016

pH concentrations showed some variations with some very low pH values during the period from May to August with single values below 4. These low pH values are typical for acid sulphate soils which occur in Brunei (Grealish and Fitzpatrick, 2013; Proum et al., 2018, Azhar et al., 2019; Marshall et al. 2019). Sulphidic minerals such as pyrite present in these soils when exposed to the air will cause an oxidation reaction in which 1 mol of pyrite contributes to 4 mol of acidity as shown in equation 10:

$$2\,FeS_2 + 7\,O_2 + 2\,H_2O \rightarrow 2\,Fe^{2+} + 4\,SO_4^{2-} + 4\,H^+ \qquad (10)$$

Sulphuric acids from these soils are usually produced either when the soil is drained or when the exposed sulphides in soil react with oxygen.

It can also be seen that the variability of pH values increased with time.

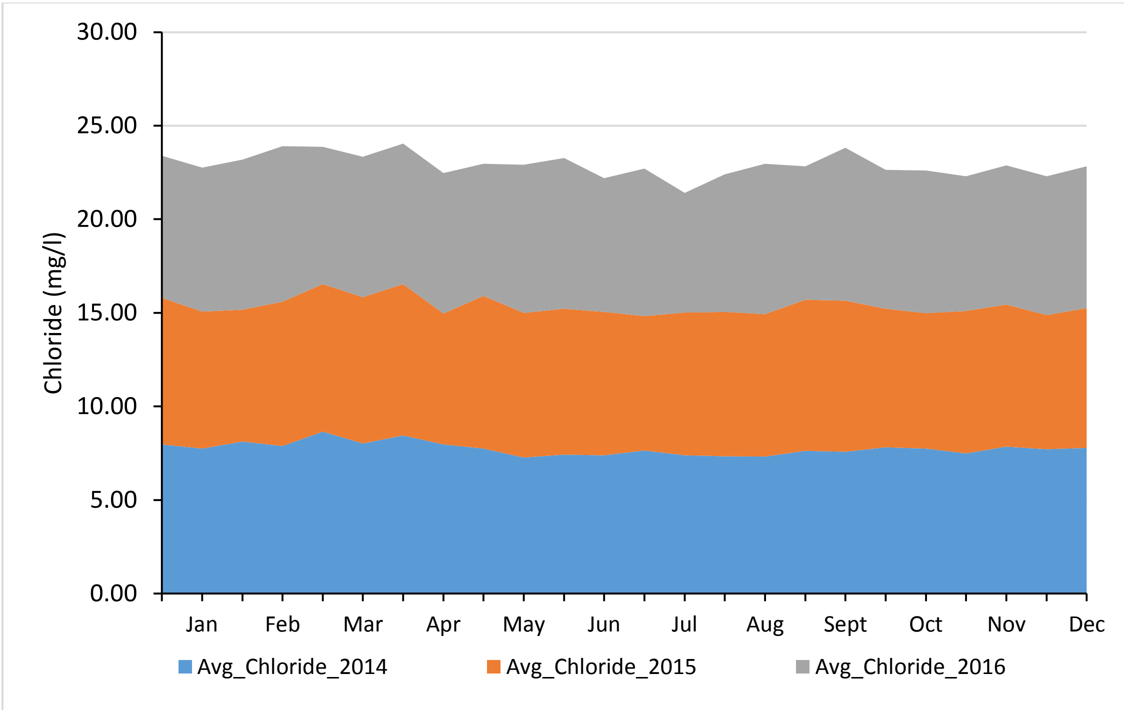

Figure 8: Stacked area chart for chloride for the years 2014 to 2016

Table 2: Concentrations of trace metals from river water as well as peat groundwater analysed with ICP-MS

Parameter	Unit	Layong 2018	Layong 2019	Peat-GW 2019
Al	mg/l	N/A	0.38	2.93
Li	µg/l	4.12	1.88	0.08
B	µg/l	814.6	16.5	22
P	mg/l	0.01	0	0.84
V	µg/l	0.68	0.62	4.65
Cr	µg/l	5.64	0.08	0.38
Fe	mg/l	0.56	2.95	8.81
Cu	µg/l	77.44	9.3	6
Zn	µg/l	27.42	42	127
As	µg/L	2.56	1.03	0.49
Se	µg/L	0.39	0.2	N/D
Br	mg/L	0.04	0.003	0.023
Sr	µg/L	34.38	4.6	100.1
Mo	µg/L	0.77	0	N/D
Cd	µg/L	0.03	0.01	1.03
Pb	µg/L	1.31	1	14.6
U	µg/L	0.2	0	N/D

The results showed that none of the analysed trace elements exceeded drinking water standards. The elevated concentration of boron in 2018, which is still below guideline values, could be related to the proximity of the coastal region of the South China Sea. None of the trace metals exceeds guideline value. It becomes obvious that higher aluminium concentrations are found in the nearby peat groundwater, which indicates that draining of peatland combined with the exposure of acid sulphate soils can lead to elevated concentrations of aluminium in the river water.

Figure 9 to 11 show the ACF and PACF plots of water quality and climate parameters. No seasonality within any year is found except for rainfall. For pH, there are significant spikes at lags 1, 8, 9 and 28 in ACF. However, from the PACF figure we can see that pH tapers non-seasonally, following lag 1. For colour, there is a linear relationship with past values at low-order lags in the

ACF. This is usually found in strongly trended series. But, PACF has no correlation of residuals after lag 1.

For turbidity, there appears to be some autocorrelation at low-order lags, but ACF exponentially decreases to zero (Figure 10). PACF coefficients taper non-seasonally after lag 2. Similar observation as for colour was found for aluminium where a high positive autocorrelation value at low-order lag values from lag 1 to 13 exists but PACF coefficients fluctuate non-seasonally. No significant correlation was found in ACF and PACF, meaning no significant linear relationship with past values, nor correlation between residual and values are found respectively. For rainfall, there are seasonal fluctuations in ACF, in the PACF significant coefficients appear at lower order lags indicating seasonality (Figure 11).

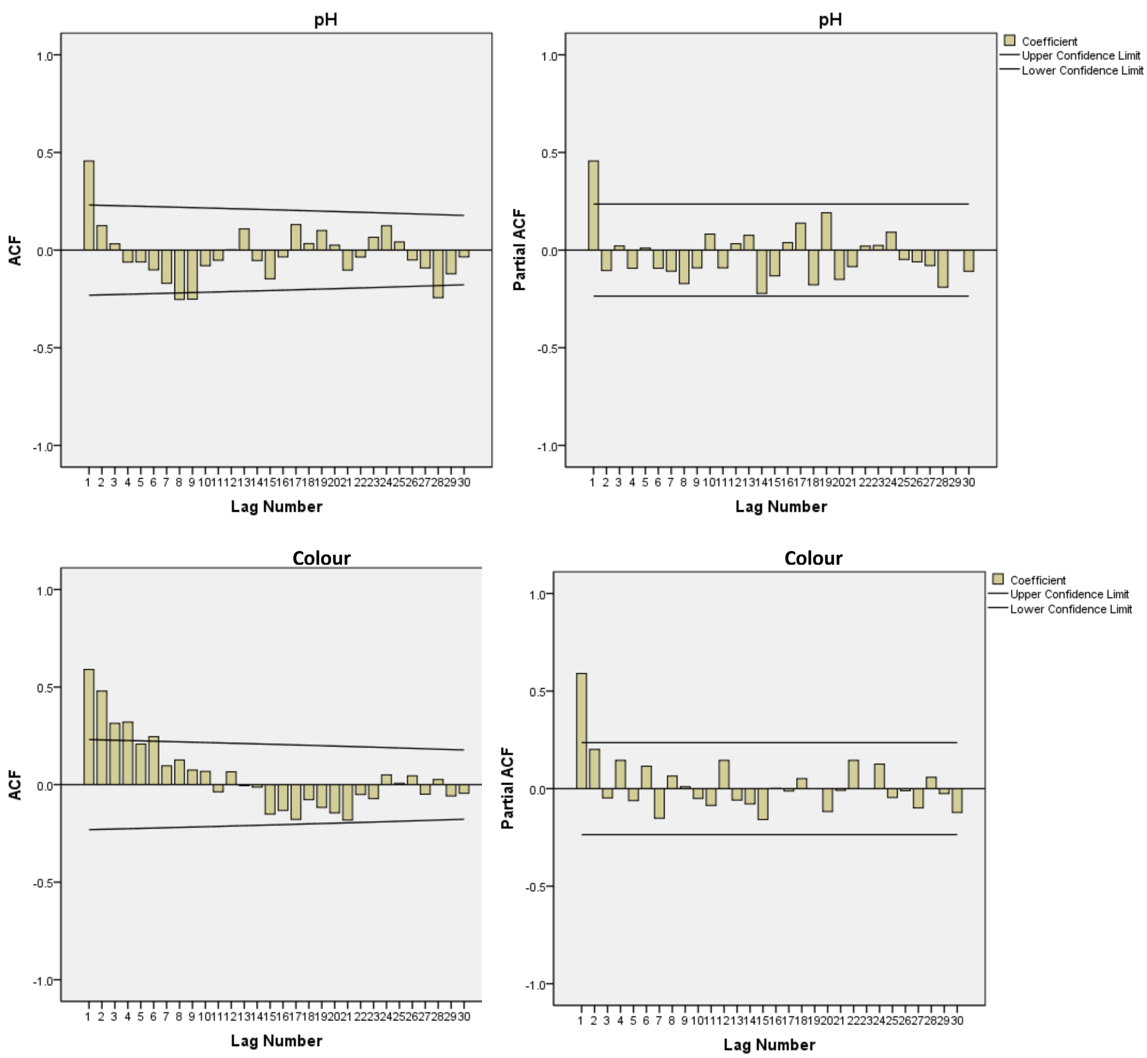

Figure 9: ACF and PACF plots for water quality parameters (pH and colour)

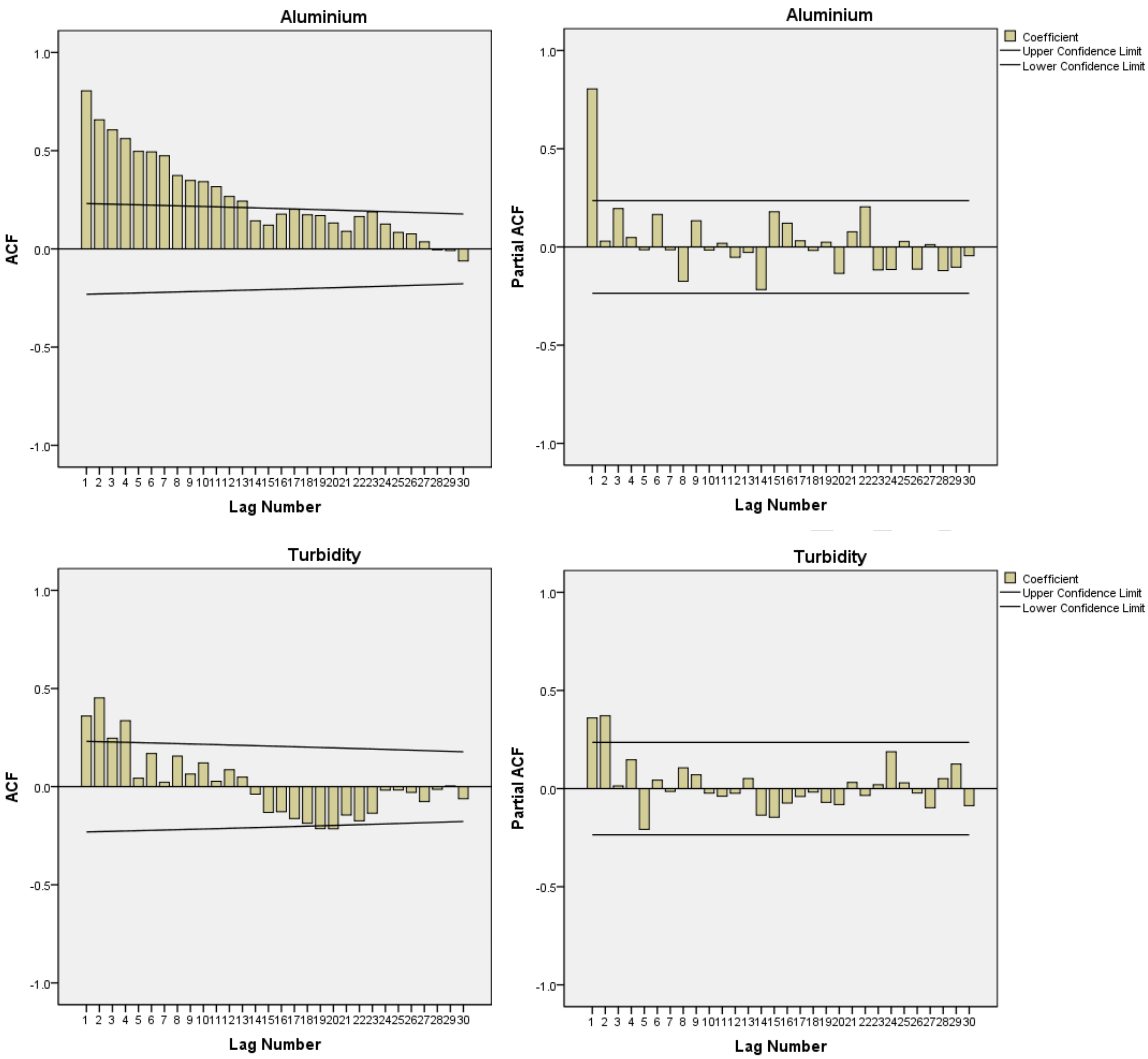

Figure 10: ACF and PACF plots for water quality (turbidity and aluminium) parameters

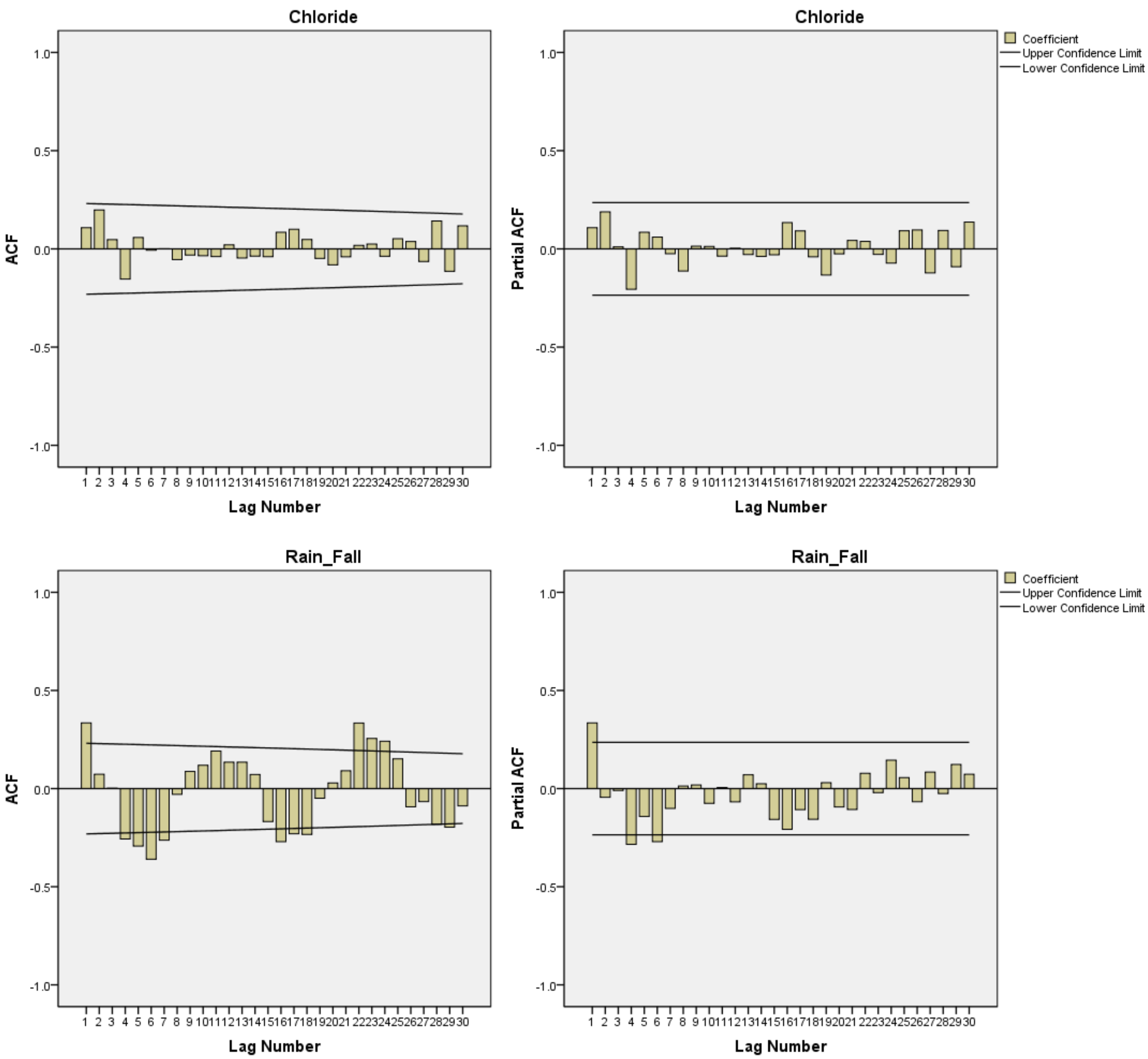

Figure 11: ACF and PACF plots for water quality (chloride) and climate (rainfall) parameters

The Pearson correlation coefficients between the parameters are shown in the below table (Table 3). It becomes obvious from Table 3 that the highest negative correlation coefficient is obtained for the parameters aluminium and pH (Figure 12). This shows that lower pH values can trigger increased aluminium concentrations in water. As pH decreases, inorganic and organic aluminium complexes tend to dissociate to offset the drop in pH which in turn increases the mobilization of inorganic monomeric aluminium. It has been recognised that increased aluminium solubility can increase with soil depth in particular when pH values are less than around 4.5 (Li and Johnson, 2016).

Table 3: Pearson correlation coefficients for the different parameters of bimonthly data for the years 2014 to 2016

	pH	**Colour**	**Turbidity**	**Aluminium**	**Chloride**	**Rain Fall**
pH	1	-0.212	-0.128	-0.353	-0.091	-0.169
Colour	-0.212	1	0.829	-0.134	-0.008	0.183
Turbidity	-0.128	0.829	1	-0.079	0.097	0.149
Aluminium	-0.353	-0.134	-0.079	1	-0.256	-0.041
Chloride	-0.091	-0.008	0.097	-0.256	1	-0.047
Rain Fall	-0.169	0.183	0.149	-0.041	-0.047	1

While the correlations with rainfall were low to moderate, the correlation of turbidity with colour was particularly strong (Figure 13), which would allow to make predictions using one of the parameters and estimating the other parameter with confidence and thus possibly saving analysis costs as both parameters are currently measured separately.

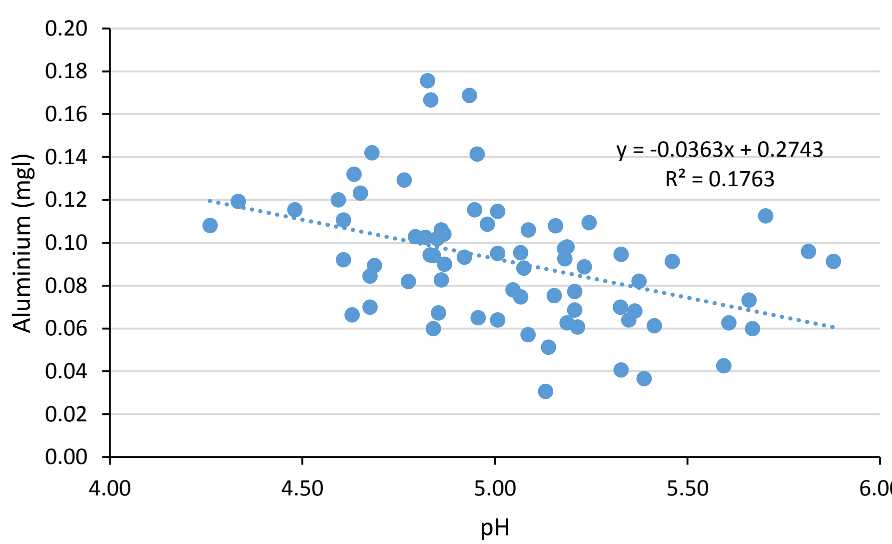

Figure 12: Aluminium against pH with linear regression trend line

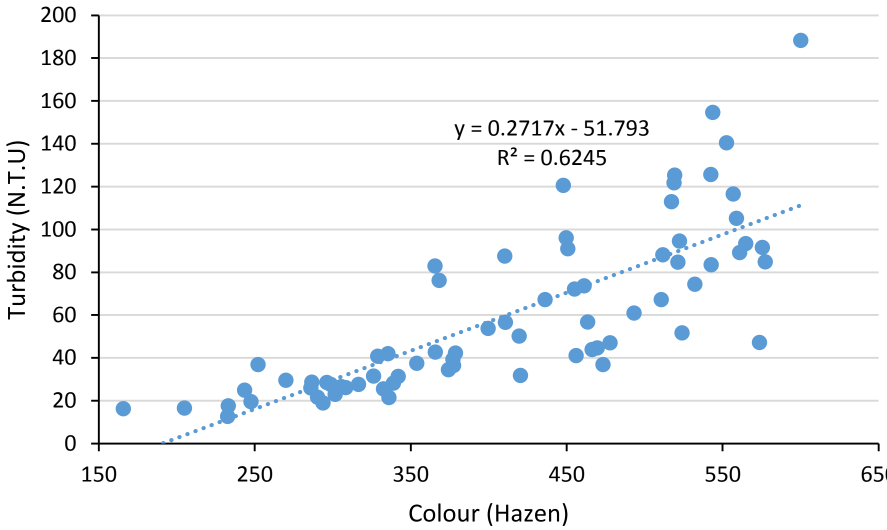

Figure 13: Turbidity against colour with linear regression trend line

In order to investigate if significantly more aluminium is found in the surface water at low pH, a two sample t-test for statistical significance was performed showing that at an alpha of 0.05 the aluminium values in water samples are statistically different at pH of 4.5 and below compared to the aluminium in water samples for pH values of 4.5 and above. Furthermore, the results showed that 53 % of all pH values lower than 4.5 were associated with the 4-month time period from May to August. Previous research (Cobb et al., 2017) showed that in particular during this time period groundwater levels in peatlands are at or near their lowest yearly groundwater level (Figure 14). The water levels were observed along several transects with water levels for each transect being very similar. pH values of tropical peatlands which are assumed to be generally fairly stable throughout the peatland have been reported to be in the range of 3 to 4 pH units (Könönen et al., 2015; Könönen et al., 2018). It is possible that the observed low pH values are from a mix of blackwater as well as whitewater sources.

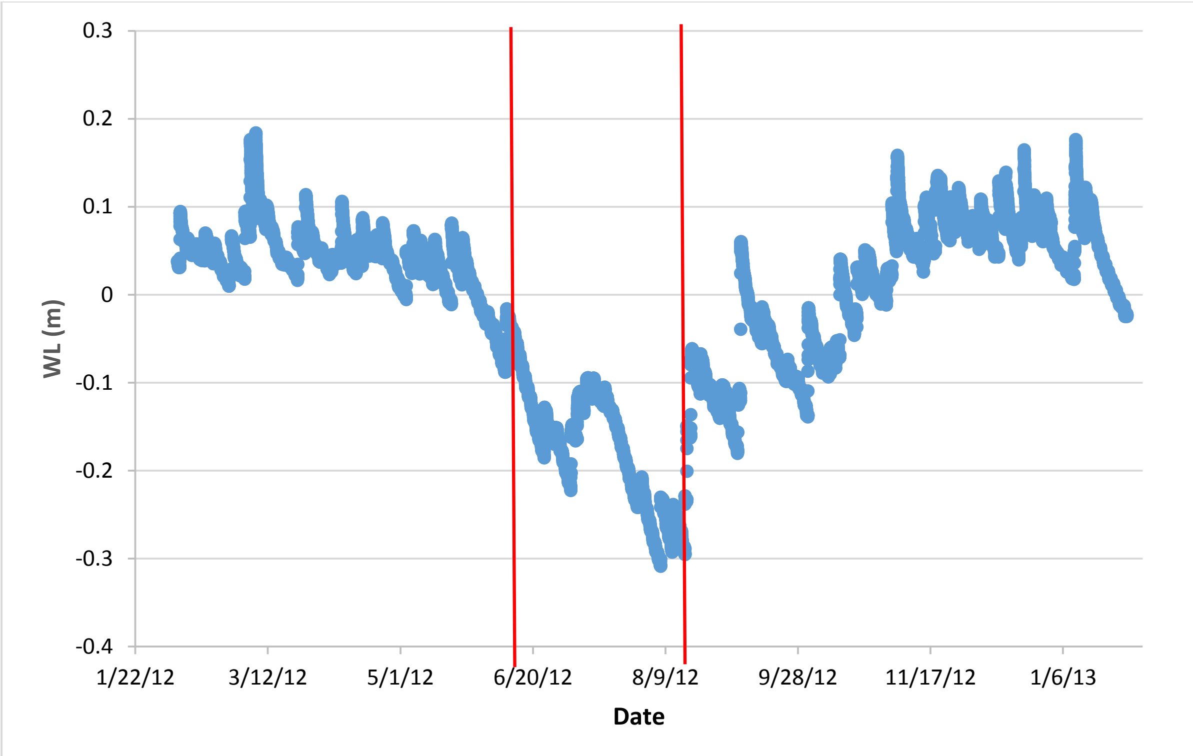

Figure 14: Waterlevels of a tropical peatland in Mendaram, Brunei Darussalam, with period of low waterlevels (red lines) observed between May and August (Cobb and Harvey 2019a, Cobb and Harvey 2019b)

In this respect the cross-correlation function (CCF) between rainfall and pH is of interest, indicating a significant correlation between pH and rainfall at a lag, indicating that pH values were low before the onset of rainfall (Figure 15). This indicates that lower pH values are likely occurring during dry spells due to the possible exposure of acid sulphate soils as well as the lowering of water levels in peat lands. After the onset of rain pH values are increasing. Thus the investigations indicate the vulnerability of these tropical peatlands and ecosystems to climate change. The CCF between aluminium and pH shows the significant correlation at lag 0, showing that low pH values lead to increased aluminium values in the river water (Figure 16).

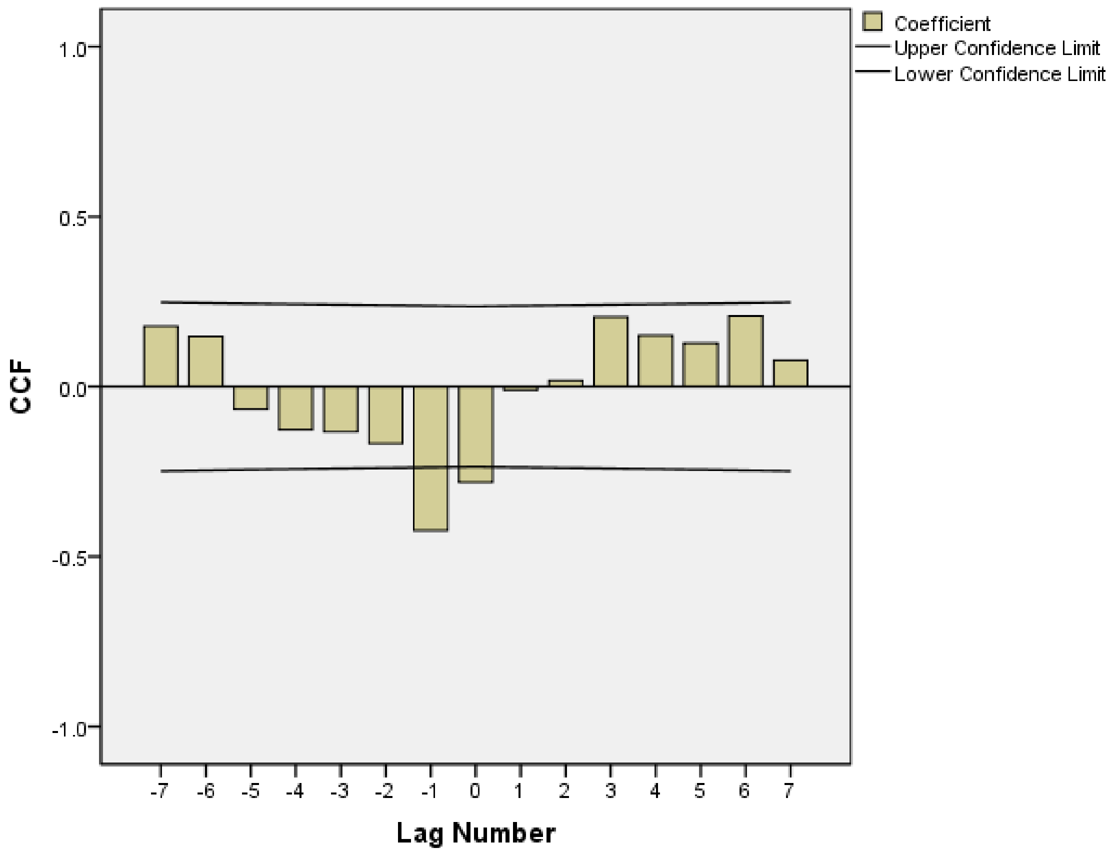

Figure 15: Cross-Correlation function between pH and rainfall showing significant correlations at a lag of -1 and 0

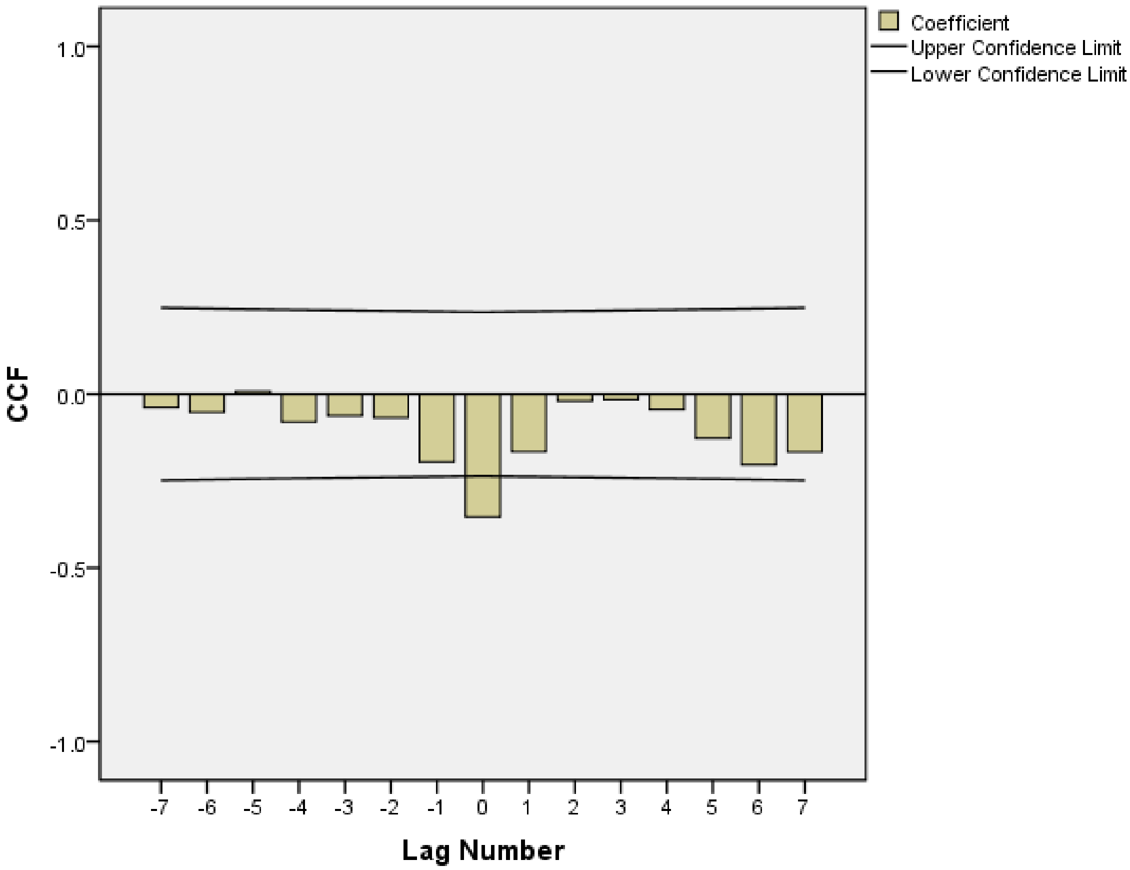

Figure 16: Cross-correlation function between pH and aluminium showing significant correlations at a lag of 0

Conclusion

The goal of the study was to show if possible changes in climate based on rainfall data can be linked to observed changes in river water quality data of the Tutong River. The river water from this location is of key importance as a source of drinking water in Brunei Darussalam.

The study analysed high frequency data (twice daily) from the river Tutong for selected water quality data over a three-year period. Starting from boxplots, XBAR and R-Charts, Pearson correlation coefficients were calculated. In addition, auto-correlation and partial auto-correlation functions were used to identify whether there are serial dependencies or seasonal patterns within each time series. The results show that a statistically significant rise in aluminium concentrations occurred during the three-year time period. The aluminium concentrations are negatively correlated with pH giving rise to higher aluminium concentrations at lower pH values. The highest aluminium concentrations were observed for pH values lower than 4.5. Furthermore, the positive correlation between aluminium concentration and water abstraction suggest that water abstraction needs to consider the rise in aluminium concentrations. Thus, possibly water abstraction may need to be reduced to avoid further increases. The highest correlation was observed between turbidity and colour, with a Pearson correlation coefficient greater than 0.8. During the observed time period an overall drop in rainfall occurred but at the same time rainfall intensity increased, which can be considered as typical for a climate change scenario. The analysis suggests that changes in pH triggered by changes in rainfall intensities as well as groundwater levels are contributing to the rise in aluminium concentration in the river water. The results indicate that climate change can have a significant impact on water quality. Long-term sampling with more water quality parameters including groundwater level measurements are suggested to confirm these findings.

Declaration of competing interest

The authors declare no conflicts of interest.

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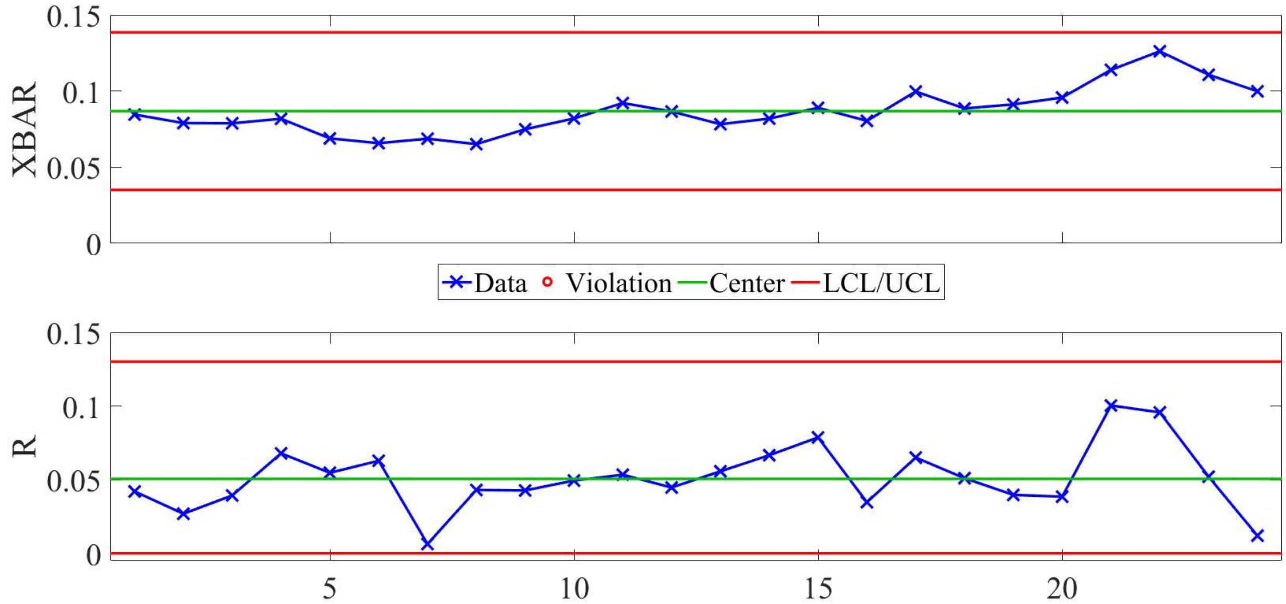
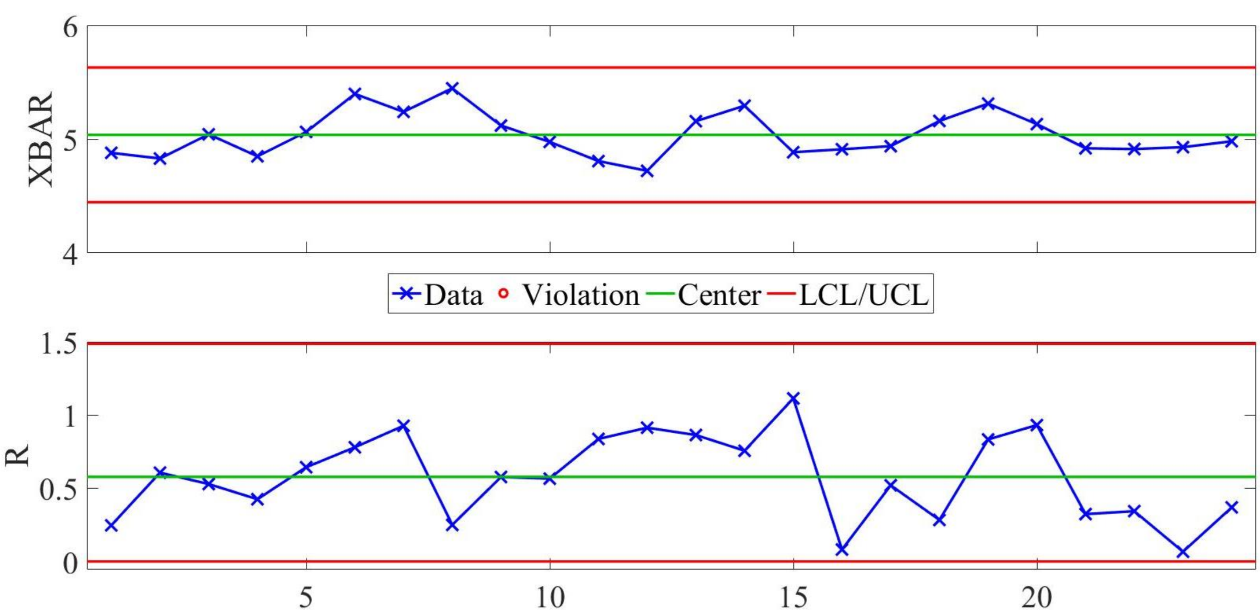
Supplementary Figures



Supplementary Figure 1: XBAR and R chart for aluminium



Supplementary Figure 2: XBAR and R chart for pH