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Investigation of Long-Term River Water Quality Trends in Hong Kong to Identify Role of Urbanization, Seasons and Pollution Sources

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Abstract This study investigated the long-term stream water quality trends of nine catchments in Hong Kong with different levels of urbanization using monthly water quality data for a 30-year period at annual and seasonal (wet and dry) scales. Raw data were modeled using redundancy analysis and Mann–Kendall test. Only one river showed a clear difference of water quality responses between the upstream and downstream monitoring stations. Nevertheless, in general, water quality of monitoring stations that had built areas less than 40% showed improving trends, whereas their downstream counterparts with built areas more than 70% showed deterioration trends for some parameters. Majority of water quality trends were season-independent. Out of the variables that were indicative of a long-term deterioration trend, total solids, total suspended solids, turbidity and electrical conductivity (all surrogates of sediment load of the river) were prominent. Nitrate concentration demonstrated an increasing trend for most streams, whereas phosphates a decreasing trend. This study concluded that the main source of pollution could be the surface runoff (nonpoint sources), not the wastewater inputs (point sources). Stream discharge was increasing and decreasing in the downstream and upstream stations, respectively. This could be attributed to the increase in imperviousness in the downstream and water extraction in the upstream. The downstream discharge increment with time would also support the fact that contamination was due to surface runoff. This study provides evidence that the Hong Kong legislative control actions on point source pollution work well, but not on nonpoint source pollution.

Keywords Long-term trends · Sediment · Urbanized and rural catchments · Water quality

1 Introduction

River health is an important aspect in ecosystem service. Nevertheless, with urbanization and economic development, rivers have been regulated for the flood conveyance. Therefore, in many urban areas, it is a common sight to see straight and/or hard-material-lined rivers (Pinto et al. 2013; Gomes et al. 2014). The urbanization results increase in the impervious area of the catchment. These two changes alone would significantly change the river hydrosystem. The increase in catchment imperviousness would negatively impact stream water quality, as runoff (i.e. nonpoint sources) brings high levels of nutrients and sediments (Angelidis et al. 1995; Walsh 2000). Also, increase in population in a catchment would result in some of its wastewaters to be discharged into streams via expedient connections (i.e. via point sources). Therefore, popular perception is urbanization

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results poor river water quality (Walsh et al. 2005; in sensu Cai et al. 2011; Glińska-Lewczuk et al. 2016), yet some see a rare chance of improved water quality (USGS 2020). These rare improvements could be due to two reasons. Firstly, the strict legislation imposed in urban areas, unlike in rural areas, may result in near elimination of untreated wastewater discharges. Secondly, in some urban areas due to restrictions on private vehicles and simultaneous increase in electric public transport, it has been seen in reduction of hydrocarbon deposits on the catchment (Parrish et al. 2011).

This study aimed at studying temporal variations of river water quality for a relatively long time scale (about 30 years). It should be noted, studies of temporal variation of stream water quality, often surrogated with stream flow rate and spans a few years, are not rare (Mouri et al. 2011), but identifying trends for a relatively longer duration (e.g. for a few decades) is not common (Tavakol et al. 2017). In this regard, Hong Kong provides a unique opportunity to investigate the variations in long-term water quality trends due to its comprehensive water quality monitoring program. It was started in 1986 covering almost all major streams and rivers (EPD 2018). There are many spatiotemporal water quality studies done in Hong Kong for relatively longer (more than 2 years) periods. As an example, Yung et al. (2001) studied water quality trends in Port Shelter water quality zone referring a 10-year data set. Xu et al. (2010) considered a 21-year data set; however, it only considered the Deep Bay area coastal waters. Zhou et al. (2007) analyzed the streams of the entire new territories, but only considered a 4-year period. The studies by Yung et al. (2001), Zhou et al. (2007) and Xu et al. (2010) are rather representatives of the common spatiotemporal extent of studies in Hong Kong, and it was conspicuous that the past studies in Hong Kong were done either for a relatively small area and/or for a shorter duration.

The streams and rivers in Hong Kong are relatively short, however, in many cases include more than two monitoring stations along its stream course, ultimately providing past data, not only in the urbanized part of the river but also in the rural and/or forested upstream. Urban or heavily built areas usually exist in the mid to downstream of the river, where the terrain is flat and close to the sea. This is particularly true for small sea front or island-type regions such as Hong Kong. Long-term trend of water quality in streams reveals information about chemical and biological changes and variations due to manmade and/or seasonal factors. Specific objectives were firstly to compare and contrast upstream and downstream water quality variations for their temporal trends. The second objective was to identify the underlying pollution sources and exploration of catchment land use in that regard.

2 Materials and Methods

2.1 Study Area

Hong Kong topography is rugged, comprising predominately volcanic rocks with granite intrusions, and the vegetation comprises a combination of broad-leaved secondary forests, shrub lands and mountain-topped grasslands (Gomes et al. 2014). It has contrasting wet and dry seasons, where more than 80% of the mean annual rainfall occurs during the hot, humid wet season between May and September (Gomes et al. 2014).

As per 2016 data, the total built-up (urban) areas was about 25% of the total land area, and over 50% was shrub land and woodland. Grassland accounts for 17%, and agriculture was about 5% (Lands Department, Hong Kong 2018). The urban areas of Hong Kong, which continues to be the densest in high-income world, host 50% of its total population and is located close to the coastal low-lying flat areas. This meant the downstream course of streams and rivers flow through urban areas, whereas the upstream course flow through the country side (rural areas). Hong Kong rural areas contain large extents of forests and grasslands. The geology of Hong Kong is dominated by granite and volcanic rocks, and in total accounts for about 75% of the area.

2.2 Methodology

This study is based on the statistical and time series analyses of monthly water quality observations (one observation per month) available from Environmental Protection Department (EPD), Hong Kong, for the period from 1986 to 2015. Water quality observations by EPD covers almost all rivers for a wide range of parameters. This study shows results of 16 monitoring stations of nine river networks (Fig. 1). All rivers had at least one upstream and one downstream monitoring station, except Tin Sum and Siu Lek Yuen nullahs. These two were selected due to low built area fraction (< 30%) and will be considered as reference catchments. The highest built area fraction of 80% was observed in downstream

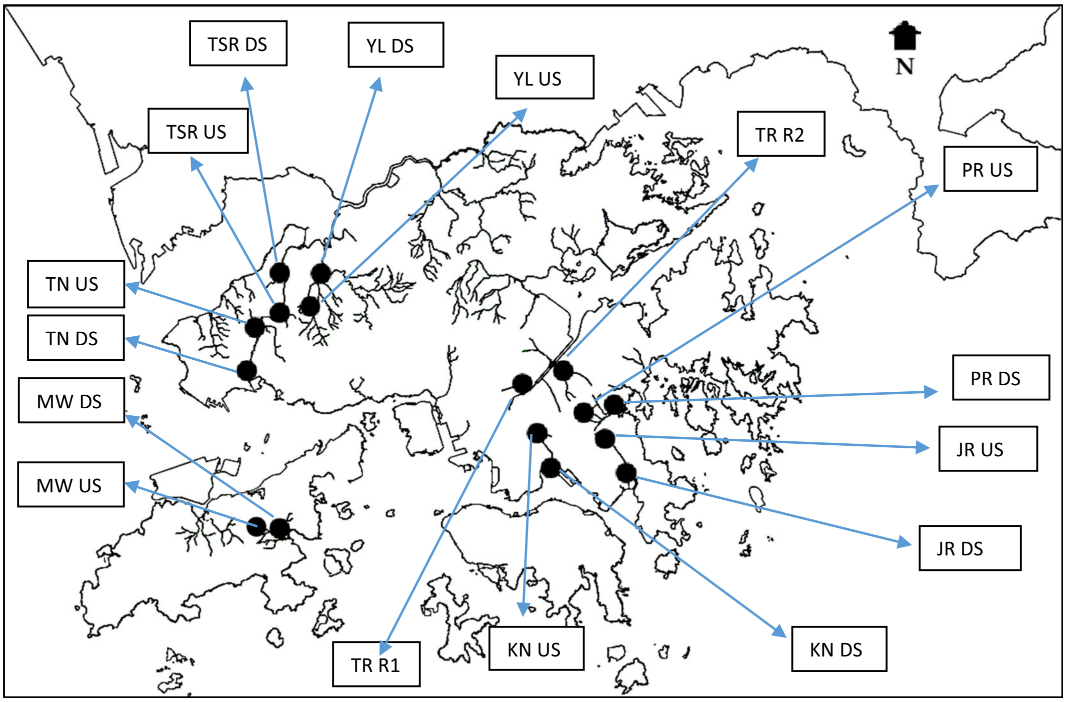

Fig. 1 Study streams and sampling locations. US (upstream), DS (downstream). Table 1 gives stream codes

monitoring station of Mui Wo River. Therefore, this study had considered monitoring stations corresponding to a wide range (20 to 80%) of built area fraction. Even though all 83 monitoring stations were considered in the preliminary analyses, it was decided to incorporate only 16 as it was evident that they reasonably reflect the status quo.

The water quality parameters considered in this study included stream discharge, nitrate-nitrogen, phosphate, total suspended solids (TSS), total solids (TS), turbidity and electrical conductivity (EC). All data were taken from Environmental Protection Department's online data base (https://www.epd.gov.hk/epd/epic/english/data_river_monitoring.html). In general, all months had data. Nevertheless, there were a few cases of missing data, and the average of the immediate before and after months were considered. Also, if a variable was shown below the level of detection, it was considered as 0 (e.g. if nitrate-nitrogen < 0.002 mg/L, then it was considered as 0 mg/L). It should be noted that the number of outliers were small relative to the number of observations (less than 2% in many cases) (data not shown) and also such outliers was the case in all monitoring stations. Therefore, outliers will be assumed uninfluential of the outcomes of this study. Land use maps constructed by Lands Department were used to identify the land use. Table 1 shows the selected rivers, monitoring stations, the percent built area and the geology (in terms of the dominant rock type) of the contributing catchment as at 2016. The net built area fraction (that is built area as seen aerially) of past years is assumed to be more or less the same or to be proportionate with the values between different catchments as of 2016.

2.3 Data Analysis

Multivariate statistical techniques are effective for categorizing, interpreting, and representing raw river water quality data (Wang et al. 2014). Here, data were modeled using redundancy analysis (RDA). RDA was selected based on the short gradient length (less than 4) of response variables (Ter Braak & Smilauer 2002). In RDA, water quality variables were treated as response variables, whereas time was considered as the explanatory variable. The sampling month was numbered, starting from one (i.e. 1986 January was assigned one). RDA analyses were done by centering and standardizing the explanatory variable. Scaling focused on explanatory variable correlations with the water quality variables, and explanatory variable scores were divided by standard deviation. A log transformation ($y' = \log(A.y + C)$; $A = 10$ and $C = 1$) was used to reduce the

Table 1 Studied streams, upstream and downstream sampling locations and the land use split of the respective contributing catchment (i.e. catchment above the station)

River	Upstream			Downstream		
	Code	Built area (%)	Major rock type (%)	Code	Built area (%)	Major rock type (%)
Mui Wo River	MW US	40	Volcanic (100)	MW DS	80	Volcanic (20), granite (80)
Ho Chung River	PR US	50	Volcanic (90), granite (10)	PR DS	70	Volcanic (100)
Tseng Lan Shue Stream	JR US	60	Volcanic (50), granite (50)	JR DS	70	Volcanic (50), granite (50)
Yuen Long Creek	YL US	50	Volcanic (40), granite (35), superficial deposits (25)	YL DS	80	Volcanic (30), granite (20), superficial deposits (50)
Tin Shui Wai Nullah	TSR US	60	Granite (100)	TSR DS	70	Granite (70), superficial deposits (20), metamorphic rocks (10)
Tuen Mun River	TN US	70	Granite (70), superficial deposits (30)	TN DS	70	Volcanic (20), granite (60), metamorphic rocks (20)
Kai Tak River	KN US	50	Granite (100)	KN DS	50	Granite (50), superficial deposits (25), reclaimed land (25)
Tin Sum Nullah	TR R1	30	Granite (100)	–	–	
Siu Lek Yuen Nullah	TR R2	20	Granite (100)	–	–	

skewness. Conditional and marginal effects of explanatory variables on response variables were assessed using a Monte Carlo permutation test (with automatic variable selection), which was done using the reduced model from CANOCO for Windows (Gomes and Asaeda 2009). The angle between two variables indicates the strength of correlation (the smaller the angle, strong positive correlation; closer to 180°, strong negative correlation). The length of the variable arrow indicates the strength of the variable. In addition, water quality response curves against time was drawn using LOESS smoother method incorporating local linear option and also generalized linear model with a quadratic fit. This was done to recheck the decision of using the linear multivariate method. RDA and response curves of water quality parameters were generated by Canoco 4.5.

One of the main objectives of trend analysis in water quality studies is to find increase or decrease of a water quality parameter within the time period of interest (Naddafi 2007). The Mann–Kendall method is a non-parametric test for detecting trends in long-term data. Instead of comparing the data values itself, this test compares the relative magnitude of a sample (Gilbert 1987). There are couple of advantages of this method: (1) this method does not require data to conform a particular distribution; (2) it is insensitive to abrupt breaks as a result of inhomogeneous time series (Jaagus 2006). Also, Mann–Kendall test can state whether the trend is statistically significant or not. Since the Mann–Kendall test is a non-parametric test, it means that the test can be carried out whether or not the dataset is normally distributed and it will not be impacted heavily by outliers. This test has been executed in MS excel using "XLSTAT" tool (Dawood 2017) and will be used to cross-validate the results of RDA.

Being a linear methods RDA and Mann-Kendall test would not properly capture unimodal or quadratic responses against time. Therefore, overall trend would hinder any intermediate variations. Figure 2a, b show the water quality response curves derived by generalized linear models with linear and unimodal fits respectively for Mui Wo River for EC. As per Fig. 2b, it was clear that even though the overall increment in EC was true, there was a decreasing trend after the mid 1990 for the downstream station. This was the case for a few variables (especially EC, TSS and TS) in a few stations. Which curve would best fit has to be decided based on F (ratio between sample means to variation within the samples), P (probability) and standard error of regression, and in the given example (Fig. 2a, b), the linear model gave the better fit, validating our decision on selecting the linear method, RDA based on the short

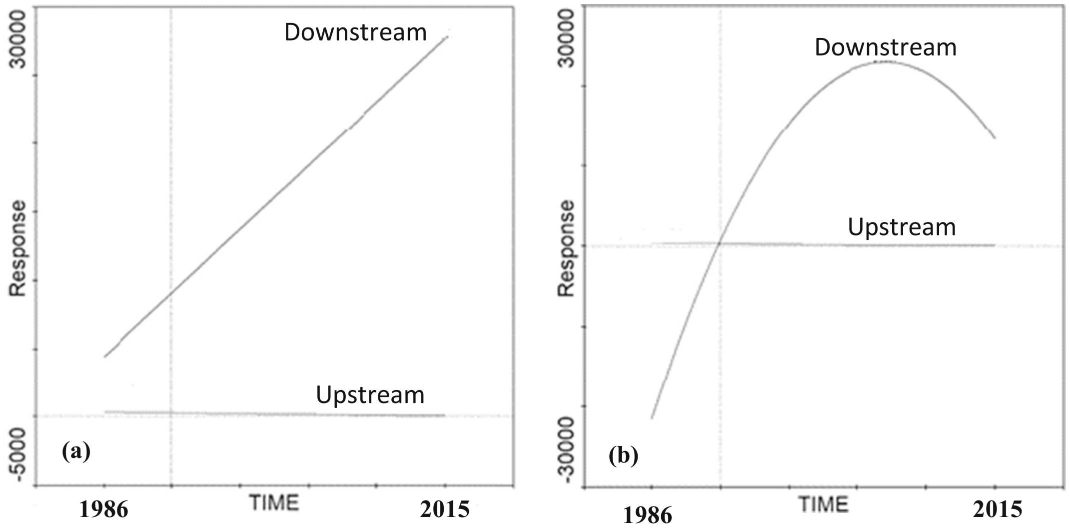

Fig. 2 **a** LOESS smoother linear and **b** generalized linear model quadratic curves for the variation of electrical conductivity of upstream and downstream stations of Mui Wo River

gradient length. For some cases (less than 20%), it was otherwise (data not shown). Nevertheless, the predictions made by linear methods such as RDA and Mann–Kendall seemed to be adequate and representative of the overall spatiotemporal trends.

3 Results

3.1 Summary of Water Quality and Stream Discharge Variations

Table 2 summarizes the average, standard deviation from the average, minimum, and maximum observations of water quality parameters and the stream discharge of different stations for the study period. These values are important as it will show the shape of the underline spatiotemporal variations. All variables at all monitoring stations showed a large spread indicating temporal (seasonal, that is within year and/or long-term) variations. Also, the upstream monitoring station showed a better water quality than the downstream with respect to the average values, and in many cases the differences were significant too (*t* test; $P < 0.05$). However, no downstream monitoring station, unless it had a similar built fraction as the upstream station or it is spatially close to the upstream station (e.g. Kai Tak River), showed a statistically significant (*t* test; $P < 0.05$) better water quality for any variable. This to a certain extent indicated that urbanization leads to poor water quality. However, this kind of snapshot results (Table 2) would not show the temporal trajectory, as it is possible to show a poor water quality in terms of average values, yet the same parameters may show improving trends. This is particularly true for discharge. As an example, average values showed the downstream discharges to be several folds more than the upstream, yet no indication whether dischargers are in increasing or decreasing trends.

3.2 Temporal Trends of Water Quality and Stream Flow

In many stations, irrespective being upstream or downstream, the correlations water quality parameters made with time indicated that for a large number of parameters, the water quality seemed to be improving with time (Fig. 3). Nevertheless, in all stations at least a single water quality parameter indicated a deterioration. Mui Wo was the only stream, where upstream and downstream monitoring stations, showed opposite trends for water quality (the upstream station showed an improvement) (Fig. 3a). Then, the two reference stations (Tim Sum Nullah and Siu Lek Yuen) also showed improvements (Fig. 3h, i). One similarity among the upstream station of Mui Wo and two reference stations were the low urbanization (less than 40%). The catchments of all other stations irrespective of being upstream or downstream were urbanized with at least of 50% built areas. The correlations observed in RDA plots had a good agreement with Mann–Kendall results (Table 3).

Table 2 Summary of discharge and water quality variation. Data shows average (standard deviation), minimum and maximum values of the raw data available with the Environmental Protection Department (EPD), Hong Kong, for the period from 1986 to 2015

Variable		MW		PR		JR		YL
		US	DS	US	DS	US	DS	US
Discharge (m^3/s)	Avg. (SD)	0.1 (0.2)	0.1 (0.3)	0.4 (0.8)	0.4 (0.8)	0.1 (0.1)	0.2 (0.2)	0.2 (0.5)
	Min.	0	0	0.0	0	0.0	0.0	0.0
	Max.	1.6	4.9	7.4	7.4	0.4	2.0	7.0
EC (μs/cm)	Avg. (SD)	156 (590)	5088 (9092)	104 (74)	6393 (8877)	261 (129)	199 (100)	582 (468)
	Min.	27	2	10	10	26	40	66
	Max.	9680	46,697	958	42,433	1100	1100	4000
Nitrate (mg/L)	Avg. (SD)	0.5 (1.8)	0.4 (0.3)	0.4 (0.4)	0.4 (0.4)	1.1 (1.1)	5.0 (26.0)	0.6 (0.7)
	Min.	0.0	0.0	0.0	0.0	0.0	0.1	0.0
	Max.	33	2.2	6.3	6.3	9.8	510	6.0
Phosphate (mg/L)	Avg. (SD)	0.3 (1.0)	0.2 (0.6)	0.1 (0.2)	0.1 (0.3)	1.5 (2.6)	1.0 (1.2)	6.6 (8.6)
	Min.	0.0	0.0	0.0	0.0	0.1	0.1	0.0
	Max.	14	7.2	1.4	4.6	22	7.9	51
TS (mg/L)	Avg. (SD)	434 (3413)	3818 (7325)	120 (194)	5378 (7675)	248 (405)	249 (1217)	520 (583)
	Min.	20	0.5	28	28	36	34	1
	Max.	40,000	36,000	2900	45,000	6000	23,000	3900
TSS (mg/L)	Avg. (SD)	11 (75)	14 (149)	7 (11)	14 (42)	46 (223)	11 (90)	139 (250)
	Min.	0.5	1	0.5	0.5	0.5	0.6	1.7
	Max.	1300	2800	130	580	3800	1700	2000

Variable	YL	TSR		TN		KN		Ref	
	DS	US	DS	US	DS	US	DS	TRR1	TR R2
Discharge (m^3/s)	0.7 (0.9)	0.1 (0.3)	0.5 (0.8)	0.2 (0.5)	8.5 (8.6)	1.7 (1.2)	7.4 (6.3)	0.1 (0.1)	0.1 (0.2)
	0.0	0.0	0.0	0.0	2.4	0.1	0.4	0.0	0.0
	8.4	3.1	2.7	6.6	14.6	7.5	21	1.4	2.0
EC (μs/cm)	1071 (2255)	332 (2064)	378 (250)	1125 (1403)	28,108 (11293)	14,302 (5647)	16,799 (4596)	201 (137)	448 (766)
	9	32	20	100	285	249	2667	60	33
	32,900	34,194	2500	21,629	48,274	20,289	30,370	1340	13,636
Nitrate (mg/L)	0.5 (2.1)	1.2 (1.2)	1 (1.7)	0.7 (1.0)	0.4 (0.3)	4.0 (1.9)	3.4 (1.9)	1.5 (1.5)	0.8 (2.1)

Table 2 (continued)

Variable	YL	TSR		TN		KN		Ref	
	DS	US	DS	US	DS	US	DS	TRR1	TR R2
	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
	26	12.4	20.7	11	2.8	2.7	10	23	25
Phosphate (mg/L)	4.5 (4.7)	0.2 (0.5)	0.6 (0.9)	3.4 (6.9)	0.2 (0.4)	1.2 (0.6)	1.4 (0.5)	0.0 (0.0)	0.2 (0.7)
	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0
	3.2	5	7.1	48	2.8	2.7	4	44	7.6
TS (mg/L)	752 (1156)	198 (413)	282 (351)	693 (751)	26,501 (12320)	45 (249)	10 (15)	403 (1495)	275 (1057)
	100	52	68	130	350	0.6	1.6	30	0.5
	9600	6300	5600	6000	82,000	3500	180	25,000	18,000
TSS (mg/L)	103 (153)	47 (155)	53 (145)	145 (283)	10 (27)	10,028 (3679)	12,503 (3783)	95 (357)	29 (86)
	3	1	1.5	2.1	0.5	550	1700	0.5	0.5
	2100	1600	2000	3800	460	16,000	27,000	5100	720

There was a contrasting difference with respect to stream discharge: many downstream stations showed a positive correlation with time, whereas negative correlations in upstream stations (Fig. 3). This was more obvious when the difference between urbanized fractions of upstream and downstream catchments were large (e.g. Mui Wo and Ho Chung) (Fig. 3a, b). It was only Tuen Mun River (Fig. 3f) showed increasing trend for discharge in both upstream and downstream stations (Fig. 3f).

3.3 The Impact of Season on Water Quality and Stream Discharge

Figure 4 shows the strength of correlations of discharge, nitrate and phosphate made with time in RDA bi-plots drawn separately for dry and wet seasons for the entire study period. Same as for the annual scale, the trends were not uniform. In addition, the strength of correlations seemed to be independent of the season. Independency from season was more obvious in downstream monitoring stations. However, for many cases, downstream discharges were increasing. This we attribute to the increase in impervious cover with time (aerial photographs and satellite images validated our claim; data not shown). Increased impervious cover of a catchment makes abstraction losses (evaporation and infiltration) play a minor role in governing the discharge (Gomes et al. 2019). Nitrate variations too proved season had no major impact on strength of correlations, and was the case for upstream as well as downstream stations. Also, other than with catchments with urban land use less than 40%, the upstream stations showed a strong negative correlation between nitrate and time. However, phosphate variation was independent from season as well as monitoring station's spatial location.

3.4 Identification of Water Quality and Discharge Trends in Lowest and Highest Quartiles of Urbanization

Figure 5 shows strength of correlations of discharge, nitrate-nitrogen, phosphate, TSS, TS and turbidity made with time at different seasons. In Fig. 5 a catchment was taken as a rural if the built area fraction was less than 40% (this included the catchments within the lowest 25% of the built area fraction, i.e. the first quartile); if it was more than 70% (this included the catchments within the highest 25% of the built area fraction, i.e. the third quartile) was taken as an urban catchment.

Table 3 Mann–Kendall results (Kendall tau co-efficient): increasing trend (+); decreasing (−) trend. Other than bold-italics, all are significant at $P < 0.05$ (see Table 1 for monitoring station code details)

Monitoring station	Discharge	Nitrate	Phosphate	Total solids	Total suspended solids	Electrical conductivity	Turbidity
MW US	− 0.14	− 0.47	−0.68	− 0.21	− 0.21	***− 0.06***	− 0.19
MW DS	0.18	0.12	−0.16	0.12	***− 0.05***	0.17	− 0.10
PR US	− 0.43	0.40	−0.24	***0.00***	***− 0.06***	0.19	***− 0.04***
PR DS	0.23	− 0.21	−0.10	***0.00***	***0.08***	0.10	***0.06***
JR US	0.14	0.34	−0.31	− 0.20	− 0.29	***− 0.05***	− 0.31
JR DS	***0.02***	***0.09***	−0.29	− 0.24	− 0.38	− 0.18	− 0.30
YL US	0.07	0.22	−0.58	− 0.33	− 0.45	− 0.21	− 0.47
YL DS	− 0.15	0.08	−0.60	− 0.45	− 0.32	− 0.32	− 0.39
TSR US	***− 0.01***	0.09	−0.32	0.28	0.21	0.25	0.26
TSR DS	***0.02***	− 0.22	−0.32	0.27	0.41	***0.00***	0.32
TN US	0.13	0.20	−0.28	− 0.52	− 0.54	− 0.18	− 0.57
TN DS	***0.02***	0.21	−0.45	***0.04***	− 0.44	0.20	− 0.38
KN US	− 0.35	0.25	−0.35	0.48	− 0.48	0.21	− 0.40
KNDS	0.60	***0.02***	−0.44	0.60	− 0.60	0.52	− 0.56
TR R1	***0.02***	− 0.33	−0.38	0.48	− 0.52	***0.03***	− 0.43
TR R2	***− 0.01***	0.09	−0.32	− 0.28	− 0.21	− 0.25	− 0.26

Catchments with built area fraction between 40 and 70% were not considered, as we wanted to explore the effect of urbanization clearly. It was conspicuous that catchments' water quality responses were different between rural and urban. However, no impact was observed based on the season with phosphates being the only exception. Phosphates showed decreases with time in both types of catchments. Irrespective of the season, rural catchments produced lower discharge with time; nevertheless, water quality seemed to be improving also (all correlations were moderately strong). Urban catchments produced more discharge (on average showed strong positive correlations) and also more contaminated water (on average a weak positive correlation for nitrate and moderately strong correlations for solid-related parameters).

4 Discussion

4.1 Water Quality Parameters that Should Be with Concern and Sources of Pollution

Considering the large number of negative or weak positive correlations between water quality parameters and time, it is reasonable to state, in general, that the water quality was improving. However, a deterioration signature for downstream monitoring stations were noted for all sediment-related parameters (TS, TSS, turbidity and EC) and also for nitrate nitrogen. Increasing trend of sediment load in downstream monitoring stations which are more urbanized strengthen the fact that urbanization increases the pollutant load (Walsh 2000).

Even though phosphate showed a decreasing trend in many cases, nitrate did not give a unique trend; however, the majority of the cases showed increments. Opposite trends were rather unexpected as nitrates and phosphorus present together in point and as well as nonpoint pollution sources (Morrison et al. 2001). One reason could be phosphorus to be in a speciation other than phosphates (e.g. in biologically unavailable forms). In this regard, point sources such as wastewater inputs could not be the main source where major composition of phosphorus is in the form of phosphate (Dueñas et al. 2003). Nevertheless, we do not exclude the possibility of expedient wastewater releases and also intentional and unintentional breach from sewerages. Even if phosphates enter the stream, alga and/or plants would quickly consume those for their metabolism. It should be noted unlike nitrates, phosphates are limited in aquatic ecosystems (Gomes and Asaeda 2009) and also depend on the geographic conditions. In rural catchments, phosphates will assimilate into stream bed sediment and plants (Miller et al. 2011; Gomes et al. 2019) and this

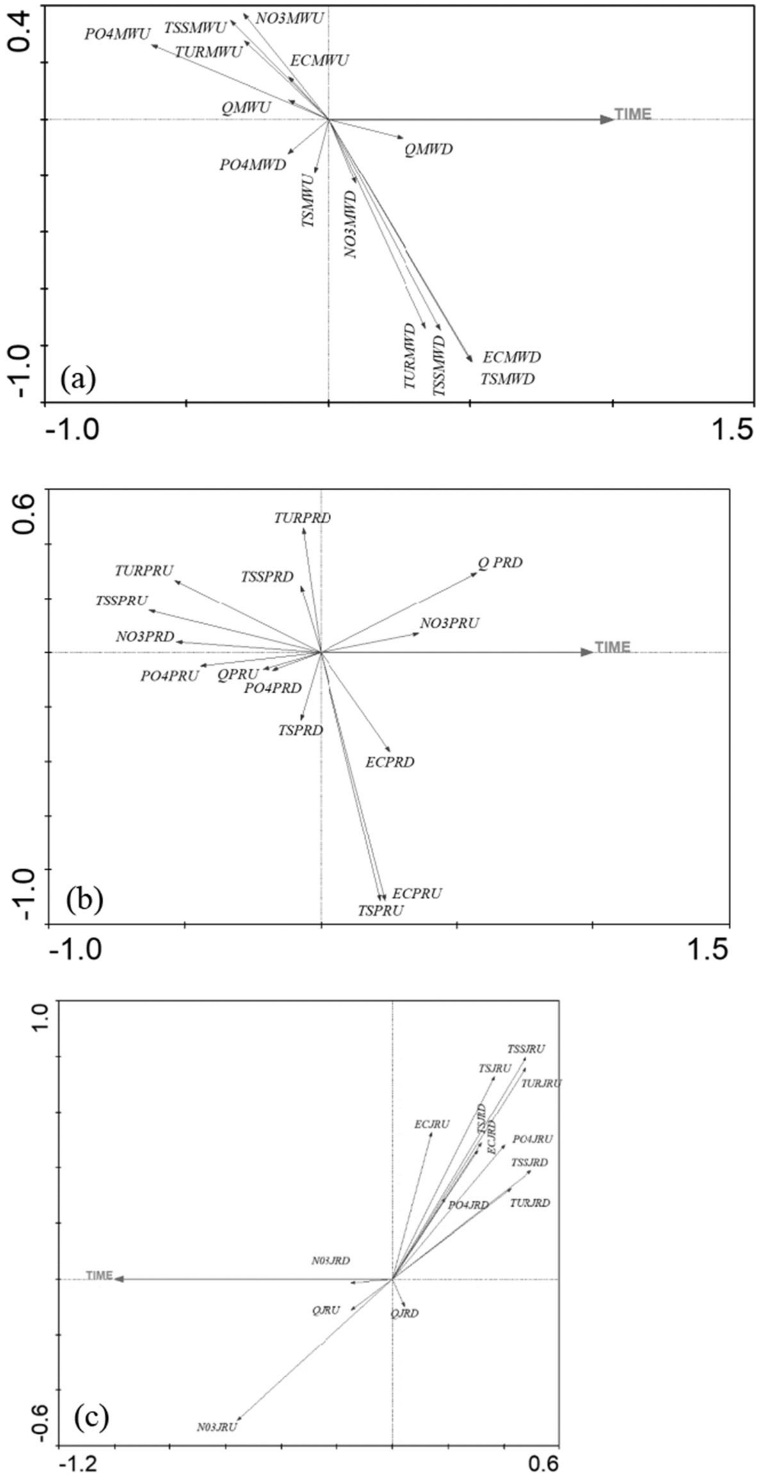

Fig. 3 Redundancy analysis bi-plots for **a** Mui Wo River; **b** Ho Chung River, **c** Tseng Lan Shue Stream, **d** Yuen Long Creek, **e** Tin Shui Wai Nullah, **f** Tuen Mun River, **g** Kai Tak River, **h** Tin Sum Nullah and **i** Siu Lek Yuen Nullah. Variable label: water quality variable/stream code/sampling location (e.g. ECJRU; (EC) electrical conductivity, (JR) Tseng Lan Shue stream, (U) Upstream sampling station). Abbreviations: Q (stream discharge); NO3 (nitrate-nitrogen); PO4 (phosphate); TS (total solids); TSS (total suspended solids); and TUR (turbidity). Table 1 give stream codes

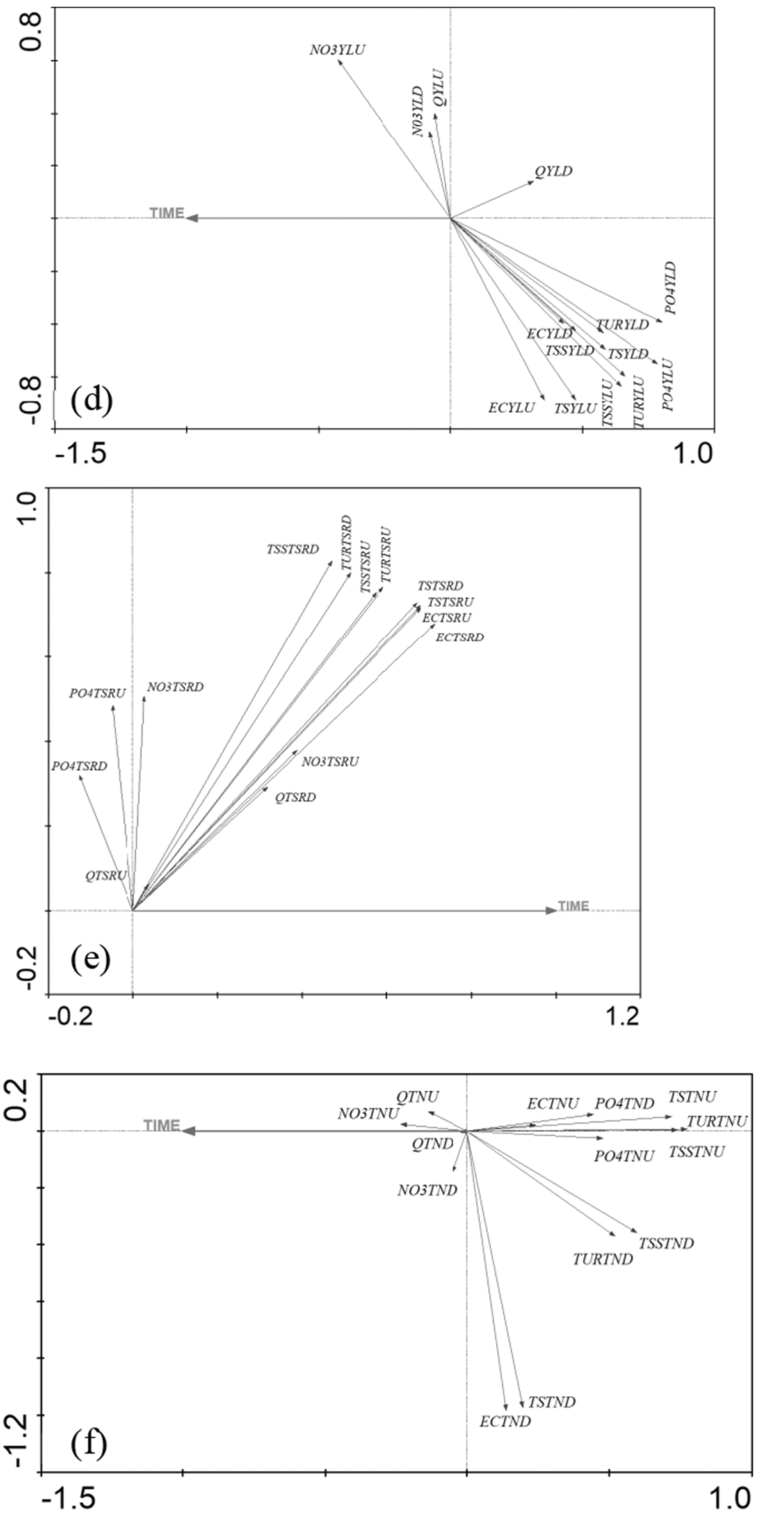

Fig. 3 (continued)

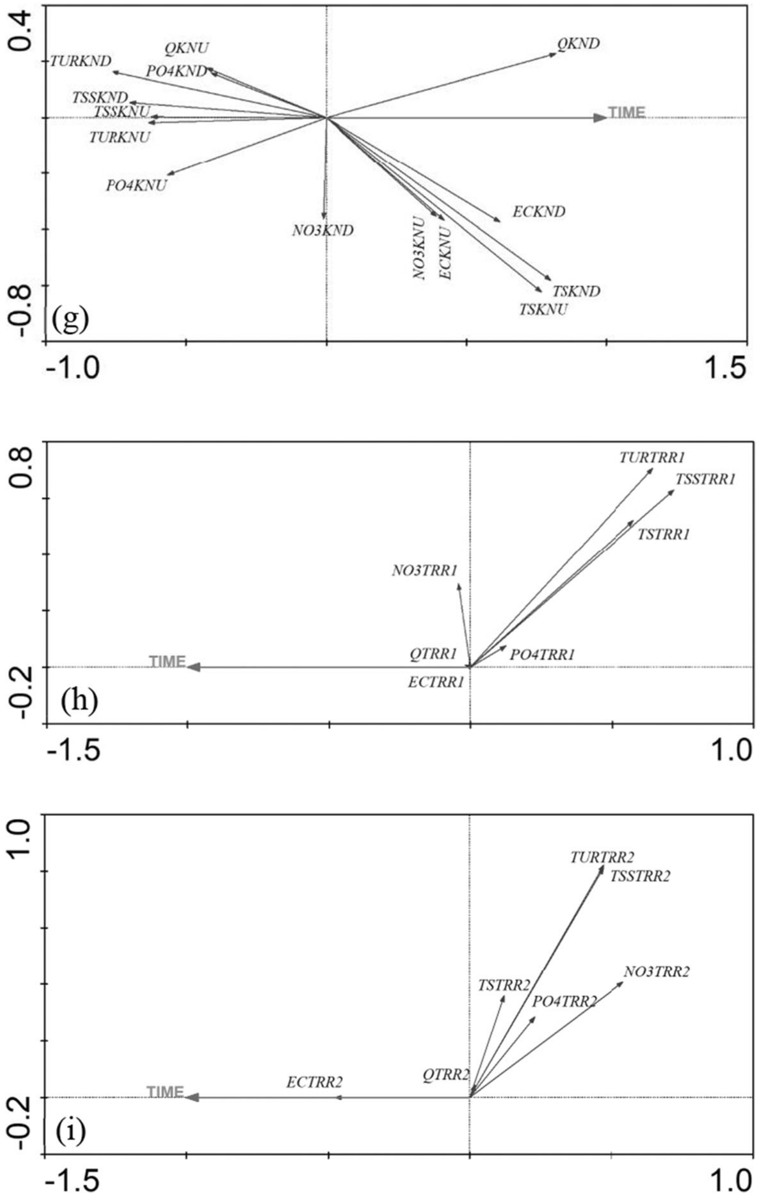

Fig. 3 (continued)

is impossible in streams of urban areas as many of them are entirely concrete-lined. However, phosphates can easily get bound to sediment of the water column (Smith et al. 1987; Thodsen et al. 2019). This could be the case in urban areas considering the increasing trends of EC, TSS, TS, and turbidity (all are surrogates of the sediment load).

It is understood standard factors depicted in the hydrological cycle such as surface runoff, ground water flow and rainfall may not able to fully explain the sediment yield to streams, but the episodic events (Imaizumi and Sidle *2007*). One such episodic event we attribute to the sediment input is surface and airborne runoff across construction sites (Russell et al. 2019). Legislative frameworks are in full force in Hong Kong to control sediment sources such as construction sites. Nevertheless, indirect and/or unexpected escape of sediments seemed to be the case (in sensu Sobota et al. 2015).

Another reason to attribute stream pollution of urbanized catchments to nonpoint sources is strict government control and availability of wastewater management infrastructure. This may not be the case for upstream stations

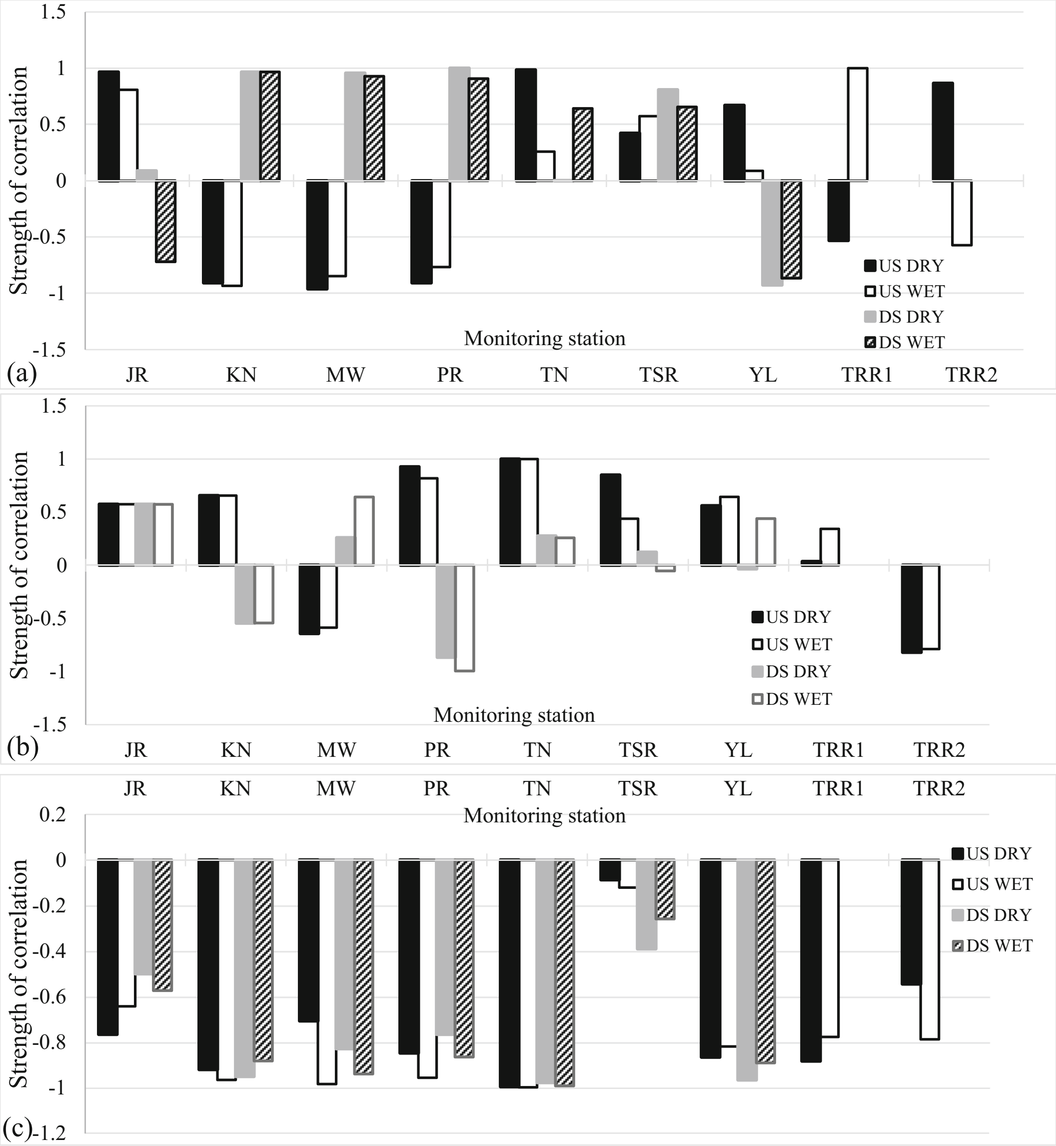

Fig. 4 Strength of correlation **a** discharge, **b** nitrate-nitrogen and **c** phosphate made with time in wet and dry seasons in upstream (US) and downstream (DS) monitoring stations. Correlations were calculated from redundancy analysis bi-plots for different scenarios based on the season and location of the monitoring station as upstream and downstream

of rural catchments, and expedient wastewater dischargers are possible (Gomes et al. 2014). However, improving water quality trends indicate government control to a certain extent is working well.

4.2 Stream Flow Generation, Contamination and Water Quality

Several upstream sections showed a negative trend in stream discharge with time. It is common the first order catchments in Hong Kong to have catch water structures (drains and dams) to collect and transport water to drinking water treatment plants (Gomes et al. 2017). Such, completely cut stream flow generated in large number of low order streams (perennial as well as ephemeral streams) reaching the higher order perennial reaches. This could be more problematic during the dry season, where rainfall is scarce. During the wet season, this was not apparent due to the heavy rainfall-induced catchment runoff and the spillage of catchwater structures.

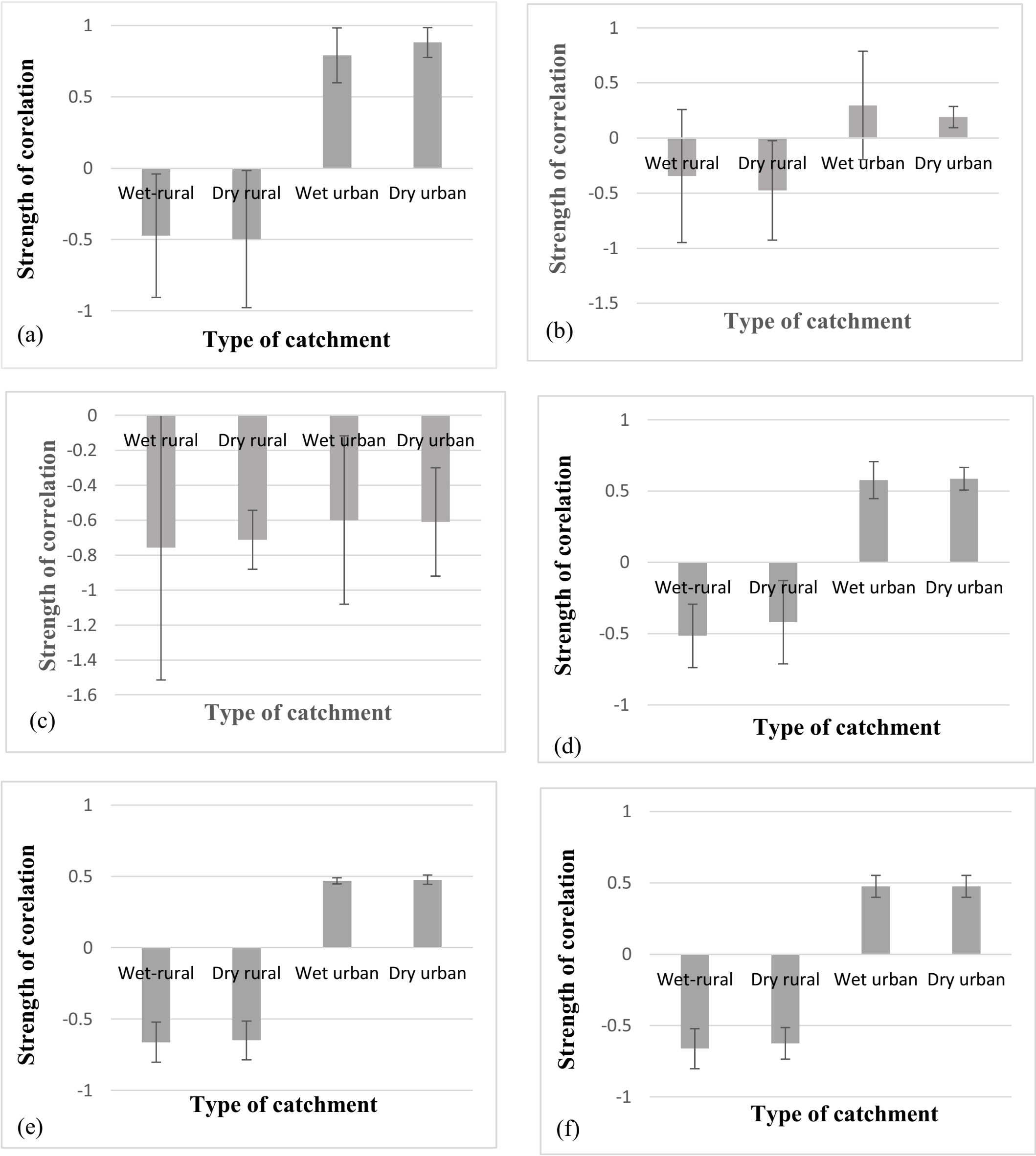

Fig. 5 Strength of correlations **a** discharge, **b** nitrate-nitrogen, **c** phosphate, **d** total suspended solids, **e** total solids and **f** turbidity made with time in rural and urban catchments. Rural: upstream station of Mui Wo river, Tin Sum Nullah amd Siu Lek Yuen Nullan, where built area fraction < 40%; and urban: downstream stations of Mui Wo river and Tin Shui Wai Nullah, where built area > 70%)

Less built area fraction of catchments of upstream monitoring stations resulted in mobilization of a low pollutant load to stream via surface runoff. The vegetated surfaces that are abundant in upstream rural areas seemed trapped contaminants (Thodsen et al. 2019). The opposite have had happened in downstream stations where surface runoff brought high loads of pollutants as results of nitrogen deposits due to vehicular traffic in urban impervious catchments (Sobota et al. 2015).

Impacts of climate change may have an impact on stream flow generation. Because of climate change, the dry season get drier, whereas the wet season get wetter (more rainfall). However, more rainfall seemed to be a reason of poor water quality in downstream areas, as it had mobilized nutrients and sediments to streams.

4.3 Management Implications

Clear, opposite trends were evident when the extremely rural and extremely urbanized catchments were analyzed. Therefore, management strategies should be based on catchment land use. It is conspicuous that the nonpoint source pollution such as urban runoff may hinder the government to achieve the goal of clean rivers. Therefore, attention should be paid to prevent nonpoint source pollution and reduce contamination of rivers. In this regard, studies should be carried out to identify the surface runoff pollutant paths. Knowing the source and path would help in developing proper contaminant reduction plans.

Infrastructure development (new, expansion and repair of existing infrastructure) is common and in an increasing trend in urban centers obviously more than rural areas due to increasing demand for housing. Also, the government strategy of keeping 60% green space in Hong Kong worked well for the upstream stations, but ever increasing concentration of urbanization by way of vertical constructions needs a careful look with respect to water quality.

Furthermore, the study proved the fact that water quality trends are different in upstream and downstream monitoring stations. Therefore, reduction of monitoring stations as shown by past studies (e.g. Wang et al. 2014; Tanos et al. 2015) is not applicable to Hong Kong.

5 Conclusions and Recommendations

This study analyzed the temporal variations of Hong Kong water quality data for a 30-year period. The catchments with built area fraction less than 40% and more than70% gave opposite trends for many water quality parameters and stream discharge, elucidating urbanization has a moderately negative impact. The study indicated point source inputs to the streams are probably on decline, but the pollutants via catchment runoff are on the rise. More investigations on why sediment supply is on the increasing trend are needed. Maybe stricter environmental standards should be imposed on micro-level activities such as road sweeping and sediment traps in storm water networks. The increasing sediment supply could be due to undefined sources (local and/or regional airborne particle transport) or from less apparent sediment paths. Therefore, sediment budget/balance studies are recommended to check the sediment pathways (e.g. is it via drains? or over banks with the surface runoff) for remedial action.

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