Spatiotemporal variability and key influencing factors of river fecal coliform within a typical complex watershed

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ABSTRACT

Fecal coliform bacteria are a key indicator of human health risks; however, the spatiotemporal variability and key influencing factors of river fecal coliform have yet to be explored in a rural-suburban-urban watershed with multiple land uses. In this study, the fecal coliform concentrations in 21 river sections were monitored for 20 months, and 441 samples were analyzed. Multivariable regressions were used to evaluate the spatiotemporal dynamics of fecal coliform. The results showed that spatial differences were mainly dominated by urbanization level, and environmental factors could explain the temporal dynamics of fecal coliform in different urban patterns except in areas with high urbanization levels. Reducing suspended solids is a direct way to manage fecal coliform in the Beiyun River when the natural factors are difficulty to change, such as temperature and solar radiation. The export of fecal coliform from urban areas showed a quick and sensitive response to rainfall events and increased dozens of times in the short term. Landscape patterns, such as the fragmentation of impervious surfaces and the overall landscape, were identified as key factors influencing urban non-point source bacteria. The results obtained from this study will provide insight into the management of river fecal pollution.

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1. Introduction

With the prevalence of "coronavirus disease 2019" in the world, the spatiotemporal distribution and influencing factors of microbial pollution in rivers (especially in urban rivers) have become the focus of scientific research. Microbial pollution around the world is routinely assessed using concentrations of fecal indicator bacteria (FIB) including *Escherichia coli* and enterococci as proxies for pathogenic organisms (Wyn-Jones et al., 2011). Such bacteria are present in the feces (Stachler et al., 2017), runoff (Molina et al., 2014) and sewage discharges (Jennings et al., 2018), and their presence is a considerable issue concerning river risk management and human health risk (Chenar and Deng, 2018). As a type of FIB, fecal coliform (FC) has been widely used in the risk assessment of microbial pollution in water (Boehm et al., 2018; Uprety et al., 2020). The National Health and Medical Research Council of Australia and the European Environment Agency (EEA) both use FC as one of the microbiological indicators of drinking water quality. The FC index is particularly important especially in areas where

marine products are abundant (Wang and Deng, 2019). Previous studies have reported two significant observations of the world-wide FC situation. On the one hand, FC is inherently bioactive, differing from other physical and chemical pollutants, and the reported amount of microbial pollution in the environment has raised concerns regarding ecosystem and human health (Frena et al., 2019). On the other hand, the state and concentration of FC in water bodies are dynamic and are related to environmental factors (Chen and Liu, 2017; Carpenter et al., 2019; Jeon et al., 2019).

A growing body of research has proven that the dynamic nature of FC survival and concentration in surface water bodies is driven by emissions and environmental factors that determine FC transport and fate (Mitch et al., 2010; Liu et al., 2015). FC can reproduce rapidly under optimal environmental conditions for growth, and reproduction varies with factors such as water temperature, temperature, solar radiation, rainfall and turbidity (Leight et al., 2016; Chen and Liu, 2017). Regression models can be applied to explore how one environmental factor affects FC levels while the remaining factors are fixed; however, it usually has poor fitness. This result may be due to the complicated and nonlinear relationship between environmental factors and FC (Fan et al., 2015; Tong et al., 2016; Wang and Deng, 2019). Several additional studies have investigated

the link between land-use types and FC concentration, including urban development levels, agriculture-dominated watersheds and comparisons of different watershed types (Sliva, 2001; Walters et al., 2011; Chow et al., 2013; Mcmichael et al., 2013; Badgley et al., 2019). Vitro et al. (2017) found that road density was positively correlated with FC contamination and negatively related to the area of water body. In addition, regions with water quality degradation due to nutrients usually have high FC concentrations, and this result has been found in other studies (Mallin et al., 2000). Forest and grass may be positively correlated with FC concentrations in water bodies because these landscapes provide places for poultry breeding (Smith et al., 2001). Together, these studies have indicated that the watershed-scale FC dynamics could be predicted by examining FC occurrence and concentration data coupled with environmental factors. However, the limited scope of these monitoring datasets and the combination of landscape patterns related to the transmission path of non-point source pollution (NPS) have not allowed for generalizable conclusions regarding how such programs coupled with environmental factors impact the contaminant levels in a complex watershed with mixed land-use types.

In this study, a typical urbanized watershed with a drainage area greater than 4000 km^2 was monitored at both the monthly scale and the event scale. The primary goal of this study was to improve our fundamental understanding of the drivers of FC in surface water systems. The objectives of the study were to 1) investigate the spatiotemporal variation in FC in a mixed land use watershed; 2) quantify the impacts of urbanization processes and environmental factors on the FC dynamics; and 3) identify the key landscape metrics influencing the event-scale FC concentration variation.

2. Materials and methodology

2.1. Study area description and division

The Beiyun River flows through the eastern suburbs of Beijing and Tianjin, and it is a tributary of the Haihe River, which is one of the seven major river basins in China. The study area is located in Beijing city, spanning from the middle northwest to the southeast, covering eight districts, with a total basin area of 4348 km^2 and a total river length of 89.4 km. Details on the Beiyun watershed, including the digital elevation model (DEM, 30 m resolution), climate, river system, conventional water quality and function, are provided elsewhere (Shen et al., 2015; Liu et al., 2018). The land use in 2017 showed approximately 20% of forest land, 30% agricultural land and 40% urban land. The urban areas are mainly located in the middle of the watershed and spread up and down gradually, showing a rural-suburban-urban gradient.

Eight main tributaries exist in the Beiyun watershed, most of which are suffering serious FC pollution because of a series of anthropogenic activities. However, water environment management in the Beiyun River is extremely challenging. The region is experiencing rapid urbanization, and FC management should have regional characteristics. Accordingly, a total of 21 water quality sampling sites (S1–S21) were selected along the mainstream and its tributaries as well as the confluence, considering the characteristics of the main stream, urbanization level, land use patterns and accessibility. Thereafter, the watershed boundaries and river network were delineated in ArcGIS with the hydrological module based on the digital elevation model (DEM, 30 m resolution). Taking each of the sampling sites as the outlet of a delineated catchment, the catchment areas (C1–C21 responding to S1–S21) were determined for further study. The catchments could be divided into five categories represented by five urban patterns with different urbanization levels (Fig. 1) considering spatial land-use types (Fig. 2). In pattern 1 (P1, C1–C3) and pattern 5 (P5, C19–C21), impervious surfaces accounted for less than 30%, which represented a low urbanization level. However, the difference between P1 and P5 was that there was a large part of forestland in P1, while cultivated land was dominant in P5. In P2 (C4–C10) and P4 (C17–C18), the impervious surface ratio was between 30% and 60%, indicating a moderate urbanization level. The central areas were characterized by a relatively higher percentage of impervious surfaces occupying approximately 80%, which were regarded as urban pattern with high urbanization level (P3).

2.2. Sample collection and analysis

A total of 441 water samples for fecal bacteria (21 samples from 21 sites for each of 20 months and a rainfall event) were collected using sterilized 500-mL plastic bottles. Sampling was conducted monthly from March 2017 to December 2018. Sampling occurred on approximately the same date each month, regardless of weather conditions, with the hope of reducing sampling errors. Additionally, a rainfall event on May 22, 2017 with an average rainfall of 29.2 mm was also included (pre-drying days of almost 2 months). Samples were collected before the rainfall event on May 20 and after the event on May 25, 2017. Manual sampling was performed due to the limitation of automatic sampling equipment in the study area. To ensure that no contamination occurred, sample collection was taken prior to field measurements at each sampling site. Sample bottles were conditioned in-stream by rinsing three times with stream water before retaining the sample. Samples were immediately placed in a cooler after sampling and shipped to the Research Centre for Eco-Environmental Science, Chinese Academy of Sciences in Beijing, China, for FC analysis within 24 h.

Water physicochemical samples for chemical oxygen demand (COD) and suspended solids (SS) were also collected at the time and were analyzed at an accredited laboratory using the Determination Methods for the Examination of Water and Wastewater 4th Edition; field measurements were conducted for pH, dissolved oxygen and water temperature. In the experiment, blank samples and quality control samples were operated first to verify the accuracy of the experimental instrument and operation. Then, the water quality indicators of COD and SS were conducted.

2.3. Selection of environmental variables

We aimed to explore the drivers of FC fate in a mixed land use watershed and thereby compiled a set of environmental factors that have been previously reported or are expected to contribute to FC dynamics at watershed scales (Chen and Liu, 2017; Jeon et al., 2019). The environmental factors are summarized in Table 1, including meteorological factors, urbanization factors, and water physicochemical factors.

Meteorological factors came from daily monitoring data of the five national meteorological stations in and around the study area (available at http://www.resdc.cn/Default.aspx), and the values were converted into monthly averages. The ordinary kriging method (Tukimat et al., 2019) used in geographical spatial interpolation was adopted to calculate the rainfall amount, temperature and solar radiation in each catchment area, and the results are detailed in the Figs. S1–S6. The urbanization factors represented by population density and road density were also calculated (Fig. S7). Water physicochemical factors were manually measured (Figs. S8–S12). To study the effect of landscape configuration on NPS-FC, landscape metrics were calculated from land use by FRAGSTATS 4.2 software (Mcgarigal and Marks, 1995). Six landscape metrics at the landscape level and eight metrics at the class
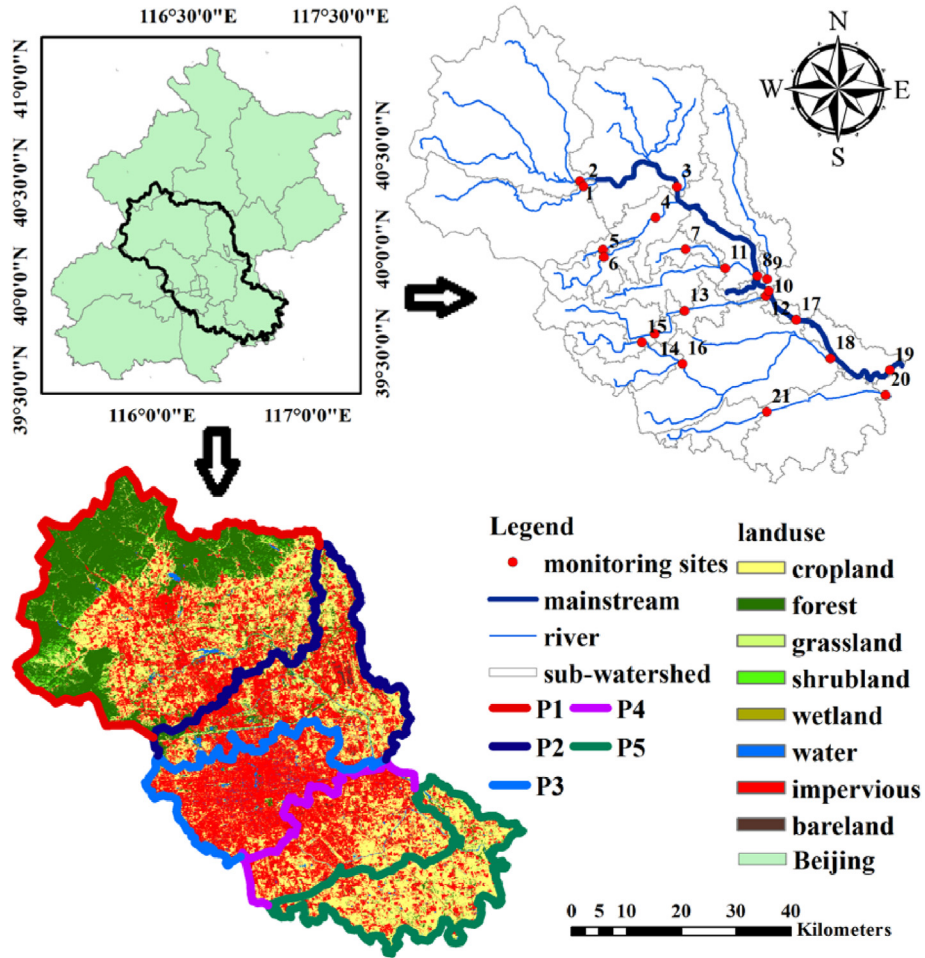
Fig. 1. Land use and urban development levels in Beiyun River watershed.
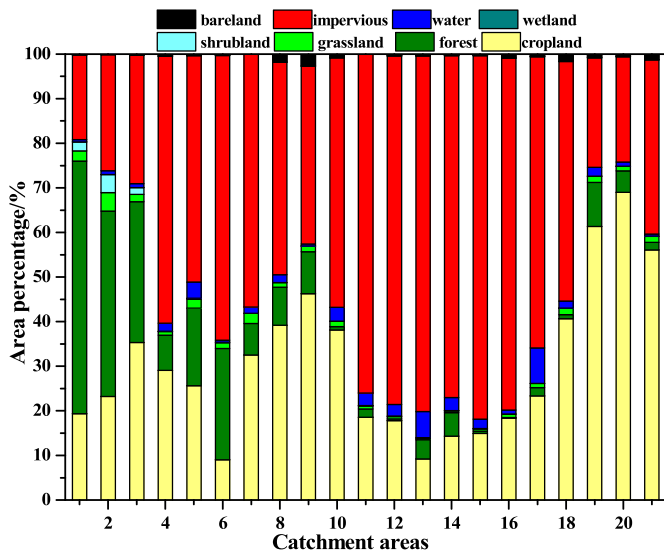

Fig. 2. Land use pattern at each catchment area in Beiyun River.

level were selected to represent the shape, structure, diversity and aggregation of the landscape.

2.4. Global autocorrelation

Global autocorrelation was calculated to evaluate the spatial independence of the monitoring sites by Moran's *I*. Briefly, the spatial statistics toolbox in ArcGIS was applied to generate the result. The sampling sites should cover the spatial characteristics of the watershed but should avoid the spatial interference of the upstream sites on downstream sites. The spatial randomness of the selected sampling sites ensured the statistical significance of the spatiotemporal variability and the key influencing factors of river FC.

The Moran's *I* ranged from −1 to 1. The scenario with a lower absolute value of *Moran's I* and Z-score (−1.65 < Z < 1.65) shows a weaker autocorrelation, and these indexes are defined as follows:

$$I = \frac{n}{S_0} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} \tag{2}$$

$$Z_I = \frac{I - E[I]}{\sqrt{V[I]}} \tag{3}$$

where z_i is the deviation of element *i* from its mean value of (x_i −

Table 1
Information on the selected environmental variables.

Factor types	Environmental variables	abbreviation/Calculation	units	Data source
Meteorological factors [a]	precipitation	pcp	mm	REDCP [b] (n = 5) [c]
	Temperature	tem	°C	
	Solar radiation	sr	langleys	
Urbanization factors	Population density	pop		REDCP
	Road dentity	road		REDCP
Water environmental factors	Water temperature	watertem	°C	Monitoring
	Turbidity (in SS)	SS	Mg/L	
	PH	PH	−	
	Chemical oxygen demand	COD	mg/L	
	Dissolved oxygen	O_2		
Landscape factors	Patch density	PD	n/100ha	Tsinghua University [d]
	Interspersion Juxtaposition Index	IJI	%	
	Largest patch index	LPI	%	
	Landscape shape index	LSI	−	
	Landscape division index	DIVI	%	
	Aggregation Index	AI	%	
	Shannon's diversity index	SHDI	−	
	Contagion index	CONTAG	%	

[a] Meteorological factor is daily data.
[b] Resource and Environment Data Cloud Platform (http://www.resdc.cn/Default.aspx).
[c] Number of weather stations.
[d] Land use in 2017 with 10-m resolution (http://data.ess.tsinghua.edu.cn).

$\overline{X}$), $w_{i,j}$ is the spatial weight between i and j, n is the total number of elements and S_0 is the sum of all spatial weights.

2.5. Multivariable regression

2.5.1. Lasso regression

To find the best combinations of environmental variables for the explanation of spatiotemporal variability of FC in different regions (P1−P5), the least absolute shrinkage and selection operator (Lasso) (Tibshirani, 1996) was conducted. Eight environmental factors, including three meteorological factors and five water environment factors (Table 1), were added for temporal regression in the fiver urban patterns. A total of 17 factors were added to the spatial regression, including three meteorological factors, five water environment factors, two urbanization factors and seven land-use areas, as shown in Fig. 2, except for bare land. Briefly, the five independent datasets of P1−P5 were temporally analyzed. The spatial analysis was conducted with annual averaging in different catchment areas.

However, this approach may have an impact on the regression analysis of urban region (P3) due to more point source inputs. Therefore, to weaken the influence of point sources, FC analysis in P3 was divided into the rainy season and dry season. The pollution load increment in the rainy season was regarded as the NPS input. Many researchers employ the rainy season and dry season when exploring the spatiotemporal changes in water quality according to precipitation (Luo et al., 2018; Han et al., 2020). Therefore, June, July and August were regarded as the rainy season in this study. March, April and November were the dry seasons of 2017, while October, November and December were the dry months of 2018 according to the monthly rainfall amount in Fig. S2. Simultaneously, the selected dry seasons excluded the snow months. The FC concentration caused by NPS was calculated by Eq. (4). The monthly flow data of each sampling section were necessary when calculating the increment of pollution load. The monthly flow data from 2013 to 2018 of two hydrological stations in the Beiyun watershed were obtained from the local Environmental Protection Bureau, based on which SWAT (Soil and Water Assessment Tool) model was calibrated and verified to simulate the monthly average streamflow of each river section. Model performance and parameter selection are shown in Fig. 3 and Table 2. Monthly SWAT-simulated streamflow
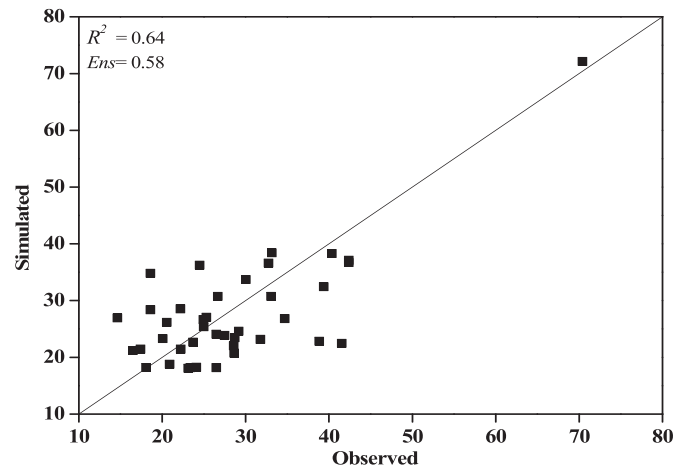
Fig. 3. Observed and simulated data by SWAT model.

can be judged as satisfactory with $R^2 > 0.6$ and $E_{NS} > 0.5$ according to previous study (Moriasi et al., 2015). Thereafter, the response relationship between NPS pollution and landscape patterns in urban areas was carried out using Lasso.

$$C_{NPS} = \frac{C_{rainy} \times Q_{rainy} - C_{dry} \times Q_{dry}}{Q_{rainy}} \qquad (4)$$

where C_{NPS} is the concentration of FC caused by NPS, C_{rainy} and C_{dry} are the FC concentrations in the rainy seasons and dry seasons, respectively, and Q_{rainy} and Q_{dry} are the streamflow in the rainy seasons and dry seasons, respectively.

A penalty function was constructed in Lasso to compress some variable coefficients to 0; this process is done to measure the goodness-of-fit and penalize against overfitting. Therefore, an optimal fitting model can be obtained. The 10-fold cross validation was introduced to minimize spurious relations when selecting variables. The final regression models were selected by the optimal λ from the cross validation (Zhao and Bondell, 2020), and the regression coefficients were obtained with statistical significance (t-statistic, P < 0.05). Data analyses were performed using R

Table 2
Calibrated values of parameter for streamflow.

No.	Parameter	Fitted_value	No.	Parameter	Fitted_value
1	V_CN2.mgt	95.876	13	V_CH_S2.rte	0.971
2	V_IGRO.mgt	0.184	14	V_CH_L2.rte	39.797
3	V_ALPHA_BF.gw	0.033	15	V_SOL_AWC.sol	0.336
4	V_GW_DELAY.gw	303.471	16	V_SOL_K.sol	1181.457
5	V_GW_REVAP.gw	0.036	17	V_SOL_BD.sol	2.429
6	V_GWHT.gw	12.336	18	V_SFTMP.bsn	−0.153
7	V_ESCO.hru	0.509	19	V_SMFMX.bsn	7.074
8	V_SLSUBBSN.hru	80.577	20	V_MFMN.bsn	18.158
9	V_CH_N2.rte	0.282	21	V_FIMP.urban.dat	0.238
10	V_CH_K2.rte	76.948	22	V_URBCOEF.urban.dat	0.509
11	V_CH_W2.rte	159.218	23	V_DIRTMX.urban.dat	1987.625
12	V_CH_D.rte	11.760			

(version 3.6.1) with the *glmnet* package (Friedman et al., 2010).

2.5.2. All subsets regression

Concentrations of FC will change significantly after rainfall events; therefore, the key landscape metrics influencing the event-scale FC concentration variation should be discussed. The computation of the FC concentration variation level, *Ra*, was based upon the following equation:

$$Ra = \frac{C_a}{C_b} \qquad (5)$$

where C_a and C_b correspond to the river FC concentration after and before a rainfall event, respectively.

The inherent diversity and complexity of landscape patterns requires diversity models to better understand how landscape patterns may influence the transport process of NPS-FC. All subsets regression provides all possible combinations of variable selection with different fitting performances. This method provides a variety of model selections. Thus, all subsets regression (Wasserman and Sudjianto, 1994) for samples that were collected before and after rainfall events were used to explore key landscape metrics to help explain *Ra*. All possible combinations of important landscape metrics for each independent multivariable regression technique were created, and the covariate coefficients were determined to be statistically significant. Data analysis was performed using Excel and R with the *glmulti* package (Calcagno and Claire, 2010).

3. Results

3.1. FC pollution in the beiyun watershed

The FC concentrations were calculated at 21 monitoring sites for global autocorrelation analysis using a GIS-based method. The results of this study, with a *Z*-score of 0.29 and a *P*-value of 0.77 (Fig. S13), showed that the pattern did not appear to be significantly different than that caused by random chance. Therefore, the arrangement of sampling sites in this study was reasonable.

According to two years of monitoring, the FC concentrations of 441 samples ranged from $20-3.50 \times 10^7$ MPN/L, 60.76% of which were greater than 1.00×10^5 MPN/L. Many studies have shown that fecal pollution may cause serious health risk to humans (Shibata and Solo-Gabriele, 2012; Corsi et al., 2016; Boehm et al., 2018; González-Saldía et al., 2019), and Shibata and Solo-Gabrieleet (2012) indicated that the enterovirus was 5−500 MPN/g in beach sand for a normal child with a risk level of 1.9×10^{-2}. González-Saldía et al. (2019) suggested that the monitoring area with FC concentration of more than 1.00×10^5 MPN/L resulted higher

health risk including ear ailments, gastrointestinal illness and symptoms of many illnesses. Therefore, if we take the FC concentration of 1.00×10^5 MPN/L as the pollution threshold, the pollution rate of river sections, which refers to the ratio of sample quantity over the threshold to the total samples, was between 10.05% and 100% (Fig. 4). The river sections in which more than half of the samples were above the threshold occurred at all urban patterns (P1−P5). The proportion of these river sections increased to 76.19% after the rainfall compared with a value of 28.57% before the rainfall event, and this change could increase the threat to human health.

3.2. Spatiotemporal dynamics of FC in the beiyun watershed

The monthly concentration of P1−P5 varied greatly during different spatiotemporal conditions from 10 to 1.00×10^6 MPN/L. As shown in Fig. 5, in most of the months, the samples collected from watershed regions of lower urban density (P1 and P5) had higher concentrations than those collected from regions with higher urban density. Incomplete sewage treatment facilities would be responsible for this phenomenon. Similar results were also obtained by Badgley et al. (2019), who analyzed FC samples collected from nine watersheds in southwestern Virginia, USA. This result illustrated different spatiotemporal changes compared with other water quality indicators, such as TN, TP and NO_3^-, in the Beiyun watershed (Liu et al., 2018). Furthermore, the FC concentration in the region of P3, which represented a higher urban density, was higher in the wet season (June to August shown in Fig. S2) than in the dry season. It was also slightly higher than that in urban-rural areas (P2 and P4) in the wet season. So, the NPS pollution caused by runoff may be responsible for this situation.

It should be noted that the FC concentration increased in April and May with less precipitation, which may have been due to the advance of the rainy season and the long antecedent dry days, according to the previous studies in which the runoff associated with rainfall was a driver of degraded water quality in receiving waters (Dila et al., 2018) and antecedent dry days increased the chance of pollutant accumulation (Nabiul Afrooz and Boehm, 2017). In addition, the whole watershed was highly polluted by FC in December and January. Studies have shown that the FC concentration was approximately 10 times higher in snowmelt runoff (Galfi et al., 2016; Dila et al., 2018), which corresponds to the snowy months of January and December in the Beiyun watershed. Consequently, the existence of FC in the dry seasons would be more complicated, indicating a detailed study should be carried out in the next step.

3.3. Influence of event-scale rainfall on FC concentration

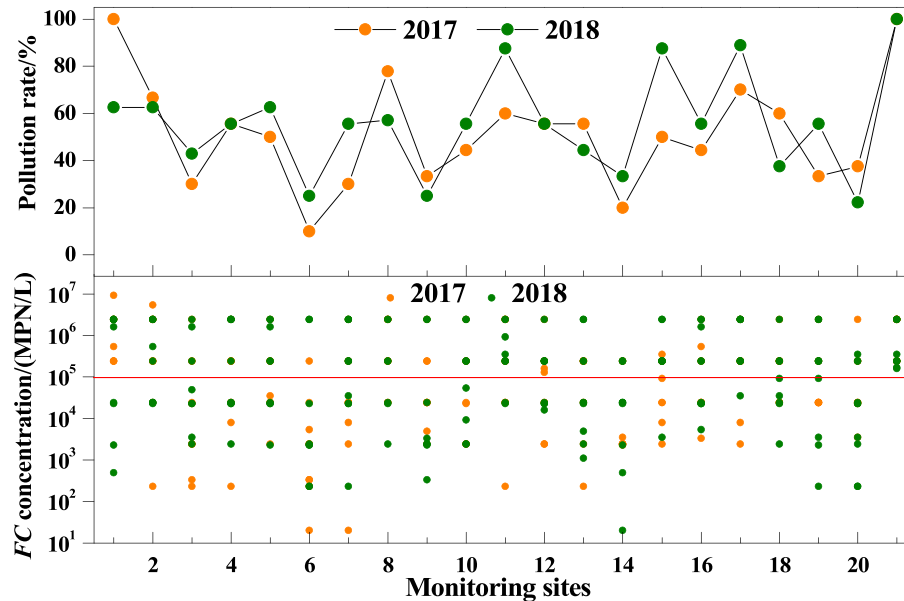The change in FC concentration before and after rainfall was

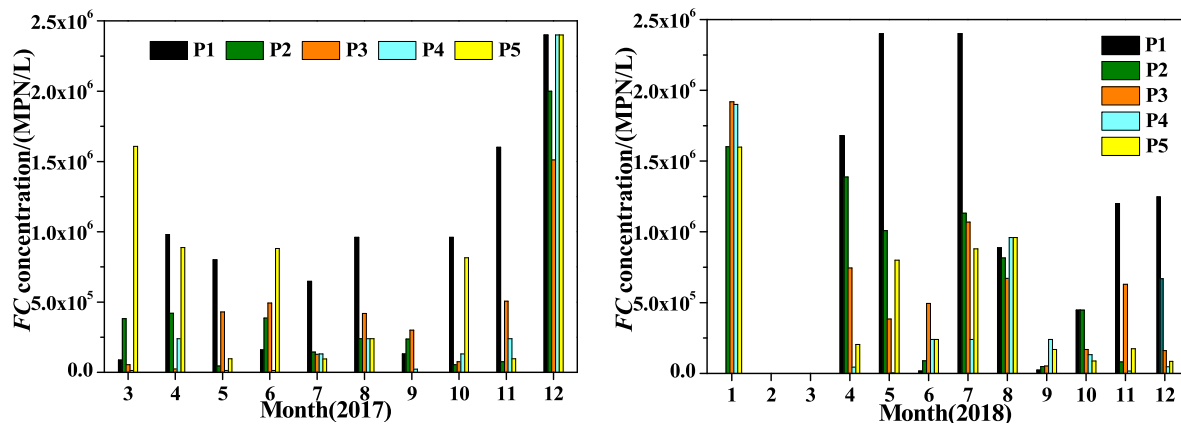**Fig. 4.** The monitoring result of *FC* in different river sections.

Fig. 5. Temporal characteristics of *FC* at different urbanization patterns (P1−P5 represent different urbanization patterns, and detailed description in Fig. 1).

analyzed to explore the response of FC concentration and rainfall runoff. As shown in Fig. 6, Ra values of 10−100 and 100−1000 were mainly concentrated in the areas with high urbanization level. Leight et al (2016) claimed that rainfall events larger than 1 inch tended to result in a significant increase in FC for the following two days. The large area of impermeable surface in urban areas is more conducive to FC entering the stream with stormwater runoff; thus, a higher Ra meant a quick and sensitive response to rainfall input in areas with a high urbanization level (P3). Ra values of 1−10 were mainly distributed along the lower Beiyun River (the regions of P4 and P5), which were urban-rural mixed areas and rural-cultivated dominated areas, respectively. However, the monitoring sites located at upstream exhibited different degrees of dilution, where the land-use types were dominated by forest. Forestland as a sink landscape can reduce NPS pollutants into water bodies, which supports the conclusion of a previous study in which the proportion of forest cover was negatively correlated with FC within a watershed (Mello et al., 2018).

4. Discussion

4.1. Environmental factors affecting FC concentration in different urban patterns

Lasso regression analysis was conducted between FC concentration (log-transformed) and environmental factors during the monitoring period, excluding December and January because of complications, and the regression was examined by cross validation (Figs. S14−S19). The spatiotemporal regression models are shown in Table 3. In this study, the FC concentration in the Beiyun River responded more actively to a combination of environmental factors, indicating that multiple environmental factors should be used to explain FC levels in water bodies. This result is consistent with previous studies (Thoe et al., 2014; Leight et al., 2016; Badgley et al., 2019; Wang and Deng, 2019). However, the temporal dynamics of FC in P3 failed due to other complex anthropogenic influences in the urban areas, particularly from the point source input. As shown
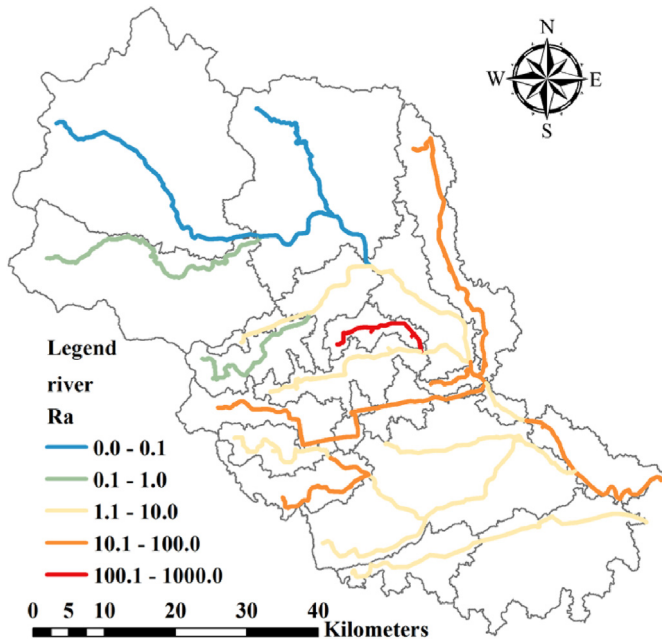
Fig. 6. Spatial dynamics of *FC* in long term and event-scale.

in Fig. S20, it was found that most failures in the regression models were consistent with the distribution and annual discharge of the wastewater treatment plants (WWTPs) in the Beiyun watershed. This result agrees with Boehm et al. (2018), who found that FC pollution in surface water will greatly increase due to the discharge of sewage water. It can be seen that the WWTPs with high discharge are mainly located in P3, indicating that point source discharge is another important source of FC pollution in this region. Consequently, this may be the main reason why FC cannot be explained by environmental factors in P3.

Furthermore, four environmental factors were selected for the models of P1, P4 and P5, while eight factors were selected for P2. It seems that the urban pattern of P2, which was characterized by a typical urban-rural mixed region, was undergoing a complex FC source situation. All of the models showed a positive correlation between FC and SS (Zimmer-Faust et al., 2018). Previous studies have also reported that SS was positively associated with FC concentration, indicating that suspended solid might be as a more suitable place to survive than in water (Fang et al., 2018). There is a

negative correlation between rainfall and FC concentration in P1, where the forest land accounted for a considerable proportion. Badgley et al. (2019) also found that natural forest negatively associated with FC. Interestingly, solar radiation was identified as another significant predictor of FC, having a negative association, which may mask the high concentration of FC caused by storm-water runoff in the wet season; this result may be especially true in April–June, which have the highest solar radiation (Fig. S6) and initial rainfall events that will bring numerous pollutants due to long antecedent dry days. The lower FC concentration during the months of September–November was mainly inhabited by living conditions, such as lower air temperature and water temperature (a positive correlation between FC and them). A previous study also showed that the optimal growth water temperatures of *E. coli* ranged from 25 °C to 37 °C (Noor et al., 2013).

For spatial regression, the annual averaging data from 21 catchments were analyzed. Table 2 shows the spatial regression model (M_S) with the factor selection process in Fig. S19. The spatial difference was mainly driven by the land use distribution that was used to distinguish different urban patterns. The spatial model in this study suggested that agricultural land, impervious land and industry were the dominant sources of the fecal pollution. This result is consistent with Crim et al. (2012), who focused on watersheds with different land uses in four countries. Unexpectedly, forest was identified as a significant factor with a positive correlation. In previous studies, forest was negatively associated with fecal pollution in surface water and has been suggested as a sink landscape (Vitro et al., 2017; Badgley et al., 2019), while only some studies, such as Smith et al. (2001), indicated a positive correlation. This may depend to a large extent on the characteristics of the watersheds, and for the studied urban watershed, the artificial forest is planted in the urban areas with a large amount of added fertilizer, which may be the source landscape of FC. Besides, population density and road density together represent the urbanization level but show opposite trends for the interpretation of FC. Roads are an important place for pollutant accumulation, while areas with high population density often have complete sewage treatment systems that reduce the discharge of FC in domestic sewage. Same conclusion was made by Vitro et al. (2017). Importantly, the sustained urban NPS caused by rapid urbanization may account for a considerable proportion of FC pollution (Bonkosky et al., 2009; Liao et al., 2015; Mattioli et al., 2017). The correlations between environmental factors and fecal pollution are expected to be conserved across watersheds with similar land-use patterns, although specific relationships may need to be

Table 3
Results of explanatory variables of regression models in Beiyun watershed (M_{P1}-M_{P5} represent the temporal regression models in different urbanization patterns, M_S is the spatial regression model).

M	Factors	Coefficient	M	Factors	Coefficient	M	Factors	Coefficient
Temporal regression at five urban patterns						Spatial regression		
M_{P1}	(Intercept)	14.81	M_{P2}	(Intercept)	−14.25	M_S	(Intercept)	−14.24
	pcp	−0.01		tem	0.38		road density	9.99×10^{-4}
	PH	−0.51		sr	−0.63		pop density	$−9.59 \times 10^{-5}$
	SS	0.09		pcp	0.03		agriculture	1.57×10^{-9}
	COD	0.09		O2	−0.34		forest	4.28×10^{-10}
M_{P3}				PH	2.88		grass	$−2.94 \times 10^{-8}$
				watertem	0.05		water	$−1.53 \times 10^{-7}$
				SS	0.10		impervious	9.40×10^{-10}
				COD	0.06		industry	9.30×10^{-9}
M_{P4}	(Intercept)	16.58	M_{P5}	(Intercept)	11.76		sr	−1.83
	sr	−0.05		pcp	0.003		SS	0.01
	pcp	0.006		O2	−0.09			
	PH	−0.71		SS	0.01			
	SS	0.04		COD	0.02			

recalibrated to more accurately explain fecal pollution and identify the main source.

4.2. Influence of landscape on FC concentration variation in urban areas

Due to the influence of point sources in urban areas, it failed to explain the temporal difference in FC by environmental factors. However, the river water quality was indeed affected by NPS, which has been confirmed by many researchers (Bonkosky et al., 2009; Chen et al., 2017). Fig. S21 also shows that there is a positive correlation between the monthly rainfall amount and the streamflow. Thus, a large amount of NPS pollution caused by rainfall runoff entered the river. Consequently, to explore the relationship between urban landscape pattern and NPS pollution, the FC concentration caused by NPS was calculated based on Eq. (4). The regression model is shown in Table 4, and cross validation is shown in Fig. S22.

As shown in Table 4, only one landscape variable, Patch density (PD), which reflects the degree of fragmentation of an area, was selected to explain NPS pollution of FC in urban areas. The model showed that the fragmentation of impervious surfaces could effectively reduce NPS-FC because of the negative correlation between FC_{NPS} and PDurban. Thus, in areas with high urbanization levels, reducing the connectivity of impervious surfaces can significantly decrease the NPS-FC. As a result, low impact development (LID) could be used as an effective measure to alleviate this problem (Ishaq et al., 2019; Li et al., 2019). However, numerous authors have observed that streambeds may be the bacterial reservoir for FC, which could be released during high-flow events (Garzio-Hadzick et al., 2010; Kim et al., 2010). At the same time, Kim et al. (2010) noted that streambed release could not be considered during rainfall events, as the stream would be dominated by surface runoff during that period, even at high streamflow. In this study, NPS-FC pollution at both seasonal and event scales was discussed without considering streambed release. Thus, an underestimation or overestimation of runoff impact may exist.

4.3. Key landscape metrics influencing event-scale FC concentration variation

The impact of landscape patterns on FC concentration distribution was explored at the rainfall event scale, as meteorological and water quality factors did not affect microbial growth during a rainfall event. Regression analysis was conducted with Ra values at 21 monitoring sites as the response variables. Fig. 7 exhibits the results of variable selection. All subsets regression for the best three models are reported in Table 5. Using these results, this study, for the first time, explained the spatial characteristics of NPS-FC in a complex watershed based on landscape metrics at the event scale. The variables of grassland, forest and water, which refer to the proportions of land-use types, showed negative effects on the NPS-FC, while impervious surface and cultivated land showed positive correlations. This result was also demonstrated in previous studies (Schoonover and Lockaby, 2006; Shen et al., 2014; Holcomb et al., 2018; Nel et al., 2018). In regions of P2 and P4, where urban-rural areas with medium levels of urbanization existed, the fragmentation of rural areas and forests as well as the complexity of

impervious surfaces and rural areas (characterized by PDrural, PDfor, LSIurban and LSIrural) explained the vulnerability of water bodies affected by NPS-FC pollution input. Moreover, the fragmentation of impervious surfaces (characterized by PDurban) could be an effective way to indicate NPS-FC based on the negative relationship between them.

Interestingly, by considering the spatial heterogeneity of forestland; the high-density forests (characterized by FOREST and LPIfor) located upstream showed a negative correlation with NPS-FC, while the fragmented forests located in urban areas showed a positive correlation with NPS-FC in the Beiyun River. The detailed classifications of forest land in remote sensing data were merged into one class in this study. However, the nurseries, orchards, and wetlands were distributed in areas other than upstream, and these land types require artificial maintenance and fertilization. Research conducted by Liu et al. (2018) in the Beiyun watershed also showed the spatial instability in the response of forestland to pollutants, indicating the importance of considering the detailed classification of land use. Our study expounded the terrestrial transmission process of FC from the perspective of landscape patterns, which will be more targeted for FC management.

4.4. Management implications

FC reproduction under suitable environmental conditions seems to be one of the primary causes for its pollution, during which urbanization levels provided significant differences. Therefore, water management strategies in complex watersheds should be reconsidered based on more detailed characteristics so that managers might identify the best policy decisions for regional watershed management. Variables that are driven by natural forces are difficult to change, but the impact of SS and landscape may be altered by the thoughtful design of city planning and runoff management facilities. For instance, in this study, controlling SS can effectively reduce FC because of the strong correlation between them in different urban patterns. However, more factors should be considered in urban areas. Kim et al. (2010) indicated that turbidity might be the best indicator of fecal pollution at low streamflow. Thus, the combination of source and process control realized by LID may effectively relieve fecal pollution in water bodies (Fletcher et al., 2015). Few studies have reported that macrophyte roots provide a larger surface area for microbe removal in water (Shingare et al., 2019). Specifically, the control of pollutant build-up and wash-off processes on roads and the restoration of the ecological function of water bodies would be a long-term strategy for FC management (Jeon et al., 2019).

A better understanding of the relationships between NPS-FC and landscape patterns will help integrate NPS-FC management into LID process and help with water quality improvements in the future. The study of the correlation between NPS-FC and landscape patterns showed that FC can be improved by reducing the connectivity of impervious surfaces with grasslands. For example, Ra will decrease by 5−10 times with a doubled level of fragmentation of impervious land according to the all subsets regression. It is especially true in areas with high urbanization levels that the NPS concentration of FC decreased exponentially with the increase in fragmentation of impervious surface. In addition, the forestland affected by human activities should be considered due to its spatial instability. Future site-specific work is needed to track the sources of FC at different urban levels and explore the efficiency of LID facilities on FC. The results from the current study provide key information that may be helpful for complex watershed management.

Table 4
Landscape variables used to explain NPS pollution in urban area.

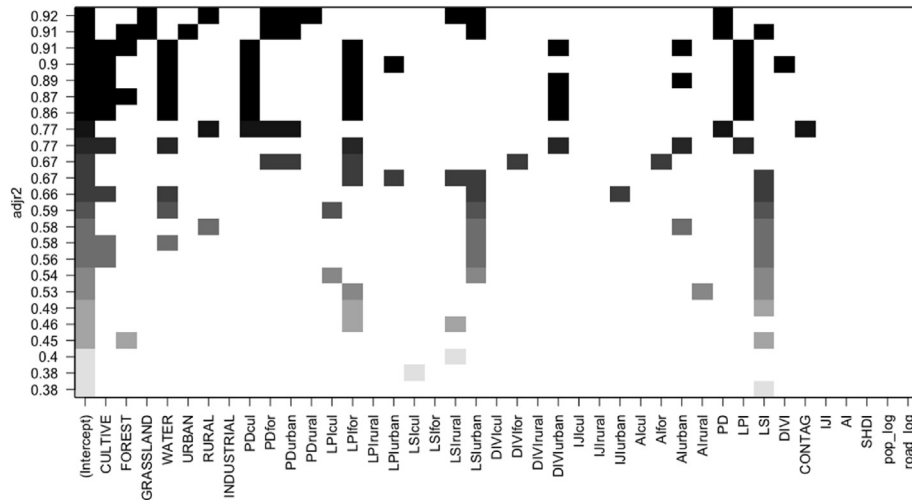| Response variable	Explanatory variable	Coefficient	Intercept
Ln (FC_{NPS})	PDurban	−13.18	14.22

Fig. 7. The best combination to explain *FC* concentration change in event-scale.

Table 5
Results of all subsets regression analysis for Ra (only the first three models were included).

Response variable	Coeff	Explanatory variable	Response variable	Coeff	Explanatory variable
Ra	−0.69	(Intercept)	Ra	−34.72	(Intercept)
	−0.57	GRASSLAND		0.28	CULTIVE [c]
	0.44	RURAL		−0.12	FOREST
	28.35	PDfor		−2.33	WATER
	−72.59	PDurban		23.84	PDcul [d]
	33.47	PDrural		−0.52	LPIfor
	0.59	LSIrural		−38.44	DIVIurban
	0.98	LSIurban		0.04	Alurban
	−22.88	PD		0.31	LPI
Ra	34.39	(Intercept)			
	−0.26	FOREST			
	−0.61	GRASSLAND			
	0.32	URBAN [a]			
	26.25	PDfor [b]			
	−46.81	PDurban			
	1.50	LSIurban			
	−16.42	PD			
	−1.40	LSI			

[a] "URBAN" refers to impervious surface; [b] "for" refers to forest land; [c, d] "CLUTIVE" and "CUL" refer to cultivated land.

5. Conclusion

The present study reports the dynamics and influencing factors of river fecal coliform collected from 21 sampling sites with 5 urban patterns over a period of two years. The introduction of urban patterns coupled with landscape metrics allowed the targeted and accurate prediction of spatiotemporal dynamic characteristics.

Despite high serious FC pollution occurred in all urban patterns, relatively high monthly concentrations were found in P1 and P5, where high-density villages are located. Rainfall events increased the polluted river sections by 47.62%, and *Ra* values of 10−100 and 100−1000 were mainly concentrated in the areas with high urbanization levels. In addition, the prediction models between FC concentration and environmental factors could be highly variable depending on urbanization levels. Regression analyses revealed that controlling SS can effectively reduce FC because of the strong correlation between them in different urban patterns, while more factors should be considered in urban. As such, future prediction of fecal pollution may require an urbanization context rather than a universal situation. Both the event-scale and seasonal-scale regression analyses showed that key landscape metrics could successfully explain the NPS-FC in a complex watershed. Reducing the connectivity of impervious surfaces in urban areas can be an effective measure to control NPS pollution of FC. This will aid in management strategies of optimal landscape planning for restoration of water quality.

It is noteworthy that the NPS-FC concentration calculated in this study contains some possible uncertainties. The NPS-FC concentration was calculated without considering streambed release. Thus, an underestimation or overestimation of runoff impact may exist. More efforts are needed to obtain more data to analyze the key influencing factors of river FC within a typical complex watershed.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.watres.2020.115835.

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