Land use and landscape pattern impacts on water quality at multiple spatial scales in a subtropical large river

Xiao Shu (✉ shuxiao198259420@sina.com)

Wuhan Botanical Garden

Weibo Wang

Wuhan Botanical Garden

Mingyong Zhu

JiaYing University

Jilei Xu

Wuhan Botanical Garden

Xiang Tan

Wuhan Botanical Garden

Quanfa Zhang

Wuhan Botanical Garden

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Abstract

The coupling between land use/landscape pattern and water quality in river system varies across different spatial and temporal scales. It is important to understand the association between water quality and land use/landscape pattern across different spatial and temporal scales for the protection of water resources. Here, we measured seasonal water quality at 12 sub-basins in the upper reaches of the Han River (UHR) between 2010 and 2018. We conducted factor analysis and redundancy analysis to determine the links between land use and water quality at multiple spatial scales and to identify the main factors influencing water quality. We found that the concentration of nutrients, including total nitrogen, total phosphorus, nitrate-N, and ammonium-N were higher during the wet season than the dry season. Total nitrogen was identified as the main driver of nutrient pollution of UHR, whereas total phosphorus was identified as another potential nutrient pollutant. We also found that water quality parameters had a stronger related to land use types over the wet season than the dry season. Croplands and urban lands increased phosphorus concentrations of river water, whereas forest and grass lands decreased the nitrogen concentrations of river water at the sub-basins scale. Land use at riparian zone scales better explained variations in water quality than land use at sub-basin scales. The explained variations in landscape metrics were generally higher over the dry season compared to that over the wet season. The largest patch index and Shannon's diversity index were the main predictors of river water quality in UHR.

Introduction

Water quality is important for habitat conservation, agriculture, and industry (Zhang et al. 2019). Increased nutrient concentrations (nitrogen and phosphorus) can lead to serious degradation of water quality in aquatic ecosystems. The degradation of water quality has become an important challenge globally (de Mello et al. 2018; Zhang et al. 2020). The management of nitrogen and phosphorus inputs into water resources is particularly important to prevent eutrophication. The increasing nutrition concentrations in rivers are mainly due to numerous natural and anthropogenic activities, such as erosion, weathering, atmospheric deposition, and domestic and industrial effluents (Bu et al. 2014; Zhang et al. 2020). Previous studies have demonstrated that spatial and temporal variations also have strong effects on nutrition concentrations in river water (Li et al. 2012; Wijesiri et al. 2018; Zhang et al. 2020).

The assessment of the spatial and temporal variation in water quality variables at the basin scale and the identification of the drivers of these variations have become particularly important because of the heterogeneity, regionality, and seasonality of water quality in rivers. Spatial variations of water quality depend on land use patterns (Zhang et al. 2019). Past research has demonstrated that there can be a strong association between water quality and land use or land cover (de Mello et al. 2018; Zhang et al. 2020), including grassland, forest, bare lands, agricultural, industrial, and urban land cover types (Ding et al. 2016; Zhang et al. 2020). The agricultural, industrial, and urban land use strongly influences nutrient concentrations (N and P) and organic pollution in rivers. The excess application of inorganic fertilizers in agricultural areas along with soil erosion has resulted in the high loading of nutrients into water bodies (Li et al. 2009; Bu et al. 2014). Organic pollutants, such as heavy metals and nutrients, are associated

with industrial and urban land uses (Bu et al. 2014; Yuan et al. 2017). However, vegetation plays a key role in filtering pollutants, sediments, and nutrients, and in reducing soil erosion. Therefore, forest and grasslands are important for preventing or reducing water quality degradation (Zhang et al. 2019). Further information on the links between land use and water quality in a watershed is crucial for effective management of water quality. Therefore, continuous long-term research on the relationship between land use and water quality in a water basin is necessary.

The correlations between water quality status and land use differ across different spatial and temporal scales. While previous research has demonstrated correlations between water quality and land use, these relationships have varied widely. For instance, some studies have shown a link between land use types at the riparian-zone scale and water quality to be stronger than land use at the basin scale (Shen et al. 2015), other studies have shown the opposite (Ding et al. 2016; de Mello et al. 2018; Zhang et al. 2019, 2020). The inconsistencies in these results are likely due to differences in locations of sampling sites. The reason may also be derived from differences in experimental design. Moreover, riverine water quality has been shown to be closely associated with both the land use and the spatial configurations of forest, agricultural, and urban areas (Bu et al. 2014). Thus, the quantification of the impact of different land use configurations and scales on water quality is required for the improvement of water resource management. Technological advancements in geographic information systems and remote sensing have facilitated the use of land use metrics in the quantification of land use structures (Li et al. 2012; Huang et al. 2016; Zhang et al. 2019). Previous research has demonstrated that land use metrics such as patch density, aggregation and diversity, landscape shape, and largest patch indices are strongly linked with water quality variation (Shen et al. 2015; Zhang et al. 2020).

The upper Han River is an important water supply for North China, including to the cities of Beijing and Tianjin, via the Middle Route of the South-to-North Water Division Project, which transfers 14 billion m³ of water per year. Therefore, management of water quality of the upper Han River (UHR) is crucial for socio-economic development. There have been many studies on the water quality challenges in the UHR (Li et al. 2009, 2012; Li and Zhang 2010). Anthropogenic development has dramatically increased pollution loading into the UHR, causing the upper Han River to become a highly-polluted tributary that feeds the Yangtze River (Li et al. 2009; Müller et al. 2012). However, there is a lack of knowledge of the long-term spatial and temporal water quality variations within the UHR and the relationship between water quality variations and patterns of land use at multiple spatial scales. Moreover, the extent to which pollution degrades water quality is also not very clear. Both the public and government sectors have been increasingly interested in the water quality of the basin. Therefore, our objectives for our study were to: (1) identify the long-term temporal water quality variability of the UHR; (2) identify the main factors affecting water quality in the river and streams; and (3) quantify the correlations between patterns of land use and variation in water quality variables for different land use scales. Our results can assist in the development of water resource management strategies and conservation policies for the inter-basin water transfer project.

Materials And Methods

Study area

The Han River is the biggest tributary feeding the Yangtze River in China. The upper reaches of the Han River [31°20'–34°10' N, 106°–112° E; 210 m–3,500 m above sea level (a.s.l)] are situated in a mountainous region with a drainage area of 95,200 km² and the river has a length of 925 km (Li et al., 2009, 2012). The UHR falls into the subtropical humid climate zone with an average annual temperature of 14 °C, and with lowest and highest temperatures of –13 °C and 43 °C, respectively. Annual precipitation ranges between 800 mm – 1,250 mm with an uneven spatial distribution, and 70%–80% of rainfall is concentrated during the wet season from May to October (Li and Zhang 2008; Li et al. 2012). The mean annual runoff of the UHR is 41.1×10^9 m³, which accounts for 70% of total basin runoff, and has a large seasonal variability (Jin and Guo 1993; Yang et al. 1997). The Danjiangkou Reservoir marks the outlet of the UHR, with the dam regarded as the most important water infrastructure in the Han River basin as the South to North Water Transfer Project starts from this reservoir (Jin and Guo 1993; Li et al. 2017).

Forests are the dominate land cover type in the UHR basin, accounting for 80% of the total basin area, and include deciduous, mixed deciduous and evergreen, and evergreen and sub-alpine meadow forests (Yang et al. 1997; Li and Zhang 2008; Li et al. 2009). Agriculture and urban areas constitute approximately 16% and 1.8% of the total area of the UHR basin, respectively. As one moves from the headwaters to the Danjiangkou Reservoir along the river network, the river starts in the Hanzhong Plain, the Ankang Plain constitutes the middle section, and the industrial center of the UHR basin is in the region of the Danjiangkou Reservoir (Shen and Liu 1998; Li et al. 2009, 2010). Large cities, including Danjiangkou, Ankang, and Hanzhong, are located along the Han River corridor.

Water sampling and analysis

A total of 240 grab samples were collected from 24 sites of 12 sub-basins of the UHR during the years 2010 to 2018. Figure 1 showing that the position of sampling sites in the UHR. Water samples were collected in the months of January and July. The sampling was timed to capture seasonal variability, with January representing the dry season and July representing the wet season. High-density polyethylene sample bottles (3 L) were submerged in nitric acid for 48 h and then rinsed twice with distilled water before use. The sample bottles were used to collect water samples from a depth of 0.2 m. Upon returning to the laboratory, samples were immediately stored in the dark at 4 °C for analysis the following day.

Hydro chemical variables, including electrical conductivity (EC), pH, oxidation-reduction potential (ORP) and dissolved oxygen (DO) were measured *in situ* using a portable multi-meter (YSI 6620, Yellow Springs, USA). Total phosphorus (TP), total nitrogen (TN), nitrate-nitrogen (NO₃⁻-N) and ammonium-nitrogen (NH₄⁺-N) were measured following standard methods (SEPA, 2002) for examining water and wastewater that are accepted worldwide (Bu et al. 2010, 2014).

Land use and landscape pattern analysis

A method of supervised classification utilizing a support vector machine (SVM) was used to classify land uses in the ENVI 5.1 software. Land use in the UHR basin was mapped using imagery captured by the Landsat Thematic Mapper (30 m resolution) in 2018. The overall classification accuracy and kappa coefficient were 87.1% and 0.82, respectively. Six classes of land use were utilized, namely croplands, forest land, grassland, water bodies, bare land, and urban land. The proportions of different land use classes were represented as percentages of total land area. The sampling sites were distributed in different rivers of the UHR basin. To study the effect of land use on river water quality at multiple spatial scales, twelve rivers (R1-R12) were studied, which are distributed in different sub-basins (C1-C12) of the UHRB (Fig. 1). We investigated land use at three spatial scales: (1) 500 m buffer; (2) 1000 m; and (3) the sub-basins (Fig.1). The buffer zones were delineated using ArcGIS9.3 and a digital elevation model (DEM) was used to calculate land use metrics (Fig. 1). Landscape pattern (land use structure) was quantified using the following metrics: patch number (NP), total area (TA), patch density (PD), edge density (ED), largest patch index (LPI), and Shannon's diversity index (SHDI). More information on these metrics is detailed in Huang et al. (2016) and Shi et al. (2017). We used FRAGSTATS V4.2.1 software to calculate these metrics.

Statistical analyses

We used variance analysis and other multivariate statistics. ANOVA (analysis of variance) was utilized to identify spatial and temporal differences in water quality variables at a level of significance of $p < 0.05$. Linkages between a single water quality variable and land use/landscape pattern variables were identified using stepwise regression modeling based on the p values (Ding et al. 2016; Zhang et al. 2020). Pollution factors affecting water quality were identified using factor analysis (FA) (Bu et al. 2014). The adequacy of the sampling data for FA was assessed using the Kaiser-Meyer-Olkin test. The correlations between land use/landscape pattern and water quality variables were identified using redundancy analysis (RDA) (de Mello et al. 2018; Zhang et al. 2019). In the RDA analysis, land use/landscape pattern and water quality variables were utilized as environmental variables and species, respectively (de Mello et al. 2018). We used SPSS 18.0 (IBM Company, USA) to conduct statistical analyses whereas RDA was carried out using the CANOCO 5.0 software package (Microcomputer Power Company, USA).

Results

Spatial and temporal variation in water quality

Fig. 2 shows the spatial and temporal variations in water quality. Water quality variables had strong seasonal patterns. DO levels were higher during the dry season, whereas the concentrations of ORP, TP, TN, $\text{NH}_4^+\text{-N}$, and $\text{NO}_3^-\text{-N}$ were elevated during the wet season. The maximum and minimum observed levels of water quality variables over the study occurred in different years for different variables. For example, the peaks in EC and TN occurred in 2010 and 2018, respectively, whereas ORP, $\text{NH}_4^+\text{-N}$, and TP

peaked in 2016, and DO and pH peaked in 2014. There was a significant positive correlation between time (year) and TN ($R = 0.79$, $p < 0.05$) during the wet season. All water quality variables, except for OPR, had clear spatial variability (Fig. 2). The lowest concentrations of TN, TP, and $\text{NH}_4^+\text{-N}$ occurred at site 19 during the dry season. Site 17 had the lowest concentrations of TN and $\text{NO}_3^-\text{-N}$, which occurred during the wet season. Sites 2, 3, and 4 had elevated values of TN, TP, and $\text{NO}_3^-\text{-N}$.

Factor analysis of water physical and chemical variables

The Kaiser-Meyer-Olkin test yielded a result of 0.69 ($p < 0.001$), which indicated that FA could effectively reduce dimensionality. Factor analysis of the water quality variables identified four components that together accounted for >70% of total variance. Factor 1 reflected the nitrogen and phosphorus pollution level of river water due to the elevated loadings of TP, TN, and $\text{NO}_3^-\text{-N}$. Factor 2 reflected the acidity or alkalinity of river water as high pH loadings (Table S1). Sampling sites 1, 2, 3, 4, and 24 had significantly higher factor scores compared to the other sampling sites (Fig. S1).

Land use and land cover of the UHR basin

The land use types (e.g. forest, urban, and croplands) differed significantly among the buffer zones and sub-basins. Forest was the dominate land cover type of the sub-basins and constituted between 30.92% (in R6) to 93.15% (in R12) of the total land area (Table 1). The mean value of the percentage of forest area within each buffer zone lower relative to the percentage of forest area within their sub-basins, with the lowest value being for the 1000 m buffer zone. Croplands was the second most important land use, and comprised between 4.81% (R11, 500 m buffer) to 67.29% (R6, 500 m buffer) of land use area (Table 1). As shown in Table 1, R6 had the highest proportion of urban land cover across all spatial scales. Overall, croplands and urban land respectively accounted for 57.99% and 10.30% of the land cover at the sub-basins scale, 67.29% and 27.39% in the 500 m buffer zones, and 65.73% and 28.95% in the 1000 m buffer zones. Grassland was the smallest proportion of land cover in R6 and R7 (0%) but was largest proportion of land cover (2.14%) in the R10 500 m buffer zone (Table 1). Water bodies showed extensive distributions from 0.12% (R3) to 16.31% (R11). The proportion of bare land was relatively low, reflecting the existence of a little amount of undeveloped land within this area.

Landscape pattern of the UHR basin

The 12 sub-basins (C1-C12) also had large variations in landscape metrics (Fig. 3). The levels of TA ($9.56 \times 10^5 \text{ km}^2$) and NP (3.22×10^4) were the highest and lowest in C1 and C11, respectively. The levels of PD (8.24 n/km^2), ED (49.46 m/ha^1), and SHDI (0.79) were the highest and lowest in C1 and C12, respectively. The landscape metric results indicated that PD, ED, and SHDI tended to vary similarly from C1 to C12. LPI was highest in C12 (92.92%) and lowest in C1 (31.45%).

Correlations between land use and water quality

Our RDA results demonstrated that there were seasonal differences in the effect of land use types on water quality variables (Fig. 4). The levels of explained variation were generally higher over the wet season compared to the dry season (Table 2). The predictors explained 76.2% of the variation for the 1000 m buffer zone during the wet season. However, the explanatory ability was lower at the sub-basins (63.6%). The variation in water quality was better explained by all axes for the 500 m buffer zone compared to the 1000 m buffer zone and the sub-basins scale over the dry season (Table 3). Urban land was the most important explanatory variable (18.8% – 20.6%) for the buffer zones and at the sub-basins scale during the wet season, whereas the most important variables explaining water quality during the dry season were grassland (22.6%), bare land (18.2%), and water bodies (11.5%) for the sub-basins, 500 m buffer zone, and 1000 m buffer zone, respectively.

Our RDA and stepwise regression modeling (SRM) analysis showed the relationships between the variation in water quality variables and land use types (Fig. 4, Table 3). For the sub-basins scale, TN had a positive related to the proportion of water bodies. TN was positively related to urban land and was negatively related to forest during the dry season. The NO_3^- -N and TP had a positive related to proportion of croplands during the wet season. The NO_3^- -N and TN had a positive and negative related to proportion of grassland, respectively. The TP and TN had a positive related to proportion of bare land during the dry and wet seasons, respectively. In the 500 m buffer zone, the TN was positively related to proportion of grassland and croplands during the dry season. The NO_3^- -N and TP had a positive related to proportion of croplands during the wet season. Croplands had a positive association with TN, EC, and TP, and had a negative association with ORP in the 1000 m buffer zone over the dry season. The proportion of croplands was positively associated with NO_3^- -N and TP, and was negatively associated with TN in the 1000 m buffer zone over the wet season.

Correlations between landscape pattern and water quality

Fig. 5 and Table S3 show ordination diagrams from RDA using sub-basins scale landscape metrics and water quality variables. The levels of explained variation were generally higher over the dry season compared to the wet season. LPI was the most important variable (22.5%) explaining water quality at the sub-basins scale over the dry season, whereas SHDI was the most important variable (15.6%) explaining water quality over the wet season (Table S3). For landscape metrics, TN and EC had positive related to ED, PD, NP, and TA, and negative related to LPI at the sub-basins scale during the dry season. ED and SHDI had positive association with TP, NO_3^- -N, and NH_4^+ -N, and negative association with TN at the sub-basins scale during the wet season. PD had a positive association with EC at the sub-basins scale during the wet season.

Discussion

Spatial and temporal variations and assessment of water quality

The seasonal variability of nutrients concentrations in rivers are largely driven by natural processes, such as runoff and soil erosion, as well as by anthropogenic activity (Li et al. 2008; Bu et al. 2010; Zhang et al. 2020). DO levels were elevated during the dry season (Fig. 2), and colder water generally has higher DO. We suspect that eutrophication during the wet season was responsible for the lower DO. Nutrients, such as TP, TN, $\text{NH}_4^+\text{-N}$, and $\text{NO}_3^-\text{-N}$, had higher concentrations during the wet season compared to during the dry season (Fig. 2), which was consistent with the results reported by some previous studies (Li et al. 2008). We found that diffuse inputs of nutrients from rainfall-runoff from urban areas and farmland contributed to elevated nutrient concentrations in the UHR basin. The inter-annual variations in water quality (Fig. 2) were largely due to increases in point source pollution and human activities in the basin. The overall TN concentrations have increased since 2010, which can be attributed to population growth and economic development in the Han River basin. The UHR basin encompasses a large area containing a wide variety of land-use types (e.g., farmland, forest, grassland, and urban land). Thus, it was expected that there would be spatial variability in water quality in the UHR basin. The factor scores derived through factor analysis were used as indicators of pollution sources in the river system. In our study, the sampling sites 1, 2, 3, 4, and 24 had higher factor scores, which indicated that the pollution sources mainly come from the sampling sites (Fig. S1; Table S1). The sampling sites had poor water quality, which demonstrated the influence of domestic sewage discharge from the cities of Shangluo, Nanyang, and Shiyan. Sampling sites 17 to 19, however, had lower factor scores, which suggested the water was less polluted. Sites 17 to 19 could be regarded as unimpacted by anthropogenic influences as they were situated in the Jinshui River basin, which is characterized by extensive forest cover with limited human activity. Thus, the water quality at these sites was optimal.

According to national and international guidelines (NEPB 2002; Table S2), and our factor analysis of water quality (Table S1), we assessed water quality of the UHRB during the wet and dry seasons. The TN concentrations of 4.17%, 41.67%, and 54.17% of the sampling sites during the dry season were of grade III, IV, and V, respectively. Most of the sampling sites (87.5%) had TP concentrations of grade II, whereas 12.5% of sampling sites were of grade III. All sampling sites had $\text{NH}_4^+\text{-N}$ concentrations of grade II, whereas the DO concentrations of most sampling sites (95.83%) were grade I, and 4.17% of the sampling sites were grade II (Table S2; Figs. S2; NEPB, 2002). During the wet season, the TP concentrations of 4.17%, 41.67%, 45.83%, 4.17%, and 4.17% of the sampling sites were grade I, II, III, IV, and V, respectively. (Table S2; Figs. S3; NEPB 2002). The water quality variables that failed to meet the Chinese State Standard (CSS) were TN and TP, with TN being the most important indicator. Thus, we identified TN as the key factor driving water quality impairment in the UHR basin, and we identified TP as a potential nutrient pollutant. Our results indicated that controlling TN could effectively improve the water quality in the UHR basin.

Impact of land use on water quality

The degradation of water quality is related to the proportion of croplands and urban land (Bu et al. 2014; Ding et al. 2016; Zhang et al. 2020). We found that urban and cropland is detrimental to water quality at the sub-basins scale (Fig. 4, Table S3). Our results agreed with some previous studies (Shi et al. 2017;

Zhang et al. 2019). The poor water quality might be a result of the excess use of pesticides and fertilizers on croplands in the UHR basin, and nutrients in croplands runoff can accelerate eutrophication in surface water bodies. The water quality variables (e.g. TN, NO_3^- -N and NH_4^+ -N) had a positive related to proportion of urban land at the sub-basins scale (Fig. 4, Table S3). Our results are supported by previous studies that found positive correlations between river water nitrogen and urban land use patterns (Ding et al. 2016). Pollutants and effluent in urban areas are transported to river systems through runoff over impervious surfaces, thereby adversely impacting riverine water quality during rainfall events. However, our RDA and SRM results demonstrated that the TP concentration did have a negative related to proportion of urban land, which was in contrast to some previous studies that found positive relationships with some water quality variables in the 500 m and 1000 m buffer zones during the dry season. This contrasting result could possibly be explained by the croplands types and there being less rainfall during our sampling time.

The good water quality had positive correlations with forest and grassland proportions (Ding et al. 2016; Huang et al. 2016; Zhang et al. 2020). Vegetation, such as forest and grassland, has been identified as major factor in mitigating degradation of water quality (Shi et al. 2017; Zhang et al. 2019). We found that the forest and grassland was negatively associated with TN at the sub-basins scale during the wet season (Fig. 4, Table S3). Our results could be attributed to a reduction in soil erosion, nutrient assimilation, and absorption. Therefore, the locations and proportions of vegetation-type land cover categories should be considered for sustainable management (Liu et al. 2018). However, the proportion of grassland had a positive association with TN in the 500 m buffer zone and at the sub-basins scale during the dry season, which was likely due to the relatively small amount of runoff and a lot of detritus being deposited directly into the river during the dry season. Some water quality variables, such as TN, were positively correlated with the proportion of water bodies. Water bodies have large surface-volume ratios and can therefore facilitate the removal of some nutrients through nitrification and absorption to sediment (Zhang et al. 2020). TN and TP was positively related to bare land (Fig. 4, Table S3), which indicated the natural contribution of nutrients through rock weathering.

Influence of landscape pattern on water quality

The landscape pattern also played an important role in the mediation of ecological processes, such as energy flows and nutrient cycles, and can adjust their effects on water quality (Bu et al. 2014; Ding et al. 2016; Zhang et al. 2020). A “patch” is defined as an area with relatively homogeneous land cover, such as patches of forest or grassland (Lee et al. 2009). TA was found to be related to basin area and NP was correlated with the degree of fragmentation of a basin (Zhang et al. 2019). We found that TN and EC were positively associated with NP and TA at the sub-basins scale during the dry season (Fig. 5; Table S4). There was a positive correlation between TA and areas of land use categories associated with human impacts. Thus, elevated TA levels contributed to nutrient loading. PD represents the number of corresponding patches divided by total area (Ding et al. 2016). ED is total length of all edge segments per unit area for the landscape (Huang et al., 2016). The high values of these metrics indicated abundant land use and elevated fragmentation, which might result in increased surface runoff and soil erosion.

Therefore, higher PD represents degraded water quality and is unfavorable for managing pollutant migration (Shi et al. 2017; Zhang et al. 2019). PD and ED were positively associated with TN and EC at the sub-basins scale in the dry season (Fig. 5; Table S4). Huang et al. (2016) similarly identified positive correlations between certain water quality variables, including EC and TN, with PD. SHDI represents the diversity of patches within a basin (Zhang et al. 2019). Degraded water quality was positively correlated with SHDI. Increased TP, $\text{NH}_4^+\text{-N}$, and $\text{NO}_3^-\text{-N}$ were related to higher SHDI values during the wet season (Fig. 5). In contrast, LPI was negatively associated with TN in the dry season and TP in the wet season (Fig. 5). LPI represents the largest area of a particular patch type divided by total area. Our results indicated that forest was the dominant land cover type and large forest patches played a role in ameliorating water pollution by filtering pollutants and nutrients. Thus, the dominance of forest was associated with high-quality water.

Impact of spatial and temporal scales on the water quality variation

Our RDA showed that the impact of land use types and landscape metrics on the water quality variables had significant seasonal variability. Similar findings have been reported in previous research (Ding et al. 2016). The water quality had a stronger link to land use types during the wet season compared to over the dry season (Table 2), which was consistent with previous reports (Shi et al. 2017). This linkage can be explained by the runoff of fertilizer and domestic sewage from croplands or urban land into rivers during the wet season, which results in water quality degradation. Therefore, the effects of land use types on water quality were more distinct over the wet season. However, other studies have found the opposite (Zhang et al. 2019). These different results are likely to be attributed to differences in basin topography, farming practices, human activities, and land use. In contrast, the explained variations of landscape metrics were generally higher in the dry season than in the wet season (Table S3). The most important factors explaining water quality over the dry and wet seasons were LPI and SHDI, respectively.

Scale dependency was evident in the influence of land use types on water quality (Table 3). We found that land cover within the 500 m and 1000 m buffer zones better explained variations in water quality than land cover at the sub-basins scale (Table 2). Thus, more attention should be placed on land management within riparian buffer zones. Shi et al. (2017) found that riparian land use had a larger effect on water quality than land use at larger spatial scales, but the opposite conclusion has been made in other studies (Ding et al. 2016; Zhang et al. 2019). These conflicting reports are likely to be attributed to differences in regional characteristics. However, different land use types had different scale effects. In our study, water quality had strong related to forest and grassland at larger scales (Table 2). Croplands, water bodies, urban land, and bare land within the buffer zones had high association with water quality (Table 2).

Conclusions

Riverine water quality in the UHR has significant spatial and temporal variations. We found that nitrogen was the key factor impairing water quality of the UHR, and phosphorus was a potential pollutant. Our

results indicated that controlling TN could effectively improve the water quality in the UHR. We found water quality to be poor at sites 1, 2, 3, 4, and 24, likely due to domestic sewage discharge from the cities of Shangluo, Nanyang, and Shiyan. RDA showed that that croplands and urban land was detrimental to water quality at the sub-basins scale. The forest and grassland were negatively associated with TN at the sub-basins scale during the wet season. The water quality was strongly linked to land use types over the wet season. In contrast, the explained variations of landscape metrics (e.g. LPI and SHDI) were in general higher during the dry season compared to the wet season. RDA showed that land cover type in the 500 m and 1000 m buffer zones better explained variations in water quality than land cover at the sub-basins scale. However, different land use metrics had different impacts at different spatial scales. Forest and grassland had higher association with water quality at larger scales. Croplands, water bodies, urban land, and bare land within the buffer zones had high association with water quality. Results of the study can provide key information for water quality conservation and land use planning at multiple scales.

Declarations

Acknowledgments

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Authorship contribution statement

Conception and design of study: SX and TX; Acquisition of data: ZM, XJ and WW; Analysis: SX and ZM; Drafting the manuscript: SX; Revising the manuscript critically for important improvement: TX and ZQ.

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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.

Data Availability

Some data and the generated code in the study are available by request from the corresponding author.

Ethics declarations:

Ethical Approval

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

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Tables

Table 1 The proportions of land use types within the 500 m buffer zone, 1000m buffer zone, and at the sub-basin scale in UHR basin, China.

Scale	River	Forest (%)	Grassland (%)	Cropland (%)	Urban (%)	Waters area (%)	Bare land (%)
Sub-basin	R1	73.30	0.61	23.35	1.79	0.83	0.12
	R2	74.21	0.99	20.41	3.80	0.49	0.11
	R3	89.34	0.34	9.37	0.71	0.21	0.03
	R4	75.68	0.00	21.37	2.60	0.20	0.05
	R5	81.03	0.97	16.01	1.36	0.59	0.03
	R6	30.92	0.00	57.99	10.30	0.78	0.00
	R7	77.99	0.00	19.90	1.77	0.29	0.06
	R8	86.46	0.33	11.56	1.24	0.31	0.09
	R9	92.32	0.36	6.51	0.50	0.27	0.04
	R10	85.60	0.36	10.97	1.99	0.91	0.17
	R11	81.77	0.05	7.18	8.86	1.93	0.22
	R12	93.15	0.14	5.71	0.17	0.79	0.04
500m buffer	R1	58.73	1.51	36.42	2.79	0.35	0.20
	R2	57.39	0.98	35.27	5.38	0.77	0.21
	R3	85.66	0.00	10.01	4.21	0.13	0.00
	R4	68.46	0.00	21.55	9.64	0.35	0.00
	R5	64.75	1.37	22.64	5.08	6.02	0.13
	R6	0.77	0.00	67.29	27.39	4.55	0.00
	R7	56.37	0.00	34.16	7.65	1.81	0.00
	R8	86.51	1.00	10.72	0.89	0.84	0.03
	R9	83.19	0.12	12.17	1.68	2.80	0.04
	R10	53.49	2.14	30.54	6.28	7.40	0.16
	R11	21.61	0.00	4.81	56.94	16.31	0.32
	R12	83.97	0.24	12.59	0.33	2.86	0.01
1000m buffer	R1	57.60	1.29	36.95	3.46	0.42	0.28
	R2	38.54	0.60	23.87	3.99	0.62	0.16
	R3	87.43	0.01	9.12	3.32	0.12	0.00
	R4	67.34	0.00	23.05	9.18	0.44	0.00
	R5	64.83	1.62	21.96	5.03	6.47	0.08
	R6	0.88	0.00	65.73	28.95	4.45	0.00
	R7	55.94	0.00	34.73	7.49	1.84	0.00
	R8	86.50	0.90	10.66	1.03	0.87	0.05
	R9	83.59	0.09	12.16	1.75	2.36	0.04
	R10	54.85	2.01	29.27	6.25	7.49	0.13
	R11	28.86	0.00	6.44	51.64	12.35	0.71
	R12	84.26	0.24	12.39	0.32	2.77	0.01

Table 2 The explanations of land use types on water quality variance by redundancy analysis (RDA).

Scale	Season	Forest [%]	Grass [%]	Cropland [%]	Urban[%]	Waters area [%]	Bare land [%]	Total explanation [%]
Sub-basin	dry	3.3	22.6	3.5	2.8	6.5	6.7	45.4
	wet	13.7	4.4	12.5	18.8	8.3	5.9	63.6
500 m buffer	dry	3.1	11.4	5.7	3.6	9.6	18.2	51.6
	wet	11.6	10.6	14.0	20.9	10.7	5.6	73.4
1000 m buffer	dry	6.9	8.0	2.4	3.6	11.5	5.9	38.3
	wet	13.5	9.8	10.7	20.6	7.8	13.8	76.2

Table 3 Stepwise multiple regression models for land use types and water quality variables during the dry and wet seasons in UHR basin, China.

Scale	Season	Parameter	Regression equation	R^2	Adjusted R^2	P Value
Sub-basin	Dry	EC	EC = 0.19 + 0.16 Grassland	0.36	0.29	0.05*
		ORP	ORP = 257.40 - 64.86 Grassland	0.41	0.35	0.05*
		TN	TN = 2.83-0.02 Forest + 0.12 Urban + 0.31Waters + 2.34 Bareland	0.75	0.61	0.05*
	Wet	EC	EC = 0.20 + 0.07 Waters	0.40	0.34	0.05*
		TP	TP = -0.73 + 0.01 Forest + 0.01 Cropland + 0.32 Bareland	0.61	0.46	0.05*
		TN	TN = 2.28 - 0.31 Grassland	0.34	0.27	0.05*
		NO ₃ ⁻ -N	NO ₃ ⁻ -N = 0.06 + 0.22 Grassland + 0.01 Cropland	0.83	0.79	0.01**
500 m buffer	Dry	EC	EC = 0.19-0.02 Waters + 0.83 Bareland	0.83	0.76	0.01**
		ORP	ORP = 195.46 + 0.56 Forest - 8.57 Grassland + 10.10 Waters -398.74 Bareland	0.94	0.91	0.01**
		TP	TP = 0.01 - 0.05 Bareland	0.60	0.51	0.05*
		TN	TN = 1.43 + 0.17 Grassland	0.39	0.32	0.05*
	Wet	EC	EC = 0.22 + 0.36 Bareland	0.48	0.42	0.05*
		NO ₃ ⁻ -N	NO ₃ ⁻ -N = 0.12 + 0.01 Cropland	0.66	0.63	0.01**
		1000 m buffer	Dry	EC	EC = 0.17 + 0.01 Cropland - 0.01 Urban - 0.01 Waters + 0.62 Bareland	0.87
ORP	ORP = 35.62 + 2.22 Forest + 1.29 Cropland + 2.91 Urban + 7.45 Waters - 146.42 Bareland			0.93	0.88	0.01**
TP	TP = 0.01 - 0.001 Waters			0.55	0.46	0.05*
TN	TN = 1.43 + 0.17 Grassland			0.35	0.29	0.05*
Wet	EC			EC = 0.19 + 0.001 Cropland + 0.22 Bareland	0.63	0.55
	NO ₃ ⁻ -N		NO ₃ ⁻ -N = 0.15 + 0.01 Cropland	0.52	0.47	0.01**

Notes: The water quality parameters without regression models are not listed.

** Significance at the 0.01 probability level.

* Significance at the 0.05 probability level.

Figures

Figure 1

Spatial distribution of monitoring stations in the upper Han River (UHR), the 12 sub-basins and the rivers we studied, and the 1000 m and 500 m riparian buffer zones. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Spatial and temporal variations of water quality variables in the UHR, China. The box represents the 25th and 75th percentiles of all data; - denote outliers; the square represents mean values of the data set, EC: electrical conductivity, ORP: oxidation-reduction potential, DO: dissolved oxygen, NO₃-N: nitrate-nitrogen, NH₄⁺-N: ammonium-nitrogen, TN: Total nitrogen, TP: total phosphorus.

Figure 3

Landscape metrics of different sub-basins scale in the UHR, China. Notes: TA: total area, NP: number of patches, PD: patch density, LPI: largest patch index, ED: edge density, SHDI: Shannon's diversity index.

Figure 4

Biplots of water quality variable (blue lines) and land use types (red lines) in the study according to redundancy analysis (RDA). (a), (c), and (e) are RDA results at the sub-basins scale, 500 m buffer zone, and 1000 m buffer zone in the dry season, respectively; (b), (d), and (f) are RDA results at the sub-basins scale, 500 m buffer zone, and 1000 m buffer zone in the wet season, respectively.

Figure 5

The relationship between water quality variables (blue lines) and landscape metrics (red lines) during the dry and wet seasons according to RDA. (a) and (b) are RDA results at the sub-basins scale in the dry season and in the wet season, respectively.

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