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How Landscape Patterns Affect River Water Quality Spatially and Temporally: A Multiscale Geographically Weighted Regression Approach

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ABSTRACT. The water quality of a river can be considered a function of its surrounding landscape. Understanding the relationship between landscape patterns and river water quality is essential for optimizing landscape patterns to reduce watershed pollution and has not yet been solved. A multiscale geographically weighted regression (MGWR) model was used to explore the associations between the landscape patterns and water quality. Our results showed that landscape metrics have varied relationships with the water quality across spatial scales in different seasons. The strongest independent influencing variable for NO_3^--N, NH_4^+-N, and TN was tea gardens, residential land, and varied seasonally, respectively. The impacts of the landscape metrics on the TP were relatively weak throughout the year at the watershed scale. The influence of landscape metrics on NO_3^--N was more significant during the flood season, whereas that on NH_4^+-N was more notable during the non-flood season. Seasonal changes in the influencing landscape metrics of TN were not regular. Although landscape composition more significantly influenced water quality than configuration, the Shannon's diversity index and patch density were important configuration indices that significantly impacted water quality. Therefore, with limited land availability, it is essential to optimize the landscape spatial configuration without changing the composition of the watershed to reduce the risk of river pollution. This study further indicated that the MGWR model can well quantify the effects of landscape pattern on water quality at the watershed scale.

Keywords: landscape pattern, water quality, multiscale geographically weighted regression (MGWR) model, watershed

1. Introduction

River water quality is an important and sensitive issue as it plays a vital role in both aquatic ecosystems and human health (Rasul et al., 2017). Recently, the loading of phosphorus and nitrogen to rivers has intensified markedly (Tong et al., 2017; Domangue and Mortazavi, 2018; Lin et al., 2022). Global surface water quality deterioration has been attributed to both natural processes and anthropogenic activities (Rasul et al., 2017; Huang et al., 2019). Rivers receive pollutants from adjacent landscapes (Shen et al., 2015). Landscape pattern changes, from natural to anthropogenically dominated land use types, directly and indirectly affect the hydrological, chemical, and biological processes of river ecosystems (Qiu et al., 2019; Wei et al., 2021). Thus, the water quality of a river can be considered a function of its surrounding landscape and environment owing to boundaries shared with land (Sharma et al., 2016). In China, the wastewater treatment ratio had reached > 90% by 2018; however, the overall water quality showed no notable improvements (Qu et al., 2019). Diffuse non-point source (NPS) pollution offsets decreases in the point sources pollution (Tong et al., 2017; Yan et al., 2022). Over the past 40 years in China, the contributions of NPS pollutants to total water pollution has reached 81% for nitrogen and 89% for phosphorus (Zou et al., 2020).

Landscape ecology emphasizes the interactions between spatial patterns and ecological processes (Forman, 1995). Land–water interactions are important and complex landscape processes (Turner and Gardner, 2015). The link between landscape patterns and river water pollution is a typical pattern-process relationship (Shen et al., 2014). Understanding the effects of landscape patterns on water quality has been an important objective of landscape ecological studies since the mid-1980s (Turner and Gardner, 2015). Landscape patterns consist of both the structural composition and spatial configuration of landscape patches (Bell, 2001). Landscape composition is often identified as the most important parameter impacting water quality; and it is more related to water quality parameters than to configuration (Uuemaa et al., 2007; Gu et al., 2019). However, some studies have shown that landscape configuration has a stronger ability than landscape composition to explain variations in water quality (Ding et al., 2016; Clément et al., 2017; Wu and Lu, 2019). Although the effects of landscape configuration on nutrient transport have been widely demonstrated, results vary significantly among different studies and regions

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(Giri and Qiu, 2016; Sun et al., 2018; Shehab et al., 2021). For example, Clément et al. (2017) reported that landscape diversity and forest edge density were the most important configuration metrics for regulating water quality in agricultural watersheds in Eastern Canada; however, Wu and Lu (2019) showed that the largest patch index had the strongest ability to explain the variance in water quality in agricultural watershed in Southeastern China. The relative importance of spatial configuration (vs. composition) for estimating or managing nutrient loads in rivers remains unresolved (Turner and Gardner, 2015). Optimizing watershed landscape patterns to reduce nutrient loss remains a critical objective for improving river water quality (Carey et al., 2013; Eryiğit et al., 2022).

The methods used in most of the studies to explain the relationship between landscape pattern and river water quality are traditional global statistical methods, such as multiple regression (Uuemaa et al., 2007; Liu et al., 2021), Pearson correlation analysis (Wang et al., 2013), cluster analysis (Shehab et al., 2021), and redundancy analysis (Shen et al., 2015; Wu and Lu, 2019). The advantage of these traditional global statistical methods is their simplicity and robustness for estimating the overall association for the entire study area; however, the spatial variation of local relationships has been hidden (Tu, 2011). Geographic information systems (GIS) have recently been combined with statistical methods to better understand the relationships between landscape pattern and water quality (Pratt and Chang, 2012; Clément et al., 2017; Gu et al., 2019). Geographically weighted regression (GWR) is a newly developed local model used to explore the potential spatial non-stationarity of relationships among variables (Fotheringham et al., 2002). GWR models can explain local variations by incorporating spatial coordinates into traditional regression models and weighting all neighboring observations using a distance decay function based on the law of geography, that is, items close to each other are more likely to be related than items far apart (Tu and Xia, 2008). GWR captures local variations by assigning greater weights to closer observations than to farther away observations (Pratt and Chang, 2012). Therefore, GWR provides an intuitive tool for exploring spatially varying relationships by examining the strength and direction of these relationships across space (Cupido et al., 2020). However, GWR models produce a single optimized bandwidth for all variables which assumes that all the factors affect water quality at the same spatial scale. This is a questionable assumption given that different processes may affect water quality at different spatial scales (Fotheringham et al., 2019). The multiscale GWR (MGWR) is an extension of the GWR that relaxes the implicit assumption within the basic GWR that all relationships operate at the same scale (Fotheringham et al., 2017). MGWR allows the conditional relationships between the response and each independent variable to vary at different spatial scales, representing a significant advance in non-Bayesian regression modeling with spatial data (Fotheringham et al., 2017). Although the better performance of the MGWR in exploring the spatially varying relationships of variables has been demonstrated for datasets such as socio-demographic characteristics and geolocated instances of Airbnb rental properties (Oshan et al., 2019; Li and Fotheringham, 2020), few studies have examined the spatial variations in relationships between landscape pattern and water quality. Therefore, identifying the performance of MGWR is important for exploring the spatial relationships between landscape pattern and water quality to optimize landscape pattern and protect water quality.

Rivers are embedded in spatially heterogeneous landscapes (Wang et al., 2014). River networks are hierarchically nested systems in which a large river forms via the environment(s) of its small low-order streams (Ding et al., 2016; Vrebos et al., 2017). Larger scale features constrain the development of smaller units, such that the resulting physical patterns across both spatial and temporal scales strongly influence river water quality (Wang et al., 2014; Zhou et al., 2021). Subwatersheds have been widely used to study the influence of landscape patterns on river water quality. Previous studies have shown that river water quality is more sensitive to landscape variables at the sub-watershed scale than at the reach and riparian corridor scales in the Tiaoxi river watershed (Cui et al., 2018). Therefore, we considered the river networks and landscape patches as a structural whole to evaluate the integrated effects of landscape patterns at the sub-watershed scale. The objectives of this study were to (1) quantify the relationship between landscape patterns and water quality and (2) reveal the spatial variations in the effects of landscape patterns on water quality across spatial and temporal scales. This study quantified the landscape determinants of river water quality on the watershed scale to provide spatially explicit information about NPS pollution drivers and help scale up intervention pathways to identify localities at high risk of NPS pollution. The results of this study can provide effective and clear spatial guidelines for local governments to optimize landscape pattern and formulate NPS pollution mitigation strategies across the Taihu Lake Basin and other intensively managed watersheds.

2. Materials and Methods

2.1. Study Area

Lake Taihu, the third largest freshwater lake in China (Figure 1), is located in the lower reaches of the Yangtze River Delta in eastern China, with a basin area of 36,900 km^2. The Taihu Lake Basin has the highest population density and GDP per capita in China (Xu et al., 2021). Rapid industrialization and urbanization as well as excessive fertilizer use have dramatically changed landscape patterns, resulting in the discharge of high nutrient loads into the river network around the lake. As a result, the Taihu Lake Basin has become the most seriously polluted area in China (Lin et al., 2017). Since the 1990s, TN and TP concentrations have increased six- to seven-fold (Yu et al., 2007). Despite intensive efforts to restore aquatic ecosystems, the water quality in Lake Taihu remains far from the expected level (Wang et al., 2019; Liu et al., 2020). Currently, point source pollution has been effectively controlled and NPS pollution has become a major concern (Qin et al., 2019).

Pollutants are commonly transferred to lakes through river inflow; therefore, upstream rivers are the main source of pollut-

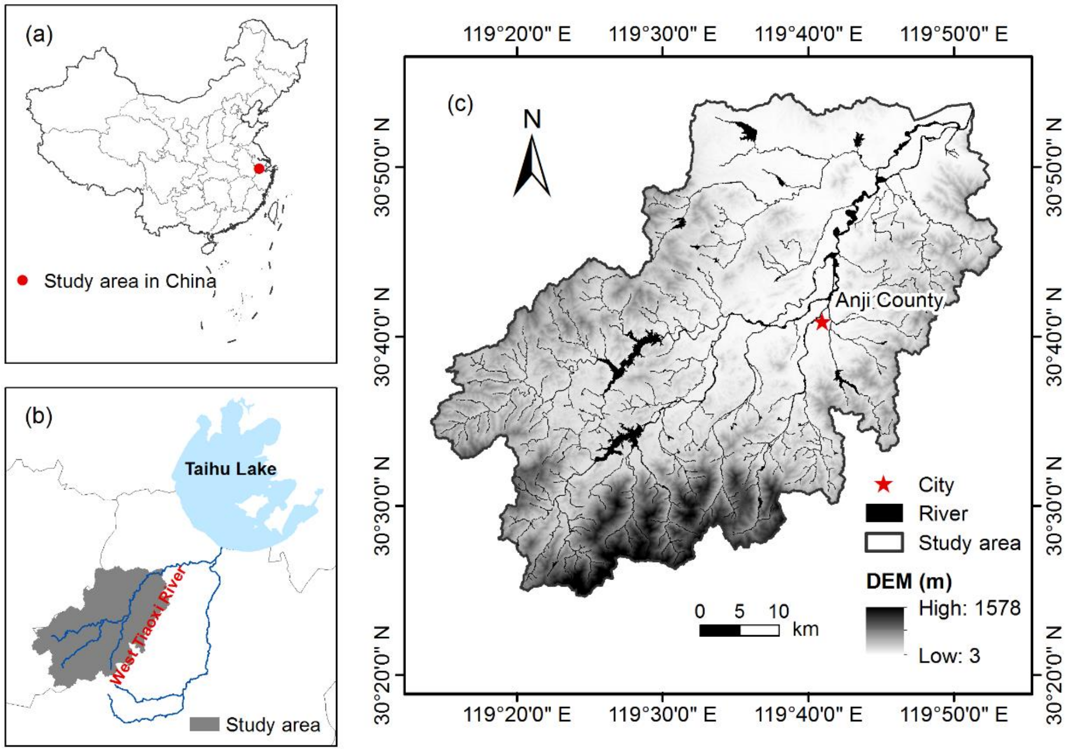

Figure 1. The location of the study area in (a) China, (b) the West Tiaoxi watershed in the Taihu Lake basin, and (c) the river system and DEM of the West Tiaoxi watershed.

ants to the lake. The West Tiaoxi River, located on the southwest edge of Taihu Lake, is one of the largest rivers flowing into Lake Taihu, accounting for 27% of the lake's total mean annual recharge and has a maximum length of 150 km (Figure 1). The river originates in the Tianmu Mountains, which are at an elevation of 1,578 m, with an annual average discharge of 15.0×10^8 m^3 a^{-1}. The West Tiaoxi River watershed, with an area of 3,654 km^2, is located in a humid subtropical zone and has a typical East Asian monsoon climate, with an average annual temperature of approximately 15.7 °C. The multi-year average precipitation is approximately 1,450 mm, with nearly 75% of the rainfall occurring from April to September, and the annual evaporation is approximately 1,300 mm. Based on local rainfall and river hydrological characteristics, June through September was considered the flood season and December through March was the non-flood season. The topography of the watershed includes hills (80%) and plains (20%). The terrain of the watershed in the south is high, whereas the landscape in the north is low and flat, with an altitude between 0 and 5 m.

The West Tiaoxi River watershed is one of the most densely populated and intensive crop production areas in the Taihu Lake Basin. Natural and planted forests dominate the upper reaches. Tea gardens are the most popular planted vegetation type for cash crops and are intensively managed for the production of green tea and other commercial products. More specifically, "White Tea" originates from this area, with Anji County within this watershed being known as the "White Tea Capital" in China (Su et al., 2017). With rapid economic development, many forests and traditional grain crops have been converted to higher-benefit cash crops such as tea gardens (Su et al., 2017). Fertilizer overuse is an important measure for increasing cash crop yields in this area. With higher population density and well-developed agricultural activity, areas of serious and heavy N losses ($\geq$ 46.4 kg ha^{-1} yr^{-1}) and P losses ($\geq$ 12.0 kg ha^{-1} yr^{-1}) accounted for 11% and 12% of the entire watershed, respectively (Wang et al., 2018). The degradation of water quality due to agricultural NPS pollution has become one of the most urgent issues in watersheds. Thus, this watershed provides an optimal case for characterizing changes in landscape patterns in relation to river water quality. Therefore, this study used the West Tiaoxi River watershed to quantify the temporal and spatial relationships between landscape patterns and river pollution processes by embedding static patterns into dynamic processes from a landscape ecology perspective.

2.2. Land Use Categorization

The land use map of the study area was obtained from remote sensing data from Landsat images in 2020, with a pixel size of 30 × 30 m, and GF-2 images with a pixel size of 3.24 × 3.24 m, in 2019 and 2020. The object-oriented classification method was applied to interpret the GF-2 images, whereas an unsupervised classification method was used to identify the Landsat images. Landscape types were classified into seven broad categories: farmland, tea garden, forest land, grassland, residential land, traffic land, and waterbody areas. Reference sites adjacent to the water sampling sites were identified for accuracy assessments based on field surveys; the overall accuracy of the classification was approximately 91.5%.

2.3. Quantification of Landscape Patterns

Because many landscape metrics are based on statistics for patch perimeter and area and are thus highly correlated, redundancy among them is virtually unavoidable (Li et al., 2005). Consequently, the metrics chosen for environmental studies should be independent of each other (Chen et al., 2019). To minimize the correlation between the selected landscape metrics, the bivariate correlation analysis principle was applied for the selection of landscape metrics. Bivariate correlation is a measure of how well two variables are associated. It is a useful measure of the relationships between landscape metrics because landscape metrics that show high levels of correlation are often calculated from the similar data sources. A total of 11 representative and effective landscape metrics with a relatively stable ability to explain the river water environment at the class and landscape levels were selected for further analysis. The percentage of the landscape area (PLAND) was calculated at the class level for different land use categories to quantify the landscape composition and 10 metrics were calculated at the landscape level to represent the landscape configuration from different aspects, including the patch density (PD), largest patch index (LPI), edge density (ED), landscape shape index (LSI), perimeter area fractal dimension (PAFRAC), aggregation index (AI), interspersion and juxtaposition index (IJI), contagion index (CONTAG), landscape division index (DIVISION), and Shannon's diversity index (SHDI). These metrics at both the class and landscape levels were computed using the widely used FRAG-STATS 4.2 software package (McGarigal et al., 2012). Three indicators were selected to describe the topographic information of the watershed: average slope (SLOPE), height difference (HD), and hypsometric integral (HI). All landscape metrics were calculated at the sub-watershed scale.

2.4. Water Sampling and Analysis

Based on river characteristics, impacts of tributaries, agricultural intensity, and urbanization level, 62 sampling sites were selected along the West Tiaoxi River (Figure 2a). Each sampling site was specified as the outlet of the delineated independent sub-watershed. Water samples were collected at 3-month intervals from June 2020 to March 2021 at all sampling sites, except for March 2020 owing to the COVID-19 pandemic. The sampling period was selected to ensure the presence of base flow conditions, which were assumed if there were at least five consecutive days of no significant rain (< 10 mm over 48 h) (Ding et al., 2016).

Nitrogen is the most important recent pollutant in the Tiaoxi River. The mean TN concentration reached 2.99 mg/L in 2019 in the East Tiaoxi River, which exceeded the Class V surface water quality standard (Yu et al., 2022). Ammonium nitrogen (NH_4^+-N), nitrate nitrogen (NO_3^--N), TN, and TP were selected to represent nutrient pollutants based on their importance inhuman and aquatic ecosystems. These four water quality parameters were measured using a continuous flow analyzer (CFA, Skalar Analytical B.V., Breda, Netherlands) in the laboratory.

2.5. Spatial Analysis

2.5.1. Sub-Watershed Delineations

To determine the association between landscape patterns and water quality at each monitoring site, a sub-watershed scale was selected (Figure 2a). Sub-watershed boundaries, representing the areas that drain into each water sampling site, were delineated using the hydrological model in ArcGIS based on the digital elevation model (DEM, 30 m resolution). Each sampling site was specified as the outlet point of a delineated sub-watershed. Thus, the water quality of a sampling site represents the water quality of its drainage area, that is, the corresponding sub-watershed.

2.5.2. Spatial Statistics

In exploring the spatially varying relationships between water quality and landscape pattern, some studies have compared the performance of OLS and GWR (Tu and Xia, 2008; Pratt and Chang, 2012); however, the advantages of MGWR over GWR and OLS have not yet been tested. Therefore, these three spatial statistical models were selected to compare their performance in exploring the relationship between landscape patterns and river water quality.

2.5.2.1. Ordinary Least Squares (OLS)

The OLS model can be expressed as follows:

$$y_i = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon_i \tag{1}$$

where y_i is the dependent variable, x_i is the independent variable, β_0 is the intercept, β_i is the coefficient, ε_i is the thermal error term, and n is the number of independent variables.

2.5.2.2. Geographically Weighted Regression (GWR)

The GWR model can be expressed as follows:

$$y_j = \beta_0\left(u_j, v_j\right) + \sum_{i=1}^{n} \beta_i\left(u_j, v_j\right) x_{ij} + \varepsilon_j \tag{2}$$

where j represents the location, (u_j, v_j) are the coordinates for each location, $\beta_0(u_j, v_j)$ is the intercept for location j, $\beta_i(u_j, v_j)$ is the local regression coefficient for independent variable x_i at location j, ε_j is the random error term, and n is the number of independent variables.

The Gaussian function was used to determine the weight while the minimizing corrected Akaike information criterion (AICc) was used to determine the optimal bandwidth (Fotheringham et al., 2002). The adjusted R^2 values, local coefficient, local R^2 values, and local residuals for each regression sampling site were generated to provide a clear visualization of the spatial variations in the relationships between the landscape patterns and water quality, as well as the model performance.

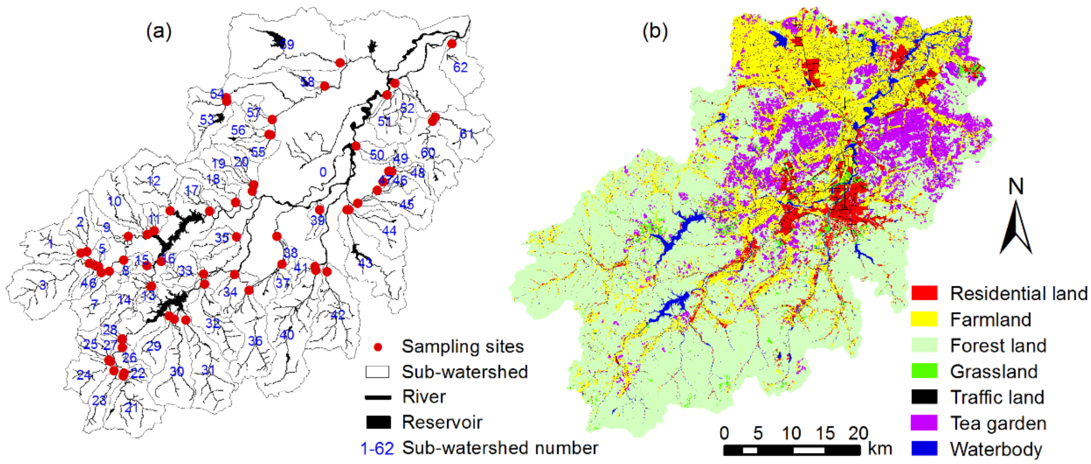

Figure 2. Distribution of (a) sub-watersheds and sampling sites and (b) landscape type map of the upper reaches of the West Tiaoxi River.

Table 1. Descriptive Statistics of Landscape Metrics at Landscape Level of 62 Sub-Watersheds

Landscape metrics	Min.	Max.	Mean	Std.	Skew-ness	Kurt-osis
PD (n/km^2)	13.38	79.19	37.27	13.91	0.89	1.19
LPI (%)	7.28	97.33	41.97	23.52	1.06	0.26
ED (m/ha)	48.52	277.3	155.86	48.90	0.19	−0.04
LSI	3.33	50.13	19.4	8.30	0.88	2.27
PAFRAC	1.17	1.40	1.25	0.04	0.69	0.53
CONTAG (%)	56.48	95.40	78.49	9.62	−0.41	−0.67
IJI (%)	56.8	83.12	70.37	6.70	0.023	−0.83
DIVISION (%)	0.05	0.97	0.71	0.24	−1.54	1.43
SHDI	0.13	1.63	0.77	0.36	0.40	−0.66
AI (%)	98.61	99.74	99.21	0.24	−0.15	−0.12

2.5.2.3. Multiscale Geographically Weighted Regression (MGWR)

The MGWR model can be formulated as follows (Fotheringham et al., 2017; Oshan et al., 2019):

$$y_j = \sum_{i=0}^{n} \beta_{bwi}\left(u_j, v_j\right) x_{ij} + \varepsilon_j \quad (3)$$

where *bwi* in β_{bwi} is the bandwidth used for the calibration of the *i*th conditional relationship. MGWR produces a separate optimized bandwidth for each relationship in the model, and the separate bandwidths have an intuitive interpretation in terms of geographical scale (Fotheringham et al., 2017). Smaller bandwidths indicate more local processes, whereas larger bandwidths indicate more regional processes.

The OLS and GWR analyses, as well as all mapping and GIS analyses, were performed using ArcGIS 10.4 while the MGWR analyses were conducted using the MGWR 2.2 software package.

2.5.2.4. Selection of Independent Variables

To examine potential multicollinearity among the independent variables, we calculated the variance inflation factor (VIF) for all variables. Before constructing the OLS, GWR, and MGWR regression models, the optimal combination of all candidate independent variables for each water quality parameter was selected via exploratory regression analysis based on the following conditions: (1) the VIFs of all independent variables in the combination were < 7.5, which indicates that collinearity had no adverse effects on the results; (2) the minimum adjusted R^2 value of the combination was > 0.5; (3) the number of independent variables in the combination did not exceed 5; and (4) an optimal combination of independent variables had the highest R^2 and smallest AICc. The selected independent variable combinations for each water quality parameter were then used to run the OLS, GWR, and MGWR models.

3. Result and Analysis

3.1. Landscape Pattern Characteristics

The study region covers an area of 2,607.8 km^2 (Figure 2b). Forests are the most dominant landscape type, covering 61.7% of the total area, with bamboo forest and arbor forest being the main components. Farmland and tea gardens account for 17.86 and 5.72% of the total area, respectively. Farmland is mainly distributed along both sides of the river, and tea garden is mainly distributed on the hillsides in the middle and lower reaches of the watershed. Residential land area accounts for 7.24% of the total area and water bodies cover 3.67% of the total area. The descriptive statistics of the landscape metrics at landscape level of the 62 sub-watersheds are listed in Table 1. High value of ED, LSI, and PAFRAC showed that the landscape was highly fragmented, with highly complex patch shapes. The high LPI value indicated that human activity significantly disturbed the landscape in the middle and downstream areas. The high CONTAG value (78.5%) showed the existence of landscape types with high connectivity, that is, forest land in the mountainous area and farmland in the plains. The IJI and AI were 70.37 and 99.21%, respectively, indicating that different landscape patches were close to each other and had a high degree of aggregation across the entire study area.

3.2. Temporal-Spatial Dynamics of River Water Quality

Table 2 lists the descriptive statistics of the water quality parameters at 62 monitoring sites. The coefficient of variation (CV) showed that the variations in NO_3^-–N and TN were relatively small, while variations in NH_4^+-N and TP were high, with CV values > 100%. A comparison of four months of water quality parameters showed that the N content during the flood season was notably lower than that in the non-flood season, while the seasonal variation in TP was small. To evaluate the water quality of the watershed, we refer to the environmental quality standard for surface water (GB 3838-2002), which uses the mean value of a water quality parameter at all monitoring sites. The NH_4^+-N concentration was at a low level; during the flood season, it almost remained in Class I standard while it was Class II during the non-flood season. The TN concentration was very high, with the pollution level far exceeding the Class V standard throughout the year, with NO_3^--N being the largest source of TN. The concentrations and fluctuation range of N pollutants were significantly higher during the non-flood season than during the flood season. The TP concentration remained in the Class II standard during the entire monitoring period, with no significant seasonal differences. Therefore, N pollution is a serious problem in the West Tiaoxi River.

The spatial variations in the water quality parameters (Figure S1) showed that the NH_4^+-N concentration at most monitoring sites was < 0.2 mg/L, with only a few monitoring sites located in urban areas or adjacent to dense residential areas reaching > 0.6 mg/L. The NO_3^--N concentrations were generally high, with most being > 4 mg/L at the monitoring sites. The NO_3^--N concentration was < 2 mg/L in the upstream head water area. The distribution pattern of TN was similar to that of NO_3^--N. TN concentration increased spatially from upstream to downstream. In most agricultural planting areas, the TN concentrations exceeded 4 mg/L, even exceeding 6 mg/L in tea planting areas. TP concentration in the study area was generally low. Sampling sites with TP concentrations of < 0.1 ml/L accounted for > 85% of the total sampling sites. Some monitoring sites with high TP concentrations are scattered only in urban areas and towns with high population densities.

3.3. Spatial Relationships between Water Quality and Landscape Pattern

3.3.1. Spatial Regression Model Selection

The goodness-of-fit of the three regression models was evaluated to search for a reasonable model that could characterize the effects of landscape patterns on river water quality (Table 3). The AICc values of the MGWR model for most water quality parameters in different months were smaller than those of the GWR and OLS models, showing that the goodness-of-fit of the MGWR model was higher than that of the GWR and OLS models. Additionally, the adjusted R^2 of MGWR is generally higher than that of the GWR and OLS models, indicating that more variations in water quality were explained by landscape variables in the MGWR model. At the same time, almost all RSS values in the MGWR model were the smallest among the three regression models, indicating that regression results closer to the real values could be obtained with fewer independent variables (Shabrina et al., 2020). The scale at which each landscape metric impacts a water quality parameter may vary across all independent variables; variations in the relationships may differ at a local scale or regional scale or may not vary with location (Fotheringham et al., 2019). Therefore, the MGWR model was selected for further analyses. The adjusted R^2 showed that the percentage of variance in the water

Table 2. Descriptive Statistics for Water Quality Parameters at the Sampling Sites in the Upper Reaches of the West Tiaoxi River

Water quality index	Month	Min. (mg/L)	Max. (mg/L)	Mean (mg/L)	Std.	CV (%)	Environmental quality standards for surface water GB 3838-2002 (mg/L)				
							I	II	III	IV	V
NH_4^+-N	Jun.	0.02	1.20	0.13	0.19	142	≤ 0.15	≤ 0.5	≤ 1.0	≤ 1.5	≤ 2.0
	Sep.	0.01	3.40	0.20	0.46	228					
	Dec.	0.05	4.35	0.41	0.58	141					
	Mar.	0.04	3.95	0.27	0.51	185					
NO_3^--N	Jun.	0.25	7.73	1.64	1.65	101					
	Sep.	0.08	4.39	1.17	0.96	82					
	Dec.	0.82	4.89	2.09	0.93	45					
	Mar.	0.38	4.87	2.02	0.93	46					
TN	Jun.	0.95	9.75	2.59	1.88	73	≤ 0.20	≤ 0.5	≤ 1.0	≤ 1.5	≤ 2.0
	Sep.	0.76	6.36	2.35	1.13	48					
	Dec.	1.32	7.62	3.11	1.23	40					
	Mar.	1.53	10.10	3.90	2.06	53					
TP	Jun.	0.012	0.20	0.05	0.04	81	≤ 0.02	≤ 0.1	≤ 0.2	≤ 0.3	≤ 0.4
	Sep.	0.00	0.63	0.09	0.14	160					
	Dec.	0.00	0.92	0.07	0.13	161					
	Mar.	0.01	0.69	0.07	0.12	167					

Table 3. Evaluation of Goodness of Fit for the OLS, GWR, and MGWR Models

Water quality parameters	Month	Akaiker's information criterion (AICc)			Adjusted R^2			Residual sum of squares (RSS)			Number of effective parameters	
		OLS	GWR	MGWR	OLS	GWR	MGWR	OLS	GWR	MGWR	GWR	MGWR
NH_4^+-N	Jun.	−159.8	−155.5	−156.3	0.89	0.88	0.89	0.22	0.22	0.21	8.11	6.95
	Sep.	−1.0	2.1	1.3	0.76	0.76	0.77	2.87	2.66	2.54	9.56	8.69
	Dec.	46.0	40.3	39.1	0.69	0.74	0.75	5.88	4.35	4.36	12.91	10.11
	Mar.	−32.0	−37.9	−41.5	0.88	0.90	0.91	1.67	1.22	1.18	13.15	10.36
NO_3^--N	Jun.	99.9	100.2	100.5	0.90	0.91	0.91	15.22	13.93	13.89	7.62	6.46
	Sep.	118.4	114.5	113.9	0.63	0.66	0.68	19.69	16.29	15.16	9.64	9.33
	Dec.	125.5	118.4	109.6	0.56	0.63	0.70	21.20	16.77	13.16	10.30	10.8
	Mar.	127.4	122.7	119.3	0.55	0.60	0.62	21.84	17.96	16.90	10.27	8.87
TN	Jun.	116.3	117.0	117.2	0.91	0.91	0.91	19.05	17.26	17.35	9.08	7.56
	Sep.	138.0	137.0	136.0	0.62	0.64	0.65	28.10	24.18	20.14	11.00	10.06
	Dec.	160.0	156.7	158.3	0.56	0.59	0.59	38.40	32.77	33.42	9.07	7.73
	Mar.	134.2	111.8	105.1	0.90	0.94	0.94	24.41	13.03	11.89	14.16	11.36
TP	Jun.	−314.5	−329.6	−328	0.79	0.87	0.85	0.02	0.01	0.01	20.08	10.75
	Sep.	−80.6	−81.6	−82.4	0.19	0.23	0.24	0.89	0.82	0.80	5.00	4.12
	Dec.	−143.2	−142.8	−142.1	0.72	0.73	0.74	0.28	0.24	0.23	11.22	10.41
	Mar.	−127.8	−123.7	−122.3	0.52	0.51	0.50	0.37	0.36	0.36	9.01	7.67

quality parameters explained by the landscape pattern in the MGWR model was the highest for NH_4^+-N, followed by NO_3^--N, TN, and TP.

3.3.2. Spatial Changes in Local Coefficient and R^2 Values for NO_3^--N

The spatial changes in the local coefficients of the variables for NO_3^--N in the MGWR model (Figure 3) showed that the NO_3^--N concentration was mainly affected by the percentage of tea garden areas (Tea%), SHDI, and SLOPE throughout the year, as well as PD in the flood season and the percentages of residential land areas (Res%) and traffic land areas (Tra%) in the non-flood season. In the non-flood season, tea% had the most significant influence on NO_3^--N in June, with a local coefficient > 1.0 in the entire watershed, but no significant influence in September. In the non-flood season, the influence of Tea% on NO_3^--N remained strong in upstream areas but decreased in the middle and downstream areas, indicating that tea plantations in mountainous upstream areas were the main source of NO_3^--N. The effects of the SHDI on NO_3^--N showed a uniform distribution throughout the watershed, with small spatial heterogeneity. Res% was positively correlated with NO_3^--N while Tra% was negatively correlated with NO_3^--N only in the non-flood season. Both correlations showed no significant spatial differences throughout the entire watershed. The PD showed a significant negative correlation with NO_3^--N with small spatial differences during the flood season.

The number of metrics that could be used to explain NO_3^--N and the variation range in the local coefficients were higher in the non-flood season than in the flood season, indicating that the process of NO_3^--N inflow to rivers was more complex and affected by more factors in the non-flood season than in the flood season and the spatial heterogeneity of the impacts of the landscape metrics on NO_3^--N was more notable during the non-flood season than during the flood season.

The local R^2 values for the spatial variation in NO_3^--N (Figure S2) showed that the percentage of variation in NO_3^--N explained by the MGWR models in June was the highest, reaching > 80% in the entire watershed; in the other three months, it was also as high as 55 ~ 70%. The explained percentage of variation in NO_3^--N in all models was relatively stable with small spatial heterogeneity, indicating that the selected independent variables could fully explain the variation in NO_3^--N at the watershed scale.

3.3.3. Spatial Changes in Local Coefficients and Local R^2 for NH_4^+-N

The spatial changes in the local coefficients for NH_4^+-N showed that NH_4^+-N is mainly influenced by the landscape composition, such as Res%, Tra%, and the percentage of waterbody areas (Wat%), during the flood season and landscape configuration metrics, such as SHDI, during the non-flood season (Figure 4). The influence of Res% on NH_4^+-N was the most significant, particularly in the middle and downstream areas with high proportions of residential land. The influence of Tra% on NH_4^+-N was notable in the flood season; the degree of influence was relatively stable throughout the entire watershed and the spatial differentiation was not obvious. The impact of the SHDI on NH_4^+-N mainly occurred during the non-flood season, presenting a negative correlation. The highest local coefficient of the landscape variables affecting the concentrations of NH_4^+-N is 0.38, indicating that the relationship between the NH_4^+-N and individual landscape metrics was weak. The spatial change in the local coefficient of each independent variable was small.

The spatial variations in the local R^2 for NH_4^+-N in the MGWR model (Figure S3) were similar to those of the local coefficient. The percentage of variation in NH_4^+-N explained by the landscape pattern was very high (> 80%) in June across the entire watershed. In the other months, high local R^2 values

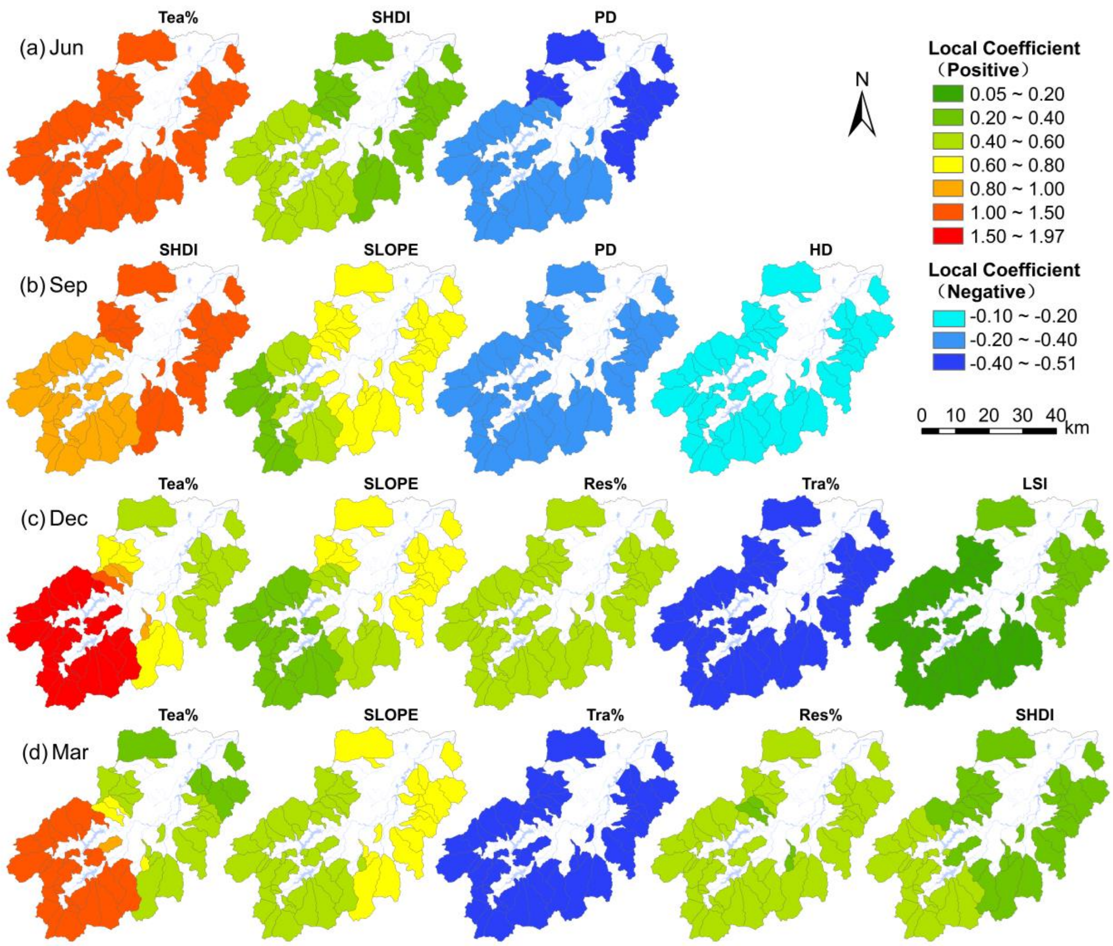

Figure 3. Spatial variations in the local coefficients of the explanatory variables for NO_3^--N in different months in the MGWR model. Note: Tea%, percentage of tea garden areas; Res%, percentage of residential land areas; Tra%, percentage of traffic land areas.

occurred in the middle and downstream areas, where highly managed landscape types such as tea garden, farmland and residential land were distributed concentrated and continuously along rivers (Figure 2(b)), covering more than 70% of this area.

3.3.4. Spatial Changes in Local Coefficients and Local R^2 for TN

Figure 5 shows the local coefficients of the MGWR models for TN in different months. Tea% was the most important impact variable for TN in March and June, with local coefficients > 1.2 in the entire watershed without notable spatial differentiation, showing a strong correlation with TN at the watershed scale. The percentage of forest land areas (For%) showed a significant negative correlation with TN in September and December, with notable spatial heterogeneity. Res%, as an explanatory variable of TN, contributed to all seasons with small spatial changes; its influence was significantly higher in the non-flood season than in the flood season. PD had a negative correlation with TN in March and June; the local coefficient was higher in the downstream area than in the upstream areas, indicating that fragmented landscape patches reduced TN in the river. The components of TN were dominated by NO_3^--N and NH_4^+-N in the study area. As the sources, influencing factors, and seasonal dynamics of NO_3^--N and NH_4^+-N were significantly different, the seasonal changes in the main influencing variables of TN were not uniform.

Among the explanatory variables of TN, the number of landscape composition metrics was significantly greater than that of the landscape configuration metrics, indicating that the landscape composition of the study area is of greater importance to the river water quality than the landscape configuration. The landscape configuration affecting the change in TN over different seasons had different metrics. The number of explanatory variables and the spatial variation in the local coefficients for TN in the non-flood season were greater than that in the flood season. These results were consistent with those obtained for NO_3^--N.

The percentage of variation in TN explained by independent variables was high in March and June, reaching > 80% in the entire watershed with small spatial changes, and medium in September and December, spatially increasing from the upper mountainous area to the downstream area (Figure S4).

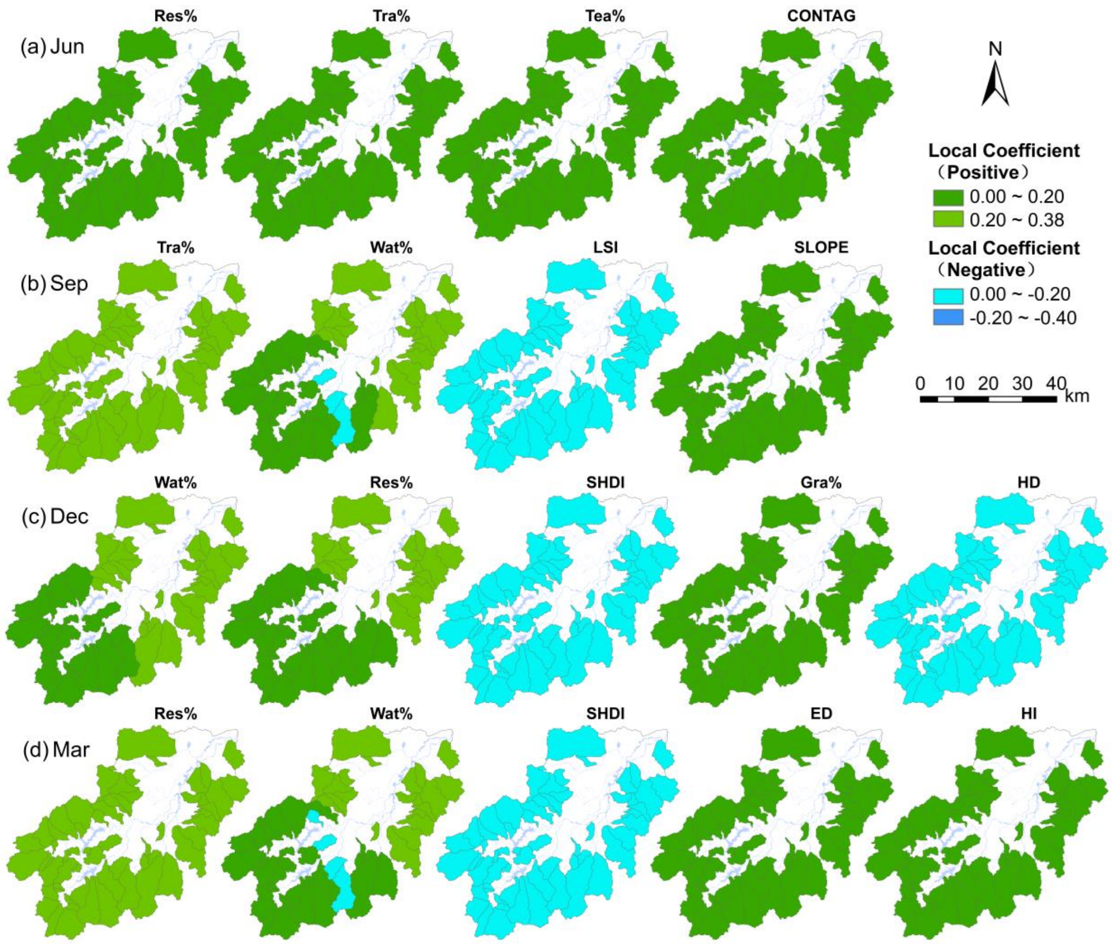

Figure 4. Spatial variations in the local coefficients of the explanatory variables for NH_4^+-N in different months in the MGWR model. Note: Res%, percentage of residential land areas; Tea%, percentage of tea garden areas; Tra%, percentage of traffic land areas; Gra%, percentage of grassland areas; and Wat%, percentage of waterbody areas.

3.3.5. Spatial Changes in Local Coefficients and Local R^2 for TP

The highest local coefficient value of all of the independent variables for TP in different seasons in the MGWR model was only 0.14 (Figure 6), indicating that the impact of the individual landscape metric on TP was relatively weak throughout the year at the watershed scale. The impacts of the landscape component metrics (Tra% and Res%) on the TP were more evident than those of the landscape configuration and topography metrics. The MGWR model again showed that TP was mainly affected by construction land, such as traffic and residential lands, while the impact of agricultural production, such as tea planting, on TP was not obvious. Although the local coefficients of the landscape configuration metrics and topography for TP were low, they still showed that these metrics had slight impacts on the TP, where the influencing metrics varied monthly. Additionally, the impacts of the independent variables on TP were higher in the non-flood seasons than in the flood season.

The percentage of variation in TP explained by the independent variables varied significantly in time and space (Figure S5). Temporally, the percentage explained in June was the highest (all > 60%), whereas it was the lowest in September (all < 50%). Spatially, the percentage explained by the independent variables in all months gradually increased from upstream to downstream. Owing to the low TP content in the upstream area (Figure S1), the relationship between TP concentration and landscape variables was weak.

4. Discussion

4.1. Impacts of Landscape Composition on Water Quality

Changes in the output and migration of pollutants by various types of landscape patches usually reflect the impacts of landscape patterns on river water quality (Shen et al., 2014). The results of the MGWR model showed that the combinations of landscape metrics could explain > 70% of the average spatial variations in the water quality parameters in different seasons. The direction of the effects (positive or negative) of the same explanatory variable on the river water quality was consistent during different seasons, but the dominant influencing variables on the water quality showed significant seasonal

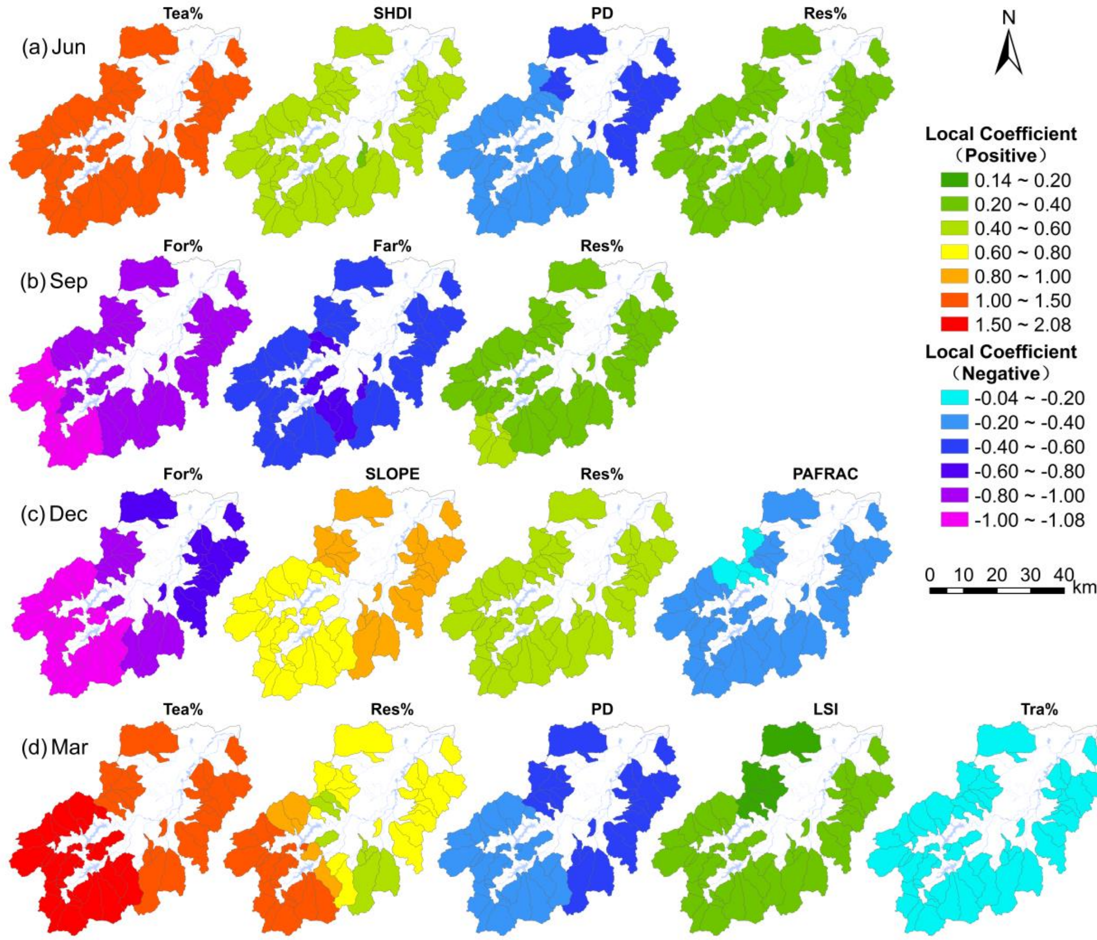

Figure 5. Spatial variations in the local coefficients of the explanatory variables for TN in different months in the MGWR model. Note: Res%, percentage of residential land areas; Tea%, percentage of tea garden areas; Tra%, percentage of traffic land areas; Far%, percentage of farmland areas; For%, percentage of forest land areas; Gra%, percentage of grassland areas

differences. Both the number of landscape variables dominating the changes in the water quality and the variation range in the local coefficient in the non-flood season were greater than that in the flood season. This reconfirmed that the migration processes of pollutants inflow into rivers in the non-flood season were more complex with higher spatial heterogeneity and were affected by more factors than that in the flood season.

In this study, landscape composition had the most significant influence on water quality, as also illustrated in other studies (Clément et al., 2017). Composition (amount) is a more fundamental metric than configuration (adjacency) because a change in any other pattern metric cannot be interpreted reliably without accounting for changes in the amount (Riitters, 2019). Different land uses affect the type and output of pollutants transported by surface and subsurface runoff (Shen et al., 2014), as well as affecting nutrient migration processes through the type and coverage of vegetation (Yong and Chen, 2002). The MGWR results showed that tea garden was the most important source of NO_3^--N and TN pollution in the river while residential and traffic land significantly affected the NH_4^+-N and TP contents. NO_3^--N was responsible for most TN in river water in the study area, which was also demonstrated by Liang et al. (2013) using a stable isotope tracer technique. Spatially, the concentrations of NO_3^--N and TN in our study area increased significantly from upstream to downstream, which was similar to the change in the proportion of tea garden and farmland, indicating that the agricultural landscape was the main source of NO_3^--N and TN in the river. The concentrations of NH_4^+-N and TP in the rivers were at low level in the entire watershed, which conformed to the Grade II water quality standards. Monitoring sites with high values were located in the sub-watersheds with densely populated townships or large villages, indicating that the concentrated and regular distribution of impervious surfaces in- creased the loading of NH_4^+-N and TP, which was consistent with other studies in highly developed watersheds (Zhang et al., 2021).

The landscape transition matrix of the study area from 2000 to 2020 (Table 4) showed that the tea garden area increased dramatically from 63.17 km^2 in 2000 to 149.17 km^2 in 2020 at the cost of high-quality farmland and forests. About 63.57% (94.82 km^2) of the tea garden in 2020 was converted from forest land and another 20.44% (30.49 km^2) came from

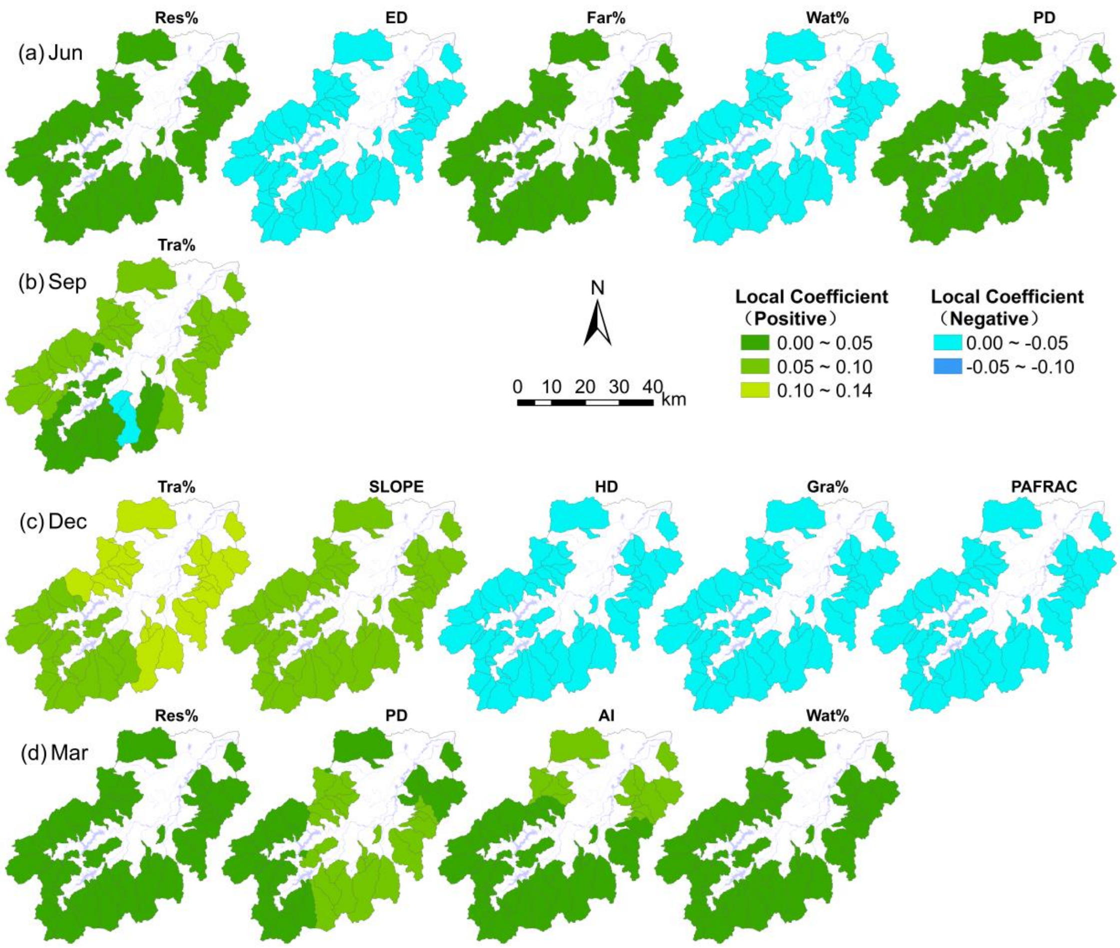

Figure 6. Spatial variations in the local coefficients of the explanatory variables for TP in different months in the MGWR model. Note: Res%, percentage of residential land areas; Tra%, percentage of traffic land areas; Far%, percentage of farmland areas; Gra%, percentage of grassland areas; and Wat%, percentage of waterbody areas.

Table 4. The Landscape Transition Matrix in the Upper Reaches of the West Tiaoxi River Watershed from 2000 to 2020 (km^2)

		2000 Residential land	Farmland	Forest land	Grassland	Traffic land	Tea garden	Waterbody	Total
2020	Residential land	27.35	121.50	26.83	4.37	0.59	5.88	2.48	188.99
	Farmland	24.72	334.66	77.06	7.17	1.21	10.73	10.21	465.77
	Forest land	19.60	201.56	1319.26	32.15	2.13	27.55	9.73	1611.99
	Grassland	2.30	18.06	19.39	2.83	0.07	2.44	0.45	45.53
	Traffic land	1.09	9.72	3.12	0.23	36.39	0.78	0.26	51.59
	Tea garden	3.37	30.49	94.82	4.62	0.09	15.46	0.32	149.17
	Waterbody	1.07	16.08	8.91	0.59	0.08	0.33	67.71	94.76
	Total	79.50	732.08	1549.38	51.96	40.56	63.17	91.16	2607.80

Note: The row presents the data of 2020, the column presents the data of 2000.

farmland. To increase tea yield, the average application rate of fertilizer in tea garden was > 2,000 kg/ha. Studies have shown that when applying fertilizers at rates of 2,700 kg/ha in tea plantations, tea plants utilize only 18.3% of the applied N and 5.5% of the applied P (Chen and Lin, 2016). Compared with the fertilization of tea garden, the average fertilizer application rate of farmland was 475 kg/ha in this region and the utilization rate of the dominant crops, such as paddy rice, was 46.4% (Liang et al., 2019). Thus, the expanding area, high fertilization rate, and low utilization rate of tea garden have resulted in a large amount of overused fertilizers flowing into the river via runoff from tea garden. Additionally, tea plantations destroy the soil NO_3^--N retention by increasing NO_3^--N production rates and decreasing microbial NO_3^--N immobilization, resulting in high NO_3^--N production (Zhu et al., 2014). Consequently, tea gardens are the largest source of NO_3^--N and TN in this watershed. Therefore, the tea garden, as a special land use model in this study, was separated from farmland as a separate landscape type. Owing to the critical influences of tea garden on river water quality, the separation of tea garden from farmland significantly weakened the influence of farmland on water quality in this watershed. Consequently, the relationship between farmland and water quality was weak in this study. This explained why our results were inconsistent with those of other similar regions. For example, Wu and Lu (2019) showed that farmland was the most important cause of watershed water quality degradation in the same province of eastern China.

The results of the MGWR model showed that forest land had the most significant impact on TN, especially in September and December. The area of forest land was relatively stable over the last 20 years (Table 4). Many studies have shown that forest land can improve the river water quality by absorbing and intercepting nutrients (Carey et al., 2013; Ding et al., 2017; Casquin et al., 2021). However, more than 70% of forest lands were located upstream of 80% of the tea garden and farmland in this study area (Yu et al., 2022). Topographically, most of the forest land in the study area could not infiltrate, intercept, deposit, or absorb pollutants from downstream "source" landscapes, thus diminishing the function of forests as "sink" landscapes (Yu et al., 2022). Therefore, the positive impact of forests on water quality could be because of the fact that they reduced the proportion of tea garden and farmland at the entire watershed scale, as opposed to purifying water quality (Wang et al., 2013).

Residential land was positively correlated with all water quality parameters during every season in the study area; it was also the dominant explanatory variable of NH_4^+-N and TP, with small seasonal differences. The area of residential land expanded rapidly in the study area, increased from 79.50 km^2 in 2000 to 188.99 km^2 in 2020 at the expense of farmland (Table 4). Although the wastewater discharge from densely populated residential land in urban area was well treated, the collection and treatment of domestic sewage in the rural areas remains insufficient (Huang et al., 2021). The increase in rural residential land has led to an increase in NPS pollution from untreated domestic sewage and household garbage. Additionally, there is a large number of scattered small-scale poultry breeding activities at the household scale in rural residential areas, causing an increase in NH_4^+-N and TP concentrations (Yu et al., 2022). Therefore, pollutants discharge from rural residential land contributed significantly to NH_4^+-N and TP concentrations.

4.2. Impacts of Landscape Configuration on Watershed Water Quality

There were variations in landscape configuration as well as in landscape composition. Landscape configuration measures the spatial arrangement, position, and geometric complexity of patches (Turner and Gardner, 2015). The spatial configuration of patches can interfere with nutrient exchange between neighboring patches and influence the efficiency of ecological fluxes (Forman, 1995). However, there is still no definite conclusion on the seasonal response of water quality to landscape configuration, which is closely related to the dominant landscape type and seasonal changes in rainfall in a specific watershed (Shi et al., 2017; Wu and Lu, 2019). In this study, the SHDI and PD are important landscape configuration indices that significantly impact water quality.

The SHDI was significantly positively correlated with NO_3^--N throughout the year, but negatively correlated with NH_4^+-N only in the non-flood season. The SHDI increased as the number of different patch types increased and/or the proportional distribution of the area among the patch types became more equitable (McGarigal et al., 2012). In the West Tiaoxi watershed, the SHDI increased owing to landscape patches of farmland, tea garden, forest land, and residential land that were mosaiced into each other and distributed evenly, where increases in intensively managed tea garden and farmland occurred at the cost of forest land reclamation. As a result, the SHDI had a negative impact on NO_3^--N and TN. This result agrees with previously reported positive relationships between the SHDI and NO_3^--N and TN in areas such as South Korea (Lee et al., 2009), the Three Gorges Reservoir Area of China (Zhang et al., 2019), and the Ave River Basin in the northern region of Portugal (Fernandes et al., 2021). The SHDI value increases along with the amount of different fragment classes or proportional fragment distribution (Shehab et al., 2021). The negative impacts of landscape diversity within watersheds are primarily related to agricultural landscapes with high development intensity, such as cash crop land and farmland. Meanwhile, the increase in the SHDI was partly due to the balanced distribution between residential land patches and the reduction in its aggregation, which decreased the proportion of residential land in the sub-watersheds. Consequently, higher SHDI may reduce NH_4^+-N losses from residential land during the non-flood season. During the flood season, with the dilution of river NH_4^+-N via large amounts of storm runoff, the impact of the SHDI on NH_4^+-N was largely offset. This is inconsistent with the positive correlation between SHDI and water quality in previous studies (Shehab et al., 2021). This inconsistency could be because the content of NH_4^+-N was low in the West Tiaoxi watershed (Table 2 and Figure S1) and the main source of NH_4^+-N was residential land (Figure 4). Therefore, the high SHDI due to fragmentation and the decreased proportion of residential land could reduce the concentration of NH_4^+-N in the study area. The contradictory effect of SHDI is related to the nature of the dominant landscape type that affects water quality parameters (Clément et al., 2017).

Landscape fragmentation reduced NO_3^--N and TN pollution, but aggravated TP pollution in this study. Previous studies generally identified that more fragmented landscapes had higher risks of nutrient loss (Lee et al., 2009; Shi et al., 2017; Shehab et al., 2021). However, some studies have reported opposite results (Shen et al., 2015). Our results showed that NO_3^--N mainly comes from tea garden and farmland with runoff during the flood season. Large unfragmented patches of tea garden and farmland requires high application rates of fertilizers. Thus, the decreasing effect of highly fragmented landscape on NO_3^--N could be partly attributed to the low pollutant load from less tea garden and farmland area. Another potential reason is that nutrient-enriched runoff from highly fragmented tea garden and farmland patches during the flood season can be easily intercepted in the migration process into rivers (Liu et al., 2021) because the complex boundaries of highly fragmented patches could promote the "sink" effect of landscape on nutrients (Clément et al., 2017). The impact of the individual landscape metric on TP was relatively weak (local coefficients of the explanatory variables for TP ≤ 0.14) (Figure 6) because of the low TP concentration in the West Tiaoxi watershed.

In general, the spatial configuration of the landscape had significant impacts on river water quality in this study, which agrees with the results of other studies (Uuemaa et al., 2007; Shen et al. 2015; Ding et al., 2016; Giri and Qiu, 2016; Clément et al., 2017; Shehab et al., 2021). This suggests that it might be possible to improve water quality by optimizing the landscape configuration without altering the landscape composition of the study area. However, the relationship between landscape pattern and water quality is complex and dynamic and is subject to continual change as a result of economic development, land use planning, and human activities (Turner and Gardner, 2015; Giri and Qiu, 2016). Trade-offs between landscape pattern and water quality for different conditions should be carefully examined and avoid "one size fits all". Landscape management and planning strategies should be constantly revised and evolved within the context of adaptive management to improve river water quality practices.

5. Conclusions

This study investigated the seasonal-spatial variations in river water quality and their relationships with landscape patterns in an intensive agricultural watershed in Southeastern China. Tea garden, as a special cash crop landscape type, is more intensively managed for economic benefits than traditional farmland. The TN concentration was at a high level with NO_3^--N being the largest contributor. The concentrations of NH_4^+-N and TP were relatively low. The water quality in the study area displayed evident spatial and temporal variations. The results revealed that MGWR, which differentiates both spatial heterogeneity and local processes, showed the highest performance in estimating the relationship between landscape pattern and water quality in comparison with GWR and OLS. The variations in N parameters can be well explained by landscape composition and configuration. However, the impacts of the landscape pattern on TP were relatively weak throughout the year at the watershed scale. Landscape composition had a more significant influence than landscape configuration on water quality. The expansion and heavy fertilization of tea garden have dramatically degraded water quality. The impacts of configuration metrics were heterogeneous with respect to seasonal variations in different pollutants. The SHDI and PD are important landscape configuration indices that significantly affect the water quality. This study suggests that river water quality can be improved by optimizing spatial configurations without changing the landscape composition of a watershed. However, trade-offs between the landscape pattern and river water quality for different seasons should be carefully examined to minimize the negative effects of the landscape pattern and avoid "one size fits all" measures. Our study provided key insights into the heterogeneous seasonal effects of landscape patterns on water quality, with a considerable contribution to the sustainable spatial planning and management of river system for more targeted NPS pollution mitigation strategies in intensive agricultural areas at the watershed scale. The proposed methodology provides a replicable approach that could provide valuable spatial information for policy suggestions and decision criteria both theoretically and methodologically.

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