Exploring the Effects of Landscape Structure at Multiple Scales on River Water Characteristics in the Khorramabad and Chalus River basins

Fatemeh Sadeghi Gorbandi (f.sadeghi1400environment@gmail.com)
Islamic Azad University of Arak
Hamid Torangzar
Islamic Azad University of Arak
Ramin Zare
Islamic Azad University of Arak
Javad Varvani
Islamic Azad University of Arak
Abbas Ahmadi
Islamic Azad University of Arak

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Abstract

Background

It is acknowledged that the landscape composition and configuration of land cover within a watershed could influence a watershed environmental and ecological quality. Therefore, rivers receive pollution from their surrounding landscape and the amount and intensity of this pollution are affected by the landscape structure around the river or within a watershed.

Methods

In this research, we estimated the relationship between landscape characteristics and water quality in two different basins. We used multiple stepwise regression analysis and redundancy analysis to explore the quantitative association between landscape metrics, at both the watershed and riparian buffer scales.

Results

The riparian buffer scales metrics were more effective in predicting water quality in comparison with the indices at the watershed scale. The landscape composition and configuration explained 80% of the variation in water quality at 100 m buffer, and the value decreased to 79% at 1000 m. At the 100 m buffer scale, ED of the forest, PLADJ, and MESH of urban areas in Khorramabad basin and AI of the forest, ED of urban, and SPLIT of agricultural lands were recognized as significant variables affecting the water quality in the Chalus basin. In other scales only metrics related to agriculture and urban were seen as dominant variables, indicating that these land-use classes are final determinatives in water quality changes in our study areas.

Conclusion

All dominant variables at each scale indicated a decreasing trend of the landscape impact on the water quality. Although in the Chalus basin human activities were insignificant, they had considerable effects on Chalus river quality, and urban and agriculture were recognized as dominant usages at all scales, implying that a large amount of forest cover cannot impede the effects of human activities in a basin.

Introduction

Water pollution sources are divided into two categories: point source and non-point source. Pollution from point sources can be practically controlled by various methods, but due to the uncertainty of the type, amount, location, and how pollutants enter surface and groundwater streams, it is difficult to control non-point sources of pollution. Water pollution through non-point sources is the result of the use of a wide range of human activities. In many countries, all agricultural and livestock activities are considered as non-point pollutants and are recognized as an important factor in determining water quality and play an important role in freshwater nutrition (Mehaffey et al., 2005) because different land covers affect the type of nutrients that enter the river through runoff (Shen et al., 2015).

It is well known that rivers receive pollution from their surrounding landscape and the amount and intensity of this pollution are affected by the composition and configuration of the landscape features around the river or within a watershed (Clément et al., 2017; Ding et al., 2016; Joshi et al., 2016; Shen et al., 2015; Xie and Ng, 2013). For example, Agricultural land uses plays an important role in affecting the water quality of adjacent streams because they are considered as point and non-point sources of pollutants (Li et al., 2008; Liu et al., 2012). Therefore, factors such as the quality and flow of rivers, not only reflect the health of the river itself but also provides information about the watershed and the landscape through which they pass (Xie and Ng, 2013).

Different studies confirm that the structural features of a watershed such as a slope and the number of land cover types in a watershed such as urban, rangeland, forest, and agriculture have significant effects on river water quality. for instance, the presence of forest cover improves river water quality in a watershed (Clément et al., 2017; Tong and Chen, 2002). Lee et al. (2009) also reported that the quality of river water decreases as the size of forest patches decreases. Therefore, altering landscape structure by clearing the forest for human activities such as agriculture has been recognized as important factors that affect the water quality of the river (Clément et al., 2017)

Natural and semi-natural habitat loss and fragmentation are two important processes that drastically change the structural pattern of land covers (Xie and Ng, 2013). Habitat loss reduces the amount of the original habitat and fragmentation increases the isolation of remnants patches (Parker and Mac Nally, 2002). Several studies have found that changes in the landscape structure patterns resulted from habitat loss and fragmentation have significant effects on the quantity and quality of river water in a watershed (Amiri and Nakane, 2009; Hunsaker and Levine, 1995; Li et al., 2013; Sliva and Williams, 2001; Xie et al., 2018; Zhou et al., 2012). Therefore, estimating the relationship between river water quality and patterns of different land-use types within a watershed is an essential step for managing and monitoring the health of the watershed (Chambers et al., 2012; Tanaka et al., 2016).

Effects of landscape patterns on river water quality occur at different spatial scales such as watershed and riparian zones (Zhou et al., 2012). Several studies have shown that land-use patterns close to the river have greater effects on the variability of river quality parameters than those farther away (Dodds and Oakes, 2008; JOHNSON et al., 1997; Shen et al., 2014). For example, at the riparian scale, the amount and spatial arrangement of different vegetation covers such as forest cover can have a significant impact on nutrient concentration, physical properties, and energy balance in a river (Casatti et al., 2012; Jackson et al., 2015). On the other hand, some studies have stated that measuring land use patterns at the watershed scale will yield more reliable results (Sliva and Williams, 2001; Zhou et al., 2012). From an ecological point of view, estimating the relationship between landscape patterns and water quality parameters at multiple scales provides valuable information about these scales and determines the spatial scale that has the most impact on rivers (Xie et al., 2018; Zhou et al., 2012). Due to human disturbances and the elements that make up a watershed, it is confirmed that there is no permanent and special scale for these effects (Alberti et al., 2007; Li et al., 2013; Margriter et al., 2014; Shen et al., 2015). Therefore, in each watershed, estimating the effects of the surrounding landscape and human disturbances on the river water quality at different scales is necessary to make suitable management decisions (Tudesque et al., 2014).

Landscape ecology is the study of the composition and configuration of ecosystems at the landscape level (Mitchell et al., 2013). Landscape configuration indicates the spatial distribution of patches within a landscape, but composition refers to non-spatial aspects of landscape features such as the area of patches (McGarigal et al., 2002). (Griffith et al. (2002); Hunsaker and Levine (1995); Snyder et al. (2005); Uuemaa et al. (2007)) found that the landscape composition and configuration account for 21 to 86% of changes in river water quality. Some studies have claimed that the effects of landscape composition on river water quality are more determinative than configuration, for example (Alberti et al. (2007); Clément et al. (2017); Lee et al. (2009); Xiao and Ji (2007); Xie et al. (2018)) found that the landscape composition compared to its configuration has a greater impact on predicting changes in water quality. Clément et al. (2017) suggested that the influence of landscape configuration appears at a certain threshold and in areas with intensive crop farming (>50%), and an improvement of water quality will come with more forests and wetlands, and the configuration of those patches is less relevant.

In the present study, the landscape and class metrics effects on the water quality of highly degraded watersheds have been explored to make such kinds of study results more applicable to urban landscape planning and water management at an operational level. This study aims to compare the effects of land use patterns in two watersheds that have a large difference in the presence of human disturbances. Both watersheds have agricultural, rangeland, forest, and urban covers, but the type of forest cover in these basins is different and also the number of human activities in these basins is different. We estimated the relationship between land use patterns and river water quality at both riparian and watershed scales using multivariate statistical analyses.

Our main questions were:

(1) What are the landscape configuration and composition relative influences on river water quality?

(2) Which landscape metrics and which land use cover is more related to water quality?

(3) How Riparian corridor and watershed-scale affect water quality characteristics?

Methods

Study area and data

The Chalus River basin, located in the west part of Mazandaran province, has an area of 110398 ha, and the length of the river in our study area is 100 km (Fig. 1). The River's branches drainage 19 catchments, mostly covered with forest, but different covers such as agriculture, grassland, bare soils, and urban areas are present. The average area of the catchments is 5810 ha (Table 1) and the average slope of the basin is 48%. The average percentage of urban areas is about 0.58%. we selected the study area consciously for especially examining the effects of landscape pattern on water quality in an area with the lowest human activities. The average percentage of forest cover is about 37% in the Chalus River basin, ranging from 1.3–77.3%.

The Khorramabad River watershed is located in the middle part of Lorestan province. It has an area of 244072 hectares and its longest river length (Khorramabad River) is 100 km (Fig. 2). The Khorramabad River's branches drainage 21 catchments, covered with different covers like agriculture, forest, grassland, bare soils, and urban. The Kakasharaf River flows to the southern and southeastern parts of the study area. These two rivers joined in the watershed outlet and flow into the Kashkan River. In general, the Khorramabad watershed most of the time has been accumulated from the alluvial deposits of permanent rivers and other seasonal rivers. The average slope and elevation of the watershed are 20 % and 1603 m, respectively (Table 2).

Using a digital elevation model (DEM) at 30m×30m resolution, watershed boundaries, digital river network, and sampling points were delineated using ArcGIS Arc Hydro extension. For this study, 42 water quality sampling points were selected based on each output of the basins. The sampling was conducted one week after raining in the early days of the rainy season. Seven representative variables were selected for testing. These variables were electrical conductivity (EC), nitrite (NO2), nitrate (NO3), dissolved oxygen (DO), phosphate (PO4), phosphor (P), and temperature (TEMP). The sampling was conducted within 6 h of collection following standard methods (Shen et al., 2014).

Table 1
Watershed area (Ha), average slope, land use summaries of Chalus River watershed.

Basin	Area (Ha)	Average slope	% Urban	% Grassland	% Forest	% Agriculture	% Bare soil
1	9424.3	58.6	0.0	21.6	22.2	0.3	55.8
2	6584.7	61.4	0.1	20.0	17.7	0.7	61.6
3	12337	62.1	0.5	27.4	25.4	3.4	43.3
4	6318.4	54	1.0	11.9	59.1	14.7	13.4
5	9961.9	51.3	5.1	2.3	12.9	50.6	29.0
6	2336.4	26	0.3	12.3	20.8	43.1	23.5
7	3562.5	33.2	0.5	0.4	82.3	16.8	0.1
8	3118.3	68.7	0.1	31.6	1.3	0.3	66.8
9	1718.6	52.9	0.3	42.5	1.5	0.0	55.7
10	8481.7	47.6	0.1	36.0	47.9	1.2	14.9
11	3842.6	47.2	0.3	32.7	59.0	2.8	5.3
12	9655.6	57.3	0.2	21.0	74.8	2.0	20.9
13	4777.8	54.5	0.3	36.5	36.3	6.0	12.5
14	6817.1	43	0.3	36.7	48.0	2.6	2.1
15	6611.0	41.4	0.9	6.5	17.9	44.1	30.7
16	4239.1	50.4	0.1	6.2	77.3	13.0	3.3
17	5737.6	25.7	0.9	11.1	48.4	33.5	6.1
18	2831.4	41.6	0.0	21.6	22.2	0.3	55.8
19	2041.9	35.6	0.1	20.0	17.7	0.7	61.6

Table 2
Watershed area (Ha), average slope, land use summaries of Khorramabad River watershed.

Basin	Area (Ha)	Average slope	% Urban	% Grassland	% Forest	% Agriculture	% Bare soil
1	10922.04	27.08	0.52	22.62	61.96	7.30	3.29
2	14723.01	25.03	0.48	37.38	31.40	23.28	3.23
3	3274.47	19.44	0.94	11.07	50.10	28.20	1.47
4	8659.89	12.91	0.55	8.81	27.17	58.25	4.75
5	5137.29	32.75	0.07	25.95	47.22	17.37	1.79
6	10932.39	23.30	15.13	38.005	17.05	20.76	-
7	11909.61	14.55	0.42	25.59	0.000	71.65	1.86
8	16086.06	19.79	0.23	19.36	13.02	62.46	1.26
9	19602.45	19.58	0.53	20.71	36.42	38.60	3.71
10	8102.88	16.30	2.45	16.77	0.79	67.57	-
11	14786.01	16.23	0.15	33.58	15.82	49.20	1.23
12	11182.77	12.83	6.60	25.56	13.66	46.32	7.83
13	12633.3	21.50	0.54	29.96	35.83	30.40	3.25
14	2073.24	28.57	15.64	49.69	49.69	15.26	0.001
15	4890.78	21.96	5.85	36.91	13.46	43.75	0.005
16	16546.14	17.94	0.13	23.29	57.55	15.36	3.65
17	3881.52	16.34	7.30	37.32	22.89	30.85	1.62
18	20501.1	22.97	0.37	31.09	49.19	58.11	4.25
19	15687.81	23.59	0.68	13.16	44.56	15.09	4.73
20	3645.9	9.66	0.61	8.29	31.12	34.90	1.84
21	14043.42	30.16	2.32	16.48	48.76	31.51	0.74
22	5398.56	14.95	0.11	29.01	61.85	5.58	3.42
23	9451.8	14.19	0.78	14.88	44.43	36.97	2.83

Quantification of Landscape Pattern

Sentinel 1A images with the least cloud cover, taken in august 2018, were used for the classification of land use and land cover (LULC) data using a maximum likelihood method. All the images were projected into the World Geodetic System (WGS) 1984 UTM 39N coordinates. Five land use and land cover types were classified: urban, forest, agriculture, grassland, and bare soil. Five spatial scales within the regional watershed, consisting of 100 m, 300 m, 500 m, and 1000 m buffer zones, and basins were created by buffering along the streams using ArcGIS $_{10.5}$ software. The LU/LC types at all scales were abbreviated as class names: AG (agriculture), UR (Prospects), GR (grassland), and FO (forest). The land use map file obtained through remote sensing image interpretation was converted into raster data with a grid size of 5 m ×5 m in the ArcGIS $_{10.5}$ platform.

Several landscape metrics including class area (CA), number of patches (NA), patch density (PD), percentage of landscape (PLAND), perimeter-area fractal dimension (PAFRAC), large patch index (LPI), effective mesh size (Kulhanek et al.), edge density (ED), total edge (TE), mean Euclidian nearest neighbor distance (ENN-MN), aggregation index (AI), and landscape shape index (Ferreira et al.), splitting index (SPLIT), clumpiness index (CLUMPY), and interspersion juxtaposition index (IJI) were used to quantify landscape patterns at different scales. These metrics represent the characteristics of patch size, shape, structure, and landscape aggregation. The landscape metrics were calculated using FRAGSTATS software (McGarigal et al., 2002) at each spatial scale described above for the map for which remote sensing data were obtained.

Statistical analysis

First, all the water quality variables and landscape metrics that did not follow a normal distribution were logarithmically transformed. The Kolmogorov-Smirnov (K-S) test was used to detect the normality of distribution of the variables for water quality, landscape composition, and habitat fragmentation (Olea and Pawlowsky-Glahn, 2009). Stepwise multiple regression analyses were performed to determine the direction and magnitude of the interaction between the landscape metrics and the individual water quality indicators. The stepwise regression has long been used to select descriptive variables for relating water quality to landscape descriptors (Mehaffey et al., 2005; Shen et al., 2014; Ssegane et al., 2012). In our study, we use the stepwise method, which starts at the forward selection, but at each stage, the possibility of deleting a predictor, as backward elimination, is considered (Chong and Jun, 2005). The probability value to enter variables into the stepwise models was set at 0.05 and the probability to remove was set at 0.1.

Redundancy analysis was used for the gradient analysis of the water quality/landscape relationship at multiple spatial scales. Before the RDA, the water quality data, including EC, NO2, NO3, DO, PO4, P, and temperature were imported into Canoco $_{4.5}$ software to test if the DCA gradient shaft length was less than 3. The result showed that the DCA gradient shaft length was less than 3. Therefore, six water quality variables, as well as all selected landscape metrics including landscape composition and configuration, were considered. RDA is a constrained linear ordination technique that describes the variation between two multivariate data sets (Ou and Wang, 2011). The forward selection method was used to identify the significant variables at multiple scales based on the Monte Carlo Permutation method (n = 499) in the process of the RDA analysis, avoiding the influence of redundant variables. Based on the RDA analysis, the influence of the landscape metrics for the catchment and riparian zones on all water quality variables was examined.

Results

The relationship between landscape structure and water quality variables

The results of stepwise multiple regression models for Chalus watershed showed (Table 3) that quality parameters including EC, DO, NO3, PO4, P, and TEMP were effectively explained by the landscape metrics (R^2= 94.8%, 62.1%, 94.8%, 51.8%, 63.8%, and 95.9% respectively). At the landscape level, only the P variable showed a significant relationship with landscape metrics (PD and SPLIT). P variable indicated a positive relationship with SPLIT and a negative correlation with PD metrics at the landscape level. In contrast, at the class level, the landscape configuration metrics of the different land-use types appeared most frequently in the model. DO exhibit a positive correlation with IJI of agriculture class and negative with MESH of grassland. EC was positively correlated with ED and ENN_MN of urban class, but negatively with PAFRAC of it. TEMP was mostly correlated to metrics related to the grassland class. Almost all classes had a considerable effect on the NO3 variable. This variable was negatively correlated with the number of patches of agriculture class and had a positive correlation to the AREA_MN of forest cover. PO4 was negatively correlated to the PAFRAC of agriculture class, while P had a negative correlation to patch density of forest cover and a positive correlation to IJI of urban class. On the whole, both landscape composition and configuration metrics had a significant influence on water quality in the Chalus watershed, but landscape configuration metrics were more related to the water quality variables (Table 3).

Table 3
Stepwise multiple regression models for landscape indices and water quality indicators in the Chalus River Watershed

Response variables	Regression equations	R^2	P
Landscape			
P	Y= 0.01475 - 0.000470 PD + 0.002355 SPLIT	72.8%	0.000
Class			
DO	Y = 7.767 - 0.000971 MESH_GR + 0.01297 IJI_AG	62.1%	0.002
EC	Y= 994 + 25.93 ED_UR - 579.0 PAFRAC_UR + 4.66 ENN_MN_UR + 0.000002 SPLIT_AG	94.8%	0.000
TEMPT	Y= 69.64 + 0.000003 TE_FO + 0.000003 TE_GR - 24.09 PAFRAC_GR - 22.63 CLUMPY_GR + 0.0703 IJI_GR - 0.01982 ENN_MN_AG	95.9%	0.000
NO3	Y= 50.29 + 0.1950 AREA_MN_FO - 32.96 PAFRAC_FO + 0.000530 CA_GR + 0.000069 TE_UR - 0.01722 NP_AG	94.8%	0.000
P	Y= 0.00546 - 0.001020 PD_FO + 0.000136 IJI_UR	63.8%	0.001
PO4	Y= 0.0715 - 0.03558 PAFRAC_AG	51.8%	0.001

The results of stepwise multiple regression models in the Khorramabad watershed indicated that TDS, DO, NO3, and NO2 were effectively explained by the landscape metrics (R^2= 88.93%, 71.84%, 94.85%, and 57.04% respectively), but TEMP was less related (R^2= 35.92%). At the landscape and class levels, PO4 did not show any correlation with landscape metrics. MESH, AREA_MN, and PD were determining metrics in the regression models at the landscape level. On the contrary, PD, PLADJ, MESH, and SPLIT values of the different land-use types were appeared most frequently in the model, at the class level. PD and AREA_MN were correlated with TDS positively, and MESH was correlated with NO3 similarity. At the class level, DO indicated a positive correlation with PD of agriculture class and MESH of grassland. PLADJ of agriculture class and SPLIT of urban areas were correlated positively with TDS. MESH of grassland had a negative relationship with TEMP, and SPLIT of the forest was positively correlated with NO2. MESH of agriculture class, PD of urban areas, and PLADJ of the forest had a positive effect on NO3.

According to regression results presented in Table 4, landscape composition metrics had no significant influence on water quality, and landscape configuration metrics were more associated with the water quality parameters. Almost all of the landscape metrics that appeared in the stepwise regression model had a positive effect on the water quality parameters.

Table 4
Stepwise multiple regression models for landscape indices and water quality indicators in the Khorramabad River Watershed

Response variables	**Regression equations**	R^2	**P**
Landscape			
TDS	Y= -516 + 44.60 PD + 39.7 AREA_MN	68.49%	0.001
NO3	Y= 6.12 + 0.000967 MESH	35.29%	0.000
Class			
DO	Y = 1.5422 + 0.1246 PD_AG + 0.000598 MESH_GR	71.84%	0.002
TDS	Y= -6096 + 66.3 PLADJ_AG + 0.000551 SPLIT_UR	88.93%	0.000
TEMPT	Y= 24.598 - 0.00560 MESH_GR	35.92%	0.030
NO2	Y= 0.309 + 0.000079 SPLIT_FO	57.04%	0.003
NO3	Y= -33.6 + 0.001373 MESH_AG + 2.857 PD_UR + 0.410 PLADJ_FO	94.85%	0.000

The relationship between the landscape structure and the water quality at multiple scales

The results of the redundancy analysis of the Chalus watershed (Table 5) showed that the proportions used to quantify the landscape explained more than 75% of the variation in water quality. The first two RDA ordination axes also explained 70 to 79% of the total correlation reflected by all axes. At the 100 m buffer zone scale, the landscape pattern metrics could account for 80% of the water quality variation. Thus, the 100 m riparian buffer was identified as the main riparian zone that had the greatest impact on the water quality. When the scale increased to a 300 m buffer, the explanatory power decreased to 78%. However, there is a considerable decrease of explanatory power at 500 m buffer (71%), but the value increased again at 1000 m and basin scales.

Table 6 shows the dominant landscape variable groups with the maximum explanatory power at each spatial scale selected based on the test of significance and importance and inspection of variance inflation factors (VIF < 10). Consistent with the results of the multiple stepwise regression, the metrics reflecting the landscape configuration had a greater impact on water quality. AI of the forest (0.33%), ED of urban areas (0.14%), and IJI of the agricultural lands (0.19%) were identified as the most important variables at the basin scale. AI of forest (0.35%), ED of urban lands (0.18%), and SPLIT of Agriculture class (0.17%) appeared as dominant metrics at the 100 m buffer zone. Similar to basin scales, the aggregation (AI) metric of forest cover also was the most significant metric for explaining water quality at a 100 m buffer zone. ED of urban class and SPLIT of agriculture class was dominant metrics at 300 m buffer zone with explaining powers of 0.28%, 0.29%, respectively. At the 500 m and 1000 m buffer zone scales, urban metrics were the most effective metrics in determining water quality.

The results of redundancy analysis for the Khorramabad watershed showed that the metrics that were used to quantify the landscape, explained more than 80% of the variation in water quality. The first two RDA ordination axes also explained more than 80% of the total reflected correlation by all axes. The landscape pattern metrics could account for 89% of the water quality variation at the 100 m buffer zone scale. Thus, the 100 m riparian buffer was the main riparian zone that had the greatest effect on the water quality. When the scale increased to a 300 m buffer, the explanatory power decreased to the rate of 83%. However, as the buffer scale increased from 500 m to1000 m, the explanatory power decreased from 84–79%.

Table 7 presents the dominant landscape variable groups with the maximum explanatory power at each spatial scale. Consistent with the results of the stepwise multiple linear regression, the metrics reflecting the landscape configuration had a greater effect on water quality. SPLIT and MESH of the urban land and PAFRAC of the agricultural lands were recognized as the most important variables at the watershed scale. The edge density (ED) of forest (0.37%), PLADJ (0.26%), and MESH (0.16%) of urban lands were the dominant metrics at the 100 m buffer zone. Metrics related to urban lands also showed significant power for explaining water quality at a 300 m buffer zone similar to previous scales. These metrics were MESH and CLUMPY of urban areas and NP of agricultural lands with explaining powers of 0.32%, 0.24%, and 0.16%, respectively. Landscape configuration metrics of urban lands were the factors affecting water quality at all riparian buffer scales, as MESH, CLUMPY, and PLAND of this class were identified to be more related to water quality variance at the 500 m and 1000 m buffer zone scales.

Figures 3 and 4 display ordination diagrams derived from the RDA using the water quality variables and selected landscape metrics representing landscape composition and configuration. The plots can be interpreted quantitatively using the landscape factor arrow length to indicate how much is the water quality variance was explained by that factor. The water quality variable arrows pointing in the same direction as the landscape factor arrows indicate a positive correlation (the smaller the angle between the arrows, the stronger the relationship).

Fig 3. Redundancy analysis biplots showing the correlation between water chemistry variables and landscape variables in the Chalus watershed.

Table 5
Redundancy analysis using the water chemistry variables at multiple scales, showing total variance explained by the ordination axes in the Chalus watershed.

	Axis1	Axis2	Axis3	Axis4	Total explained variance
Basin					
Eigenvalues	0.604	0.142	0.006	0.003	77%
Cumulative percentage correlation of landscape-water quality data	60.4	74.6	75.2	75.6	
100 m					
Eigenvalues	0.628	0.170	0.005	0.001	80%
Cumulative percentage correlation of landscape-water quality data	62.8	79.9	80.4	80.4	
300 m					
Eigenvalues	0.633	0.138	0.016	0.001	78%
Cumulative percentage correlation of landscape-water quality data	63.3	77.1	78.7	78.8	
500 m					
Eigenvalues	0.576	0.132	0.009	0.001	71%
Cumulative percentage correlation of landscape-water quality data	57.6	70.8	71.7	71.7	
1000 m					
Eigenvalues	0.536	0.186	0.016	0.006	74%
Cumulative percentage correlation of landscape-water quality data	53.6	72.2	73.9	74.4	

Table 6

Selected environmental explanatory variables for further RDA analysis in the second step which related landscape pattern metrics, including composition and spatial configuration of landscapes, with water quality, by Monte Carlo permutation test (n = 499) (variables with the value of variance inflation factors >10 have been removed) in Chalus watershed.

Scale	Dominant variables	Importance	P -value
Basin			
	AI_FO	33%	0.002
	IJI_AG	19%	0.004
	ED_UR	14%	0.014
100 m			
	AI_FO	35%	0.020
	ED_UR	18%	0.020
	SPLIT_AG	17%	0.074
300 M			
	ED_UR	28%	0.004
	SPLIT_AG	29%	0.024
500 M			
	PAFRAC_UR	31%	0.016
	ED_UR	27%	0.004
1000 M			
	MESH_UR	27%	0.002
	PAFRAC_UR	27%	0.010
	LPI_AG	13%	0.004

Table 7
Redundancy analysis using the water chemistry variables at multiple scales, showing total variance explained by the ordination axes in the Khorramabad watershed.

	Axis1	Axis2	Axis3	Axis4	Total explained variance
Watershed					
Eigenvalues	0.563	0.119	0.073	0.006	76%
Cumulative percentage correlation of landscape-water quality data	56.3	68.2	75.5	76.1	
100 m					
Eigenvalues	0.720	0.153	0.010	0.007	89%
Cumulative percentage correlation of landscape-water quality data	72.0	87.3	88.3	89.0	
300 m					
Eigenvalues	0.635	0.166	0.025	0.005	83%
Cumulative percentage correlation of landscape-water quality data	63.5	80.1	82.6	83.1	
500 m					
Eigenvalues	0.624	0.173	0.037	0.007	84%
Cumulative percentage correlation of landscape-water quality data	62.4	79.7	83.4	84.1	
1000 m					
Eigenvalues	0.600	0.157	0.032	0.004	79%
Cumulative percentage correlation of landscape-water quality data	60.0	75.7	79.0	79.4	

Table 8

Selected environmental explanatory variables for further RDA analysis in the second step, which was related to the landscape pattern metrics, including composition and spatial configuration of landscapes, with water quality, by Monte Carlo permutation test (n = 499) (variables with the value of variance inflation factors >20 have been removed) Khorramabad watershed.

Scale	Dominant variables	Importance	P -value
Watershed			
	SPLIT_UR	35%	0.002
	MESH_UR	18%	0.014
	PAFRAC_AG	13%	0.004
100 m			
	ED_FO	37%	0.014
	PLADJ_UR	26%	0.002
	MESH_UR	16%	0.074
300 M			
	MESH_UR	32%	0.004
	CLUMPY_UR	24%	0.024
	NP_AG	15%	0.004
500 M			
	MESH_UR	31%	0.016
	SPLIT_AG	23%	0.012
	CLUMPY_UR	18%	0.004
1000 M			
	PLAND_UR	31%	0.002
	SPLIT_AG	21%	0.010
	CLUMPY_UR	13%	0.004

Discussion

Landscape configuration and water quality at landscape and class levels

Our study indicated that the metrics reflecting landscape spatial configuration had a stronger relationship to the water quality variables than composition metrics for both basins under study (Tables 2 and 4). Stepwise regression and redundancy analyses showed that the water quality variables were more explained by the configuration metrics (e.g., PD, IJI, MESH, and SPLIT) of land use classes in comparison with landscape composition metrics, as reflected by the high frequency of occurrences in the best models (Tables 2 and 4). Note that composition metrics also were important in the analysis, as they were more effective for some of the water variables than configuration metrics. Our results are inconsistent with studies that claimed landscape configuration indices are more important than composition indices in predicting stream water quality in watersheds (Alberti et al. (2007); Clément et al. (2017); Lee et al. (2009); Xiao and Ji (2007)). Both basins showed that in addition to the number of land use classes, their position and distribution are also important.

At the landscape level, only phosphor (P) was included in the regression models in the Chalus basin (Table 2). The variable was positively correlated with SPLIT at the basin scale, indicating that a greater fragmentation of land use types leads to degraded water quality. Other related studies have obtained similar conclusions (Lee et al., 2009; Shen et al., 2014; Xiao and Ji, 2007). In the Khorramabad basin, TDS and NO3 showed a positive correlation with PD, AREA_MN, and MESH at the landscape level (Table 4), implying that increasing fragmentation of land use types leads to degraded water quality. Shen et al. (2014) also showed that the CONTAG metric was negative with total suspended solids (TSS) and IJI had a positive relationship with most water quality variables; indicating that a more fragmented landscape, the more degraded water quality. P had a positive correlation with PD of land use types, and it is high if the density of patches and their distance from each other are high. Although Lee et al. (2009) also Showed similar results about PD and Shen et al. (2014) found that PD was negatively related to the concentration of CODCr in the rainy season (R^2= 0.431). We did not find any relationship between water variable and landscape metrics at the landscape level but, Liu et al. (2012) found that ED had negative correlations with NO2, NO3, TN, TP, and TSI concentrations at landscape level in agriculture-dominated watersheds in China, indicating that more complexed landscapes have less-polluted rivers. (Uuemaa et al., 2007) also found that edge density was negatively correlated with total nitrogen concentrations in Estonian rivers, and concluded that more complex landscape patterns can retain more nutrients and organic matter.

Shen et al. (2014) indicated that IJI had a positive relationship with most of the water quality parameters; a higher IJI indicates a fragmented landscape, and subsequently presents degraded water quality. In the present study, DO was negatively correlated to IJI, and P was positively correlated with SPLIT of agriculture areas in the Chalus basin (Table 2), and in the Khorranabad basin DO was positively correlated to patch density of agriculture (Table 4), implying that fragmented agricultural lands lead to decreasing river water quality in both basins. The results of Griffith et al. (2002) in 271 catchments in the central USA, are consistent with our results and Indicated that the presence of small agricultural areas increases land cover diversity and thus negatively affects stream water quality. However, Zhou et al. (2012) found that the percentage of agricultural land use was positively correlated with the concentrations of DO at the subwatershed scale and patch density (PD) of agriculture was negatively correlated with DO at the scales of subwatershed, catchment, and buffer zones.

grasslands are considered to act as a buffer, play a retention function, decrease the amount of surface runoff, absorbing part of runoff, and thus reducing non-point source pollution (Ouyang et al., 2010). In our study, MESH of grassland was negatively correlated with DO in the Chalus basin, implying that more fragmented grasslands lead to decreased water quality. In the Khorramabad basin, LPI and PLAND of grassland were negatively correlated with NO3, contrary to the study done by Lee et al. (2009) that showed the LPI of grassland was positively correlated with the water quality parameters. Lee et al. (2009) also showed that the LPI of grasslands was positively correlated with the water quality variable.

Streams and rivers that pass through urbanized landscapes often have higher levels of water pollutants and more nutrient loads, thus reduced biodiversity (Meyer et al., 2005). our study showed that distant urban patches in the Chalus basin lead to increase electrical conductivity (EC) because EC was mostly affected by urban metrics such as ED, ENN_MN, and PAFRAC and had a positive relationship with ENN_MN of urban patches. In the Khorramabad basin, NO3 was positively correlated with PD of urban lands, indicating that dispersed urban areas lead to increasing degraded water quality. This result is also true for TDS that had a positive correlation with SPLIT of urban areas (Table 4).

Effects of forest cover on water quality in the Chalus basin showed that NO3 had a positive relationship with the mean area of forest patches and P had a negative relationship with the density of forest patches. In the Khorramabad basin, only NO2 showed a negative relationship with the SPLIT of the forest, implying that fragmented forest cover leads to degraded water quality in the basin. Our results are consistent with the studies that claim in forested catchments, water quality will start to deteriorate as the landscape becomes more fragmented, and resulting in higher landscape diversity and lower landscape contagion Clément et al. (2017). In general, forest cover in the present study did not affect the water quality variable considerably in both basins and our results only showed that the more fragmented forest, the more deteriorated water quality. However, inconsistent with our results, Lee et al. (2009) reported a negative relationship between the LPI of forest and water quality parameters. meaning that the widespread distribution of forests could improve the water quality of the watershed to a certain extent.

On the whole, PD, IJI, and SPLIT of different land uses were the most important metrics which had significant relationships with the water quality indicators (Tables 2 and 4). Similar to Shen et al. (2015) our results also showed that metrics at the class level are a better predictor than metrics at the landscape level for the water quality variables.

Impacts of landscape metrics on water quality at multiple scales

The influence of the landscape on the water quality is scale-dependent, and our study also confirms this fact, as reported by others (Sliva and Williams, 2001; Zhou et al., 2012). The impact of landscape patterns on river water quality is different at riparian buffer zones and basin scales, thus a controversial issue. Some studies have shown that near covers to the river have greater effects on river quality than distant covers or the entire catchment. For example, JOHNSON et al. (1997) found that TP and TSS were much better explained by the land use within the stream riparian buffer than the entire catchment. While, Sliva and Williams (2001) showed that at the catchment, landscape metrics had a slightly greater influence on the water quality than the 100 m buffer in their study area and Alberti et al. (2007) found that it was not possible to determine which scale was more correlated to river quality changes.

It is acceptable that the landscape patterns of riparian buffer zones have important effects on aquatic ecosystems (Alberti et al., 2007; Shen et al., 2015). Consistent with our results, Shen et al. (2015) showed that the water quality changes were better correlated with the buffer metrics than the basin scale. In both basins, the selected landscape metrics at the 100 m buffer zone explained more than 80% of water quality variation, which has proven the importance of the landscape pattern for the 100 m riparian buffer zone (Tables 5 and 7). JOHNSON et al. (1997) predict 56% of the variation in water quality in summer and 40% in autumn and Galbraith and Burns (2007) found 68.8% of the variation in the chemical and physical variables. Shen et al. (2014) showed 46.9% and 24.5% of the variation in water quality in rainy and dry seasons respectively. Since the effects of landscape patterns at the 100 m buffer zone are much stronger than earlier studies, landscape planners should focus on the riparian buffer zones and enhancing their function to improve the river water quality in the Chalus and Khorramabad River basins.

Dominant Landscape Metrics At Multiple Spatial Scales

Many of the earlier studies have identified urban areas as dominant factors contributing to degraded water quality. In our study, forest cover, agriculture, and urban areas were recognized as important explanatory variables for water quality. It is known that urban land uses play primary roles in decreasing river water quality passing through urbanized landscapes (Lee et al., 2009; Shen et al., 2014; White and Greer, 2006), and Agricultural areas can result in non-point source pollution by runoff from bare soils, pastures and crop fields (Mehaffey et al., 2005).

At the 100 m buffer scale, ED of the forest, PLADJ, and MESH of urban areas in Khorramabad basin and AI of the forest, ED of urban, and SPLIT of agricultural lands were recognized as significant variables affecting the water quality in the Chalus basin (Tables 6 and 8). Forest edge density (ED) also showed a positive influence on water quality at 100 m buffer riparian scale with TDS and appeared as the most dominant metrics in multivariate analysis at 100 m scale. In other scales only metrics related to agriculture and urban were seen as dominant variables, indicating that these land-use classes are final determinatives in water quality changes in our study areas. As the scale increased, all dominant variables at each scale indicated a decreasing trend of the landscape impact on the water quality. Joshi et al. (2016) also showed that the largest patch index of urban (LPI) and aggregation index of forest (AI) were the most important predictors for NH3-N, NO3-N, and TP. Clément et al. (2017) proposed that a forest edge is beneficial for water quality with a density of higher than 36 m/ha. They also compared two catchments with similar characteristics, and different forest edge densities, and water quality. Their results indicated that in the catchment with the higher edge density, water quality is better, implying complex woodlands following river corridors and gullies, improves the filtration capacity.

Although in Chalus basin human activities were insignificant, they had considerable effects on Chalus river quality, and metrics of urban and agriculture were recognized as a dominant variable at all scales, implying that a large amount of forest cover cannot impede the effects of human activities in a basin because this kind of activities have been created near rivers and have more impacts on the river than distant natural covers.

Conclusion

In summary, our results showed that:

1. Water quality variables were better explained with the buffer riparian zones than basin scale, and 100 m buffer is the most effective buffer zone for affecting the water quality.
2. Both landscape composition and configuration had significant impacts on water quality, but in our study, landscape configuration indices were more effective than composition metrics in explaining river water quality.
3. Among the dominant landscape metrics representing both the landscape composition and the spatial configuration, the AI of the forest was recognized as the most significant variable influencing the water quality at the basins.
4. Landscape metrics at the class level can predict river water quality in the study of watersheds more effectively in comparison with the indices at the landscape level.

Abbreviations

NP: Number of Patches; DIVISION: Landscape Division Index; ENN-MN: Mean Euclidean Nearest-Neighbor Distance; Area_MN: Mean Patch Area; ED: Edge Density; PAFRAC: Perimeter-Area Fractal Dimension; LSI: Landscape Shape Index; SPLIT: Splitting Index; AI: Aggregation Index;

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Competing interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Availability of data and material

Data are available on request from the authors only based on logical requests.

Code availability

Code available on request from the authors only based on logical requests.

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Authors' contributions

FS has written the paper and has done the sampling part of the paper.

HT has reviewed the paper, helped to write, and interpreted the results.

RZ helped to write, and interpreted the results.

JV helped in statistical analysis part of paper and landscape metrics.

AA edited grammar, and helped to respond to the paper's questions.

References

1. Alberti M, Booth D, Hill K, Coburn B, Avolio C, Coe S, Spirandelli D (2007) The impact of urban patterns on aquatic ecosystems: An empirical analysis in Puget lowland sub-basins. Landscape urban planning 80(4):345–361
2. Amiri BJ, Nakane K (2009) Modeling the linkage between river water quality and landscape metrics in the Chugoku district of Japan. Water resources management 23(5):931–956
3. Casatti L, Teresa FB, Gonçalves-Souza T, Bessa E, Manzotti AR, Gonçalves CdS, Zeni JdO (2012) From forests to cattail: how does the riparian zone influence stream fish? Neotropical Ichthyology 10(1):205–214
4. Chambers PA, McGoldrick DJ, Brua RB, Vis C, Culp JM, Benoy GA (2012) Development of environmental thresholds for nitrogen and phosphorus in streams. J Environ Qual 41(1):7–20
5. Chong I-G, Jun C-H (2005) Performance of some variable selection methods when multicollinearity is present. Chemometrics intelligent laboratory systems 78(1-2):103–112
6. Clément F, Ruiz J, Rodríguez MA, Blais D, Campeau S (2017) Landscape diversity and forest edge density regulate stream water quality in agricultural catchments. Ecological indicators 72:627–639

7. Ding J, Jiang Y, Liu Q, Hou Z, Liao J, Fu L, Peng Q (2016) Influences of the land use pattern on water quality in low-order streams of the Dongjiang River basin, China: a multi-scale analysis. Science of the total environment 551:205–216
8. Dodds WK, Oakes RM (2008) Headwater influences on downstream water quality. Environmental management 41(3):367–377
9. Ferreira PA, Boscolo D, Lopes LE, Carvalheiro LG, Biesmeijer JC, da Rocha PLB, Viana BF (2020) Forest and connectivity loss simplify tropical pollination networks. Oecologia 192(2):577–590
10. Galbraith LM, Burns CW (2007) Linking land-use, water body type and water quality in southern New Zealand. Landscape Ecol 22(2):231–241
11. Griffith J, Martinko E, Whistler J, Price K (2002) Relationships among landscape pattern, NDVI and stream water quality in the US Central Plains. J Environ Qual 31:846–859
12. Hunsaker CT, Levine DA (1995) Hierarchical approaches to the study of water quality in rivers. Bioscience 45(3):193–203
13. Jackson C, Leigh D, Scarbrough SL, Chamblee J (2015) Herbaceous versus forested riparian vegetation: narrow and simple versus wide, woody and diverse stream habitat. River Res Appl 31(7):847–857
14. JOHNSON L, Richards C, HOST G, ARTHUR J (1997) Landscape influences on water chemistry in Midwestern stream ecosystems. Freshw Biol 37(1):193–208
15. Joshi NK, Otieno M, Rajotte EG, Fleischer SJ, Biddinger DJ (2016) Proximity to woodland and landscape structure drives pollinator visitation in apple orchard ecosystem. Frontiers in ecology evolution 4:38
16. Kulhanek K, Steinhauer N, Rennich K, Caron DM, Sagili RR, Pettis JS, Ellis JD, Wilson ME, Wilkes JT, Tarpy DR (2017) A national survey of managed honey bee 2015–2016 annual colony losses in the USA. J Apic Res 56(4):328–340
17. Lee S-W, Hwang S-J, Lee S-B, Hwang H-S, Sung H-C (2009) Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. Landscape Urban Planning 92(2):80–89
18. Li S, Gu S, Liu W, Han H, Zhang Q, 2008, Water quality in relation to land use and land cover in the upper Han River Basin, China, *Catena* **75**(2):216-222
19. Li S, Xia X, Tan X, Zhang Q (2013) Effects of catchment and riparian landscape setting on water chemistry and seasonal evolution of water quality in the upper Han River basin, China. PloS one 8(1):e53163
20. Liu W, Zhang Q, Liu G (2012) Influences of watershed landscape composition and configuration on lake-water quality in the Yangtze River basin of China. Hydrol Process 26(4):570–578
21. Margriter SC, Bruland GL, Kudray GM, Lepczyk CA (2014) Using indicators of land-use development intensity to assess the condition of coastal wetlands in Hawai ‘i. Landscape ecology 29(3):517–528

22. McGarigal K, Cushman SA, Neel MC, Ene E, 2002, FRAGSTATS: spatial pattern analysis program for categorical maps
23. Mehaffey MH, Nash M, Wade T, Ebert D, Jones K, Rager A (2005) Linking land cover and water quality in New York City's water supply watersheds. Environ Monit Assess 107(1-3):29–44
24. Meyer JL, Paul MJ, Taulbee WK (2005) Stream ecosystem function in urbanizing landscapes. Journal of the North American Benthological Society 24(3):602–612
25. Mitchell MG, Bennett EM, Gonzalez A (2013) Linking landscape connectivity and ecosystem service provision: current knowledge and research gaps. Ecosystems 16(5):894–908
26. Olea RA, Pawlowsky-Glahn V (2009) Kolmogorov–Smirnov test for spatially correlated data. Stoch Env Res Risk Assess 23(6):749–757
27. Ou Y, Wang X (2011) GIS and ordination techniques for studying influence of watershed characteristics on river water quality. Water Sci Technol 64(4):861–870
28. Ouyang W, Skidmore AK, Toxopeus A, Hao F (2010) Long-term vegetation landscape pattern with non-point source nutrient pollution in upper stream of Yellow River basin. J Hydrol 389(3-4):373–380
29. Parker M, Mac Nally R (2002) Habitat loss and the habitat fragmentation threshold: an experimental evaluation of impacts on richness and total abundances using grassland invertebrates. Biol Cons 105(2):217–229
30. Prospects WU, 2014, The 2014 Revision, Highlights (ST/ESA/SER. A/352)
31. Shen Z, Hou X, Li W, Aini G (2014) Relating landscape characteristics to non-point source pollution in a typical urbanized watershed in the municipality of Beijing. Landscape Urban Planning 123:96–107
32. Shen Z, Hou X, Li W, Aini G, Chen L, Gong Y (2015) Impact of landscape pattern at multiple spatial scales on water quality: A case study in a typical urbanised watershed in China. Ecol Ind 48:417–427
33. Sliva L, Williams DD (2001) Buffer zone versus whole catchment approaches to studying land use impact on river water quality. Water Res 35(14):3462–3472
34. Snyder MN, Goetz SJ, Wright RK, 2005, STREAM HEALTH RANKINGS PREDICTED BY SATELLITE DERIVED LAND COVER METRICS 1, JAWRA Journal of the American Water Resources Association 41(3):659–677
35. Ssegane H, Tollner E, Mohamoud Y, Rasmussen T, Dowd J (2012) Advances in variable selection methods I: Causal selection methods versus stepwise regression and principal component analysis on data of known and unknown functional relationships. Journal of hydrology 438:16–25
36. Tanaka MO, de Souza ALT, Moschini LE, de Oliveira AK (2016) Influence of watershed land use and riparian characteristics on biological indicators of stream water quality in southeastern Brazil. Agr Ecosyst Environ 216:333–339
37. Tong ST, Chen W (2002) Modeling the relationship between land use and surface water quality. Journal of environmental management 66(4):377–393
38. Tudesque L, Tisseuil C, Lek S (2014) Scale-dependent effects of land cover on water physico-chemistry and diatom-based metrics in a major river system, the Adour-Garonne basin (South

Western France). Sci Total Environ 466:47–55

39. Uuemaa E, Roosaare J, Mander Ü (2007) Landscape metrics as indicators of river water quality at catchment scale. Hydrol Res 38(2):125–138
40. White MD, Greer KA (2006) The effects of watershed urbanization on the stream hydrology and riparian vegetation of Los Penasquitos Creek, California. Landscape urban Planning 74(2):125–138
41. Xiao H, Ji W (2007) Relating landscape characteristics to non-point source pollution in mine waste-located watersheds using geospatial techniques. J Environ Manage 82(1):111–119
42. Xie Y, Yu X, Ng NC, Li K, Fang L (2018) Exploring the dynamic correlation of landscape composition and habitat fragmentation with surface water quality in the Shenzhen river and deep bay cross-border watershed, China. Ecol Ind 90:231–246
43. Xie YJ, Ng CN (2013) Exploring spatio-temporal variations of habitat loss and its causal factors in the Shenzhen River cross-border watershed. Appl Geogr 39:140–150
44. Zhou T, Wu J, Peng S (2012) Assessing the effects of landscape pattern on river water quality at multiple scales: a case study of the Dongjiang River watershed, China. Ecol Ind 23:166–175

Figures

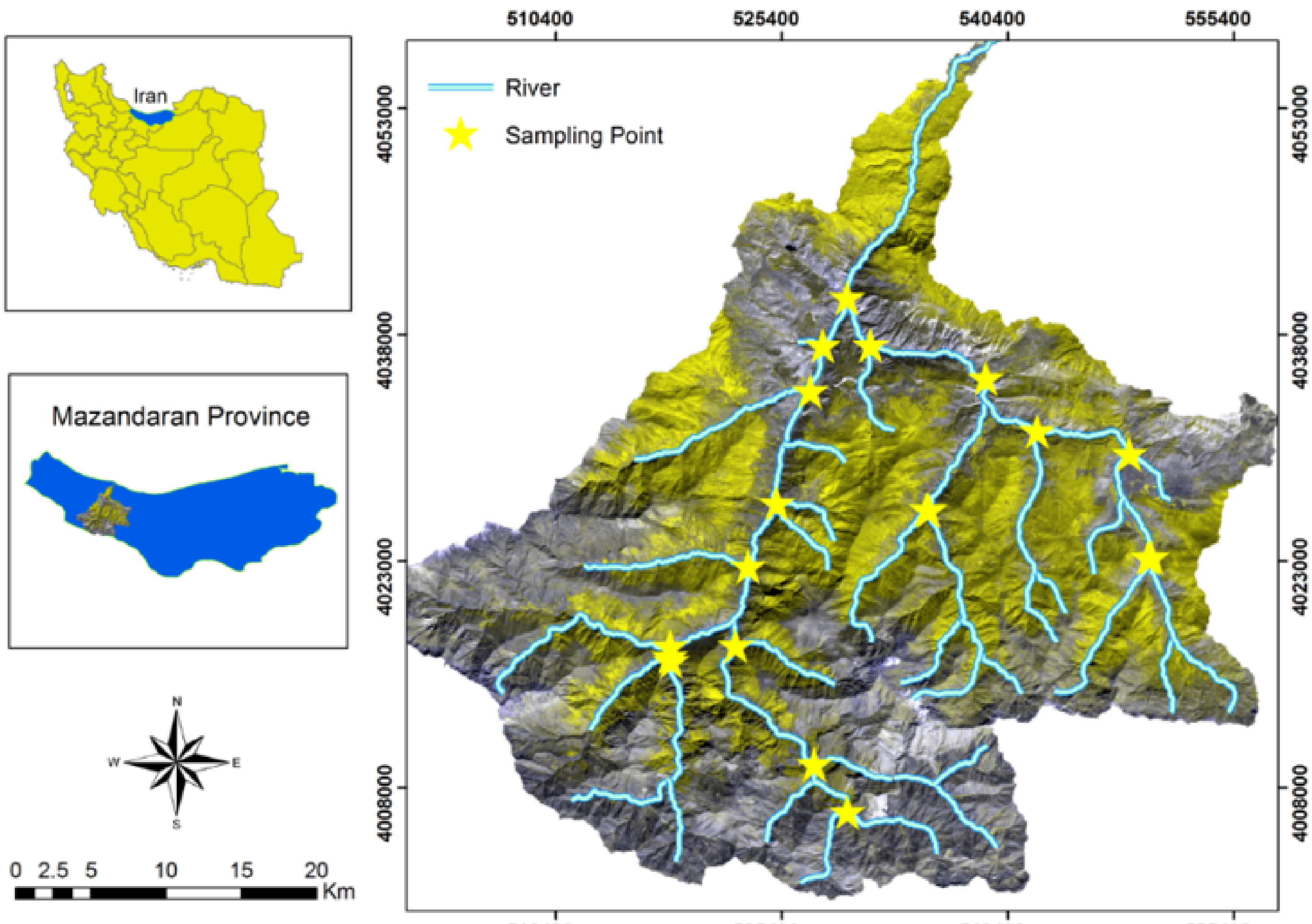

Figure 1

Location of Chalus river basin in Iran.

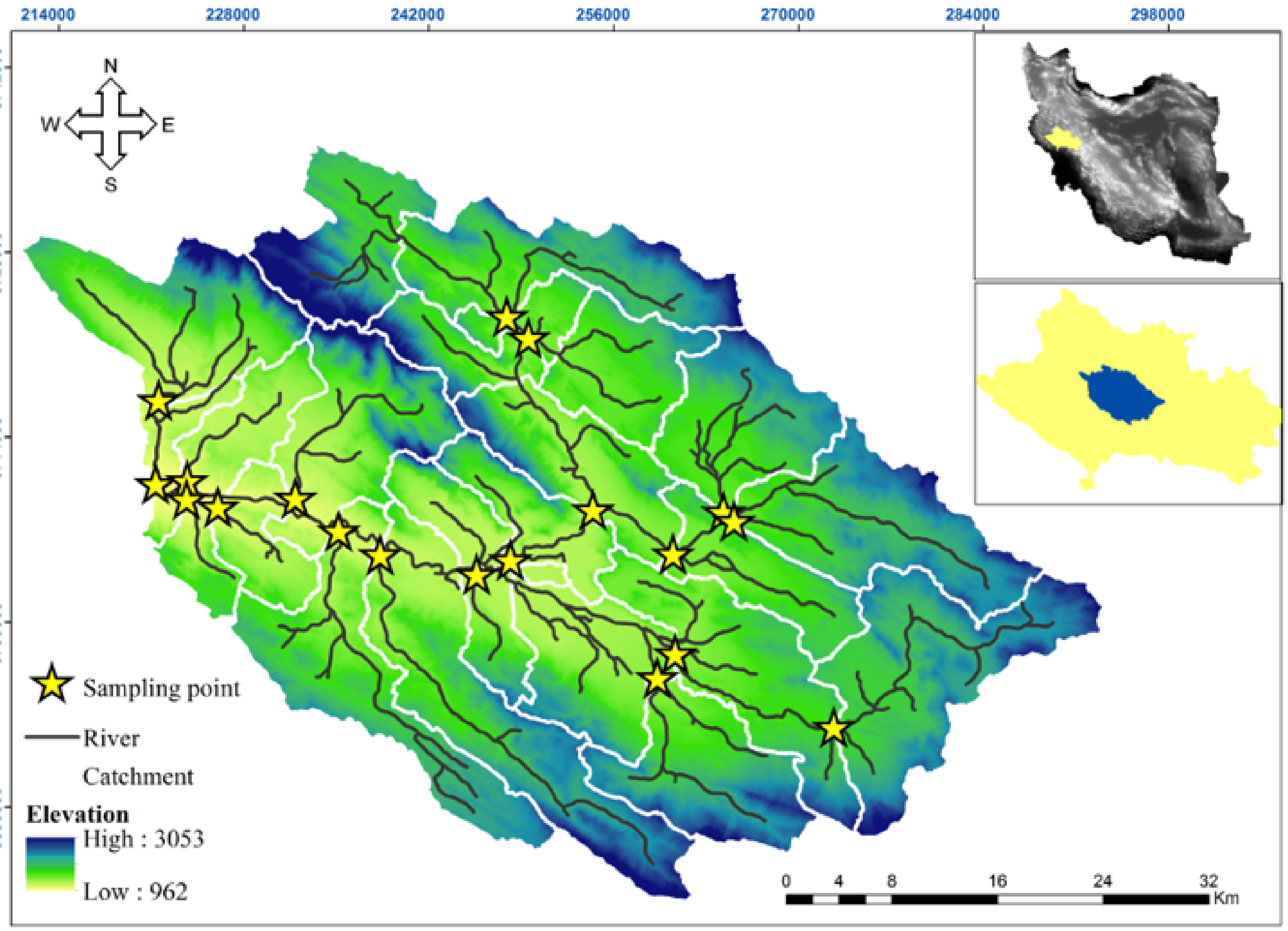

Figure 2

Location of Khorramabad river basin in Iran.

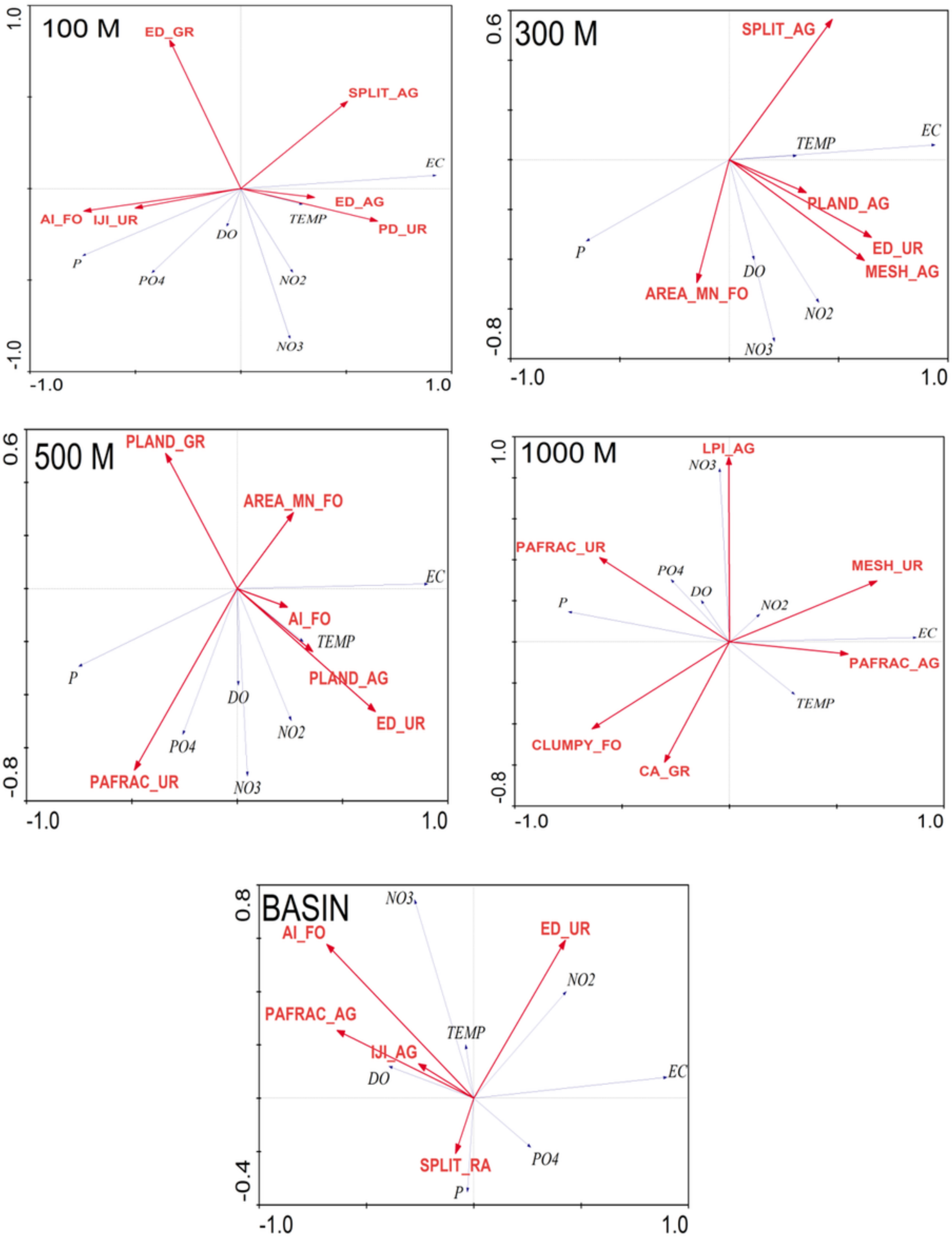

Figure 3

Redundancy analysis biplots showing the correlation between water chemistry variables and landscape variables in the Chalus watershed.

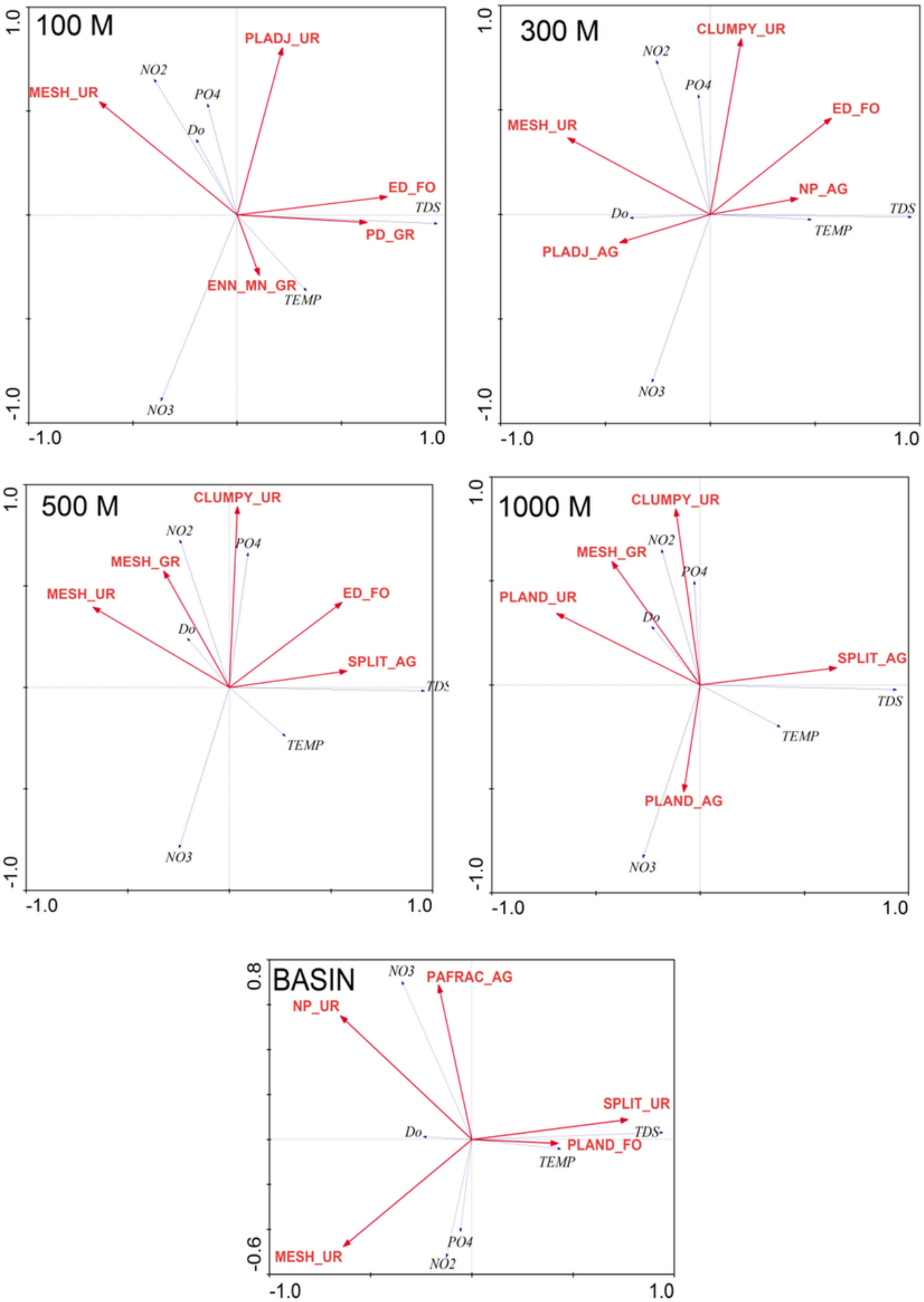

Figure 4

Redundancy analysis biplots showing the correlation between the water chemistry variables and landscape variables in the Khorramabad watershed.