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Configurationally analysis of relationships between land-cover characteristics and river water quality in a real scenario

M. Mirzaei[1] · A. Jafari[2] · A. Riyahi Bakhtiari[3] · S. Mohebbi[4] · S. Joorabian Shooshtari[5] · H. K. Soureshjani[6]

Abstract

The composition and configuration of land uses/covers (LULC) have a key role in determining the quality of surface waters. This study investigated the relationships between 207 landscape metrics (LMs) at landscape and class levels and water quality parameters (WQPs) by analytically approach in Mazandaran sub-basins, north of Iran. For this purpose, at first the basic WQPs were identified by principal component analysis (PCA). Then, stepwise linear regression analysis was applied to recognize optimal LMs for estimating each of the WQPs individually. Finally, the effect of the spatial configuration of LULC classes on WQPs and their variability was analytically evaluated by real samples. According to the PCA results, SAR, TDS, pH, PO_4^{3-}, and NO_3^- were identified as principal WQPs in Mazandaran Rivers. The results also showed that the interspersion and juxtaposition index of bare lands, related circumscribing circle of agriculture, percentage of the forest, connectivity index of residential, and percentage of agriculture were the optimal metrics for estimating SAR, pH, TDS, PO_4^{3-}, and NO_3^- levels, respectively. The metrics at the class level also had more ability to describe the WQPs. In this study, a suitable model for future LULC establishment in Mazandaran Province with the aim of improving effects on surface water quality was proposed.

Keywords Land cover/use · Landscape metrics · Surface water quality · Landscape management · Caspian sea sub-basin

✉ A. Jafari
    jafari.ali@sku.ac.ir

[1] Department of Environment, Tarbiat Modares University, Tehran, Iran

[2] Faculty of Natural Resources and Earth Sciences, Shahrekord University, Shahrekord, Iran

[3] Department of Environment, School of Natural Resources and Marine Sciences, Tarbiat Modares University, Tehran, Iran

[4] Department of Rangeland, School of Natural Resources and Marine Sciences, Tarbiat Modares University, Tehran, Iran

[5] Department of Environment, Faculty of Natural Resources and Environment, Malayer University, Malayer, Hamedan, Iran

[6] Ferdowsi University of Mashhad, Mashhad, Iran

Introduction

Water quality is a key factor for different water usages, i.e., industrial, agricultural, and residential applications. Land use/cover (LULC) in a watershed has a significant effect on the quality and quantity of water in basin outlet (Nakane and Haidary 2009). Human activities, i.e., developing industrial, agricultural, and residential areas, led to sharp changes in natural landscapes. Consequently, the type and proportion of land use in a basin can be changed during the time. These changes altered the drainage pattern of basin and type and amount of contaminants (Tiwari et al. 2018; Iqbal et al. 2019; Mirzaei et al. 2020). Typically, after human developing activities, the availability and amount of contamination are increased (Lee et al. 2009; Yan et al. 2018). For example, when a grassland changes to agriculture land the pattern of drains, potential erosion, light and temperature regime, available chemicals, and soil organic particles will be affected (Griffith 2002). In other words, as runoff passes through different LULC, it is likely to be exposed to a variety of contaminants (Schoonover and Lockaby 2006; Hashemi et al. 2016; Mirzaei et al. 2020).

Therefore, when the effects of LULC on the quality of water are measured, in addition to the size of each cover, the composition and spatial configuration of them should also be considered. In this regard, landscape metrics (LMs) can quantify specific spatial characteristics of patches, class or landscape scale (Amiri and Nakane 2009; Lausch et al. 2015; Wu et al. 2012; Lamine et al. 2018). Some studies took specific advantage of applying LMs and statistical analyses to estimate surface WQPs and recognize existing relationships. For instance, Shi et al. (2017) investigated the relationships between LULC characteristics and river water quality. They stated that analyses of spatial development patterns (size, density, aggregation, and diversity of LULC in landscape) were important factors in estimating river water quality. De Mello et al. (2018) developed an empirical model for LULC effects on river water quality. Mirzaei et al. (2020) investigated and modeled the interaction of water quality parameters (WQPs) and land use/cover. These results confirmed that LULC compositions were significantly influenced on surface WQPs. Also, in numerous studies relations between surface water quality and LULC characteristics were investigated based on linear and nonlinear statistical models (Mehaffey et al. 2004; Amiri and Nakane 2009; Lee et al. 2009; Yang 2012; Lowicki 2012; Wu et al. 2012; Mirzaei et al. 2020); however, they did noted scribe these relationships with the analytical landscape metric maps. In other words, LMs were used only as a numerical variable in the modeling process, and no proper analysis of its impact on water quality was provided. For instance, exactly what happens to the mesh size metric of agriculture lands, which leads to an increase in nitrate concentration in the river's water, was not explained.

This study was conducted in parts of the Caspian Sea basin, Mazandaran Province, northern Iran. According to the researches carried out in Mazandaran Province (Gholamalifard et al. 2012; Talebi-Amiri et al. 2009; Mirzaei et al. 2013,2020), over the past two decades, LULC changes, in particular, the conversion of Hyrcanian forests to residential and industrial development had been faster, and consequently the establishment of inappropriate land use are more visible. This will disrupt the natural drainage system of the region and change the amount and contribution of available pollutants for superficial flows and ultimately change the quality of these streams. Therefore, the availability of spatial tools for quantification and understanding of the relationships between land-use patches configuration and surface WQPs can provide solutions for the conservation and survival of these ecosystems and go toward sustainable landscape management. In other words, success in the sustainable management of landscape and conservation of aquatic ecosystems relies on a better understanding of the relationships between the landscape characteristics and the responses of WQPs to these characteristics (Alberti et al. 2007; Amiri and Nakane

2009). Because the Mazandaran province has a relatively high density of rivers and due to the precipitation distribution in all seasons, the rivers are always affected by non-point sources pollutions. That is, the Mazandaran Province was more appropriate for conducting the current study.

Therefore, we tried to investigate the relationship between WQPs and LMs in class and landscape level with explicitly recognizing effects in Mazandaran sub-basins. Altogether, this study was designed with the following aims: (1) model the relation between LMs–WQPs using multiple linear regressions and recognizing more appropriate metrics for forecasting each of WQPs and (2) analysis of LMs–WQPs relationships using some actual examples of LMs maps of studied sub-basins and providing management solutions for improving river water quality in the study area.

Materials and methods

Study area

As shown in Fig. 1, the study area located on the southern coast of the Caspian Sea and covered an area of 2,613,213 hectares (latitude: 35°45′ to 36°59′, longitude: 50°10′ to 54°42′). Therefore, the study area covers the north of Iran and includes Mazandaran Province and parts of Tehran, Gilan, and Golestan provinces. The dominant LULC of the study area is the Caspian-Hyrcanian mixed forests. These forests are a source of biodiversity and one of the most valuable forests of the world, which considered as a natural museum. Hyrcanian forest has a vital role in soil conservation, carbon storage, gentler air, and water purification (Gholamalifard et al. 2012,2013; Joorabian-Shooshtari et al. 2018), which degrading these forests is one of the major environmental challenges of recent decades (Mirzaei et al. 2013). The average annual rainfall is 977 mm, and its spatial distribution from the west to the east of the study area is reduced, while its time distribution is almost regular. The water drainage density in the study area is 2.33 km/ha (Mirzaei et al. 2013). Most of the existing rivers in Mazandaran are permanent and include large rivers, e.g., Babolrood, Tajan, Sangrud, Haraz, Nekarood, Sardabrood, CheshmehKilah, Glendrood, Garmarood, Chalous Rood, Nesarood, Chalkrood, and Safarood.

Methods

Land-use/cover map generation

The Landsat satellite images of Mazandaran Province were obtained in six frames to classify the land-use type of the terrain by satellite images and digital interpretation. The Lambert Conformal Conic coordinate system was defined for them. The images were mosaically matched, and the study
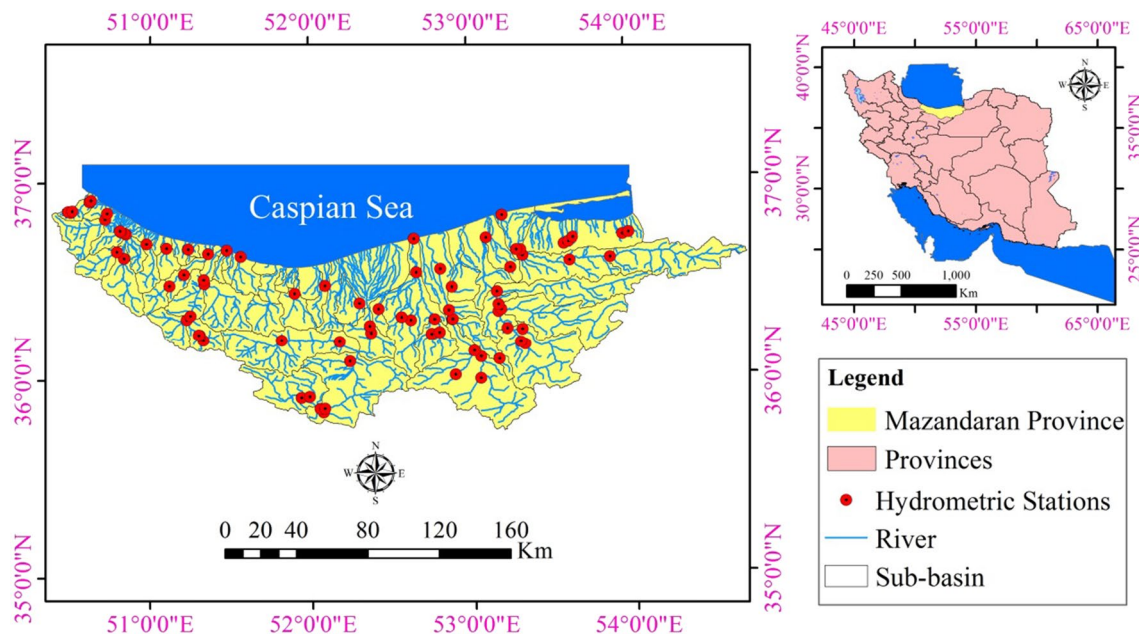
Fig. 1 Location of the study area in Iran

area was cut. Digital maps of Iran Cartographic Center in 1: 25,000 and 1: 50,000 scales were used to determine the ground control points for image geometry correction. In the next step, a multistage combination process with the use of multiple sources including Landsat, ETM and OLI satellite imagery, Google Earth virtual images, and achieved MODIS images of Terra Satellite (IGBP) was used to prepare the most accurate LULC map for 2014. In this process, visual interpretation and comparisons methods, supervised and unmatched classification, and Tasseled Cap, NDVI, and Isocluster analyses were used in the Google Earth software, Erdas Imagine, and Idrisi Taiga. It is worth mentioning that manual digitization has been performed for phenomena such as river and road as well as border control for land use, to be more accurate. Finally, seven land-use types (agricultural, forest, grassland, barren land, urban (residential), roads, and surface water (water bodies) were classified from the Landsat images.

Water quality data collection

In this study, water quality data of 85 sampling stations from February 2012 to February 2014 were obtained from Iran's Water Resources Management Company in an Excel file format. The parameters included total dissolved solids (TDS), electrical conductivity (EC), acidity (pH), nitrate (NO_3^-), phosphate (PO_4^{3-}), carbonate (CO_3^{2-}), bicarbonate (HCO_3^-), sulfate (SO_4^{2-}), calcium (Ca^{2+}), magnesium (Mg^{2+}), potassium (K^+), sodium (Na^+), sodium absorption ratio (SAR), sodium percent (Na%), permanent hardness (Per. H), and temporal stiffness (Tem. H), which are

measured on a monthly basis. Continuity and sampling frequencies were checked for individual parameters measured in this organization. Finally, 74 stations with continuous data were selected and the other stations were deleted.

Principal component analysis (PCA)

Since WQPs are highly correlated, it is therefore necessary to select the principal parameters that provide a good description of the water quality in the studied rivers. PCA is a very popular multivariate statistics method that can use to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one (called principal components: PCs) that still contains most of the information in the large set (Wold et al. 1987; Abdi and Williams 2010). Usually, the original data are standardized before performing the PCA. Since the WQPs have different units and their variation ranges is not the same, it is necessary to standardize them before entering into the analysis. Therefore, following equation was used to convert water data to standard form in the SPSS software:

$$Z = \frac{X - \overline{X}}{\text{SD}} \tag{1}$$

where $\overline{X}$ is the mean of inputs. SD is denotes standard deviation, and Z is the standard input value of X.

In the next step, the appropriateness of the statistical sample society for conducting the PCA was examined by the Kaiser–Meyer–Olkin (KMO) test. A high KMO value (close to 1) generally indicates that the PCA results are

useful (Shrestha and Kazama 2007), which in this study: KMO = 0.73. The Varimax rotation was also used to maximize the sum of the variances of the squared loadings as all the coefficients will be either large or near zero, with few intermediate values (Ouyang, 2005; Riitters et al. 1995).

In PCA, a correlation matrix is formed, and the PCs that transform a large set of variables into a smaller one are extracted. The results of a PCA are usually discussed in terms of factor loadings (the weight by which each standardized original variable should be multiplied to get the component score). The factor loadings ($-1 <$ factor loading $< +1$) are the correlation coefficients between the variables (rows: in this study water quality parameters) and factors (columns or PCs). Subsequently, based on the maximum factor loading, the principal variables can be identified in each PC (Lausch and Herzog 2002).

LMs calculation and analysis

In this study, FRAGSTATS version 4.0 (McGarigal et al. 2002) was used for the extraction of information and analysis of the metrics at class and landscape levels for each of the WQPs. Table 1 provides more details of the LMs used in this study.

Determination of optimal LMs

McGarigal et al. (2002) introduced 39 metrics in landscape and 24 metrics in class-level. Considering the existence of seven land-use/cover types in the study area, there are a totally of 207 metrics ($7*(39+24)=207$), which play a key role as independent variables for the main parameters of water quality. Therefore, it is necessary to reduce the number of inputs of the model and the best metrics that have a better description of each of the WQPs, enter into the relevant model. For this purpose, since multiple linear regressions are good tools for selecting independent variables and reducing inputs (Noori et al. 2010), this approach was used. Leading regression was performed in three steps due to the large volume of data. In the first step, the optimal metrics were selected at class-level; the second step, the optimal metrics were chosen at landscape-level, and the third step, the metrics taken from the first and second steps, entered to the progressive regression and ultimately the best set of metrics selected and introduced for the modeling stage. The selection of optimal metrics for each of the main WQPs should be made in such a way that, while having good correlation and high ability to describe water quality changes, it also has a lack of correlation of errors in the prediction and intersection of the internal Independent variables. For this purpose, the variance inflation factor (VIF) and the Durbin–Watson coefficient have been used. If the VIF value is less than 10, it indicates a lack of internal correlation between independent

variables. Also, if the Durbin–Watson value is close to 2 (i.e., 1.5–2.5), it shows the lack of correlation of errors in the prediction of the regression model. In models developed by multiple linear regressions, it is automatically reduced to internal correlation (VIF less than 10) and optimal inputs at the 5% significance level (Mirzayi et al. 2014).

Modeling WQPs and LMs

After the statistical verification of the data and the selection of independent and dependent variables, multiple linear regressions were used to model the relationship(s) between WQPs and LMs. The general multiple linear regression is as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \in_i$$

where Y_i is the predicted value of the dependent variable, β_0 is the intercept, β_1 through β_p are the regression coefficients, X_{i1} through X_{ip} are independent variables and $\in$ is the model's error.

It is worth noting that for each of the main WQPs (dependent variables), different metrics were selected and modeling was done for each of them individually. Landscape metrics were considered as an independent variable, and water quality parameters were considered as a dependent variable in regression modeling and imported into different columns in Excel. Then, all statistics were performed by using the IBM *SPSS software* to model linkage between LMs and river water quality parameters.

We used 70% of the data randomly for train the model and 30% of the remaining data for test the validity. Nash–Sutcliffe value (NASH), root mean squared error (RMSE), and R-Squared (R^2) indexes were applied to assess the performance of models. The indices are calculated according to the 2–4 equations:

$$\text{NASH} = 1 - \sum_{i=1}^{n} \left(q_0 - q_p\right)^2 \Big/ \sum_{i=1}^{n} \left(q_0 - \overline{q}_0)\right)^2 \qquad (2)$$

$$R^2 = \left\{ \sum_{i=1}^{n} \left(q_0 - \overline{q}_0\right)\left(q_p - \overline{q}_p\right) \Big/ \left[\sum_{i=1}^{n} \left(q_0 - \overline{q}_0\right)^2 \right]^{0.5} \left[\sum_{i=1}^{n} \left(q_p - \overline{q}_p\right)^2 \right]^{0.5} \right\}^2 \qquad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(q_0 - q_p\right)^2} \qquad (4)$$

where q_0 and q_p are the obtained and predicted values, $\overline{q}_0$ is the mean value of the obtained data, and n is the total number of site being modeled.

Table 1 Details of the LMs used in this study

Metrics name	Metric abbreviation	Range/description
Patch cohesion index	COHESION	$0 < COHESION < 100$; Increases as the patches of the corresponding patch type become less connected
Mean shape index	MSI	$MSI \leqq 1$, without limit; The ratio between the perimeter of a patch and the perimeter of the simplest patch in the same area
Total edge	TE	$TE \geq 0$, without limit; Measures the total edge
Area-weighted mean fractal dimension index	FRAC_AM	$1 \leqq FRAC \leqq 2$; Fractal dimension: ratio of perimeter per unit area. Increases as patches become more irregular
Area-weighted mean shape index	SHAPE_AM	A larger value of SHAPE_AM means the area is more complex and irregular in shape
Landscape shape index	LSI	$LSI \geq 1$, without limit; The complexity of landscape structure
Total class area	CA	$CA > 0$ without limit; CA is a measure of landscape composition
Related circumscribing circle	CIRCLE	$0 < CIRCLE < 1$; CIRCLE equals 1 minus patch area (m^2) divided by the area (m^2) of the smallest circumscribing circle
Clumpiness index	CLUMPY	$-1 \leqq CLUMPY \leqq 1$; CLUMPY equals the proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution
Connectivity index	CONNECT	$0 \leqq CONNECT \leqq 100$
Landscape division index	DIVISION	$0 \leqq DIVISION < 1$; DIVISION equals 1 minus the sum of patch area (m^2) divided by total landscape area (m^2), quantity squared
Edge density	ED	$ED \geq 0$ without limit; ED equals the sum of the lengths (m) of all edge segments involving the corresponding patch type, divided by the total landscape area (m^2), multiplied by 10,000
Euclidean nearest neighbor distance	ENN	$ENN > 0$ without limit; The average distance between two patches in a landscape
Fractal dimension index	FRAC	$1 \leqq FRAC \leqq 2$; FRAC equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2)
Interspersion and juxtaposition index	IJI	$0 < IJI \leqq 100$; The adjacency of each patch with all other patch types
Largest patch index	LPI	$1 \leqq LPI \leqq 100$; LPI equals the percentage of the landscape comprised by the largest patch
Effective mesh size	MESH	Ratio of cell size to landscape area $\leqq MESH \leqq$ total landscape area
Normalized landscape shape index	NLSI	$0 \leqq NLSI \leqq 1$
Perimeter–area ratio	PARA	$PARA > 0$ without limit, PARA equals the ratio of the patch perimeter (m) to area (m^2)
Percentage of landscape	PLAND	$0 < PLAND \leqq 100$; PLAND quantifies the proportional abundance of each patch type in the landscape
Shape index	SHAPE	$SHAPE \leqq 1$ without limit
Splitting index	Split	$1 \leqq SPLIT \leqq$ number of cells in the landscape area squared, SPLIT equals the total landscape area (m^2) squared divided by the sum of patch area (m^2) squared

Results and discussion

Principal WQPs

In reducing the complexity of input water quality data, the first five developed principal components (PC) could explain approximately of 90.53% of the total variance in the data sets. According to the PCA results, SAR, TDS, pH, PO_4^{3-}, and NO_3^- parameters had the highest factor loading in the

PC1, PC2, PC3, PC4, and PC5, respectively, and they were considered as the best variables in describing the water quality of Mazandaran during the sampling period (Fig. 2).

Best LMs for estimating WQPs

The best LMS which were capable to describe the variance in WQPs (TDS, pH, NO_3^-, PO_4^{3-} and SAR) determined based on linear modeling and results are presented in Table 2. The models that have the highest coefficient of
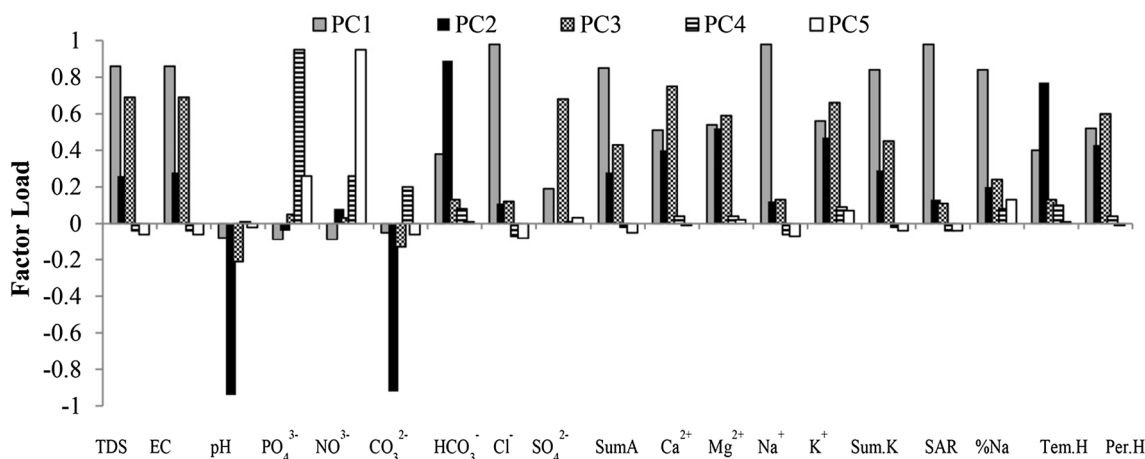
Fig. 2 Factor loading of the WQPs in the rotated component matrix of PCA

determination (R^2) and the lowest standard error predictive value were selected as the best model for estimating WQPs. Also, for these models, the VIF and Durbin–Watson coefficient, which indicates the lack of internal correlation between independent variables and lack of correlation of predictive errors in these models (VIF < 10 and Durbin–Watson > 1.5), is presented. All appropriate metrics were selected at class-level. In other words, class-level metrics provide more detailed information on land use existing in the watershed and more explanatory of WQPs variance in the study area. According to this finding, Li et al. (2005) and Lee et al. (2009) also recommended class-level metrics in surface WQPs estimating in these studied cases.

Configurationally analysis of the relationships between LMs and WQPs

The structural characteristics of the landscape can be described through a large number of numerical indicators

(metrics) that for certain purposes should be used appropriate types of metrics. Proper use of metrics and their interpretation can show either change in patterns over time or signs of ecological processes in the landscape. Metrics also provide the possibility of comparison between the desired situation and planned situation. In other words, understanding the relationship between landscape structure and function (e.g., surface water quality) makes it possible to predict the ecological consequences of different land management and planning scenarios and ultimately helps to move toward planning for a more sustainable land. In fact, it is possible to assume an optimal spatial arrangement of ecosystems and land uses for each landscape or each main part of a landscape. Such an optimal arrangement of the elements of the landscape will increase the integrity and achieve the basic human needs and create a sustainable environment. The uses of landscape metrics provide a perspective to aid the spatial design process. Accordingly, we analyzed the relationships

Table 2 Summary result of the more accurate MLR in modeling the relationships between WQPs and LMs

WQP	The structure of regression models	Durbin–Watson	VIF	Train			Test		
				RMSE	R^2	CE	RMSE	R^2	CE
SAR	$0.001 + 0.149*(PLAND\_A) + 0.296*(MESH\_A) + 0.908*(IJI\_BL)$	1.85	1.24	0.43	0.79	0.79	0.39	0.81	0.76
pH	$1.002 + 0.295*(DIVISION\_F) - 0.513*(ED\_R) - 0.357*(DIVISION\_F) + 0.199*(CA\_F) - 0.944*(CIRCLE\_MN\_A) - 0.463*(ED\_A)$	1.88	1.40	0.21	0.82	0.82	0.33	0.56	0.51
TDS	$0.809 - 2.159(PLAND\_F)\ 1.564*(LPI\_F) + 0.554*(ENN\_MN\_R) + 0.980(CIRCLE\_MN\_R) + 0.125*(SHAPE\_MN\_A)$	2.01	3.05	60.78	0.82	0.82	78.54	0.73	0.73
PO_4^{3-}	$-0.145 + 0.391*(PLAND\_A) + 0.259*(ED\_R) + 0.220*(DIVISION\_R) + 0.523*(CONNECT\_R) + 0.406*(SPLIT\_A)$	1.80	1.99	0.03	0.75	0.75	0.03	0.63	0.62
NO_3^-	$0.119 - 0.316*(PLAND\_F) + 0.439*(PLAND\_A) - 0.145*(ED\_W) + 0.382*(NLSI\_A)$	2.23	2.77	0.84	0.65	0.65	1.26	0.44	0.41

A agriculture, *BL* bare land, *F* forest, *R* residential, *RL* rangeland, *Ro* road, *W* water resources

between WQPs and LMs in Mazandaran Province and provide a basis for land-use planers in the following sections.

Relationships between LMs and SAR

Table 2 shows the percentage (PLAND_A) and effective mesh size (MESH_A) of agricultural land had a direct and significant relationship with SAR. According to this result, if the percentage of agricultural in two sub-basins is the same, taking a higher value of perforation will increase SAR levels at the outlet point. In this order, two sub-basins were compared to show the effect of perforation on the SAR levels in adjacent surface waters. In Fig. 3, two sub-basins located on the upstream of the hydrometric station with cod-no 4 (Glourd) and 46 (Rosen), which have nearly identical composition and approximately the same extent of agricultural, were selected for comparison. The value of agriculture mesh size metric in the Glourd was 0.41 and in the Rosen was 0.60. The mean annual SAR of these two sub-basins was significantly ($P < 0.05$) different (2.30 and 0.33, respectively). In other words, if agricultural land use is not connected and stained by patches of other land use, as shown in Fig. 3, the SAR will increase in adjacent rivers. The reason for this can be due to the concentration of agricultural wastewaters in the same places and the reduction in the possibility of self-purification and deposition of salts during transplantation. Forest patches among agricultural areas led to decrease in pollutant loads and increase in rate of water purification and deposition of suspended sediments, which is practically not possible in integrated agricultural lands without fragmentation. Increase in the residential areas was reason for increase in value of SAR in the Karkheh River, Iran (Salajegheh et al. 2011), while landscape metric of agricultural areas has significant effect for SAR increase in Mazandaran rivers.

The results also showed a positive relationship between the increase of the interspersion and juxtaposition index

of the bare lands (IJI_BL) and SAR levels in sub-basins of Mazandaran Province. To understand and compare the spatial implication of this metric, two sub-basins were also considered: cod-no 39 (Punjab) and 55 (Wali-Abad). In Punjab sub-basin, the pattern of land use is such that the bare lands are away from other classes. While in Wali-Abad sub-basin is in such a way that the bare lands are close to other classes such as forests, agriculture, and residential areas (Fig. 4). In the study area, bare lands have less green-covered and are exposed to soil erosion more than forests and rangelands. As a result, the potential of sodium solution in soil layers increases in this land-use type. Deforestation for agriculture and then land release due to their low productivity is common in Mazandaran Province (Mirzaei et al. 2013). This results in locating bare lands in the vicinity of other land use/covers and as a result of increasing the interspersion and juxtaposition index and finally increasing SAR in the rivers of the study area.

### Relationships between LMs and pH

According to Table 2, the agricultural edge density metric (ED_A) and the related circumscribing circle of agriculture (CIRCLE_A) have a negative and significant relation with pH levels and cause to increase Mazandaran rivers acidification. The edge density increases if the small patches with irregular shapes are prevalent in the landscape matrix. To illustrate the effect of this metric, the pattern of agricultural lands in two sub-basins located upstream of the hydrometric stations, Walt (cod-no: 61) and Jangal-Dareh (cod-no: 79), was considered (Fig. 5).

The average agricultural edge density in Walt and Jangal-Dareh sub-basins was 27.78 and 31.01 m/ha, respectively. Meanwhile, in spite of different areas of agricultural lands in these sub-basins (Walt, 3721.53 ha vs. Jangal-Dareh, 2387.8 ha), due to the small size and irregular
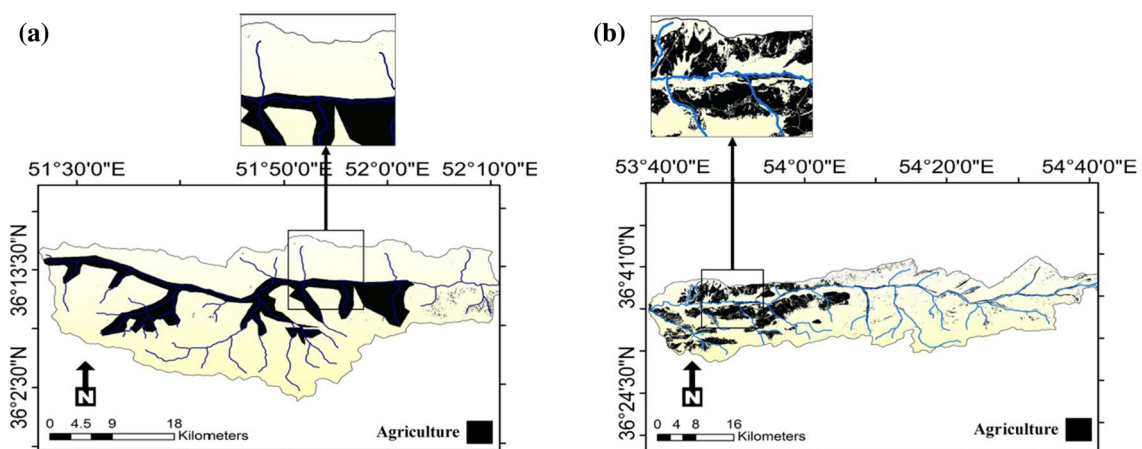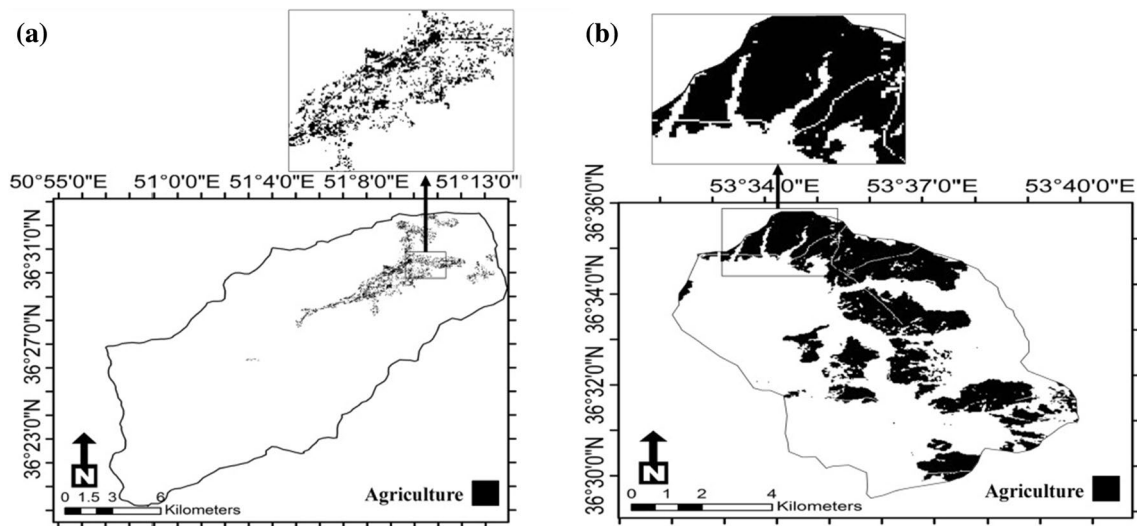

Fig. 3 Comparison of effective mesh size metric for agricultural lands in the Rosen (**a**) and Glourd (**b**) and sub-basins
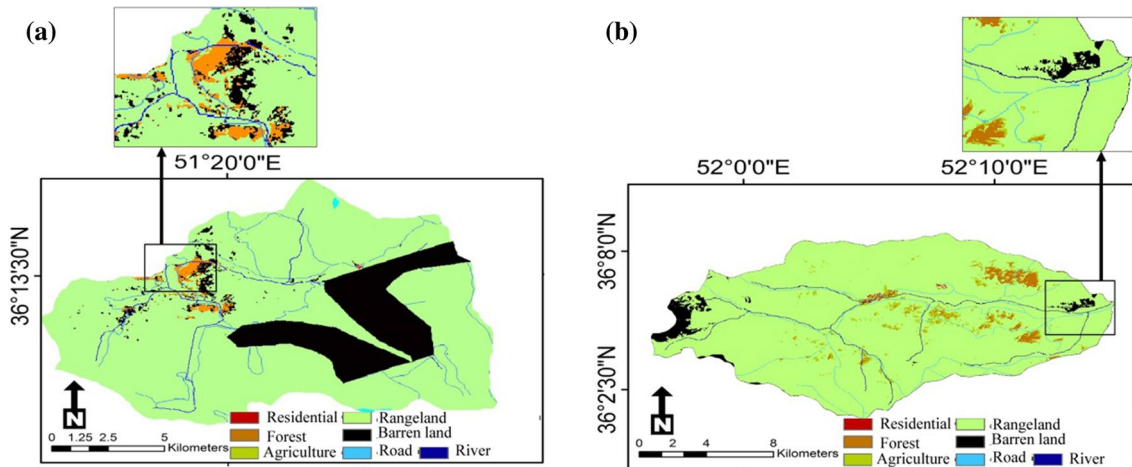
Fig. 4 Comparison of the dispersion and proximity index of bare lands in the Wali-Abad (**a**) and Punjab (**b**) sub-basins

**Fig. 5** Comparison of agriculture edge density in the Jangal-Dareh (**a**) and Walt (**b**) sub-basins

shape of the patches in Jangal-Dareh, the edge density measure for Walt has increased. There was a significant difference ($P < 0.05$) in the mean annual pH in two sub-basins (Walt: 8.42 vs. Jangal-Dareh: 7.70). This indicates the significance of the agricultural edge density on rivers pH in the study area in a more descriptive manner.

The related circumscribing circle of agriculture was another metric, which has a negative relationship with pH levels in Mazandaran Province (Table 2). To compare the effect of this metric, two sub-basins were compared on the upstream of Waspol (cod-no: 57) and Agoskeshi (cod-no: 49) (Fig. 6). The average of this metric for agricultural land in the Waspol and Agoskeshi sub-basin was 0.37 and 0.41, respectively, while the agricultural land area was greater in Waspol (Waspol, 1069.69 vs. Agoskeshi 627.3

Ha), but the average annual pH was lower in the Agoskeshi (Waspol, 8.40 and Agoskeshi, 8.01).

As illustrated in Fig. 6, the high values of the agricultural circumscribing circle in the Agoskeshi sub-basin can be attributed to the extended shape of agricultural patches along the river's margin. In general, the negative relationship between the circumscribing circle metric and the river's pH is prevalent in the study area especially in the mountainous regions because of the configuration of agricultural land use which is linearly embedded along the rivers. Similar to the results, in the regression equation developed by Wu et al. (2012), also agricultural land-use metrics had caused acidification of the Sihu River in China. This is due to increasing the margin of agricultural land, increasing its penetration to other land use, and also

(a)

(b)
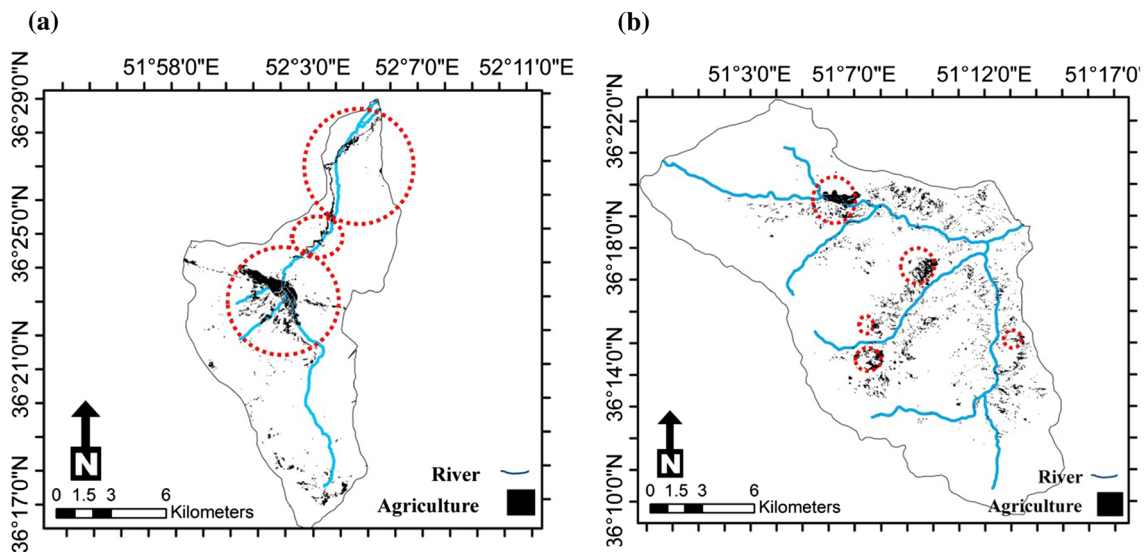
Fig. 6 Comparison of the circumscribing circle metric of agricultural land use in the Agoskeshi (**a**) and Waspol (**b**) sub-basins

with the increase of small patches, which have the potential of affecting the surface water quality and lowering of pH levels in the outlet of sub-basins. It is worth mentioning that agricultural practices such as fertilization with Sulfur-containing, manganese sulfate, etc., fertilizers, which produce acidic compounds after dissolving in water, as well as the decomposition of agricultural residues, are the main reasons for reducing pH by agricultural land use.

According to Table 2, the residential edge density (ED_R) also reduced the pH of rivers in the study area. In other words, if residential areas are not connected and distributed in small patches, they will have a greater edge density and reduce the pH of the rivers. Sewage from residential areas and the sedimentation of sulfur and nitrogen soils cause acidic runoff. Similarly, the results of Mahmoudi et al. (2007) showed that urban and irrigated areas in the Karkheh River basin are the most important factors in reducing pH, increasing salinity and increasing the number of anions and cations.

As shown in Table 2, the division and total patches area of forest had also a positive and significant effect on river pH in Mazandaran Province. Although the effect of forest area is very common and understandable, but to facilitate understanding of the forest division effects, Ramsar (cod-no: 78) and Tobon (cod-no 68) sub-basins were compared (Fig. 7). The division index increases by fragmenting the large and connected forest patches into small and scattered patches (its value varies between 0 and 1). The value of this metric in Ramsar and Tobon sub-basin was 0.60 and 0.91, respectively, which is due to the differences between forest patches configuration as illustrated in Fig. 7. It should be noted that the main trees of the study area are beech, hornbeam, oak, maple,

and alder which are often alkaline (Ahmadi and Sheikholeslami 2003). Broad-leaf trees absorb more nitrates and thus prevent soil nitrogen washing and reduce the production of related acids. In line with the results, Norton and Fisher (2000) noted that forest cover has adjusted the water pH of rivers and the role of this LULC in improving the water quality of rivers is vital. Contrary to the results of the current study, Amiri and Nakane (2009) have reported a reduction in the pH of the Chicago Rivers, which could be due to differences in tree species in the two studied regions.

Relationships between LMs and TDS

According to regression models presented in Table 2, the value of the largest patch index of forest (LPI_F) can significantly reduce the TDS levels in the studied rivers. The calculation of LPI is based on the percentage of the landscape that is occupied by the largest patch of a land use and can be assigned as dominance land use in a landscape. The difference of this metric with the percentage of area metric is that the total area of a land use in the landscape may be high, but due to the small size and scattered patches, its largest patch metric is low.

For a visual comparison of the largest patch metric, two sub-basins are shown in upstream of Shirgah (cod-no: 25) and Parvij-Abad (cod-no: 14) hydrometric stations (Fig. 8). The largest patch metric in Shirgah and Parvij-Abad was 94.1% and 34.9%, respectively, while both sub-basins had an almost equal forest cover (Shirgah: 27,474.5 and Parvij-Abad: 30,687.3 ha). While the average annual TDS at these stations was examined, the results showed a significant difference ($P < 0.05$) for this parameter.

(a)   **(b)**
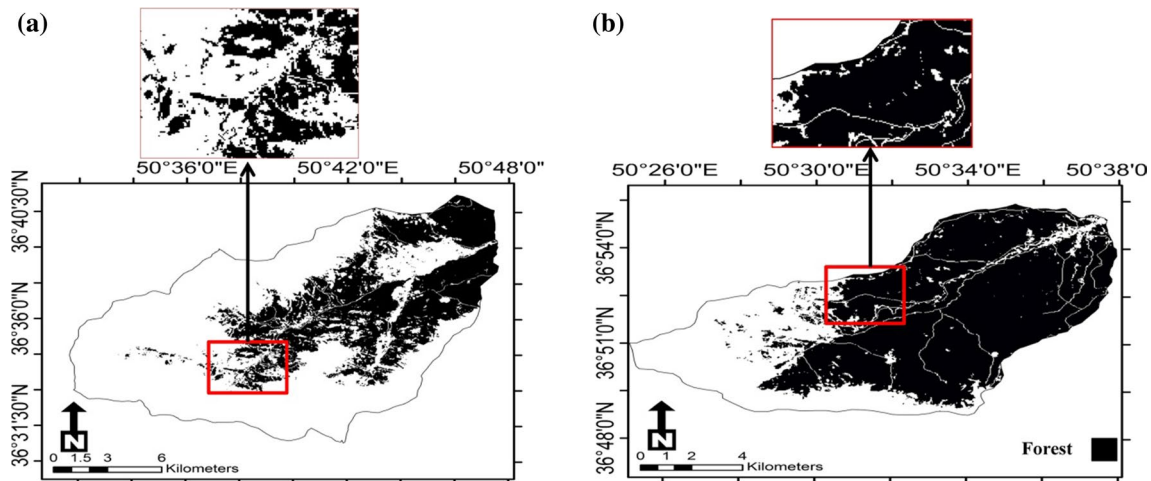
Fig. 7 Comparison of forest division metric in the Tobon (**a**) and Ramsar (**b**) sub-basins

(a)   **(b)**
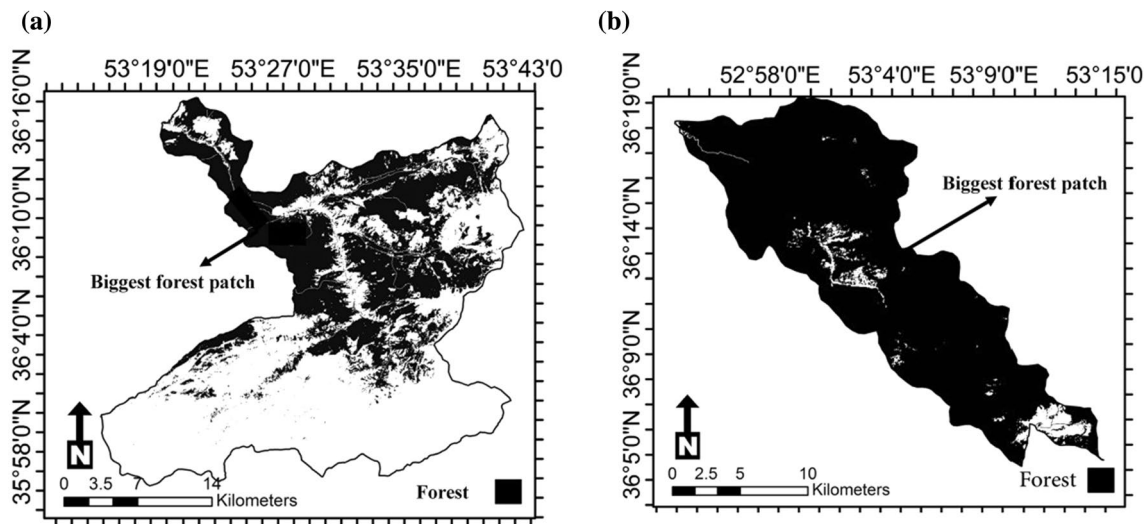
Fig. 8 Comparison of the largest forest patch metric in the Parvij-Abad (**a**) and Shirgah (**b**) sub-basins

Therefore, it can be concluded that the large patches of forest cover play a key role in reducing the load of soluble materials, and in the basins where the value of this metric is higher, the water quality at the outlet of the basin has been better.

According to this result, Hatt et al. (2004) described the forests as a water quality improvement factor that prevented the soil from erosion and solution of minerals because the forest cover decreases the flow of surface water and provides more time for deposition and absorption of solutions. The results of Mirzaei et al. (2013) in the study area indicate an increase in the area in residential, agricultural, range-land, and roads (7387, 54,655, 88,986, and 4768 ha, respectively), and a sharp decline of the forests (162,867 ha) during 1984–2010. This has led to a reduction in the largest patch

of forest cover in parts of the study area, and even in some cases, the landscape matrix has changed from forests to pasture and agriculture.

Regression models presented in Table 2 also shows a positive and significant relationship between the related circumscribing circle (CIRCLE_A) and Euclidean nearest neighbor distance (ENN_A) metrics of residential areas with TDS at the outlet point of the sub-basins. In the previous sections, the effect of CIRCLE on the spatial configuration of land use has been mentioned. The ENN metric illustrates the closeness of the patches of a land-use type together and is calculated in such a way that in a clump distribution shows lower value and in a discrete dispersion, shows a higher value. In Fig. 9, to compare the ENN metric in residential land use, parts of the sub-basins of the Walt (cod-no: 61) and the

Tallar-Shirgah (cod-no: 25) are shown. The average ENN_A metric in Walt sub-basin was 703.5 and in Talear-Shirgah was 924.2 m, which can be explained by the difference in residential patches configuration in these two sub-basins.

According to the results and due to the positive relationship of TDS with CIRCLE and ENN metrics, if residential areas in the study area were close to each other and have a circular configuration, the TDS in rivers will be reduced and water quality will be improved. In many studies, residential land use has been mentioned as an impervious surface which can provide superfluous anions and cations to water and, as a result, reduce the water quality, as illustrated by the studies conducted by Bahar et al. (2008), Wilson and Weng (2010) and Alberti et al. (2007).

The average agricultural shape index (SHAPE_A) was also another metric in describing TDS changes in the studied rivers. The value of this metric was increased with the rise of the sides and the distance from the square shape. In order to display changes in this metric, parts of the sub-basins of Kelardasht (cod-no: 60) and Zarandin (cod-no: 80) are illustrated in Fig. 10. According to this figure, in Kelardasht, most agricultural patches have a regular and square-like shape, while in Zarandin agricultural patches are complex with irregular shapes and more sides, which cause the average of the shape metric in the two sub-basins, are 1.19 and 1.41, respectively.
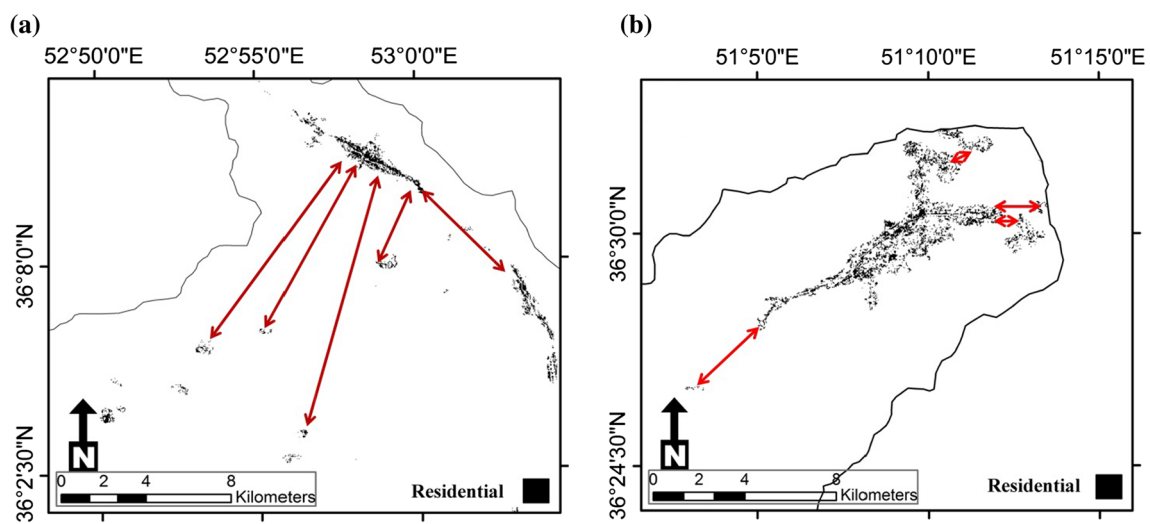

Fig. 9 Comparison of the Euclidean nearest neighbor distance metric of the residential land use in the Tallar-Shirgah (a) and Walt (b) sub-basins
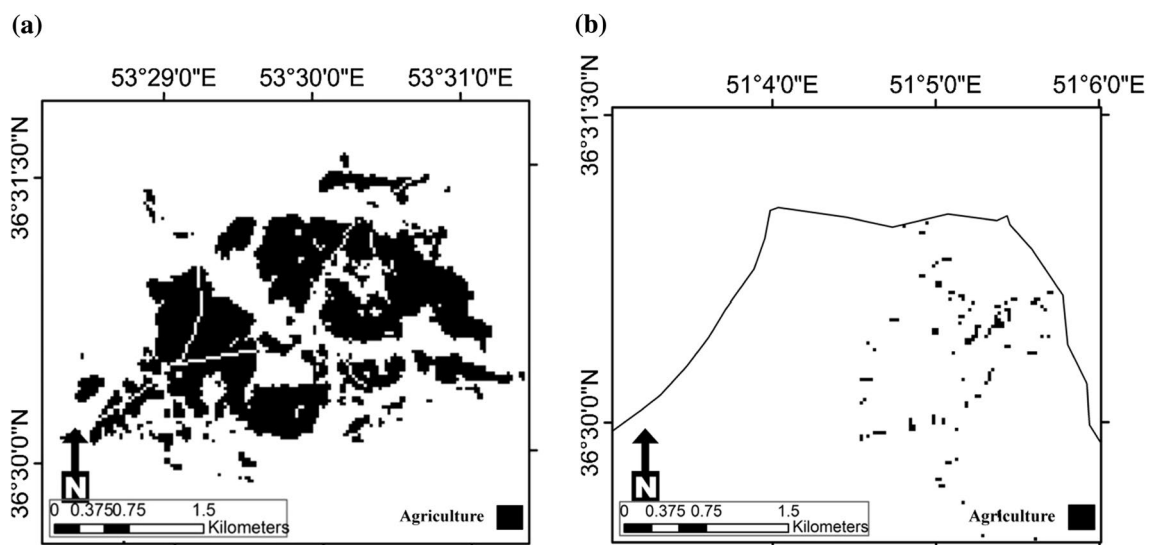

Fig. 10 Comparison of agricultural patches shape metric in the Zarandin (a) and Kelardasht (b) sub-basins

Relationships between LMs and PO₄³⁻

According to Table 2, the percentage of agricultural area: PLAND_A, residential edge density: ED_R, residential division index: DIVISION_R, residential connectivity index: CONNECT_R and agricultural splitting index: SPLIT_A metrics increase the amount of phosphate in the studied rivers. So it can be said that residential land-use metrics have a significant role in describing phosphate changes in the studied rivers. By increasing the residential edge density, division and splitting in residential area, the amount of soluble phosphate in the rivers were increased (Table 2). The implication and effects of edge density and division metrics were presented in the previous sections. However, for describing the effect of connectivity index, Nowshahr (cod-no: 59) and Gordkol (cod-no: 84) sub-basin were compared in Fig. 11. The residential connectivity index in Nowshahr and Gordkol sub-basin was 3.66% and 28.57%, respectively, which visual comparison of the distances between residential patches in these two sub-basin can explain this difference. It should be noted that the annual concentration of phosphate in the Gordkol hydrometric station was significantly higher than Nowshahr hydrometric station.

Regarding the impact of residential metrics on river water quality in Mazandaran Province, it can be said that if the residential patches are large (according to the division and edge density metrics) and in the distance of each other (according to connectivity index) phosphate levels in the outflows of the rivers will be decrease. For example, the phosphate levels

at the outlet of the basin will decrease if urban development policies are such that to prevent the formation of small towns with complex shapes and built them in areas with less connectivity with other patches.

In this regard, Amiri (2006), Tong and Chen (2002), and Ngoye and Machiwa (2004) had found that residential land-use metrics are significant factor in increasing phosphate levels in rivers, which due to the importance of this parameter in the field of non-point-source pollutants, they provided management strategies to reduce phosphate levels. In another study, Udeigwe et al. (2007) noted a positive and significant relationship between residential land-use and river phosphate levels. Phosphate often enters rivers from residential wastewater and is used as a detergent (Powley et al. 2016; Minareci and Çakır 2018). Meanwhile, spatial planning in residential development, based on landscape metrics, can play a significant role in reducing nutrient influx into downstream ecosystems (Yang 2012).

In accordance with Table 2, increasing the splitting and percentage of agriculture cover increase the availability of phosphate to surface water. To understand the concept of this metric, two sub-basins with a different splitting index are shown in Fig. 12. The agricultural splitting metric for Sarokulla (cod-no: 19) and Tallar-Shirgah (cod-no: 26) sub-basin was 4.11 and 18,837.3, respectively. Even the visual comparison shows that there are small patches of agricultural land use in Tallar-Shirgah sub-basin, which led to the splitting of landscape and the increase of this metric. Similar
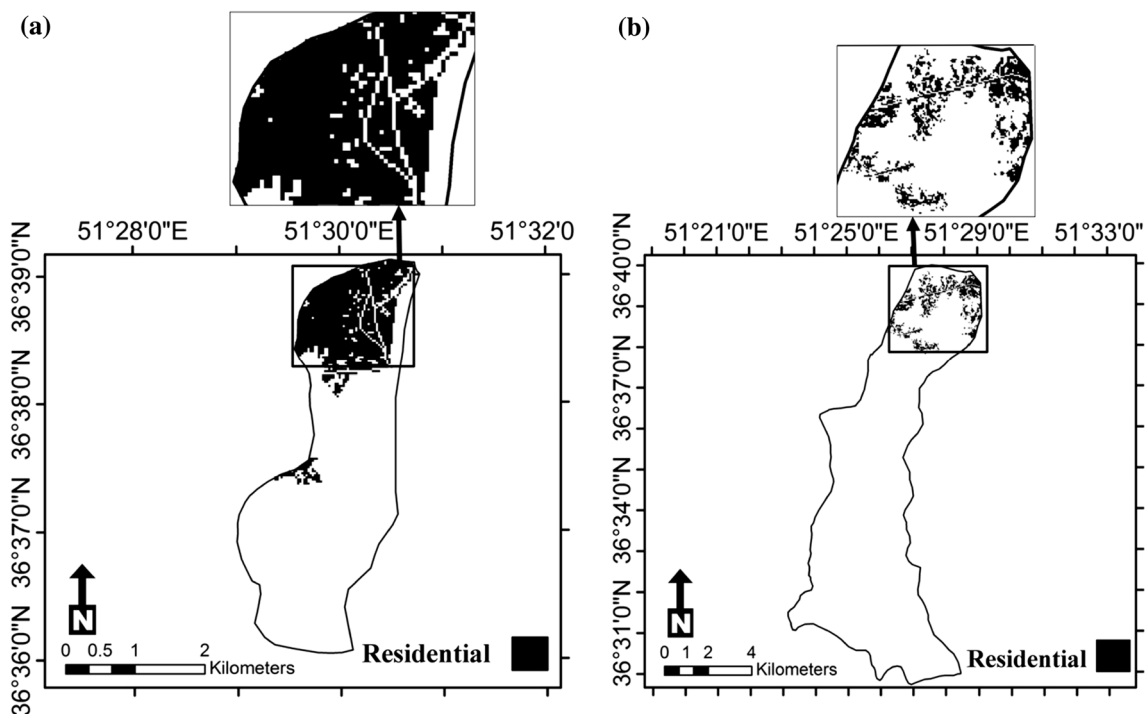
Fig. 11 Comparison of residential connectivity metric in the Gordkoln (**a**) and Nowshahr (**b**) sub-basins
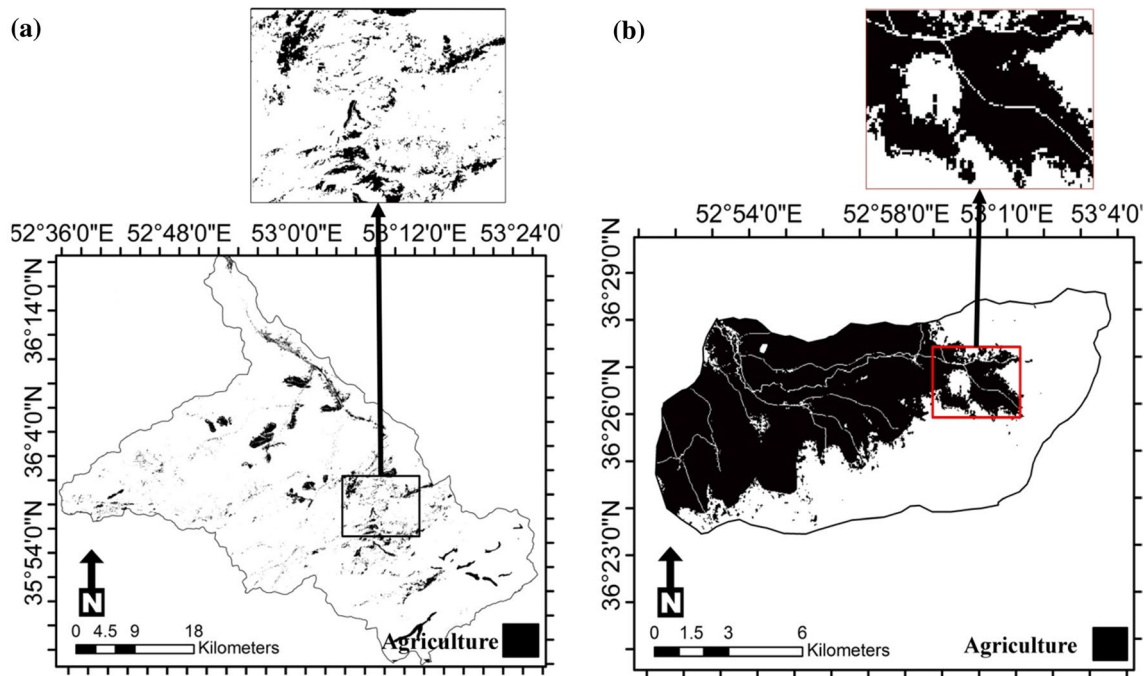
Fig. 12 Comparison of agricultural land-use splitting metric in the Tallar-Shirgah (**a**) and Sarokulla (**b**) sub-basins

to these results, Tafangenyasha and Dube (2008) and Mehaffey et al. (2004), obtained a significant correlation between the land-use/cover metrics and soluble phosphate in rivers.

Range of pH was between 7.17 and 10.20, with average of 8.19 in river waters of Mazandaran Province during sampling periods. According to weak correlation between pH and PO_4^{3-} in the study area, increase or decrease in pH does not seem to have significant changes in phosphate.

Regarding the climatic conditions of Mazandaran Province and the high level of crop cultivation, especially rice and citrus in the county, increasing use of fertilizer (including nitrates and phosphates) and agricultural pesticides (Nejatkhah-Manavi et al. 2009) can lead to contamination of rivers water. According to the Agricultural Organization of Mazandaran Province, more than 170 thousand tons of nitrogen and phosphate fertilizers are consumed on average annually in the province (Mirzayi et al. 2016). Therefore, the positive effect of agricultural land-use metrics on increasing phosphate and nitrate levels can be explained in the current study.

Relationships between LMs and NO_3^-

According to Table 2, the percentage and normalized landscape shape index (NLSI) of agricultural land-cover metrics have a direct relationship with nitrate levels in the outlet of sub-basins in the study area. NLSI is an advanced metric for quantifying the shape of patches in a landscape and its value increases from 0 to 1 as the shape of a patch changes from a

square to polygons. The sub-basins of Koohestan (cod-no: 8) and Waspol (cod-no: 57) were selected for the visual comparison of this metric (Fig. 13). The value of NLSI in these sub-basins was 0.04 and 0.42, respectively, which can be attributed to irregular forms of agricultural patches in the Waspol sub-basin (Fig. 13). Therefore, according to the results, only the agricultural area cannot be a factor in describing the water nitrate content in the rivers. In fact, if two sub-basins have the same characteristics and similar land-use composition, the shape of agricultural patches (so-called NLSI) can be a nitrate driver in surface waters that is very important in regional planning. In confirmation of this finding, Burkart and James (1999), Turner and Rabalais (2003), and Ngoye and Machiwa (2004) introduced agricultural land-use metrics as a key factor affecting nitrate uptake in surface water.

The percentage of forest (PLAND _F) land cover has a negative effect on the nitrate output from the basin (Table 2). This could be due to poor erosion in the forest cover, as well as the preservation of nitrate in the litters and forest floor vegetation cover. In other words, nitrogen mineralization and nitrate reduction in forests are occurring by vegetation in the forest floor preventing nitrate from being washed and transferred to streams and rivers (Adams and Attiwill 1982; Minick et al. 2016). The results of Norton and Fisher (2000) and Ngoye and Machiwa (2004) have also estimated forest land cover as a nitrate moderator. Similar to the results of the current study, Amiri (2006) reported the forest land cover as a reducing agent in nitrate levels at the outlet of the Yamaguchi River basins in Japan. Since forest cover is the

Fig. 13 Comparison of agricultural normalized shape metric in two sub-basins of the Waspol (**a**) and Koohestan (**b**) sub-basins
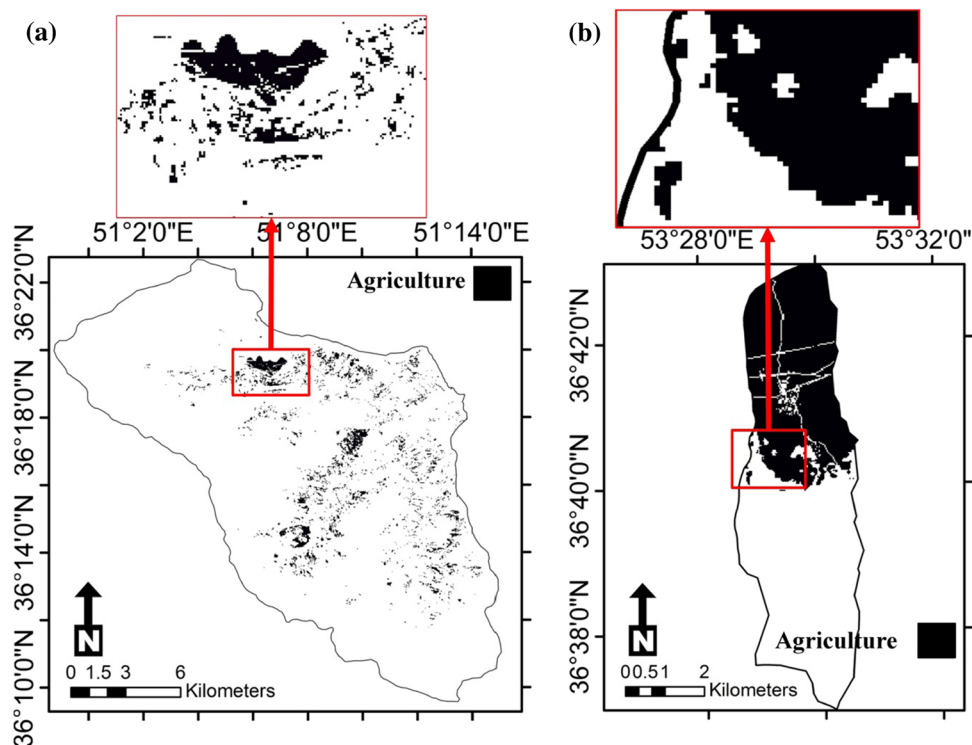
predominant cover in the province and due to the moderating role of forests in nitrate levels, forest conservation, increasing forest levels can be an optimal solution for maintaining water quality in the studied rivers.

As shown in Table 2, surface water resources (including dams and wetlands) have a significant negative effect on nitrate output from the basin. Similar to the results, the water resources-related metrics in Amiri and Nakane (2009) study have also a significant effect on the reduction in nitrate levels in the Chicago Rivers. They considered surface water resources as a nitrate deposition bed. However, the regression model is proposed by Norton and Fisher (2000) for prediction of nitrate levels, despite the use of water resources as one of the LULC, only forest cover and wheat were introduced as the effective variables and water resources did not have any significant effect on this parameter. It is worth noting that the ability of water bodies to improve runoff quality depends on several parameters such as their vegetation, depth, bed soil type, size, or climate variables (Moreno et al. 2008). Therefore, according to the obtained results, the edge density of water bodies has a significant effect on decreasing the amount of nitrate in the rivers of the Mazandaran Province.

Conclusion

Given that the establishment of any LULC has a significant impact on the water quality and the available pollutants of the outlet of the basin, in this study, landscape metrics at class and landscape levels were used to describe the changes in WQPs of Mazandaran Province Rivers in the North of Iran. The results indicated that despite the fact that LMs had a significant relationship with WQPs, but when class-level metrics were entered into the regression models, the LMs were eliminated. This shows the ability of class-level metrics for describing surface water quality. In other words, metrics at the class-level can provide more detailed information on the land-use characteristics in the basin. While landscape-level metrics are a brief quantitative presentation of the land-use pattern in the basin and water quality follows fine-scale relations, this allowed the regression models to more appropriately link the dependent variables (WQPs) and class-level metrics. Similar to the current study results, Li et al. (2005) and Lee et al. (2009) pointed out the class-level metrics have more potential to describe WQPs changes.

Many studies had used the results of the analysis of the relationship between LMs and surface water quality to provide management solutions for sustainable development, such as Jones et al. (2001), Griffith (2002), Uuemaa et al. (2005), Lee et al. (2009), and Li et al. (2018). In the present study, the best LMs for each WQP were determined. Among the seven land-use types classified in the study area (residential, forest, agriculture, water resources, rangeland, bare land, and road), residential, agriculture, and forest have the greatest potential for describing river water quality changes, and the metrics related to these land-use types were introduced in most regression models as the optimal

variables. Along with these results, in Hively et al. (2011) and Wu et al. (2012) studies, residential, agricultural, and forest LULC had the most impacts on water quality. Agricultural and residential land use declined and the forest improved the quality of surface water, respectively, while rangeland, bare lands, water bodies, and roads, despite covering a large fraction of the study area, were excluded from the study process, statistically. This was especially evident for the rangeland and the road. However, this finding cannot confirm the ineffectiveness of the mentioned land use and elimination of their related metrics could be due to the greater correlation between residential-, agricultural-, and forest-related metrics with WQPs.

The results of this study can be used as a good strategy for regional planning and evaluation of environmental impacts in development programs. According to the results, the town construction or forestry can lead to a decrease and increase in the quality of river water, respectively. But land-use configuration patterns and land-use ecology principles can less negative impact on river water quality and even increase their quality level. For example, according to the results, the edge density of residential areas has reduced the pH levels of the studied rivers. Therefore, if the residential areas are distributed in small patches, they will be having more edge density and as a result lower pH of the rivers. However, if the area of forest cover is equal in two landscapes, integrated and extensive forests are more capable for pH adjustment.

It is worth noting that changing the shape or pattern of the current deployment in a short time is difficult and somewhat impossible, but the present results can be used in long-term development planning. Therefore, according to the results, if the water quality of rivers is a major factor in the planning of Mazandaran Province, it is better to focus on the optimal composition and configuration of residential, agricultural, and forest LULC in the province landscape.

References

Abdi H, Williams LJ (2010) Principal component analysis. Wiley Interdiscip Rev Comput Stat 2(4):433–459

Adams MA, Attiwill PM (1982) Nitrogen mineralization and nitrate reduction in forests. Soil Biol Biochem 14(3):197–202

Ahmadi T, Sheikhuleslami A (2003) The role of soil physical and chemical properties in pure stands of oak (*Quercus castaneifolia*) in Galandroud forest (west Mazandran state). J Pajouhesh Sazandegi 63:59–68 **(In Persian with English Abstract)**

Alberti M, Booth D, Hill K, Coburn B, Avolio C, Coe S, Spirandelli D (2007) Theimpact of urban patterns on aquatic ecosystems: an empirical analysis on Puget lowland sub-basins. Lands Urban Plan 80(4):345–361

Amiri BJ (2006) Modeling the relationship between land cover and river water quality in the Yamaguchi prefecture of Japan. J Ecol Field Biol 29(4):343–352

Amiri BJ, Nakane KA (2009) Modeling the linkage between river water quality and landscape metrics in the Chugoku district of Japan. Water Resour Manag 23(5):931–956

Bahar MM, Hiroo O, Masumi Y (2008) Relationship between river water quality and land use in a small river basin running through the urbanizing area of central Japan. Limnology 9(1):19–26

Burkart MR, James DE (1999) Agricultural-nitrogen contributions to hypoxia in the Gulf of Mexico. J Environ Qual 28(3):850–859

De Mello K, Valente RA, Randhir TO, dos Santos ACA, Vettorazzi CA (2018) Effects of land use and land cover on water quality of low-order streams in Southeastern Brazil: watershed versus riparian zone. CATENA 167:130–138

Gholamalifard M, ZareMaivan H, Joorabian Ss, Mirzaei M (2012) Monitoring land cover changes of forests and coastal areas of northern iran (1988–2010): a remote sensing approach. J Persian Gulf 3(10):47–56

Gholamalifard M, Joorabian Shooshtari S, Hosseini Kahnuj S, Mirzaei M (2013) Land cover change modeling of coastal areas of Mazandaran Province using LCM in a GIS environment. J Environ Stud 38(4):109–124

Griffith JA (2002) Geographic techniques and recent applications of remote sensing to landscape-water quality studies. Water Air Soil Pollut 138(1–4):181–197

Hashemi F, Olesen JE, Dalgaard T, Børgesen CD (2016) Review of scenario analyses to reduce agricultural nitrogen and phosphorus loading to the aquatic environment. Sci Total Environ 573:608–626

Hatt BE, Fletcher TD, Walsh CJ, Taylor SL (2004) The influence of urban density and drainage infrastructure on the concentrations and loads of pollutants in small streams. Environ Manag 34(1):112–124

Hively WD, Hapeman CJ, McConnell LL, Fisher TR et al (2011) Relating nutrient and herbicide fate with landscape features and characteristics of 15 sub watersheds in the Choptank river watershed. Sci Total Environ 409(19):3866–3878

Iqbal MS, Islam MM, Hofstra N (2019) The impact of socio-economic development and climate change on *E. coli* loads and concentrations in Kabul River Pakistan. Sci Total Environ 650:1935–1943

Jones KB, Neale AC, Nash MS, Van RD, Wickham JD, Riitters KH, O'Neill RV (2001) Predicting nutrient and sediment loadings tostreams from landscape metrics: a multiple watershed study from the United States Mid-Atlantic region. Landsc Ecol 16(4):301–312

Joorabian-Shooshtari S, Shayesteh K, Gholamalifard M, Azari M, López-Moreno JI (2018) Land cover change modelling in Hyrcanian forests Northern Iran: a landscape pattern and transformation analysis perspective. Cuad Investig Geogr 44(2):743–761

Lamine S, Petropoulos GP, Singh SK, Szabó S, Bachari NEI, Srivastava PK, Suman S (2018) Quantifying land use/land cover spatiotemporal landscape pattern dynamics from Hyperion using SVMs classifier and FRAGSTATS. Geocarto Int 33(8):862–878

Lausch A, Herzog F (2002) Applicability of landscape metrics for the monitoring of landscape change: issues of scale resolution and interpretability. Ecol Indic 2(1):3–15

Lausch A, Blaschke T, Haase D, Herzog F, Syrbe RU, Tischendorf L, Walz U (2015) Understanding and quantifying landscape structure—a review on relevant process characteristics data models and landscape metrics. Ecol Model 295:31–41

Lee SW, Hwang SJ, Lee SB, Hwang HS, Sung HC (2009) Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. Landsc Urban Plan 92(2):80–89

Li X, Jongman RH, Hu Y, Bu R, Harms B, Bregt AK, He HS (2005) Relationship between landscape structure metrics and wetland nutrient retention function: a case study of Liaohe Delta China. Ecol Indic 5(4):339–349

Li K, Chi G, Wang L, Xie Y, Wang X, Fan Z (2018) Identifying the critical riparian buffer zone with the strongest linkage between landscape characteristics and surface water quality. Ecol Indic 93:741–752

Lowicki D (2012) Prediction of flowing water pollution on the basis of landscape metrics as a tool supporting delimitation of Nitrate Vulnerable Zones. Ecol Indic 23:27–33

Mahmoudi B, Hamidifar M, Khorasani N (2007) Study of land use change in Karkheh watershed and its role in physical and chemical quality of Karkheh River. In: Fourth national conference on watershed management sciences and engineering management of watersheds proceeding. https://www.civilica.com/Paper-WATERSHED04-WATERSHED04_022.html

McGarigal K, Cushman SA, Neel MC, Ene E (2002) FRAGSTATS: spatial pattern analysis program for categorical maps. In: Computer software program produced by the authors at the University of Massachusetts Amherst available at the following web site: https://www.umass.edu/landeco/research/fragstats/fragstats.html

Mehaffey MH, Nash MS, Wade TG, Ebert DW, Jones KB, Rager A (2004) Linking land cover and water quality in New York City's water supply watersheds. Environ Monit Assess 107(1):29–44

Minareci O, Çakır M (2018) The study of surface water quality in Buyuk Menderes River (Turkey): determination of anionic detergent phosphate boron and some heavy metal contents. Appl Ecol Environ Res 16(4):5287–5298

Minick KJ, Pandey CB, Fox TR, Subedi S (2016) Dissimilatory nitrate reduction to ammonium and N_2O flux: effect of soil redox potential and N fertilization in loblolly pine forests. Biol Fertil Soils 52(5):601–614

Mirzaei M, Riyahi-Bakhtiyari A, Salman-Mahini A, Gholamalifard M (2013) Investigating the land cover changes in Mazandaran province using landscape ecology's metrics between 1984–2010. Iran J Appl Ecol 2(4):37–55 **(in Persian with English Abstract)**

Mirzaei M, Jafari A, Gholamalifard M, Azadi H, Shooshtari SJ, Moghaddam SM, Gebrehiwot K, Witlox F (2020) Mitigating environmental risks: Modeling the interaction of water quality parameters and land use cover. Land Use Policy 95:103766

Mirzayi M, Riyahi Bakhtiyari A, Salman Mahini A, Gholamalifard M (2014) Analysis of the physical and chemical quality of Mazandaran province (Iran) rivers using multivariate statistical methods. J Mazandaran Univ Med Sci 23(108):41–52

Mirzayi M, Riyahi Bakhtiyari A, Salman Mahini A, Gholamalifard M (2016) Modeling relationships between surface water quality and landscape metrics using the adaptive neuro-fuzzy inference system a case study in Mazandaran Province. J Water Wastewater 27(1):81–92

Moreno MD, Mander Ü, Comín FA, Pedrocchi C, Uuemaa E (2008) Relationships between landscape pattern wetland characteristics and water quality in agricultural catchments. J Environ Qual 37(6):2170–2180

Nakane K, Haidary A (2009) Sensitivity analysis of stream water quality and land cover linkage models using montecarlo method. Int J Environ Res Public Health 4(1):121–130

Nejatkhah-Manavi P, Pasandi AA, Saghali M, Beheshtinia N, Mirshekar D (2009) Study of nitrate and phosphate in eastern south Caspian Sea in spring and summer. J Mar Sci Technol Res 4(3):11–19 **(In Persian with English Abstract)**

Ngoye E, Machiwa JF (2004) The influence of land-use patterns in the Ruvu river watershed on water quality in the river system. Phys Chem Earth 29(15):1161–1166

Noori R, Sabahi M, Karbassi A, Baghvand A, TaatiZadeh H (2010) Multivariate statistical analysis of surface water quality based on correlations and variations in the data set. Desalination 260(1):129–136

Norton M, Fisher T (2000) The effects of forest on stream water quality in two coastal plain watersheds of the Chesapeake Bay. Ecol Eng 14(4):337–362

Ouyang Y (2005) Evaluation of river water quality monitoring stations by principal component analysis. Water Res 39(12):2621–2635

Powley HR, Durr HH, Lima AT, Krom MD, Van Cappellen P (2016) Direct discharges of domestic wastewater are a major source of phosphorus and nitrogen to the Mediterranean Sea. Environ Sci Technol 50(16):8722–8730

Riitters KH, Hunsaker CT, James DW, Yankee DH, Timmins SP, Jones KB, Jackson BL (1995) A factor analysis of landscape pattern and structure metrics. Landsc Ecol 10(1):23–39

Salajegheh A, Razavizadeh S, Khorasani N, Hamidifar M, Salajegheh S (2011) Land use changes and its impacts on river water quality. J Environ Stud 37(58):81–86 **(In Persian)**

Schoonover JE, Lockaby BG (2006) Land cover impacts on stream nutrients and fecal coliform in the lower Piedmont of West Georgia. J Hydrol 331(3–4):371–382

Shi P, Zhang Y, Li Z, Li P, Xu G (2017) Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales. CATENA 151:182–190

Shrestha S, Kazama F (2007) Assessment of surface water quality using multivariate statistical techniques: a case study of the Fuji river basin, Japan. Environ Model Softw 22(4):464–475

Tafangenyasha C, Dube LT (2008) An investigation of the impacts of agricultural runoff on the water quality and aquatic organisms in a Lowveld Sand river system in Southeast Zimbabwe. Water Resour Manag 22(1):119–130

Talebi-Amiri S, Azari-Dehkord F, Sadeghi SH, Soofbaf SR (2009) Study on landscape degradation in Neka watershed using landscape metrics. J Environ Sci 6(3):133–144 **(in Persian with English Abstract)**

Tiwari S, Mandal NR, Saha K (2018) A geospatial analysis of anthropogenic activities and their impacts on river Narmada. Available at SSRN 3214250

Tong ST, Chen W (2002) Modeling the relationship between land use and surface water quality. J Environ Manag 66(4):377–393

Turner RE, Rabalais NN (2003) Linking landscape and water quality in the Mississippi River Basin for 200 years. Bioscience 53(6):563–572

Udeigwe TK, Wang J, Zhang H (2007) Predicting runoff of suspended solids and particulate phosphorus for selected Louisiana soils using simple soil tests. J Environ Qual 36(5):1310–1317

Uuemaa E, Roosaare J, Mander Ü (2005) Scale dependence of landscape metrics and their indicatory value for nutrient and organic matter losses from catchments. Ecol Indic 5(4):350–369

Wilson C, Weng Q (2010) Assessing surface water quality and its relation with urban land cover changes in the Lake Calumet area Greater Chicago. Environ Manag 45(5):1096–1111

Wold S, Esbensen K, Geladi P (1987) Principal component analysis. Chemom Intell Lab Syst 2(1–3):37–52

Wu MY, Xue L, Jin WB, Xiong QX, Ai TC, Li BL (2012) Modeling the linkage between landscape metrics and water quality indices of hydrological units in Sihu basin Hubei Province China: an allometric model. Procedia Environ Scie 13(1):2131–2145

Yan X, Liu M, Zhong J, Guo J, Wu W (2018) How human activities affect heavy metal contamination of soil and sediment in a long-term reclaimed area of the Liaohe River Delta North China. Sustainability 10(2):338

Yang X (2012) An assessment of landscape characteristics affecting estuarine nitrogen loading in an urban watershed. J Environ Manag 94(1):50–60