RESEARCH ARTICLE

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Multi-scale analysis of the relationship between landscape patterns and a water quality index (WQI) based on a stepwise linear regression (SLR) and geographically weighted regression (GWR) in the Ebinur Lake oasis

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Abstract

Water quality is highly dependent on landscape characteristics. This study explored the relationships between landscape patterns and water quality in the Ebinur Lake oasis in China. The water quality index (WQI) has been used to identify threats to water quality and contribute to better water resource management. This study established the WQI and analyzed the influence of landscapes on the WQI based on a stepwise linear regression (SLR) model and geographically weighted regression (GWR) models. The results showed that the WQI was between 56.61 and 2886.51. The map of the WQI showed poor water quality. Both positive and negative relationships between certain land use and land cover (LULC) types and the WQI were observed for different buffers. This relationship is most significant for the 400-m buffer. There is a significant relationship between the water quality index and landscape index (i.e., PLAND, DIVISION, aggregation index (AI), COHESION, landscape shape index (LSI), and largest patch index (LPI)), demonstrated by using stepwise multiple linear regressions under the 400-m scale, which resulted in an adjusted R^2 between 0.63 and 0.88. The local R^2 between the LPI and LSI for forest grasslands and the WQI are high in the Akeqisu River and the Kuitun rivers and low in the Bortala River, with an R^2 ranging from 0.57 to 1.86. The local R^2 between the LSI for croplands and the WQI is 0.44. The local R^2 values between the LPI for saline lands and the WQI are high in the Jing River and low in the Bo River, Akeqisu River, and Kuitun rivers, ranging from 0.57 to 1.86.

Keywords Landscape index · Water quality parameter · Geographically weighted regression · Multi-scale · WQI

Introduction

The degradation of water quality is a hot topic and a global issue (Chen et al. 2016a; Roebeling et al. 2015). Studies highlight this topic in arid areas due to global warming and economic advancement (Chen et al. 2016b, c). Global warming and economic development are associated with changes in land use and land cover (LULC) through infrastructure development; therefore, human activities and social and economic factors influence patterns in LULC and landscape (Xu et al. 2016). Intensive LULC changes in watersheds and the rapid response of water quality pollutants from different sources may cause substantial deterioration in water quality (Wang et al. 2017a). Therefore, the direct or indirect threat of water quality pollutants to the quality of life for local populations and the health of ecosystems requires analysis.

Early studies link the water quality index to different LULCs within a watershed (Bolstad and Swank 1997; Donohue et al. 2006). The relationship between river water quality and the landscape pattern has been explored in many previous studies (Collins et al. 2013; Souza et al. 2013; Chen et al. 2016a). Zhao et al. (2012) show that there was a significant positive correlation between an urban LULC area and water quality parameters. In addition, Wan et al. (2014) report a significant correlation between croplands, urban areas, and

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total phosphorus and nitrogen in rivers. Ahearn et al. (2005) indicate a close relationship between the nitrate-N content in water and the cropland and grassland areas in the river watershed. Some researchers have analyzed the effect of land use and land cover on water quality on different scales (Jarvie et al. 2002; Woli et al. 2004; Sahu and Gu 2009; Li et al. 2009a). Different scales showed different results. Guo et al. (2010) indicate that the influence of LULC on total phosphorus (TP) changes with buffer size, and Zhang (2011) report that LULC significantly governed river TP loads. Tran et al. (2010) report that cropland and urban areas can decrease nonpoint source inputs in 200-m river zones. Therefore, when analyzing the correlation between landscape patterns and water quality in river, selecting the proper spatial scale is an important factor. A multi-scale approach is advocated in some recent studies, which have characterized the influence of the landscape index at different scales.

However, two main arguments were often ignored. First, when the relationship between water quality parameters and landscape pattern in watershed is explored, it is uncertain because the water environment is complex and changeable, and a single water quality parameter does not reflect the entire water quality environment. Based on this analysis, a water quality index that reflects the entire water environment is proposed to evaluate to the entire water environment. Several methods have been introduced to evaluate the status of water quality in rivers and lakes (Jena et al. 2013; Misaghi et al. 2017). Water quality index (WQI) is used for assessing the water quality of a drinking water source (Qiu et al. 2013; Xu et al. 2017; Anuar et al. 2017). Second, the relationship between water quality parameters and landscape patterns has been explored with global statistical methods in many previous studies, but some significant hidden local variations and spatial characteristics may have been neglected (Chen et al. 2016a). Local, rather than global, parameters will be estimated by the geographically weighted regression (GWR) model.

Therefore, the WQI and GWR methods will be used to explore the relationship between landscape patterns and the WQI in a multi-scale analysis. The main objectives of this study are (1) to analyze the temporal and spatial patterns of water quality in the Ebinur Lake oasis, (2) to extract an effective buffer based on relationships between LULC and the WQI, (3) to establish a WQI suit to assess water quality in arid regions, and (4) to identify and quantify the relationship between LULC types and the WQI.
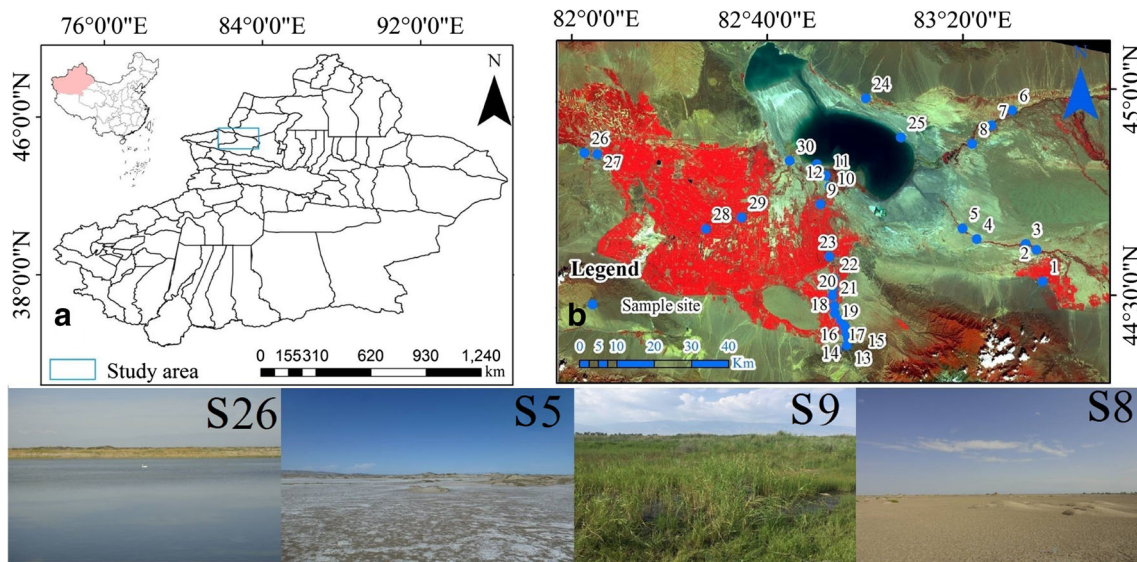
Study area

The Ebinur Lake oasis is in the center of Eurasia, located in northwest Xinjiang at 44° 02′–45° 10′ N and 81° 46′–83° 51′ E (Fig. 1). This region has a typical temperate arid continental climate. The study region is located inland; moisture sources

in the study area are derived from the Atlantic Ocean (7000 km), but overall, there is limited water vapor transport from maritime areas. The total area of the watershed area is 50,621 km². It is surrounded by a mountainous region (24,317 km²; Alatau Mountains) and plain areas (26,304 km²) to the north, west, and south (Wang et al. 2017a, b). The Ebinur Lake oasis was once fed by 12 branch rivers belonging to three major river systems, including the Bo River, the Ebinur Lake River, and the Kuitun River. The west Bo River (BR) valley, the south Jing River (JR) oases, the Dandagai desert, and east of the lower Mutetaer desert zone reach the Akeqisu–Kuitun River (A-KR). Artificial reservoirs (RES) are distributed to the southwest of the watershed (Ma et al. 2016; Chao et al. 2016; Li et al. 2016).

Materials and methods

Site description and the water quality data

Water samples were collected on 15 July 2016 from 30 locations within the Ebinur Lake oasis (Fig. 1), a typical arid area of the river. Most rivers in Xinjiang are characterized by low water yield, short length, small environmental water capacity, poor self-cleaning capability, and low tolerance to pollution (Ma et al. 2016). To represent different oasis LULCs, in this study, 30 sites (1–30) are selected based on local hydrological, geological, and human activity characteristics, as well as landscape (Fig. 1). S1, S2, S3, S4, and S5 are in the Akeqisu River, which is a river in the mountain-desert river system. S1 is located at the middle upstream. These sites are near Toutuo County, which is considered an urban area, and the sample sites are distributed around large areas of cropland. S2, S3, S4, and S5 are located downstream; these sites are near Ebinur Lake, and the sample sites are distributed around large areas of forest grassland and saline land, but this river has broken down and does not enter Ebinur Lake. S9 through S23 are located on rivers along the Jinghe River system, which has a total length of 66.1 km (Liu et al. 2011). The Jinghe River system is the main agricultural area for the Ebinur Lake oasis. S13 is location upstream. Both of these sites are near the Xiatianji reservoir, which is critical for river water adjustment. S16 and S17 sample sites are near the Dandagai desert. S20 and S22 are located at midstream, and both sample sites are near Jinghe County, where human activity is the main factor controlling water quality. S11 is located at the Ebinur estuary, an ecological environment of poor quality with nearby soil salinization where desertification is extremely serious. S26 and S27 are located at the edge of the oasis; these sample locations are at Bo River (midstream), near Bole City. This is a large city in the Ebinur Lake oasis, where human activities are mainly industrial and agricultural, including animal husbandry. S28 and S29 are located midstream of the Bo River;

Fig. 1 **a** A map of the study area, photographs of the study site, and photographs of four selected sampling locations. **b** A satellite map of the study area for the following sites: water body (sample site 26), saline land (sample site 5), forest grassland (sample site 9), and desert (sample site 8)

these two points are the center of the whole oasis. S30 is located at Ebinur Lake estuary, where nearby soil salinization and desertification are extremely serious. S6 through S8 are in the Kuitun River, where rivers have broken down, and there are large deserts around the river. S24 and S25 are located at the lake bed, where water bodies are mainly brine, and there is a large amount of saline land around the river.

Collected samples were kept at low temperatures in cold storage (under 2 °C) during transport before water quality measurements were carried out in the laboratory. Samples were transported in polyethylene plastic bottles, which were previously washed in 10% HCl and cleaned with deionized water to minimize changes in the water chemical characteristics. Temperature and pH were recorded at the time of sampling in the field. All other measurements were conducted within one week after the sample collection. The concentrations for five-day worth of biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP), iron, copper, zinc, ammonia nitrogen (NH_4^+-N), magnesium, sulfate ions (SO_4^{2-}), phosphate (PO_4^{3-}), and chromium VI (Cr^{6+}) were determined according to corresponding standard methods, shown in Table 1.

Data acquisition and processing

We used GF-1 remote sensing images obtained in July 2016 as data sources (see http://www.cresda.com/CN/). These images were not influenced by clouds, fog, or snow cover, and their quality was good. We conducted radiation and orthographic corrections for the remote sensing image data, combined with 1:50,000 digital elevation model (DEM) data. The ENVI 5.1 (The Environment for Visualizing Images 5.1 by Harris Geospatial Corporation, USA) radiometric calibration tool

and the gain and deviation ratio in the G-F 1 image data head document were used for the radiometric calibration of the GF-1 data and included five bands: B (0.45–0.52 um), G (0.52–0.59 um), R (0.63–0.69 um), NIR (0.77–0.89 um), and PAN (0.52–0.89 um). Then, the ENVI5.1 FLAASH atmospheric correction model was used for the atmospheric correction of remote sensing images. Data fusion at different resolutions or different spectrums was beneficial for image classification and interpretation. PAN bands and four multispectral band images were used for image fusion.

Land use and land cover data

Seven LULC types were analyzed, including urban areas, croplands, forest grassland (i.e., trees, grass, bushes, sparse trees, shrubs, and other vegetation), water bodies (i.e., lakes, rivers, ponds, and reservoirs), other land types (i.e., medium- and low-cover grasslands and bare land), saline land, and deserts. We used a decision tree classification approach when classifying these types. Specifically, we established the following seven land use and land cover types with the Environment for Visualizing Images software (ENVI Version 5.0): urban areas, cropland, forest grassland, water bodies, salinized land, desert, and others. These classifications were based on actual conditions in the research zone. The final result showed that the overall accuracy was 87.31% and the kappa coefficient was 0.88. Table 2 shows a confusion matrix with a maximum likelihood supervised classification.

Construction buffers in rivers

This study references a previously used method (Karr and Schlosser 1978; Shen et al. 2015). To analyze the relationship

Table 1 Water quality parameters and experiment methods

Number	Water quality parameters	Experiment methods
1	COD	According to the dichromate method (GB 11914-1989) using a standard COD digestion apparatus (K-100) to determine COD
2	BOD_5	According to the dilution and inoculation method (HJ 505-2009) with a constant temperature incubator (HWS-150 type) for determining the content of BOD_5
3	TP	According to the ammonium molybdate spectrophotometric method (HJ 636-2012) using a visible light spectrophotometer 722 N for determining the content of TP
4	TN	According to the ultraviolet spectrophotometry (HJ 535-2009) by using an ultraviolet visible light spectrophotometer, UV-6100, for determining the content of TN
5	NH_4^+-N	According to Nessler's reagent spectrophotometer with the amount of visible light spectrophotometer 722 N for determining NH_4^+-N
6	Iron	According to the chemical analysis of tungsten method, the ortho-phenanthroline photometric method was used for the determination of iron content
7	Copper	According to the chemical analysis of ferrotitanium method, the DDTC photometric method used for the determination of copper content
8	Zinc	According to the spectrophotometric method with PAN method determination of zinc content
9	Mg	According to the acid chrome blue K method
10	SO_4^{2-}	According to the methylene blue method (GB T5750.5-2006)
11	PO_4^{3-}	According to the phosphorus molybdenum blue colorimetric method (GB T5750.5-2006)
12	Cr^{6+}	According to the photometry of diphenylcarbazide method (GB T5750.5-2006)

between LULC types and the WQI at different distances, this study constructed a wide range of buffer zones (e.g., 100, 200, 300, 400, and 500 m) for the sites through ArcGIS 10.2 (Environmental Systems Research Institute, Inc., Redlands, CA, USA).

Selected landscape index

A landscape pattern index reflects the characteristics of the spatial configuration (Cadavid Restrepo et al. 2017; Yang et al. 2017) to reduce redundancy. Here, six landscape indexes were selected, including the largest patch index (LPI), the landscape shape index (LSI), the landscape segmentation

index (DIVISION), the connectivity index (COHESION), PLAND, and the aggregation index (AI). These parameters were calculated using Fragstats 3.3 software (McGarigal et al. 2012). Landscape indexes describing landscape are in Table 3.

Calculating the WQI

The WQI reflects the composite influence of different water quality parameters (Sahu and Sikdar 2008). The WQI has critical health effects whose presence above critical concentration limits could limit the usability of the resource for domestic and drinking purposes (Varol and Davraz 2015; Şehnaz

Table 2 The calculation of a confusion matrix by a maximum likelihood supervised classification

LULC	Water body	Saline land	Cropland	Forest grassland	Desert	Urban land	Other land	Total	User's accuracy (%)
Water body	144	0	0	0	0	0	0	144	100
Saline land	0	57	0	0	0	19	26	102	55.88
Cropland	0	46	101	0	0	0	0	147	68.71
Forest grassland	0	46	0	101	0	0	0	147	68.71
Desert	1	0	0	0	114	0	0	115	99.13
Urban land	0	0	0	0	0	99	17	116	85.34
Other land types	0	0	0	0	0	0	77	77	100
Total	145	103	101	101	114	118	120	Overall = 87.31%	
Producer's accuracy (%)	99.31	55.34	100	100	100	83.89	64.17	Kappa = 0.80	

Table 3 Landscape metrics used in the present study

Index	Symbol	Definition
Largest patch index	LPI	LPI quantifies the percentage of total landscape area comprised by the largest patch
Landscape shape index	LSI	LSI provides a standardized measure of total edge or edge density that adjusts for the size of the landscape
Connectivity index	COHESION	COHESION is equal to 1 minus the sum of the plaque perimeter divided by the circumference patch multiplied by the area of the square root sum, the reciprocal of the square root of the difference, finally multiplied by 100
PLAND	PLAND	The number of adjacent plaques, including focus types, is divided by the number of adjacent cells, including the focus class, before multiplying by 100 to retrieve the percentage
Landscape segmentation index	DIVISION	DIVISION is equal to 1 minus the area of the plaque divided by the sum of squares of the entire landscape
Aggregation	AI	AI takes into account only adjacencies involving the focal class, not adjacencies with other patch types

Şener et al. 2017). The relative weight (W_i) was computed from the following equation:

$$W_i = \frac{W_i}{\sum_{n=1}^{n} W_i} \tag{1}$$

where W_i is weight of each parameter, W_i is the relative weight, and n is number of parameters. Then, a quality rating (Q_i) by the WHO (2008) was performed, and the result was multiplied by 100:

$$Q_i = \frac{C_i}{S_i} \times 100 \tag{2}$$

where C_i is the concentration of each chemical parameter in each water sample (mg/L), Q_i is the quality rating, and S_i is the drinking water standard for each chemical parameter (mg/L). The WQI equations were calculated as follows:

$$SI_i = W_i \times q_i \tag{3}$$

$$WQI = \sum_{i=1}^{n} SI_i \tag{4}$$

where SI_i is the sub-index of the ith parameter and Q_i is the quality rating based on the concentration of the ith parameter.

Standard water quality assessment

The calculated WQI values were classified into five categories as follows (Wang et al. 2017c; Şehnaz Şener et al. 2017; Wu et al. 2018): when the WQI value > 50, water quality was excellent and suitable for drinking (I water quality); 50 > WQI value > 100 meant that the water quality was acceptable (II water quality); 100 > HIX > 200 implied that water quality was poor (III water quality); when 200 > HIX > 300, water quality was very poor (IV water quality); finally, a value of HIX < 300 indicated that the water was unsuitable for drinking (V water quality).

Stepwise linear regression model

A parametric stepwise regression analysis was performed at every step for variables in previous steps (Qiu et al. 2016). We constructed a stepwise linear regression (SLR) model. SPSS (version 19.0) software was selected to construct the SLR model.

$$y = \beta_0 + \beta x_1 + \beta x_2 + \cdots\cdots \beta_k x_x + \varepsilon \tag{5}$$

where $\beta_0, \beta_1 \ldots \beta_k$ is an unknown parameter of $k + 1$, β_0 is a regression constant, $\beta_1 \ldots \beta_k$ is the regression coefficient, and Y is the interpreted variable.

Geographically weighted regression model

As an extension of global statistical models, the geographically weighted regression (GWR) embeds location data into regression parameters to assess the local relationships between independent and dependent variables (Li et al. 2014; Chen et al. 2016a; Li et al. 2017; Dziauddin et al. 2015). The distribution of sample sites resulted in a significant advantage in developing GWR models for Ebinur Lake oasis. The formula is as follows:

$$y_i = \beta_0(u_j, v_i) + \sum_{i=1}^{p} (u_j, v_i) x_{ij} + \varepsilon_j \tag{6}$$

where (u_j, v_j) are the coordinates for location j, $\beta_0(u_i, v_j)$ is the local regression coefficient for independent variables x_i at location j, and $\beta_0(u_i, v_j)$ and ε_j are the intercept and error term, respectively.

Statistical analysis and model assessment

Data were analyzed using the SPSS19.0 (19.0, SPSS, Chicago, IBM, USA) software for statistical calculations, drawing, and analyses. Data analyses were performed using Origin 8.0 (OriginLab Corporation, America). R^2 is the fit

coefficient of the model; the closer this value is to 1, the higher the relative accuracy of the model. Figure 2 shows a technical flowchart for this study.

Result and analysis

Statistical analysis of land use and land cover under the multi-scale method

This study used river scales at 100-, 200-, 300-, 400-, and 500-m buffers as examples (Fig. 3). The value of the area for urban areas declined slightly within the buffer zones, with high values for sample 28 and sample 29, which were only 56.2 and 48.2% for the 100- and 200-m scale, respectively. The lowest values were for samples 25 and 34, which were only 0% at different scales. The proportion of other land in samples 16 and 17, however, was up to 74.93% at the 100-m buffer scale, which reflects the existence of a large amount of undeveloped land within this area. It is the main feature of land use in a dry area. The proportion of saline land in samples 3, 4, and 10 was up to 60% at the 100-m buffer scale; with an increase in percentage, the value declines in the buffer scale, which reflects the existence of a large amount of undeveloped land within this area.
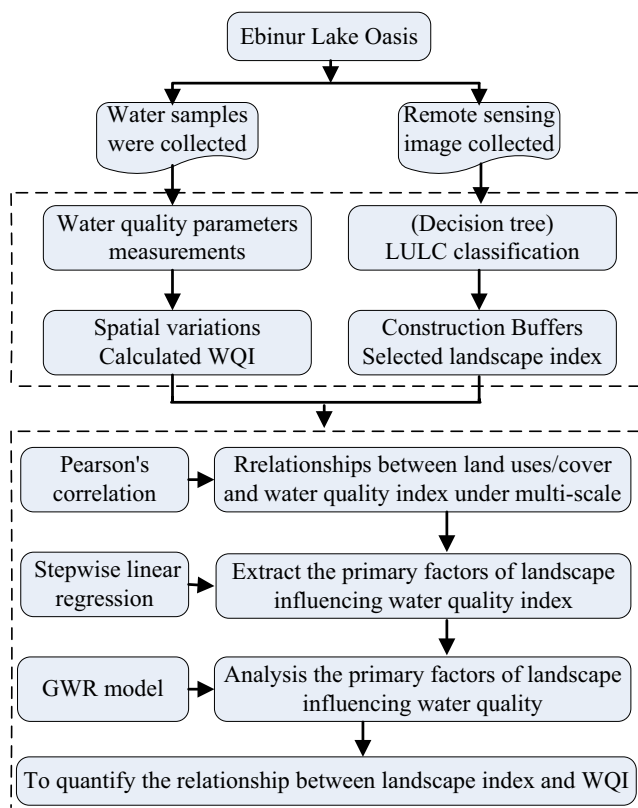

Fig. 2 Overall flowchart of the study

Spatial variations in water quality

In this study, TN, NH_4^+-N, TP, DO, copper, zinc, iron, BOD_5, and COD were selected. Spatially, TP is high in most areas of the Ebinur Lake oasis (Fig. 4). The highest value is observed in the Bo River (0.53 g/kg), because the water sample site is located in Jinghe County, where the effects of human factors are severe, and the content of TP in water bodies is high and affects the entire river. Copper, Fe, and zinc are lower in most areas in the Ebinur Lake oasis (Fig. 4). The highest values are observed in the Jing River, reaching 5.88, 0.13, and 1.72 g/kg because the water sample site is located midstream of the Bo River where the effects of mining are severe, and the content copper in water bodies is high and affects the entire river. COD and BOD_5 are lower in most areas in the Ebinur Lake oasis (Fig. 4). The highest value is observed in the Ebinur Lake, reaching 12.1 and 1721 g/kg.

Calculation of the WQI

TP, TN, BOD_5, NH_4^+-N, iron, copper, zinc, SO_4^{2-}, COD, PO_4^{3-}, and Cr^{6+} were considered when calculating the WQI value for each sample. The analysis results for all 30 sampling points were used for quality evaluation. The World Health Organization (WHO 2008) limits were utilized for calculations. Distribution maps of the water quality parameters (TP, TN, BOD_5, NH_4^+-N, iron, copper, zinc, SO_4^{2-}, COD, PO_4^{3-}, and Cr^{6+}) and a final WQI map of the river are shown in Fig. 5 and Table 4.

Spatially, content for the WQI is high in most areas of the Bo River downstream of Ebinur Lake (Fig. 4). The highest value is observed in the Kuitun River (438), which belongs to the V category since this water is unsuitable for drinking; this is because the water sample was located in the town of Tuotuo, where the effects of human factors are severe, and the water quality is the worst in the river. Therefore, water quality is poorer, and the content of the WQI is higher. The best water quality in the Ebinur Lake oasis was located in the upper reaches of the Bo River. With a WQI value less than 100, it belongs to the I grade water quality category and is suitable for drinking. Poor water quality has been observed midstream in the Boertala River, where the sample located in Wenquan County was taken; the effects of human factors there are severe, and there are water quality mutations and water quality index anomalies.

Extracted effective buffer based on relationships between land use and land cover and WQI

To show that the LULC area has very different impacts on the WQI, the Pearson correlation coefficient was calculated (Fig. 6). Urban areas, saline areas, and deserts were

Fig. 3 Statistical analysis of land use and land cover area under a multi-scale method
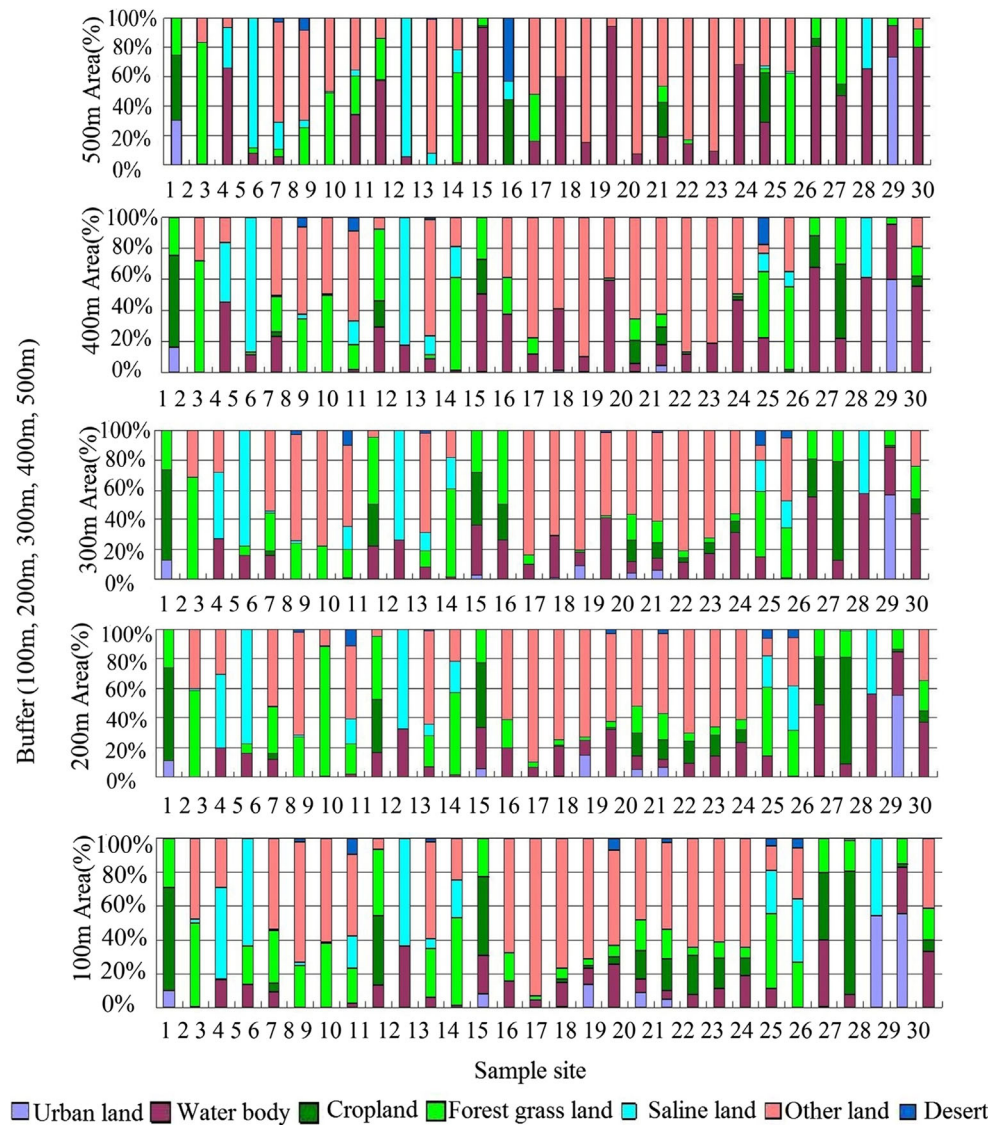
positively correlated with the WQI. The results found that urban areas were positively correlated with the WQI, with r correlation coefficients of 0.73 ($p < 0.05$), 0.89 ($p < 0.01$), 0.90 ($p < 0.01$), 0.92 ($p < 0.01$), and 0.77 ($p < 0.01$). The highest correlation appears at 400 m, with an r correlation coefficient of 0.92 ($p < 0.01$). The saline areas were positively correlated with the WQI, with r correlation coefficients of 0.57 ($p < 0.05$), 0.68 ($p < 0.05$), 0.75 ($p < 0.05$), 0.82 ($p < 0.05$), and 0.76 ($p < 0.05$). The highest correlation appeared at 400 m, with an r correlation coefficient of 0.82 ($p < 0.05$). The desert was positively correlated with the WQI, with r correlation coefficients of 0.53 ($p < 0.05$), 0.54 ($p < 0.05$), 0.60 ($p < 0.05$), 0.80 ($p < 0.05$), and 0.70 ($p < 0.05$). The highest correlation appeared at 400 m, with an r correlation coefficient of 0.80 ($p < 0.05$). Forest grasslands, other types of land, water bodies, and croplands were negatively correlated with the WQI. Pearson results showed that forest grasslands were negatively correlated with the

WQI, with r correlation coefficients of 0.64 ($p < 0.05$), 0.68 ($p < 0.05$), 0.69 ($p < 0.05$), 0.82 ($p < 0.05$), and 0.63 ($p < 0.05$). The highest correlation appeared at 400 m, with an r correlation coefficient of 0.82 ($p < 0.05$). The other land types were negatively correlated with the WQI, with r correlation coefficients of 0.44 ($p < 0.05$), 0.46 ($p < 0.05$), 0.53 ($p < 0.05$), 0.74 ($p < 0.05$), and 0.68 ($p < 0.05$). The highest correlation appeared at 400 m, with an r correlation coefficient of 0.74 ($p < 0.05$). Water bodies were negatively correlated with the WQI, with r correlation coefficients of 0.47 ($p < 0.05$), 0.54 ($p < 0.05$), 0.56 ($p < 0.05$), 0.62 ($p < 0.05$), and 0.51 ($p < 0.05$). The highest correlation appeared at 400 m, with an r correlation coefficient of 0.62 ($p < 0.05$). Croplands were negatively correlated with the WQI, with r correlation coefficients of 0.44 ($p < 0.05$), 0.46 ($p < 0.05$), 0.50 ($p < 0.05$), 0.56 ($p < 0.05$) and 0.51 ($p < 0.05$). The highest correlation appeared at 400 m, with an r correlation coefficient of 0.56 ($p < 0.05$).
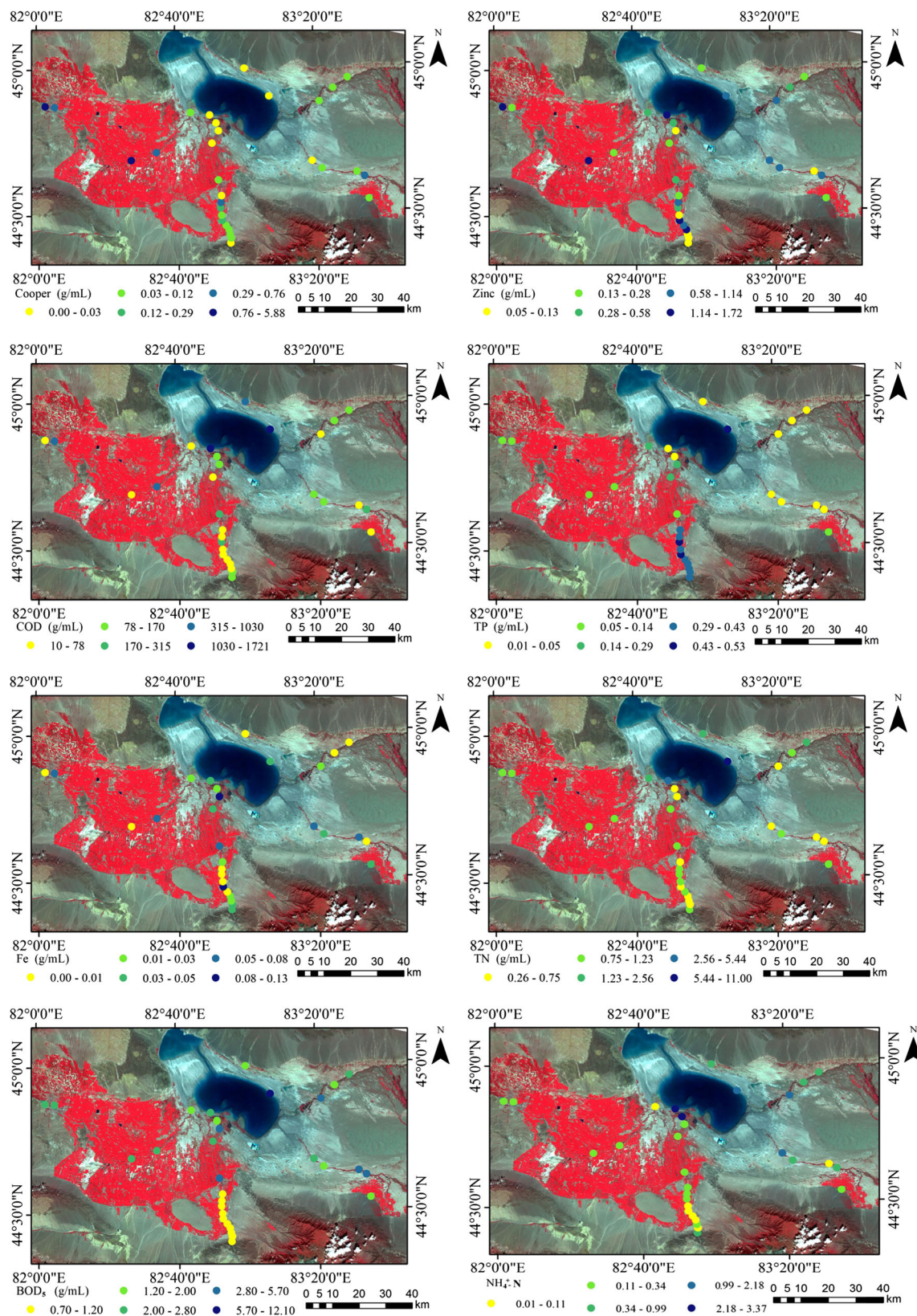
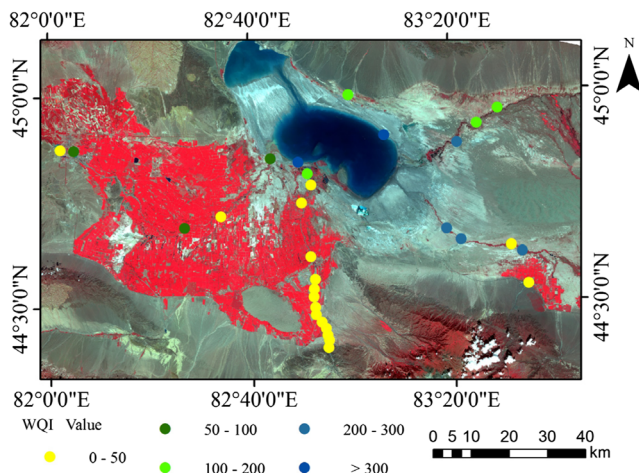**Fig. 4** Spatial-temporal distribution of water quality in the Ebinur Lake oasis

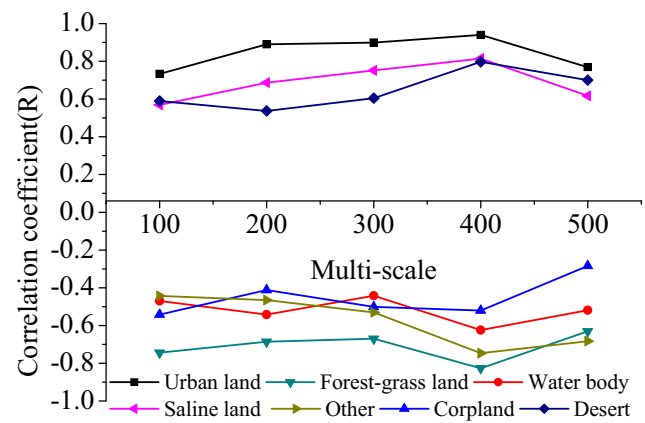Fig. 5 Spatial characteristics of the WQI in the Ebinur Lake watershed

Fig. 6 Pearson relationships between the following LULC types: forest grasslands, water bodies, croplands, saline lands, other land types, and deserts. The WQI is within a buffer from 100 to 500 m

Regional relationships between the water quality index and landscape patterns

Landscape index statistics

Figure 7 shows the differences in the following indexes at different scales: PLAND, DIVISION, AI, COHESION, LSI, and LPI. PLAND values ranged from 0 n/ha to 78% within the 400-m buffer zone, showing the highest degree of landscape fragmentation. The values of DIVISION were highest at the 400-m buffer scale, ranging from 0.4 to 0.11, which shows that the landscape became increasingly diverse. The value of COHESION and AI both show dispersion and interspersion of the land use types.

Extract the primary factors influencing landscape WQI

Using the stepwise multiple linear regression method, the contribution of land use land cover type to the WQI was

analyzed. R^2, F, and p values are used to test significance levels, as shown in Table 5. For urban areas, the regression analysis between landscape indexes and the WQI indicated that there is a significant relationship between the WQI and COHESION, with an adjusted R^2 of 0.63. For water bodies, the regression analysis between landscape indexes and the WQI indicated that there is a significant relationship between the WQI and COHESION, with an adjusted R^2 of 0.64. For croplands, the regression analysis between landscape indexes and the WQI indicated that there is a significant relationship between LSI, DIVISION, and the WQI, with an R^2 of 0.77. For forest grasslands, the regression analysis between landscape indexes and the WQI indicated that there is a significant relationship between LSI, LPI, and the WQI, with an R^2 of 0.79. For saline areas, the regression analysis between landscape indexes and the WQI indicated that there is significant relationship between the LPI and the WQI, with an R^2 of 0.71. For other types of land, the regression analysis between landscape

Number	Parameters	WHO standards (2008)	Weight (W_i)	Relative weight (W_i)
1	COD	15.00	4.00	0.117
2	BOD_5	3.00	5.00	0.147
3	TP	0.10	3.00	0.088
4	TN	0.50	3.00	0.088
5	NH_4^+-N	0.50	3.00	0.088
6	Mg	30.00	2.00	0.059
7	Fe	0.30	1.00	0.029
8	Cu	1.00	1.00	0.029
9	Zn	1.00	2.00	0.059
10	SO_4^{2-}	250.00	4.00	0.117
11	PO_4^{3-}	50.00	5.00	0.0174
12	Cr^{6+}	0.05	1.00	0.0294
			34	1

Table 4 Assessment of the water quality using WQI

Fig. 7 Statistics of landscape indexes (PLAND, DIVISION, AI, COHESION, LSI, and LPI)
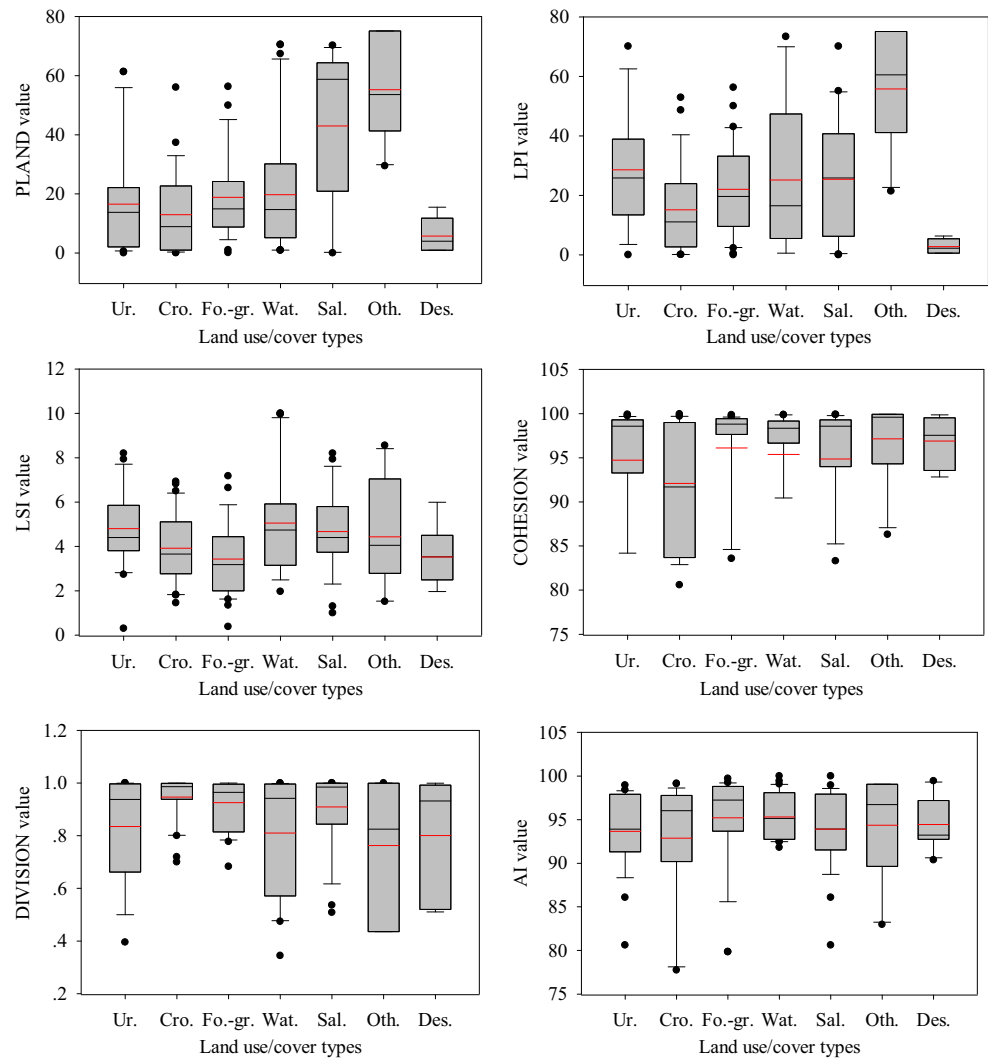
indexes and the WQI indicated that there is significant relationship between the LSI, PLAND, and the WQI, with an R^2 of 0.88. For deserts, the regression analysis between landscape indexes and the WQI indicated that there is significant relationship between PLAND and the WQI, with an R^2 of 0.81.

Analysis of the primary factors in landscape that influence the WQI

Spatially, local R^2 and residual values show a consistent trend, where the residual showed a drastic change. The local R^2 between the LPI, LSI of forest grasslands, and the WQI was

Table 5 Results of the stepwise linear regression between the WQI and landscape indexes

| LULC	Variable	Autonomous variable	Model	Adjust R^2	Std. error	F	p
Urban land	WQI	COHESION	WQI = −7.48 COHESION + 844.29	0.63	80.04	18.59	$p < 0.01$
Water body	WQI	COHESION	WQI = 11.66 COHESION − 959.93	0.64	61.47	34.22	$p < 0.01$
Cropland	WQI	LSI, DIVISION	WQI = 41.33 LSI − 894.43 DIVISION + 831.15	0.77	75.83	35.07	$p < 0.01$
Forest grassland	WQI	LSI, LPI	WQI = 33.63 LSI − 2.89 LPI + 98.27	0.79	64.52	44.51	$p < 0.01$
Saline land	WQI	LPI	WQI = −6.01 LPI + 372.476	0.71	82.64	27.01	$p < 0.01$
Other land	WQI	LSI, PLAND	WQI = 30.466 LSI − 3.492 PLAND + 176.389	0.88	42.44	40.626	$p < 0.01$
Desert	WQI	PLAND	WQI = 10.4.9 PLAND + 21.224	0.81	29.42	29.92	$p < 0.01$
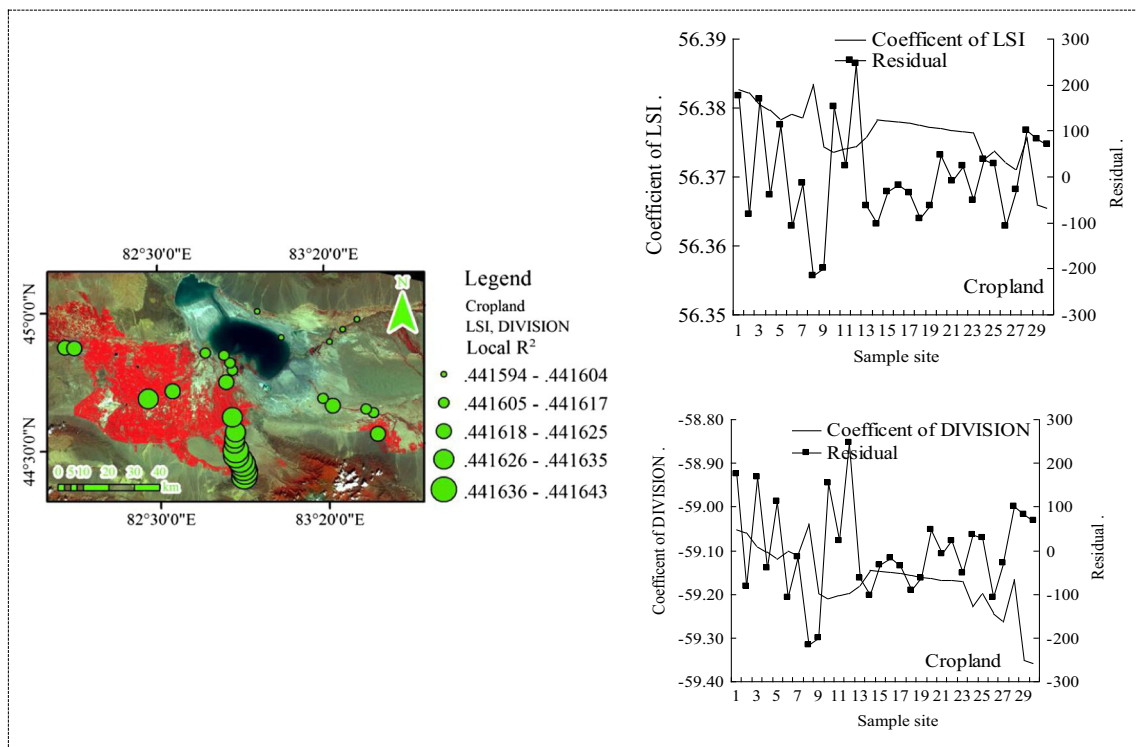
Fig. 8 Local coefficients in the GWR model for the WQI

high in the Akeqisu River and the Kuitun rivers and was low in the Bo River; the value ranged range from 0.57 to 1.86. The coefficient between LPI, LSI of forest grasslands, and the WQI was high in the Akeqisu River and the Kuitun rivers and was low in the Bo River. The residual between the forest grasslands and WQI was 240 in the Jing River. The local R^2 between the LPI, DIVISION for croplands, and the WQI was high in the Akeqisu River and Kuitun rivers (0.41). The coefficient between the LPI, DIVISION for croplands, and the WQI was high in the Akeqisu River and the Kuitun rivers and was low in the Bo River. The residual between croplands and the WQI was 260 in the Jing River. The local R^2 between the COHESION for urban land and the WQI was high in the Akeqisu River and the Kuitun rivers and was low in the Bo River, with a range from 0 to 4.13. The coefficient between COHESION for urban land and the WQI was high in the Akeqisu River and the Kuitun rivers and was low in the Bo River. The residual between urban land and the WQI was 256 in the Jing River. Saline area was a special land use type in the watershed; there was a large distribution of salt in the watershed, and the distribution was less upstream of the Jing River. The local R^2 between LPI for urban land and the WQI was high in the Akeqisu River and the Kuitun rivers and was low in the Jing River (close to 0); other rivers ranged from 0 to 0.72. The coefficient between the LPI for urban land and the WQI was high in the Akeqisu River and the Kuitun rivers and was low in the Bo River. The residual between urban land and the WQI was 300 in the Jing River. For water bodies and other

types of land, absolute values of the local regression coefficients, local R^2, and residuals showed a consistent trend, and the residual showed a drastic change (Fig. 8).

Discussion

Relationships between the WQI and land use and land cover landscape

Forest grasslands, other types of land, water bodies, and croplands had negative effects on the WQI value in this study, whereas saline land types, deserts, and urban areas had positive effects on the WQI. Negative and positive relationships between certain LULCs and water quality parameters were found in different buffers. Statistics indicate that saline areas mainly occurred in the Bo River, Jinghe River, surrounding villages and towns of Ebinur Lake, downstream of the Daheyanzi River, and north of Bole City in the Ebinur Lake oasis (Mi et al. 2010). Severe soil salinization seriously affected the farming of crops; therefore, some farmers increase the amount of chemical fertilizer to increase yield. Others even abandon the land, thereby resulting in land use and land cover change, and worse, water and soil pollution.

There are many studies that show cropland being negatively correlated with water quality (Chen et al. 2016); however, cropland had negative effects on the WQI value in this study. The results indicate that croplands improve water quality in
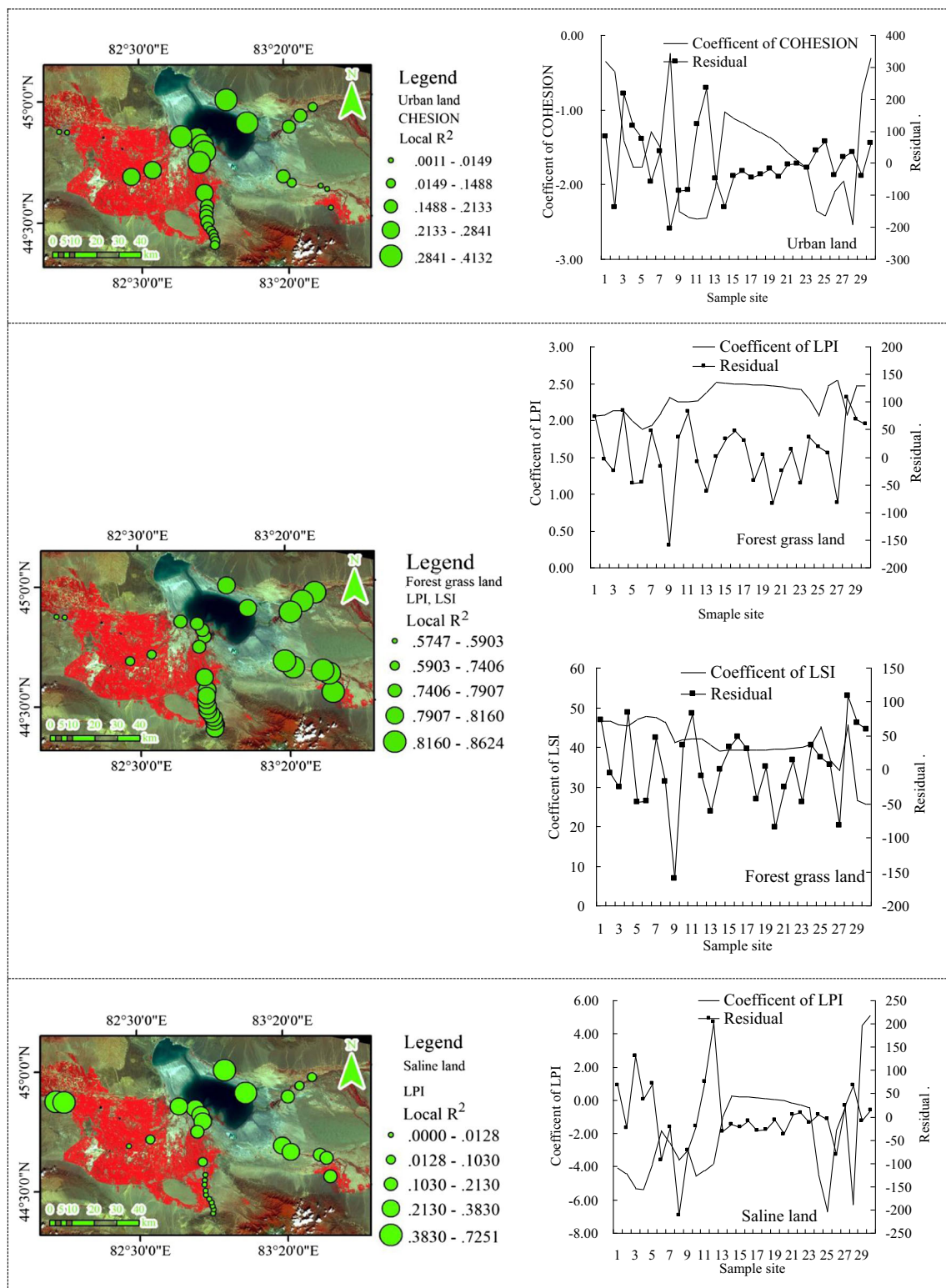
Fig. 8 (continued)

the Ebinur Lake oasis. These results are not consistent with most previous studies (Li et al. 2009b; Tu 2011; Wu 2013; Wan et al. 2014; Chen et al. 2016; Shi et al. 2017). Because the study area is located in the arid areas of Xinjiang, desert dust

and salt dust are major environmental hazards in this study area. Desert dust and salt dust seriously affect the atmosphere and water quality and accelerate the degradation of vegetation and threaten ecological security in the oasis. However, with
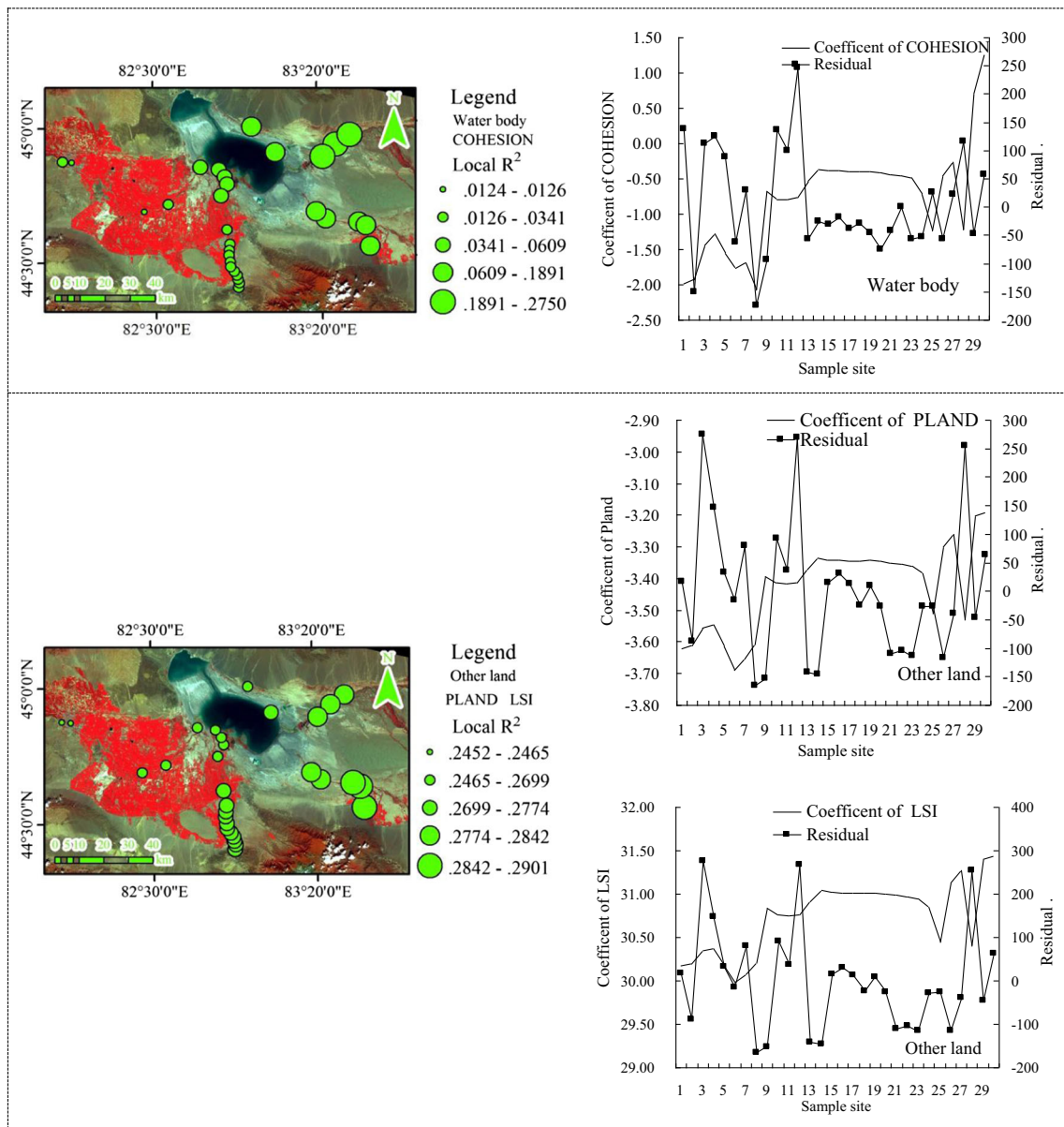
Fig. 8 (continued)

economic development of and population growth, human improvement of desert land and saline land increases the area of croplands (Yu et al. 2017). Therefore, croplands are the largest cover of vegetation, indicating that croplands are positively correlated with water quality in the Ebinur Lake oasis.

Most rivers in Xinjiang are characterized by low water yield, short length, small environmental water capacity, poor self-cleaning capability, and low tolerance to pollution. Hence, an artificial change in land use and the exploration for resources in lake regions has led to an evident correlation between LULC types and the WQI. In addition, scientifically utilizing and protecting water resources in Ebinur Lake, as well as scientifically applying chemical fertilizers and improving their application rates, are important issues that should be

addressed to achieve sustainable development in agricultural irrigation zones in the Jinghe oasis and in rivers in Xinjiang.

Scale effects on varying relationships

Determining an effective buffer in water quality management was the key problem in this study, and the influence of land use and land cover and landscape on WQI values varied spatially. The relationship was most significant at the 400-m buffer in this study. Carey et al. (2011) indicated that a riparian buffer was the key element in land use and land cover when formulating policy. Buck et al. (2004) suggested that the "scale" effects of land management should be given more attention. Chen et al. (2016) reported that forest land and water

quality were positively correlated within the 200-m buffer zone. Ebinur Lake has become the most significant area of ecological degradation. This study area has the typical characteristics of a mountain oasis-desert environment. It can be characterized as a desert-oasis region, where the researched land area is large, the population is small, the changing landscape characteristics are small, and the desert area is located in an ecologically fragile district. The effective buffer zone in this area is 400 m and has a direct relationship with the local desert-oasis ecosystem.

Management implications

The oasis is the foundation of human existence in Xinjiang. Urban and saline areas, which have a positive effect on the WQI value of the river, are mainly dispersed along the river in this study. The Alashan Mountain, located in the northwestern part of the watershed, is consistent with a typical continental climate. This region is windy and has scarce rainfall and frequent salt storms in the Ebinur Lake oasis. Therefore, it is important to control saline land runoff. Saline areas have a strong impact on water quality at a large scale for ecosystem security. Zhang et al. (2017) reports that salt dust from the Ebinur Lake oasis has a great impact on the climate of East Asia.

Conclusion

This study explored the relationships between land use and land cover landscape patterns and water quality in the Ebinur Lake oasis in China. The WQI was used to identify threats to water quality and contribute to better water resource management. The results showed the following:

(1) The calculated WQI was between 56.61 and 2886.51. The prepared WQI map shows poor water quality.
(2) The WQI varied spatially and was influenced by land use. Both positive and negative relationships between land use and the WQI were found at different buffers. This relationship was most significant at the 400-m buffer.
(3) There was a significant relationship between the water quality index and landscape (i.e., PLAND, DIVISION, AI, COHESION, LSI, and LPI) using stepwise multiple linear regressions under a 400-m scale, with an adjusted R^2 between 0.63 and 0.88.
(4) Absolute values of the local regression coefficients for the LPI and LSI for forest grassland and the WQI were high in the Akeqisu River and the Kuitun rivers and were low in the Bo River, ranging from 0.57 to 1.86. The absolute value of the local regression coefficient between the LSI for cropland and the WQI was 0.44. The absolute

values of the local regression coefficients between the LPI for saline lands and the WQI were high in the Jing River and low in the Bo River, the Akeqisu River, and the Kuitun rivers, ranging from 0.57 to 1.86.

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