

# Scale Effects on Spatially Varying Relationships Between Urban Landscape Patterns and Water Quality

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**Abstract** Scientific interpretation of the relationships between urban landscape patterns and water quality is important for sustainable urban planning and watershed environmental protection. This study applied the ordinary least squares regression model and the geographically weighted regression model to examine the spatially varying relationships between 12 explanatory variables (including three topographical factors, four land use parameters, and five landscape metrics) and 15 water quality indicators in watersheds of Yundang Lake, Maluan Bay, and Xinglin Bay with varying levels of urbanization in Xiamen City, China. A local and global investigation was carried out at the watershed-level, with 50 and 200 m riparian buffer scales. This study found that topographical features and landscape metrics are the dominant factors of water quality, while land uses are too weak to be considered as a strong influential factor on water quality. Such statistical results may be related with the characteristics of land use compositions in our study area. Water quality variations in the 50 m buffer were dominated by topographical variables. The impact of landscape metrics on water quality gradually strengthen with expanding buffer zones. The strongest relationships are obtained in entire watersheds, rather than in 50 and 200 m buffer zones. Spatially varying relationships and effective buffer zones were verified in this study. Spatially varying relationships between explanatory

variables and water quality parameters are more diversified and complex in less urbanized areas than in highly urbanized areas. This study hypothesizes that all these varying relationships may be attributed to the heterogeneity of landscape patterns in different urban regions. Adjustment of landscape patterns in an entire watershed should be the key measure to successfully improving urban lake water quality.

**Keywords** Urban landscape pattern · Water quality · Spatially varying relationship · Ordinary least squares regression · Geographically weighted regression · Scale effects

## Introduction

The degradation of water quality is a key global environmental issue (Palmer et al. 2004; Zhao et al. 2011). With rapid urbanization, urban sprawl leads to water quality degradation. This is due to the increasing presence of impervious surfaces and human activities in the process of urbanization within watersheds (Brett et al. 2005; Schoonover et al. 2005; Zhao et al. 2006; Tu et al. 2007; Du et al. 2010; Pinto et al. 2013; Sun et al. 2013). Moreover, many natural and anthropogenic factors, including precipitation intensity, soil types, topographical and geological characters, urbanization, agricultural activities, and industrial and sewage discharge can affect the water quality (Baker 2003). Water quality has significant correlations with changes in landscape patterns and human activity (Azous and Horner 2001; Allan 2004). Water bodies are an important part of the landscape in urban areas, and water quality is influenced by the composition of land use types and spatial configuration of land use patterns within a watershed or catchments (Sliva and Willams 2001;

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Donohue et al. 2006; Moreno et al. 2006; Hwang et al. 2007; Jung et al. 2008; Guo et al. 2010; Li et al. 2012). Land use has been one of the key contributing factors for urban water pollution (Changnon and Demissie 1996; Mander et al. 1998; Foley et al. 2005; Grimm et al. 2008). For example, urban and agricultural land uses have a strong positive influence on nitrogen and sediments loads; on the other hand, grassland negatively contributes to water nutrient loads (Basnyat et al. 1999; Wang 2001; Tong and Chen 2002; Moreno et al. 2006).

Previous studies have mainly focused on the impact of land use types on water quality at varying spatial scales using the percentage of land use, such as impervious land, forestland, agriculture land, and wetland and so on (Sliva and Willams 2001; Hwang et al. 2007; Jung et al. 2008; Guo et al. 2010; Li et al. 2012). A number of studies have shown conflicting results on the impact of land use on water quality at different scales (Johnson et al. 1997; Sliva and Willams 2001; Sawyer et al. 2004). We should point out that most previous studies focusing on the relationship between land use and water quality were only carried out in watersheds and subwatersheds. However, due to the complexity and variability in spatial patterns of land uses, the trend of impacts of land uses on water quality has still not been explored explicitly.

From an ecological landscape perspective, the spatial configuration of landscapes may play a critical role in determining natural habitats, hydrological processes, energy flows, and nutrient cycles (Alberti et al. 2007). Recent studies have focused on examining the relationships between the spatial configuration of landscapes and water quality at various scales (Amiri and Nakane 2009; Lee et al. 2009; Shiels 2010; Carey et al. 2011; Jager et al. 2011; Huang et al. 2013; Zhang et al. 2013).

However, the effects of land use types and its spatial structures on water quality are always simultaneous in a watershed. Land use types and its spatial structures should be investigated together in order to examine which factors exert the most important influence. Guo et al. (2010) proposed a dynamic hypothesis that the impact of land use on water quality could vary with the expansion of the buffer size and that there should be an effective buffer zone where the strongest linkage occurs between land use and water quality. They also pointed out when beyond or under the effective buffer zone, the impact of land use on water quality should become weak or insignificant, given that the land use characteristics themselves varied with distance.

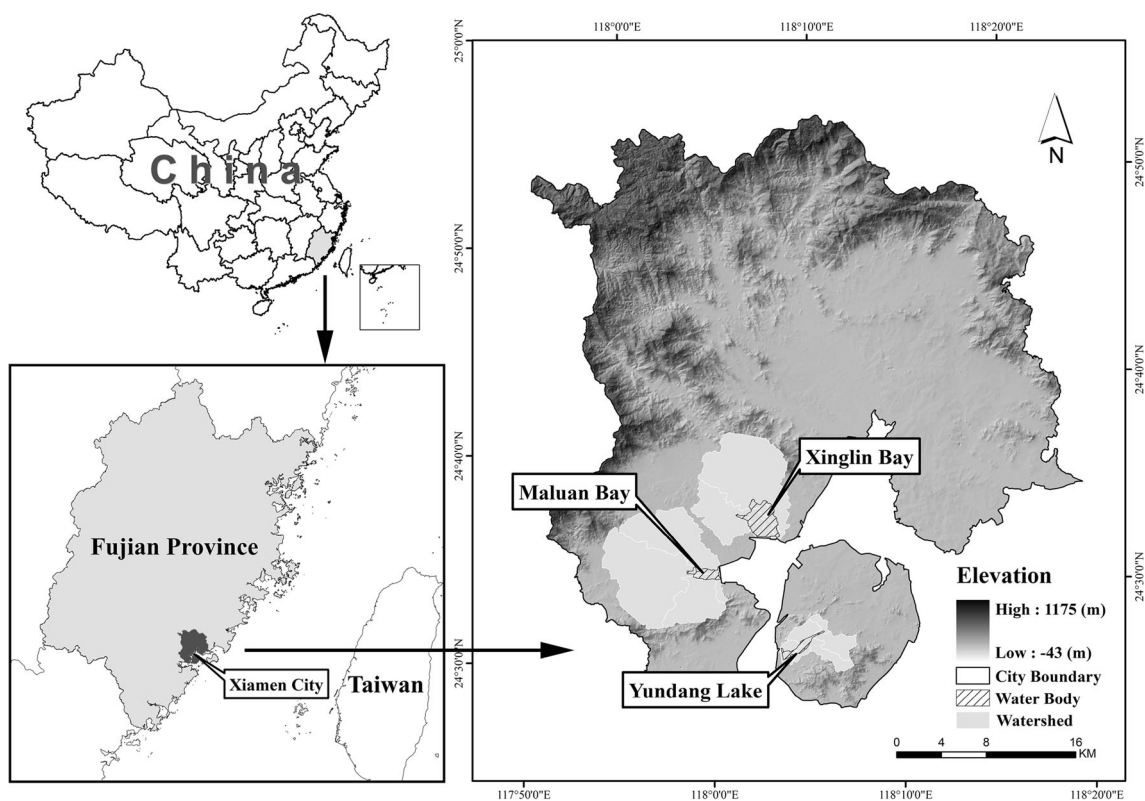
The primary statistical methods to analyze relationships between land use and water quality are the conventional statistical methods, such as Pearson's correlation, simple correlation, single linear model, multiple linear regression model, nonparametric statistical analysis, nonlinear multiple regression, and ordinary least squares regression (OLS)

(Seeboonruang 2012). The conventional statistical methods are “global statistics” that analyze the average situation for the whole study area. It is assumed that the relationships are constant over space. Land use parameters and landscape metrics are used as independent variables and water quality parameters obtained from observed statistical data act as dependent variables in the regression. These conventional statistical methods utilize global statistics that analyze the average situation for the whole study area, and usually, they are unable to explore the local variations in the relationships between independent variables and water quality indicators (Tu 2011). In recent years, a simple but powerful statistical method called geographically weighted regression (GWR) has been developed based on the OLS model to explore continuously varying relationships over space (Brunsdon et al. 1998; Fotheringham et al. 2002). The “local statistics” methods, such as GWR, attempt to capture spatial variations by allowing regression model parameters to change over space and can calculate a set of local regression results including local parameter estimates, the values of the *t* test on local parameter estimates, local  $R^2$  values, and local residuals for each regression point. Given its strong advantage, GWR model has been applied to explore the spatially varying relationship between land use and water quality in several previous studies (Tu 2011; Pratt and Chang 2012; Yu et al. 2013).

In this study, we investigated the spatially varying relationships between topographical variables, land use parameters, landscape metrics, and water quality parameters using OLS and GWR models in Yundang Lake, Maluan, and Xinglin Bay of Xiamen City, China. Our objectives are (1) to determine which of the above-mentioned explanatory variables have the largest impact on water quality; and (2) to analyze scale effects of the relationships between explanatory variables and water quality parameters across an urbanization gradient within watersheds.

## Study Area

Xiamen City is situated in the southeast coast of Fujian province, China. Mean annual precipitation is 1,530 mm, with significant spatial and temporal differences. Rainfall distribution in Xiamen City is uneven. The flood season lasts from April to October, accounting for 80 % of total annual rainfall. Precipitation gradually reduces from the northwest (above 2,000 mm) to the southeast (about 1,100 mm) (Lin 2009). Figure 1 shows a location map of three watersheds in Xiamen, including Yundang Lake, Maluan Bay, and Xinglin Bay. There is great spatial difference in the level of urbanization among the three study watersheds. Yundang Lake is located in the center of



**Fig. 1** Sketch map of Yundang Lake, Maluan Bay and Xinglin Bay

Xiamen Island, and the water area is up to 1.6 km<sup>2</sup>. There is no river flowing onto the lake; it only exchanges regularly with sea water through water gates. The areas around the water body are highly urbanized and mainly covered by commercial, residential, and recreational lands. In the early stages, industrial and residential sewage is drained off into water body without treatment, causing the water pollution of Yundang Lake to become increasingly serious. Since 1980s, government had taken some engineering measures to improve water quality of Yundang Lake. In recent years, the water quality has improved significantly as a whole, but parts of waters are still polluted serious. So adjustment of land use patterns at watershed scale should be the key measure to successfully improve urban lake water quality in the next step. Maluan Bay is located at the junction of Haicang district and Jimei district and has a water area of 2.1 km<sup>2</sup>. A small stream drains into Maluan bay from west to east. Water body exchanges the water through gate during the flux and reflux. The dominant land use types around the water body are industrial and residential lands. It belongs to a less urbanized area. Xinglin Bay is located at the Jimei district and has a water area of 6 km<sup>2</sup>. The lake was completely separated with outside sea by dam and only releases flood water to sea when extreme perception event happened. The areas around the Xinglin Bay have been constructing in Xiamen, which are expanding from the

inside to the outside of the island, and it is at the period of transition from an agricultural landscape to an urban landscape.

## Materials and Methods

### Water Quality Parameters

Water quality data were collected and analyzed on a quarterly basis (four times per year) from each of the 30 selected sampling sites. Water sampling was carried out quarterly from March 2011 to January 2012 (spring 2011.3, summer 2011.7, autumn 2011.11, and winter 2012.1). Generally, sampling time is selected in sunny day and tries to avoid any antecedent rain for the representation of water quality data. Thirteen sites for Yundang Lake, ten sites for Xinglin Bay, and seven sites for Maluan Bay were selected based on watershed characteristics. Water temperature (Temp), pH, dissolved oxygen (DO), chlorophyll a (Chl), salinity (Sal), and conductivity (Cond) were measured with Multi-Parameter Water Quality Monitoring Equipment (YSI int.) at three depths of approximately 0.1, 0.5, and 1.0 m. Surface water was collected for measurement of total organic carbon (TOC), total nitrogen (TN), total phosphorus (TP), and seven metal elements (including As,

**Table 1** Explanatory variables used in analysis (McGarigal and Marks 1995)

Category	Variables
Land use composition	Percentages of green (VEG), agriculture (AGR), urban (URB), road (ROA), fish pond (FIS), bare land (BAR)
Topographical factors	Mean subwatershed slope (SLO), mean subwatershed elevation (ELE), slope standard deviation (SLO_STD)
Landscape metrics (landscape level)	Patch density (PD), largest patch index (LPI), landscape shape index (LSI), Shannon's diversity index (SHDI), Shannon's evenness index (SHEI)

Hg, Pb, Cu, Fe, Zn, and Se). Water quality samples were measured by the standard analytical method for surface water quality. TOC-VCPH Total Organic Carbon Analyzer was used to measure TOC and TN. The ammonium molybdate spectrophotometric method was used to measure TP. The atomic fluorescence spectrometric method was applied to determine As and Hg. The atomic absorption spectrophotometric method was used to measure Pb, Cu, Fe, Zn, and Se. We used annual mean values of water quality parameters as dependent variables.

#### Land Use Data

Land use information within the watersheds was interpreted from SPOT5 imagery (2011-4-24) using ArcGIS 9.3 Desktop GIS software. This remote imagery covers most parts of Xiamen city, with a spatial resolution of 2.5 m. According to watershed characteristics, land use types are classified into seven broad categories, namely, (1) green land, including forest and shrub land; (2) agricultural land, including paddy field and dry land; (3) urban land, including industrial, residential, and recreational land; (4) road land; (5) water areas; (6) bare land, including bare ground and bare rocks; (7) fish pond areas, which are controlled ponds for breeding fish. The orthorectification procedure was utilized to the remote image in order to correct geometric distortions. Based on Google Earth map and visual interpretation, land use maps of three watersheds were finally derived, and the total classification accuracy was more than 90 %. Land cover polygons representing different land covers were then converted to a 10.0 m raster grid, which allowed for the measurement of land use composition and landscape metrics using FRAGSTATS3.3 software.

#### Explanatory Variables

Topographic, land use composition, and landscape variables are shown in Table 1. The watersheds were

automatically delineated with the use of a 10.0 m digital elevation model (DEM) in ArcSWAT extension of ArcGIS 9.1 software (Winchell et al. 2007). The SWAT model divided the watersheds of Yundang Lake, Maluan Bay, and Xinglin Bay into 8, 3, and 7 subwatersheds, respectively, based on the outlet location of each watershed and upstream rivers (Fig. 2). The riparian areas were created by buffering the lake/bay 50 and 200 m. The land use composition and topographic variables in each of the 18 delineated subwatersheds were calculated using the Spatial Analyst tools in ArcGIS.

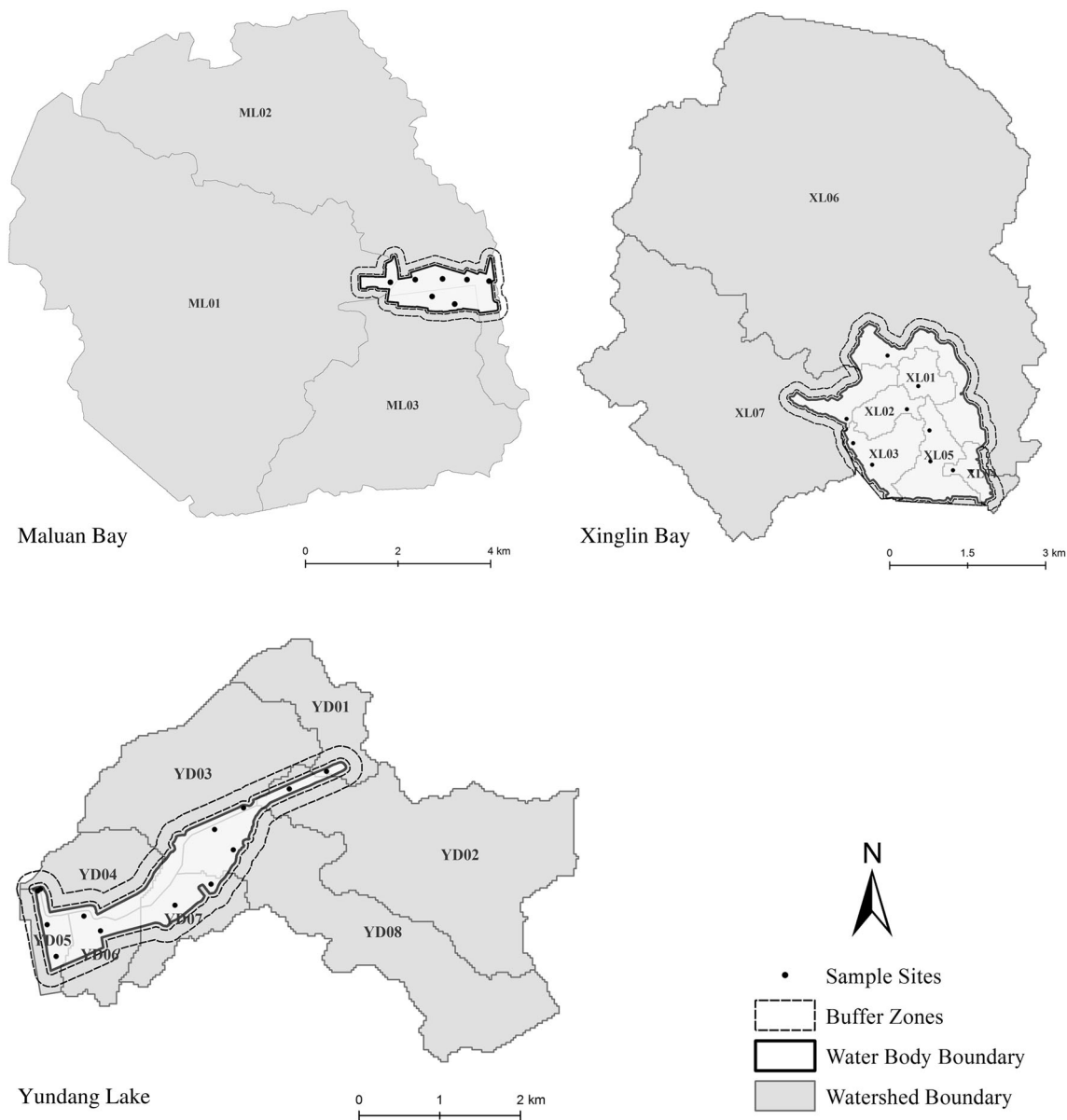
In this study, five landscape metrics at the landscape level were calculated using the raster version of FRAGSTATS 3.3 (Table 2) based on 10.0 m-resolution land use data.

#### Analysis Methodology

Multivariable OLS and GWR models were developed to explore the relationship between independent variables and water quality parameters from global and local perspectives. The regression coefficients from OLS models can help us to find the dominant factors of varying water quality at 50, 200 m and watershed scales. The local regression coefficients at different sampling points from GWR models can reflect the strength of relationships between explanatory variables and water quality parameters across an urbanization gradient. The dependent variable is a factor calculated from the fifteen water quality parameters, and the explanatory variables are the seven land use composition parameters, three topographical factors, and five landscape metrics. The Kolmogorov–Smirnov (K–S) goodness of fit test was used to test for normality of the distribution of the water quality and independent variables. For water quality parameters, the TP and Fe were transformed logarithmically [ $\log(x + 1)$ ], Cond was removed due to unresolved skewness. For independent variables, the percentages of fish ponds and agricultural land were removed, because they were only present in one watershed. At a watershed scale, the mean subwatersheds elevation, PD, and LPI were transformed logarithmically, and LSI was transformed, respectively. At a 200 m buffer scale, the slope standard deviation was transformed. OLS and GWR were performed using ArcGIS 9.3. An advantage of running an OLS regression in ArcMap is the output from the process which includes the residual for each site, allowing the researcher to more easily test the residuals for spatial autocorrelation (Pratt and Chang 2012).

The OLS and GWR model can be, respectively, expressed as Eqs. (1) and (2):

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \varepsilon, \quad (1)$$



**Fig. 2** Location map of monitoring sites and schematic of watershed delineation for Yundang Lake (YD01–YD08), Maluan Bay (ML01–ML03), and Xinglin Bay (XL01–XL07)

where  $x_i$  is the independent;  $y$  is the dependent variable;  $P$  denotes the number of independent variables;  $\beta_0$  and  $\beta_i$  represent intercept and coefficient, respectively;  $\varepsilon$  represents error.

The GWR model allows local rather than global parameters to be estimated for the location of samples, and the above model can be rewritten as:

$$y_j = \beta_0(u_j, v_j) + \sum_{i=1}^p \beta_i(u_j, v_j)x_{ij} + \varepsilon_j, \quad (2)$$

where  $u_j$  and  $v_j$  are the coordinates for each location  $j$ ,  $\beta_0(u_j, v_j)$  is the intercept for location  $j$ ,  $\beta_i(u_j, v_j)$  is the local

parameter estimate for independent variable  $x_i$  at location  $j$ . The model is calibrated using an exponential distance decay function.

$$w_{ij} = \exp(-d_{ij}^2/b^2). \quad (3)$$

The weight of site  $j$  as it effects site  $i$ ,  $W_{ij}$ , is calculated using the distance ( $d$ ) between sites  $i$  and  $j$  with  $b$  acting as the kernel bandwidth. The weight decreases rapidly when the kernel is smaller than the distance. Both fixed and adaptive kernel bandwidth can be chosen for GWR. We used adaptive kernel bandwidth here, because the density of sample sites varied across watersheds. The optimal

**Table 2** Landscape metrics used in analysis

Metrics (abbreviation)	Descriptions
Patch density (PD)	Number of patches per unit area (number per 100 ha)
largest patch index (LPI)	Percentage of the landscape in the largest patch (unit: %)
landscape shape index (LSI)	Measures the perimeter-to-area ratio for the landscape as a whole (unitless)
Shannon's diversity index (SHDI)	Based on information theory; indicates the patch diversity in a landscape (unitless)
Shannon's evenness index (SHEI)	The observed Shannon's Diversity Index divided by the maximum Shannon's Diversity Index for that number of patch types (unitless)

bandwidth was determined by minimizing the corrected Akaike Information Criterion (AICc). Given that multicollinearity existed among the explanatory variables, one explanatory variable acted as the independent variable, and water quality acted as the dependent variable in the regression models (Tu 2011). GWR models produce a set of local regression results, including local residual and  $R^2$  results, as well as a global  $R^2$  by ArcGIS software (Tu and Xia 2008). The Global Moran's I for the residuals from both OLS and GWR models were calculated to test the model's accuracy. If significant spatial autocorrelation exists in an OLS model, then the model violates the assumption of randomly distributed and independent residuals in regression models. The efficiency of the model is therefore suspect. In addition, the residuals may contain some geographic information that the model does not include and is therefore lost (Clark 2007). GeoDa 0.9.5-I (Beta) analysis software was used to calculate the Global Moran's I statistics.

In order to evaluate the variability of water quality data in each watershed, the coefficient of variations (CV) was calculated. The CV-value is defined as

$$CV = SD/MV, \quad (4)$$

where SD is the standard deviation, and MV is the mean value.

## Results

### Spatial Variations in Land Use Composition and Water Quality Parameters

Obvious heterogeneity of land uses and spatial gradient of urbanization exist in the three watersheds (Table 3). The dominant land use types in Yundang Lake watershed are residential and commercial land (total  $\approx 60\%$ ), and the proportion of urban built-up areas can be 96%, which

indicate that the Yundang Lake watershed is represented as a highly urbanized area. In the Maluan Bay watershed, there are larger areas of fish ponds ( $\approx 24\%$ ); commercial and industrial lands have been expanding rapidly in recent years. All this indicates that the Maluan watershed is a peri-urbanization area. The proportion of urban built-up area in the Xinglin Bay watershed is about 66%, and the bare land in the process of development and construction is larger than other watersheds ( $\approx 20\%$ ). Therefore, the Xinglin Bay watershed is a rapidly urbanized area. Maluan Bay and Xinglin Bay watersheds are represented as less urbanized watersheds.

As shown in Table 4, there are significant differences in topographical factors and landscape metrics between three watersheds. Higher mean slope, mean elevation, and slope deviation are observed in Yundang watershed, and lower values of such topographical factors are found in Xinglin watershed. For landscape metrics at landscape level, the values of LSP and SHDI are higher in Xinglin Bay and lower in Yundang Lake. The result shows obviously differences of landscape pattern in three watersheds and confirms our division of urbanization gradients for these study areas.

The CVs (%) across different sampling sites, which range from 1.15 to 83.95%, indicate that there are large spatial variations for water quality data (Table 5). In general, the spatial variations of Temp, Chl, TOC, Hg, As, Pb, and Fe in highly urbanized watershed were greater than in less urbanized watersheds. However, spatial variations of other water quality parameters like Cond, Sal, pH, DO, TN, Cu, Zn, and Se in less urbanized watersheds were greater than those in highly urbanized watersheds. In the Yundang Lake watershed, the CVs of Chl, TP, Pb, Cu, and Fe ( $CV > 50\%$ ) were greater than the other water quality parameters. In the Maluan Bay watershed, the CVs of Chl and Pb were greater than the other water quality parameters. In the Xinglin Bay watershed, the spatial variations of Pb and the CVs of Cu and Zn were greater than the other water quality parameters.

### Spatial Analysis of OLS Regression Models

Final models were selected when every variable in the model was significant ( $P < 0.05$ ), and the adjusted coefficient of determination (Adj.  $R^2$ ) is larger than 0.6. As shown in Table 6, the correlation of explanatory variables with water quality varied with the spatial scales. The regression coefficients for explanatory variables indicate that landscape metrics (such as SHDI and SHEI) and topographical factors like elevation and slope are the dominated variables for predicting water quality parameters at three spatial scales, while the correlations between percentage of land use types and water quality parameters

**Table 3** Land use composition in the watershed of Yundang Lake, Maluan Bay, and Xinglin Bay in 2011

Watershed	Percentages of land use types (%)								
	Urbanization types	Commercial/ industrial/ recreational land	Road land	Green land	Bare land	Fish pond	Residential land	Agricultural land	built-up area
Yundang Lake	High urbanization area	19.63	5.64	32.05	4.13	0.00	38.54	0.00	95.86
Maluan Bay	Peri-urbanization area	20.36	2.18	26.97	10.94	23.92	15.63	0.00	65.14
Xinglin Bay	Rapid urbanization area	7.67	5.85	27.03	19.44	6.47	25.29	8.26	65.84

**Table 4** Topographical factors and Landscape metrics in the watershed of Yundang Lake, Maluan Bay, and Xinglin Bay

Watershed	Topographical factors			Landscape metrics (landscape level)				
	Mean slope	Mean elevation	Slope standard deviation	Patch density	Largest patch index	Landscape shape index	Shannon's diversity index	Shannon's evenness index
Yundang Lake	5.86	35	7.99	5.94	18.22	11.8	1.37	0.77
Maluan Bay	3.85	25	6.07	2.27	21.71	13.11	1.73	0.83
Xinglin Bay	3.16	17.6	5.23	5.41	11.63	17.55	1.81	0.87

are extremely weak compared with other explanatory variables ( $|\beta_i| \approx 0$ ). Thus, the impact of land use composition on water quality can be neglected and is not discussed in the followed sections.

Variation in water quality at the 50 m buffer scale is dominated with topographical variables. Mean subwatershed slope is negatively correlated to the concentrations of Sal, TOC, Hg, As, Cu, Fe, and Se. However, higher standard deviation of the slope corresponds to increasing concentrations of Sal, Hg, As, Cu, and Se. Compared with topographical variables, the impact of landscape metrics on water quality is relatively small because of less number of occurrences and low frequency of the regression coefficients.

At 200 m buffer scale, landscape metrics becomes the main factors for most of the water quality parameters, while topographical variables influence on water quality weakens.

At the watershed scale, SHDI and SHEI are the main indicators, and their impacts on water quality strengthen further. SHEI has a negative correlation with Sal, Hg, As, and Se while being positively related to Temp, DO, Chl, and Fe. SHDI has a completely opposite impact on water quality variation compared with SHEI. However, it should be pointed out that there are significant correlations between TN and TP, and landscape metrics and topographical variables at the watershed scale rather than at 50 and 200 m buffer scales. Specifically, mean subwatershed elevation has a positive correlation with the concentration of TN and TP; PD, LPI, SHDI, and SHEI have negative correlations with the concentration of TN and TP.

The values of Adj.  $R^2$  in OLS models could indicate the ability of explanatory variables to explain water quality parameters. As shown in Table 6, the values of Adj.  $R^2$  at the watershed scale are generally larger than those at the 50 and 200 m buffer scales, which reflect the scale effects of dominant factors and the existence of the effective buffer zone.

Table 7 shows the results of Moran's I statistics on the residuals from the OLS model. Significant negative spatial autocorrelations are observed, Temp at the 50 m buffer scale (Moran's  $I = -0.2$ ,  $P < 0.05$ ), Sal at the watershed (Moran's  $I = -0.21$ ,  $P < 0.05$ ), DO at the 200 m buffer and watershed scales (Moran's  $I = -0.2$ ,  $P < 0.05$ ), Hg at the 50 m buffer scale (Moran's  $I = -0.2$ ,  $P < 0.05$ ), and Fe at the watershed scale (Moran's  $I = 0.19$ ,  $P < 0.05$ ). The results indicate that these OLS models might miss the variables that explain the variation and are unsuitable for identifying the relationships between explanatory variables and water quality parameters.

#### Spatial Analysis of Local GWR Models

In the previous sections, the global relationships at three spatial scales have been obtained by means of OLS models, but these results may miss some local relationships and cannot reflect the spatially varying relationships. Therefore, the GWR method was applied to explore spatially varying relationships between explanatory variables and water quality parameters along the gradient of the urbanization level. As shown in Tables 6 and 7, the global coefficient of determination ( $R^2$ ) and local parameter

**Table 5** Statistical summary of the water quality parameters in the Yundang Lake, Maluan Bay, and Xinglin Bay watersheds

Watershed	Parameter	Min.	Max.	Mean	Std. Deviation	CV (%)	N
Yundang Lake	Temp (°C)	15.02	22.62	20.21	1.68	8.29	13
	Cond (ms/cm)	38.34	41.60	39.94	0.89	2.23	13
	Sal (ppt)	25.47	26.85	26.42	0.40	1.52	13
	pH	7.74	8.10	7.97	0.12	1.46	13
	DO (mg/L)	4.27	9.48	6.81	1.27	18.70	13
	Chl (µg/L)	0.57	6.34	2.45	1.78	72.63	13
	TOC (mg/l)	0.88	2.60	1.98	0.54	27.42	13
	TN (mg/l)	1.44	4.28	1.97	0.85	43.30	13
	TP mg/l)	0.54	2.41	1.05	0.56	52.98	13
	Hg (µg/L)	0.16	0.55	0.30	0.12	40.61	13
	As (µg/L)	11.80	20.12	14.72	2.34	15.92	13
	Pb (µg/L)	0.09	1.23	0.38	0.31	82.05	13
	Cu (µg/L)	0.90	12.72	6.20	3.40	54.88	13
	Fe (µg/L)	15.88	82.74	37.83	19.40	51.28	13
Zn (µg/L)	3.24	11.09	5.95	2.37	39.80	13	
Se (µg/L)	143.30	243.68	178.89	28.84	16.12	13	
Maluan Bay	Temp (°C)	21.44	22.12	21.75	0.25	1.15	7
	Cond (ms/cm)	29.74	31.69	30.69	0.63	2.05	7
	Sal (ppt)	18.45	19.76	19.09	0.42	2.22	7
	pH	8.00	8.59	8.29	0.21	2.50	7
	DO (mg/L)	8.27	11.50	9.74	1.27	13.05	7
	Chl (µg/L)	6.29	22.13	12.49	6.33	50.66	7
	TOC (mg/l)	3.92	8.10	5.22	1.37	26.31	7
	TN (mg/l)	1.60	2.16	1.98	0.18	9.22	7
	TP (mg/l)	0.77	1.08	0.93	0.15	16.13	7
	Hg (µg/L)	0.16	0.32	0.21	0.06	26.48	7
	As (µg/L)	10.19	12.72	11.00	0.99	8.97	7
	Pb (µg/L)	0.09	0.85	0.33	0.25	77.17	7
	Cu (µg/L)	3.65	7.94	5.80	1.49	25.74	7
	Fe (µg/L)	14.49	26.02	19.16	3.73	19.45	7
Zn (µg/L)	4.27	10.37	6.12	1.97	32.23	7	
Se (µg/L)	125.28	152.36	136.36	9.23	6.77	7	
Xinglin Bay	Temp (°C)	22.12	23.90	22.94	0.54	2.35	10
	Cond (ms/cm)	1.99	3.55	2.69	0.40	15.00	10
	Sal (ppt)	1.02	3.34	1.69	0.70	41.55	10
	pH	8.31	9.66	9.07	0.39	4.30	10
	DO (mg/L)	7.30	16.26	12.52	2.57	20.49	10
	Chl (µg/L)	23.26	45.13	33.11	6.69	20.20	10
	TOC (mg/l)	4.98	9.65	6.27	1.31	20.90	10
	TN (mg/l)	2.40	7.56	3.49	1.57	44.92	10
	TP (mg/l)	1.66	4.26	2.42	0.83	34.36	10
	Hg (µg/L)	0.07	0.13	0.09	0.02	23.16	10
	As (µg/L)	1.85	2.34	2.06	0.17	8.49	10
	Pb (µg/L)	0.54	4.93	1.62	1.32	81.92	10
	Cu (µg/L)	0.64	6.44	2.30	1.85	80.54	10
	Fe (µg/L)	76.42	139.14	114.86	20.13	17.52	10
Zn (µg/L)	3.29	30.10	9.42	7.91	83.95	10	
Se (µg/L)	5.31	10.19	7.19	1.26	17.50	10	



**Table 6** Multivariable regression models for explanatory variables and water quality parameters at the watershed, 50 and 200 m buffer scales

Scales	Parameters	Topographical indicators			Landscape metrics					Adj. R <sup>2</sup>
		ELEV	SLOPE	SLOPE_STD	PD	LPI	LSI	SHDI	SHEI	
50 m	Sal	+	–	+				–	–	0.86
	pH	–	+	–				–	+	0.72
	DO	–	+	–						0.58
	Chl	–	+	–					+	0.69
	TOC	–	–					+		0.71
	Hg		–	+						0.74
	As	+	–	+					–	0.89
	Cu		–	+				+	–	0.79
	Fe	–	–	–				+	+	0.70
200 m	Se	+	–	+				+	–	0.87
	Sal	+	+					+	–	0.74
	pH							–	+	0.73
	DO	–	+					–	+	0.67
	Chl	–		+				–	+	0.70
	TOC	–	–					+	–	0.64
	Hg	+	+					+	–	0.64
	As		+					+	–	0.83
	Cu	–	+					+	–	0.83
Watershed	Fe	–	–						+	0.61
	Se		+	–				+	–	0.79
	Temp	+					–	+	–	0.85
	Sal						+	+	–	0.91
	pH	–					–	–	+	0.85
	DO	–						–	+	0.79
	Chl						–	–	+	0.82
	TOC						–	–	+	0.72
	TN	+					–	–	–	0.79
	TP	+					–	–	+	0.82
	Hg						+		+	0.64
	As						+	+	–	0.93
	Fe						–	–	–	0.75
Se						+	+	–	0.92	

estimates from GWR models are summarized. The local parameter estimates can be used to reflect the relationships between the independent variable and dependent variable at different sampling sites. The global  $R^2$  values from GWR model reflect the ability of explanatory variables to explain the spatial variation in the water quality parameters at all sampling sites. There are 180 (12 times 15) GWR models in this study. We are not able to present all the results from GWR models due to space limitations. The two key water quality parameters of DO and Chl were selected to examine the spatially varying relationships. DO is the most important indicator of the health of a water body and its capacity to support a balanced aquatic ecosystem. Chlorophyll is a commonly used parameter for monitoring phytoplankton biomass and nutrient status. It

can help track and predict deadly algae blooms. Nutrient enrichment leads to increased production of organic matter and resulting in low levels of dissolved oxygen which is killing marine life (Pelley 1998).

As shown in Table 8, the values of global  $R^2$  in GWR models range from 0.003 to 0.998, and the median value is larger than 0.6. The local parameter estimates from GWR models are shown in Table 9. Topographical variables and landscape metrics have a wider range of values. Wider ranges of values imply that explanatory variables might have a larger impact on water quality variations.

A clear spatially varying relationship exists along the gradient of the urbanization level as shown in Figs. 3 and 4. Figure 3 shows the spatial pattern of local parameter estimates from GWR models for DO and mean subwatershed

**Table 7** Global Moran’s I of the residuals from OLS models

Water quality parameters	50 m buffer	200 m buffer	Watershed
Temp	<b>−0.20</b>	−0.11	−0.20
Sal	−0.03	−0.12	<b>−0.21</b>
pH	−0.02	0.10	0.15
DO	−0.04	<b>−0.20</b>	<b>−0.20</b>
Chl	−0.01	−0.01	−0.13
TOC	−0.14	−0.02	0.07
TN	−0.13	0.01	0.14
TP	−0.11	0.04	−0.02
Hg	<b>−0.20</b>	−0.11	−0.10
As	−0.07	0.06	0.01
Pb	−0.02	−0.17	−0.10
Cu	−0.03	−0.08	0.11
Fe	0.04	0.04	<b>0.19</b>
Zn	−0.12	−0.06	−0.01
Se	−0.08	0.08	0.05

Note bold number indicates values significant at  $P < 0.05$  level

elevation, mean subwatershed slope and SHDI at three spatial scales. At the 200 m buffer scale, stronger negative correlations between DO and mean subwatershed elevation are found in the less urbanized areas. At the 50 and 200 m buffer scales, positive correlations are observed between DO and mean subwatershed slope in highly urbanizes areas, while negative correlations are shown in less urbanized areas. Similarly, inside the 200 m buffer zones, DO has positive correlations in the highly urbanized areas, while there are negative correlations with SHDI in the less urbanized areas.

Figure 4 shows the spatial pattern of local parameter estimates from GWR models for Chl and mean

subwatershed elevation, mean subwatershed slope, and SHDI at three spatial scales. At the 50 m buffer scale, the concentration of Chl is positively related to mean subwatershed elevation in highly urbanized areas, while Chl is negatively related to mean subwatershed elevation in less urbanized areas. At the 50 and 200 m buffer scales, stronger correlations between Chl and the mean subwatershed slope are found in less urbanized areas. Stronger negative correlations are found at 50 m buffer scale for both less and highly urbanized areas. At the watershed scale, Chl is positively related to SHDI in the highly urbanized areas, while Chl is negatively related to SHDI within less urbanized areas. The results from GWR models indicate that the spatially varying relationships between explanatory variables and water quality parameters depend on the spatial analysis scale and the urbanization level of the watershed.

As shown in Table 10, significant positive spatial autocorrelations are found in the GWR model for DO and SHDI (Moran’s  $I = 0.2045$ ,  $P < 0.05$ ) and in the GWR model for Chl and SHDI (Moran’s  $I = 0.4296$ ,  $P < 0.05$ ). Significant autocorrelations made the two GWR models unsuitable for examining the relationships between SHDI and water quality parameters.

## Discussion

### Dominant Factors Influencing Water Quality

This study found that the dominant factors varied with the spatial analysis scale. Topographical variables dominated the water quality variations at the 50 m buffer scale. Several other studies also noted the importance of topographical variables. For example, Pratt and Chang (2012)

**Table 8** Statistical summary of global coefficient of determination ( $R^2$ ) for GWR

Explanatory variables	Watershed			50 m buffer			200 m buffer		
	Min.	Max.	Median	Min.	Max.	Median	Min.	Max.	Median
ELEV	0.312	0.998	0.773	0.235	0.997	0.725	0.369	0.998	0.791
SLOPE	0.277	0.998	0.829	0.284	0.997	0.750	0.274	0.998	0.785
SLOPE_STD	0.261	0.998	0.835	0.386	0.998	0.776	0.300	0.999	0.811
URB	0.318	0.998	0.765	0.213	0.998	0.769	0.216	0.998	0.738
ROA	0.259	0.998	0.733	0.257	0.998	0.757	0.265	0.998	0.768
VEG	0.313	0.998	0.764	0.031	0.998	0.751	0.395	0.998	0.767
BAR	0.003	0.995	0.709	0.042	0.998	0.694	0.218	0.998	0.712
PD	0.414	0.998	0.766	0.210	0.999	0.760	0.381	0.998	0.766
LPI	0.131	0.894	0.626	0.316	0.998	0.781	0.270	0.998	0.722
LSI	0.242	0.997	0.762	0.260	0.998	0.761	0.338	0.999	0.799
SHDI	0.238	0.878	0.606	0.437	0.998	0.773	0.421	0.998	0.836
SHEI	0.282	0.993	0.750	0.192	0.998	0.781	0.333	0.998	0.788

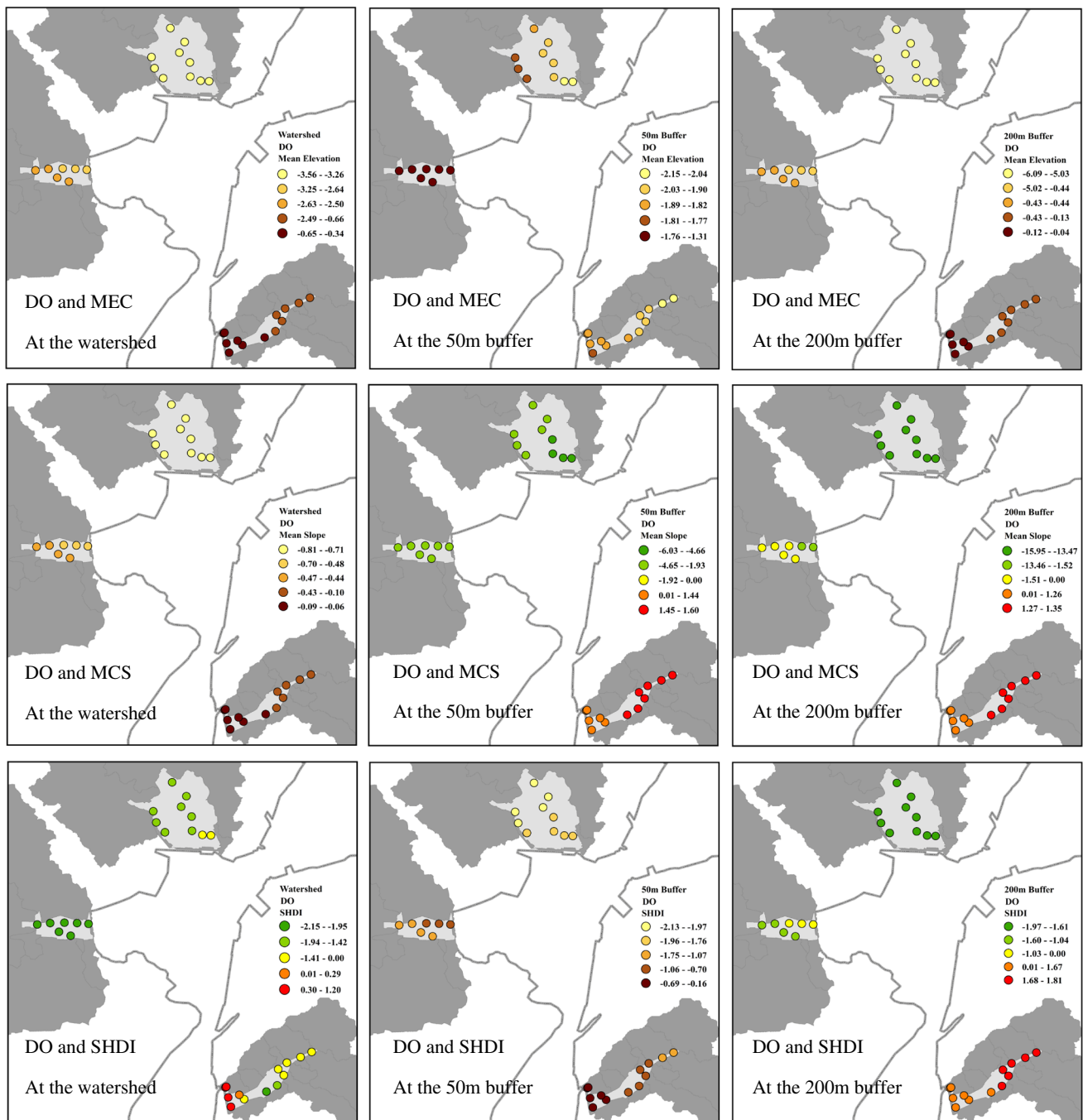
**Table 9** Statistical summary of local parameter estimates for GWR models

Scales	Explanatory variables	Yundang Lake		Maluan Bay		Xinglin Bay	
		Min.	Max.	Min.	Max.	Min.	Max.
Watershed	ELEV	−5.23	84.56	−14.29	56.33	−4.42	28.09
	SLOPE	−0.91	8.41	−1.06	6.14	−0.81	10.77
	SLOPE_STD	−0.88	6.49	−1.04	5.64	−0.68	9.30
	URB	−0.85	0.10	−0.28	1.13	−0.14	0.42
	ROA	−0.19	1.70	−7.10	0.37	−0.62	0.08
	VEG	−0.12	0.91	−3.81	0.68	−0.33	0.16
	BAR	−4.29	0.30	−1.88	0.57	−0.17	0.18
	PD	−7.73	24.12	−83.22	11.84	−19.25	2.05
	LPI	−24.77	3.99	−28.84	14.07	−5.32	5.61
	LSI	−222.19	139.03	−13.17	39.88	−18.68	8.74
	SHDI	−299.21	28.92	−17.13	78.38	−11.62	44.20
50 m buffer	SHEI	−211.31	32.06	−68.00	287.26	−18.01	3.07
	ELEVATION	−9.92	8.02	−3.48	0.40	−16.13	13.86
	SLOPE	−31.67	46.59	−18.74	2.94	−52.02	15.71
	SLOPESTD	−13.11	37.86	−10.43	3.41	−107.73	8.05
	URB	−0.27	0.30	−0.71	0.04	−0.23	0.02
	ROA	−25.09	17.75	−5.60	1.03	−8.40	1.14
	VEG	−0.22	0.31	−5.45	0.88	−0.05	0.08
	BAR	−2.64	0.89	−1.91	0.33	−0.04	0.09
	PD	−0.10	0.09	−1.12	0.29	−0.06	0.01
	LPI	−0.47	2.10	−0.10	0.88	−0.30	0.03
	LSI	−8.22	26.67	−2.26	0.89	−0.67	4.67
200 m buffer	SHDI	−38.47	124.81	−32.52	6.78	−3.88	28.93
	SHEI	−139.26	49.25	−23.31	6.60	−18.89	8.60
	ELEVATION	−14.11	21.95	−2.28	0.75	−10.29	39.19
	SLOPE	−19.97	41.90	−9.62	2.93	−55.67	182.02
	SLOPESTD	−16.30	10.22	−4.33	1.76	−6.91	2.46
	URB	−0.65	0.11	−1.23	0.02	−0.24	0.02
	ROA	−1.32	2.69	−1.06	0.10	−0.55	0.09
	VEG	−0.17	0.93	−4.31	0.66	−0.31	0.06
	BAR	−1.87	0.63	−1.99	0.34	−0.06	0.17
	PD	−2.20	0.38	−3.76	0.61	−0.03	0.03
	LPI	−0.69	0.28	−0.11	1.01	−0.29	0.10
	LSI	−8.39	19.62	−4.98	1.27	−0.68	3.88
	SHDI	−20.17	72.03	−32.97	7.02	−3.71	26.93
	SHEI	−53.29	105.78	−58.51	7.24	−13.01	45.96

suggested that not only a flat slope may be acting as a sink for total solids (TS) and slowing runoff, but it also may be receiving more pollutants from outside areas and has more residence time to carry more pollutants into the water body. However, Chang (2008) suggested that highly variable slopes could act as sinks for oxygen demand, sediment and nutrients rather than their sources. Our results also showed that mean subwatersheds slope is negatively correlated to the concentrations of Sal, TOC, Hg, As, Cu, Fe, and Se,

which indicate highly variable slopes could act as the sink of water pollutants.

Landscape characteristics play an important role in pollutant transport and retention (Chen et al. 2002). Landscape metrics are the mainly influencing factors at the watershed and 200 m buffer scales, especially SHDI and SHEI. In our study area, landscape characteristics appear to be most important in determining water parameters at the 200 m buffer zone or larger scales. However, previous studies

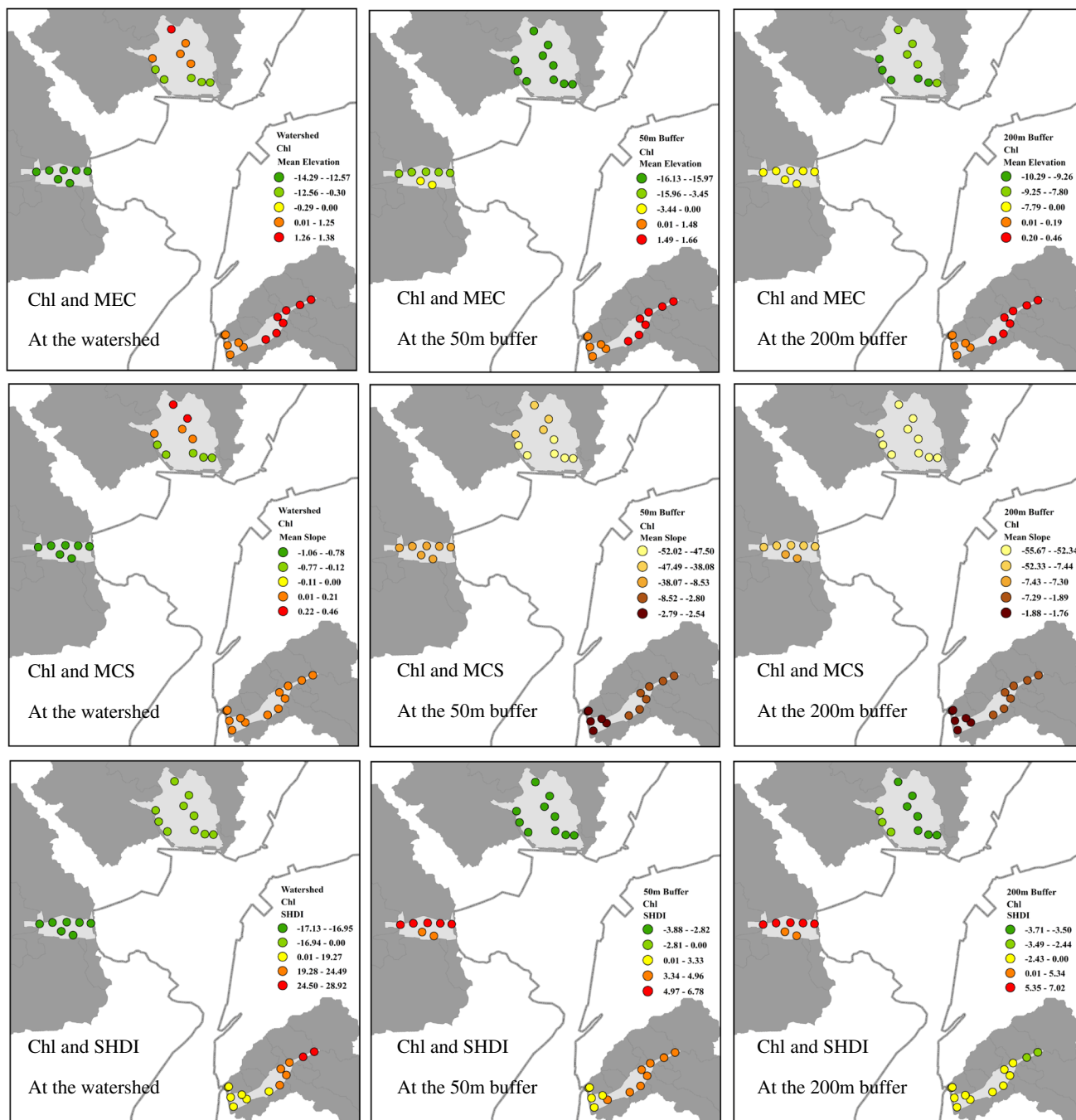


**Fig. 3** Spatial patterns of the local parameter estimates obtained from GWR models of DO and explanatory variables: *MCE* mean subwatershed elevation, *MCS* mean subwatershed slope, and SHDI at the watershed, 50 and 200 m buffer scales

generally take landscape metrics as single explanatory variables. Huang et al. (2013) found that SHDI is significantly positively correlated with  $COD_{Mn}$ . Lee et al. (2009) also reported that degraded water quality was positively associated with SHDI, PD, and ED and negative to LPI.

Our study suggested that the difference of dominant factors in different buffers is due to the urban landscape heterogeneity in the buffer zones. The value of SHDI

generally increased with the size of buffer zone (50, 200 m and entire watersheds from the edge of lakes). It indicated that the spatial pattern of land use is singular in the near-lake zones (50 m buffer), and human activity is relatively weak. The topographical variables in the subwatersheds become more important for the pollution export to lakes. With increasing distance from the lakes, the interspersion and diversity of land use types increase, and human activity



**Fig. 4** Spatial patterns of the local parameter estimates obtained from GWR models of Chl and explanatory variables: *MCE* mean subwatersheds elevation, *MCS* mean subwatersheds slope, and SHDI at the watershed, 50 and 200 m buffer scales

**Table 10** Global Moran’s I of the residuals from GWR models

Explanatory variables	Watershed		50 m buffer		200 m buffer	
	DO	Chl	DO	Chl	DO	Chl
ELEV	-0.0708	0.0339	0.0172	0.0835	-0.0251	0.1373
SLOPE	-0.0513	0.0525	0.1032	0.1209	0.0092	0.0839
SHDI	<b>0.2045</b>	<b>0.4296</b>	0.0205	0.0825	0.0607	0.0961

Note bold number indicates values significant at  $P < 0.05$  level

density strengthens. Thus, the spatial patterns of land use in the entire watershed and 200 m buffer zone dominate the variations in water quality. Lee et al. (2009) suggested that land use patterns affect the hydrological and chemical runoff processes that carry pollutants and nutrients into streams, rivers, reservoirs, and lakes, while the proportions of certain land use types determine the pollutant and nutrient loadings from watersheds. Water quality is likely degraded when different land use types are greatly interspersed and when the number of types increases at the landscape level.

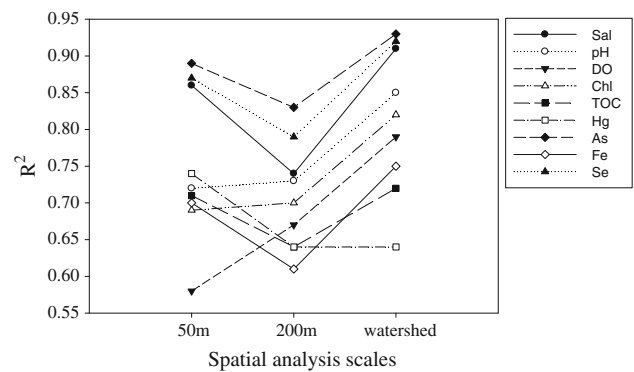
However, our results indicated that the major sources of TN and TP are the non-point pollutions at the watershed rather than at 50 and 200 m buffer scales. This finding is similar to Nielsen et al. (2012). The correlations between landscape metrics and concentrations of TN and TP indicated that diversity and complexity of landscape pattern were negative, which indicated that diversity and complexity of landscape pattern could reduce pollution loading into lakes. Increase of landscape diversity and complexity at the watershed scale could improve the water quality of lakes.

Water quality in Bay/lake is influenced by various factors such as water exchange with ocean/river and water circulation effects, point-source pollutions, and non-point-source pollutions. In our study area, three bays are all isolated from West Sea by sluices and exchanged the water at regular intervals. Furthermore, we did not carried out sampling when the sea flooded in. Thus, the influence of tide to water quality is relatively weak. In addition, the non-point-source pollution has become the major source of pollution with other conditions unchanged. We illustrated that the dominant factors that impact on water quality gradually varied with the expansion of buffer zones, which change from topographical factors to landscape metrics. The impact of human activity on water quality is obvious in a watershed.

#### Scale Effect on Spatially Varying Relationships

As mentioned in the above discussion section, the scale effect is embodied in the difference of dominant factors at different buffers. On the other hand, the scale effect is also embodied in the differences across effective buffer zones for a given water quality parameter.

Guo et al. (2010) suggested that the impact of land use on water quality could vary along the expansion of the buffer size and that there should be an effective buffer zone where the strongest linkage occurs between land use and water quality. Study would support Guo's hypothesis. As shown in Fig. 5, the curves of  $R^2$  values from OLS models are fluctuating at different buffers. It can help us to identify the most effective buffer zone for water quality parameters.



**Fig. 5** Variation of  $R^2$  value obtained from OLS models at three spatial analysis scales

The effective buffer zone to pH, DO, and Chl is within watersheds, the weakest buffer zone is in the 50 m buffer zone; the effective buffer zone for Sal, TOC, As, Fe, and Se is the same as the watershed, the weakest buffer zone is in the 200 m buffer zone; unlike the other water quality parameters, the effective buffer zone to Hg is within the 50 m buffer zone. The results indicate that the watershed scale is the effective spatial analysis scale for most of the water quality parameters in the study area, which seems to be consistent with the findings of previous studies in some other watersheds (Lee et al. 2009; Pratt and Chang 2012; Trolle et al. 2012). This is because the independent variables at the watershed scale could capture much more information which can offer better explanations for variations in the water quality. However, the studies of Johnson et al. (1997), Sawyer et al. (2004), and Huang et al. (2013) found that land use pattern near water bodies is a better predictor of water quality than in the other buffer zones. Thus, we concluded that the effective buffer zone does exist, but it varies in the different watersheds for given water quality parameters.

#### Spatially Varying Relationships Along the Urbanization Gradient

The heterogeneity of land use patterns in different urban regions might contribute to weakness or even offset of relationships between land use pattern and water quality. Tu (2011) found that spatial diversity in the relationships between land use and water quality parameters existed at the watershed scale with different levels of urbanization in eastern Massachusetts, USA.

In this study, the relationships between explanatory variables and water quality parameters at different sampling sites vary along the urbanization gradient, and clear spatial differences in the relationships are observed (Figs. 3, 4). The results obtained from GWR models show

that both positive and negative relationships exist in the study area. At 200 m buffer scale, higher mean subwatershed elevation and mean subwatershed slopes are related to a poor water quality condition in highly urbanized areas, while the relationship between mean subwatershed elevation and the water quality condition is not clear in less urbanized areas. At the watershed scale, higher landscape diversity is related to poor water quality conditions in highly urbanized areas, while the relationship between landscape diversity and water quality conditions is not clear in less urbanized areas.

The results from GWR models indicated that the spatially varying relationships between explanatory variables and water quality parameters are more diversified and complex in less urbanized areas than in highly urbanized areas. This is presumably due to various spatial differences for landscape characteristics in each subwatershed of the less urbanized areas. So the less urbanized areas may have complex “delivery” mechanisms for the pollutants. The stronger or even adverse impacts of land use patterns on water quality are usually observed in less urbanized watersheds rather than in highly urbanized watersheds.

## Conclusions

In this study, we examined the relationship between 12 explanatory variables and 15 water quality indicators in the three coastal lake watersheds of Xiamen city, China. Both OLS and GWR models were used in order to identify the spatially varying relationships and scale effects along the urbanization gradient. We concluded that (1) topographical features of subwatersheds are identified as key variables in near-lake zones, while landscape metrics are the dominant factors of water quality in the whole watershed and 200 m buffer zones. The impact of landscape metrics on water quality gradually strengthens with the expansion of buffer zones. At the watershed scale, increasing the landscape diversity may improve the water quality of lakes. Land uses are too weak to be considered as a strong influential factor on water quality. (2) Study would support Guo’s hypothesis (Guo et al. 2010), which confirms the existence of effective buffer zones and their variations within different watersheds. (3) Spatially varying relationships between explanatory variables and water quality parameters are more diversified and complex in less urbanized areas than in highly urbanized areas. So we should pay more attention to the relationships between landscape patterns and water quality in less urbanized areas. Integrating more explanatory variables of watershed characteristics can help us to identify the key pollution causes and to establish more reasonable pollutant control policies for urban water bodies.

This study proposed that adjustment of landscape patterns in a watershed is the key measure to improve urban lake water quality, and implementing effective buffer zones are ideal measure to reduce pollutant load into lakes.

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## References

- Alberti M, Booth D, Hill K, Coburn B, Avolio C, Coe S, Spirandelli D (2007) The impact of urban patterns on aquatic ecosystems: an empirical analysis on Puget lowland sub-basins. *Landsc Urban Plan* 80:345–361
- Allan JD (2004) Landscapes and riverscapes: the influence of land use on stream ecosystems. *Annu Rev Ecol Evol S* 35:257–284
- Amiri BJ, Nakane K (2009) Modeling the linkage between river water quality and landscape metrics in the Chugoku District of Japan. *Water Resour Manag* 23:931–956
- Azous AL, Horner RR (2001) Wetlands and urbanization: implications for the future. CRC Press LLC, Boca Raton
- Baker A (2003) Land use and water quality. *Hydrol Process* 17:2499–2501
- Basnyat P, Teeter LD, Lockaby BG (1999) Relationships between landscape characteristics and nonpoint source pollution inputs to coastal estuaries. *Environ Manag* 23:539–549
- Brett MT, Arhonditsis GB, Mueller SE (2005) Non-point-source impacts on stream nutrient concentrations along a forest to urban gradient. *Environ Manag* 35:330–342
- Brunsdon C, Fotheringham S, Charlton M (1998) Geographically weighted regression: modeling spatial non-stationarity. *J Royal Stat Soc* 47:431–443
- Carey RO, Migliaccio KW, Li YC, Schaffer B, Kiker GA, Brown MT (2011) Land use disturbance indicators and water quality variability in the Biscayne Bay Watershed, Florida. *Ecol Indic* 11:1093–1104
- Chang H (2008) Spatial analysis of water quality trends in the Han River basin, South Korea. *Water Res* 42:3285–3304
- Changnon SA, Demissie M (1996) Detection of changes in stream-flow and floods resulting from climate fluctuations and land-use drainage changes. *Clim Change* 32:411–421
- Chen LD, Fu BJ, Zhang SR, Qiu J, Guo XD, Yang FL (2002) A comparative study on nitrogen-concentration dynamics in surface water in a heterogeneous landscape. *Environ Geol* 42:424–432
- Clark SD (2007) Estimating local car ownership models. *J Transp Geogr* 15:184–197
- Donohue I, McGarrigle ML, Mills P (2006) Linking catchment characteristics and water chemistry with the ecological status of Irish rivers. *Water Res* 40:91–98
- Du NR, Ottens H, Sliuzas R (2010) Spatial impact of urban expansion on surface water bodies—a case study of Wuhan, China. *Landsc Urban Plan* 94:175–185
- Foley JA, Ruth D, Asner GP, Barford C, Bonan G, Carpenter SRF, Chapin S et al (2005) Global consequences of land use. *Science* 309:570–574
- Fotheringham AS, Brunsdon C, Charlton M (2002) Geographically weighted regression: the analysis of spatially varying relationships. Wiley, Chichester
- Grimm NB, Faeth SH, Golubiewski NE, Redman CL, Wu JG, Bai XM, Briggs JM (2008) Global change and the ecology of cities. *Science* 319:756–760

- Guo QH, Ma KM, Yang L, Cai HK (2010) Testing a dynamic complex hypothesis in the analysis of land use impact on lake water quality. *Water Resour Manag* 4:1313–1332
- Huang JL, Li QS, Pontius RG, Klemas V, Hong HS (2013) Detecting the dynamic linkage between landscape characteristics and water quality in a subtropical coastal watershed, Southeast China. *Environ Manag* 51:32–44
- Hwang SJ, Lee SW, Son JY, Park GA, Kim SJ (2007) Moderating effects of the geometry of reservoirs on the relation between urban land use and water quality. *Landsc Urban Plan* 82:175–183
- Jager HI, Bevelhimer MS, King RL, Smith KA (2011) Landscape influences on headwater streams on Fort Stewart, Georgia, USA. *Environ Manag* 48:795–807
- Johnson LB, Richards C, Host GE, Arthur JW (1997) Landscape influences on water chemistry in Midwestern stream ecosystems. *Freshw Biol* 37:193–208
- Jung JW, Lee SW, Hwang HS, Jang JH (2008) The effects of spatial variability of land-use on stream water quality in a coastal watershed. *Paddy Water Environ* 6:275–284
- 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* 92:80–89
- Li YL, Liu K, Li L, Xu ZX (2012) Relationship of land use/cover on water quality in the Liao River basin, China. *Procedia Environ Sci* 13:1484–1493
- Lin JH (2009) Assessment of sustainable utilization of water resources in Xiamen. *Environ Sci Manag* 34:155–164
- Mander U, Kull A, Tamm V, Kuusemets V, Karjus R (1998) Impact of climatic fluctuations and land use change on runoff and nutrient losses in rural landscape. *Landsc Urban Plan* 41:229–238
- McGarigal K, Marks BJ (1995) Fragstats: spatial pattern analysis program for quantifying landscape structure. General Technical Report PNW-GTR-351. Pacific Northwest Research Station, USDA-Forest Service, Portland
- Moreno JL, Navarro C, De Las Heras J (2006) Abiotic ecotypes in south-central Spanish rivers: reference conditions and pollution. *Environ Pollut* 143:388–396
- Nielsen A, Trolle D, Søndergaard M, Lauridsen TL, Bjerring R, Olesen JE, Jeppesen E (2012) Watershed land use effects on lake water quality in Denmark. *Ecol Appl* 22:1187–1200
- Palmer M, Bernhardt E, Chornesky E, Collins S, Dobson A, Duke C et al (2004) Ecology for a crowded planet. *Science* 304:1251–1252
- Pelley J (1998) Is Coastal Eutrophication out of control? *Environ Sci Technol* 10:462–466
- Pinto U, Maheshwari BL, Ollerton RL (2013) Analysis of long-term water quality for effective river health monitoring in peri-urban landscapes—a case study of the Hawkesbury-Nepean river system in NSW, Australia. *Environ Monit Assess* 185:4551–4569
- Pratt B, Chang H (2012) Effect of land cover, topography, and build structure on seasonal water quality at multiple spatial scales. *J Hazard Mater* 209–210:48–58
- Sawyer JA, Stewart PM, Mullen MM, Simon TP, Bennett HH (2004) Influence of habitat, water quality, and land use on macro-invertebrate and fish assemblages of a southeastern coastal plain watershed, USA. *Aquat Ecosyst Health* 7:85–99
- Schoonover JE, Lockaby BG, Pan S (2005) Changes in chemical and physical properties of stream water across an urban–rural gradient in western Georgia. *Urban Ecosystems* 8:107–124
- Seeboonruang U (2012) A statistical assessment of the impact of land uses on surface water quality indexes. *J Environ Manag* 101:134–142
- Shiels DR (2010) Implementing landscape indices to predict stream water quality in an agricultural setting: an assessment of the Lake and River Enhancement (LARE) protocol in the Missis-sinewa River watershed, East-Central Indiana. *Ecol Indic* 10:1102–1110
- Sliva L, Willams DD (2001) Buffer zone versus whole catchment approaches to studying land-use impact on water quality. *Water Res* 35:3462–3472
- Sun RH, Chen LD, Chen WL, Ji YH (2013) Effect of Land-Use Patterns on Total Nitrogen Concentration in the Upstream Regions of the Haihe River Basin, China. *Environ Manag* 51:45–58
- Tong STY, Chen W (2002) Modeling the relationship between land use and surface water quality. *Environ Manag* 66:377–393
- Trolle D, Søndergaard M, Lauridsen TL, Lauridsen TL, Bjerring R, Olesen JE et al (2012) Watershed land use effects on lake water quality in Denmark. *Ecol Appl* 22:1187–1200
- Tu J (2011) Spatially varying relationship between land use and water quality across an urbanization gradient explored by geographically weighted regression. *Appl Geogr* 31:376–392
- Tu J, Xia ZG (2008) Examining spatially varying relationships between land use and water quality using geographically weighted regression I: model design and evaluation. *Sci Total Environ* 407:358–378
- Tu J, Xia ZG, Clarke KCC, Frei A (2007) Impact of urban sprawl on water quality in Eastern Massachusetts, USA. *Environ Manag* 40:1983–2000
- Wang X (2001) Integrating water-quality management and land-use planning in a watershed context. *J Environ Manag* 61:25–36
- Winchell M, Srinivasan R, Di Luzio M, Arnold JG (2007) ArcSWAT interface for SWAT user's guide. Blackland Research Center, Texas Agricultural Experiment station and USDA Agricultural Research Service, Texas
- Yu DY, Shi PJ, Liu YP, Xun B (2013) Detecting land use-water quality relationships from the viewpoint of ecological restoration in an urban area. *Ecol Eng* 53:205–216
- Zhang G, Guhathakurta S, Dai G, Wu LY, Yan LJ (2013) The control of land-use patterns for storm water management at multiple spatial scales. *Environ Manag* 51:555–570
- Zhao SQ, Da LJ, Tang ZY, Fang HJ, Song K, Fang JY (2006) Ecological consequences of rapid urban expansion: Shanghai, China. *Front Ecol Environ* 4:341–346
- Zhao SN, Lin JY, Cui SH (2011) Water resource assessment based on the water footprint for Lijiang City. *Int J Sust Dev World* 18:492–497