ASSESSMENT OF SURFACE WATER QUALITY AT LARGE WATERSHED SCALE: LAND-USE, ANTHROPOGENIC, AND ADMINISTRATIVE IMPACTS¹

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ABSTRACT: Understanding the impacts that influence water quality is critical to the development of best management practices at the large watershed scale. This study describes the spatiotemporal variation in surface water quality and identifies their main impact in the Haihe River basin, China. Multivariate statistical techniques are applied to analyze the similarities among the sampling sites and to identify the main pollution sources in surface water. Results show that: (1) the basin can be clustered into two regions, water quality being better in the mountainous *vs.* plain regions; (2) water quality improves due to implementation of a strict state policy on environmental pollution control, prodded by the hosting of the Olympic games in the cities of Beijing and Tianjin; and (3) agricultural and residential land uses as well as livestock-breeding are the main sources affecting water quality in the mountainous regions, whereas rural waste discharge — including domestic waste sewage, human and animal feces, and solid waste — significantly influences water quality in the plain regions. The waste discharge of industrial factories may be a significant source of water pollution in the plain regions. Results indicate that the environmental management from pollution sinks and sources, long-lasting legal framework, and adequate economic incentives should be improved to optimize the large-scale watershed management under the background of the rapid development of countries like China.

(KEY TERMS: surface water; water-quality change; ammonium; chemical oxygen demand; Haihe River; China.)

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INTRODUCTION

Surface water quality has become an environmental concern, particularly in developing countries, owing to rapid urbanization and intensified land reclamation (Carpenter *et al.*, 1998; Huang *et al.*, 2011; Mouri *et al.*, 2011). The land-use and anthropogenic impacts on water quality are more complicated at

large-scale watersheds than local-scale watersheds. Investigating the spatial and temporal variation of surface water quality at the large watershed scale is particularly useful in the development of an effective water management system (He *et al.*, 2000; Johnson *et al.*, 2001; Baker, 2003).

Multivariate statistical methods can be used to characterize and evaluate temporal and spatial variations of surface water quality with complicated

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datasets (Vega *et al.*, 1998; Simeonov *et al.*, 2003; Singh *et al.*, 2004; Huang *et al.*, 2011). Spatially referenced regressions of contaminant transport on watershed attributes model has been used as a hybrid process-based and statistical modeling approach for estimating pollutant sources and contaminant transport in surface waters (Smith *et al.*, 1997; Preston *et al.*, 2011). Recent studies in large watersheds, taking advantage of remote sensing data and geographical information techniques, have been oriented toward quantifying the combined influence of watershed characteristics, land-use changes, and social and economic factors on nutrient discharges into rivers (Tong and Chen, 2002; Shrestha and Kazama, 2007; Gemesi *et al.*, 2011; Lu *et al.*, 2011; Wise and Johnson, 2011).

Shortage of water resources is acute in northern China because of limited rainfall and high human demand. The Haihe River basin (HRB) is one of the most important regions in China, covering eight provinces and municipalities. These include the capital Beijing, Tianjin City, the provinces Hebei, Shandong, Shanxi, Henan, Liaoning, and the Inner Mongolia Autonomous Region. It is a highly urbanized watershed in which water shortage and allocation conflicts are becoming increasingly more serious (Zhao *et al.*, 2010). The annual water availability per capita is only 305 m³, merely 1/7 of the average in China and <1/24th of the world's estimated mean value (Xia *et al.*, 2006). Several water diversion projects have been implemented to resolve the water resource problems in the basin (Wang *et al.*, 2010; Zhu *et al.*, 2010c). For example, about 0.5 and 0.44 billion m³ of water were imported from the Yellow River into the city of Tianjin and the Hebei province in 2011 (HWCC, 2011). The HRB will receive 5.0 billion m³ of clean water by the South-to-North Water Diversion Project (SNWDP) from the Yangtze River when the first phase of SNWDP is completed around the year 2014 (Zhang *et al.*, 2011a). Most studies have confirmed that water pollution may induce economic losses directly as well as the water shortage crisis in the HRB (Gao *et al.*, 2006; Xia and Huang, 2006). On the other hand, more recent studies have also showed that water pollution can aggravate the disequilibrium of existing water resources, and then have an impact on the efficient utilization of imported clean water (Zhang *et al.*, 2011b).

Many efforts have been directed toward describing the spatial distribution of the surface water quality in the main stream of the HRB (Liu *et al.*, 2001; Wu *et al.*, 2011b), the estuarine area of the Bohai Sea (Liu *et al.*, 2007), and several large tributaries (Liu *et al.*, 2008; Sun *et al.*, 2011; Wu *et al.*, 2011a; Zhang *et al.*, 2011b). However, these studies mainly focused on one or several watersheds, and the results were

likely to be site- or region-specific. The water management policy has a significant effect on the temporal and spatial variations of water quality in China (Zhang *et al.*, 2011b). Recent studies have focused on the temporal changes of water quality in Beijing city related to the 2008 Olympic Games (Mead and Brajer, 2008; Ge *et al.*, 2011), but few studies were implemented on the surface water quality over time in the HRB. This narrow focus necessitates an investigation over the entire basin on the spatial and temporal variations in water quality on the one hand and on identifying the main factors impacting this quality on the other hand. This study focuses on (1) describing the temporal and spatial variations in water quality between 2006 and 2010 in the HRB and (2) identifying the relationship between water-quality parameters and large-scale catchment factors including land-use and anthropogenic impacts.

MATERIALS AND METHODS

Study Area

The HRB lies between 35°3'23"N and 42°43'48"N latitude, and 111°58'4"E and 119°49'15"E longitude in northern China. It consists of more than 300 tributaries, and is divided into several large river systems, such as the Luan, Yongding, Daqing, Ziya, Zhangwei, and Tuhaimajia. The Yongding, Daqing, and Ziya Rivers converge near Tianjin City to form the Haihe River. These rivers flow east into the Bohai Sea, which is the innermost gulf on the coast of northeastern and north China. The total 2005 population in this region was about 137 million, accounting for 10.2% of the nation's population. In 2005, the HRB produced 13% of the total national GDP in an area of 318,000 km², accounting for 3.3% of the overall land area of China (Ma *et al.*, 2010; Zhu *et al.*, 2010c). The HRB is affected by East Asian monsoons, and annual rainfall is predominantly concentrated in the summer (Chu *et al.*, 2010). Over the past decades, booming population and intensifying economic development have had a significant impact on the ecosystem in the basin, leading to severe water shortages, considerable water pollution, and the destruction of the natural river morphologies (Yang and Tian, 2009; Wang *et al.*, 2010).

Choosing an appropriate spatial observational unit is critical when examining the quantitative relationship between water-quality descriptors and catchment factors. Many water-quality studies have used spatial observational units at the scale of subwatersheds (Johnson *et al.*, 2001; Hively *et al.*, 2011) or

buffers around monitoring stations (Dunn *et al.*, 2011; Gemesi *et al.*, 2011; Yang, 2012). In the HRB, the subwatershed boundaries are difficult to delineate due to the strong human disturbance, such as canals, dams, or reservoirs. Water resource management in China is implemented based on administrative regions rather than watershed boundaries. County is the basic unit of administrative management in China. It is therefore germane to study the variation of water quality in the HRB by using the counties as spatial observational units.

The National Environmental Monitoring Center of China (NEMCC) has set water-quality monitoring sites along most rivers in the HRB. From these, 80 sites were chosen for continuous measurement of perennial flow from 2006 to 2010 (Figure 1). The selected monitoring sites are located in 51 counties in the basin. The overall area of the 51 counties is 96,791 km², accounting for 30.44% of the total area of the basin.

Water-Quality Parameters

Ammonium (NH₄⁺) and chemical oxygen demand (COD) are important parameters indicative of inorganic and organic pollution, respectively. They have been used as the primary restrictive descriptors of water pollution control goals in the 12th Five-Year Plan of China (2011-2015). NH₄⁺ and COD concentrations were used as representative parameters of water quality in this study. They were manually collected monthly by the NEMCC. The annual mean values were calculated from the monthly data over the years from 2006 to 2010. Known standards in the sampling, preservation, transportation, and analysis of water samples were used for quality assurance purposes. These standards include staff education in the field and laboratory, selection of analytical method, criterion of field sampling and laboratory equipment, internal and external checks, data verification and documentation, and so on (SEPBC, 2002). The mean concentration value of all monitoring stations located within a county was taken as being representative for water pollution in it.

Land-Use and Anthropogenic Descriptors

Land-use data in 2008 were derived from Landsat TM (NASA, Washington, D.C.) images in a 30-m resolution. Land-use types were classified into 25 groups, their accuracy being validated by the Chinese Research Academy of Environmental Sciences. We reclassified land-use data into five categories to suit our research objectives: agricultural land, forest land,

grass land, residential land, and water area. Anthropogenic descriptors of each county were collected from the 2008 demographic yearbook of China (NBSC, 2008). This dataset includes population density, proportion of rural population, gross domestic product of primary and secondary industry, agricultural machinery gross power, and annual crop and meat production (Table 1).

Data Treatment and Analytical Methods

Multivariate statistical methods, including cluster analysis and principal component analysis (PCA), were used to analyze the variation in water quality and its relationship with land-use and anthropogenic descriptors. These statistical methods tend to require variables to conform to a normal distribution (Groeneveld and Meeden, 1984). There are several inter-related approaches to determine normality, such as values of skewness and kurtosis, Kolmogorov-Smirnov test, and Shapiro-Wilk test. We tested whether the distribution of independent and dependent variable was normal by analyzing its kurtosis and skewness. Both skewness and kurtosis are 0 in a normal distribution (Huang *et al.*, 2011). The kurtosis values of the original data ranged from -1.596 to 19.836, and the skewness values from -1.415 to 4.08. Next, the original data were transformed into the form $x' = \ln(x)$. The kurtosis and skewness values of transformed data ranged from -1.397 to 4.457 and from -1.733 to 0.492, respectively, indicating that the transformed variables showed a near normal distribution. In the case of PCA and cluster analysis, all transformed variables were *z*-scale standardized to minimize the effects of difference units and variance of variables and to render the data dimensionless (Güler *et al.*, 2002).

The cluster analysis group samples were based on information found in a dataset that describes the relationships among samples, and aims to distinguish between similar samples within a group and samples in other groups. Hierarchical agglomerative clustering is the most common approach (McKenna, 2003). It provides intuitive similarity relationships between each sample with respect to the entire dataset, and is typically illustrated by a dendrogram. Cutting the dendrogram at a given distance at which the clusters merge will produce a clustering result at a selected precision (Singh *et al.*, 2004; Shrestha and Kazama, 2007). In this study, we carried out a hierarchical agglomerative cluster analysis to identify the spatial similarity of water-quality parameters by means of the Ward's method, using squared Euclidean distances as a measure of similarity. The Ward's method uses an analysis of the variance to evaluate the distances between clusters in

FIGURE 1. Locations of Monitoring Sites in the Haihe River Basin.
The blank areas on the map are counties with no sampling data.

an attempt to minimize the sum of squares of any two possible clusters that can be formed at each step. The Euclidean distance usually is an indicator of the similarity between two samples. It can be represented as the difference between analytical values from the samples. The spatial variability of water quality may be clustered at a given significance level, that is, the quotient between the linkage distances for a particular case divided by the maximal linkage distance ($D_{\text{link}}/D_{\text{max}}$). The Ward's method with squared Euclidean distances has proven to be an extremely powerful grouping technique in water-quality studies (Akbal *et al.*, 2011; Huang *et al.*, 2011). We examine the difference of variables for

each of the clusters by conducting a one-way ANOVA that offers F -values and significance levels to show whether any of these mean differences are significant.

The PCA transforms a number of possibly correlated metrics into a smaller number of uncorrelated factors. Its operation can be thought of as exposing the internal structure of the data in a way that best explains the variance in the data (Shrestha and Kazama, 2007; Ma *et al.*, 2010). Eigenvalues represent the amount of variance explained by the data matrix. Loadings represent the relative importance of a given variable in a given component. A positive or negative loading means that the variable

TABLE 1. Descriptors of Land-Use and Anthropogenic Descriptors for the 51 Counties of the Haihe River Basin.

	Descriptors (acronym)	Unit	Mean	Standard Deviation	Minimum	Maximum
Anthropogenic descriptors	Population density (POPD)	10 ⁴ Person/km ²	415.33	265.73	43.49	940.17
	Proportion of rural population (POPRU)	%	88.55	4.83	72.05	97.00
	Gross domestic product of primary industry (GDP1)	10 ⁴ Yuan	71,079.78	49,283.35	12,867.00	254,511.00
	Gross domestic product of secondary industry (GDP2)	10 ⁴ Yuan	150,421.37	127,020.00	24,188.00	522,390.00
	Agricultural machinery gross power (AMP)	10 ⁴ kW	50.25	46.14	10.00	231.00
	Annual crop production (CP)	10 ⁴ kg	196,581.53	129,874.00	14,239.00	621,470.00
	Annual meat production (MP)	10 ⁴ kg	34,277.61	24,714.54	4,825.00	109,301.00
Land-use descriptors	Proportion of agricultural land (PAGL)	%	52.89	27.49	7.11	88.23
	Proportion of residential land (PRSL)	%	9.85	7.49	0.33	29.80
	Proportion of forest land (PFRL)	%	23.75	23.63	0.03	67.72
	Proportion of grass land (PGSL)	%	11.59	13.01	0.00	49.88
	Proportion of water area (PWTR)	%	1.92	1.98	0.00	8.08

correlates positively or negatively with the component. In this study, a PCA of normalized variables was carried out to extract significant information of land-use and anthropogenic descriptors. Linear combinations of the original variables and eigenvectors resulted in new variables, called principal components (PCs). As a result, a small number of PCs embed approximately the same amount of information as do the much larger set of original descriptors. The Kaiser-Meyer-Olkin (KMO) and Bartlett's test were performed to examine the sensitivity of the data for PCA. KMO is a measure of sampling adequacy and a high KMO value (close to 1) generally indicates that PCA may be useful. The significance level of Bartlett's test indicates whether there are significant relationships among variables. The PC values were calculated from the PC loadings and the values of original land-use and anthropogenic variables.

$$z_{ij} = P_{i1}x_{1j} + P_{i2}x_{2j} + P_{i3}x_{3j} + \cdots + P_{im}x_{mj}, \quad (1)$$

where z is the PC value, P the PC loading, x the measured value of variable, i the PC number, j the sample number, and m the total number of measured variables.

Finally, Spearman's rank correlation coefficients (Spearman's rho) were used to study correlation between the water-quality parameters and PC values to demarcate the main pollution sources in the HRB (Shrestha and Kazama, 2007). All mathematical and statistical computations were made using Microsoft Office Excel 2007 (Microsoft Company, Redmond, WA) and SPSS 16.0 software (IBM Company, New York).

RESULTS

Spatial Similarity and Site Grouping

We used hierarchical cluster analysis on normalized datasets of NH_4^+ and COD between 2006 and 2010 to distinguish the counties with similar degrees of water pollution. Cluster analysis generated a dendrogram, grouping the 51 counties into different clusters at different significance levels (Figure 2). According to the dendrogram and priori knowledge (e.g., land-use, anthropogenic, and industrial status) available in the HRB, we grouped all 51 counties into two statistically significant clusters at $(D_{\text{link}}/D_{\text{max}}) \times 100 < 5$. These two clusters have obvious differences of mean NH_4^+ and COD concentration (Figure 3). The results of ANOVA also show that the difference between groups are all significant ($p < 0.01$), indicating each of the NH_4^+ and COD concentrations reliably distinguish between the two clusters.

Cluster 1 includes 33 counties mainly located in the northern and western regions of the HRB (Figure 4). These counties hold 50 water-quality monitoring stations with an average altitude of 406 m above sea level (asl), and are designated as mountainous regions. Cluster 2 includes 18 counties in the eastern regions of the HRB. These counties have 30 water-quality stations with an average altitude of 28 m asl, and are designated as plain regions (Figure 4). The mean proportions of forest and grass land in the mountainous regions are 34.01 and 17.31%, respectively, and substantially higher than those in the plain regions (4.92 and 1.1%, respectively). The mean population density and GDP in the mountainous

FIGURE 2. Dendrogram Showing Different Clusters of Sampling Sites Located on the Haihe River Basin.

regions are 327.61 person/km² and 2,052 million RMB Yuan/year, which are less than the 576.16 person/km² and 2,513 million RMB Yuan/year in the plain regions. The average NH₄⁺ and COD concentrations between 2006 and 2010 are 1.0 and 17.81 mg/l in the mountainous regions, significantly lower than the 23.35 and 176.01 mg/l in the plain regions.

FIGURE 3. Mean Values of NH₄⁺ and COD Concentration for the 51 Counties of the Haihe River Basin. Circles represent mountainous regions whereas dots represent plain regions.

FIGURE 4. Spatial Similarity and Grouping of Water Pollution in the Haihe River Basin. The pie size represents the relative value of NH₄⁺ and COD concentration.

FIGURE 5. Annual Variations in NH_4^+ and COD Concentration from 2006 to 2010 in the Haihe River Basin. Note that knick point in 2007 indicates an improvement of water quality.

Annual Variation in Water Quality

We calculated the annual mean values of NH_4^+ and COD concentrations in 51 counties from 2006 to 2010. The temporal curve of variations in NH_4^+ concentration is similar to that of COD (Figure 5). The concentrations of NH_4^+ and COD increase from 2006 to 2007 both in the mountainous regions and plain regions, with a clear discontinuity on the temporal curve in 2007. The concentrations decline gradually between 2007 and 2010 in the mountainous regions. In contrast, they decline sharply between 2007 and 2009 in the plain regions, but increase by 8.88 and 6.99% for NH_4^+ and COD concentrations, respectively, in 2010 compared with those in 2009.

The water pollution degrees of 51 counties were evaluated by NH_4^+ and COD concentrations between 2006 and 2010, against China's national standard of surface water quality (GB3838-2002). According to GB3838-2002, Grade I-III water represent the fairly good water quality, whereas Grades IV and V water generally are only used for industrial and agricultural water consumption or for landscape need. Water quality worse than Grade V, designated as Grade VI in this study, cannot be used directly. The water quality of 18 counties in the plain regions is all at Grade VI between 2006 and 2010. The counties with Grade II and III surface water increase in the mountainous regions and the counties with Grade VI decline noticeably, indicating that the degree of pollution was mitigated between 2006 and 2010 (Figure 6).

Principal Components of Land-Use and Anthropogenic Descriptors

A group of 12 variables, including land-use and anthropogenic descriptors, were used in the PCA. We adopted varimax rotation to maximize the variance of the PC loading. Eigenvalues provide a measure of the

FIGURE 6. Water-Quality Grades in the Mountainous Regions from 2006 to 2010 Based on NH_4^+ and COD Concentration. Water-quality standard ranges between grades I to VI, I being the best.

significance of each PC. Five PCs were selected for the analysis because their cumulative eigenvalues accounted for more than 92% of the total variance in the mountainous and 88% in the plain regions. The KMO and Bartlett's test in this study indicated that PCA was useful (Table 2).

Among the five PCs in the mountainous regions, as shown in Table 2, PC1 explains 35.24% of the total variance, and has strong positive loadings on proportions of agricultural land, and negative loadings on grass land and forest land, thus representing the impact of the difference between natural and human land uses. PC2, explaining 29.86% of the total variance, has clear positive loadings on annual meat production and the GDP of the primary industry. This indicates that PC2 represents the cultivating and livestock-breeding factors. PC3, which explains 11.42% of

TABLE 2. Loadings of Land-Use and Anthropogenic Descriptors on the Significant Principal Components (PC) in the Haihe River Basin.

Parameters	Mountainous Regions					Plain Regions				
	PC1	PC 2	PC 3	PC 4	PC 5	PC 1	PC 2	PC 3	PC 4	PC 5
Population density	0.79						0.86			
Proportion of rural population				0.93				−0.89		
Agricultural machinery gross power	0.52	0.71				0.85				
Gross domestic product of primary industry		0.93				0.77	0.54			
Gross domestic product of secondary industry		0.68				0.72				
Annual crop production		0.72			0.54	0.76	0.57			
Annual meat production		0.97					0.73			
Proportion of grass land	−0.81									0.89
Proportion of forest land	−0.81					0.59			0.73	
Proportion of residential land	0.76							0.89		
Proportion of agricultural land	0.93								−0.91	
Proportion of water area			0.96							0.71
Eigenvalue	4.23	3.58	1.37	1.23	0.66	2.95	2.13	1.99	1.96	1.57
% Total variance	35.24	29.86	11.42	10.21	5.49	24.56	17.73	16.56	16.34	13.06
Cumulative % variance	35.24	65.1	76.52	86.72	92.22	24.56	42.29	58.85	75.19	88.25
KMO measure	0.706					0.745				
Bartlett's test (sig.)	0.000					0.000				

the total variance, has positive loadings on the proportion of water areas. PC4, contributing 10.21% of the total variance, has positive loadings on the proportion of the rural population. Finally, PC5, which explains the lowest variance (5.49%), has positive loadings on annual crop production, thus denoting the impact of the intensity of land use.

In the plain regions, PC1 (24.56% of the total variance) has greatest positive loadings on agricultural machinery gross power, thus representing the level of agricultural and industrial development. PC2 (17.73% of the total variance) has clear positive loadings on the population density. PC3 (16.56% of the total variance) has strong negative loadings on the rural population proportion and positive loadings on the residential land proportion. PC4 (16.34% of the total variance) has strong negative loadings on the proportion of agricultural land. PC5 (13.06% of the total variance) has positive loadings on the proportion of grass land.

Relationship Between Water Quality and Principal Components

Spearman's rho showed the relationships between PC values and concentrations of NH_4^+ and COD (Table 3). In the mountainous 33 counties, NH_4^+ and COD concentrations are significantly correlated to PC1 between 2006 and 2010. The average Spearman's rho is 0.418 ($p < 0.05$) between NH_4^+ and PC1, and 0.481 ($p < 0.01$) between COD and PC1. In addition, PC2 was positively correlated to COD concentration between 2006 and 2009, with an average correlation coefficient of 0.375 ($p < 0.05$). Correspondingly, in the 18 plain counties, significant correlations were found

between the water-quality parameters and PC3, except for 2009 and 2010. The average correlation coefficient is -0.586 ($p < 0.05$) between NH_4^+ and PC3, and -0.469 ($p < 0.05$) between COD and PC3.

DISCUSSION

Management of Pollution Sinks in the Mountainous Regions

This study reveals the relationships between water-quality parameters and land-use and anthropogenic descriptors and may provide useful implications for the environmental management in the HRB. The results show that, in the mountainous regions, the most significant factors influencing nutrient discharges into rivers are the increased acreage of agricultural land, as well as the reduced acreage of forest and grass land. Besides, the residential land uses and livestock-breeding can increase the contaminants contributing to COD in the rivers. This result is consistent with that of most watersheds in North American and European regions (Baker, 2003; Bechmann *et al.*, 2008; Wise and Johnson, 2011). In the mountainous regions, environmental protection projects should be established for the pollution sinks especially for water resources having an important usage. Water reservoirs dedicated to drinking water need special protection measures. Understanding the transport pathways for ammonium and organic contaminants could help managers establish buffer strips or other management practices in mitigating non-point source discharges from agricultural fields and

TABLE 3. Spearman's Rho Between Water-Quality Parameters and Principal Components (PCs) of Land-Use and Anthropogenic Descriptors.

Region	Year	NH ₄ ⁺					COD				
		PC1	PC2	PC3	PC4	PC5	PC1	PC2	PC3	PC4	PC5
Mountainous regions with 33 counties	2006	0.388*	-	-	-	-	0.495**	0.344*	-	-	-
	2007	0.352*	-	-	-	-	0.514**	0.411*	-	-	-
	2008	0.512**	-	-	-	-	0.397*	0.385*	-	-	-
	2009	0.421*	-	-	-	-	0.568**	0.358*	-	-	-
	2010	0.415*	-	-	-	-	0.430*	-	-	-	-0.404*
	Average	0.418*	-	-	-	-	0.481**	0.375*	-	-	-0.404*
Plain regions with 18 counties	2006	-	-	-0.631**	-	-	-	-	-0.496*	-	-
	2007	-	-	-0.577*	-	-	-	-	-0.451*	-	-
	2008	-	-	-0.550*	-	-	-	-	-0.461*	-	-
	2009	-	-	-	-	-	-	-	-	-	-
	2010	-	-	-	-	-	-	-	-	-	-
	Average	-	-	-0.586*	-	-	-	-	-0.469*	-	-

Note: Spearman's rho is significant at the 0.01 (**) and 0.05 level (*).

watersheds (Polyakov *et al.*, 2005). Pollutant transport is influenced by the chemical and physical properties of the pollutant as well as the hydrologic cycle. The transport pathways within buffer strips are often different for various contaminants and these may affect the utility of buffers at reducing nonpoint source pollution. For example, nitrogen retention relies on plant uptake, microbial immobilization, and bacterial denitrification (Martin *et al.*, 1999), whereas the movement of soluble phosphorus depends largely on plant uptake, soil chemical and physical properties, and subsurface flow paths (Abu-Zreig *et al.*, 2003). Some contaminants such as nitrates and chloride are highly soluble in water and can move easily through the soil profile whereas ammonia nitrogen is generally transported to surface waters attached to eroded soil particles and organic material. Accordingly, as the main impact on the dissolved oxygen depletion, fresh organic contaminants are usually washed into rivers by quick surface runoff and heavy rains. Therefore, appropriate buffer planning should start by defining potential pollutants of great concern for a given area. Other factors such as precipitation, flow convergence, infiltration rate, subsurface flow, and relief characteristics will have great effect on vegetation buffer performance (Herron and Hairsine, 1998). It indicates that vegetative buffers should be used in conjunction with land-management systems that include nutrient management and sediment and erosion control in mountainous regions.

Management of Pollution Sources in the Plain Regions

In the plain regions, the high NH₄⁺ and COD concentrations are serious issues in surface water bodies.

The correlation analysis shows that water-quality parameters have significant negative correlations with PC3. The result indicates that a high proportion of rural population and low urbanization rates are the most significant factors influencing water quality in them. This result differs from previous studies showing that high urbanization rates and human population density generally result in poor water quality (Du *et al.*, 2010; Han *et al.*, 2011). The anomalous results of the present study may be explained by considering the potential pollution sources in the rural areas of the HRB. According to previous studies, total nitrogen loads discharged with waste water through surface runoff totaled 51,966 tons for crop farming in the HRB in 2007 (Zhu *et al.*, 2010b). The overall rural waste loads reached more than 3,200,000 tons total nitrogen and 2,100,000 tons COD in 2007 (Zhu *et al.*, 2010a). As Zhu *et al.* (2010a) pointed out, the waste loads of total nitrogen and COD in the downstream plains involved more than 70% of the entire watershed. Rural waste mainly includes domestic waste sewage, human and animal feces, and solid waste. Although rural waste has little impact on the discharges into rivers in the dry season, heavy rainstorms in the rainy season cause the waste water to rush into neighboring rivers and underground aquifers. In the plain regions, management strategies should focus on controlling pollution sources particularly from the rural areas. Specific measures should be developed to manage the multiple sources of waste discharges including domestic waste sewage, human and animal feces, and solid waste particularly during the rainy season. Also, there is an urgent need for drainage systems to reduce waste discharges into adjacent rivers in the rural areas.

The NH_4^+ and COD concentrations show that water quality improved from 2006 to 2010 in the HRB, particularly for a noticeable fall in both NH_4 and COD concentration values in 2008. One reason for this improvement is the implementation of projects and the policies of environmental protection formulated after China's success in her winning bid for the 2008 Olympic Games (Fu, 2008). In 2005, the government stated specific goals consonant with policies and measures to reduce COD loads to 85.8% by the end of 2010 (Li *et al.*, 2008). Many factories in the plain regions responsible for heavy pollution had to be closed or relocated for the Games. These administrative strategies resulted in a rapid decline of waste discharge into rivers. Hosting the Games in the cities of Beijing and Tianjin resulted in a noticeable discontinuity of NH_4^+ and COD concentrations in the whole region. After the Games, most of the environmental controls were removed to reestablish a high rate of economic development (Ge *et al.*, 2011). Environmental pollution quickly became serious again, as has been corroborated by observational research on air quality (Shen *et al.*, 2011). Correspondingly, water pollutant concentrations noticeably rebounded in the plain regions after the Olympics. As shown in Table 3, there are no significant correlations in the plain regions between water-quality parameters and land-use and anthropogenic factors in 2009 and 2010. This result indicates that water pollution is possibly derived from additional factors, such as point-source pollution from industrial factories. There is a growing agreement in China that watershed management should depend on a long-lasting legal framework instead of temporary administrative command-and-control approaches (Fu, 2008). The effluent permit limits in watershed management should be based on control units other than administrative units. Therefore, legal control units are needed to be regionalized based on the water pollutant loadings as well as the watershed ecosystem functions and capability in the HRB.

Official and Economic Incentives of Clean Water

Imported clean water from the Yangtze River aims to hold Grade II level in 2014. However, our study indicates that only 24% of all counties attained Grade II water-quality standards in 2010 in the HRB. Chinese experts and managers have in recent years paid close attention to environmental issues. It has been suggested at present that promoting water saving and reducing waste water discharge would be the feasible and effective solution to mitigate water shortage before the SNWDP scheme is implemented. The Ministry of Environmental Protection of China initiated several specific projects with more than 30 billion

RMB Yuan (about 4.8 billion US dollars) on water pollution monitoring and prevention in the 12th and 13th Five-Year Plans of China (2011-2020) (Zhang *et al.*, 2011b). As one of eight closely observed watersheds in China, the HRB has received abundant financial support.

Recent studies reveal that the economic loss due to water pollution reached a total of 7.61 billion RMB Yuan (about 1.2 billion US dollars) in 2005, and that about 90.1% of the total economic loss occurred in the plain regions of the HRB (Lü and Duan, 2010). This illustrates the necessity to establish adequate economic measures to provide incentives for reducing waste discharges into rivers. In addition to the direct investment of government, official policies and economic incentives might be developed into the improvement of clean water. For instance, methane from straw resources has been regarded as a green energy to offset traditional energy consumption and reduce nutrient discharge into surface and underground waters (Lu *et al.*, 2009). More capital and supporting facilities are needed to promote the popularization of green energy. The use of green manure from human and animal feces should be encouraged by establishing economic compensation and government incentives to reduce nutrient discharge into rivers.

CONCLUSIONS

This study showed a case study targeting the HRB, an exemplary large-scale river system across northern China. Our analysis shows that agricultural and residential land uses as well as livestock-breeding have the most impact on waste discharges into rivers in the mountainous regions, whereas waste discharges from rural regions and industrial factories are the prime factors influencing water quality in the plain regions. The study in the mountainous and plain regions provides more insight into the impacts of land uses and anthropogenic factors on water quality and may provide useful action points for watershed management. Given that many world-wide watersheds face the growing problems caused by the increasing impacts of land uses and human demand on ecosystem services, the methods and results identified in this study can provide implications on watershed management of other similar regions particularly in developing countries like China.

This study illustrates that application of multivariate statistical techniques is helpful for water-quality assessment at the large-scale watershed. The cluster analysis identifies the spatial and temporal variations in surface water quality, whereas the PCA extracts

most of the information of land-use and anthropogenic impacts. Regression models with spatially referenced watershed attributes may improve the capability of modeling and prediction of water quality in further research. A possible limitation in the present study is that data of land-use and anthropogenic descriptors are collected from the 2008 demographic yearbook of China, which does not achieve a perfect match with water-quality parameters from 2006 to 2010. And our further analysis could be more meaningful if such gaps are filled by collecting more land-use and anthropogenic data in different years. Another possible limitation is that water-quality data of a county is very likely influenced by the number and location of sampling sites. This problem needs to be controlled by adding more sampling sites and distributing them evenly in each county in further research. Lastly, the monthly and seasonal variations of water quality may be quantified as another potential improvement with more effects of data collection to guide decisions in specific environmental management.

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