Effect of Land-Use Patterns on Total Nitrogen Concentration in the Upstream Regions of the Haihe River Basin, China

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Abstract Nutrient loading into rivers is generally increased by human-induced land-use changes and can lead to increased surface water pollution. Understanding the extent to which land-use patterns influence nutrient loading is critical to the development of best-management practices aimed at water-quality improvement. In this study, we investigated total nitrogen (total N) concentration as a function of land-use patterns and compared the relative significance of the identified land-use variables for 26 upstream watersheds of the Haihe River basin. Seven land-use intensity and nine landscape complexity variables were selected to form the land-use pattern metrics on the landscape scale. After analyzing the significance of the land-use pattern metrics, we obtained five dominant principal components: human-induced land-use intensity, landscape patch-area complexity, area-weighted landscape patch-shape complexity, forest and grassland area, and landscape patch-shape complexity. A linear regression model with a stepwise selection protocol was used to identify an optimal set of land-use pattern predictors. The resulting contributions to the total N concentration were 50% (human-induced land-use intensity), 23.13% (landscape patch-shape complexity), 14.38% (forest and grassland area), and 12.50% (landscape patch-area complexity), respectively. The regression model using land-use measurements can explain 87% of total N variability in the upstream regions of Haihe River. The results indicated that human-related land-use factors, such as residential areas, population, and road density, had the most significant effect on N concentration. The agricultural area (30.1% of the study region) was not found to be significantly correlated with total N concentration due to little irrigative farmland and rainfall. Results of the study could help us understand the implications of potential land-use changes that often occur as a result of the rapid development in China.

Keywords Total nitrogen · Landscape metrics · Land-use intensity · Multivariate regression · Principle component analysis · Haihe River basin

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Introduction

Understanding the effect of landscape patterns on the process and function of the landscape structure is a key issue in landscape ecology (Wu and Hobbs 2007). Land-use patterns are found to be significantly correlated with water quality and the health of aquatic ecosystems within a watershed (Ye and others 2009). Investigation of the relationship between surface water quality and land-use patterns is particularly useful to the development of an effective water-management system (He and others 2000; Baker 2003).

During the past several decades, growing human population and intensifying development have profoundly impacted the ecological conditions in the Haihe River. There is a growing concern about the worsening water quality resulting from the temporal and spatial variation of land uses in the region (Zhang and others 2009; Wang and others 2010). Many studies have been conducted to

describe the spatial distribution of water quality in the main stream of the Haihe River (Liu and others 2001), the estuarine area to the Bohai Sea (Liu and others 2007), and several local tributaries, such as Jiyunhe River (Liu and others 2008) and Zhanghe River (Zhang and others 2009). The relationship of land use with water quality is complex, and any correlation observed in one watershed is likely to be site- or region-specific. Few studies, however, have examined the effects of land-use patterns on water quality in the entire Haihe River basin, which consists of upstream mountainous regions and downstream alluvial plains. Human activities and land-use changes are quite different in the extent to which they affect water quality within the river's nested subwatersheds. Cumulative impacts from both the headwaters and surrounding landscapes cannot be readily distinguished from downstream regions in such a large-scale basin (Hunsaker and Levine 1995; Wang and others 2005). However, the impacts of land uses on water quality in first-order headwater streams is relatively clear compared with that of higher-order streams. Dodds and Oakes (2006, 2008) suggested that protection of downstream riparian zones alone was not sufficient to protect water quality and that the influence of small upland streams should not be ignored, even at times when these headstreams are unlikely to be flowing. Therefore, it is important to investigate the relationship between water quality and land-use patterns in the upstream watersheds. Such relationships would offer a effective tool not only for identifying the spatial variation of water quality but also for predicting nutrient inputs to the downstream regions of the Haihe River.

Process-based water-quality models have highly complicated mass–balance structure to provide predictions in relatively fine temporal scales. Examples of this type of model include BASINS (Tong and Chen 2002), HSPE (Diaz-Ramirez and others 2005), and SWAT (Zhang and others 2009). These models are now virtually used in most of the total maximum daily loads assessments in the Untied States (Haggard and others 2003). However, in some developing countries, such as China, there are growing concerns about whether sufficient water-resource data and knowledge of biogeochemical processes exist to reliably support the general use of such highly complex descriptions of processes. The complexity of these models requires intensive data for calibration, which generally limits their applications to relatively small watersheds (Meixler and Bain 2010). In contrast, multivariate statistical models have the advantage of being readily applicable to large watersheds and being able to quantify the errors in model parameters and predictions.

Many relatively simple statistical models have been used for investigating the sources and impact factors of nutrient losses (Johnson and others 1997; Qian and others 2005;

Shrestha and Kazama 2007; Lee and others 2009), for example, the spatially referenced regressions 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 and others 1997; Hoos and McMahon 2009). A variety of metrics representing human activities intensity and land-use changes have been proposed to establish quantitative relationships with water quality. These metrics include human population, road density, urban impervious areas, topographic characteristics, stream configurations, and landscape heterogeneity (Johnson and others 2001; Hatt and others 2004; Chang and others 2008; Ye and others 2009). New development in spatial data acquisition and processing techniques has enabled scientists to quantify the land-use patterns over broader areas with more diverse landscape metrics (Smith and others 1997; Ouyang and others 2010; Mouri and others 2011).

In this study, several multivariate statistical techniques were used to detect land–water relationships in the 26 upstream watersheds of the Haihe River basin. The objective of the study was to assess the relationship of land-use intensity and landscape complexity and to identify the significance of land-use pattern factors that influence the total nitrogen (total N) concentration. This analysis was intended to guide decision-making process as to where efforts to decrease total N loading can be most effectively targeted to improve local water quality.

Methods

Study Area

The Haihe River basin, as one of the greatest basins in northern China, is formed by seven large rivers, i.e., Luan River, North Canal, Yongding River, Daqing River, Ziya River, South Canal, and Tuhaimajia River. The basin consists of >300 tributaries that spread out like a palm-leaf fan over a large area before converging near Tianjin. The converged river flows east and empties into the Bohai Sea. Its drainage area covers 318,000 km^2, accounting for 3.3% of the total land area of China (Fig. 1). The total population in the region was 134 million in 2005, accounting for 10.2% of the nation's total population.

Annual rainfall in the Haihe River basin is predominantly concentrated in summer (Chu and others 2010). Heavy rain in the past has caused torrents of the upstream tributaries to rush into low-lying middle and lower reaches, bursting onto farmlands in the alluvial plain with floods. During recent decades, water-conservancy facilities, such as reservoirs, ponds, man-made dams, and artificial canals, have effectively brought the river under control. More than

Fig. 1 Location and elevation of the sampling sites and the 26 upstream watersheds in the Haihe River basin
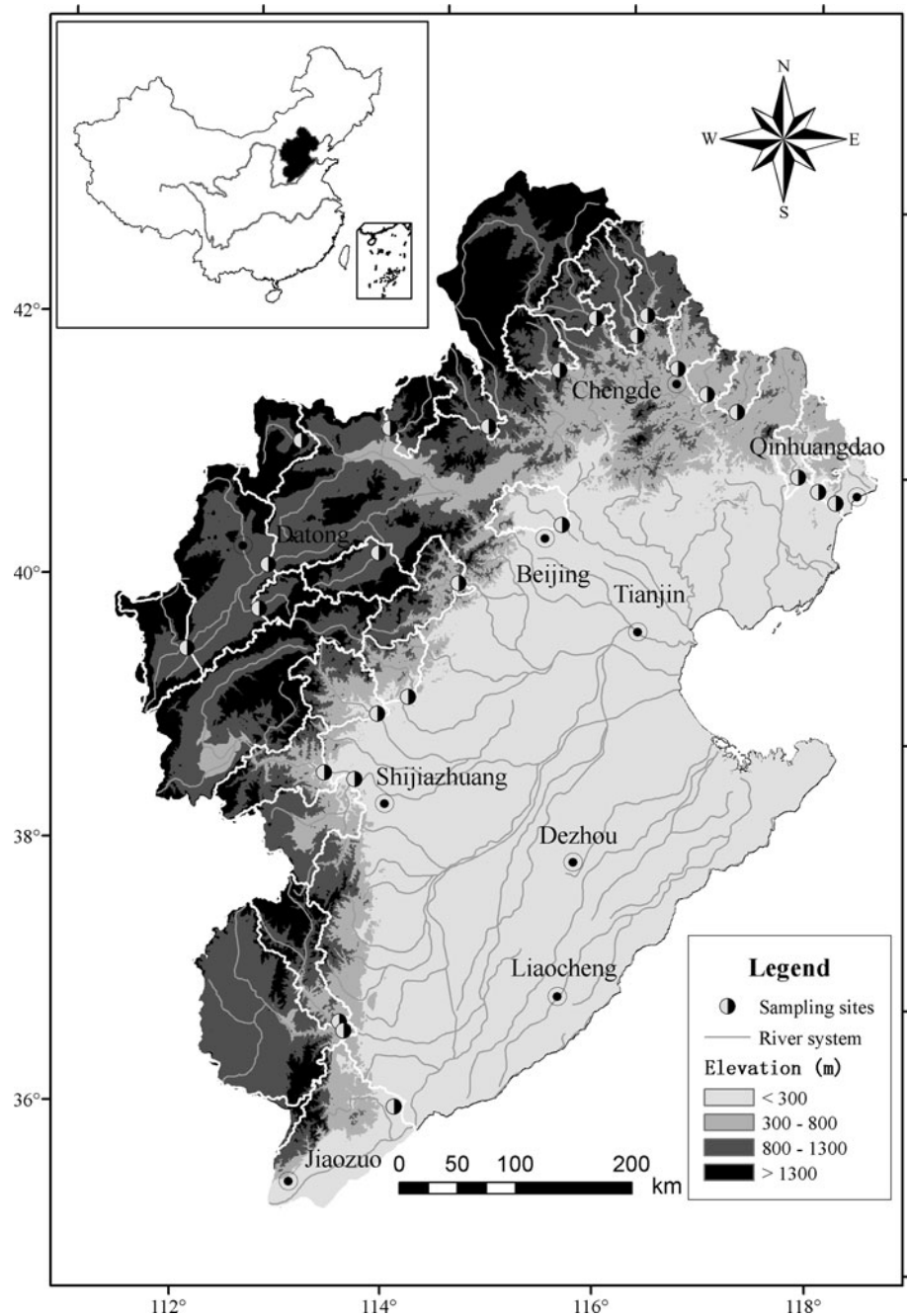
1,915 reservoirs and dams have been built to cover >85% of the mountainous watersheds. These water conservancy facilities interrupt the hydrometric affiliation and the nutrient transport from upstream to downstream reaches.

A digital elevation model at a 100-m resolution from the 1:250,000 national topographical databases was used in this study. The Haihe River basin was divided into numerous subbasins using the hydrology module of ArcGIS software (ESRI Company, USA). Among the delineated subbasins, 26 of them in the upstream regions were selected for the analysis of land–water relationships.

The selection of these upstream watersheds was based on the existence of perennial flow in the Haihe River basin. The overall area of 26 upstream watersheds is 96,036 km², which accounts for 30.2% of the total area of Haihe River basin. The water-sampling sites were generally located at the outlets of these subbasins (Fig. 1).

N-Concentration Data Collection

Water quality was characterized by the mean values sampled and measured in May and August 2009. The

water-quality data set consisted of nine water-quality parameters, including water temperature, pH, electric conductivity, turbidity, dissolved oxygen, ammonic N, nitrate N, total N, and total phosphorus (P). Because of the large area, a multiparameter water-quality monitor (YSI 6600; YSI Company, USA) was used to measure water temperature, PH, electric conductivity, dissolved oxygen, and turbidity. A photometer (PhotoLab S12; WTW Company, Germany) was used to measure ammonic N, nitrate N, total N, and total P by the methods and test reagents developed by WTW, a Nova Analytics company. Because the measurements among total N, ammonic N, and nitrate N were highly correlated with each other, we only used total N concentration as an indicator to characterize the N loading into rivers.

Metrics for Land-Use Pattern

The land-use data were derived from Landsat TM images (30-m resolution) in 2008, which were produced and released by Chinese Research Academy of Environmental Sciences. The land uses were classified into 25 types, and its accuracy was assessed before release. According to our research objectives, we reclassified the land uses into seven categories: agricultural land, forest land, grass land, urban land, rural land, water, and unused land (Table 1; Fig. 2). Population data were derived from demographic yearbooks of China in 2008. Road data were derived from the 1:250,000 national database. Road density was represented by road length (km) per square kilometers and from grade 1 to grade 5 roads as classified by the ministry of transport of China.

Land-use patterns were characterized by land-use intensity and landscape complexity variables. The land-use intensity metrics were calculated by the spatial module of the ArcGIS software, and the landscape complexity metrics were calculated by the Fragstats package embedded in the ArcGIS software (Table 2).

Analytical Methods

Several statistical methods, including Pearson correlation analysis, principal component analysis (PCA), and multivariate regression analysis, were used to analyze the relationships between the land-use pattern and total N concentration.

Pearson correlation analysis quantified the associations among the total N concentration, land-use intensity, and landscape complexity metrics. PCA transformed a number of possibly correlated metrics into a smaller number of uncorrelated factors. Its operation could be thought of as showing the internal structure of the data in a way that best explained the variance in the data. As a result, a small number of factors could account for approximately the same amount of information as do the much larger set of original metrics. Finally, a step-wise multivariate regression analysis was used to evaluate the relative importance of different land-use factors on total N concentration. All mathematical and statistical computations were performed using Microsoft Office Excel 2007 (Microsoft Company, USA) and SPSS 16 software (IBM Company, USA).

Results

Spatial Pattern of Land Uses and Total N Concentration

The tributary drainage areas in the upstream regions of Haihe River ranged from 778 to 12,965 km^2 (average 3,694 km^2). Forest had the greatest area ratio (35.2%) followed by agriculture (30.1%) and grass land (29.4%). The urban and rural areas made up 4.0% of the entire research regions, whereas water areas only occupied approximately 1.0%. The mean population density was 269 capita/km^2, with a range from 63.31 capita/km^2 in the Xiaoluanhe River watershed to 1832.62 capita/km^2 in the Wenyuhe River drainage basin. Road density ranged from 0.36 km/km^2 in the Baihe River to 0.77 km/km^2 in the Weihe River (average 0.51 km/km^2). Five watersheds had

Table 1 Scheme of land-use classification in the Haihe River basin

Land-use/cover classes	Description
Farm land	All areas including irrigated and rainfed farmland
Forest land	All forest areas, including arbor trees, shrubs, brushes, and young trees
Grass land	All herbaceous vegetation with a cover ratio > 5%, including natural grass lands and cultivated grasslands that are regularly mowed for hay or grazed by livestock
Urban land	Urban areas with high density of commercial and industrial buildings
Rural land	Rural areas with a various amount of vegetation cover commonly found in housing divisions
Water	All areas of open water, including canals, rivers, lakes and reservoirs
Unused land	All unused lands and other hard-to-use lands, including bare, salt, alkaline and gravel lands

Fig. 2 Land-use/-cover map of
the Haihe River basin in 2008
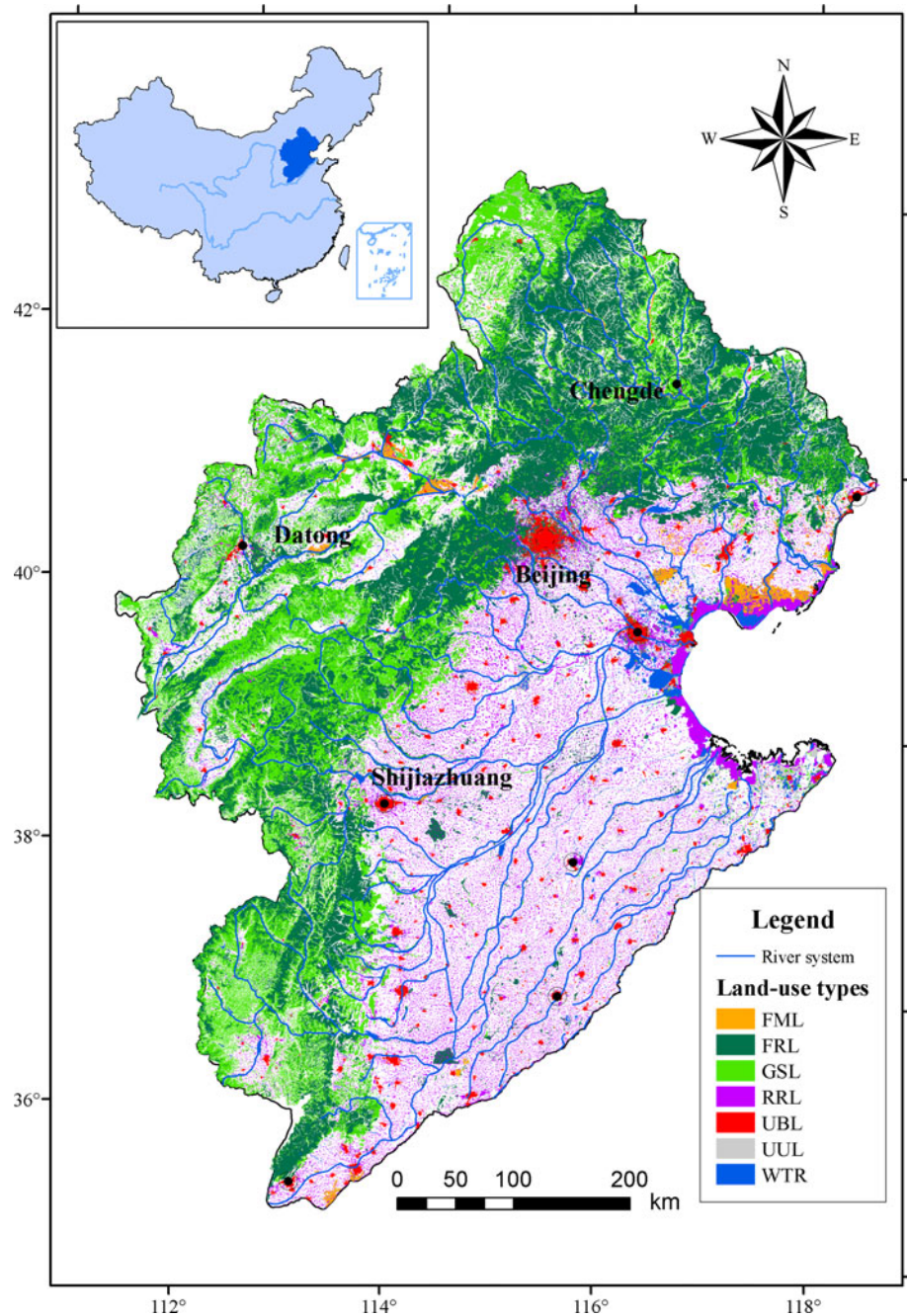
significant cultivated lands (maximum 51.31%). Overall,
the studied upstream regions of the Haihe River were pri-
marily occupied by forest (maximum 80.25%) and grass-
land (maximum 46.77%) (Table 3).

Measured average total N concentration was 3.67 mg/l
for all of the watersheds monitored in the study. The highest
value (10.11 mg/l) of the total N concentration was detected
in the Wenyuhe River, which flows through the suburb and
urban areas of Beijing. The lowest value (0.61 mg/l) was
found in the Jumahe River, which drains from Taihang
Mountains with intensive forests and grasslands (Fig. 3).

Correlation Between Total N Concentration and Land-Use Metrics

Pearson correlations of all available land-use metrics with
measured total N concentrations of the studied watersheds
are listed in Table 4. As shown, 16 land-use metrics had
correlation coefficients >0.3 with total N concentration.
Seven of the metrics were quantities that characterize the
degree of land-use intensity in the areas. These included
population density, road density, and farmland, urban land,
rural land, forest land, and grass land proportions. The

Table 2 Land-use intensity and landscape complexity metrics in the Haihe River basin

Metric types	Index	Full name	Unit
Land-use intensity	PDI	Population density	10^4 capita/km^2
	RDI	Road density	km/km^2
	PFML	Proportion of farmland	%
	PUBL	Proportion of urban land	%
	PRRL	Proportion of rural land	%
	PFRL	Proportion of forest land	%
	PGSL	Proportion of grass land	%
Landscape-type complexity	SDI	Shannon's diversity index	
	SEI	Shannon's evenness index	
Landscape patch-area complexity	TE	Total edge	m
	MPS	Mean patch size	ha
	PSSD	Patch size SD	ha
	PED	Patch edge density	m/ha
	MPE	Mean patch edge	m
	PSCOV	Patch size coefficient of variation	%
	NUMP	Number of patches	
	MEDPS	Median patch size	ha
Landscape patch-shape complexity	AWMSI	Area weighted mean shape index	
	MSI	Mean shape index	
	MPAR	Mean perimeter-area ratio	
	MPFD	Mean patch fractal dimension	
	AWMPFD	Area weighted mean patch fractal dimension	

Metric definitions from McGarigal and Marks (1995)

landscape complexity metrics included three groups, with each describing landscape-type complexity, landscape patch-area complexity, and landscape patch-shape complexity, respectively. The landscape-type complexity metrics had Shannon's diversity index (SDI) and Shannon's evenness index (SEI), both with correlation coefficients >0.3. The landscape patch-area complexity metrics included mean patch size (MPS), patch size SD (PSSD), patch edge density (PED), and mean patch edge (MPE), all with correlation coefficients >0.3. Last, the landscape patch-shape complexity metrics had area weighted mean shape index (AWMSI), mean perimeter-area ratio (MPAR), and area weighted mean patch fractal dimension (AWMPFD), all with correlation coefficients >0.3.

Significant positive correlations between total N concentration and population density, urban land proportion, and rural land proportion variables were obtained. Road density, farmland proportion, SDI, and SEI variables were also positively correlated with total N concentration, whereas landscape patch-area and patch-shape metrics were most negatively correlated with total N concentration. These correlations clearly demonstrated that the land uses linking to human activities were significantly associated with total N loading, whereas land uses with complex geometry were likely to mitigate total N loading in the studied areas.

Correlations were also detected between land-use intensity and landscape complexity metrics. For example, positive correlations existed between land-use intensity (population density, road density, and urban land, rural land, and farmland proportions) and Shannon indices (SDI and SEI), whereas negative correlations existed between forest land proportion and Shannon indices. This result suggested that land-use intensification did not always lead to simplification of the landscape complexity, especially landscape-type complexity. Therefore, dimensionality clustering and reduction were necessary to further evaluate relationships between land uses and total N concentrations.

PCA of Land-Use Metrics

A mixture of variables, including human-induced land-use intensity, landscape-type complexity, landscape patch-area complexity, and landscape patch-shape complexity, were used in PCA. Varimax rotation was adopted to maximize the variance of the principal component (PC) loading. Eigenvalues provide a measure of the significance of each PC. Five PCs were selected for the analysis because their cumulative eigenvalues explained >90% of the total variance (Table 5).

As listed in Table 5, among the five PCs, PC1 explained 30.13% the total variance and had strong positive loadings on population density, road density, and urban land and rural land proportions, thus representing human-induced factors. PC2, explaining 18.64% of the total variance, had obvious positive loadings on MPS, MPE, and PSSD and negative loadings on PED. By definition, MPS, MPE, and PSSD decreased whereas PED increased when many small patches occupied a watershed. This means that PC2 represented the impact of landscape patch-area complexity. PC3, which explained 16.77% of the total variance, had strong positive loadings on AWMSI and AWMPFD, thus representing the impact of the area-weighted patch-shape complexity. PC4, explaining 14.81% of the total variance, had strong positive loadings on the proportions of forest and grass land. Therefore, this factor represented the impact of increasing forests and grasslands. Finally, PC5,

Table 3 Summary of watershed characteristics and measured total N concentrations in the upstream regions of the Haihe River basin

Name	Monitoring station	Area (km²)	Total N (mg/l)	Proportion of land-use types						Population density (capita/km²)	Road density (km/km²)
				Farm land	Urban land	Rural land	Forest land	Grass land	Water		
Baihe	Yangtianzhen	2363	3.65	20.8	0.13	0.83	55.55	22.22	0.46	54	0.38
Beidaihe	Beidaihe	1401	3.00	37.92	8.56	5.87	32.47	12.47	2.50	738	0.63
Caohe	Xidayang	2267	2.64	8.29	0.00	2.00	37.27	51.84	0.07	278	0.44
Chaohe	Zhangsanying	2515	6.32	23.67	0.22	0.61	60.03	14.82	0.45	43	0.30
Dashahe	Wangkui	3723	2.82	7.51	0.05	0.39	35.01	55.66	1.08	90	0.44
Dongyanghe	Youyi	3388	1.36	34.42	0.38	3.75	10.47	46.77	2.90	137	0.50
Heihe	Badaying	2995	3.30	25.22	0.01	0.29	63.89	10.24	0.34	66	0.36
Huangshuihe	Dongyulin	4044	3.56	46.47	0.58	2.75	20.60	28.37	0.94	161	0.55
Huliuhe	Huliuhe	3170	6.27	42.06	0.46	2.23	30.09	23.31	1.28	142	0.45
Hunhe	Zhenziliang	1568	1.83	36.70	0.34	1.82	15.17	45.00	0.75	170	0.54
Hutuohe	Gangnan	4455	3.67	10.89	0.00	0.54	46.05	41.65	0.71	147	0.47
Jumahe	Shidu	3828	0.61	14.01	0.15	1.00	64.17	20.16	0.39	193	0.39
Laoniuhe	Liying	1305	6.17	13.72	0.07	0.39	68.72	16.64	0.35	125	0.42
Puhe	Kuancheng	1479	5.11	25.19	0.62	1.36	51.47	20.72	0.36	135	0.48
Qinglonghe	Taolinkou	2770	1.51	21.03	0.11	1.35	57.55	17.18	2.62	450	0.55
Qingshuihe	Zhangjiakou	2480	0.98	25.44	0.08	1.00	52.83	20.18	0.39	90	0.37
Qingzhanghe	Hezhang	4687	4.86	17.21	0.22	1.19	42.70	37.74	0.80	118	0.48
Sangganhe	Cetian	10266	5.48	44.50	1.32	4.17	17.52	29.47	1.95	244	0.53
Weihe	Xincun	9484	3.03	51.31	3.59	8.31	23.16	12.80	0.71	625	0.77
Wenyuhe	Beiguanzha	2228	10.11	20.43	10.68	13.97	44.29	7.94	1.93	1833	0.69
Wuliehe	Chengde	1870	2.97	23.48	0.00	0.62	53.62	22.06	0.13	103	0.38
Xiaoluanhe	Guojiatun	2126	1.95	16.22	0.00	0.34	80.25	2.61	0.57	63	0.31
Yanghe	Yanghe	778	1.37	9.31	0.00	1.43	54.32	32.96	1.63	208	0.55
Yehe	Huangbizhuang	4549	4.55	29.58	0.98	3.94	30.51	33.94	0.88	333	0.53
Yixunhe	Miaogong	3332	3.21	28.41	0.25	0.65	42.68	27.61	0.29	64	0.36
Zhuozhanghe	Zhangze	12965	5.10	34.40	0.49	2.44	16.12	45.52	0.99	238.67	0.53

which explained the lowest variance (9.92%), had strong positive loadings on MPAR, thus representing the impact of the more complicated landscape patch-shape. The values of five PCs were calculated by the PC loadings and the values of land-use pattern metrics.

Importance of Different Land-Use Metrics on Total N Concentration

Multivariate regression analysis was conducted to determine if statistical correlations occurred between land-use component factors and total N concentration. We followed the criterion of the stepwise approach and selected the forward algorithm provided in the SPSS software.

There were four PCs significant at a level of $p < 0.05$: PC1, PC5, PC4, and PC2 (Table 6). Regression with PC1 as the only predictor, model 1 was able to account for 63% of the variation in total N concentration. By adding other landscape complexity factors, however, the model

accuracy (models 2 and 3) increased noticeably. In model 4, all four variables were included, and the model could account for 87% of the variation in total N concentration. Figure 4 compared the measured to the predicted total N concentration of the 26 watersheds studied. Although it was difficult to define the absolute contribution of each variable to the total N concentration regression, their relative contributions could be evaluated by comparing their standardized regression coefficients. The contribution of PC1, PC5, PC4, and PC2 on the total N concentration variations was 50, 23.13, 14.38, and 12.50%, respectively. PC1 was significantly positively correlated with total N concentration, indicating that the intensification of human-induced land uses could result in increased total N loadings. The negative correlation of PC5 suggested that the shape complexity of landscape patches could potentially mitigate the total N loading. Increase in forest and grassland would decrease total N loading as evidenced by the negative correlation of PC4. Moreover, increasing

Fig. 3 Measured total N concentrations in the upstream watersheds of the Haihe River basin
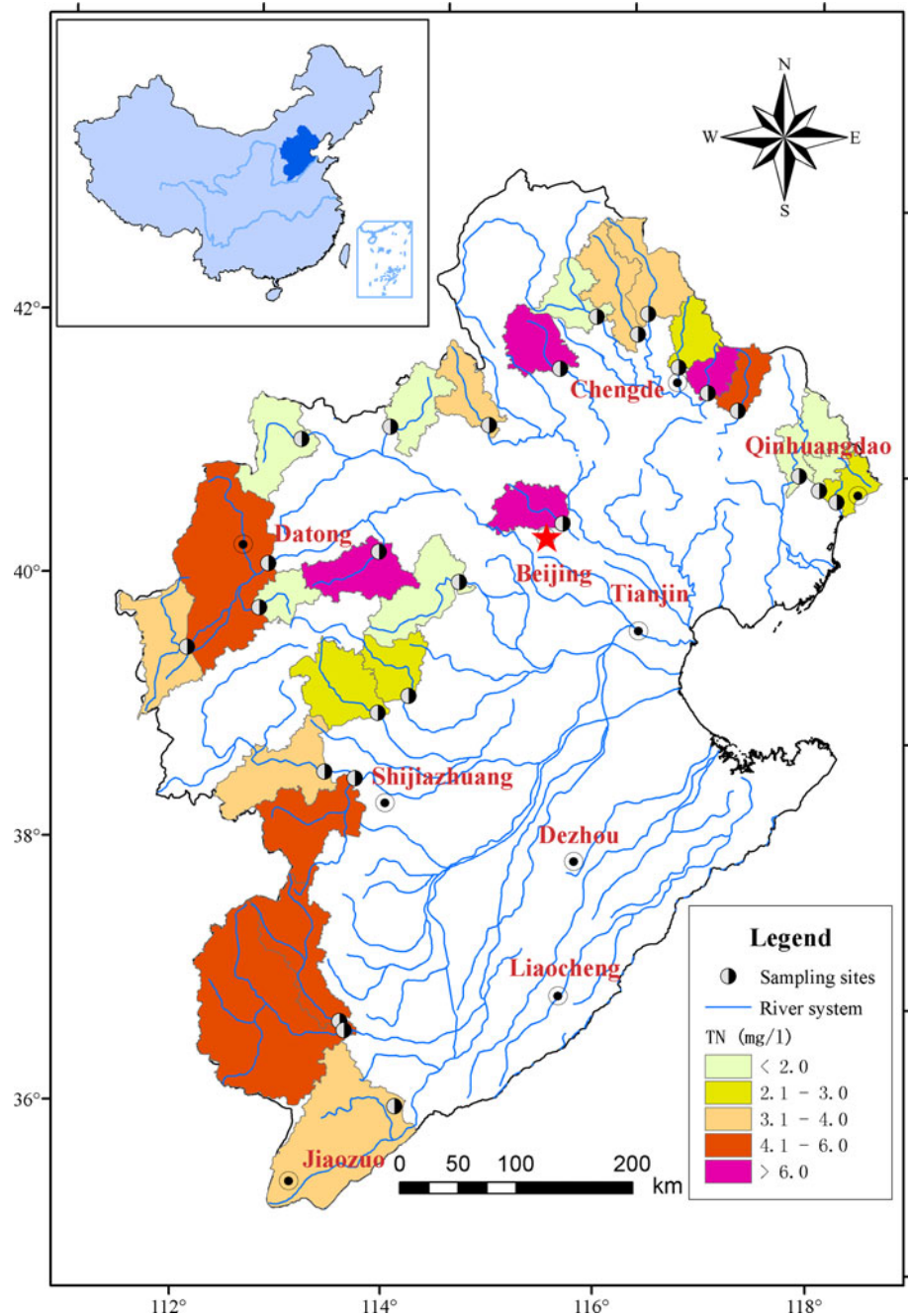
landscape patch size would decrease total N loading as shown by the PC2 negative correlation.

Discussion

Relationship Between Land-Use Intensity and Landscape Complexity

Land-use intensification could induce changes in landscape complexity at the field and landscape levels (Concepcion

and others 2008). Harvest data have been proposed as an effective index for land-use intensity and the proportion of arable land per farm as a simple predictor of the landscape complexity (Roschewitz and others 2005). In contrast, Persson (Persson and others 2010) regarded the proportion of farmland and annual crops as indicators of land-use intensity and the amount of field borders as a better indicator of complexity than the field sizes. Other landscape diversity metrics may be considered as different aspects of landscape complexity in large spatial scales. In our study, the first component (PC1) could be interpreted by

Table 4 Results of Pearson correlation analysis for land-use intensity and landscape complexity metrics in the upstream watersheds of the Haihe River basin

	Total N	SDI	SEI	AWMSI	MSI	MPAR	MPFD	AWMPFD	TE	PED	MPE
Total N	1.00										
SDI	**0.40**	1.00									
SEI	**0.37**	0.96	1.00								
AWMSI	**−0.33**	0.21	0.15	1.00							
MSI	−0.17	−0.46	−0.49	0.21	1.00						
MPAR	**−0.36**	0.42	0.35	0.09	0.06	1.00					
MPFD	0.12	−0.24	−0.21	0.17	0.37	−0.47	1.00				
AWMPFD	**−0.37**	−0.07	0.00	0.83	0.28	0.15	−0.49	1.00			
TE	0.16	0.27	0.27	0.49	−0.34	−0.02	0.16	0.49	1.00		
PED	**0.37**	0.39	0.37	0.05	−0.40	−0.09	0.35	0.36	0.57	1.00	
MPE	**−0.32**	−0.55	−0.57	0.12	0.89	−0.19	0.24	0.15	−0.44	−0.61	1.00
MPS	**−0.38**	−0.52	−0.52	0.03	0.69	−0.17	0.05	−0.09	−0.47	−0.78	0.92
NUMP	0.16	0.34	0.33	0.41	−0.43	−0.01	0.16	0.41	0.98	0.62	−0.52
MEDPS	−0.12	−0.46	−0.54	−0.06	0.76	0.02	−0.08	0.00	−0.44	−0.40	0.73
PSCOV	0.08	0.43	0.39	0.81	−0.23	0.21	−0.10	0.50	0.59	0.11	−0.32
PSSD	**−0.34**	−0.06	−0.09	0.71	0.47	0.07	0.04	0.37	−0.03	−0.59	0.53
PDI	**0.68**	0.64	0.58	0.00	−0.33	0.33	−0.04	−0.09	0.04	0.33	−0.41
RDI	**0.49**	0.77	0.76	0.28	−0.55	0.47	−0.27	0.02	0.30	0.36	−0.67
PFML	**0.36**	0.63	0.54	0.53	−0.26	0.25	−0.22	0.39	0.41	0.22	−0.33
PUBL	**0.61**	0.70	0.64	0.03	−0.28	0.46	−0.17	−0.06	0.00	0.25	−0.36
PRRL	**0.64**	0.77	0.73	0.18	−0.45	0.26	−0.10	0.02	0.19	0.38	−0.53
PFRL	**−0.34**	−0.68	−0.71	−0.30	0.56	−0.10	0.01	−0.21	−0.53	−0.45	0.64
PGSL	**−0.35**	0.01	0.15	−0.09	−0.33	−0.25	0.24	−0.02	0.29	0.24	−0.33

	MPS	NUMP	MEDPS	PSCOV	PSSD	PDI	RDI	PFML	PUBL	PRRL	PFRL	PGSL
total N												
SDI												
SEI												
AWMSI												
MSI												
MPAR												
MPFD												
AWMPFD												
TE												
PED												
MPE												

Table 4 continued

	MPS	NUMP	MEDPS	PSCOV	PSSD	PDI	RDI	PFML	PUBL	PRRL	PFRL	PGSL
MPS	1.00											
NUMP	-0.51	1.00										
MEDPS	0.54	-0.53	1.00									
PSCOV	-0.28	0.55	-0.37	1.00								
PSSD	0.59	-0.11	0.18	0.56	1.00							
PDI	-0.34	0.18	-0.37	0.21	-0.10	1.00						
RDI	-0.56	0.39	-0.62	0.60	0.02	0.70	1.00					
PFML	-0.36	0.38	-0.26	0.68	0.24	0.11	0.46	1.00				
PUBL	-0.31	0.11	-0.28	0.22	-0.06	0.91	0.65	0.24	1.00			
PRRL	-0.45	0.30	-0.47	0.45	0.00	0.93	0.79	0.38	0.88	1.00		
PFRL	0.62	-0.56	0.67	-0.52	0.11	-0.14	-0.58	-0.66	-0.18	-0.39	1.00	
PGSL	-0.30	0.30	-0.48	-0.05	-0.31	-0.30	0.04	-0.15	-0.38	-0.24	-0.58	1.00

Full names of variables are in Table 2

Boldface values indicate the correlation coefficients between Total N concentration and land-use variables are larger than 0.3

population density, road density, and the proportion of residential areas within a watershed. These new metrics were directly influenced by human-induced land-use types; thus, they could be used as alternative indicators for land-use intensity on a watershed scale.

Correlation analysis showed that land-use intensity was related to many, but not all, indicators of landscape complexity (Table 4). Land-use intensity metrics, including population density, road density, and urban and rural land proportions, were found to be positively correlated with landscape-type complexity as represented by SDI and SEI. This result indicated that land-use intensification in a watershed scale could enhance land-use diversity by increasing farmland, road, and residential areas. Landscape patch-area metrics characterized the degree of forest fragmentation as reflected in the relationship that decreased MPS and MPE corresponded to increased PED. Our results showed that the proportion of forest had a significant positive correlation with MPE and MPS, and road density was the most significant effect on the landscape fragmentation. It indicated that land-use intensification had significant negative impacts on landscape patch size. Interestingly, rural area, similar to urban area, had a high correlation with landscape fragmentation. Opposite to aggregated urban areas, scattered rural areas might break the forest and grassland into fragments through extended roads to connect each other, which might also generate nonpoint source pollution by speeding up runoff and soil erosion.

Effect of Land-Use Intensity on Total N Concentration

Nutrient loading was influenced by a combination of natural and anthropogenic factors, and their relative influences could change over a range of temporal and spatial scales (Baker 2003). Our results suggested that total N concentration in the upstream watersheds was strongly and positively related to human-related land-use types as expressed by both proportion of residential areas and density of human population and roads. The linkage between water quality and density of human population and roads was consistent with the findings in other areas (Morrice and others 2008; DeCatanzaro and others 2009). Moreover, similar to the research by Wilson and Weng (2010), the proportion of residential areas had significant impacts on total N concentration in our study because of the point-source discharges. Our results suggested the association of better water quality in watersheds with less urbanization and more forests. Human-induced point source pollution was the primary factor affecting total N concentration in the upstream areas of the Haihe River basin.

The results of correlation analysis and PCA demonstrated that the simple proportion of agricultural areas did not show a significant relationship with total N concentration

Table 5 Loadings of land-use intensity and landscape complexity metrics on significant principal components for the upstream watersheds of the Haihe River basin

| Metric type	PC1	PC2	PC3	PC4	PC5
SDI	0.74	−0.18	0.17	0.41	0.34
SEI	0.71	−0.16	0.09	0.53	0.26
AWMSI	0.10	0.20	**0.93**	0.09	0.07
MPAR	0.28	0.03	−0.07	−0.08	**0.85**
AWMPFD	−0.07	−0.14	**0.94**	−0.06	−0.18
PED	0.24	**−0.88**	0.23	0.09	−0.18
MPE	−0.37	0.69	0.13	−0.43	−0.21
MPS	−0.27	**0.86**	−0.05	−0.31	−0.19
PSSD	0.05	**0.79**	0.56	−0.04	0.08
Population density	**0.95**	−0.15	−0.07	−0.15	0.01
Road density	**0.74**	−0.19	0.14	0.34	0.32
Proportion of urban land	**0.92**	−0.11	−0.03	−0.16	0.19
Proportion of rural land	**0.96**	−0.16	0.11	0.05	0.06
Proportion of forest land	−0.25	0.31	−0.29	**0.83**	−0.17
Proportion of grass land	−0.27	−0.21	−0.14	**0.82**	−0.29
Proportion of farmland	0.22	−0.13	0.61	0.30	0.51
Eigenvalue	4.82	2.98	2.68	2.37	1.59
Total variance (%)	30.13	18.64	16.77	14.81	9.92
Cumulative variance (%)	30.13	48.78	65.54	80.36	90.28

Boldface values indicate strong loadings

Table 6 Regression results with component factors as predictor variables and total N concentration as response variable for the upstream watersheds of the Haihe River basin

Model		Unstandardized coefficients		Standardized coefficients	t	p	Partial correlations	R	F
		B	SE	Beta					
1	(Constant)	4.63	0.78		5.93	0.00		0.63	41.23
	PC1	5.12	0.80	0.80	6.42	0.00	0.80		
2	(Constant)	4.63	0.63		7.34	0.00		0.77	38.50
	PC1	5.12	0.64	0.80	7.95	0.00	0.86		
	PC5	−2.39	0.64	−0.37	−3.71	0.00	−0.61		
3	(Constant)	4.63	0.56		8.21	0.00		0.82	34.40
	PC1	5.12	0.58	0.80	8.90	0.00	0.88		
	PC5	−2.39	0.58	−0.37	−4.16	0.00	−0.66		
	PC4	−1.50	0.58	−0.23	−2.61	0.02	−0.49		
4	(Constant)	4.63	0.50		9.20	0.00		0.87	34.00
	PC1	5.12	0.51	0.80	9.96	0.00	0.91		
	PC5	−2.39	0.51	−0.37	−4.65	0.00	−0.71		
	PC4	−1.50	0.51	−0.23	−2.92	0.01	−0.54		
	PC2	−1.32	0.51	−0.20	−2.57	0.02	−0.49		

despite previous studies indicating negative relationships with most water-quality characteristics (Tong and Chen 2002). Other studies have also reported that the effect of agricultural areas on water quality depended on farming practices and climatic characteristics (Baker 2003; Lee and others 2009). The contrasting results of the present study could possibly be explained by the farmland types and there being less rainfall during our sampling time. In the upstream watersheds of the Haihe River, although the proportion of agricultural lands could be as high as 30.1% of the total areas, only a small fraction (<1%) of the farmland was irrigated. It is therefore our hypothesis that the lack of irrigation and
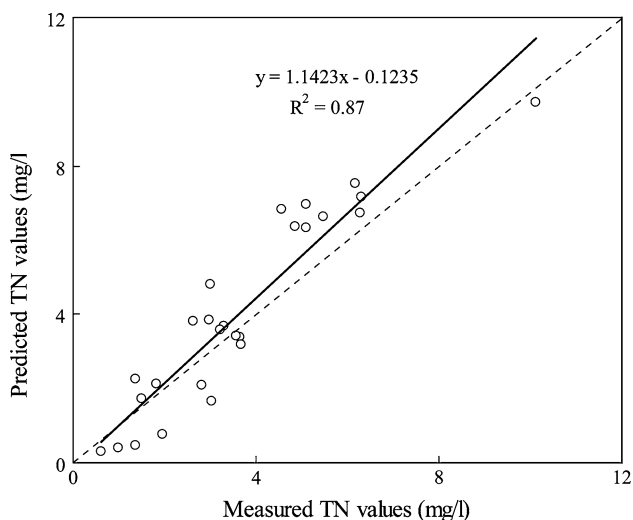
Fig. 4 Model-predicted versus measured total N concentrations in the upstream watersheds of the Haihe River basin. The *dashed line* is the 1:1 line, indicating a perfect correlation

drainage systems minimized the negative impact of the agricultural land uses on total N loading in the region. In these areas, large amounts of precipitation could be the major contributor to transport nutrient to the rivers. In addition, the water-quality data used in this study were collected in 2009, and there were no records of extreme rainfall that would have caused massive runoff and erosion during the sampling period. In fact, the 2009 summer precipitation was the lowest in the past 10 years, leading to significant regional drought in autumn and winter in that year (Ai and others 2010).

The most important contributors to total N loading in the upstream Haihe River basin were the unrestricted discharges of wastewater and the scarcity of purifying water infrastructures, particularly in the rural areas. This was not consistent with similar watersheds in North American and European regions where nonpoint source pollution was more predominant (Baker 2003).

Effect of Landscape Complexity on Total N Concentration

The complex geometry and patterns of land uses can adjustment their effects on water quality (Johnson and others 1997). Many studies have found that more complex landscape shapes within a watershed can considerably relieve the negative effects on water quality in areas adjacent to rivers (Hwang and others 2007). However, the relationship between patch density and water quality was not clear. A negative relationship between PED and total N concentration was found in rivers of Estonia (Uuemaa and others 2005), whereas a positive relationship was significant in South Korea (Lee and others 2009). Our results showed the positive correlation of PED and total N concentration.

This indicated that the relationships between land uses and water quality were complex and perhaps region-specific. Landscape patch size and density always tended to be associated with forest fragmentation, and highly fragmented forests could not function effectively to filter nutrient loadings. Lee and others (2009) found that highly interspersed land uses, particularly residential areas, might represent the worst case from the perspective of water-quality management for adjacent aquatic systems. In our study, we also found that total N concentration increased when different land uses were greatly interspersed and the number of land-use (especially for roads and residential areas) types increased. Our results showing high correlations between landscape complexity and land-use intensification may suggest that total N concentration was primarily associated with the negative impacts of interspersion and the diversity of human-induced land-uses.

Implications for Environmental Management in the Haihe River

The Haihe River is a highly urbanized watershed, and water shortages and allocation conflicts are increasingly serious. The study analyzed the relationships between land use and total N concentrations and could provide some useful implications for the environmental management.

The results indicated that point-source effluent contributed more than non–point-source effluent to the total N load of the Haihe River. This result is consistent with previous studies. For example, total N loads discharged with wastewater through surface runoff totaled 51,966 tons from crop farming (Zhu and others 2010a), which is little greater than that of livestock and poultry breeding (41,500 ton) in the Haihe River in 2007 (Zhu and others 2010b). In addition, total N loads of rural solid waste reached >3,000,000 tons in 2007 (Zhu and others 2010c). Solid waste had little impact on surface and underground water during the dry season, but during the rainy season heavy rains might cause wastewater to rush into neighboring reaches and underground water.

Therefore, several management techniques should be employed to mitigate nutrient loading into the Haihe River. First, solid-waste treatment technologies should be improved in the rural areas. The use of green manure from human and animal feces to decrease nutrient loading should be encouraged through economic compensation and government incentives. Methane from straw resources has been regarded as a green energy to save traditional energy consumption and decrease nutrient discharge into surface and underground water. More official capitals and supporting facilities are needed to promote the popularization of the green energy. Second, infrastructure should be improved with more investment in the rural areas. Water-purifying infrastructures and waste-treatment plants are basic

demands of water-resource management. We should also invest more in water supplies and drainage systems in rural areas to decrease waste discharges into adjacent rivers in the rainy season. Third, centralized management of separated rural regions could make water infrastructures more efficient. Less road construction in centralized rural regions could also decrease fragmentation of forests and grasslands.

Conclusion

Many studies have demonstrated that both natural watershed characteristics and land-use practices influence the nutrient conditions of receiving waters (Ripa and others 2006). Additional natural controlling variables, such as geologic, edaphic, and climatic characteristics, can also influence a river's chemical and biotic quality (O'Neill and others 1988). Although these natural variables may improve the predictive capabilities of a water-quality model, researchers have focused on the effects of modifiable land-use attributes for the purpose of managing or planning a watershed's ecosystem (Shiels 2010). The current study illustrates the usefulness of multivariate statistical techniques for the analysis and interpretation of effects of land-use patterns on watershed water quality.

Our analysis showed that human-induced factors increased total N loading due to not only to transformation of natural lands into residential and traffic areas but also lowering of the quality of remnant forest in watersheds with small and highly dense edged areas. The results indicated that human-induced factors, such as population density, road density, and residential areas, were strong indicators of water quality in the upstream regions of the Haihe River basin.

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