Effects of land use on processes governing water quality in urbanizing catchments: A case study in the Liangjiang New Area, China

Kun Luo1*, Conglin Wu1, HeZhen Zheng1, Xuebin Hu2, Qiang He2, Junrong Shao1
1Changjiang Survey, Planning, Design and Research Co., Ltd. Wuhan, Hubei 430010, China
2Key Laboratory of Three Gorges Reservoir Region’s Eco-Environment, Ministry of Education, Chongqing University, 400045, China
*Corresponding author’s e-mail: luokun@cjwsjy.com.cn

Abstract. Understanding the effects of land use on processes governing water quality is important for watershed planning and management. This study evaluated the difference in pollution factors due to land use in Liangjiang New Area. Water samples were collected in April (dry season) and September (wet season) of 2014 and 2015 at 20 subcatchments. According to the similarity in land use compositions, cluster analysis divided subcatchments into four land use groups, representing different urbanization levels. The factor analysis identified five pollution factors which explained more than 80% of the variance in data, and revealed nutrients pollution, anaerobic conditions, soil erosion, effects of eutrophication and oxygen consumption in the rivers, respectively. Using the analysis of principal component scores, we found that the magnitudes of pollution factors were significantly different among the land use groups. Moreover, urban land use had a significantly positive relationship with pollution factors, whereas forest land and farmland displayed opposite effects.

1. Introduction
Human activities on land use changes, including urbanization, industrial and agricultural activities, have important impacts on river water quality within a watershed [1,2]. Many studies in the world have shown significant correlations between land use types and water quality parameters, and indicated that different land use types are associated with different water pollution problems [1-6]. In the area covering different types of watersheds, however, the pollution sources might change, and little is known on the relationship between land use and processes governing water quality [7,8]. To avoid missing the spatial variation, it is essential to cluster sites with similar land use characteristics before processing multivariate environmental data [7].

Principal component analyses (PCA) and factor analysis (FA), as the multivariate analytical tools, have been widely applied to interpreter heterogeneous water quality data sets, and identify pollution factors governing water quality [9,10]. They are designed to reduce the number of variables to several principal components (PC), which are often interpretable as key processes explaining the variability of observed
water quality. Furthermore, the analysis of principal components scores can help to understand the magnitudes of processes varying in space and time [10]. For example, using the analysis of scores, Selle et al. (2013) identified the dominant pollution factors governing water quality in Ammer catchment in southwestern Germany. Bu et al. (2014) clarified the distributions of pollution sources in Taizi River basin by analyzing factor scores in different sampling zones.

The Chongqing Liangjiang New Area (LJNA) is an economic link to eastern China and the world. It is the third national new area of China after those in the Pudong and Binhai new areas, but is unique in that it is the first inland new area [11,12]. Although the rapid urbanization promoted economic development, however, the continuously growing population, construction and economic activities have resulted in significant land use change and serious water pollution, as well. From the view of watershed planning and management, it is important to identify the potential pollution sources and their relationships with land use. The objectives of this study were: 1) to investigate the potential pollution sources and their distribution in LJNA; 3) to identify the relationships between land use and those pollution sources.

2. Materials and methods

2.1. Study sites

The LJNA is 1200 km², including 20 subcatchments (figure 1), each of which occupies a river that is a tributary of either the Yangtze or Jialing Rivers. The annual average air temperature is 18.2°C (between 7°C in January and 29°C in July). The long-term annual precipitation is approximately 1105 mm, and 70% of which concentrated in the rainy season from May to September. The topography is mainly characterized by mountain ranges and hills, with elevations between 145 and 857 m. Purplish soil, paddy soil and yellow-brown soil (Haplumbrepts) are the three principle soil types, covering 46.45%, 29.43% and 14.94% of the total area, respectively. The population of permanent residents in LJNA in 2013 was 2 million, with 1.6 million in urban area and 0.4 million in rural area. The volume of treated municipal sewage was about 138.8 million m³, accounting for 88.13% of the total sewage discharge. Rice, wheat and maize were the main agricultural products in the LJNA. Livestock, which were mainly raised in the rural area, include pig, chicken and duck. Thus the main pollution sources in LJNA include untreated municipal sewage, agricultural fertilizer, livestock waste, and urban surface runoff [13].

2.2. Sampling Sites and water quality analysis

In order to integrate the cumulative impacts of land use alteration in the subcatchments, water samples were collected at headwater stream confluences with the Jialing and Yangtze Rivers (figure 1). Thus, a total of 20 sampling sites representing different land use patterns within subcatchments are selected in the study area. Samples were collected twice a year during two years: once in April (dry season) and once in September (wet season). Fifteen representative parameters were selected to measure, including pH, dissolved oxygen (DO), oxidation reduction potential (ORP), electrical conductivity (EC), Turbidity, total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), ammonium nitrogen (NH₄⁺-N), nitrite (NO₂⁻), nitrate (NO₃⁻), suspended solids (SS), chemical oxygen demand (COD), chlorophyll a (Chl-a) and fecal coliform (FC).

2.3. Spatial data

Digital elevation model (DEM) data and Landsat Thematic Mapper imagery (2013) were applied to delineate watershed boundaries and map the land use composition in the LJNA at a 5 m resolution (figure 2 and 3). By combining the similar land-use types into one broad category, the original and detailed land-use classes were organized into seven types: 1) urban land (URB), including urban residential, commercial and industrial land; 2) rural residential land (RUR); 3) forest (FOR), including wooded areas and mixed
forest areas; 4) grassland (GRA); 5) farmland (FAR), including dry farmland and paddy field; 6) water bodies (WAT), including rivers, reservoirs and ponds; and 7) unused land (UNU), including barren land and other bare ground. The areas and proportions of land-use types in all the 20 subcatchments in the LJNA were calculated using ArcGIS 10.0.

2.4. Statistical analysis
Cluster analysis (CA) was applied to classify subcatchments into different groups according to their similarity in land use patterns. Prior to cluster analysis, the land use data was standardized using z-scale transformation. The output was visualized as a dendrogram.
Factor analysis (FA) was employed to identify pollution factors that influence water quality in the LJNA. The suitability of data for FA was examined using the Kaiser-Mayer-Olkin (KMO) statistics and Bartlett’s sphericity test. In order to prevent misclassification due to extensive disparities in data dimensionality, z-scale transformation was applied to standardize the water quality data before FA [14].

To investigate the distributions of pollution factors, we calculated the score of each rotated component in different land use groups, using the following equation:

$$RC_s = \sum_{i=1}^{n} (a_{ki}p_i)$$

Where $RC_s$ is the scores for the $s$th rotated component; $s$ is the number of rotated components; $i$ is the number of water quality parameters; $a_{ki}$ is the values of component score coefficient of the $i$th parameter on $k$th principal component. $p_i$ is the z-scale standardized values of the $i$th parameter.

One-way analysis of variance (ANOVA) with post hoc Tukey’s HSD test was used to test the significant differences of each rotated component scores under different land use groups. The relationships between land use types and pollution factors were investigated using Pearson’s correlation analysis with statistical significance at $p < 0.01$ and $p < 0.05$ levels (2 – tailed). All of the statistical analysis, including cluster analysis, principal component analysis, correlation analysis and one-way ANOVA, were all performed with IBM SPSS 20.0.

3. Results and discussion

3.1. Land use patterns in the LJNA

Urban land, farmland and forest land were three principle land use types in the LJNA, but their compositions were significantly different in 20 subcatchments (figure 3). In S1, S2, S4 and S8, urban land was the dominant land cover, accounting for over 70% of the land area. Farmland was mainly centralized in S7, S12, S15, S17 and S19, with ranging from 40% to 50%. Forest land accounted for the majority in S11, S14 and S18, occupying >55% of the land areas. The other land use types, including grass land, unused land and rural land, accounted for less than 10% of each subcatchment.

Four land use groups of subcatchments were derived using cluster analysis (figure 4). The first group was formed by four subcatchments (green color in figure 4), including S10, S11, S14 and S18. The second group consisted of eight subcatchments (blue color in figure 4), including S7, S12-13, S15-17 and S19-20. The third and fourth group comprised each four subcatchments. S4-6 and S9 (pink color in figure 4) were in group III, and S1-3 and S8 (red color in figure 4) were in group IV. Table 1 presents the mean values of land use composition in different groups.

![Figure 4](image-url)  
**Figure 4.** Classification of the subcatchments of the 20 sampling sites in the Liangjiang New Area, according to their land-use types.

![Figure 5](image-url)  
**Figure 5.** The score of each rotated component in different land use groups (values not sharing a common letter were significantly different ($P < 0.05$)).
Table 1. Statistical descriptives for environmental variables measured for each month in Longjing Lake.

|                | I       | II      | III     | IV      |
|----------------|---------|---------|---------|---------|
| Urban land (%) | 11.5 (1.5-17.0) | 27.4 (8.2-43.1) | 51.1 (37.3-68.5) | 75.5 (50-91.40) |
| Rural land (%) | 6.7 (3.1-11.6)  | 6.9 (4-10)   | 5.3 (2.7-10)   | 1.4 (0-4.8)    |
| Forest land (%)| 54.3 (43.3-61.9) | 21.3 (6-33.7) | 14.2 (11.8-18.4) | 10.1 (4.3-22.4) |
| Grassland (%)  | 0.7 (0.2-1.7)  | 0.2 (0-0.5)  | 0.4 (0-0.7)    | 0.8 (0-2.5)    |
| Farmland (%)   | 24.7 (14.2-37) | 40.7 (22.3-49.1) | 23.5 (11.4-29.6) | 10.9 (0.9-19.2) |
| Water (%)      | 1.1 (0.5-1.7)  | 2.9 (1.6-4.5) | 2.7 (0.2-4.5)  | 0.7 (0.2-1.7)  |
| Unused land (%)| 0.9 (0.2-1.1)  | 0.6 (0.2-1.1) | 2.8 (1.7-4.1)  | 0.5 (0-0.6)    |

3.2. Water quality characteristics in the LJNA

One-way ANOVA showed that most water quality parameters except DO, ORP, turbidity, SS, COD and Chl-a were significantly different between land use groups. During both wet and dry seasons, FC, EC and nutrient (TP, SRP, TN and NH$_4^+$-N) concentrations in group III and IV were significantly higher than in group I and II ($p < 0.05$). However, seasonal changes in most water quality parameters were not recorded in this study.

FA was conducted to identify the pollution factors in the LJNA (table 2). With a KMO test result of 0.703 (> 0.5), and a significant result for the sphericity test ($p < 0.000$), FA was determined to be appropriate for the water quality data set. Five principal components with eigenvalues >1 were retained, explaining almost 82% of the total variance in the water quality data set in wet season. RC1 accounted for 40.9% of the variance, and had strong positive loadings on TP, SRP, TN, NH$_4^+$-N and FC and moderately positive loadings on COD and EC. This factor mainly pointed to high nutrient loadings and fecal contamination in the rivers. Scores for RC1 were significantly higher in group III and IV than in group I and II ($p < 0.05$). This result supported previous studies indicating the positive relationship between urban land cover and nutrient concentrations and bacteria densities [15,16].

RC2 explained 12% of the variance, and had strong negative loadings on pH and DO. Past studies suggested that the factors containing DO and pH with negative loadings indicate the presence of anaerobic conditions in the river [17]. Moreover, the negative loadings for DO and pH were attributed to the anaerobic fermentation of organic matter, which produced organic acids and resulted in possible depletion of oxygen in water [18].

RC3 consisted of SS and turbidity with strong positive loadings, accounting for 11.5% of the variance. This factor was related to land use conversions, exceptional rainfall events, and modification of soil erosion, transport, and deposition over watershed [19]. In LJNA, the construction activities and agricultural cultivations were the important sources increasing sediment supply. Scores for RC3 were positive in group II and III but negative in group I and IV (figure 5), which indicated most of the sediment export occurred in subcatchments affected by both farmland and urban land.

RC4, which explained 9% of the variance, is positively contributed by NO$_3^-$ and Chl-a. This factor pointed to the eutrophication effects in the river. Moreover, the positive correlations of this factor with Chl-a and NO$_3^-$ suggested that NO$_3^-$ facilitated phytoplankton growth. Scores for RC4 were positive in group IV and significantly higher than in other groups (figure 5), which suggested high risk of eutrophication for rivers in urbanized catchment.

RC5 explained 8.3% of the variance, and showed strong negative correlation with ORP. This factor indicated the oxygen consumption in the river, and was related to the release of phosphorus from benthic sediments (Li et al., 2016). Scores for RC5 show no significant difference between different land use groups (Figure 5), which indicated the oxygen depletion was a common problem for rivers in LJNA.
Table 2. Loadings of water quality parameters on five rotated components for datasets.

| Wet season  | RC1      | RC2      | RC3      | RC4      | RC5      |
|-------------|----------|----------|----------|----------|----------|
| TP          | 0.909    | 0.150    | 0.120    | 0.126    | 0.106    |
| SRP         | 0.924    | -0.033   | -0.050   | -0.005   | -0.075   |
| SS          | 0.007    | 0.002    |          | 0.865    | 0.141    |
| TN          | 0.870    | 0.169    | -0.091   | 0.353    | 0.061    |
| AN          | 0.938    | 0.230    | -0.034   | -0.123   | 0.032    |
| COD         | 0.585    | 0.508    | 0.053    | -0.037   | 0.200    |
| NO3-        | 0.178    | -0.059   | 0.124    |          | 0.868    |
| NO2-        | 0.529    | 0.396    | -0.241   | 0.161    | 0.564    |
| DO          | -0.487   | -0.719   | -0.059   | -0.210   | -0.015   |
| pH          | 0.038    | -0.919   | -0.087   | 0.025    | 0.067    |
| EC          | 0.594    | 0.291    | 0.131    | 0.401    | 0.042    |
| ORP         | -0.014   | 0.058    | -0.049   | -0.042   |          |
| Turbidity   | 0.028    | 0.101    | 0.893    | -0.068   | 0.270    |
| Chl-a       | 0.054    | 0.489    | -0.177   | 0.629    | 0.208    |
| FC          | 0.741    | -0.206   | 0.048    | 0.362    | 0.103    |
| Eigenvalue  | 6.149    | 1.798    | 1.732    | 1.345    | 1.251    |
| % variance  | 40.992   | 11.989   | 11.546   | 8.969    | 8.342    |
| %Cumulative variance | 40.922   | 52.980   | 64.527   | 73.496   | 81.838   |

3.3. Relationships between land use and principal components

Table 3 shows the results of correlation analysis between land use types and scores principal components in LJNA. From Table 3, we found that scores of RC1 were positively correlated with the proportions of urban land and unused land \((p < 0.01 \text{ or } p < 0.05)\), but negatively related to farmland and forest land \((p < 0.05)\). This result suggested that the urban and unused land areas were the primary contributors to the increased nutrient loadings and fecal pollutions in LJNA. The negative relationships between farmland cover and RC1 contradicted the widespread idea that agricultural land use had negative effects on nutrient parameters and microbiological contaminants [2,5]. On the background of rapid urbanization in the LJNA, large quantities of farmland were requisitioned for real estate and infrastructure development.

Table 3. Pearson’s correlation coefficients between land use types and rotated components.

| Farmland | Unused land | Forest land | Grassland | Urban land | Rural land | Waters |
|----------|-------------|-------------|-----------|------------|------------|--------|
| RC1      | -0.313a     | 0.402a      | -0.373a   | 0.256      | 0.433a     | -0.125 | -0.002 |
| RC2      | 0.135       | -0.126      | -0.198    | -0.176     | 0.438b     | 0.342a | 0.246 |
| RC3      | 0.194       | 0.011       | -0.082    | -0.237     | -0.050     | 0.223  | 0.263 |
| RC4      | -0.313a     | -0.347b     | -0.321b   | -0.115     | 0.407b     | -0.265 | -0.238 |
| RC5      | -0.215      | -0.121      | 0.003     | -0.287     | 0.107      | -0.049 | -0.013 |

\(^a p < 0.05 \text{ (2 – tailed).} \)

\(^b p < 0.01 \text{ (2 – tailed).} \)

RC2 showed significantly positive correlations with the proportions of urban and rural land uses. Since RC2 indicated anaerobic conditions in the rivers, urban land and rural land were related to the input of organic matters, which leads to decreased pH and DO due to anaerobic fermentation. Numerous studies have reported the positive contributions of urban land use to organic compounds in the river water [2,5].

RC3 indicated the effects of soil erosion, and was not significantly correlated with any land use types. Moreover, scores of RC3 were not significantly different among land use groups. Thus, although human activities on land use changes might influence catchment soil erosion, these changes could not determine the sediment input into rivers.
RC4 was positively correlated with the proportion of urban land cover, indicating positive relationship between urban land use and the risk of eutrophication in the river. On one hand, the elevated nutrients and light levels in urban stream typically favor greater algal biomass [15]. On the other hand, urban areas are generally centralized in relatively flat ground and associated with low river velocity, which benefits the development of plankton assemblages[4].

RC5 was related to oxygen consumption, and displayed no significant relationships with any land use types. Although scores of RC5 were not significantly different among land use groups, we noticed that the values of ORP were significantly different between wet and dry seasons. Thus, seasonal variation might be the key factor influencing river oxygen consumption by changing water temperature and input of organic wastes from non-point sources.

5. Conclusion
In this study, we employed the FA approach to identify pollution factors governing water quality variability in LJNA. We found that nutrients pollutions, anaerobic conditions, soil erosion, effects of eutrophication and oxygen consumption were five key environmental problems faced by rivers. Moreover, the analysis of principal component scores suggested that the magnitudes of pollution factors were various in different land use groups. Urban land use showed a significantly positive relationship with pollution factors, whereas forest land and farmland displayed opposite effects. Thus, the river water quality in LJNA was mainly contaminated by possible pollution sources distributed in urban land areas..

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