



New insight into the correlations between land use and water quality in a coastal watershed of China: Does point source pollution weaken it?



Pei Zhou^{a,b}, Jinliang Huang^{a,b,*}, Robert Gilmore Pontius Jr^c, Huasheng Hong^{a,b}

^a Coastal and Ocean Management Institute, Xiamen University, Xiamen 361102, China

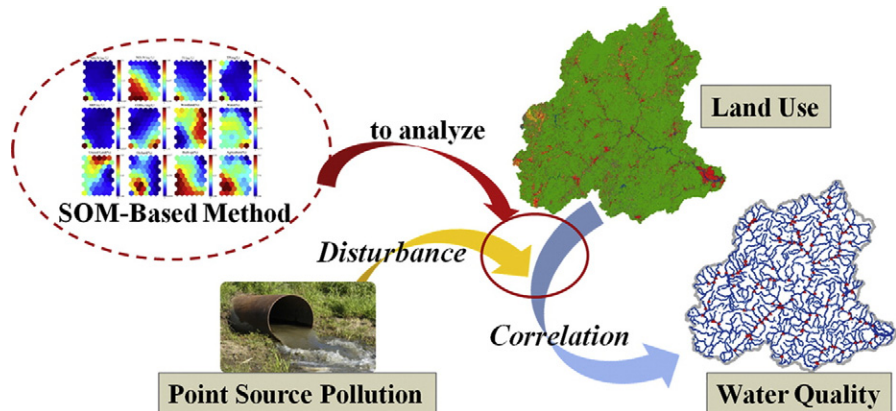
^b Fujian Provincial Key Laboratory of Coastal Ecology and Environmental Studies, Xiamen University, Xiamen 361102, China

^c Graduate School of Geography, Clark University, Worcester, MA 01610, USA

HIGHLIGHTS

- We develop a self-organizing map-based approach.
- Different patterns of water quality are delineated and visualized across watershed.
- Spatial variation of the land use–water quality correlation is analyzed.
- Point source pollution can weaken or hide the land use–water quality correlation.

GRAPHICAL ABSTRACT



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ABSTRACT

Uncovering the associations between land use and river water quality is useful for managing land-based pollution in the catchment–coast continuum. However, it is not clear how land use affects water quality in the context of simultaneous point source (PS) pollution. In this study, we develop a self-organizing map (SOM)-based approach to explore the relationship between land use and water quality in the Minjiang River Watershed, Southeast China. Water samples from 139 headwater sub-watersheds were associated with six land use categories, namely, Woodland, Agriculture, Orchard, Built-up, Unused land and Water. Sampling sites are delineated into six clusters based on six water quality parameters: ammonium-N, nitrate-N, total nitrogen, soluble reactive phosphate, total phosphate and potassium permanganate index. Local relationships between land use and water quality among four clusters that have sufficient sample sizes are further identified. There is no significant land use–water quality correlation in one of the four clusters (including 37 sub-watersheds). And the greater the PS pollution is, the less significant the land use–water quality correlations are in clusters. The results demonstrate how PS pollution weakens the land use–water quality correlation. Our method can help to determine whether non-point source or PS pollution exerts greater influence on the quality of the water coming from watershed.

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* Corresponding author.

E-mail address: jluang@xmu.edu.cn (J. Huang).

1. Introduction

Land use within a watershed has important effects on water quality of rivers, lakes, estuarine and coastal waters (Huang et al., 2013a, Bu et al., 2014, Hur et al., 2014). Watershed land use affects water quality through non-point source (NPS) pollutants, which are major contributors of contaminants to the catchment-coast continuum (Swaney et al., 2012). As the Secretary-General of the United Nations reported, land-based sources of pollution contribute to more than 80% of the pollutants entering the seas (UN General Assembly, 2004). *Water Quality and Sustainable Practices on Land* is included in the nine priority objectives for a national ocean policy articulated by the US National Ocean Council, in order to enhance water quality by promoting and implementing sustainable practices on land (US National Ocean Council, 2010). Therefore, exploring the linkage between land use and surface water quality, particularly in coastal watersheds, is critical for developing watershed management practices (Uuemaa et al., 2005, Xiao and Ji, 2007, Wan et al., 2014) and controlling land based pollution in coastal bays (Huang et al., 2013a).

Many statistical methods have been widely employed to reveal the relationships between land use and water quality (Céréghino and Park, 2009, Bierman et al., 2011, Huang et al., 2013b), such as correlation analysis (Lee et al., 2009, Bu et al., 2014, Li et al., 2015), multiple regression (Huang et al., 2013b, Bu et al., 2014, Park et al., 2014), and redundancy analysis (Maarten et al., 2008, Shen et al., 2015). Researchers usually apply these methods to analyze the overall relationship between land use and water quality for the entire study area (Huang et al., 2013b, Bu et al., 2014). Nevertheless, the pollution sources might vary across the study area, especially among watersheds that are dominated by various uses (Baker, 2003), therefore the global approach to use the abovementioned statistics might miss the spatial variation of the relationships and hide some local relationships between land use and water quality (Kang et al., 2010). Recently, geographically weighted regression (GWR) has been used to capture spatial variations by incorporating spatial coordinates into the regression model (Tu and Xia, 2008, Tu, 2011). GWR frequently uses only one land use indicator as the independent variable to analyze the indicator's association with each water quality dependent variable. When dealing with multivariate data, a large number of GWR models are performed to account for the large number of land use categories and water quality variables. Therefore, GWR is of limited value to make land use management strategies because of the excessive detailed spatial variation in the results. How should we process multivariate environmental data to make appropriate management strategies while considering the spatial variation? A plausible way is to cluster sites with similar characteristics and then to analyze the land use-water relationships in each cluster (Martin et al., 2011). By use of clusters, we can reveal land use-water quality patterns that global statistics may hide (Löhr et al., 2010, Choi et al., 2014) and thus simplify land use management. What's more, researchers seldom consider the influence from point source (PS) pollution on land use-water quality relationships. PS pollution is not proportional with the land use area. A small area with intensive industrial or domestic discharge can generate severe PS pollution. Therefore, PS pollution might cause huge uncertainty concerning the linkage between land use and water quality.

A self-organizing map (SOM) is a branch algorithm that uses an artificial neural network. A SOM is a versatile tool for the classification and association of samples and their variables (Vesanto et al., 2000, Compin and Céréghino, 2007, Bierman et al., 2011, Li et al., 2012, Kohonen, 2001, Kohonen, 2013). SOMs have become popular in environmental studies because SOMs can deal with nonlinearities (Kalteh et al., 2008, Jeong et al., 2010, Kohonen, 2013). Kalteh et al. (2008) and Céréghino and Park (2009) reviewed applications of SOMs to environmental science, especially regarding water resources classification. Chon (2011) reviewed the applications of the SOM techniques in ecological sciences.

Our previous studies used multiple linear regression and GWR to detect the global and local variations in relationships between land use and water quality in a coastal watershed (Huang et al., 2013b, Huang et al., 2015). However, we need more attempts to know how land use affects water quality in the presence of PS pollution. In this study, we develop a framework that integrates SOM, cluster analysis, backward stepwise regression and correlation analysis, to explore the river water quality variation and its relationship with land use at 139 sampling sites across the Minjiang River Watershed. We hypothesize that severe PS pollution might weaken the correlation between land use and water quality. We suspect that exclusion of the water quality data that are influenced by PS pollution will result in a stronger correlation between land use and water quality. Specifically, we aim (1) to delineate the pattern of water quality variation among 139 headwater sub-watersheds, (2) to explain the roles of NPS pollution from land use and PS pollution in controlling each water quality pattern, and (3) to reveal the spatial variation of the land use-water quality correlation and the influence of PS pollution on the correlation.

2. Materials and methods

2.1. Study area

The Minjiang River Watershed covers 60,992 km² and is the largest watershed in Fujian Province, China (116°23'–119°43' E, 25°23'–28°19' N) (Fig. 1). The watershed is in a subtropical zone with a monsoon climate: the annual average temperature is 16–20 °C and annual average precipitation is 1617 mm, of which 70% occurs between April and September (Chen et al., 2011).

The study area mainly consists of three cities: Sanming, Nanping and Fuzhou (Fig. 1). More than 12 million residents use the Minjiang River as their source of water for residential, industrial and agricultural activities. The watershed's gross domestic product accounts for more than thirty percent of Fujian Province's economic output. Population in the watershed accounts for about thirty five percent of Fujian Province. Sanming City is in the western part of the study area, which is the most important industrial base for raw material in Fujian Province. Industry in Sanming City mainly is in Yong'an and Sanming and Shaxian Counties. Sanming City is also the main agricultural production base for Fujian Province. Jian'ou County is famous for its lotus, pear and rice. Ninghua County is famous for its agricultural production, especially rice. Taining County is developing ecotourism recently. Nanping City located in the central part of the study area, which is one of the main forest areas in the south of China. It is the main bread basket and provides about one third grain for Fujian Province. Recently poultry production is developing in Nanping City. Fuzhou City is the capital of Fujian Province, and is located the downstream end of the study area. Pollution from residential land and poultry production accounts for the major contaminants in Fuzhou City.

According to Fujian Statistical Yearbook (Fujian Statistical Bureau, 2014), industrial water consumption of Fuzhou, Sanming and Nanping Cities in 2013 are 523, 1627, 224 million tons (Fig. 2A). Treated industrial waste water accounts for 34%, 36% and 35% of the water consumption. The chemical oxygen demand in treated waste water decreases by 94%, 86% and 85% from the untreated industrial waste water. The ammonia removal rate is 84%, 64% and 90% in industrial waste water treatment facilities. In terms of the sewage, the volume of treated wastewater in Fuzhou, Sanming, Yong'an, Nanping, Shaowu, Wuyishan, Jian'ou and Jiansyang Counties are 214.7, 39.4, 24.4, 17.5, 6.3, 5.2, 4.6 and 4.9 million m³. Treated sewage accounts for 86%, 85%, 86%, 89%, 88%, 86%, 67% and 86% of the total sewage discharge (Fig. 2B). However, according to Chinese *Environment quality standard for surface water* (GB 3838-2002) (Ministry of Environmental Protection of the People's Republic of China, 2002), the treated waste water still does not meet standards for drinking water. Furthermore, the concentrations of some pollutants discharged from waste water treatment facilities exceed the highest

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