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Exploring spatially varying and scale-dependent relationships between soil contamination and landscape patterns using geographically weighted regression

Cheng Li [a], Fangbai Li [a], Zhifeng Wu [b], Jiong Cheng [a, *]

[a] Guangdong Key Laboratory of Integrated Agro-environmental Pollution Control and Management, Guangdong Institute of Eco-Environmental Science and Technology, Guangzhou, 510650, China

[b] School of Geographical Sciences, Guangzhou University, Guangzhou, 510006, China

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ABSTRACT

Landscape pattern is an important determinant of soil contamination at multiple scales, and a proper understanding of their relationship is essential for alleviating soil contamination and making decisions for land planners. Both soil contamination and landscape patterns are heterogeneous across spaces and scale-dependent, but most studies were carried out on a single scale and used the conventional multivariate analyses (e.g. correlation analysis, ordinary least squared regression-OLS) that ignored the issue of spatial autocorrelation. To move forward, this paper examined spatially varying relationships between agricultural soil trace metal contamination and landscape patterns at three block scales (i.e. 5 km × 5 km, 10 km × 10 km, 15 km × 15 km) in the Pearl River Delta (PRD), south China, using geographically weighted regression (GWR). This paper found that GWR performed better than OLS in terms of increasing R square of the model, lowering Akaike Information Criterion values and reducing spatial autocorrelation. GWR results revealed great spatial variations in the relationships across scales, with an increasing explanatory power of the model from small to large block scales. Despite a few negative correlations, more positive correlations were found between soil contamination and different aspects of landscape patterns of water, urban land and the whole landscape (i.e. the proportion, mean patch area, the degree of landscape fragmentation, landscape-level structural complexity, aggregation/connectivity, road density and river density). Similarly, more negative correlations were found between soil contamination and landscape patterns of forest and the distance to the river and industry land ($p < 0.05$). Furthermore, most significant correlations between soil contamination and landscape variables occurred in the western PRD across scales, which could be explained by the prevailing wind, the distribution of pollutant sources and the pathway of trace metal inputs.

1. Introduction

With China's rapid industrialization, urbanization and agricultural intensification in recent decades, trace metal contaminants have been widely found in different types of land uses especially in farmland and caused a lot of public concern (Ministry of Environmental Protection and Ministry of Land and Resource, 2014). For instance, in one of the most densely populated and economically developed regions in China, the Pearl River Delta, 43.4% of 350 soil samples were contaminated with trace metals especially for Ni (20.9%), Hg (18.6%) and Cd (18.3%), threatening agricultural safety and human health (Yang, Zhang, Wan, Luo, & Gao, 2007). How to manage the land to prevent and control soil contamination has become a major problem faced by the government for sustainable agricultural development.

Under the disturbances of natural and intensive human activities, soil contamination is extremely complex and is featured with point and non-point source pollution (Wuana & Okieimen, 2011). Solid particles or sediments containing trace metals in the water and smoke released from factories and automobiles were eventually deposited to soils from several to hundreds of kilometers from the pollutant source by wind and water flow. Landscape can be considered as a mosaic of different types of land uses or covers. The

* Corresponding author.
E-mail addresses: licheng1210@126.com (C. Li), cefbli@soil.gd.cn (F. Li), gzuwzf@163.com (Z. Wu), CJsoil@126.com (J. Cheng).

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diffusion and deposition of trace metals into the soil was influenced by the composition and configuration of landscape (i.e. landscape pattern) across spatial scales from sample site, sample plot, ecosystem, and watershed to region. Previous studies found that landscape patterns, including different land use types (Fritsch et al., 2011, 2010; Schwarz et al., 2012), land use change (Wu et al., 2013), and the number, density and proximity of industrial plants, rivers and roads (Chrastny, Komarek, & Hajek, 2010; Ding, Cheng, Wang, & Zhuang, 2017; Gu et al., 2012; Shen et al., 2017), and the dominance, shape complexity and diversity of land uses (Lin, Teng, & Chang, 2002), had close associations with soil contamination at multiple scales. The problem, however, is that conventional multivariate analyses used in previous studies, such as the ordinary least square regression(OLS), principal component analysis and correlation analysis, assumed the independence of variables and unchanged relationships between variables across space, which might bias the estimate of parameters, causing misleading conclusions and ineffective interventions (Black, 2014; Foody, 2003; Li, Zhao, Xie, & Wang, 2010). In fact, both soil contamination and landscape patterns are related to locations and heterogeneous over space (Rodriguez, Nanos, Grau, Gil, & Lopez-Arias, 2008; Wu, Dennis, Luck, & Tueller, 2000). The general statistical analyses are likely to mask spatial relationships due to the ignorance of spatial heterogeneity (Su, Xiao, & Zhang, 2012; Tutmez, Kaymak, & Tercan, 2012). As pointed by Guo, Ma, and Zhang (2008), "ignoring spatial heterogeneity causes biased parameter estimates, misleading significance tests and suboptimal predictions". In light of this, it seemed more appropriate for local spatial regression approaches, such as geographically weighted regression (GWR), to capture the spatially varying relationships.

GWR was first proposed by Brunsdon, Fotheringham, and Charlton (1996) and Fotheringham, Charlton, and Brunsdon (1998), which was similar to OLS but included the spatial coordinates of the explanatory variable and weighted the slope parameter by a distance-adjusted kernel function during the regression analysis (Su et al., 2012). It can output a set of spatially explicit coefficients or indicators with site-specific information, providing appropriate descriptions and predictions of the geographical interactions (Foody, 2003; Su et al., 2012). Although GWR has limitations in addressing spatial error dependence and might generate spurious spatial patterns and extreme regression coefficients(Cho, Lambert, & Chen, 2010), it has advantages in exploring spatial relationships and has been extensively applied in many fields, such as plant ecology (Chen et al., 2016; Zhao, Gao, Wang, Liu, & Li, 2015), molecular ecology (Felizola Diniz-Filho, Soares, & de Campos Telles, 2016), environmental science (Czarnota, Wheeler, & Gennings, 2015) and social science (Ansong, Ansong, Ampomah, & Adjabeng, 2015; Chi, Grigsby-Toussaint, Bradford, & Choi, 2013; Goovaerts et al., 2015; Su, Lei, Li, Pi, & Cai, 2017). In addition, with regard to the scale-dependent characteristics of soil trace metal contents (Lowicki, 2012; Lv, Liu, Zhang, & Dai, 2013, 2014; Nanos & Rodriguez Martin, 2012), landscape patterns (Wu, 2004) as well as their relationships (Li, Li, Wu, & Cheng, 2015), multi-scale approach is needed which was usually ignored in previous studies.

To move forward, this study used GWR to explore the spatially varying relationships between soil contamination and landscape patterns at multiple scales, with a case study of the Pearl River Delta region in China featured with rapid industrialization, intensive agriculture and extensive soil contamination. Specifically, we proposed two research questions: (1) What is the spatial non-stationary relationship between landscape patterns and soil trace metal contamination in agricultural top soils in the Pearl River Delta, and (2) how the relationships varied across geographical areas and spatial scales?

2. Materials and methods

2.1. Study area

The Pearl River Delta (PRD) is located in the south central part of Guangdong Province in southern China (112-116°E, 21-24°N) (Fig. 1). It covers about 41,200 km^2 and has a southern subtropical monsoon climate with an annual mean temperature and precipitation of 22 °C and 1900 mm, respectively. The PRD region is an alluvial plain receiving the sediment and effluents from three rivers of Xijiang, Beijiang and Dongjiang, which is dominated by three major parent materials of the alluvial deposits, granite and sand-shales. This plain includes nine prefectural cities (Guangzhou-GZ, Shenzhen-SZ, Zhuhai-ZH, Foshan-FS, Jiangmen-JM, Dongguan-DG, Zhongshan-ZS, Huizhou-HZ and Zhaoqing-ZQ). It is one of the most densely populated (~33million) and economically developed (GDP: ~30 billion US dollars in 2005) regions in China (National Bureau of statistics, 2006).

2.2. Assessment of soil contamination with trace metals

The concentration data of four trace metals (i.e. As, Cd, Cr and Pb) for 1384 agricultural top soils (0–20 cm) in the PRD region from April 2002 to December 2005 was acquired from Guangdong Institute of Eco-environmental Science and Technology (Fig. 1). These soil samples were collected in farmland (1181; 928 in vegetable field, 233 in paddy field and 20 in dry land), orchard (186) and forest land (17), respectively, putting sampling priorities on heavily polluted soils where food security was seriously threatened. The methods of hydride generation atomic fluorescence spectrophotometry (As), graphite furnace atomic absorption spectrophotometry (Cd) and flame atomic absorption spectrophotometry (Cr, Pb) were used to measure the concentrations of the four trace metals (Cai et al., 2012; Ma, Pan, Wan, Xia, & Luo, 2004; Xia, Wan, Yang, Ma, & Luo, 2004). For soil sampling and chemical analyses of the trace metals, see details in Li et al. (2015).

The single-factor contamination index (i.e. geo-accumulation index, I_{geo}) was calculated according to Eq. (1), which represented soil contamination level of trace metals (Tang, Ma, Zhang, & Mao, 2013):

$$I_{geo} = \log_2(C_i/1.5B_i) \tag{1}$$

where C_i and B_i refer to the measured and background concentrations of trace metals in the surface soils of agricultural land (CNEMC-China Environmental Monitoring Center, 1990).

The comprehensive contamination index (P_{nm}) was calculated as a modified Nemerow synthetic pollution index based on the geo-accumulation index (I_{geo}) as follows:

$$P_{nm} = \mathrm{power}\left(\left(I^2_{geo_{max}} + I^2_{geo_{ave}}\right)\Big/2, 0.5\right) \tag{2}$$

where $I_{geo\ max}$ and $I_{geo\ ave}$ refer to the maximum and average contamination levels of the four trace metals in the surface soil of agricultural land.

2.3. Land use data and landscape metrics

A land use and cover map of 2005 (1:100,000) with high quality (the overall accuracy >90%) was acquired from Guangdong Academy of Sciences, Guangzhou, China. The land use and cover types were initially classified into 38 subclasses and then six categories for the purpose of our study: (1) Forest, (2) Water, (3) Farmland, (4) Urban land, (5) Orchard and (6) Others (Fig. 1). The original vector