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ORIGINAL PAPER

The association between heavy metal soil pollution and stomach cancer: a case study in Hangzhou City, China

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Abstract Stomach cancer (SC) is a severe health burden, with nearly half of the world's cases found in China. Noticeably, the emissions of heavy metals into the environment have increased alongside rapid urbanization and industrialization in China. However, as regards carcinogenic associations, the relationship between heavy metals and SC is yet unclear. Based on 9378 newly diagnosed SC cases in Hangzhou City from 2009 to 2012, this work is concerned with the quantitative characterization of the spatial distribution pattern of SC incidence and its geographical association with soil heavy metals by means of a novel geographical model. The results show that (a) Cd is one of the severe soil pollutants in Hangzhou; (b) higher SC incidence clusters are in central Hangzhou, whereas lower clusters are found in the northeast and southwest with a male to female incidence ratio about 2.2:1; (c) although when considered separately, the heavy metals in this work do not have a considerable impact on the distribution of SC incidence in Hangzhou City, nevertheless, the joint effects of multiple heavy metals have significant impacts on SC risk. The present work calls for a rigorous quantitative assessment of the integrated heavy metal soil pollution and its effects on SC incidence.

Keywords Stomach cancer · Heavy metal · Spatial distribution · GeoDetector

Introduction

Stomach cancer (SC) incidence and mortality rates provide quantitative estimates of how common the disease is within a population during a specified time period and are routinely used by health providers and government agencies. Although the SC incidence and mortality have decreased slowly over recent decades, it is still the fifth most common cancer and the third leading cause of cancer mortality in the world. In 2012, it is estimated that there are about 951,000 new

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SC cases (631,000 males and 320,000 females) worldwide with an age-standardized incidence of about 12.1/100,000 individuals (i.e., 17.4/100,000 for males and 7.5/100,000 for females), which accounts for 6.8% of the total number of new cancer cases, and about 723,000 new SC deaths (469,000 males and 254,000 females) with an estimated mortality of about 8.9/100,000 (i.e., 12.8/100,000 for males and 7.2/100,000 for females) accounted for 8.8% of the total number of new cancer deaths (Ferlay et al. 2015). East Asia, especially China, is the most SC-burdened region, with almost 50% of new cases occurring in this region. Here, the estimated age-standardized incidence is 35.4/100,000 and 13.8/100,000 for males and females, respectively. According to Chinese cancer statistics published in 2017, SC is the second and fourth most common cancer among males and females, respectively, with an age-standardized incidence of 30.58/100,000 and 12.35/100,000, respectively (Chen et al. 2017). According to 2015 cancer prediction studies for China, the number of estimated new SC cases is about 679,100 (477,700 males and 201,400 females) and the number of estimated new SC deaths is about 498,000 (339,300 males and 158,700 females) (Chen et al. 2016). Therefore, it is widely acknowledged that SC is an important public health issue in China (Wang et al. 2009).

Numerous studies have investigated potential SC risk factors. By far, the best-established risk factor is Helicobacter pylori infection (Sitas 2016). Other well-established SC risk factors include male sex, family SC history, and smoking (Brenner et al. 2009). Given the currently limited potential for exposure assessment and confounding factors control, further researches are needed to determine in a rigorous manner other factors that are likely to be related to SC risk, including salt and salted food intake (Wang et al. 2009), intake of fruits and vegetables (Brenner et al. 2009), nitrate and nitrite ingestion (Bryan et al. 2012), green tea consumption—either beneficial or detrimental (Myung et al. 2009; Huang et al. 2017), alcohol intake (Crew and Neugut 2006), as well as household environment and socioeconomic status (Matthews 1990), and occupation exposure to various types of dust (Krstev et al. 2005). Among all SC risk factors, heavy metals, such as Cd, Cr, As, Pb, and Hg, are classified as certain/probable carcinogens by the International Agency for Research on Cancer indicating that exposure may increase SC risk (Yuan et al. 2016). Following rapid economic development and urbanization in China, the emissions of heavy metals into the environment are increasing, implying that more attention should be paid to heavy metals contamination and its impact on human health (Zhao et al. 2014).

Due to the uneven distributions of environmental exposure, lifestyle, socioeconomic status, and genetic risk factors, SC incidence exhibits a significant heterogeneous spatial variation with a higher than ten times difference between low- and high-risk areas (Wang et al. 2009). Studying the geographical distribution of SC could lead to a better understanding of the disease and identify high/low-risk areas with the resulting risk factors, thus providing an important reference for cancer pathology exploration, cancer prevention and control, and the allocation of public health resources (López-Abente et al. 2018; Rapant et al. 2014).

Based on combined SC surveillance records and heavy metal contamination found in farmland topsoil data, the goal of the present study is twofold: (*a*) reveal the spatial distribution pattern of SC incidence in Hangzhou City during the period 2009–2012 and (*b*) determine whether SC incidence's geographical variation could be explained by the spatial variation of exposure to heavy metal soil pollution.

Materials and methods

Data sources

Patient records are anonymized by the Cancer Registry Center prior to analysis. Totally, 9378 newly diagnosed SC cases (International Classification of Disease: ICD-10: C16) during 2009–2012 were obtained from the Hangzhou Center for Disease Control and Prevention (CDC). Since 2009, all new cancer cases in Hangzhou were registered and managed with CanReg4 software, as recommended by the International Association of Cancer Registries (IACR), whereas the completeness and reliability of the cancer data were checked and evaluated by the Chinese National Cancer Center. During the 4 years mentioned above, the 9378 SC cases have been recorded according to the patients' detailed residential information. All cases were allocated to specific townships (200 townships in total). The 2010 population data at the township level (about 6.78 million records) were obtained from the Hangzhou Public Security Bureau (PSB) to calculate SC incidence: The total number of cases was divided by the corresponding population and adjusted by means of an indirect method (Estève, et al. 1994). This method incorporated the most recent SC incidence of each age category in China as a reference, which is available by the Chinese National Cancer Center (Hao and Chen 2012). When calculating the 4-year average incidence, the total population for each township was estimated by multiplying their 2010 population by four.

Soil heavy metal samples were collected and analyzed by the Zhejiang Provincial Department of Agriculture. Specifically, a total of 2150 surface soil samples (0–15 cm) were randomly collected from the study area in 2012. All the in situ samples were from rice, fruit, vegetable, and tea farmlands. Five subsamples within 1 km radius of the primary sampling point were collected and mixed thoroughly to get a representative sample. Sampling sites were recorded by a Global Positioning System (GPS), and the location of the sampling sites is shown in Fig. 1a. All soil samples were air-dried at room temperature and then ground to 100 meshes for chemical analysis. To determine the Cr, Pb, Cd, and As concentrations, soil samples were digested with a mixture of nitric acid (HNO_3) and perchloric acid ($HClO_4$), and the concentrations were determined by plasma mass spectrometry (ICP-MS, TMO, USA) (Yang et al. 2017). For Hg determination, soil samples were digested with a mixture of nitric acid (HNO_3) and hydrogen peroxide (H_2O_2) in a microwave-accelerated reaction system, and the concentration was determined through atomic fluorescence spectrometry (Qiao et al. 2011). Blind duplicates and standard reference materials (GSS-3, China National Center for Standard Materials) were used for quality assurance and control (Hu et al. 2017). Standard sample recovery ranged between 90 and 110%, and the relative standard deviations of duplicate samples were between 3 and 8%. Finally, the spatial distributions of heavy metals were estimated in terms of the ordinary kriging technique based on point data (Christakos 1992; Olea 2006; Christakos 2017).

Statistical analysis

Since geo-referenced data are becoming more accessible, the incorporation of geographical location makes it possible to construct SC incidence maps that can be used to test the existence of significant spatial variation in SC incidence values. Moran's I test was employed in this work to assess the global distribution pattern of SC incidence (e.g., if there is significant

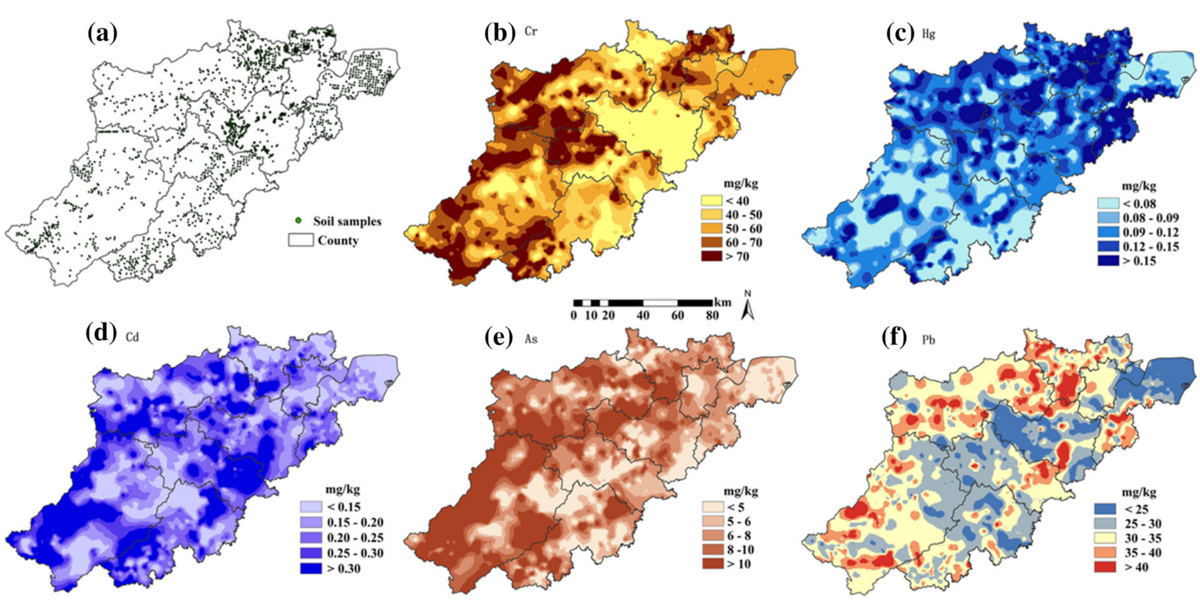

Fig. 1 Locations of sampling points (**a**) and the distribution of soil heavy metals (**b–f**) in Hangzhou, China

evidence that there exists a spatial variation pattern in SC incidence). Moran's I value is calculated as:

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}, \quad (1)$$

where z_i and z_j are the differences between local SC incidences (at locations i and j, respectively) and the overall mean incidence, n is the number of data, $w_{i,j}$ is the spatial weight between positions i and j, and W is the sum of spatial weights calculated as follows:

$$W = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}. \quad (2)$$

The Moran I values fall between − 1.0 and + 1.0. Specifically, if the SC incidence tends to cluster spatially (i.e., high incidence levels occur near other high levels, and low incidence levels occur near other low levels), the Moran's I value will be positive; if high SC incidence levels occur near low levels, the Moran's I value will be negative (discrete distribution); and if incidence levels are randomly distributed, the Moran's I value will tend to zero (Epperson and Li 1996).

Hotspots analysis was implemented in this work to detect local clusters of SC incidence. The Z score and the corresponding p value are calculated at each location i as

$$Z = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{SW}, \quad (3)$$

where x_j is the incidence level at location j, $w_{i,j}$ is the spatial weight of neighbor i to j, n is the number of data, $\bar{X}$ is the overall mean incidence, and S and W are the correlation coefficients which are calculated by,

$$S = \sqrt{\frac{1}{n^2}\left[n \sum_{j=1}^{n} x_j^2 - \left(\sum_{j=1}^{n} x_j\right)^2\right]}, \quad (4)$$

$$W = \sqrt{\frac{1}{n-1}\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}. \quad (5)$$

A Z score less than − 2.58, or ranging from − 2.58 to − 1.96 indicates statistically significant low clusters in space at the 0.01 or the 0.05 level, respectively; a Z score greater than 2.58, or ranging from 2.58 to 1.96 indicates statistically significant high clusters at the 0.01 or the 0.05 level, respectively; and a Z score ranging from − 1.96 to 1.96 represents a random incidence distribution.

The GeoDetector (Wang and Hu 2012) was used to determine the spatial correlation between SC incidence and its risk factors (soil heavy metals). GeoDetector is a new spatial stratification statistical technique that has been successfully used in exploring risk factors in neural tube defects (Wang et al. 2010), soil fluoroquinolone residues (Li et al. 2013), and thyroid cancer studies (Fei et al. 2016). The basic assumption of GeoDetector is that if a risk factor has a significant impact on the response variable (e.g., SC incidence), their spatial distribution patterns should be similar. The flowchart of the GeoDetector technique is shown in Fig. 2. First, the SC incidence data (I layer) is converted to a grid form with Arcmap 9.3 software. Next, heavy metal (risk factors) layers (S, E, etc.) are classified into different subregions (s_1, s_2, s_3 and e_1, e_2, e_3) according to the following principle: Minimize the dispersion variance of heavy metals within the subregions and maximize the dispersion variance of the metals between the subregions. Afterward, the incidence layer I is overlaid with one heavy metal layer (e.g., S) at a time. The area of each subregion (s_1, s_2, s_3) and the corresponding SC incidence variance are calculated. Finally, the power of determinant (PD) was estimated as:

$$\mathrm{PD} = 1 - \frac{1}{AV} \sum_{i=1}^{N} A_i V_i, \quad (6)$$

where A is the total area of the study region, V is the overall incidence variance, A_i is the area of subregion i, and V_i is the incidence variance in subregion i. The PD value measures impact strength, where a value ranging from 0 to 1 represents the impact (from the weakest to the strongest) of the specified risk factor on SC incidence (Wang et al. 2010). Specifically, if the SC incidence (I) is completely controlled by the risk factor (S), the incidence variance in every subregion should be 0, thus, PD = 1, whereas if incidence (I) is totally uncorrelated with the risk factor (S), the PD = 0.

After calculating each risk factor's impact on SC incidence, the GeoDetector can also quantify the

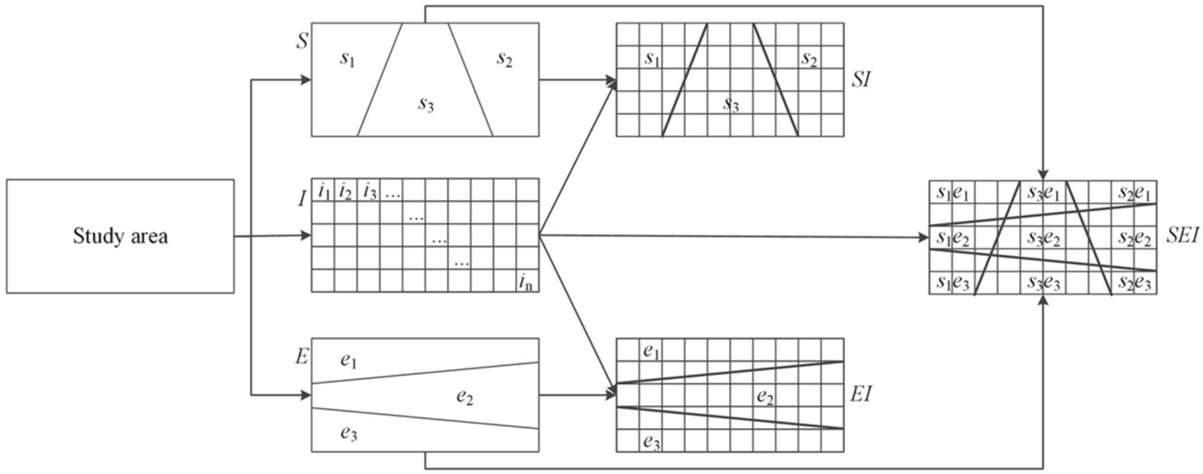

Fig. 2 Flowchart of GeoDetector

combined effect of two risk factors acting together. For instance, by overlaying risk factor layers *S* and *E* in Arcmap 9.3, a new layer *SE* is formed (Fig. 2). The attribute of layer *SE* is determined as the combination of the attributes of layers *S* and *E* (i.e., s_1e_1, s_1e_2, s_1e_3, s_2e_1, s_2e_2, s_2e_3, s_3e_1, s_3e_2, and s_3e_3). Based on the *PD* values of layers *S*, *E*, and *SE*, the GeoDetector can address the important issue of whether two factors acting together have a stronger or weaker effect on SC incidence than when they act separately (Li et al. 2013; Wang et al. 2010).

Results

Over the 4-year study period, 9378 patients were newly diagnosed with SC, which varied by gender and location (Table 1). The mean SC incidence for males (47.53/100,000) was about 2.2 times higher than that for females (21.51/100,000). The incidence varied greatly by township. For males, the highest incidence was observed in Jiangnan (107.89/100,000) and the lowest in Qianjin, which did not have a single SC diagnosis from 2009 to 2012. For females, the highest incidence was observed in Xinqiao (52.35/100,000), whereas there were no SC cases diagnosed in Qianjin, Linjiang, and Lishan.

The mean concentrations of Cr, Pb, Cd, Hg, and As were 52.90, 31.66, 0.27, 0.13, and 8.99 mg/kg, respectively (Table 2). The mean concentration of Cd was higher than the corresponding background value (0.20 mg/kg), which implied the existence of Cd pollution in Hangzhou soil. Heavy metals with relatively large Coefficients of Variation (CV) indicated that their spatial distributions were heterogeneous in the study region. According to their skewness and kurtosis coefficients and the K–S test values ($p < 0.05$), the distributions of the five heavy metals were not statistically normal. Therefore, a logarithmic

Table 1 Descriptive statistics for stomach cancer in Hangzhou, China, from 2009 to 2012

	Hangzhou		High cluster		Low cluster	
	Male	Female	Male	Female	Male	Female
Case	6468	2910	997	367	306	105
Incidence[a]	47.53	21.51	74.39	30.10	26.72	12.61
Maximum	107.89	52.35	107.89	52.35	45.74	23.08
Minimum	0	0	53.84	17.99	0	0

[a]Indirect age-standardized stomach cancer incidence (1/100,000)

Table 2 Descriptive statistics of heavy metal concentration (mg/kg)

Heavy metal	N	Min	Max	Median	Mean	SD	CV	Skewness	Kurtosis
Cr	2150	10.50	104.00	54.40	52.90	20.13	0.38	− 0.024	− 0.572
Pb	2150	17.00	62.60	30.90	31.66	8.75	0.38	0.720	0.454
Cd	2150	0.05	1.42	0.20	0.27	0.22	0.81	2.431	6.846
Hg	2150	0.03	0.50	0.11	0.13	0.08	0.62	1.602	3.073
As	2150	2.63	43.20	7.07	8.99	6.24	0.69	2.309	6.222

N is the number of samples, *SD* standard deviation, *CV* coefficient of variation

transformation was applied to the original dataset before kriging interpolation over the region of interest.

The spatial distributions of male and female SC incidence at the town level are represented by the maps of Fig. 3. For both genders, high incidence areas were located at the Hangzhou center, and low incidence areas in northeastern and southwestern Hangzhou. Considering the spatial heterogeneity of SC incidence at the township level, it is necessary to test whether the spatial SC pattern is statistically significant or not (otherwise said, to test whether a significant spatial correlation structure existed in the SC data). For this purpose, Moran's I test values were calculated, and the male and female SC incidences were found to be about 0.672 ($p < 0.01$) and 0.202 ($p < 0.01$), respectively, which indicated a statistically significant positive clustering of SC incidence. Hence, hotspots analysis was subsequently employed to determine where the significant local clusters were located.

We employed a hotspots analysis to determine where the statistically significant ($p < 0.05$) local clusters were located (Table 1; Fig. 4). For males, a significantly high cluster was located mainly in the eastern center area of Hangzhou (shown in red color), whereas significantly low clusters were located in northeastern and southwestern Hangzhou (shown in blue color). High clusters were detected in 24 towns and included 997 male SC cases with mean incidence about 74.39/100,000 (ranging from 53.84 to 107.89/100,000); low clusters were detected in 18 towns and included 306 male SC cases with mean incidence about 26.72/100,000 (ranging from 0.00 to 45.74/100,000). The cluster distributions of females were similar to those of males: Significantly high clusters were detected in 19 towns and included 367 female SC cases with mean incidence about 30.10/100,000 (ranging from 17.99 to 52.35/100,000), and significantly low clusters were detected in 18 towns and included 105 female SC cases with mean incidence about 12.61/100,000 (ranging from 0.00 to 23.08/100,000).

The spatial distributions of heavy metals estimated by kriging interpolation are shown in Fig. 1b–f. Heavy metals were extensively detected in the soil, and their distributions exhibited considerable spatial variations. High Hg concentrations were found mainly in northeastern Hangzhou, whereas high concentrations of Cr,

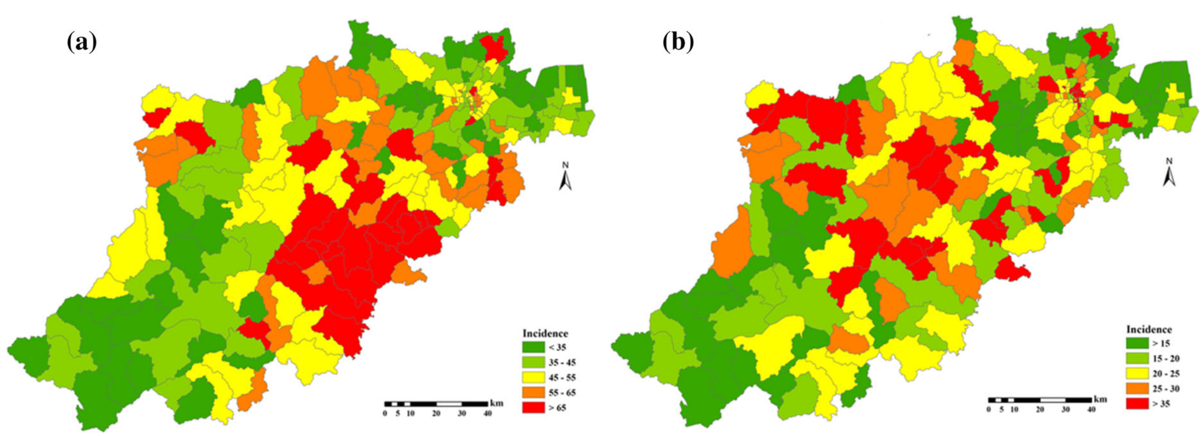

Fig. 3 Distribution of 4-year average male (**a**) and female (**b**) stomach cancer incidence (Hangzhou City, 2009–2012)

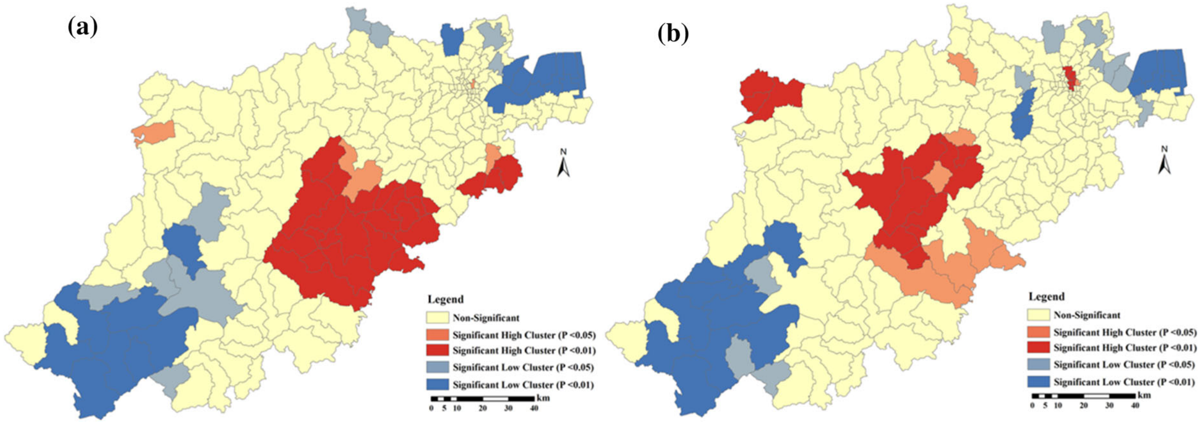

Fig. 4 Cluster maps of 4-year average male (**a**) and female (**b**) stomach cancer incidence (Hangzhou City, 2009–2012)

As, and Pb were located mainly in the west, and high Cd concentrations were found in west and east.

The effects (in terms of *PD* values) of the different heavy metals on SC incidence distribution across space are:

$$\mathrm{Cr}\,(0.097) > \mathrm{As}\,(0.044) > \mathrm{Cd}\,(0.040) > \mathrm{Hg}\,(0.019) > \mathrm{Pb}\,(0.009) \quad \text{for males;}$$

and

$$\mathrm{Cr}\,(0.031) > \mathrm{As}\,(0.028) > \mathrm{Hg}\,(0.028) > \mathrm{Pb}\,(0.013) > \mathrm{Cd}\,(0.008)$$

for females (Table 3). For both genders, each individual heavy metal had no statistically significant effect on SC incidence distribution ($p > 0.05$). Also, we observed no significant change of SC incidence with increasing heavy metal concentration. However, when considering the interaction effect, the joint effects of all heavy metal pairs showed a nonlinear enhancement effect. Overall, the *PD* value of a pair of interacting heavy metals is greater than the sum of their respective *PD* value. Especially for males, the joint effects of paired heavy metals Cr–Cd, Cr–As, Cd–As, and Cr–Pb exhibited statistically significant impact on the distribution of SC incidences ($p < 0.01$) (Table 4).

Table 3 Power of determinant (PD) values of heavy metal in soil on stomach cancer distribution

Gender	Cr	Pb	Cd	Hg	As
Male	0.097	0.009	0.040	0.019	0.044
Female	0.031	0.013	0.008	0.028	0.028

Table 4 Interaction power of determinant (PD) values of heavy metal in soil on stomach cancer distribution

Heavy metals	Male	Female
Cr ∩ Pb	0.159''	0.083
Cr ∩ Cd	0.182''	0.066
Cr ∩ Hg	0.136	0.079
Cr ∩ As	0.168''	0.079
Pb ∩ Cd	0.091	0.056
Pb ∩ Hg	0.060	0.085
Pb ∩ As	0.094	0.106
Cd ∩ Hg	0.075	0.053
Cd ∩ As	0.166''	0.062
Hg ∩ As	0.091	0.084

''Statistically significant at 0.01 level

Discussion

Cancer incidence distributions exhibit distinct patterns across geographical regions that are spatially heterogeneous due to the spatially uneven distribution of environmental risk factors (e.g., pollutants exposure, socioeconomic status, lifestyles, etc.). Rigorous studies of the geographical distribution of a disease can both improve our understanding of the disease and provide important information for risk assessment purposes. This study found a distinct SC incidence pattern in Hangzhou City characterized by significantly higher clusters in central Hangzhou City versus lower clusters in northeast and southwest during the period 2009–2012. By combining SC incidence data analysis with soil heavy metal data processing, this study found that no individual heavy metal demonstrated a statistically significant influence on the spatial distribution of SC incidence, whereas the joint effect of two heavy metals had a nonlinear enhancement phenomenon.

Unlike the national mean SC incidence level, Hangzhou had a slightly higher incidence rate than the national mean incidence and did not remain at a relative stable level (Chen et al. 2016, 2017). The Hangzhou male and female SC incidence decreased from 49.09 to 45.21/100,000 and from 22.44 to 20.78/100,000, respectively. Moreover, male SC incidence was about 2.2 times higher than female SC, which was consistent with the findings of previous studies (Malekzadeh et al. 2009; Pakzad et al. 2016). Higher rates of SC in males may be because they smoke more than females and have a higher risk of Helicobacter pylori infection; additionally, males are less likely to comply with sanitation requirements (Pakzad et al. 2016).

Making and analyzing disease incidence maps is a basic tool of regional public health assessment (López-Abente et al. 2018; Rapant et al. 2014). Based on the generated SC incidence maps and hotspots analysis, our study found a distinct SC distribution pattern. Significantly higher clusters were located in central Hangzhou, whereas lower clusters were located in northeastern and southwestern Hangzhou. The considerable differences between SC incidence values across space could be attributed to the uneven distribution of environmental factors. Previous studies have found positive correlations of poor socioeconomic/education level with SC prevalence, which is linked to the fact that people with low socioeconomic/education level usually consume large amounts of food with carcinogenic preservatives and they experience a higher prevalence of Helicobacter pylori infection (Crew and Neugut 2006; Pakzad et al. 2016), which are both important SC risk factors. Other factors, like poor nutrition, hygiene, or lack of awareness for disease prevention and clinical centers in rural areas, could also contribute to higher SC risk (Amin et al. 2015).

Our study found that Cd is one of the severe soil pollutants in Hangzhou. The mean Cd concentration is higher than the corresponding background value, and the Cd-polluted area estimated by the geostatistical Kriging technique is higher than the national Cd mean value (MEP and MLR 2014). As a trace element with a long biological half-life, the Cd in soil can be transmitted through the food chain and accumulated in humans. Slightly high Cd concentrations in the environment can be biomagnified through the food chain and eventually cause adverse health effects such as inducing carcinogenicity (Waalkes 2003; Yuan et al. 2016). However, while the mean concentrations of other heavy metals (Cr, Hg, Pb, As) were lower than the background value, there is no definitive value below which heavy metal would not cause cancer and it should not be neglected that even a low heavy metal concentration in soils could be a cancer contributor (Chen et al. 2015; Putila and Guo 2011).

The GeoDetector was used in this study to explore the spatial correlation between SC incidence and soil heavy metal concentration. As a relatively new technique for spatial variation analysis, GeoDetector has been used successfully in environmental and public health research. Wang et al. (2010) firstly implemented this method to assess the association of birth defects with soil and geomorphic factors. Li et al. (2013) made useful suggestions for fluoroquinolone control by using GeoDetector to analyze the impacts of vegetable planting models, planting age, greenhouse area, and topographic elevation on the distribution of fluoroquinolone residues in the soil. Fei et al. (2016) investigated the association of environmental factors (e.g., soil and geomorphic factors) with chronic disease (i.e., thyroid cancer) and provided valuable information for cancer risk detection. We found that individual heavy metal concentrations had no significant effect on the distribution of SC incidence; however, a joint effect does exist between two heavy metal types and that all possible combinations of metal types revealed a nonlinear enhancement effect. The joint effects of the Cr–Cd, Cr–As, Cd–As, and Cr–Pb particularly exhibited statistically significant impacts on the distribution of SC incidence, which implies that such combinations have a considerable impact on SC risk. Heavy metals like As, Cd, Cr, Hg, and Pb, which exist in abundance in the environment and are considered as certain or possible carcinogens, can be accumulated in the environment and biomagnified via the food chain (Jan et al. 2010; Han et al. 2018; López-Abente et al. 2018). It is noteworthy that previous studies have also suggested the existence of an association between heavy metal exposure and SC risk (McKinley et al. 2013; Welling et al. 2015).

As an ecological study, the present work cannot rigorously assess the association of heavy metal exposure and SC risk at the individual level. However, an ecological study is an important and direct way to generate valuable hypotheses and provide evidence for future environmental and health research. This work detected statistically significant joint effects in heavy metal concentrations on the distribution of SC incidence. We developed a comprehensive index (Nemerow Index) that measures the integrated soil pollution by heavy metals. In addition, principal component analysis (PCA) was employed to obtain factors that represent multiple heavy metal pollution (i.e., two principal factors were selected based on eigenvalue > 1 that accounted for about 60% of the total variance). However, in terms of the GeoDetector technique, neither the Nemerow Index nor the principal factors detected any significant effects of heavy metals on the SC distribution. Considering the fast growth of urbanization and industrialization, heavy metal emissions in the environment have been increasing. Therefore, it is an urgent matter to evaluate quantitatively the integrated heavy metal pollution of soils and assess their cancer impacts.

Conclusions

SC incidences in Hangzhou, China, exhibit distinct spatial distribution patterns, with a male to female ratio of about 2.2:1. Statistically significant higher clusters were located in central Hangzhou, whereas lower clusters were found in northeastern and southwestern Hangzhou. The mean SC incidence of high clusters was about 2.6 times higher than that of low clusters. Heavy metal pollution is unevenly distributed over Hangzhou, with Cd as the most concerning soil pollutant within the city. Any individual heavy metal does not have a considerable impact on the distribution of SC incidence, but the joint effects of heavy metals generated a nonlinear enhancement effect. Further studies are needed to improve the quantitative assessment of integrated heavy metal soil pollution and its cancer effects. Also, the SC incidence distribution could be studied using hospitals as geographical points rather than towns.

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