Spatial distribution of soil heavy metal pollution estimated by different interpolation methods: Accuracy and uncertainty analysis

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Abstract

Mapping the spatial distribution of contaminants in soils is the basis of pollution evaluation and risk control. Interpolation methods are extensively applied in the mapping processes to estimate the heavy metal concentrations at unsampled sites. The performances of interpolation methods (inverse distance weighting, local polynomial, ordinary kriging and radial basis functions) were assessed and compared using the root mean square error for cross validation. The results indicated that all interpolation methods provided a high prediction accuracy of the mean concentration of soil heavy metals. However, the classic method based on percentages of polluted samples, gave a pollution area 23.54–41.92% larger than that estimated by interpolation methods. The difference in contaminated area estimation among the four methods reached 6.14%. According to the interpolation results, the spatial uncertainty of polluted areas was mainly located in three types of region: (a) the local maxima concentration region surrounded by low concentration (clean) sites, (b) the local minima concentration region surrounded with highly polluted samples; and (c) the boundaries of the contaminated areas.

1. Introduction

Heavy metals in the soil have an effect on environmental and food quality, and may threaten human health. The accuracy of heavy metal spatial distribution maps is critical for risk control (Sene-sil et al., 1999). Contaminants always vary greatly over the land surface, so it is very difficult to acquire an accurate spatial distribution of heavy metals. The presence of a certain proportion of samples exceeding the given regulatory threshold was the classic method for characterizing the degree of soil pollution (Chen et al., 1997; Cheng et al., 2007). However, there are many limitations in the classic evaluation method, and these probably lead to errors, or uncertainty in pollution assessment.

The classic statistical method usually requires the data to be subject to a number of assumptions: independence of observations from each other, exact or approximate normality of observations, large and repeated sampling. But in soil pollution surveys, the soil heavy metal content is usually a skewed normal distribution and is spatially autocorrelated (Kishné et al., 2003; Hu et al., 2006). Considering the cost of soil sampling and analysis, dense and repeated sampling is usually impractical. Mapping the spatial distribution of soil pollution requires spatial interpolation methods. Consequently, interpolation techniques such as inverse distance weighting (IDW), kriging and Spline have been extensively used in soil investigations and pollution mapping (Imperato et al., 2003; McGrath et al., 2004; Amini et al., 2005; Lee et al., 2006).

Interpolation accuracy is related to the precise definition of the polluted area and its boundaries. Consequently, this directly affects the accuracy of pollution assessment. There are a lot of studies of the performance of the spatial interpolation methods mentioned above, but the results are not clear-cut (Shi et al., 2009). Some of them found that the kriging method performed better than IDW (Panagopoulos et al., 2006; Yasrebi et al., 2009); while others showed that kriging was no better than alternative methods (Got-way et al., 1996).

Soil heavy metal pollution studies focus on the identification of high pollution risk areas. Samples from high pollution risk areas are usually local spatial outliers (Zhang et al., 2009). Interpolation techniques all have a smoothing effect, which underestimates the local high values and overestimates the local low values (Journel et al., 2000). This smoothing effect leads to bias in soil pollution assessment and has an effect on relevant environmental decision.
making (Goovaerts, 2000). It is essential to minimize the bias in pollution assessment caused by interpolation techniques, and to understand the uncertainty of soil heavy metal pollution assessment introduced by interpolation error and the differences in pollution assessment between various interpolation techniques.

The objectives of this paper are to assess the uncertainty associated with a polluted area (i.e., the degree of pollution and the extent of the contaminated area) using different interpolation methods, and to investigate the relationship between the accuracy of prediction and local variation in soil heavy metal content.

2. Materials and methods

2.1. Sampling and analyses

The study area was located in the middle of Tongzhou District, Beijing, China (116°31′–116°56′E, 39°40′–39°51′N). The area covering 605 km² had a continental monsoon climate, in winter cold and dry, in summer hot and rainy. The average annual precipitation was about 620 mm. The annual precipitation was less than annual evaporation and the rainfall concentrated in June, July and August. The survey region was located downstream of industrial areas southeast of Beijing, where several rivers form a fan-shaped alluvial plain. The main soil type was fluvo-aquic soil. The food crops were mainly wheat, corn and vegetables. Inadequate rainfall and lack of surface water, which cannot meet the needs of crops. In order to ensure agricultural production, most of the agricultural soils had been irrigated with sewage from Beijing city since the 1960s (Yang et al., 2005).

A total of 137 surface soil samples (0–20 cm) were collected from the study area (Fig. 1). Soil samples were distributed evenly across the study area, and the average distance between sample locations was approximately 2 km. The samples were air-dried, ground, screened through a sieve of 2 mm mesh size, and then digested with HNO₃ and H₂O₂ by method 3050B recommended by USEPA (USEPA, 1996). The concentrations of copper (Cu) and lead (Pb) were analyzed with a flame atomic absorption spectrometer, cadmium (Cd) with a graphite furnace atomic absorption spectrometer (Vario 6, Jena Co. Ltd., Germany). The standard reference material of GSS-1 for soils, obtained from the Center of National Standard Reference Material of China, was used for quality assurance and quality control.

2.2. Interpolation methods tested

Interpolation is the process of predicting the values of attributes at unsampled sites. Differing from classic modeling approaches, spatial interpolation methods incorporate information about the geographic position of sample points (Isaaks and Srivastava, 1990; Schloeder et al., 2001). The rationale behind spatial interpolation is that points closer to each other have more correlations and similarities than those further away. In this study, the most widely used interpolation methods, inverse distance weighting, ordinary kriging, local polynomial and radial basis functions were evaluated.

2.2.1. Inverse distance weighting (IDW)

Inverse distance weighting is based on the premise that the predictions are a linear combination of available data. The interpolating function is:

\[ Z(x) = \sum_{i=1}^{n} w_i Z_i / \sum_{i=1}^{n} w_i, \]

where \( Z(x) \) is the predicted value at an interpolated point, \( Z_i \) is at a known point, \( n \) is the total number of known points used in interpolation, \( d_i \) is the distance between point \( i \) and the prediction point, and \( w_i \) is the weight assigned to point \( i \). Greater weighting values are assigned to values closer to the interpolated point. As the distance increases the weight decreases (Shepard, 1968) and \( u \) is the weighting power that decides how the weight decreases as the distance increases.

2.2.2. Ordinary kriging (OK)

Kriging is based on the assumption that the parameter being interpolated can be treated as a regionalized variable. As with IDW, the kriging estimator is given by a linear combination of the observed values with weights. Depending on the stochastic properties of random fields, different types of kriging apply. The
type of kriging determines the linear constraint on weights implied by the unbiased condition. There are several types of kriging including simple kriging, ordinary kriging, universal kriging, etc. and ordinary kriging is the most commonly applied method. The weights of OK are derived from the kriging equations using a semivariance function. The parameters of the semivariance function and the nugget effect can be estimated by an empirical semivariance function (Webster and Oliver, 2007). An unbiased estimator of the semivariance function is half the average squared difference between paired data values:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (z(x_i) - z(x_i + h))^2$$

(2)

where \( \gamma(h) \) is the semivariance value at distance interval \( h \); and \( N(h) \) is the number of sample pairs within the distance interval \( h \); \( z(x_i + h) \) and \( z(x_i) \) are sample values at two points separated by the distance interval \( h \).

2.2.3. Radial basis functions (RBFs)

Radial basis functions is the name given to a large family of exact interpolators which use a basic equation dependent on the distance between the interpolated point and the sampling points (Aguilar et al., 2005). RBFs are conceptually similar to fitting a rubber membrane through the measured sample values while minimizing the total curvature of the surface. The prediction value by RBFs can be expressed as the sum of two components (Mitasova and Mitas, 1993):

$$Z(x) = \sum_{i=1}^{m} a_i f_i(x) + \sum_{j=1}^{n} b_j \psi(d_j)$$

(3)

where \( \psi(d_j) \) shows the radial basis functions and \( d_j \) the distance from sample site to prediction point \( x \), \( f_i(x) \) is a trend function, a member of a basis for the space of polynomials of degree \( \leq m \). The coefficients \( a_i \) and \( b_j \) are calculated by means of the resolution of the following system of \( n + m \) linear equations; \( n \) is the total number of known points used in the interpolation as below:

$$Z(x_k) = \sum_{i=1}^{m} a_{ik} f_i(x_k) + \sum_{j=1}^{n} b_j \psi(d_j) \quad \text{for} \quad k = 1, 2, \ldots, n$$

$$\sum_{j=1}^{n} b_j f_j(x_k) = 0 \quad \text{for} \quad k = 1, 2, \ldots, m.$$  

(4)

In this study we have evaluated the following functions; completely regularized spline (CRS), inverse multi-quadratic function (IMQ), multi-quadratic function (MQ), spline with tension (ST), thin-plate splines (TPS). The radial basis function used for each case gives the following expressions:

**CRS:**  
$$\psi(d) = \ln(cd/2)^2 + E_1(cd)^2 + \gamma$$

**IMQ:**  
$$\psi(d) = (\sqrt{d^2 + c^2})^{-1}$$

**MQ:**  
$$\psi(d) = \sqrt{d^2 + c^2}$$

**ST:**  
$$\psi(d) = \ln(cd/2) + I_0(cd) + \gamma$$

**TPS:**  
$$\psi(d) = c^2 d^2 \ln(cd)$$

(5)

where \( d \) is the distance from sample to prediction location, \( c \) is a smoothing factor, \( I_0 \) is the modified Bessel function and \( r \) is Euler’s constant.

2.2.4. Local polynomial interpolation (LP)

Polynomial interpolation is a process of finding a formula (often a polynomial) whose graph will pass through a given set of points. Global polynomial interpolation fits a polynomial to the entire surface, while local polynomial interpolation can be seen as a combination of global polynomial methods and the moving average procedure. Instead of fitting the polynomial to the entire dataset it is fitted to a local subset defined by a window, as in the moving average model. The size of this window needs to be large enough for a reasonable number of data points to be included in the process.

2.3. Comparison of interpolation methods

Cross validation and validation with an independent data set are the commonly used methods for comparing the interpolation methods. Because the sample size was limited, cross validation was applied in this study. Cross validation involves consecutively removing a data point, interpolating the value from the remaining observations and comparing the predicted value with the measured value (Mueller et al., 2004). The mean relative error (MRE) and the root mean square error (RMSE) calculated from the measured and interpolated values at each sample site were used to compare the accuracy of predictions:

$$\text{MRE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Z'(x_i) - Z(x_i)}{Z(x_i)} \right|$$

RMSE = \left( \frac{1}{n} \sum_{i=1}^{n} \left[ Z'(x_i) - Z(x_i) \right]^2 \right)^{1/2}

(6)

(7)

where \( Z(x_i) \) is the observed value at location \( i \), \( Z'(x_i) \) is the interpolated value at location \( i \), and \( n \) is the sample size. Smaller MRE and RMSE values indicate fewer errors.

Cross validation only validates the prediction accuracy at a sample site and cannot reflect the spatial difference of interpolation techniques. Therefore, in this study, we used the raster analysis function of ESRI ArcGIS to compare the area and spatial differences of contaminated areas estimated by difference interpolation methods.

2.4. Data analysis

The dispersion of a sample and its neighbors was described by local variation. Among the parameters for the measurement of local variation, standard deviation and coefficient of covariance were the most extensively used. The standard deviation of samples must be understood in the context of the mean of the samples, while the coefficient of variation is a dimensionless number. When comparing data sets with different units, or widely different means, it is better to use the coefficient of variance than the standard deviation. In this study, the local coefficient of variance (CV) of a location (sample) is calculated from the sample and its neighbors:

$$\text{Local CV} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \frac{(x_i - u)^2}{u}}$$

(8)

where \( n \) is the number of samples, \( u \) is the mean of the sample and its neighbors. In this study, neighbors are defined by Voronoi polygons. Voronoi polygons are created at every location within a polygon and are closer to the sample point in that polygon than any other sample point. After the polygons are created, neighbors of a sample point are defined as any other sample point whose polygon shares a border with the chosen sample point.

Inverse distance weighting (IDW), ordinary kriging (OK), local polynomial and five radial basis functions (CRS, IMQ, MQ, ST, TPS) were selected to evaluate the effect of interpolation method on pollution assessment (size of polluted area and degree of pollution). In order to analyze the effect of model parameters on pollution assessment, the weighting power of IDW used 1–4, and the regression coefficient of LP used 1–3. OK required the distributions of samples to be normal, if not, a normal transform should be
applied to the sample data. Kolmogorov–Smirnov test was used to testing the normality of the distributions of Cd, Cu and Pb. The results showed that Pb was normal distribution, while Cd and Cu were normal distribution after log transformation. The spatial structure and variogram model were fitted by Variowin (Pannatier, 1996). For Cu, Cd and Pb, the exponential model is the best fitting model to calculate an experimental variogram. ESRI ArcGIS was used to interpolate soil heavy metals and to compare the differences in pollution evaluation among interpolation methods.

3. Results

3.1. Accuracy of interpolation methods

The root mean square error (RMSE) values of cross validation are summarized in Table 1. The results indicate that OK and RBF-IMQ interpolations have the minimum RMSE, and LP3 interpolation has the largest error. In addition to LP3, RBF-TPS and LP2 have larger RMSE values than the other methods. The weight parameter has a significant influence on the accuracy of interpolation. The greater the weighting power of IDW, the greater RMSE of interpolation. The higher the order of LP, the larger the RMSE of cross validation. The results of mean relative errors (MRE) of interpolation are similar to the RMSE. OK and RBF-IMQ are more accurate than other methods, with smaller MRE. Among the elements, Cd has the largest MRE of interpolation, and Pb has the smallest MRE of interpolation.

3.2. Interpolation accuracy and local coefficient of variance

Heavy metals in soil are spatially correlated. Values at points closely distributed are more likely to be similar than those points sparsely distributed. Therefore, most interpolation techniques use only a few neighboring sample points to predict the value at unsampled sites. In this study, we evaluated the effect of the local CV on the accuracy of interpolation. According to the local CV, samples were placed in five classes. The mean cross validation MRE of each class was calculated. From the scatter plot of local CV and MRE (Fig. 2) we recognized that the MRE of interpolation was significantly related to local CV. The greater the local CV, the greater the mean absolute error of interpolation. When CV < 0.4, the MRE of interpolation is less than 35%; when CV > 0.4, the MRE of interpolation is greater than 50%. As the local CV of samples increase, the interpolation accuracy declines. When the CV < 0.4, OK has lower MRE than other methods; when 0.4 < CV < 0.8, the OK method has a higher interpolation error than other methods.

3.3. Prediction accuracy of mean and coefficient of variance

The predicted mean values of Cd, Cu and Pb are in the ranges 0.105–0.110 mg kg⁻¹, 22.57–22.84 mg kg⁻¹, and 27.65–27.88 mg kg⁻¹, respectively (Table 2). All the interpolation techniques have similar prediction accuracy for the mean. The CV for Cd has the largest value (56.27%), and Pb has the smallest. Except for LP3, the CV predicted by all interpolation methods are less than the original value. The LP3 method gave a greater predicted CV than the original value. After interpolation, the CV of Cd is reduced by 13.32–35.66%, Cu by 4.08–8.53% and Pb by 2.13–9.72%. The more variation in sample sites, the greater reduction of CV after interpolation. The maximum and minimum coefficients of variance are estimated by RBF-TPS and RBF-IMQ, respectively. The bigger the weighting power, the bigger the CV estimated using IDW, and the smaller the estimated error. The bigger the regression coefficient, the bigger the CV estimated using LP.

3.4. Estimation of polluted area

There are two methods to calculate the size of the polluted area from soil samples. One is the proportion of contaminated sites, and the other method calculates the polluted area from an interpolation map of soil heavy metals. In this study, according to the background concentration – baseline concentration classification, Cd was classified to three levels, while Cu and Pb were classified to four levels. The details of classification standards are listed in Table 3.

According to the classification standards, for Cd the sample ratio for Level 3 “slightly polluted” is 3.65% of total samples. The sample ratio at Level 4 “moderately polluted” for Cu and Pb were 8.03% and 9.49%, respectively. The polluted area estimated from sample ratios over the limits (Table 3) is significant higher than that estimated by interpolation techniques (Table 4). There are large differences in heavy metal polluted area estimates using different interpolation methods. The “slightly polluted” area of Cd estimated using all interpolation methods ranged from 0 to 2.12%; the “moderately polluted” area of Cu changes from 0 to 6.14%, and Pb changes from 0 to 6.06%. Compared with the “sample ratio over the pollution limits” method, the polluted areas of Cd, Cu and Pb were reduced by 41.92%, 23.54% and 36.14%, respectively. Among the interpolation methods, RBF-TPS estimated the largest polluted area, while RBF-IMQ estimated no polluted area. OK and LP also estimated smaller polluted areas than other interpolation methods. The weighting power of IDW had a significant influence on the estimated polluted area; a bigger contaminated area was estimated when a greater weighting power was selected. Also the

<table>
<thead>
<tr>
<th>Table 1</th>
<th>The prediction accuracy of different methods.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Methods</td>
<td>Root mean squared error (RMSE)</td>
</tr>
<tr>
<td></td>
<td>Cd</td>
</tr>
<tr>
<td>IDW1</td>
<td>0.060</td>
</tr>
<tr>
<td>IDW2</td>
<td>0.062</td>
</tr>
<tr>
<td>IDW3</td>
<td>0.064</td>
</tr>
<tr>
<td>IDW4</td>
<td>0.067</td>
</tr>
<tr>
<td>LP1</td>
<td>0.062</td>
</tr>
<tr>
<td>LP2</td>
<td>0.067</td>
</tr>
<tr>
<td>LP3</td>
<td>0.116</td>
</tr>
<tr>
<td>OK</td>
<td>0.060</td>
</tr>
<tr>
<td>EBF-CRS</td>
<td>0.062</td>
</tr>
<tr>
<td>RBF-MQ</td>
<td>0.059</td>
</tr>
<tr>
<td>RBF-MQ</td>
<td>0.066</td>
</tr>
<tr>
<td>RBF-ST</td>
<td>0.061</td>
</tr>
<tr>
<td>RBF-TPS</td>
<td>0.069</td>
</tr>
</tbody>
</table>
higher order of LP gave, the larger estimated polluted area. The polluted area estimated by RBF changed with kernel functions. RBF-TPS estimated the largest polluted area, and RBF-IMQ estimated no polluted area. The order of the other three kernel functions ranked by the polluted area was RBF-MQ > RBF-CRS and RBF-CRS > RBF-ST.

3.5. Spatial distribution of pollution areas

In ArcGIS spatial analyst extension, the interpolated surfaces of heavy metals were converted to raster images. The values of clean, pollution warning, slightly polluted and moderately polluted cells (pixels) were assigned to 1–4, respectively. Then a subtraction

Table 2

<table>
<thead>
<tr>
<th>Methods</th>
<th>Predicted mean (mg kg(^{-1}))</th>
<th>Predicted coefficient of variance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cd</td>
<td>Cu</td>
</tr>
<tr>
<td>IDW1</td>
<td>0.108</td>
<td>22.81</td>
</tr>
<tr>
<td>IDW2</td>
<td>0.107</td>
<td>22.77</td>
</tr>
<tr>
<td>IDW3</td>
<td>0.106</td>
<td>22.72</td>
</tr>
<tr>
<td>IDW4</td>
<td>0.105</td>
<td>22.67</td>
</tr>
<tr>
<td>LP1</td>
<td>0.110</td>
<td>22.57</td>
</tr>
<tr>
<td>LP2</td>
<td>0.109</td>
<td>22.60</td>
</tr>
<tr>
<td>LP3</td>
<td>0.110</td>
<td>22.74</td>
</tr>
<tr>
<td>OK</td>
<td>0.108</td>
<td>22.70</td>
</tr>
<tr>
<td>RBF-CRS</td>
<td>0.108</td>
<td>22.70</td>
</tr>
<tr>
<td>RBF-IMQ</td>
<td>0.109</td>
<td>22.84</td>
</tr>
<tr>
<td>RBF-MQ</td>
<td>0.108</td>
<td>22.61</td>
</tr>
<tr>
<td>RBF-ST</td>
<td>0.108</td>
<td>22.71</td>
</tr>
<tr>
<td>RBF-TPS</td>
<td>0.107</td>
<td>22.61</td>
</tr>
<tr>
<td>Original value</td>
<td>0.109</td>
<td>22.70</td>
</tr>
</tbody>
</table>

Fig. 2. The relationship between coefficient of variation and mean relative error of cross validation.
was performed on any two rasters of pollution assessment, on a cell by cell basis, to get many subtraction results. Taking Pb as an example, in order to highlight the difference, several representative results were selected to assess the difference in pollution area between different interpolation techniques. RBF-TPS and IDW4 were chosen to indicate high polluted area estimates, OK and LP were selected to indicate low polluted area estimates. IDW4 and IDW2 were selected to assess the impact of weighting parameters on polluted area calculations. The results indicate that there are great spatial differences in the pollution assessment results (Fig. 3), especially at the local maxima and minima regions. The local maxima regions indicated the concentration of central samples higher than the surrounding samples, and local minima regions indicated the concentration of samples lower than the surrounding samples (Fig. 3). At local maxima regions, the pollution levels estimated by RBF-TPS and IDW2 are two levels higher than the results from OK (Fig. 3b and c). At the local minima regions, the pollution levels estimated by RBF-TPS and IDW2 are lower by two levels than the results from OK (Fig. 3b and c). At the transitional regions from high to low Pb concentration (Fig. 3a), comparison with the results of OK and LP, in the higher concentration part, the results of pollution assessment using RBF and IDW are higher by one pollution level; however, in the lower concentration part the results are lower by one pollution level (Fig. 3b and c). The spatial distribution of polluted area estimates by RBF is very similar to IDW. But the results of RBF indicate a larger polluted area than IDW (Fig. 3e). The difference between OK and LP mainly exists in the transition region from high to low Pb concentration (Fig. 3d). The results of IDW4 minus IDW2 show that distance weighting parameters expand the spatial scope of local maxima values, leading to a larger estimated contaminated area. The size of the contaminated area increased as concentric circles (Fig. 3f). Overall, the differences (uncertainty) in pollution evaluation among the interpolation methods mainly occurred at the three types of region, (a) local maxima concentration region with a highly polluted sample surrounded by low polluted (clean) samples, (b) local minima concentration region of a clean sample surrounded by high polluted samples and (c) the transition area from high to low concentration.

### 4. Discussion

The results demonstrate that all the interpolation techniques have an influence on the pollution area estimation. Even with the same type of interpolation method, the results varied with the parameters of the method. Heavy metals in soil are relatively difficult to move, and easily accumulate (Wang et al., 1997). Samples from high pollution risk areas usually had local maxima values but they account for a small proportion of the total samples. The target of the interpolations was to estimate the spatial means as accurately as possible. In order to minimize the estimated error of the global mean, interpolation techniques smooth the original data. Thus the local maxima were underestimated, and local minima were overestimated, which probably leads to the high pollution risk area being underestimated and the clean area overestimated. Therefore, the pollution area estimated by interpolation methods was smaller than that estimated by statistical methods.

According to the RMSE for cross validation (Table 1), OK and RBF-IMQ are more accurate than other methods, with RBF-TPS and RBF-MQ having the biggest estimated error. However, the polluted area calculation results (Table 4) show that the polluted area estimated by RBF-TPS and RBF-MQ are more similar to the results by statistical methods. The polluted area estimated by OK and RBF-IMQ are significantly smaller than the results by statistical methods. Therefore, RMSE as a measure of overall sample prediction accuracy, cannot describe the estimated error of local extreme values. Due to the smoothing effect, the lower the RMSE, the lower the effectiveness of pollution evaluation depends on accurate and efficient mapping of soil heavy metals. Among the factors that most affect soil pollution mapping are the number of soil samples, the distance between sampling locations, and the choice of interpolation method (Kravchenko, 2003). Generally, a larger number of samples will produce a more accurate pollution map (Mueller et al., 2001). However, due to the cost of sample collection and analysis, the use of large numbers of samples is usually impractical. Besides, the cost of collecting and analyzing larger sample numbers may exceed the potential benefits of accuracy improvement. Spatial structure is another factor that affects soil pollution mapping. Samples with a strong spatial structure were mapped more accurately than samples that had weak spatial structure (Kravchenko, 2003). As seen from Fig. 2 methods with lower local coefficients of variation were mapped more accurately than those that had higher local coefficients of variation. When the local coefficient is small, all interpolation methods have smaller interpolation errors. As the local coefficient of variation increases, the interpolation error increases and the differences between

<table>
<thead>
<tr>
<th>Methods</th>
<th>Heavy metal polluted area proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cd (Level 3)</td>
</tr>
<tr>
<td>IDW1</td>
<td>0.07</td>
</tr>
<tr>
<td>IDW2</td>
<td>0.56</td>
</tr>
<tr>
<td>IDW3</td>
<td>0.99</td>
</tr>
<tr>
<td>IDW4</td>
<td>1.28</td>
</tr>
<tr>
<td>LP1</td>
<td>0.00</td>
</tr>
<tr>
<td>LP2</td>
<td>0.00</td>
</tr>
<tr>
<td>LP3</td>
<td>1.71</td>
</tr>
<tr>
<td>OK</td>
<td>0.00</td>
</tr>
<tr>
<td>RBF-CSR</td>
<td>0.41</td>
</tr>
<tr>
<td>RBF-ST</td>
<td>0.27</td>
</tr>
<tr>
<td>RBF-TPS</td>
<td>2.12</td>
</tr>
<tr>
<td>RBF-MQ</td>
<td>1.22</td>
</tr>
<tr>
<td>RBF-IMQ</td>
<td>0.00</td>
</tr>
<tr>
<td>Sample ratio</td>
<td>3.65</td>
</tr>
</tbody>
</table>
interpolation methods also increases. The effect of the weighting power of IDW is associated with the coefficient of variation; when the local CV is less than 0.8, the optimal weighting power is one, and when the local CV is larger than 0.8, four is the optimal weighting power. Larger weighting powers always increase the extent of the polluted area estimated.

Interpolation methods determine how discrete sample data are converted into a continuous map. The interpolation precision depends on how well that interpolation technique reflects the spatial variation and correlation of soil attributes (Zhu et al., 2004). Kriging quantifies the spatial autocorrelation among measured points and accounts for the spatial configuration of the sample points around the prediction location. Consequently, OK provides a theoretical best linear unbiased estimation. In practice, it is very difficult to acquire an ideal semivariogram with a small sample size. Also, in many situations, soil heavy metals do not obey the intrinsic hypothesis (Webster, 2000). OK is a low-pass filter that smooths out the local detail information (extreme values). In a high variation region that has weak spatial correlation, the smoothing effect of OK is much stronger (Goovaerts, 1999; Li, 2005). As a result, the local maxima was underestimated and the polluted area probably underestimated.

A polynomial is usually not used as an interpolator, but applied to define the trends and patterns in the data. The interpolated surface is very smooth, giving rise to detailed information that exists in a local region being smoothed out. IDW and RBFs are exact interpolators that predict a value that is identical to the measured value at a sampled location. The local peaks (maxima) or troughs are reserved in the outer surface. Where IDW creates a surface from measured samples, based on the extent

Fig. 3. The difference of heavy metal polluted area estimated by each two interpolation techniques.
of similarity, RBF are based on the degree of smoothing (Smith et al., 2007). The RBFs can predict values above the maximum and below the minimum measured values. However, the maximum and minimum values in the interpolated surface using IDW can only occur at sample points. IDW is very sensitive to weighting power, which controls how the weighting factors drop off as distance from prediction location increases. The greater the weighting power, the smaller the effect that samples far from the prediction location have during interpolation. As the weighting power increases, the prediction value approaches the value of the nearest sample. Therefore, larger polluted areas are estimated using IDW4 than IDW2.

In general, IDW, LP and RBFs are easy to use, because less input parameters. In contrast, OK is more difficult to use. Typically, OK interpolation including the follow steps, statistic test, data transformation and inverse transformation, spatial structure analysis, semivariance function fitting and so on. The semivariance function fitting is subjective, different researchers may have different results.

Interpolation accuracy is relative concept; the criteria are varying with the purpose of interpolation. The mainly two purposes of soil pollution mapping are analyzing the spatial pattern of soil pollution and identifying of the contaminated areas. In purpose of analyzing the spatial pattern of pollution, the prediction result of overall spatial trend of soil heavy metal should be as precise as possible. It is no doubt that OK has the strongest ability to predict the overall trend of soil pollution. However, in purpose of identifying of the contaminated areas, the interpolation techniques are required to predict the local feature of soil pollution (especially local hotspot and local cold spot) more precisely. The local maxima are likely to be smoothed out by OK. While using IDW and RBFs for interpolation, the local maxima (hotspot) and local minima (cold spot) are reserved in the pollution map.

It should be clear that all the interpolation results have errors. Identifying a region as contaminated should not merely based on the result of interpolation results. It is suggested that the natural background and human activities should be considered before make a decision. Underestimating polluted areas reduces the cost of remediation, but increases the cost of contamination. In order to acquire a more reliable pollution assessment, we can add more samples from the uncertainty region of pollution evaluation. The uncertainty of pollution evaluation is mainly located at the region of high local variation, so additional sampling at the uncertainty region is advised.

5. Conclusions

All interpolation methods tested have a high prediction accuracy of the mean content for soil heavy metals, but underestimate the coefficient of variance. The greater the coefficient of variance of heavy metals in soil samples, the greater the decline in coefficient of variance after interpolation. The polluted area estimation using interpolation methods is smaller than that of the classic method based on an estimate of the number of samples over pollution limits. Ordinary kriging and RBF-IMQ that have lower RMSE estimate a smaller size for the polluted area. RBF-TPS and IDW4 that have larger RMSE estimate a larger size for the polluted area. The greater the weighting power, the larger the polluted area estimated by IDW.

The uncertainty in soil heavy metal pollution assessment (degree of pollution and contamination area distribution) is mainly located in the following regions: (a) the local maxima region with a small number of isolated samples of high pollution levels surrounded by less polluted samples; (b) the local minima region with central clean (less pollution) samples surrounded by relatively high polluted samples; (c) the boundary of contaminated areas.

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