Mapping the probability of exceeding environmental quality standards for Cd and Pb concentrations in soil of northern Tarim Basin using Bayesian geostatistical model

Weimo Wu¹, Jiaping Wu³, Jiaqiang Wang² and Qi Cao²

¹ College of Environmental & Resource Sciences, Zhejiang University, Hangzhou 310058, China; ² College of Plant Science, Tarim University, Alar 843300, China; ³ Ocean College, Zhejiang University, Zhoushan 316021, China

Abstract. Cadmium and Pb are important hazardous trace metals in the biosphere, and they are considered to pose a great threat to environmental health. The probability map exceeding the environmental quality standard (EQS) can be used to measure the uncertainty of the spatial distribution of soil Cd and Pb and provides useful information for decision-making for environmental management. Many researchers have focused on Cd and Pb environmental problems in agricultural soils, and there are few studies that have investigated the Cd and Pb contents exceeding EQS in natural soils of the arid desert areas of northwest China. We collected 150 samples at 0-0.05 m and 0.05-0.1 m depths in the natural solonchak soil of northern Tarim Basin, Xinjiang Province. The average concentrations of Cd and Pb were 0.45 mg/kg and 42.13 mg/kg at 0-0.05 m, and 0.29 mg/kg and 16.88 mg/kg at 0.05-0.1 m, respectively. The soil Cd and Pb concentrations were increased in comparison with the environmental background values. In addition, the soil Cd and Pb concentrations at 0-0.05 m were significantly higher than those at 0.05-0.1 m. We used the Bayesian geostatistical model to predict the spatial distribution of Cd and Pb concentrations and to map the probability of soil Cd and Pb exceeding the EQS. These probability maps are expected to be helpful for soil environmental protection of northern Tarim Basin.

1. Introduction
Cadmium and Pb pollution in soil environment has increased rapidly due to industrialization, urbanization and agricultural modernization over the past few decades[1,2]. The State Environmental Protection Agency of the People’s Republic of China (PRC) published the Environmental Quality Standards (EQS) (GB 15618-1995 and GB15618-2018) to categorize the environmental quality of soils corresponding to standard grades for heavy metal concentrations in soils[3,4]. The Chinese EQS for soils provided standard values for Cd and Pb concentrations according to the soil application function and protection target[5]. In 2014, the Ministry of Environmental Protection and Ministry of Land and Resources of the PRC issued the Report on the National General Survey of Soil Contamination, which indicated that 7.0% and 1.5% of Chinese soils were contaminated by Cd and Pb, respectively[6]. Facing this grim situation, in May 2016, the State Council of the PRC issued the Action Plan for Soil Environmental Prevention and Pollution Governance, which requires that the Chinese government takes detailed measures to monitor, prevent and remediate soil pollution[5,7].
Depending on the regulatory purpose, the estimation of the spatial distribution of soil Cd and Pb concentrations can be described at a fine scale or in geographic regions. Risk assessments using the probability that a field or a region with soil Cd and Pb concentrations exceeding the EQS are of practical significance as they can specify locations where the soil needs pollution control or remediation for better management.

Geostatistical methods play a significant role in environmental risk assessments, in modeling spatial distributions and in identifying locations where the risk of soil Cd or Pb concentrations exceeding regulatory thresholds is higher according to probability maps[8,9,10,11]. Bayesian geostatistical models can take the uncertainty of model parameters into account and evaluate the predictive uncertainty. Based on Bayesian geostatistical model, the probability map exceeding regulatory thresholds have been applied in environmental risk assessments[12,13,14,15,16].

In China, many studies have focused on the soil Cd and Pb pollution issues in agricultural soils[17, 18]. There is lack of studies on evaluating the Cd and Pb contents in arid desert areas of northwest China, particularly in Tarim Basin, Xinjiang Province. The Tarim Basin is the largest internal basin in China. The desert ecological system in Tarim Basin is very sensitivity and fragile, the soil contamination by heavy metals may results in degradation of environmental quality and the risks of ecosystem health [19], so it is important to investigate and evaluate the soil Cd and Pb concentrations in this area.

In recent years, there are more and more studies on the Cd and Pb pollutions and their potential health and ecological risks in agricultural soils in the oases of Tarim Basin. Compared with soil background value in Xinjiang Province, soil Cd and Pb concentrations have a increasing trend, the range of soil Cd and Pb concentrations in 0-0.2 m depth were 0.04-0.69 mg/kg and 0.99-88.44 mg/kg, respectively[20,21,22,23]. The Cd and Pb in agricultural soils of northern Tarim Basin are mainly originated from anthropogenic pollution[23]. Until now, studies on Cd and Pb pollutions are seldom focused on natural soils or uncultivated soils in arid desert areas of the Tarim Basin[24]. In this study, we used the Bayesian geostatistical model to map the concentrations of Cd and Pb in the solonchak soil of the northern Tarim Basin, and to map the risk probability exceeding the EQS.

2. Materials and methods

2.1. The study area
The study area (81°4′ E, 40°54′ N) shown in Figure 1 was located in the northern Tarim Basin of Xinjiang Province, China, between the southern Tianshan Mountains and the Taklimakan Desert. The distance between the study area and the Taklimakan Desert was approximately 55 kilometers. Due to being located in the extremely arid desert area of China, the annual average precipitation was only 45.7 mm, the annual potential evaporation was 2110.5 mm, and the annual average temperature was 11.2 °C[24]. The soil group was solonchak soil that developed from fluvial alluvium. The natural vegetation in the study area was distributed sparsely, and the common flora consisted of halophytic shrubs (dominated by *Tamarix* spp.) and herbs. A part of the study area has been reclaimed as farmland and is cultivated crops such as cotton and rice. The study area is an important reserve resource for farmland, but at present it is included into the shrub ecological reserve.

2.2. Soil sampling and elemental analysis
Soil samples were collected from the designed locations (144 sites) in November 2015 by a regular grid of 5 arc-seconds by 5 arc-seconds in a 2.2 km² sampling area (Figure 1). With an additional 6 sites, the total number of sampling sites was 150, and the location of each sampling site was recorded by a highly precise Global Position Systems receiver. Samples of 0-0.05 m and 0.05-0.1 m were collected using a soil drill.
Figure 1. Location map of the study area (a) and soil sampling sites in the study area (b). The background of (b) is the Planet image (https://www.planet.com/) obtained on Oct 9, 2018 with resolution of 3 m x 3 m.

Soil samples were air-dried, crushed and passed through a 2-mm sieve. The total concentrations of Cd and Pb were determined by digestion in HCL/HNO₃/HF/HClO₄ with analysis by graphite furnace atomic absorption spectrophotometry. The detection limits (DLs) for the measurements of Cd and Pb concentrations were 0.01 mg/kg and 0.1 mg/kg, respectively. Soil pH value was determined by in 5:1 water: soil ratios. The air-dried soil moisture content was determined by oven drying at 100-105 °C. All concentrations of soil Cd and Pb were larger than DLs and expressed on a dry soil weight basis.

Table 1 shows the descriptive statistics of soil Cd and Pb concentrations. The soil Cd and Pb concentrations in 0-0.05 m were significantly higher than those in 0.05-0.1 m (P < 0.05). For example, the means of Cd in 0-0.05 m and 0.05-0.1 m were 0.45 and 0.29 mg/kg, respectively. The mean and median of Pb in 0-0.05 m were almost twice as large as those in 0.05-0.1 m.

Table 1. Descriptive statistics of minimum (Min), maximum (Max), mean, standard deviation (SD) and quantiles of Cd and Pb concentrations (mg/kg) and pH values of soil samples.

| Elements | Soil depth | Min | Max | Mean | SD  | 25%  | 50%  | 75%  | 75%  |
|----------|------------|-----|-----|------|-----|------|------|------|------|
| Cd       | 0-0.05 m   | 0.33| 0.72| 0.45 | 0.13| 0.36 | 0.38 | 0.38 | 0.57 |
|          | 0.05-0.1 m | 0.09| 0.45| 0.29 | 0.08| 0.23 | 0.30 | 0.30 | 0.37 |
| Pb       | 0-0.05 m   | 20.87| 76.39| 42.13| 13.7| 32.02| 36.73| 52.19|      |
|          | 0.05-0.1 m | 9.35| 32.9| 16.88| 5.33| 12.33| 15.96|      |      |
| pH       | 0-0.05 m   | 7.35| 9.8 | 8.49 | 0.50| 8.13 | 8.46 | 8.87 |      |
|          | 0.05-0.1 m | 7.73| 9.6 | 8.59 | 0.37| 8.32 | 8.6  |      |      |
2.3. Detrending and normal score transformation of data
In geostatistical mapping, the target variable is often required to satisfy three conditions: (1) there is no trend; (2) the target variable is second-order stationary or intrinsically stationary; and (3) the target variable (approximately) follows a normal distribution[25].

The trends for Cd (0-0.05 m) and Pb (0-0.05 m) concentrations data were modeled as 2-order polynomial regression models with the coordinates being the independent variables. After detrending, the regressing residuals were normal score transformed using the Geostatistical Software Library (GSLIB)[25]. The normal score transformed data were followed normal distribution and were used to modeling Bayesian geostatistical models. The predicted values then were normal score back transformed as the original unit of mg/kg using GSLIB.

2.4. Bayesian Geostatistical model specification
We used a Bayesian geostatistical model to characterize the spatial distributions of target variables (the normal score transformed soil Cd and Pb concentrations) in the study area. Data \( y(s_i) \) is observed at location \( s_i (i = 1, 2, \ldots, n) \), which is assumed to be a realization of an underlying Gaussian process (GP) \( f(s) \)[26]. The observed data also has a measurement error \( e \), i.e.

\[
y(s_i) = f(s_i) + e(s_i)
\]

Where \( e(s) \) represents an independent white-noise process that captures microscale variations and measurement error, and its associated variance is the nugget effect \( \sigma^2_e \). The \( f(s) \) is assumed to be a stationary and isotropic GP.

\[
y|f, \sigma_e \sim \text{Normal}(f(s), \sigma^2_e) \\
f|M, C \sim \text{GP}(M, \Sigma) \\
\Sigma: s, a^2, \phi, \sigma^2_e \rightarrow \text{Covariance matrix}
\]

\( M \) is a constant mean function (overall mean \( m \)). \( \Sigma \) is a spatially structured covariance matrix whose element is defined by the covariance function \( \text{Cov}(\cdot, \cdot) \). The covariance function includes parameters of partial sill \( \sigma^2 \), spatial range \( \phi \).

We used a spherical covariance function to model the spatial dependence of the GP for soil Cd (0-0.05 m) and Pb (0-0.05 m):

\[
\text{Cov} \left( f(s_i), f(s_j) \right) = \sigma^2 \left[ 1 - 1.5 \frac{||s_i - s_j||}{\phi} + 0.5 \left( \frac{||s_i - s_j||}{\phi} \right)^3 \right]
\]

Where \( ||s_i - s_j|| \) is the Euclidean distance between two generic locations \( s_i \) and \( s_j \), \( \phi \) is the actual range in spherical model with unit of meter.

There are a total of four parameters \( m, \sigma^2, \phi \) and \( \sigma^2_e \) in above Bayesian geostatistical model to be inferenced. Let a parameter vector \( \theta = (m, \sigma^2, \phi, \sigma^2_e) \). According to Bayesian theory, the posterior distribution of parameters \( p(\theta|y) \) is proportion to the prior \( p(\theta) \) multiplying likelihood \( p(y|\theta) \):

\[
p(\theta|y) \propto p(y|\theta)p(\theta)
\]

Where \( p(y|\theta) \sim \text{Normal}(m, \Sigma + \sigma^2_e I) \)

Typically, independent priors are chosen for the four Bayesian geostatistical model parameters, i.e.

\[
p(\theta) = p(m)p(\sigma^2)p(\phi)p(\sigma^2_e)
\]

Due to the overall mean being a constant, its prior value was set as \( p(m) \propto 1 \). We set vague priors for \( \sigma^2, \phi \) and \( \sigma^2_e \), and they followed exponential distributions[27].

\[
\sigma^2 \sim \text{Exponential}(7e - 5) \\
\phi \sim \text{Exponential}(4e - 3) \\
\sigma^2_e \sim \text{Exponential}(5e - 9)
\]

The exponential distribution density function is as following:

\[
\text{Exponential}(x|\beta) = \beta e^{-\beta x}
\]

Where \( x \) is a random variable, and \( \beta \) is the exponential distribution parameter.

The Bayesian geostatistical models were fitted by the Markov Chain Monte Carlo (MCMC) algorithm using the Python package Bayesian Stochastic Modeling (PyMC) Gaussian process.
module[27]. The convergence diagnostics were assessed by plotting and inspecting the traces of the observed MCMC samples. We set the number of iterations, burn-in and thin to 8000000, 4000000, and 4000 respectively to gain a convergence MCMC samples. The numbers of resulting posterior distribution sample and posterior predictive distribution sample were 1000. We also conducted sensitivity analysis to investigate the effect of different prior specification on the posterior distribution inference[26].

Model validation was performed by calculating validation metrics using the leave-one-out cross-validation method[28]. The validation metrics included the mean error (ME), root mean squared error (RMSE), root mean square standardized error (RMSSE), and Pearson correlation coefficient ($r$).

2.5. Mapping soil Cd and Pb spatial distributions and the probability of exceeding the EQS

The mean of the posterior predictive distribution was mapped using ArcGIS 10.1. The estimation of the uncertainty of prediction is very important in environmental assessments. In this study, the uncertainty of prediction for each location was assessed by the variance of the posterior predictive distribution and exceedance probability.

The predictive probability of the soil Cd or Pb concentrations $y(s)$ at a location $s$ exceeding the EQS can be calculated by:

$$\text{Prob}[y(s) > \text{EQS}] = \frac{n^*(s)}{1000}$$

Where $n^*(s)$ is the number of samples whose $y(s)$ value being larger than the EQS in the 1000 posterior predictive distribution sample.

In this study, the EQS for soil Pb (0-0.05 m) and Cd (0-0.05 m) were set as 35 mg/kg (Grade I level of Pb in GB15618-1995 [3]) and 0.6 mg/kg (Screening value of Cd in GB15618-2018 [4]), respectively (Table 2).

| GB15618-1995 | Grade I | Grade II | Grade III |
|--------------|---------|----------|-----------|
|               | Natural background | pH≤6.5 | 6.5<pH≤7.5 | pH>7.5 | pH>6.5 |
| Cd           | <0.20   | <0.30    | <0.60     | <1.0    |         |
| Pb           | <35     | <250     | <300      | <350    | <500    |

| GB15618-2018 | Risk values | pH≤5.5 | 5.5<pH≤6.5 | 6.5<pH≤7.5 | pH>7.5 |
|--------------|--------------|--------|------------|------------|--------|
| Cd           | Screening value | 0.3    | 0.3        | 0.3        | 0.6    |
| Pb           | Screening value | 700    | 90         | 120        | 170    |

* Screening value used for other types of agricultural land excluding paddy.

In the Chinese EQS (GB15618-1995) (Table 2), the soils with grade I environmental quality were aimed at protecting the regional natural ecology and maintaining the soil environmental quality at a natural background level. The grade II soils were mainly used for agricultural production, the ranked level of EQS for grade II soils depend on its pH value. The grade III soils were used for agricultural and forestry production. The GB15618-1995 was applied to natural soil, agricultural soils and forestry soil, etc.[3]

On June 22, 2018, Ministry of Ecology and Environmental of China issued the new Soil Environmental Quality Risk Control Standard for Soil Contamination of Agricultural Land (GB15618-2018) (Table 2). Risk values include screening value and intervention value, the latter is larger than the former. When soil contaminant concentration exceeds screening value, there is a soil contamination risk of agricultural land. The GB15618-2018 is only applied to agricultural lands[4].
There were 98% soil samples in 0-0.05 m whose pH values were larger than 7.5, and pH values were all larger than 7.5 for soil samples in 0.05-0.1 m (Table 1). According, for agricultural soils, in GB15618-2018, screening value of Cd and Pb are 0.6 and 170 mg/kg, respectively; in GB 15618-1995, EQS value of Cd and Pb are 1.0 and 350 mg/kg, respectively.

For soil samples in 0.05-0.1 m, the maximum of Cd concentration was 0.45 mg/kg which was lower than the screening values (0.6 mg/kg) in GB15618-2018 and Grade II EQS (1.0 mg/kg) in GB15618-1995, and the minimum of Cd concentrations was 0.33 mg/kg, which was higher than the Grade I (0.2 mg/kg) in GB15618-1995. The maximum of sample Pb concentration in 0.05-0.1 m was 32.9 mg/kg, which was lower than the screening value (170 mg/kg) in GB15618-2018 and Grade I (35 mg/kg) in GB15618-1995. Therefore we did not map probabilities exceedance and spatial distribution for soil Cd and Pb concentrations in 0.05-0.1 m depth.

3. Results and discussion

3.1. Posterior distributions of model parameters

Methods that are rooted in the frequentist approach, also called conventional geostatistical methods[29], cannot easily reveal the uncertainty of all model parameters (e.g., the spatial structure parameters). As a solution, a Bayesian approach allows one to summarize the uncertainty of each parameter by treating parameters as random variables[26]. The summary statistics of the marginal posterior distributions of model parameters are reported in Figure 2.

![Figure 2](image_url)

**Figure 2.** Marginal posterior distributions of the Bayesian geostatistical model parameters.
The residuals of Cd (0-0.05 m) and Pb (0-0.05 m) were normal score transformed; therefore, their means of \( m \) were close to 0. The posterior distributions of \( \Phi \) and \( m \) were almost the same for the soil Cd and Pb. There were relative large differences of the posterior distributions of \( \sigma_\Phi^2 \) and \( \sigma^2 \) among soil Cd concentrations. For example, the posterior mean of \( \sigma_\Phi^2 \) was 0.45 for Cd and 0.14 for Pb.

Figure 3 shows the results of the cross-validation presented within the scatter diagram and the prediction measurements of the ME, RMSE, RMSSE and \( r \). In general, the Bayesian geostatistical models provided reasonable level of accuracy and precision for the prediction of soil Cd and Pb concentrations. The points near the 45° line suggest a small bias between the observed and predicted values. The values of ME were low and close to 0. The RMSE values for Cd and Pb were 0.56 and 0.2, respectively. The Pearson coefficient \( r \) of Cd was 0.88, and \( r \) of Pb was very close to 1. Previous studies showed that the Bayesian geostatistical model performs better than ordinary kriging and Gaussian spatial predictive process in terms of RMSE[15]; Among indicator kriging (IK), indicator cokriging and Bayesian kriging, estimation errors (ME and RMSE) of spatial distributions of soil magnetic susceptibility calculated using Bayesian kriging was smaller than that of using IK and indicator cokriging[30].

![Figure 3. Scatterplot between measured and predicted (posterior mean prediction) Cd and Pb contents in 0-0.05 m soils and validation metrics ME, RMSE, RMSSE and r.](image)

### 3.2. Predicted spatial distributions and predicted uncertainty

The Bayesian geostatistical model generates a posterior predictive distribution at each predicted grid point location. Figure 4 shows the spatial distributions of the Bayesian geostatistical predictions of soil Cd and Pb concentrations (mean and variance) in the study area. The soil Cd and Pb concentrations at 0-0.05 m, were relatively high in the west of the study area and low in the east. In this study, predictive uncertainty is represented by predictive variance and exceedance probability. The posterior predictive variances for soil Cd and Pb were small, for example, the highest predictive variance for Cd (0-0.05 m) was only about 0.003 mg²/kg².

The soil Cd and Pb concentrations in the study area were significantly higher than the soil environmental background concentration of Xinjiang Province[31] (Table 3). Our findings are consistent with other studies in Tarim Basin. For example, Eziz et al (2018) reported that the average contents of Cd and Pb in Yanqi Basin (Yanqi Basin is a part of the Tarim Basin) exceeded by 1.67 and 3.01 times of the background values for irrigation soils in Xinjiang, respectively[32]. By comparison
with the background values of soils in the 1990s, the soil Cd and Pb concentrations in China increased over the past 20 years[33,34]. Elevated Cd and Pb were observed in the study area, which suggests that there was a degree of Cd and Pb pollution in the arid desert area soils of the northern Tarim Basin.

![Map of the mean (left) and variance (right) of the posterior predictive distributions for Cd and Pb concentrations in 0-0.05 m soils.](image)

Figure 4. Map of the mean (left) and variance (right) of the posterior predictive distributions for Cd and Pb concentrations in 0-0.05 m soils.

| Elements | Soil horizon | Minimum | Maximum | Mean | Median |
|----------|--------------|---------|---------|------|--------|
| Cd       | A            | 0.036   | 0.147   | 0.072| 0.070  |
|          | C            | 0.035   | 0.217   | 0.091| 0.081  |
| Pb       | A            | 14.62   | 25.25   | 18.49| 16.91  |
|          | C            | 11.68   | 25.52   | 19.52| 20.56  |

*The A and C horizons were the solonchak soil topmost mineral horizon and parent material horizon, respectively.*

Atmospheric deposition is believed to be one of the major sources of Cd and Pb in soils[35,36]. The dust fall in spring and summer was approximately 100 g·m⁻²·month⁻¹ in the northern Tarim Basin[37]. The Cd and Pb concentrations in the total suspended particulate were measured as 0.01 and 0.14 µg·m⁻³ in the Taklimakan desert area[38]. As a desolate area, the Taklimakan desert also suffers from a certain degree of Cd and Pb pollution in the dust aerosol, which suggests that atmospheric deposition may be one of the sources of the Cd and Pb in the soils of the northern Tarim Basin. In
addition, highway S215 (Figure 1(b)), with a north-south direction, was to the west of the study area, and the distance between the highway and the study area was approximately 0.55-1.2 kilometer, roadside soils in the surface layer easily accumulate Cd, Pb and other heavy metals due to automobile exhausts[36, 39].

3.3. Mapping the probability of exceeding EQS

Figure 5 shows the probability maps of the 0-0.05 m soil Cd and Pb concentrations that exceeded the Chinese EQS. The probability of exceeding the EQS varied between 0 and 1 with means of 0.15 and 0.76 for Cd (0-0.05 m) and Pb (0-0.05 m), respectively. Figure 5 shows that there was a high risk (probability > 0.8) of the 0-0.05 m soil Cd concentration exceeding the EQS (0.6 mg/kg) in the northwest and southwest corners of the study area, and the soils in these sites could be viewed as contaminated with Cd, which is therefore not suited for agricultural production purpose. For the 0-0.05 m soil Pb concentrations, the high probability (> 0.8) of Pb exceeding EQS (35 mg/kg) mainly occurred to the west and east of the study area.

![Figure 5. Map of the probability that Cd and Pb concentrations in 0-0.05 m exceeds the EQS.](image)

4. Conclusions

This study mapped the risk of soil Cd and Pb concentrations exceeding the Chinese EQS and assessed the prediction of uncertainty in the natural uncultivated solonchak soil of the northern Tarim Basin, Xinjiang Province, China. The maps of the risk of soil Cd and Pb exceeding the EQS can be used to delineate specific areas or sites where the soil should be utilized for specific aims according to the environmental quality or to help make environmental management decisions, such as the environmental remediation of soil Cd and Pb. We found that in the arid desert area of the northern Tarim Basin, the soil Cd and Pb concentrations in the 0-0.05 m layer were higher than those in the 0.05-0.1 m layer, and the current contents of soil Cd and Pb were higher than the environmental background concentrations determined three decades ago, which suggest that there may be anthropogenic effects on the soil concentrations of Cd and Pb. Therefore, the identification of the soil Cd and Pb pollution sources in the study area is needed in the future.

Acknowledgments

This research was financially supported by the National Science Foundation of China [Project no. 40961028]. We thank George Christakos who made helpful comments on the early manuscript.

References

[1] Alloway B J 2013 Sources of Heavy Metals and Metalloids in Soils. In: Alloway B (eds) Heavy Metals in Soils. *Environmental Pollution*, vol 22. Springer, Dordrecht
[2] Carré F, Caudeville J, Bonnard R, Bert V, Boucard P, Ramel M 2017 Soil Contamination and Human Health: A Major Challenge for Global Soil Security. In: Field D J, Morgan C L S, McBratney A B (eds) Global Soil Security. Progress in Soil Science. Springer, Cham

[3] The State Environmental Protection Agency of the People's Republic of China 1995 Environmental Quality Standards for Soils (GB 15618-1995)

[4] Nanjing Institute of Environmental Sciences, Ministry of Ecology and Environment of China, Soil Environmental Quality Risk Control Standard for Soil Contamination of Agricultural Land (GB 15618-2018), Ministry of Ecology and Environment of China: Beijing, China

[5] Qin T, Dong F 2017 Legislative Progress on Soil Contamination Prevention and Control in China. In: Ginzky H, Heuser L, Qin T, Ruppel Q, Wegerdt P (eds), International Yearbook of Soil Law and Policy 2016. International Yearbook of Soil Law and Policy, vol 2016. Springer, Cham

[6] Ministry of Environmental Protection and Ministry of Land and Resources of the People’s Republic of China 2014 Report On the National General Survey of Soil Contamination. [online] Available at http://www.gov.cn/foot/site1/20140417/782bcb88840814ba158d01.pdf [Accessed 25 Jan 2019]

[7] The State Council of the People’s Republic of China 2016 Action Plan for Soil Environmental Prevention and Pollution Governance. [online] Available at http://www.gov.cn/zhengeee/content/2016-05/31/content_5078377.htm [Accessed 22 Jan 2019]

[8] Brus D J, de Grujter J J, Walvoort D J, de Vries F, Bronswijk J J, Römkens P F, de Vries W 2002 Mapping the probability of exceeding critical thresholds for cadmium concentrations in soils in the Netherlands J Environ Qual 31(6) 1875-1884

[9] Amini M, Afyuni M, Khademi H, Abbaspour K C, Schulin R 2005 Mapping risk of cadmium and lead contamination to human health in soils of Central Iran Sci Total Environ 347(1-3) 64-77

[10] Guagliardi I, Cicchella D, DeRosa R, Buttafuoco G 2015 Assessment of lead pollution in topsoils of a southern Italy area: Analysis of urban and peri-urban environment. J Environ Sci (China) 33 179-187

[11] Huang J, Liu W, Zeng G, Li F, Huang X, Gu Y, Shi L, Shi Y, Wan J 2016 An exploration of spatial human health risk assessment of soil toxic metals under different land uses using sequential indicator simulation Ecotox Environ Safe 129 199-209

[12] Le N D, Zidek J V 2006 Statistical Analysis of Environmental Space-Time Processes Springer Series in Statistics. Springer, New York, NY

[13] Lee D J, Toscas P 2015 Flexible geostatistical modeling and risk assessment analysis of lead concentration levels of residual soil in the Coeur D’ Alene River Basin Environ Eco Stat. 22(3) 551-570

[14] Roy P K, Hossain S S 2014 Predicting arsenic concentration in groundwater of Bangladesh using Bayesian geostatistical model Environ Ecol Stat 21 583-597

[15] Hussain I, Shafeek M, Faisal M, Soomro Z A, Hussain M, Hussain T 2014 Distribution of total dissolved solids in drinking water by means of Bayesian kriging and Gaussian spatial predictive process Water Qual Expo Health 6 177-185

[16] Orton T G, Saby N P A, Arrouays D, Jolivet C C, Villanneau E J, Paroissien J, Marchant B P, Caria G, Barriuso E, Bispo A, Briand O 2012 Analyzing the spatial distribution of PCB concentrations in soils using below-quantification limit data J Environ Qual 41 1893-1905

[17] Shi T, Zhang Y, Gong Y, Ma J, Wei H, Wu X, Zhao L, Hou H 2019 Status of cadmium accumulation in agricultural soils across China(1975-2016): From temporal and spatial variations to risk assessment Chemosphere 230 136-143

[18] Huang Y, Wang L, Wang W, Li T, He Z, Yang X 2019 Current status of agricultural soil pollution by heavy metals in China: A metal-analysis Sci Total Environ 651 3034-3042

[19] Zhang M, Xu J 2011 Nonpoint source pollution, environmental quality, and ecosystem health in China: Introduction to the special section J Environ Qual 40 1685-1694
[20] Fu Y, Dou X, Lai N, Huang J, Wang X, Wang Z 2016 Distribution characteristics and risk assessment of soil heavy metal contents in Wensu County of southwest Xinjiang Xinjiang Agricultural Sciences 53(12) 2280-2289
[21] Sun Y, Zhou J, Zeng Y, Chen Y, Wang S, Du J 2018 Assessment of heavy metal (Metalloid) pollution and potential ecological risk for farmland soil in Yutian County of Xinjiang. Xinjiang Agricultural Sciences 55(12) 2271-2278
[22] Gu S, Zhou J, Zeng Y, Chen Y, Wang S, Du J 2018 Soil heavy metal (Metalloid) pollution and exological risk assessment of agricultural land in Qiemo County of Xinjiang, China Journal of Xinjiang Agricultural University 41(2) 145-150
[23] Mamut A, Eziz M, Mohammad A 2018 Spatial distribution and sources identification of heavy metals in farmland soils of Yanqi County, Xinjiang Environmental Monitor Management and Technology 30(3) 11-16
[24] Zhao Chengyi, Hu Shunjun 2010 Chinese Ecosystem Observation and Research Dataset. Farmland Ecosystem Station: Xinjiang Aksu Station (1999-2007) China Agricultural Press, Beijing
[25] Deutsch C V, Journel A G. 1998 GSLIB Geostatistical Software Library and User’s Guide, second edition. Oxford University Press, New York
[26] Gelfand A E, Banerjee S 2017 Bayesian modeling and analysis of geostatistical data Annu Rev Stat Appl 4 245-266
[27] Patil A, Huard D, Fonnesbeck C J 2010 PyMC: Bayesian stochastic modelling in Python. J Stat Softw 35 (4) 1-81
[28] Li J, Heap A D 2011 A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors Ecol Inform 6(3-4) 228-241
[29] Diggle P J, Ribeiro Jr P J 2007 Model-based Geostatistics. Springer Science + Business Media, LLC
[30] Fabijańczyk P, Zawadzki J, Magiera T 2017 Magnetometric assessment of soil contamination in problematic area using empirical Bayesian and indicator kriging: a case study in Upper Silesia, Poland Geoderma 308 69-77
[31] Environmental Monitoring Station of Xinjiang Province, China 1991 Background Values of Soil Elements in Xinjiang Province, China
[32] Eziz M, Mohammad A, Mamut A, Anayit M 2018 Assessment of heavy metals pollution and its health risk of farmland soils of Yanqi Basin in Xinjiang Province Asian Journal of Ecotoxicology 13(2) 171-181
[33] Wang L, Cui X, Cheng H, Chen Fei, Wang J, Zhao X, Lin C, Pu X 2015 A review of soil cadmium contamination in China including a health risk assessment Environ Sci Pollut Res 22(21) 16441-16452
[34] Zhang X, Chen D, Zhong T, Zhang X, Cheng M, Li X 2015 Evaluation of lead in arable soils, China Clean Soil Air Water 43(8) 1232-1240
[35] Smolders E, Mertens J 2013 Cadmium. In: Alloway B (eds). Heavy Metals in Soils. Environmental Pollution 22 Springer,Dordrecht
[36] Steinnes E 2013 Lead. In: Alloway B (eds). Heavy Metals in Soils Environmental Pollution 22 Springer,Dordrecht
[37] Li J 2009 Characteristics, source, long-range transport of dust aerosol over the central Asia and its potential effect on global change. PhD Thesis. Shanghai: Fudan University
[38] Guo G, Chen T, Song B, Yang J, Huang Z, Lei M, Chen Yu C 2007 Emission of heavy metals from road traffic and effect of emitted lead on land contamination in China: A primary study Geographical Research 26(5) 922-930