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Comparison of the Interpolation of Lead and Zinc Accumulation in the Soils around Zanjan Lead and Zinc Corporation Using laboratory and Landsat Data

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ABSTRACT

Background: This aimed to compare the interpolation of lead and zinc concentration at the National Lead and Zinc Corporation using Landsat satellite and laboratory data to introduce an optimal interpolation method.
Methods: After collecting the laboratory data, geostatistical approaches were applied to model the spatial distribution of lead and zinc, including radial basis functions, inverse distance weighting, and ordinary kriging (Gaussian, spherical, exponential, and circular). Estimation accuracy was evaluated by cross-validation and MAE, MBE, and RMSE diagnostic statistics.
Results: The Gaussian model had the lowest error and was the optimal method for modeling lead and zinc. After investigating the correlations between the Landsat 5 satellite bands and soil element concentrations, the spatial distribution of lead and zinc was re-zoned in the ArcGIS software. In both methods, estimation accuracy was evaluated by cross-validation and MAE, MBE, and RMSE diagnostic statistics.
Conclusion: The MAE and RMSE of the satellite data of lead were 38.36 and 91.73, while they were 52.93 and 74.57 for zinc, respectively. The experimental data of lead were 53.04 and 125.18while they were 108.15 and 239.25 for zinc, respectively. The accuracy of the satellite data in the interpolation of the investigated elements had lower error and higher accuracy.

1. Introduction

Soil contamination is a significant environmental concern due to rapid industrialization and rising dependence on agrochemicals in the recent years [1]. Among various pollutants, heavy metals are particularly hazardous due to their toxicity and stability [2]. Heavy metals are considered detrimental to the public health at specific levels of exposure [3]. Therefore, the rapid and occasional observation of heavy metals are important in the regions with a higher risk of contamination [4]. A common method used to investigate the dispersion of heavy metals in soil based on field sampling is chemical analysis followed by geostatistical interpolations, which may be time-consuming and costly [5]. In addition, such studies could only provide limited data in a specific place and at the specific time without describing the spatial

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and temporal dynamics of heavy metal concentrations [6]. Mapping based on spectral responses is a novel method used regionally with satellite sensors or in detail with airborne hyperspectral sensors and laser altimetry [7].

Remote sensing is considered to be a reliable and environmentally-friendly method for the assessment of heavy metal compounds in soil. Remote sensing satellite systems have evolved to provide higher spatial and spectral resolutions for explorations on the planet. Satellite data could anticipate the physical, chemical, and biological properties of soil by relying on the laboratory and filed observations of soil, as well as the relevant data derived from remote sensing, along with quantitative approaches to deduce the spatial patterns of soil on various temporal and spatial scales [8, 9].

Several studies have been focused on the measurement of heavy metals by using satellite data, laboratory data, and geostatistical analysis [10-17]. The present study aimed to compare the concentration zonation of lead and zinc in the surrounding of the National Lead and Zinc Corporation (NILZ) using laboratory and satellite data to introduce a novel, optimal method for estimating the amount of these compounds in soil.

2. Materials and Methods

2.1. Study Area and Sampling

Zanjan province is located in the northwest of Iran, covers a large metalliferous site, and is regarded as a traditional mining area. The NILZ Company was founded in 1992 and currently consumes approximately 300,000 tons of raw ore for the production of 55,000 t of lead and zinc each year [18]. It has been estimated that NILZ tailings are approximately 2.5 million tons, containing various toxic elements, especially zinc and lead [19].

In this study, 121 soil samples were collected from various locations based on the predetermined spots by GPS1 (Figure 1); the sampling region covered approximately 172 square kilometers. Each sampling station indicated a square block grid (dimension: 2 m), and five topsoil samples (corners and centers) were collected from each region, mixed, and applied as one composite sample. Sampling was performed in June 2010. The samples were collected from the depth of 0-15 centimeters, air-dried, and passed through a two-millimeter sieve to extract large residues, pebble-sized materials, plant roots, and other materials. Following that, the soil samples were dissolved at the HNO_3-$HClO_4$ ratio of 7:14, and analysis was carried out on the digest solutions using atomic absorption spectrophotometry. The soil samples were examined in terms of the total concentrations of zinc and lead [20].

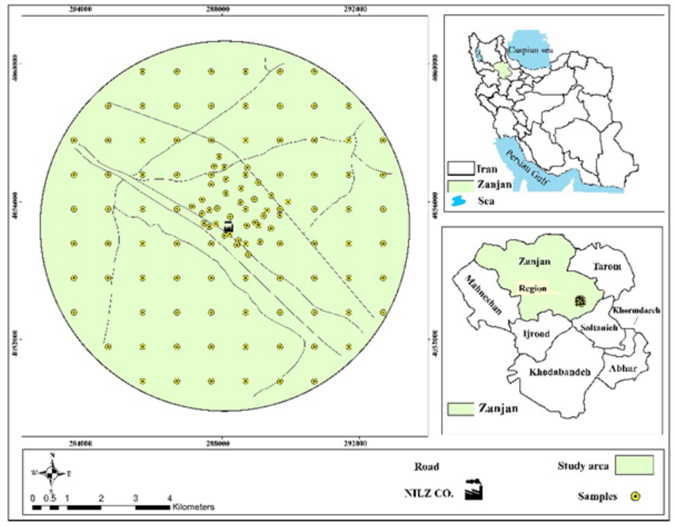

Figure 1; Distribution of sampling points and location of study area

2.2. Statistical Analysis

Data analysis was performed in SPSS version 20 using conventional statistical analysis (mean, range, minimum, maximum, variance, skewness, kurtosis, and standard deviation) for the measurement of heavy metals to achieve a basic understanding of the related data [21]. In addition, Pearson's correlation-coefficient was applied to assess the correlations of the examined concentrations of zinc and lead in soil with the Landsat bands. The Curve Expert Professional 1.6 software was also used to fit the most appropriate regression model for estimating the concentration of lead and zinc using the selected satellite bands. Preceding geostatistical analyses and the normalization of data were also performed using logarithm [22].

2.3. Satellite Data

The required satellite images were obtained from the USGS2 database, and attempts were made to match the time of the satellite imagery with the time of experimental data collection to avoid the possibility of changes in the spectral reflections [23]. Notably, the satellite images of the sampling time in the USGS database were related to Landsat 5 and 7 satellites. Given that some sensors of Landsat 7 were off at the time of sampling and the images had striping errors, the applied satellite images belonged to Landsat 5. The remote sensing approach for the measurement of heavy metal content in soil is a time- and cost-effective procedure and a novelty in the current research as only few studies have accomplished the mapping of heavy metal content using satellite data to optimum accuracy [24].

2.4. Geostatistical Analysis

Interpolation is the process of predicting the values of various attributes at non-sampling locations. Differing from classic modeling methods, spatial interpolation approaches integrate the data on the geographic positions of sampling points. The logic behind spatial interpolation is that the spots that are closer to each other have more significant correlations and similarities compared to those that are located at greater distances [25]. In the current research, inverse distance weighting (IDW; power: 5, 10, and 15), radial basis functions (RBFs), and ordinary kriging (Gaussian, spherical, exponential, and circular) were the most extensively used interpolation approaches. The geostatistical methods used in the present study were performed in the ArcGIS 10.3 software.

2.5. Inverse Distance Weighting (IDW)

IDW is a commonly used interpolation method, which is applied to predict the values of unmeasured spots through measuring the surrounding values of the predicted locations [26]. IDW is based on the assumption that the effect of the phenomenon decreases with increased distance. To estimate the unknown spots, the surrounding samples should have more participation than those located at a farther distance [27]. The interpolating function is as follows:

$$z(x) = \frac{\sum_{i=1}^{n} w_i z_i}{\sum_{i=1}^{n} w_i}, \quad w_i = d_i^{-u} \tag{1}$$

where Z(x) is the estimated value at an interpolated spot, z_i shows a known spot, n is the total number of the known spots used in interpolation, d_i represents the distance between spot i and the prediction spot, and wi shows the weight allocated to spot i. Higher weighting values are allocated to the values closer to the interpolated spot. As the distance increases, the weight decreases, and u is the weighting power that decides the weight reduction mode as the distance increases [28].

2.6. Radial Basis Functions (RBFs)

RBFs refer to a large group of precise interpolators, which use a simple equation for the distance between the sampling spots and interpolated spot. RBFs are notionally the same as fitting a rubber membrane through the measured sample values while reducing the total curvature of the surface [29].

2.7. Kriging

Kriging is based on the assumption that the interpolated parameter could act as a regionalized variable. The interpolating function is as follows:

$$Z^* = \sum_{i=1}^{n} w_i\, z(x_i) \tag{2}$$

where $Z(x_i)$ is the observed value at location x_i, Z^* shows the interpolated value, and w_i is the statistical weight for sample x_i [30].

Due to the small sample size in the present study, cross-validation was used to continually eliminate a data point, interpolate the value from the remaining observations, and contrast the anticipated value with the measured value. In addition, the root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE) were evaluated based on the interpolated and measured values at each sampling point to compare the accuracy of the predictions.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Z^*(x_i) - Z(x_i)| \tag{3}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}[Z^*(x_i) - Z(x_i)] \tag{4}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}[Z^*(x_i) - Z(x_i)]^2 / n} \tag{5}$$

In the equations above, $Z(x_i)$ is the observed value at site x_i, $Z^*(x_i)$ shows the interpolated value at site x_i, and n is the sample size. Notably, smaller MAE and RMSE values indicated fewer errors [31].

3. Results and Discussion

The descriptive statistics regarding heavy metal concentrations indicated a significant change in the content of heavy metals among the soil samples. Accordingly, the concentrations of lead and zinc varied between ND and 980.33, 50.88, and 2511.04 mg/kg, respectively, with the mean concentration estimated at 75.70 and 180.38 mg/kg, respectively. The normal range of lead and zinc concentration in soil is 0.1-20 and 3-50 mg/kg, respectively, and the critical limits have been determined to be 100 and 300 mg/kg, respectively [32]. Both mean values of these heavy metals were higher than the normal ranges in the current research. In addition, the mean concentration of lead and zinc was 3.7 and 3.6 times higher than their normal values, which distinctly illustrated the anthropogenic contribution and pollution levels in the studied region.

In the geostatistical analyses, the normalization of data was performed using logarithm. Table 1 shows the results of the pattern modeling of lead and zinc spatial distribution using various geostatistical methods. Accordingly, the Gaussian model was the optimal method for the modeling of the distribution pattern with the lowest RMSE and the proximity of the MBE to zero for zinc, as well as the lowest MAE for lead. Figures 2 and 3 depict the estimated maps of lead and zinc, respectively. According to the maps, the highest concentration of lead and zinc was estimated in the waste accumulation site in the vicinity of the company' location and along Abhar-Zanjan road, which is the route to Zanjan-Dandi road to supply the required feed from Angoran mine.

In the second phase of the present study, the reflection rates of Landsat 5 satellite bands were extracted for all the sampling points, and the correlations between the lead and zinc concentrations in the samples with the reflection rates of the similar points in all the bands were investigated.

Table 1: Results of modeling spatial distribution pattern of lead and zinc by various geostatistical methods

MAE		MBE		RMSE		Model	Method
Pb	Zn	Pb	Zn	Pb	Zn		
68.81	125.20	12.81	13.46	152.67	264.50	5	IDW
67.57	119.66	14.02	11.31	148.13	251.12	10	
68.04	120.86	16.36	14.17	145.98	249.62	15	
54.07	108.16	-3.08	-3.48	125.18	240.07	Spherical	OK
54.07	108.12	-3.08	-3.50	125.18	240.43	Circular	
54.07	107.45	-3.08	-3.81	125.18	239.72	Exponential	
53.04	108.15	-3.08	-3.41	125.18	239.25	Gaussian	
59.18	114.65	5.43	5.50	137.65	247.15	-	RBF

The findings indicated a significant, negative correlation between the measured concentrations of lead and zinc in soil and the reflection of bands four and five. The correlations in band four were considered significant for both elements at 95% probability level. In band five, the correlations for lead and zinc were also significant at 99% and 95% probability levels, respectively. In addition, the increased concentration of the heavy metals in soil reduced soil reflection, which confirmed the negative correlation of this phenomenon.

The results obtained by Kemper and Sommer (2002) and Choe *et al.* (2008) [11, 12] have also indicated significant, negative correlations in the near-infrared band (band four) with the heavy metal content of soil. According to the results of the present study, lead and zinc concentrations could be estimated via the near-infrared and mid-infrared bands. Table 2 shows the estimated regression models for estimating the concentrations of the two elements. Correspondingly, the changes in the zinc content were linear with the reflections of satellite bands four and five. Furthermore, the trend of the reflectance changes in bands four and five for lead was observed to be parabolic and linear, respectively. In order to estimate the concentrations of zinc and lead at each sampling station, the near-infrared and mid-infrared band reflections were entered into the models, and the predicted values were used for the re-preparation of the interpolation maps in the ArcGIS software (Figures 4 and 5). The maps show that the spatial distribution pattern of lead and zinc was relatively similar, and the concentration of the two elements was also higher at the waste accumulation site.

The comparison of the cross-validation results using the experimental and satellite data methods clarified that the MAE and RMSE statistics were in the satellite data methods for lead (38.36 and 91.73, respectively) and zinc (52.93 and 74.57, respectively), as well as in the experimental data for lead (53.04 and 125.18, respectively) and zinc (108.15 and 239.25, respectively). Therefore, it could be concluded that the satellite data methods had fewer errors and higher accuracy compared to the experimental data in the interpolation of the studied elements.

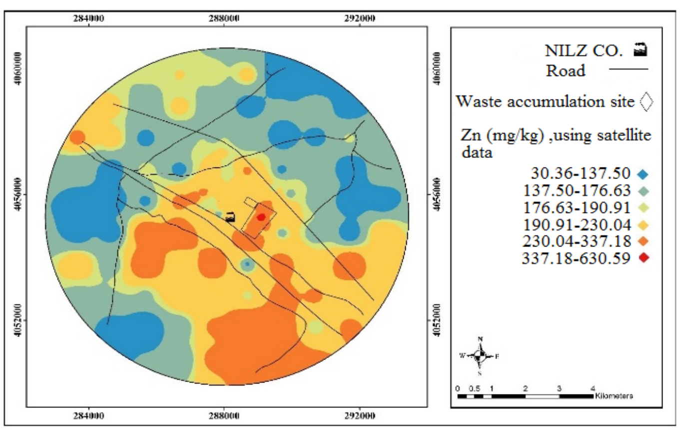

Figure 2: Spatial distribution of lead in soil

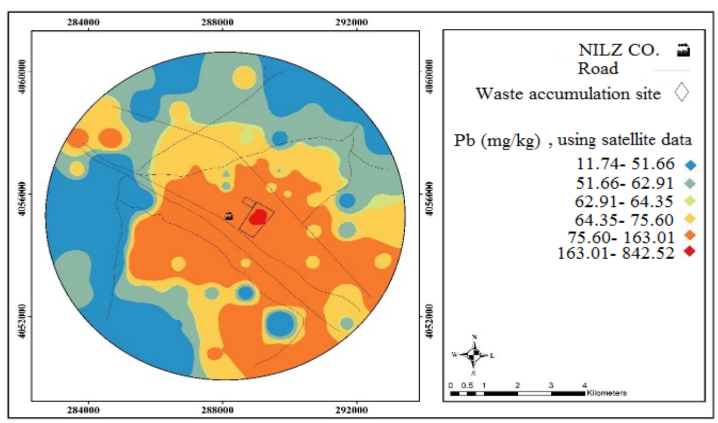

Figure 3: Spatial distribution of zinc in soil

Table 2: Multivariate Regression Models to Approximate Concentrations of Lead and Zinc in Soil

Model	r^2	SE	r
$Pb = 4178.283429 + 447.064144(Band4) - 396.915429(Band5) - 6.802303(Band4^2) + 1.971353(Band5^2) + 0.019786(Band4^3) - 0.001662(Band5^3) + 2.772821(Band4) \times (Band5) + 0.008014(Band4^2) \times (Band5) - 0.014865(Band4) \times (Band5^2)$	0.276	137.144	0.525
$Zn = -1029.083761 + 244.758128(Band4) - 116.919274(Band5) - 5.396531(Band4^2) - 0.450222(Band5^2) + 0.048130(Band4^3) - 0.008650(Band5^3) + 3.585196(Band4) \times (Band5) - 0.066420(Band4^2) \times (Band5) + 0.037897(Band4) \times (Band5^2)$	0.087	257.221	0.296

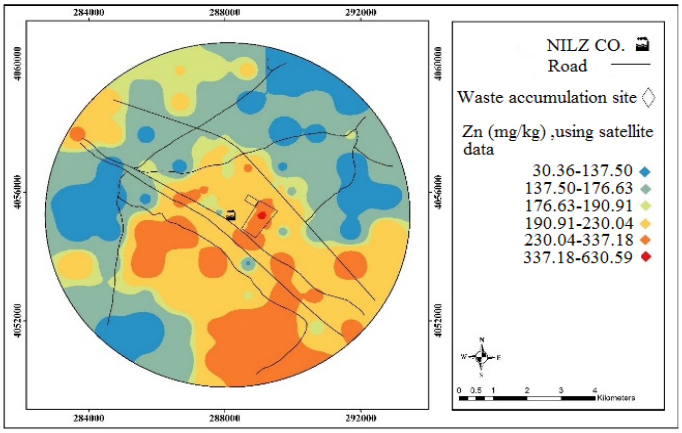

Figure 4: Spatial distribution of zinc in soil (satellite data)

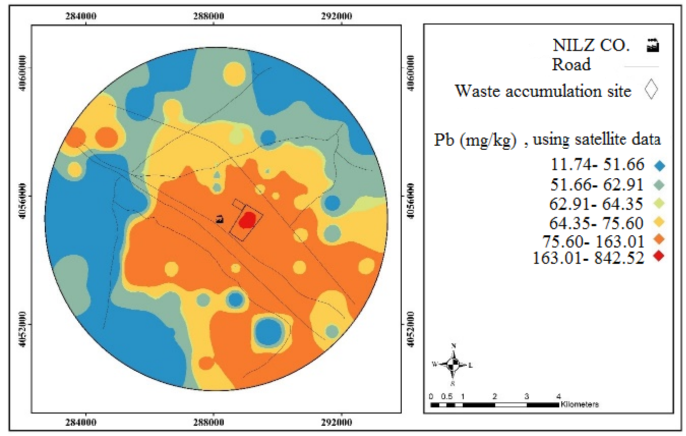

Figure 5: Spatial distribution of lead in soil (satellite data)

4. Conclusion

This study aimed to compare the interpolation of lead and zinc concentrations in the vicinity of Zanjan National Lead and Zinc Corporation using laboratory and Landsat data to introduce a new and optimal method for the estimation of heavy metals in soil. According to the obtained maps based on the experimental data, the highest concentrations of lead and zinc was detected in the waste accumulation site and along Abhar-Zanjan road, which is the feed supply route from Angoran mine. Notably, the dispersion of zinc along this road was higher than lead possibly due to the higher mobility of zinc [33]. On the other hand, the estimated maps based on the satellite data illustrated the highest concentration of lead and zinc at the waste accumulation site. Furthermore, the estimated maps by the satellite data in the southern, southeastern, and northwestern regions of the study area indicated that the relatively large anomaly of lead and zinc has been extrapolated. After field studies, it was observed that these areas are the location of industrial units such as Saba Tire Yarn, Zanjan Oil Company, Arta Beton, Shahid Ghaiti Power Plant, and the waste accumulation sites of these units. The comparison of the results of the cross-validation of the laboratory and satellite data methods revealed that the satellite data error in the interpolation of the studied elements was lower than the experimental data, which confirmed the higher accuracy of the satellite data in the interpolation of lead and zinc.

Authors' Contributions

All the authors contributed to the preparation of this article. Z.M.A., A.A.Z., and Y.K., designed the study, drafted the manuscript, and contributed to data collection and data analysis.

Conflicts of Interest

The Authors declare that there is no conflict of interest.

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References

1. Cai L, Xu Z, Ren M, Guo Q, Hu X, Hu G, *et al.* Source Identification of Eight Hazardous Heavy Metals in Agricultural Soils of Huizhou, Guangdong Province, China. *Ecotoxicol Environ Saf.* 2012; 78: 2-8.

2. Mahurpawar M. Effects of Heavy Metals on Human Health. *Int J Res Granthaalayah.* 2015; 530: 1-7.

3. Amirah M, Afiza A, Faizal W, Nurliyana M, Laili S. Human Health Risk Assessment of Metal Contamination Through Consumption of Fish. *J Environ Pollut Hum Health.* 2013; 1(1): 1-5.

4. Schwartz G, Eshel G, Ben Dor E. Reflectance Spectroscopy as a Tool for Monitoring Contaminated Soils. *Soil Contam.* 2011; 6790.

5. Shi T, Chen Y, Liu Y, Wu G. Visible and Near-Infrared Reflectance Spectroscopy an Alternative for Monitoring Soil Contamination by Heavy Metals. *J Hazard Mater.* 2014; 265: 166-76.

6. Liu M, Liu X, Zhang B, Ding C. Regional Heavy Metal Pollution in Crops by Integrating Physiological Function Variability with Spatio-Temporal Stability Using Multi-Temporal Thermal Remote Sensing. *Int J Appl Earth Obs Geoinf.* 2016; 51: 91-102.

7. Teeuw RM. Mapping Hazardous Terrain Using Remote Sensing. *England: Geological Society of London*; 2007.

8. Wang G, Du W, Carranza EJM. Remote Sensing and Gis Prospectivity Mapping for Magmatic-Hydrothermal Base-and Precious-Metal Deposits in the Honghai District, China. *J Afr Earth Sci.* 2017; 128: 97-115.

9. Grunwald S, Thompson J, Boettinger J. Digital Soil Mapping and Modeling at Continental Scales: Finding Solutions for Global Issues. *Soil Sci Soc Am J.* 2011; 75(4): 1201-13.

10. Ferrier G. Application of Imaging Spectrometer Data in Identifying Environmental Pollution Caused by Mining at Rodaquilar, Spain. *Remote Sens Environ*. 1999; 68(2): 125-37.

11. Kemper T, Sommer S. Estimate of Heavy Metal Contamination in Soils after a Mining Accident Using Reflectance Spectroscopy. *Environ Sci Technol*. 2002; 36(12): 2742-7.

12. Choe E, Van der Meer F, Van Ruitenbeek F, Van der Werff H, De Smeth B, Kim KW. Mapping of Heavy Metal Pollution in Stream Sediments Using Combined Geochemistry, Field Spectroscopy, and Hyperspectral Remote Sensing: a Case Study of the Rodalquilar Mining Area, Se Spain. *Remote Sens Environ*. 2008; 112(7): 3222-33.

13. Anderson K, Croft H. Remote Sensing of Soil Surface Properties. *Prog Phys Geogr*. 2009; 33(4): 457-73.

14. Yuan GL, Sun TH, Han P, Li J. Environmental Geochemical Mapping and Multivariate Geostatistical Analysis of Heavy Metals in Topsoils of a Closed Steel Smelter: Capital Iron and Steel Factory, Beijing, China. *J Geochem Explor*. 2013; 130: 15-21.

15. Li X, Liu L, Wang Y, Luo G, Chen X, Yang X, *et al*. Heavy Metal Contamination of Urban Soil in an Old Industrial City (Shenyang) in Northeast China. *Geoderma*. 2013; 192: 50-8.

16. Gu YG, Li QS, Fang JH, He BY, Fu HB, Tong ZJ. Identification of Heavy Metal Sources in the Reclaimed Farmland Soils of the Pearl River Estuary in China Using A Multivariate Geostatistical Approach. *Ecotoxicol Environ Saf*. 2014; 105: 7-12.

17. Uyan M. Determination of Agricultural Soil Index Using Geostatistical Analysis and Gis on Land Consolidation Projects: a Case Study in Konya/Turkey. *Comput Electron Agric*. 2016; 123: 402-9.

18. Parizanganeh AH, Bijnavand V, Zamani AA, Hajabolfath A. Concentration, Distribution and Comparison of Total and Bioavailable Heavy Metals in Top Soils of Bonab District in Zanjan Province. *Open J Soil Sci*. 2012; 2(02): 123.

19. Khosravi Y, Zamani AA, Parizanganeh AH, Yaftian MR. Assessment of Spatial Distribution Pattern of Heavy Metals Surrounding a Lead and Zinc Production Plant in Zanjan Province, Iran. *Geoderma Reg*. 2018; 12: 10-7.

20. Zamani AA. Environmental Analytical Chemistry: Contribution to Studies on Heavy Metals in the Environment. *Ph. D. Thesis: Zanjan University*. 2012.

21. Zhang X, Lin F, Wong MT, Feng X, Wang K. Identification of Soil Heavy Metal Sources from Anthropogenic Activities and Pollution Assessment of Fuyang County, China. *Environ Monit Assess*. 2009; 154(1-4): 439.

22. Cai L, Xu Z, Bao P, He M, Dou L, Chen L, *et al*. Multivariate and Geostatistical Analyses of the Spatial Distribution and Source of Arsenic and Heavy Metals in the Agricultural Soils in Shunde, Southeast China. *J Geochem Explor*. 2015; 148: 189-95.

23. Weidong L, Baret F, Xingfa G, Qingxi T, Lanfen Z, Bing Z. Relating Soil Surface Moisture to Reflectance. *Remote Sens Environ*. 2002; 81(2-3): 238-46.

24. Wang F, Gao J, Zha Y. Hyperspectral Sensing of Heavy Metals in Soil and Vegetation: Feasibility and Challenges. *ISPRS J Photogramm Remote Sens*. 2018; 136: 73-84.

25. Xiao Y, Gu X, Yin S, Shao J, Cui Y, Zhang Q, *et al*. Geostatistical Interpolation Model Selection Based on Arcgis and Spatio-Temporal Variability Analysis of Groundwater Level in Piedmont Plains, Northwest China. *SpringerPlus*. 2016; 5(1): 425.

26. Harder C. The ArcGIS Book: 10 Big Ideas about Applying Geography to Your World. *Esri Press*; 2015.

27. Belief E. GIS Based Spatial Modeling to Mapping and Estimation Relative Risk of Different Diseases Using Inverse Distance Weighting (Idw) Interpolation Algorithm and Evidential Belief Function (Ebf)(Case Study: Minor Part of Kirkuk City, Iraq). *Int J Eng Technol*. 2018; 7(4.37): 185-91.

28. Xie Y, Chen TB, Lei M, Yang J, Guo QJ, Song B, *et al*. Spatial Distribution of Soil Heavy Metal Pollution Estimated by Different Interpolation Methods: Accuracy and Uncertainty Analysis. *Chemosphere*. 2011; 82(3): 468-76.

29. Aguilar FJ, Agüera F, Aguilar MA, Carvajal F. Effects of Terrain Morphology, Sampling Density, and Interpolation Methods on Grid Dem Accuracy. *Photogramm Eng Remote Sensing*. 2005; 71(7): 805-16.

30. Arslan H. Estimation of Spatial Distrubition of Groundwater Level and Risky Areas of Seawater Intrusion on the Coastal Region in Çarşamba Plain, Turkey, Using Different Interpolation Methods. *Environ Monit Assess*. 2014; 186(8): 5123-34.

31. Webster R, Oliver MA. Geostatistics for Environmental Scientists. *England: John Wiley and Sons*; 2007.

32. Parizanganeh A, Hajisoltani P, Zamani A. Assessment of Heavy Metal Pollution in Surficial Soils Surrounding Zinc Industrial Complex in Zanjan-Iran. *Procedia Environ Sci*. 2010; 2: 162-6.

33. Mehes Smith M, Nkongolo K, Narendrula R, Cholewa E. Mobility of Heavy Metals in Plants and Soil: a Case Study from a Mining Region in Canada. *Am J Environ Sci*. 2013; 9(6): 483-93.