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Research Article

Geostatistical analysis of arsenic contamination in soil and comparison of interpolation techniques in Nadia district of Bengal, India

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Abstract

The contamination of soil and water with arsenic directly or indirectly affects millions of people, particularly in Southeast Asia. Efficiently managing contaminated sites cost-effectively requires an understanding of the spatial distribution of contamination in soil. In this study, different interpolation methods, including Ordinary Kriging (OK), Inverse Distance Weighted (IDW), Radial Basis Function (RBF), and Empirical Bayesian Kriging (EBK), were evaluated in the Bengal region to determine their effectiveness in predicting the Olsen extractable As content in the soil. The study found that the mean Olsen extractable content in soil was 1.45 mg kg^{-1}, with a range of 0.48 to 3.57 mg kg^{-1}. Geostatistical analysis showed that the northern side of Nadia had relatively high contamination, while the southern side had relatively lower contamination. The Root Mean Square Error (RMSE) values of the different interpolation methods ranged from 0.52 to 0.54, with corresponding mean cross-validation (CV) values ranging from -0.005 to 0.008. The predicted minimum and maximum values of as-in soil were in close agreement with the measured values for IDW interpolation, followed by OK, RBF, and EBK. The study found that IDW consistently provided the most precise predictions of pollution in the soil throughout space. These findings have significant implications for managing contamination in the Nadia West Bengal and other regions facing similar challenges.

Keywords extractable arsenic, GIS, interpolation

Introduction

Arsenic (As) is a class (I) carcinogen, which poses a very serious threat to both the health of humans and the environment and affects millions of people all over the world [1]. Arsenic has entered terrestrial and aquatic habitats through both natural geological processes and human activities, contaminating soil and groundwater [2]. In the last three decades, increased levels of As in drinking water and food sources like rice have become a major concern for public health around the world [3]. The Ganga Delta Plains, where a sizable percentage of the population is located, is one of the worst affected by As pollution [4]. In the rice-rice cropping system prevalent in Bangladesh and Bengal (India), arsenic-contaminated groundwater is frequently used to irrigate rice crops, leading to the accumulation of As in agricultural soils [2]. In regions where rice is a staple diet, the increased amount of As in the grain of rice cultivated on soil with elevated as levels represent a serious hazard to human health [5-6]. In humans, toxicity manifests as hyperkeratosis, hyperpigmentation, and cancer [7]. Rice is a staple food in Bengal. Researchers found that consuming contaminated rice or rice-based products led to an increase in healthcare costs and related human health problems [8]. A growing body of evidence suggests that exposure to hazardous substances poses significant risks to human health and the long-term viability of agricultural systems.

The study of the spatial distribution of contaminants in agricultural soils is very much important to minimize risk to human health and helps in the preparation of remediation strategies and site-specific management plans. However, variation in pollutants on land surfaces makes metalloid spatial distribution difficult to measure. Traditional soil contamination assessment relied on a percentage of samples exceeding a regulatory standard [9]. The basic statistical procedure assumed data were independent, exact, or near normal, and sampled frequently. However, soil pollution assessments show skewed normal and geographically auto-correlated pollutant concentrations [9-10]. Due to the high cost of collecting soil samples and having them analysed, it is often difficult to conduct dense and repetitive sampling. Mapping of contaminants in the environment, various interpolation techniques are used. In soil investigations and pollution mapping, interpolation techniques such as inverse distance weighting (IDW), kriging, cokriging, local polynomial interpolation, radial basis functions, Universal Kriging, and Spline have been used extensively [9-11]. While some studies have determined that kriging interpolation is the most accurate method [12], others have found that IDW interpolation is on par with or even more accurate than OK interpolation [13-14]. It is of the utmost importance to lessen the influence of interpolation methods' bias on pollution assessments. Bhunia et al., [15] analyse five GIS-based interpolation approaches for determining soil organic carbon distribution (SOC). The cross-validation method of the root means square error (RMSE) and the highest interpolation R^2 value made ordinary kriging (OK) the most dependable method of the five. Saha et al., [16] evaluated four different types of interpolation techniques and found that the IDW interpolation model was the most effective one for determining the spatial distribution patterns of hazardous metal concentration in the surface soils. With this background, the present investigation was carried out to assess the concentration of extractable As in the soil of Nadia, and the evaluation of the most accurate GIS interpolation techniques for mapping extractable As in the soils of the studied area. In the course of this research, we took soil samples to carry out a high-resolution survey to investigate the extent of As contamination and its spatial dependency.

Methodology

Sampling location and analysis of samples

In this study, 201 soil (0-15 cm) samples were collected from Nadia Bengal. The sampling location was marked with GPS and presented using ArcGIS software (Figure 1). The collected soil samples were processed and used for the analysis of extractable As. Arsenic in soil was extracted with 0.5 M sodium bicarbonate ($NaHCO_3$, pH=8.50) in the soil to solution 1:20, and shaking time was 30 min [17] and As content in extract was determined by hydride generator atomic absorption spectrometer (HG-AAS) using potassium iodide, ascorbic acid, and sodium borohydride in the acidic medium as reducing agent.

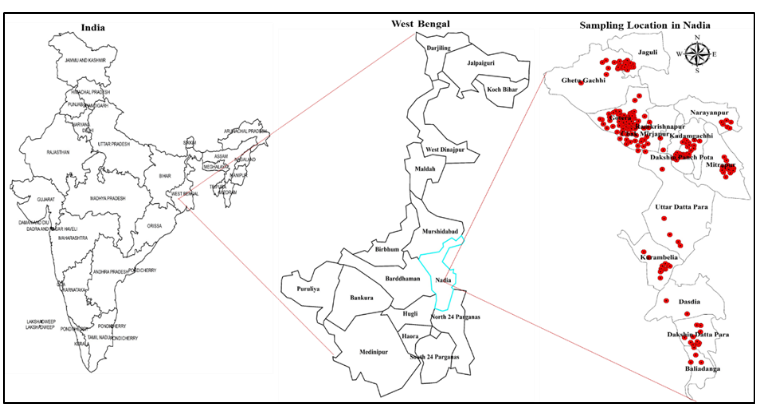

Figure 1. Sampling locations (N = 201)

Interpolation and spatial analysis

Interpolations for OK, IDW, RBF, and EBK were computed and analyzed using ArcGIS-10.5. Utilizing the ArcGIS Geostatistical Wizard, interpolation maps for the extractable As in soil were created. Depending on the statistical properties of the dataset, the best-fit model is generated using the Geostatistical Wizard [9]. This Geostatistical Wizard provides different measures to select the best-fit model for interpolation, out of different measures, some of the most important and common measures viz. root mean square error (RMSE) and mean of cross-validation (CV), prediction, and error plots were used [18]. RMSE values closer to zero indicate numerically close predicted values, hence they were used to directly evaluate the interpolation's prediction.

Statistical analysis

Descriptive statistics of different parameters were calculated using SAS 9.2 software pack [19].

Results and Discussion

Characterization of collected soil samples

Olsen extractable as spanning from 0.48 to 3.57 mg kg^{-1} (1.45 mg kg^{-1}). Only one sample was found that has extractable As content <0.5 mg kg^{-1} indicating 0.5% of its contribution in total samples (201). Extractable As content ranging from 0.50 -1.50 mg kg^{-1} have 119 samples (59.2%) while 48.0 (23.9%) and 33.0 (16.4%) samples fall in the range of 1.50 to 2.00 mg kg^{-1} and 2.00 to 3.57 mg kg^{-1}, respectively. Soil As concentrations in Nadia range from 47.7± 0.14 to 49.3± 0.19 mg kg^{-1} [6], with results from another study showing 1.34 to 14.09 mg kg^{-1} [20]. Based on the analysis of 189 soil samples in Nadia, West Bengal [21] found that the total As concentration in surface soil varied from 5.00 to 95.6 mg kg^{-1}, while in non-contaminated areas, As in soils varied from 0.1 to 10 mg kg^{-1} [22]. A study conducted by Golui et al., [23] in Malda, West Bengal, reported a neutral to alkaline pH range with higher OC content in the soil. Further, they reported that total and extractable As content in the soil range from 16.8 to 606 µg kg^{-1} and 0.84 to 11.5 mg kg^{-1}, respectively. In this study area rice based cropping system was followed for decades. During rice cultivation, a huge quantity of groundwater is contaminated as used for irrigating crops [21]. These practices are built As in soil which is easily available to plants and enters into the food chain and affects human health.

Interpolation of extractable As and cross-validation analysis of models

Maps prepared using different interpolation techniques viz. IDW, OK, EBK and RBF showed higher extractability on the northern side compared to the southern side. The predicted minimum value of extractable As using IDW, OK, EBK, and RBF were 0.49, 0.58, 0.67, and 0.60 mg kg^{-1}, respectively while corresponding predicted maximum values were 3.55, 3.42, 2.94, and 3.26 respectively (Table 1). Map of extractable As prepared using IDW, OK, EBK, and RBF interpolation method revealed that <0.50 mg kg^{-1} extractable As in soils confined to the area of 0.002, 0.01, 0.01 and 0.002 %, respectively, in range of 0.50-1.50 mg kg^{-1} area confined in the map was 59.6, 63.0, 59.6 and 61.9% respectively while 39.0, 35.5, 38.5 and 37.1% area was in the range of 1.50 to 2.00 mg kg^{-1}. Less than 2.00% of the area in each interpolation technique were within the range of 2.00 to 3.55 mg kg-1 (Table 1 and Figure 2 and 3). The predicted minimum value of extractable As in soil was 0.49, 0.58, 0.67, and 0.60 mg kg^{-1} while the predicted maximum was 3.55, 3.42, 2.94, and 3.26 mg kg^{-1} (Table 1). The predicted minimum and maximum values were in close agreement with the measured value in the case of IDW interpolation while other interpolation methods have to smooth effect on the prediction of minimum and maximum. For the selection of best interpolation methods, the most common measures are mean CV, RMSE, and slope of regression function (prediction function and error function) (Figure 4). The mean CV value for extractable As were -0.005, 0.004, 0.008, and -0.003 in the case of IDW, OK, EBK, and RBF, respectively while corresponding RMSE were 0.53, 0.54, 0.52, and 0.53 respectively. The slope of the prediction function was 0.32, 0.25, 0.29, 0.28 in IDW, OK, EBK, and RBF, respectively while the corresponding slope of the error function was -0.68, -0.75, -0.71, and -0.72, respectively (Table 1). The highest slope of the prediction function was observed

Table 1. Semi variogram components for extractable arsenic in soils of the study area

Parameter	Extractable As (mg kg^{-1})			
	IDW	**OK**	**EBK**	**RBF**
Mean	-0.005	0.004	0.008	-0.003
RMSE	0.53	0.54	0.52	0.53
Prediction Function	0.32 x + 0.96	0.25 x + 1.06	0.29x + 1.02	0.28x + 1.01
Error function	-0.68 x + 0.96	-0.75x + 1.06	-0.71x + 1.01	-0.72x + 1.01
Predicted minimum	0.49	0.58	0.67	0.60
Predicted maximum	3.55	3.42	2.94	3.26
Range (mg kg^{-1})	**Area (%)**			
<0.50	0.002	0.01	0.01	0.002
0.50-1.50	59.6	63.0	59.6	61.9
1.50-2.00	39.0	35.3	38.5	37.1
2.00-3.55	1.34	1.69	1.93	1.01

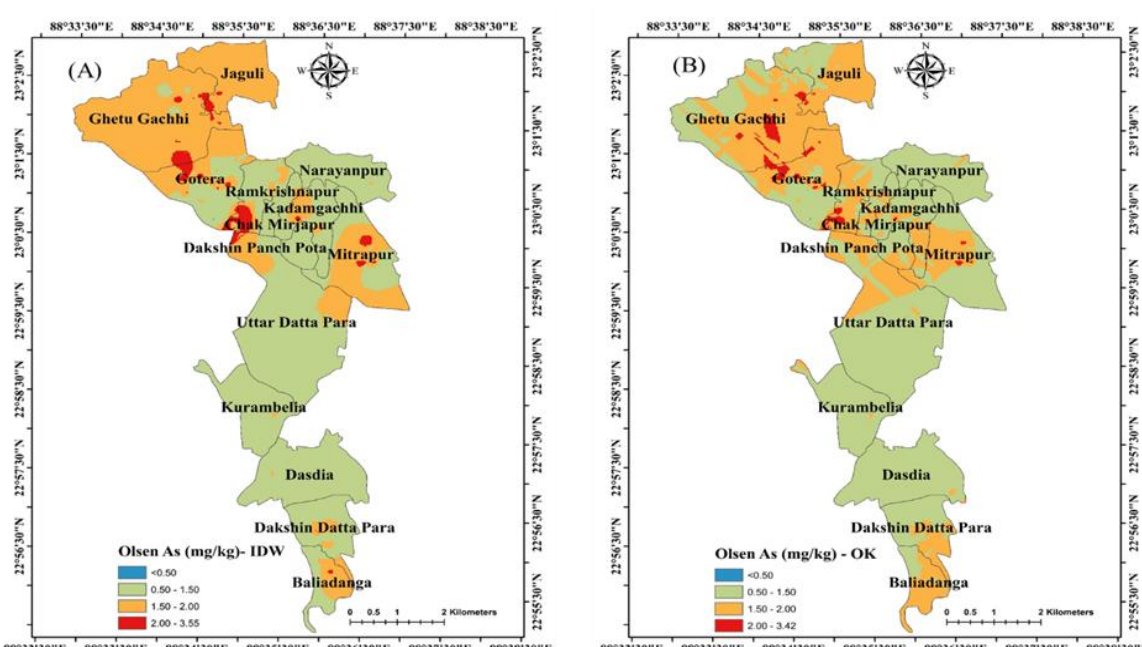

Figure 2. Maps of extractable As in soil using various interpolation methods (A) Inverse Distance Weighting (IDW) (B) Ordinary Kriging (OK)

in IDW interpolation while the lowest slope was observed in OK (Table 1). Therefore, based on mean CV, RMSE, and slope factor IDW can be used for interpolation of extractable as in the studied area. Extractable As maps were produced with the OK, IDW, RBF, and EBK interpolation techniques. Local maximum values were frequently seen in soil samples with a higher As concentration. Nonetheless, they comprise a negligible portion of all gathered samples. The objective of interpolation methods was to determine the spatial means as closely as possible.

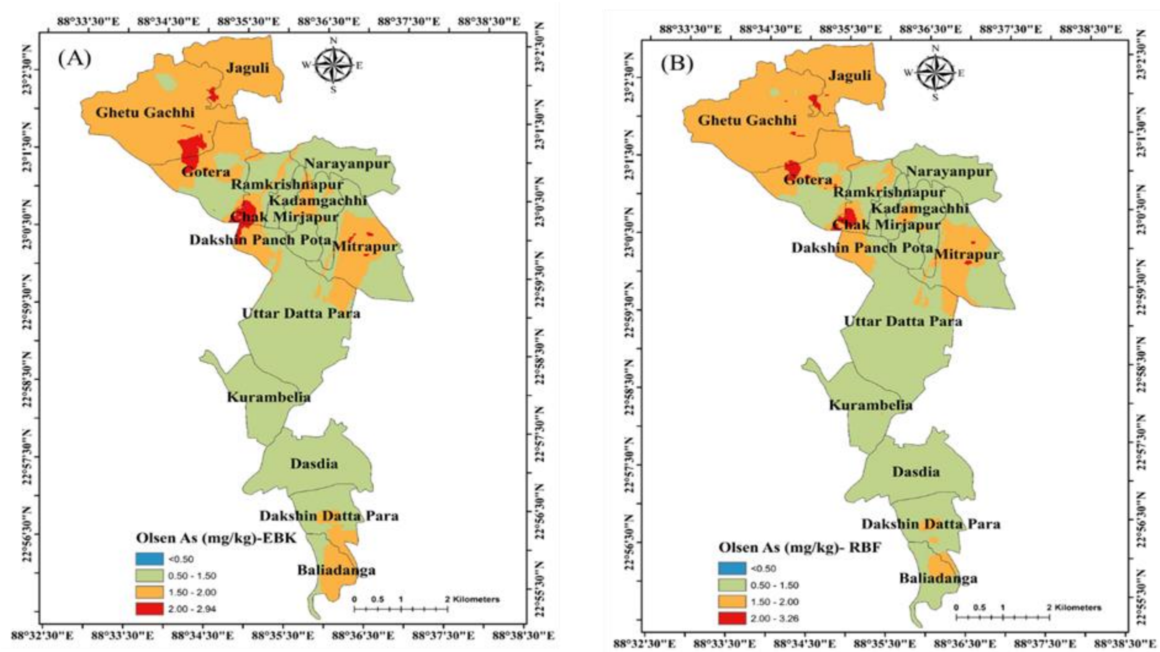

Figure 3. Maps of extractable As in soil using various interpolation methods (A) Empirical Bayesian Kriging (EBK) (B) Radial Basis Function (RBF)

Interpolation techniques smooth the initial data to decrease the projected global mean's inaccuracy. As a result, the local maximums and minimums were overestimated, whilst the local maximums were underestimated, causing the clean area to be overestimated and the high pollution risk area to be underestimated. In consequence, the contaminated area assessed using interpolation techniques was smaller than that calculated using statistical methods. The accuracy of metal and metalloid mapping is crucial for the efficacy of pollution assessment. Accuracy is affected by the number of samples, the distance between sampling locations, and the sampling technique [24]. Higher sampling densities would result in more accurate mapping of heavy metal contamination [24]. Due to the costs, time, and labor needed in sampling, as well as the cost of sample processing, a high sampling density is impractical [9]. Manjarrez-Domnguez et al., [24] used the IDW, OK, and RBF methods to interpolate a set of data on As concentration. They found that the way IDW, OK, and RBF showed As dispersion was the same. Even though the other categories didn't change much between the three approaches, they all focused on the same area with more As. The data revealed that IDW offered more precise interpolation [24]. The precision of the models may change, then, depending on the specifics of the data analysis. Nonetheless, little distinctions existed between the models. There are fewer input parameters needed to run an IDW, LP, or RBF, making them easier to use and thus simpler to operate [9]. Instead, standard Kriging necessitates additional work on the part of the user. Statistical tests, data transformation and inverse transformation, spatial structure analysis, semi variance function fitting, and so on are examples of processes that might improve the quality of an otherwise acceptable ordinary Kriging interpolation [9]. Due to the subjective nature of semi variance function fitting, many researchers may yield conflicting results [9]. The root-mean-squared error (RMSE) and the mean CV values of the interpolations over space are helpful metrics when evaluating the accuracy of interpolation prediction models [25-26]. With RMSE values close to zero, it's clear that the estimated extractable As content in soil is a good approximation of the observed value. This suggests that the measured As is quite similar to the interpolated (predicted) extractable As content.

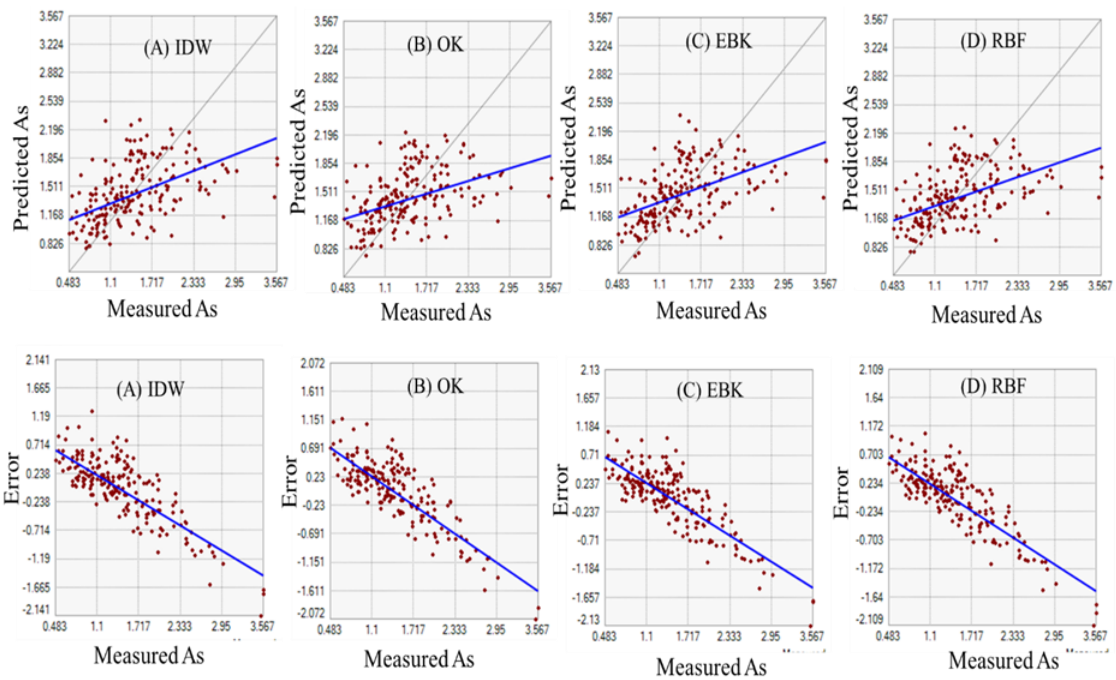

Figure 4. Predicted parameters and error values with measured values using best interpolation methods (A) Inverse Distance Weighting (IDW) (B) Ordinary Kriging (OK) (C) Empirical Bayesian Kriging (EBK) (D) Radial Basis Function (RBF)

Conclusion

The study investigated the extractable arsenic (As) content in soils of Nadia, West Bengal, India. This study evaluated different interpolation methods to understand the spatial distribution of arsenic contamination in soil in the Bengal region. The geostatistical analysis showed that the northern side of Nadia had relatively high contamination, while the southern side had relatively lower contamination. The study found that IDW consistently provided the most precise predictions of arsenic pollution in the soil throughout space. The findings of this study have significant implications for managing arsenic contamination in the Bengal region and other regions facing similar challenges. The use of appropriate interpolation techniques can help to identify areas of high contamination and can be used to manage contaminated sites cost-effectively. This study also highlights the need for continued monitoring of arsenic contamination in soil and water in the region to minimize health risks associated with exposure to this potent carcinogen. Overall, this study provides valuable insights into the spatial distribution of arsenic contamination in soil in the West Bengal region and can guide the effective management of contaminated sites in the region.

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