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Assessment of Heavy Metal Contamination in Soils Surrounding a Thermal Power Plant in Isfahan Province, Iran, Using Pollution Indices and Multivariate Statistical Analysis

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Abstract

Anthropogenic activities contribute to the accumulation and mobilization of heavy metals within the soil matrix, which functions as a terminal reservoir for these pollutants and thereby poses substantial ecological and human health risks. This study evaluated the impact of a fossil-fueled thermal power plant in Isfahan Province, Iran, on heavy metal accumulation in the surrounding topsoil. Fifty surface soil samples were collected, and the concentrations of eight toxic metals—Cd, Co, Cr, Cu, Mn, Ni, Pb, and Zn—were determined. Statistical analyses, including factor analysis and Pearson correlation, revealed three distinct metal groupings: Group I (Ni, Pb, Cd), Group II (Cu, Cr, Co), and Group III (Zn, Mn). Group I metals were associated with both natural and anthropogenic sources, while Groups II and III were primarily linked to geogenic origins. To quantify contamination levels, the contamination factor (CF) and geoaccumulation index (I_{geo}) were calculated. The results indicated moderate to high contamination levels for Pb and Cd, with Cd exhibiting very high CF values across all samples. Furthermore, multivariate calibration using principal component regression (PCR) and partial least squares regression (PLS) was employed to predict the pollution load index (PLI). Both methods demonstrated accurate and robust performance in predicting the PLI across calibration and prediction datasets, with R^2 values ranging from 0.861 to 0.965.

Keywords

Multivariate statistical analysis, Contamination factor, Geoaccumulation index, Soil contamination

1. INTRODUCTION

Energy is a cornerstone of socioeconomic development, playing a particularly critical role in developing nations [1]. Among the various energy forms, electricity is central to modern infrastructure, driving both industrialization and urban expansion [2]. Electricity generation relies on multiple sources, including thermal, nuclear, hydroelectric, wind, and solar power. Thermal power plants, in particular, produce electricity by converting mechanical energy—generated through high-temperature, high-pressure steam—into electrical energy via turbine systems [3].

Fossil fuels such as natural gas, heavy fuel oil, and coal are commonly used in thermal power plants to generate steam. In Iran, natural gas serves as the primary fuel for electricity production throughout most of the year. However, during peak demand periods, especially in winter, power plants often switch to liquid fuels like heavy fuel oil or mazut to ensure an uninterrupted energy supply [4]. Mazut, a low-grade heavy fuel with a carbon chain length of 12 to 70 atoms and a thermal value of 41.7 MJ/kg [5,6], contributes significantly to environmental pollution when combusted. The burning of fossil fuels in thermal power plants releases various atmospheric pollutants, including sulfur oxides (SOx), nitrogen oxides (NOx), carbon monoxide (CO), and particulate matter such as fine dust and fly ash [7,8]. Fly ash is of particular concern, as it contains elevated concentrations of toxic heavy metals that vary depending on the type of fuel used—typically including cadmium, chromium, mercury, nickel, lead, and zinc [2]. Fly ash emitted from combustion stacks often exhibits higher concentrations of naturally occurring toxic metals than those found in the original fuel or surrounding soils [7].

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Soil functions as a terminal sink for airborne pollutants, allowing heavy metals to accumulate and persist over extended periods, particularly in agricultural regions [2]. Unlike organic contaminants, heavy metals are non-biodegradable and can irreversibly alter soil structure, reduce crop yield and quality, and pose significant health risks through bioaccumulation in the food chain [9].

Although extensive research has investigated the environmental impacts of coal-fired thermal power plants [2,8–11], comparatively fewer studies have focused on gas- and oil-fired facilities [1,3,5,12,13]. Previous investigations have documented elevated concentrations of heavy metals in soils and sediments surrounding such plants, with contamination levels generally decreasing as the distance from the emission source increases [3,13]. Moreover, emissions from natural gas combustion tend to be lower in particulate matter and sulfur compounds; however, nitrogen oxides remain a significant environmental concern [12].

This study aims to evaluate the occurrence and enrichment levels of eight toxic metals—Cu, Cr, Co, Cd, Pb, Mn, Zn, and Ni—in soils surrounding an oil- and natural gas-fired power plant located in Isfahan Province, Iran. Multivariate statistical techniques were employed to identify potential sources of contamination. To assess the extent of soil pollution, the contamination factor (CF) and geoaccumulation index (I_{geo}) were calculated. Additionally, principal component regression (PCR) and partial least squares regression (PLS) were applied to predict the pollution load index (PLI), which serves as a comprehensive indicator of overall heavy metal contamination in the soil samples.

2. Experimental

2.1 Study Area and Sampling

The study site (Figure 1) is located approximately 10 km northwest of Isfahan in central Iran. The thermal power plant has a production capacity of 8 × 250 megawatts. Units 1–4 were constructed between 1982 and 1989, and Units 5–8 between 1996 and 1998. Each boiler unit is designed for dual-fuel operation, utilizing both natural gas and fuel oil, with a maximum steam generation capacity of 705 tons per hour.

The plant is situated near major industrial facilities, including the Iran Chemical Industries Investment Company—which annually produces 50,000 tons of linear alkyl benzene and 46,000 tons of normal paraffin—and the Isfahan Oil Refining Company, which is responsible for over 20% of Iran's oil-related products.

Sixty-seven samples from the study area were selected using the grid method. To reduce sample handling and associated costs, 17 samples (sampling sites: 4, 6, 14, 18, 20, 28, 30, 34, 38, 40, 46, 50, 52, 54, 56, 60, and 64) were randomly omitted. The remaining 50 topsoil samples, collected from a depth of 0–15 cm, were analyzed for heavy metal concentrations. Among these, 12 samples (sampling sites: 1, 7, 13, 19, 25, 31, 37, 43, 49, 55, 61, and 67) were selected for physico-chemical soil analysis.

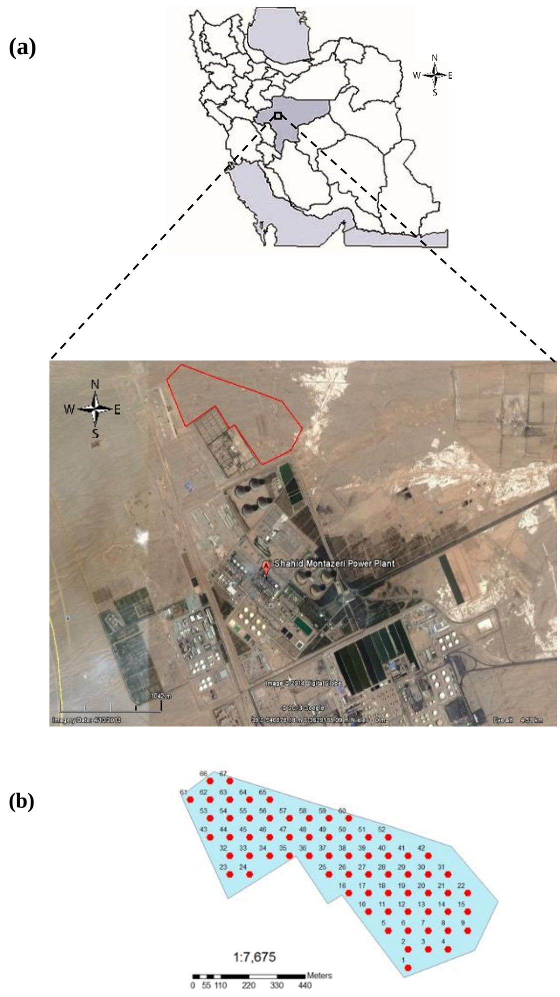

Fig. 1. Geographical location of Isfahan Province, location of the thermal power plant and study area (a) sampling sites (b)

All soil samples were air-dried at room temperature, homogenized, and sieved through a 2-mm mesh. Soil pH and electrical conductivity (EC) were measured using saturated paste extracts. Particle size

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distribution (sand, silt, and clay) was determined using the hydrometer method. Equivalent calcium carbonate (ECC) content was quantified via the back titration method [14]. Available phosphorus (P) was measured following the method of Olson et al. [15], and soil organic carbon was determined using the Walkley–Black technique [14]. Available potassium was extracted using ammonium acetate and quantified by flame atomic emission spectrometry [16].
Heavy metal concentrations (Cu, Cr, Pb, Co, Cd, Mn, Ni, and Zn) were measured using flame atomic absorption spectroscopy (air–acetylene flame) following acid digestion with HNO_3 and HCl [17]. Results were expressed in milligrams per kilogram (mg/kg) of dry soil matter.

2.2 Statistical Analysis

Descriptive and multivariate statistical analyses were performed using Minitab software (version 17, Minitab Inc.). Descriptive statistics—including minimum, maximum, mean, median, kurtosis, and skewness—were calculated to summarize the distribution of the data.
To examine relationships among variables, Pearson's correlation coefficients were computed, with statistical significance set at $p < 0.05$. Principal Component Analysis (PCA) was employed to reduce data dimensionality by transforming correlated variables into a smaller set of uncorrelated principal components (PCs), while preserving most of the original variance. For improved interpretability, Varimax rotation was applied to the PCs, generating rotated factors that emphasize underlying patterns. Factor Analysis (FA) was used to identify latent variables responsible for the observed correlations among the measured parameters [18].
PCR and PLS approaches were applied as supervised learning techniques to model and predict the pollution load index (PLI). Both methods establish predictive relationships between input variables (X) and a target output variable (y) using a calibration dataset. PCR involves performing PCA on the input matrix X, followed by multiple linear regression using selected PCs that best explain the variance in y. In contrast, PLS extracts latent variables by maximizing the covariance between X and y, thereby enhancing predictive accuracy [19].

2.3 Evaluation of Trace Element Contamination in Soils

To quantify soil contamination, the Contamination Factor (CF) and Geoaccumulation Index (I_{geo}) were calculated. Contamination Factor (CF) was computed using the equation (1):

$$CF = \frac{(C_n)_{soil}}{(C_n)_{background}} \quad (1)$$

where $(C_n)_{soil}$ and $(C_n)_{background}$ represent the concentrations of metal n in the soil sample and background environment, respectively [20].
CF values were classified as follows: CF<1 (low contamination), $1 \leq CF \leq 3$ (moderate contamination),$3 \leq CF \leq 6$ (high contamination), and CF > 6 (very high contamination).
Geoaccumulation Index (I_{geo}) was calculated using the equation (2):

$$I_{geo} = log_2(\frac{C_n}{1.5B_n}) \quad (2)$$

where C_n is the measured concentration of metal n in the soil, and B_n is its background concentration in shale. Pollution levels were categorized as: $I_{geo} \leq 0$: Practically unpolluted (Class 0), $0 < I_{geo} \leq 1$: Unpolluted to moderately polluted (Class 1), $1 < I_{geo} \leq 2$: Moderately polluted (Class 2), $2 < I_{geo} \leq 3$: Moderately to heavily polluted (Class 3), $3 < I_{geo} \leq 4$: Heavily polluted (Class 4), $4 < I_{geo} \leq 5$: Heavily to extremely polluted (Class 5) and $I_{geo} \geq 5$: Extremely polluted (Class 6) [21].
Pollution load index (PLI) was used to assess the overall pollution level of soil samples. It was calculated as the geometric mean of the individual CF values for all metals:

$$PLI = (CF_1 \times CF_2 \times ... \times CF_n)^{1/n} \quad (3)$$

where n is the number of metals analyzed. PLI values were used to classify the soil samples into four contamination levels: unpolluted (PLI $\leq$ 1), moderately polluted (PLI between 1 and 3), highly polluted (PLI between 3 and 5), and very highly polluted (PLI > 5) [22].

3. RESULTS AND DISCUSSION

3.1 Soil Characteristics

Table 1 summarizes the physico-chemical properties of 12 soil samples collected from the study area. The pH values ranged from 7.21 to 7.88, with a mean of 7.67, indicating slightly alkaline conditions—primarily due to elevated carbonate content. Calcium carbonate ($CaCO_3$) levels varied between 30.0% and 42.5%, averaging 35.0%. The mean organic matter (OM) content was 0.71%, with a wide range from 0.32% to 1.64%, indicating low to moderate fertility.
Electrical conductivity (EC), an indicator of salinity and nutrient availability, ranged from 0.63 to 11.25 mS/dm, with a mean of 2.12 mS/dm. Particle size analysis revealed clay content between 9.0% and 21.0% (mean: 14.3%), silt between 5.0% and 47.0% (mean: 28.3%), and sand between 17.0% and 86.0% (mean: 54.9%). Based on these proportions, the

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soils were classified as sandy loam (sites 1, 13, 19, 37, 43, 49, 55, 61, and 67), loam (sites 7 and 31), and loamy sand (site 25).

Table 1. Summary statistics for the physico-chemical soil properties

Characteristic	Minimum	Maximum	Mean	Standard deviation
pH	7.2	7.8	7.6	0.2
EC (mS/cm)	0.6	11.2	2.1	3.0
$CaCO_3$ (%)	30.0	42.5	35.0	4.2
OM (%)	0.3	1.6	0.7	0.4
Clay (%)	9.0	21.0	14.3	2.8
Silt (%)	5.0	47.0	28.3	10.0
Sand (%)	17.0	86.0	54.9	17.0

3.2 Heavy Metals Concentrations in the Soils

Table 2 presents the concentrations of eight heavy metals in the soil samples. The mean values (in mg/kg) were as follows: Mn (336.84) > Zn (95.80) > Ni (54.51) > Pb (42.87) > Cr (20.79) > Cu (14.67) > Co (14.02) > Cd (4.67). A one-sample t-test ($p < 0.05$) revealed that the average concentrations of most toxic metals (excluding Co and Zn) significantly differed from their respective background values reported for Isfahan Province [23].

Analysis of heavy metal concentrations in the soil samples revealed varying levels of contamination across different elements. For copper (Cu), 96% of the samples exhibited concentrations below the regional background level of 25.70 mg/kg, indicating minimal Cu contamination. Although the mean concentration of zinc (Zn) exceeded its background value (79.60 mg/kg), 72% of the samples remained below this threshold, suggesting only slight enrichment of Zn in the study area. All samples showed manganese (Mn) and chromium (Cr) concentrations below their respective background levels (641.2 mg/kg for Mn and 90.9 mg/kg for Cr), confirming the absence of significant enrichment for these elements.

In contrast, cadmium (Cd) and lead (Pb) were found at elevated levels in nearly all samples. Cd concentrations exceeded the background value of 0.26 mg/kg in 100% of the samples, while Pb surpassed its threshold of 28.10 mg/kg in 98% of cases—highlighting a strong anthropogenic influence on their distribution. The average concentration of nickel (Ni) was slightly below its background level (59.30 mg/kg), with 28% of samples exceeding this value. Additionally, cobalt (Co) concentrations were above the background level (13.3 mg/kg) in 68% of the samples, suggesting possible accumulation due to human activities.

Table 2. Summary statistics for the eight heavy metal concentrations in soil samples of study area (mg/ kg) (n=50)

Characteristic	Cu	Zn	Mn	Cd	Pb	Ni	Cr	Co
Minimum	8.50	41.50	291.00	3.50	26.50	38.00	12.00	10.00
Maximum	38.50	349.50	402.00	6.50	61.50	75.50	32.50	18.00
Mean	14.67	95.80	336.84	4.76	42.87	54.51	20.79	14.02
standard deviation	5.12	80.50	26.69	0.70	7.83	9.03	3.76	1.95
CV (%)	34.90	84.03	7.92	14.74	18.26	16.57	18.10	13.92
Skewness	3.12	2.13	0.33	0.56	0.00	0.29	0.27	-0.26
Kurtosis	11.57	3.68	-0.59	0.32	-0.20	-0.72	1.11	-0.34
Background value [a]	25.70	79.60	641.20	0.26	28.10	59.30	90.90	13.30
Percentage [b]	4.00	28.00	0.00	100.00	98.0	28.0	0.00	68.00

[a] Soil heavy metal background value of Isfahan Province (mg/kg) [21]
[b] The percent of soil heavy metal exceeding the background value of Isfahan Province

3.3 Correlation and Factor Analysis

Table 3 shows Pearson correlation coefficients among the heavy metals. Significant correlations ($p < 0.05$) were observed for Cu/Ni ($r = 0.30$), Zn/Pb ($r = – 0.33$), Ni/Cd ($r = 0.30$), and Ni/Pb ($r=0.54$). However, overall correlation strengths were relatively low, indicating limited linear relationships among most metal pairs.

Table 3. The correlations between the contents of 8 heavy metals

	Cu	Zn	Mn	Cd	Pb	Ni	Cr	Co
Cu	1.0							
Zn	0.15	1.00						
Mn	-0.07	0.24	1.00					
Cd	0.02	-0.07	-0.09	1.00				
Pb	0.05	-0.33*	-0.25	0.17	1.00			
Ni	0.30*	0.11	-0.11	0.30*	0.54*	1.00		
Cr	0.26	0.14	-0.08	-0.11	-0.21	0.11	1.00	
Co	0.23	0.14	-0.08	0.02	0.07	0.12	0.18	1.00

*Significant at the 0.05 probability level (two-tailed)

To further explore underlying patterns, factor analysis was conducted (Table 4). The factor analysis revealed three principal components that explain the distribution patterns of heavy metals in the soil. Three factors with eigenvalues greater than 1 were extracted, explaining a cumulative variance of 61.4%. Figure 2a visualizes the relationships among the metals. Factor 1 (F1), accounting for 21.5% of the total variance, exhibited strong positive loadings for Pb, Cd, and Ni, indicating that these elements likely originate from a combination of natural and anthropogenic sources such as industrial emissions and fossil fuel combustion—especially given the notable enrichment of Pb and Cd and partial enrichment of Ni. Factor 2 (F2), which also explained 21.5% of the variance, showed moderate to strong negative loadings for Cu, Cr, and Co; the concentrations of these metals were generally near or below their background levels,

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suggesting that their presence is primarily controlled by natural geogenic processes. Factor 3 (F3) accounted for 18.4% of the variance and was characterized by high positive loadings for Mn and Zn, both of which were largely below background concentrations, implying that their distribution is governed by lithogenic factors.

Table 4. Varimax-rotated factor loadings for the measured variables

Variable	F1	F2	F3	Communality
Cu	0.196	**-0.698**	0.060	0.529
Zn	-0.016	-0.331	**0.765**	0.696
Mn	-0.049	0.251	**0.767**	0.654
Cd	**0.642**	0.107	0.047	0.426
Pb	**0.711**	0.033	-0.472	0.729
Ni	**0.804**	-0.365	0.006	0.78
Cr	-0.29	**-0.715**	-0.018	0.595
Co	0.073	**-0.592**	-0.010	0.356
Eigenvalue	1.694	1.666	1.403	
Variance (%)	0.212	0.208	0.175	
Cumulative (%)	21.500	42.000	59.500	

Figure 2b illustrates the distribution of soil samples based on their scores for Factor 1 (F1) and Factor 2 (F2), revealing that most samples are clustered near the center of the plot, indicative of similar chemical compositions across the study area. However, several sampling stations displayed distinct separation, suggesting localized variations in contamination. For instance, Station 66 shows a negative correlation with F1 due to lower concentrations of Cd (4.0 mg/kg), Pb (26.5 mg/kg), and Ni (40.0 mg/kg). In contrast, Station 1 stands out with the highest levels of Pb (61.5 mg/kg) and Ni (75.5 mg/kg), along with the second-highest Cu concentration (32.5 mg/kg), suggesting notable anthropogenic impact. Station 42 is distinguished by low Cu (8.5 mg/kg) and elevated Pb (61.5 mg/kg), while Station 12 is negatively associated with F2 due to its elevated Cu (38.5 mg/kg) and Co (16.0 mg/kg) levels. These spatial patterns point to localized contamination likely driven by industrial emissions and fossil fuel combustion near the power plant.

3.4 Environmental Pollution Levels

To assess the degree of heavy metal contamination in the soil samples, two indices were calculated: The contamination factor (CF) and the geoaccumulation index (I_{geo}). As illustrated in Figure 3, CF values for chromium (Cr), manganese (Mn), and copper (Cu) were below 1 in all or nearly all samples, indicating low contamination levels for these metals. Zinc (Zn) showed more variability, with 72% of samples having CF values below 1, 20% between 1 and 3, and 8% exceeding 3. This indicates that Zn contamination is generally low, though moderate to high levels were observed in specific locations (sampling sites 1, 24, 61, 55, 63, and 57). Lead (Pb) contamination was more widespread, with over 98% of samples falling within the moderate contamination range (CF between 1 and 3). Nickel (Ni) exhibited low contamination in 72% of samples, while the remaining 28% showed moderate levels. Cobalt (Co) also demonstrated moderate contamination in 72% of samples. Cadmium (Cd) displayed a notable contamination profile, as CF values exceeded 6 in all samples. Such consistently high levels point to widespread contamination and underscore the considerable anthropogenic impact of Cd in the study area.

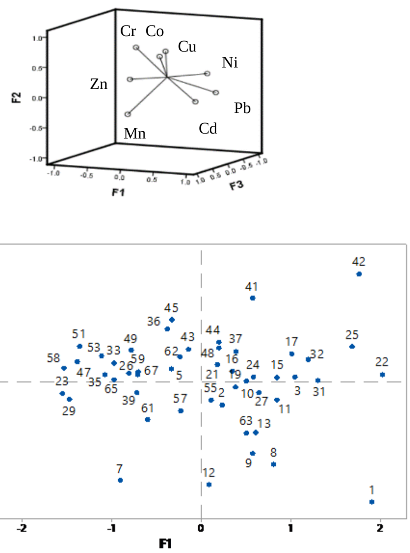

Fig. 2. Factor analysis 3-D loading plot (a), Score plot of F_1 versus F_2 (b)

The I_{geo} index was used to further evaluate pollution levels relative to natural background concentrations. As shown in Figure 4, the average pollution ranking of the eight metals was Pb > Cd > Zn > Cr > Mn > Ni > Co > Cu. For Cr, Mn, Ni, Co, and Cu, all I_{geo} values were below zero (Class 0), indicating that these elements are essentially unpolluted across the study area.

Zn displayed a broader distribution: 80% of samples were unpolluted (Class 0), while the remaining 20% ranged from moderately

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polluted to extremely polluted, with 4% of samples falling into Class 6.

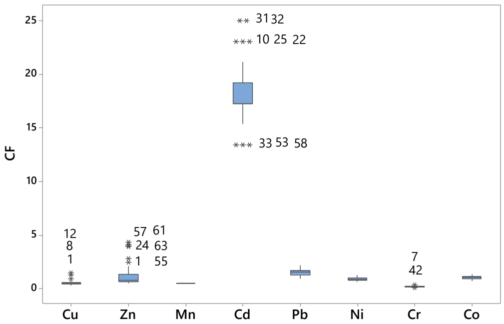

Fig. 3. Contamination factor index (CF) values for 8 heavy metals in the studied soils

Cd was consistently classified in Class 1 (I_{geo} between 1 and 2), suggesting soils were unpolluted to moderately polluted. Pb showed the most diverse pollution profile, with 42% of samples in Class 0 and the remaining 58% distributed across Classes 1 to 6. Specifically, 4% were moderately polluted (Class 2), 10% heavily polluted (Class 4), 14% heavily to extremely polluted (Class 5), and 30% extremely polluted (Class 6). These results highlight Pb and Cd as the dominant pollutants in the study area, with localized zones of severe contamination.

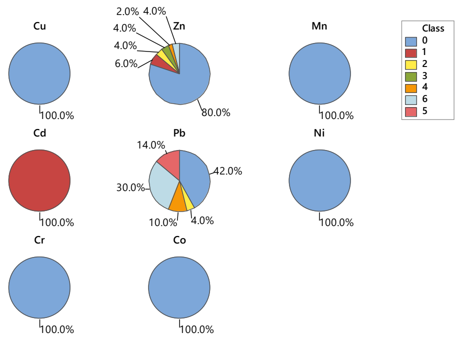

Fig. 4. Pie charts of the relative proportions of geo-accumulation index (I_{geo}) values according to Müller class

3.5 Multivariate Calibration

To predict the pollution load index (PLI) with high accuracy, both PLS and PCR models were applied. Leave-one-out cross-validation was used to determine the optimal number of latent factors (principal components) that best represent the calibration data while minimizing overfitting. A total of 50 soil samples were analyzed, of which 80% (40 samples) were randomly selected as the calibration set, while the remaining 20% (10 samples) were reserved for prediction. To evaluate the predictive performance of the multivariate calibration models, three statistical metrics were used: the root mean square error of calibration (RMSEc), the root mean square error of prediction (RMSEp), and the coefficient of determination (R^2). Additional details regarding model performance parameters are available in referenced literature [19, 24]. As summarized in Table 5, both models performed well using four latent factors; however, the PLS model consistently demonstrated superior predictive accuracy. Specifically, PLS yielded higher R^2 values and lower RMSEs across both calibration and prediction datasets. Figure 5 illustrates the strong correlation between observed and predicted PLI values for both models, confirming the reliability of the multivariate calibration approach and underscoring the effectiveness of PLS in predicting environmental pollution levels in complex soil systems.

Table 5. Statistical parameters calculated for the calibration and prediction sets using PLS and PCR models

Models	PCs	Calibration				Prediction	
		R^2cal	RMSEc	RMSEcv	R^2cv	R^2pred	RMSEp
PCR	4	0.861	0.043	0.055	0.775	0.927	0.038
PLS	4	0.922	0.032	0.040	0.882	0.965	0.026

4. CONCLUSIONS

This study investigated the extent of heavy metal contamination in soils surrounding a fossil-fueled power plant in Isfahan Province, Iran. The results demonstrated that the average concentrations of several hazardous metals—particularly Pb, Cd, and Ni—significantly exceeded regional background levels, indicating notable enrichment. Contamination factor (CF) analysis revealed moderate to high contamination for Pb and Cd, and partial enrichment for Ni, suggesting that these metals predominantly originate from anthropogenic activities such as industrial emissions and fuel combustion. Geoaccumulation index (I_{geo}) values further supported these findings, with nearly 60% of soil samples falling into the moderately to extremely polluted categories for Pb, and all samples exhibiting moderate pollution levels for Cd. Multivariate factor analysis confirmed that Pb, Cd, and Ni are associated with a mixed origin, influenced by both natural and human-induced sources, while the remaining metals appear to be primarily governed by natural geogenic processes. These findings underscore the environmental impact of industrial operations in the region and highlight the need for continued monitoring and targeted mitigation strategies.

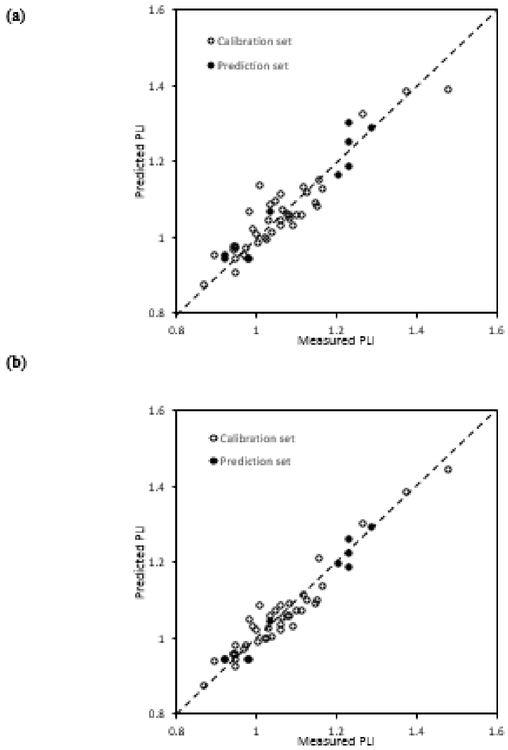

Fig. 5. Parity plot of the measured and predicted values of the PLI by the PCR (a) and PLS (b) approaches

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ارزیابی آلودگی فلزات سنگین در خاک‌های اطراف یک نیروگاه حرارتی در استان اصفهان، ایران، با استفاده از شاخص‌های آلودگی و تحلیل آماری چند متغیره

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چکیده

فعالیت‌های انسانی موجب تجمع و جابجایی فلزات سنگین در ماتریس خاک می‌شود؛ محیطی که به‌عنوان مخزن نهایی این آلاینده‌ها عمل کرده و در نتیجه، خطرات قابل‌توجهی برای محیطزیست و سلامت انسان به‌همراه دارد. این مطالعه به بررسی تأثیر یک نیروگاه حرارتی با سوخت فسیلی در استان اصفهان، ایران، بر میزان تجمع فلزات سنگین در خاک سطحی اطراف آن پرداخته است. در مجموع، پنجاه نمونه خاک سطحی جمع‌آوری شد و غلظت هشت فلز سمی شامل کادمیوم، کبالت، کروم، مس، منگنز، نیکل، سرب و روی اندازه گیری شد. تحلیل‌های آماری، از جمله تحلیل عاملی و همبستگی پیرسون، سه گروه‌بندی فلزی متمایز را شناسایی کرد: گروه اول (نیکل، سرب، کادمیوم)، گروه دوم (مس، کروم، کبالت) و گروه سوم (روی، منگنز). فلزات گروه اول با منابع طبیعی و انسانی مرتبط بودند، در حالی که منشا گروه‌های دوم و سوم عمدتا زمین‌زاد بودند. برای تعیین سطوح آلودگی، فاکتور آلودگی (CF) و شاخص زمین انباشتگی (I_{geo}) محاسبه شدند. نتایج نشان داد که سرب و کادمیوم دارای سطوح آلودگی متوسط تا زیاد هستند و کادمیوم در تمامی نمونه‌ها مقادیر بسیار بالایی از CF را نشان داد. علاوه بر این، از روش های کالیبراسیون چند متغیره شامل رگرسیون مؤلفه‌های اصلی (PCR) و رگرسیون حداقل مربعات جزئی (PLS) برای پیش‌بینی شاخص بار آلودگی (PLI) استفاده شد. هر دو مدل عملکرد دقیق و قابل اعتمادی در پیش‌بینی PLI با مقادیر R^2 بین ۰/۸۶۱ تا ۰/۹۶۵ را در مجموعه داده‌های کالیبراسیون و پیش‌بینی نشان دادند.

کلید واژه ها

تحلیل آماری چند متغیره، فاکتور آلودگی ، شاخص زمین‌انباشت، آلودگی خاک

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