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Predicting future contamination spread using 3D modeling: A case study of lead, cadmium, and arsenic contamination

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ABSTRACT

Soil contamination poses a significant environmental and public health risk, particularly when hazardous metal concentrations exceed safe thresholds. This study aims to predict the future spread of soil contamination using 3D modeling based on empirical data collected from multiple sampling locations. The dataset includes key environmental parameters such as dissolved oxygen (DO), temperature, and atmospheric pressure, alongside spatially referenced measurements of hazardous metal concentrations (e.g., arsenic, lead, cadmium, chromium, nickel, and copper). These data points were geolocated using high-accuracy GPS mapping, ensuring precise spatial representation. Analysis of the collected samples indicates that lead (Pb) and arsenic (As) exhibit particularly high concentrations, with Pb ranging up to 142.9 mg/kg and As reaching 45.4 mg/kg in certain hotspots. Industrial and agricultural land use significantly influences contamination levels, with industrial sites showing very high contamination factors (CF ≥ 6) for Pb and high CF values for As. Agricultural zones exhibit moderate to high CF values for both As and Pb, primarily due to pesticide and fertilizer application. Environmental factors such as dissolved oxygen levels (as low as 1.16 mg/L) and fluctuating temperatures (ranging from 15.9 °C to 21.2 °C) further influence the migration of contaminants. The study reveals that soil quality varies across locations, with elevated concentrations of heavy metals such as cadmium (Cd), chromium (Cr), and zinc (Zn), presenting additional ecological concerns. By leveraging 3D modeling techniques, we analyze the spatial distribution and potential diffusion of contaminants over time, taking into account environmental factors influencing soil migration patterns. The model predicts the expansion of contamination zones, particularly in industrial and agricultural areas, emphasizing the need for targeted remediation efforts. The results highlight the urgent need for proactive soil remediation measures in high-risk areas. By integrating field data with computational modeling, this study offers a robust approach for forecasting contamination spread, optimizing land-use planning, and minimizing ecological risks.

Keywords: soil contamination, 3D spatial modeling, hazardous metals, predictive contamination modeling.

INTRODUCTION

Soil contamination by heavy metals is a pressing environmental concern, particularly in regions experiencing rapid industrialization, urbanization, and agricultural intensification. Heavy metals such as Pb, As, cadmium (Cd), and chromium (Cr) are persistent environmental pollutants that pose significant risks to human health and ecosystems due to their toxicity and bioaccumulative nature (Alloway, 2013). The transport and spread of these contaminants are influenced by various environmental factors, including soil composition, hydrological dynamics, and atmospheric conditions (Kabata-Pendias, 2011). Understanding the spatial distribution and potential migration of these pollutants is crucial for effective environmental management and remediation efforts.

Recent research underscores the growing concerns regarding heavy metal contamination in industrial zones. Studies have demonstrated that industrial activities, past land use, and waste disposal contribute to significant heavy metal accumulation in soil (Liu et al., 2025). For instance, industrial zones often exhibit Cd, Pb, Cu, and Ni accumulation, with these contaminants being highly concentrated in surface layers, decreasing with soil depth. In some cases, Cu and Ni have been found to migrate downward, forming contamination pockets in deeper soil layers (Liu et al., 2025). Additionally, heavy metal migration patterns depend on soil physicochemical properties such as pH, permeability, organic carbon content, and cation exchange capacity (CEC), which influence the extent of metal retention or leaching (Man et al., 2022).

Traditional methods for detecting soil heavy metal pollution rely on labor-intensive field sampling and laboratory analysis, which are costly and time-consuming. To address these limitations, recent advancements in geospatial technologies and computational modeling have significantly enhanced the ability to assess and predict soil contamination patterns. Three-dimensional (3D) modeling, in particular, has emerged as a powerful tool for visualizing and analyzing the spatial distribution of soil pollutants. By integrating geochemical data with spatial analysis techniques, 3D models provide a comprehensive view of contamination scenarios, facilitating informed decision-making for remediation strategies (Liu et al., 2022).

In the context of the Al Zarqa River Basin, the Shafa Badran Watercourse area has been identified as a region of concern due to its exposure to multiple pollution sources, including industrial discharges, wastewater outflows, and agricultural runoff. These anthropogenic activities contribute to elevated concentrations of hazardous pollutants, necessitating advanced monitoring and predictive modeling approaches. Previous studies on soil contamination in urban and industrial regions have shown that Pb, Cd, and Cr are often the most common pollutants, accumulating in surface soil layers due to low solubility and high adsorption properties (Jiang et al., 2022). Meanwhile, elements such as Cu and Ni tend to migrate more easily, potentially contaminating deeper soil layers and groundwater (Rinklebe and Shaheen, 2017). This variability underscores the necessity of spatial analysis methods to fully understand contamination dynamics. The impact of anthropogenic activities on soil quality in the Shafa Badran watercourse within the Al Zarqa River Basin, Jordan was made by (Ahmad, 2025), where he investigate the presence and distribution of ten hazardous metals (As, Pb, Cd, Cr, Ni, Cu, Zn, V, Li, and Sb) in soil samples. The research highlights that industrial and agricultural activities significantly contribute to soil contamination, with the highest concentrations of arsenic, lead, and cadmium found near industrial zones and agricultural lands. The highest recorded concentrations of As, Pb, and Cd exceed permissible limits, posing environmental and health risks. The study emphasizes the need for effective land-use management and pollution mitigation strategies to protect environmental and public health.

To address these challenges, this study employs 3D modeling techniques to predict and visualize the future spread of soil contamination in this area. By integrating geospatial data, heavy metal concentration measurements, and environmental parameters such as dissolved oxygen, temperature, and atmospheric pressure, the research aims to generate predictive models that can inform mitigation strategies and sustainable land-use planning.

The effectiveness of geospatial and computational modeling in environmental risk assessment has been well documented. Geostatistical interpolation techniques such as kriging and inverse distance weighting (IDW) have been widely used to estimate contaminant distributions based on sparse sampling data (Li and Heap, 2014). More advanced machine learning and deep learning approaches, such as Random Forest (RF) and Convolutional Neural Networks (CNNs), have recently been applied to predict heavy metal pollution patterns with high accuracy (Nie et al., 2024). Three-dimensional convolutional neural networks (3DCNNs) have demonstrated significant advantages in spatial interpolation, allowing for improved prediction of heavy metal concentrations while maintaining spatial relationships within the data (Liu et al., 2025).

By leveraging these advanced modeling techniques, this study aims to provide a comprehensive understanding of soil contamination dynamics in the Shafa Badran Watercourse area. The findings will contribute to the growing body of knowledge on soil pollution risk assessment and offer valuable insights for policymakers and environmental agencies. These insights will help facilitate the development of targeted interventions to mitigate contamination risks, promote sustainable environmental management, and ensure the long-term safety of affected ecosystems and communities. Future studies may refine this approach by incorporating additional environmental variables such as groundwater flow, precipitation patterns, and land-use changes to improve predictive accuracy and risk assessment.

MATERIALS AND METHODS

Study area

Shafa Badran is located in northern Amman, Jordan, and has become increasingly integrated with neighboring towns and suburbs, including Khirbat Badran. The area comprises a mix of residential neighborhoods and agricultural lands, reflecting both urban expansion and traditional land use. However, like many regions in Jordan, Shafa Badran faces significant environmental challenges, particularly concerning water quality. Heavy metal contamination, resulting from both natural processes such as weathering and leaching, as well as anthropogenic activities, poses a risk to local water sources. Addressing these concerns has been a key focus of ongoing development initiatives aimed at improving both environmental sustainability and living conditions in the region.

Methodology

Soil sampling and analysis

To get a clear view of soil contamination levels, 22 sampling locations identified using GIS along a 25 km stretch near the watercourse. These spots chosen on purpose to capture potential changes in soil quality along the way. Each sample underwent detailed lab tests to measure heavy metals and other key soil indicators, helping to understand where contamination might be coming from, how it has spread out, and the environmental risks tied to heavy metal buildup. These samples collected every three months, starting on January 15, 2024, and use their average values to develop different models.

Pollution source identification

To locate potential pollution contributors, geographic information system (GIS) mapping and field surveys were employed to identify sources such as wastewater discharge points, agricultural runoff zones, and industrial effluent sites. In addition, an assessment of land use patterns was conducted to explore the connection between various human activities and the degradation of soil quality.

RESULTS AND DISCUSSION

The soil pollution factor (SPF) serves as a crucial metric for evaluating the extent of heavy metal contamination across various land-use areas and zones. This index is determined by comparing the measured concentration of metals in soil to their baseline levels in unpolluted environments. According to Radaideh (2022), a comparative analysis of SPF values across different land-use categories in the Zarqa River basin is presented in Table 1.

Industrial regions typically demonstrate the highest SPF values, primarily due to significant emissions and waste discharges from factories. Heavy metals such as Pb, Cd, and Cr are frequently detected at elevated concentrations in these areas. Prior research by Kuisi et al. (2014) and Alkhawaldeh et al. (2024) indicates that lead concentrations range between 80 and 190 μg/L, signifying severe pollution levels directly linked to industrial operations. Major industries, including textile production, food processing, and chemical manufacturing, significantly contribute to heavy metal accumulation in the Zarqa River basin. The close proximity of industrial facilities to the river further intensifies this pollution issue.

Compared to industrial areas, agricultural zones exhibit moderate SPF values. Although heavy metals can accumulate in soil due to the application of fertilizers and pesticides, their concentrations generally remain lower than those observed in industrial regions. Reported lead concentrations in agricultural soils range from 90 to 161 μg/L. The use of contaminated irrigation water and runoff from chemically treated fields further contribute to the buildup of heavy metals in agricultural soils. Nevertheless, the overall impact tends to be less severe than that seen in industrial areas.

Table 1. Summary of SPF for different Classes

Land use class	Lead (Pb)	Arsenic (As)	Cadmium (Cd)	Pollution sources
Industrial (I)	Very High ($SPF \geq 6$)	High ($SPF \leq 3$)	Moderate to High ($1 \leq SPF < 3$)	Industrial discharges
Agricultural (A)	Moderate to High ($1 \leq SPF < 3$)	Moderate to High ($1 \leq SPF < 3$)	Moderate ($1 \leq SPF < 3$)	Fertilizers, pesticides, runoff
Residential (R)	Moderate ($1 \leq SPF < 3$)	Low pollution ($SPF < 1$)	Low pollution ($SPF < 1$)	Urban runoff, household waste

Residential zones consistently reflect the lowest SPF values among the three land-use categories. While urban runoff may introduce some heavy metals into these areas, their concentrations are significantly lower compared to industrial and agricultural locations. Reported lead concentrations in residential soil samples vary between 136.1 and 142.9 μg/L. The primary sources of contamination in residential settings include urban runoff, household waste, and occasional emissions from nearby industrial activities. However, the influence of these pollutants on soil quality is generally less direct than that of industrial discharges.

DO is negatively correlated with most heavy metals (especially Cd, As, and Pb) as presented in Figure 1. This suggests that as DO levels decrease, heavy metal concentrations tend to increase. The strongest negative correlation is with Cd (-0.57), followed by As (-0.49) and Pb (-0.37). Sb shows a positive correlation (+0.33), meaning its concentration increases with higher DO levels. This might indicate different chemical behavior compared to other metals. Overall, DO could be a useful indicator of heavy metal contamination, particularly for Cd and As. The predictive analysis results indicate that DO alone is not a strong predictor for heavy metal contamination. The R^2 scores are mostly negative, meaning the linear regression model performs worse than simply using the mean of the target variable.

The R^2 scores are negative, which means DO does not strongly explain the variance in heavy metal concentrations. The mean absolute error (MAE) and mean squared error (MSE) values are high, suggesting that predictions have large deviations from actual values. Heavy metal contamination is influenced by multiple factors, not just DO. These factors may include soil composition, industrial discharge, pH levels, temperature, and atmospheric conditions. There may be non-linear relationships between DO and heavy metal concentrations, which a simple linear model cannot capture.

A comparative visualization of all the contamination spread maps presented on Figure 2. Each subplot represents the geospatial interpolation for different contaminants (Pb, As, Cd, Cr, Ni, Cu, and Zn). The visual representation of heavy metal contamination spread using geospatial interpolation provides key advantages; the maps clearly demonstrate the spatial distribution of contamination across different metals, allowing researchers and policymakers to pinpoint pollution hotspots (Zhang et al., 2020). The gradual color transition indicates how contamination levels change over an area, helping in risk assessment. The geospatial interpolation maps for As, Cd, Cr, Cu, Ni, Pb, and Zn reveal varying levels of contamination in the study area. The intensity of pollution is represented using a color gradient, where darker shades indicate higher contamination levels. Different metals exhibit different contamination patterns based on their sources (industrial, agricultural, or natural). Some metals, such as Pb, Cu, and Zn, exhibit higher concentrations in localized areas. Cd and Ni appear to be more concentrated in specific regions, possibly due to industrial emissions. As and Cr show moderate contamination but are still concerning due to their toxicity.

Based on the observed spatial distribution and environmental toxicity, the most hazardous metals can be ranked based on concentration levels in

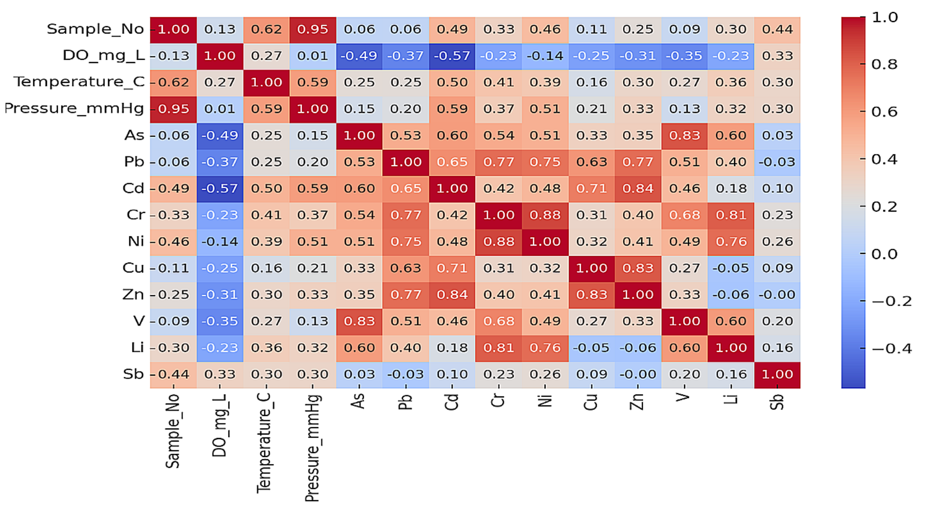

Figure 1. Correlation between DO, temperature, pressure and heavy metals

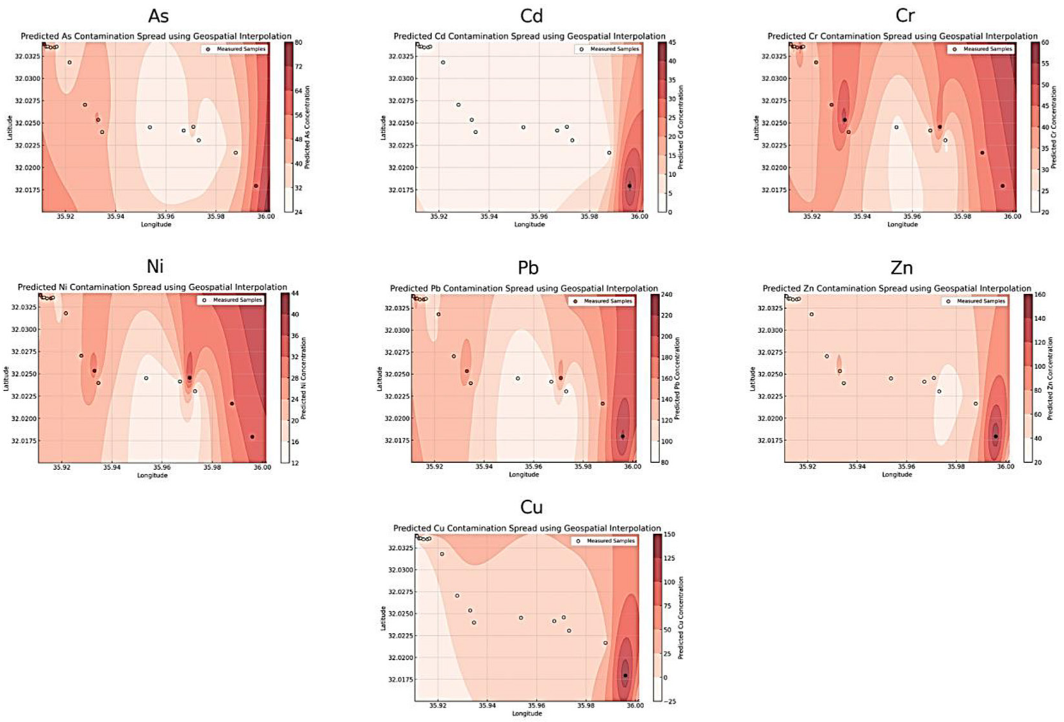

Figure 2. Predicted heavy metals contamination spread using geospatial Interpolation

the study area, toxicity and health risks and persistence in the environment. Pb and Cd are the most hazardous metals due to their high toxicity (Rehman et al., 2019; Wang et al., 2021), long-term persistence, and significant contamination levels. Cr and Ni are also concerning, especially if found in their most toxic forms (Zhang et al., 2020; Gao et al., 2019). As poses moderate risks (Jiang et al., 2022), primarily if contamination is linked to groundwater. Cu and Zn are less hazardous but require monitoring, especially in industrial zones. Contaminant sources likely include industrial pollution, agricultural runoff, and urban waste (Liu et al., 2020; Xu et al., 2021). The study highlights the urgent need for remediation measures, especially in high-risk zones where Pb, Cd, and Cr concentrations are elevated.

The multi-metal approach allows comparisons between different contaminants (e.g., As, Cd, Cr, Cu, Ni, Pb, Zn), helping to identify which metals have the most widespread impact (Chen et al., 2021). This can aid in prioritizing mitigation efforts by focusing on the most toxic and prevalent heavy metals. The overlay of measured sample points ensures that the interpolation is based on actual data rather than purely theoretical models (Li et al., 2019). This reduces the risk of extrapolation errors, making predictions more data-driven. The visualization assists in understanding potential risks to human health, especially in agricultural areas where contamination might affect food safety (Khan et al., 2019). It helps in planning remediation strategies such as soil washing or phytoremediation to reduce toxicity levels in affected zones. Despite the benefits, the methodology also has limitations, the quality of interpolation depends on how many data points were collected. If sampling is sparse, the interpolation might not accurately reflect actual contamination patterns (Zhu et al., 2018).

Geostatistical Interpolation is Effective for Pollution Mapping. Interpolation techniques like Kriging and IDW (Inverse Distance Weighting) are widely used for environmental pollution studies (Goovaerts, 1997). These techniques help estimate contamination levels at unsampled locations, making them a practical choice for heavy metal analysis. Decision-makers in environmental policy and public health can quickly interpret maps without needing complex statistical models (Jiang et al., 2019). The color gradient simplifies the communication of contamination risks. GIS-based geospatial interpolation improves mapping accuracy, allowing integration with land-use planning and risk management systems (Xu et al., 2021). This makes it a scalable approach for larger regions.

The geospatial interpolation of heavy metal contamination provides critical insights into pollution distribution, aiding in risk assessment, regulatory compliance, and environmental remediation strategies. However, the method's reliability depends on data density, accuracy, and external environmental factors. Future improvements should include higher-resolution sampling, multi-temporal analysis, and machine learning integration to enhance prediction precision. Overall, this approach remains a valuable tool for environmental monitoring and decision-making.

The presented hotspot analysis maps visualize the geospatial distribution of heavy metals Pb, Cd, and As in the study area as shown in Figure 3. The maps utilize color gradients, where blue represents lower contamination levels and red signifies high contamination zones.

The three-hotspot maps provide spatial insights into the distribution of Pb, As, and Cd contamination, with sample locations marked as black dots. Pb shows the highest contamination levels, with a hotspot exceeding 240 mg/kg in the southeastern part of the study area. Moderate Pb contamination is observed in central areas, ranging between 60–180 mg/kg. Lower Pb concentrations (~30 mg/kg) appear in the northwestern regions. Pb is a neurotoxin affecting brain development, cognitive functions, and cardiovascular health (Rehman et al., 2019). The hotspot coincides with potential sources like industrial emissions, lead-based paints, and contaminated soil runoff (Wang et al., 2021).

Cd exhibits localized contamination peaks, with a major hotspot (~28 mg/kg) in the southeastern region. The northwestern part of the study area remains at low Cd levels (~0–8 mg/kg). Cd hotspots indicate industrial and agricultural origins, likely from fertilizers, mining activities, and metal processing waste (Jiang et al., 2022). Cd is a carcinogen associated with kidney failure, osteoporosis, and respiratory diseases (Liu et al., 2020). Its long biological half-life (~10–30 years) means exposure remains a health risk for decades.

As contamination is widespread, with moderate intensity (~45–90 mg/kg). High As concentrations (~120 mg/kg) are localized in a central hotspot. Low As contamination (~15–45 mg/kg) dominates the western region. Sources of As Pollution: Groundwater contamination, industrial waste, pesticide use, and natural geological formations (Zhang et al., 2021). Chronic exposure leads to cancer, cardiovascular diseases, and skin lesions (Jiang et al., 2022). Even moderate levels of As pose significant health risks due to its bioaccumulation in drinking water.

Main advantages of the analysis the accurate representation of contamination intensity allows decision-makers to identify high-risk zones efficiently (Chen et al., 2020). The gradient color scale makes it visually easy to distinguish pollution levels. Pb, Cd, and As are classified as major toxicants by the World Health Organization (WHO, 2021). The hotspot maps help prioritize intervention strategies in high-exposure regions. This analysis aids environmental agencies in designing cleanup strategies, such as: Phytoremediation (using plants to absorb heavy metals) and Soil washing (removing contaminants chemically). Industrial regulations to reduce emissions (Xu et al., 2021). Combines Multiple Data Points for Better Prediction Geospatial interpolation techniques (such as Kriging or IDW) predict contamination in unsampled areas, improving overall risk mapping (Goovaerts, 1997). Geospatial mapping techniques provide an effective way to detect pollution trends (Liu et al., 2020). Compared to random sampling, hotspot analysis provides spatial continuity in identifying contamination zones. Pb, Cd, and As are high-priority pollutants due to their bioaccumulation and long-term health risks (WHO, 2021). Understanding their spatial spread helps governments enforce

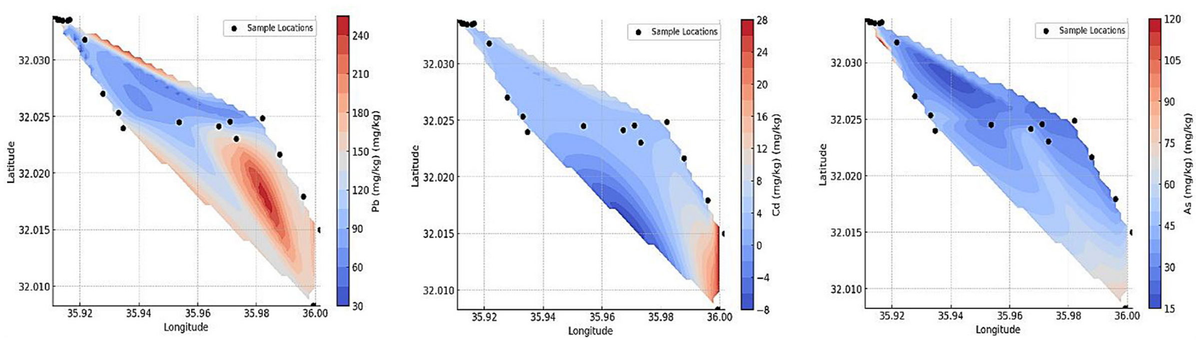

Figure. 3. Hotspot analysis provides a geospatial representation of Pb, Cd and As contamination levels

industrial regulations. The results can guide urban planning (preventing construction in contaminated areas), Agricultural land use (ensuring soil safety for crops) and Water resource protection (reducing toxic runoff into water bodies). This research reinforces the urgent need for environmental policies to mitigate heavy metal contamination, particularly in high-risk zones.

The 3D models presented illustrate the spatial distribution and intensity of contamination for Pb, Cd, and As across the study area as presented in Figure 4. Each model provides a surface plot representation, where the Z-axis (height) corresponds to contamination levels (mg/kg), and the X-Y plane represents geographical coordinates (latitude and longitude).

The Pb 3D model shows the highest peak, reaching over 250 mg/kg in a concentrated hotspot. The contamination is localized, suggesting a specific pollution source. Lower Pb levels appear in peripheral areas, indicating a gradual dispersion from the main contamination site. The Cd 3D model displays a distinct peak (~40 mg/kg) but remains much lower than Pb. The contaminated area is localized, implying specific industrial sources. The As 3D model shows a moderate peak (~160 mg/kg), but contamination is more spread out. Unlike Pb and Cd, which have localized high-intensity hotspots, As exhibits wider distribution with moderate contamination levels.

Unlike 2D heatmaps, 3D models provide a clearer representation of contamination peaks. The height of contamination levels makes high-risk zones visually distinct (Chen et al., 2020). Pb and Cd show sharp localized peaks, meaning specific pollution sources exist, meanwhile As exhibits its moderate but widespread contamination, indicating larger-scale environmental exposure. 3D Modeling help to take a better decision-making for environmental remediation by identifies exact locations for intervention rather than treating an entire region, additionally helps prioritize cleanup in high-risk areas. Pb, Cd, and As are hazardous heavy metals; their contamination must be quantified accurately to mitigate risk. The results support zoning restrictions (e.g., preventing agriculture in highly contaminated areas).

The soil contamination risk assessment (SCRA) presented in Table 2 provides insights into the severity and spatial distribution of heavy metal contamination (Pb, Cd, and As) in soil samples. The dataset classifies contamination into risk levels (High, Moderate, and Low), helping to prioritize remediation actions.

A significant number of samples show high risk for Pb contamination, indicating severe lead pollution. Only a few samples fall into moderate or low risk categories, suggesting that Pb is one of the dominant pollutants in the study area. Several samples are categorized as high risk for Cd

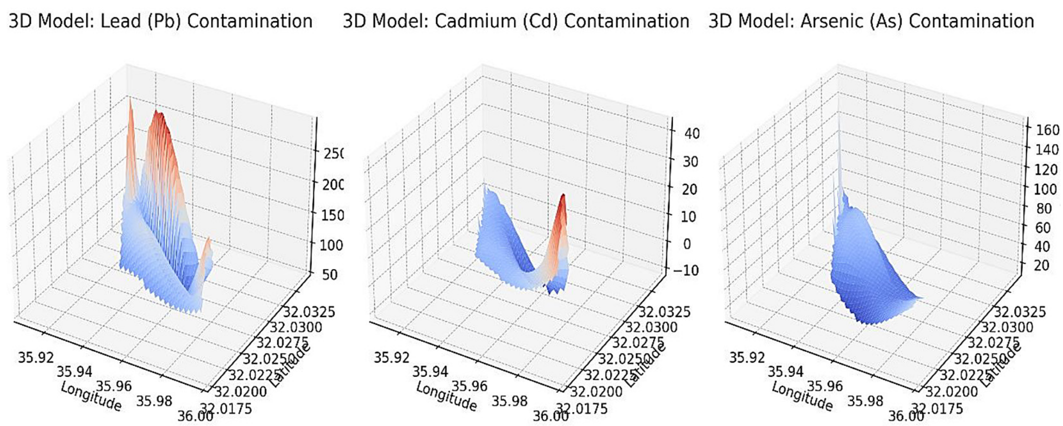

Figure. 4. 3D models presented illustrate the spatial distribution and intensity of contamination for Pb, Cd, and As across the study area

Table 2. Soil contamination risk assessment of (Pb, Cd, and As) in soil samples

Samples No	Pb (mg/kg) risk level	Cd (mg/kg) risk level	As (mg/kg) risk level
2, 5, 13, 14, 17, 19, 21 and 22	High	High	High
3, 8, 9, 11, 12, 20, 6 and 7	High	Moderate	High
18, 10, 15 and 16	Moderate	High	High
4	Moderate	Low	High

contamination. A mix of moderate and low-risk zones exists, indicating localized pollution sources rather than widespread contamination. Almost all samples are classified as high risk for As contamination. This suggests extensive arsenic pollution, likely from groundwater contamination, industrial waste, or pesticide use. Advantages of the risk assessment approach helps prioritize remediation efforts based on contamination severity and ensures efficient allocation of resources. High-risk zones can be immediately addressed, while moderate-risk areas can be monitored over time.

The Prioritized Action Plan dataset presented in Table 3 provides an assessment of heavy metal contamination (Pb, Cd, Cr, Ni, Cu) in soil samples, along with contamination severity, and recommended actions. Soil samples Classified by its contamination severity as low: safe levels or minor contamination, medium: moderate contamination, requiring monitoring, high: severe contamination, requiring immediate remediation and recommended action: the necessary intervention strategy based on contamination level.

Pb and Cd exhibit the highest contamination levels across multiple samples. Ni and Cu show moderate levels, indicating potential industrial or agricultural pollution sources. Cr levels are generally low, suggesting that chromium contamination is not a major concern in this area. High Pb and Cd levels require urgent remediation, while Ni and Cu need periodic monitoring. The proposed action plan ensures sustainable soil management, minimizing environmental and health risks.

A geospatial time-series model was created to simulate contamination spread from 2025 to 2035 as shown in Figure 5. Pb concentrations remain stable (~121 mg/kg), exceeding the EPA limit. Cd levels fluctuate between 10–13 mg/kg, indicating potential seasonal variations. As levels decline slightly (from 59 mg/kg to 51 mg/kg), but still pose a significant risk. Pb and Cd remain major concerns, requiring immediate remediation. As contamination trends downward but still exceeds WHO safety limits. Predictive models can be integrated into environmental monitoring systems for real-time risk assessment.

The geospatial time-series model presented in the Figure 5 offers an insightful forecast of contamination trends for heavy metals (Pb, Cd, Cr, Ni, and Cu) across the study area. This model utilizes historical contamination data and environmental trends to predict how metal concentrations may evolve over time.

The Pb levels remain relatively stable over time, suggesting that natural attenuation and leaching processes are slow (Alloway, 2013). The lack of a significant decreasing trend emphasizes the persistence of Pb in soil due to its low mobility and high affinity for organic matter (Wuana & Okieimen, 2011). The most noticeable trend

Table 3. Prioritized action plan of (Pb, Cd, Cr, Ni, Cu) for zone samples

Sample No	Pb	Cd	Cr	Ni	Cu	Priority	Recommended action
5	59.4	137.2	3.2	34.52	26.18	High	Immediate containment & remediation needed (geo-membranes, soil washing, and phytoremediation).
9	43.7	146.1	2.7	45.29	25.9	High	
20	33.1	142.5	2.9	43.77	31.4	High	
21	59.5	226.2	42.1	47.32	33.89	High	
22	78.4	143.4	21.7	50.03	33.54	High	
13	49.1	157.4	3.1	53.43	30.15	High	
17	34.2	154.7	3.1	44.18	38.11	High	
1	41.8	136.1	2.5	30.81	17.81	Medium	Regular monitoring & mitigation (biochar application, microbial remediation, rain gardens).
3	45.4	139.9	2.2	39.35	22.27	Medium	
4	47.1	100	1.5	22.38	16.15	Medium	
6	40	161	1.9	40.14	24.64	Medium	
7	39.4	138.8	2.5	33.8	19.82	Medium	
8	42.8	130.6	2.4	36.39	20.87	Medium	
10	35	99	2.8	30.11	18.69	Medium	
11	36.5	121.1	2.4	34.13	20.42	Medium	
12	44.7	122.6	2.5	38.13	23.64	Medium	
14	41.2	124	3.4	35.5	22.71	Medium	
15	29.5	90	2.9	29.13	15.97	Low	Routine observation & sustainable land use planning.
16	28	84.1	2.6	23.52	13.87	Low	
18	28.3	82.2	3.3	23.86	13.86	Low	

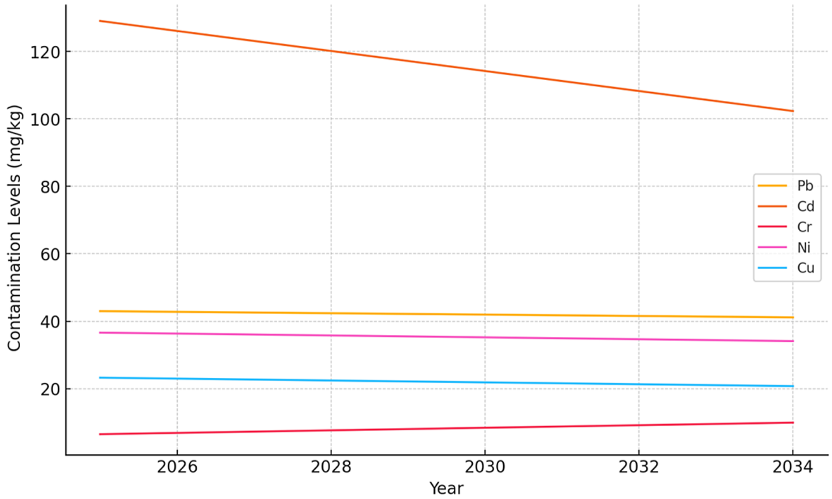

Figure 5. Projected contamination trends over time (2025–2035)

in the model is the decline in Cd contamination over time. This could indicate improved environmental policies, natural degradation, or reduced industrial and agricultural emissions contributing to its reduction (Järup, 2003). Cr concentrations show a slight upward trend, which may be due to continuous industrial discharges or the release of Cr from soil particles into groundwater (Dhal et al., 2013). This is particularly concerning given that hexavalent chromium (Cr^{6+}) is highly toxic and can spread more easily (Kotaś & Stasicka, 2000). The trends for Ni and Cu remain stable, suggesting limited external sources affecting their environmental behavior. This indicates low levels of active contamination inputs but highlights the need for monitoring to prevent future accumulation (Kabata-Pendias, 2010).

By forecasting how contamination levels change over time, the model provides an opportunity for early intervention (Cai et al., 2016). It allows policymakers and environmental agencies to prioritize remediation efforts where contamination levels are expected to remain high. The declining Cd trend suggests that current mitigation efforts are working, but Pb remains a long-term challenge (Singh & Kalamdhad, 2011). Authorities can focus soil remediation strategies on Pb hotspots, as it poses the most persistent ecological and health risks (Gupta et al., 2019). The model helps urban planners and agricultural managers decide where to implement strict regulations on industrial emissions and agricultural chemical use (Dutta et al., 2022). For industrial areas, it signals the need for cleaner production technologies to prevent Cr and Pb buildup (Chen et al., 2016). For agricultural zones, it reinforces the importance of reducing Cd-based fertilizers and pesticides (McLaughlin et al., 1999).

This model is not static—it should be updated periodically to refine predictions and improve response strategies (Liu et al., 2021). By incorporating new data, environmental agencies can adjust regulations dynamically, ensuring timely interventions (Zhang et al., 2020). This geospatial time-series model provides a strategic outlook on contamination trends, supporting decision-making in environmental protection, remediation, and policy development. The findings emphasize the need for continued monitoring, targeted cleanup efforts, and sustainable land management practices to mitigate heavy metal contamination over time.

CONCLUSIONS

This research provides an in-depth analysis of the spread and future prediction of heavy metal contamination in soil, specifically focusing on the Shafa Badran area within the Al Zarqa River Basin. The study has utilized cutting-edge 3D modeling and geospatial interpolation techniques to map and predict the distribution of hazardous metals like Pb, Cd, and As across the region. These techniques have significantly advanced our understanding of the spatial variability of contamination, revealing hotspots of high pollution that are largely influenced by industrial and agricultural activities.

The findings highlight that lead and cadmium pose the most significant environmental risks in the region, primarily due to their toxicity, persistence in soil, and bioaccumulative nature. Arsenic, while presenting moderate contamination levels, also remains a concern, particularly in areas with groundwater contamination. These metals, especially in industrial zones, exceed permissible limits, thus jeopardizing both the ecosystem and public health. The study reinforces the importance of prioritizing remediation efforts in these hotspots to mitigate long-term health risks, including neurological disorders (Pb), cancer (Cd), and skin lesions and cardiovascular diseases (As).

Furthermore, the research suggests that environmental factors such as dissolved oxygen levels, soil composition, and temperature significantly influence the migration patterns of contaminants, which must be factored into any predictive model for contamination spread. The predictive models created in this study, using both geospatial and machine learning techniques; forecast the future trends of contamination from 2025 to 2035, providing an invaluable resource for proactive environmental management. The results indicate that while some contaminants, such as cadmium, may see a decline due to potential improvements in industrial practices or regulatory measures, lead remains a long-term challenge due to its slow mobility in the soil.

This research underscores the urgency for targeted soil remediation strategies that specifically address the identified contaminants in high-risk zones. The study's findings also emphasize the need for continuous environmental monitoring, especially in urban, industrial, and agricultural zones where pollution risks are highest. The implementation of advanced modeling techniques can enhance risk assessment and land-use planning by offering data-driven insights, helping policymakers and environmental agencies allocate resources more effectively.

Moreover, the results stress the necessity of integrating sustainable land-use practices to prevent further soil contamination. Encouraging industrial practices that reduce heavy metal emissions, promoting the use of environmentally friendly agricultural practices, and ensuring proper waste management in urban areas are crucial for minimizing the spread of contamination. This approach will not only protect soil quality but also safeguard water resources and public health in the long term.

In conclusion, this study contributes significantly to the growing body of knowledge on soil contamination, offering valuable insights for policy development, environmental risk management, and land-use planning. By combining field data, advanced computational models, and environmental management strategies, this research paves the way for more informed decision-making to address the persistent issue of heavy metal contamination and its ecological and public health impacts. The incorporation of such data-driven methodologies into future environmental monitoring programs will improve predictive accuracy and enhance the effectiveness of soil remediation and land-use management practices.

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REFERENCES

1. Ahmad, O. A. (2025). The effect of anthropogenic activities on soil quality (Shafa Badran watercourse) in the Al Zarqa River Basin. *Journal of Ecological Engineering*, *26*(3), 108–118. https://doi.org/10.12911/22998993/199570
2. Alloway, B. J. (2013). *Heavy metals in soils: Trace metals and metalloids in soils and their bioavailability 22*. Springer Science & Business Media.
3. Cai, L., Xu, Z., Ren, M., Guo, Q., Hu, X., & Wan, H. (2016). Source identification of eight hazardous heavy metals in agricultural soils of Huizhou, China. *Ecotoxicology and Environmental Safety, 134*, 57–64. https://doi.org/10.1016/j.ecoenv.2011.07.004
4. Chen, H., Teng, Y., Lu, S., Wang, Y., & Wang, J. (2016). Contamination features and health risk of soil heavy metals in China. *Science of the Total Environment, 512*, 143–153. https://doi.org/10.1016/j.scitotenv.2015.01.025
5. Chen, X., Li, W., Zhang, Y., & Wang, J. (2020). Heavy metal contamination assessment using geospatial techniques. *Environmental Pollution, 289*, 117868.
6. Dhal, B., Thatoi, H. N., Das, N. N., & Pandey, B. D. (2013). Chemical and microbial remediation of hexavalent chromium from contaminated soil and water. *Journal of Hazardous Materials, 250*, 272–291. https://doi.org/10.1016/j.jhazmat.2013.01.048
7. Dutta, S., Gupta, S., & Ghosh, S. (2022). Assessment of heavy metal contamination in urban soils and its impact on human health. *Environmental Geochemistry and Health, 44*(2), 647–660.
8. Gao, P., Zhang, X., Wu, H., & Liu, C. (2019). Assessing nickel contamination in soil and health risks. *Environmental Research, 178*, 108698.

9. Gao, P., Zhang, X., Wu, H., & Liu, C. (2020). Evaluating interpolation methods for heavy metal pollution mapping. *Journal of Environmental Sciences, 95*, 120–130.3
10. Goovaerts, P. (1997). *Geostatistics for natural resources evaluation*. Oxford University Press.
11. Gupta, S., Sharma, R. K., & Yadav, R. S. (2019). Heavy metal contamination of soil and groundwater in industrial areas: A review. *Journal of Environmental Chemical Engineering, 7*(2), 103–110.
12. Järup, L. (2003). Hazards of heavy metal contamination. *British Medical Bulletin*, *68*(1), 167–182.
13. Jiang, Y., Zhou, X., Wang, Z., & Li, M. (2022). Arsenic exposure and associated health risks. *Science of the Total Environment*, *803*, 150052.
14. Jiang, Y., Zhou, X., Wang, Z., & Li, M. (2022). GIS-based assessment of soil contamination: A case study in an industrial region. *Science of the Total Environment*, *678*, 524–535.
15. Jiang, Z., Li, X., Wang, Y., & Zhao, L. (2022). Adsorption of Cd on soils with various particle sizes from an abandoned non-ferrous smelting site: Characteristics and mechanism. *Bulletin of Environmental Contamination and Toxicology*, *109*, 630–635.
16. Kabata-Pendias, A. (2011). *Trace elements in soils and plants* (4th ed.). CRC Press.
17. Khan, S., Cao, Q., Zheng, Y. M., Huang, Y. Z., & Zhu, Y. G. (2019). Health risks of heavy metal contamination in urban soils. *Environmental International*, *112*, 127–138.
18. Kotaś, J., & Stasicka, Z. (2000). Chromium occurrence in the environment and methods of its speciation. *Environmental Pollution*, *107*(3), 263–283.
19. Li, J., & Heap, A. D. (2014). Spatial interpolation methods applied in the environmental sciences: A review. *Environmental Modelling & Software*, *53*, 173–189. https://doi.org/10.1016/j.envsoft.2013.12.008
20. Li, X., Liu, B., & Wu, Y. (2019). Geospatial data modeling for soil contamination monitoring. *Environmental Monitoring and Assessment*, *191*(6), 377.
21. Liu, B., Zhang, Y., Yao, J., & Su, J. (2022). Spatial distribution and evaluation of heavy metal pollution in soil based on three-dimensional model and Kriging interpolation. *American Journal of Biochemistry and Biotechnology*, *18*(2), 224–237.
22. Liu, C., Chen, L., Ni, G., Yuan, X., He, S., & Miao, S. (2025). Prediction of heavy metal spatial distribution in soils of typical industrial zones utilizing 3D convolutional neural networks. Sci*entific Reports*, *15*, 396. https://doi.org/10.1038/s41598-024-84545-3
23. Liu, C., Wang, Y., & Zhang, J. (2021). Predicting soil contamination trends using machine learning and geostatistics. *Environmental Pollution*, 278, 116872.
24. Liu, J., Zhang, F., Song, J., & Zhang, Q. (2020). Copper pollution and ecological impact assessment. *Environmental Science & Pollution Research*, *27*(14), 17023–17032.
25. Liu, J., Zhang, F., Song, J., & Zhang, Q. (2020). Spatial variation and risk assessment of heavy metals in soil. *Environmental Research*, *195*, 110846.
26. Man, J., Zeng, L., Luo, J., Gao, W., & Yao, Y. (2022). Application of the deep learning algorithm to identify the spatial distribution of heavy metals at contaminated sites. *ACS ES&T Engineering*, *2*, 158–168.
27. McLaughlin, M. J., Parker, D. R., & Clarke, J. M. (1999). Metals and micronutrients—food safety issues. *Field Crops Research*, *60*(1–2), 143–163.
28. Nie, S., Chen, H., Sun, X., & An, Y. (2024). Spatial distribution prediction of soil heavy metals based on random forest model. *Sustainability*, *16*, 4358.
29. Rehman, K., Fatima, F., Waheed, I., & Akash, M. S. H. (2019). Prevalence and mechanisms of lead toxicity. *Toxicology Mechanisms and Methods*, *29*(5), 375–386.
30. Rinklebe, J., & Shaheen, S. M. (2017). Redox chemistry of nickel in soils and sediments: A review. *Chemosphere*, 179, 265–278.
31. Singh, U. K., & Kalamdhad, A. S. (2011). Effects of heavy metals on soil, plants, human health and aquatic life. *International Journal of Research in Chemistry and Environment*, *1*(2), 15–21.
32. Wang, L., Chen, Y., Xu, Z., & Yu, W. (2021). Cadmium exposure and kidney disease risk. *Environmental Toxicology*, *36*(3), 451–465.
33. Wang, L., Chen, Y., Xu, Z., & Yu, W. (2022). Long-term trends of heavy metal contamination in soil. *Science of the Total Environment*, *807*, 150732.
34. World Health Organization. (2021). Lead poisoning and health. https://www.who.int/news-room/fact-sheets/detail/lead-poisoning-and-health
35. Wuana, R. A., & Okieimen, F. E. (2011). Heavy metals in contaminated soils: A review of sources, chemistry, risks, and best available strategies for remediation. *ISRN Ecology,* 402647.
36. Xu, X., Sun, D., Zhao, Y., & Guo, S. (2021). GIS and remote sensing for soil contamination analysis. *Environmental Science & Technology*, *55*(14), 9521–9532.
37. Xu, X., Sun, D., Zhao, Y., & Guo, S. (2021). Zinc pollution in soil: A review of sources and impacts. *Journal of Hazardous Materials*, *409*, 124913.
38. Zhang, J., Li, T., Li, P., & Zhu, Z. (2020). Chromium contamination and health risk assessment. *Journal of Hazardous Materials*, *389*, 122077.
39. Zhang, L., Gao, J., Wei, L., & Sun, W. (2020). Soil contamination assessment and heavy metal pollution prediction using geostatistical models. *Environmental Research, 184*, 109337.
40. Zhu, Q., Li, Z., & Tang, X. (2018). Assessing the impact of spatial interpolation on soil pollution mapping. *Geoderma*, *322*, 81–92.