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Impact of Urban Layout and Topography on Lead Concentration in Dust of Public Green Spaces

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Background: Lead (Pb) contamination in urban environments poses significant health risks, especially in densely populated areas. Urban parks, which offer vital green spaces, can serve as indicators of heavy metal pollution, including Pb from vehicular emissions. This study assesses Pb contamination and its spatial drivers in the surface dust of small parks in central Isfahan, Iran.
Methods: Dust samples were collected from 45 urban parks and analyzed for Pb concentration using inductively coupled plasma mass spectrometry (ICP-MS). Generalized Linear Models (GLMs) were applied to assess the relationship between Pb levels and environmental spatial variables, including road density from Kernel Density analysis, elevation, and normalized difference vegetation index (NDVI).
Results: Pb concentrations ranged from 28.7 to 36.7 mg/kg, with road density showing a positive correlation, while elevation and NDVI were negatively associated with Pb levels. The model explained 50% of the variance in Pb concentrations, highlighting traffic and topography as significant contributors to Pb deposition.
Conclusion: The study underscores the need for targeted pollution control measures, particularly in low-lying, high-traffic areas. Increasing urban vegetation was found to mitigate Pb contamination, suggesting a potential role for urban greening in mitigating pollution.

1. Introduction

In recent decades, the global population has increasingly gravitated toward urban areas, driven by factors such as economic opportunities, improved infrastructure, and social amenities (Yu et al., 2019). This mass urban migration, combined with high population growth rates in developing countries, has resulted in rapid urban expansion and densification worldwide (Angel et al., 2021). According to the United Nations, more than 55% of the global population lived in urban areas in 2018, and this figure is projected to rise to 70%, particularly in developing regions where urban growth rates are highest (UNDESA, 2018). As cities expand to accommodate this growing population, it becomes crucial to assess their capacity to support such growth, ensuring they can provide essential resources and services (such as water, energy, food, and waste management) while maintaining environmental quality. Urban green spaces, particularly parks, play a crucial role in mitigating the adverse effects of urban densification. These green oases not only provide recreational spaces and aesthetic value but also deliver essential ecosystem services that enhance the quality of life for urban residents. From regulating microclimates (Asgarian et al., 2015) and improving air quality (Lin et al., 2023) to supporting biodiversity (Aronson et al., 2017), parks contribute in multifaceted ways to urban sustainability. A pressing issue in urban environmental quality assessment is the monitoring of contaminants, and urban parks often serve as sentinel sites due to their relatively lower intensity of human activities compared to other urban areas (Marija et al., 2017). This characteristic makes parks ideal locations for studying contamination indicators and assessing

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environmental health risks associated with urban living. In the growing densely populated urban centers, vehicular emissions exert an increasing impact, contributing to health crises and affecting a significant portion of the urban population across all demographic groups (Kumar et al., 2021). Among the various pollutants of concern in urban environments, Potentially Toxic Elements (PTEs) have drawn substantial attention due to their chronic and carcinogenic effects on urban populations and their diverse sources, which are integral to urban functioning, particularly vehicular emissions (Hwang et al., 2016). PTEs such as lead (Pb) stand out due to their persistence in the environment and their adverse health effects on humans. Pb has been shown to have multi-system, long-term impacts, affecting the nervous, cardiovascular, immune, hematologic, and respiratory systems, and even causing chromosome and DNA damage (Huang et al., 2021). Pb contamination in urban settings has been extensively studied, with urban park dust emerging as a reliable medium for assessing the distribution and potential risks associated with Pb exposure. For instance, Sultan et al. (2022) conducted a multi-sample analysis of soil dust and vegetation biomass in urban green spaces in a South Asian megacity, finding that urban green areas, particularly those with specific vegetation types, can serve as effective candidates for mitigating urban PTEs contamination, especially in response to increasing Pb-rich vehicular emissions. Similarly, J. M. Wang et al. (2021) demonstrated that localized traffic emissions are a primary factor contributing to elevated levels of PTEs in these urban land uses. In the urban parks of Beijing, China, Liu et al. (2020) indicated that older parks in the city's historical sections may also play a significant role in the accumulation of Pb in park dust. Given the distance from vehicular emission sources, studies by Yang et al. (2024) and Xie et al. (2024) revealed that urban topographical features significantly influence the deposition of PTEs in surface dust, with low-lying areas such as parks being more prone to PTE-rich deposition. Moreover, the role of park vegetation in blocking vehicular emissions has been well demonstrated by Hrotkó et al. (2021), who showed that PTEs, particularly Pb, tend to be trapped in higher concentrations on autumn leaves. Thus, during certain seasons, foliated parks may experience reduced levels of PTEs in their surface dust. Collectively, these studies suggest that the enrichment of surface dust in parks with Pb can serve as a valuable indicator of urban contamination and provide insights into the factors governing the transport and deposition of pollutants across urban land uses. Understanding and addressing PTE pollution in urban park environments is crucial for effective environmental management and public health protection strategies. This is particularly relevant in Isfahan City, where increasing vehicular activity and car dependency have contributed to a highly PTE-contaminated urban environment. Given the strong correlation between Pb concentrations and vehicular emissions, alongside the uniform distribution of urban green parks in Isfahan, this study aims to identify Pb sources in the city and explore the physical characteristics of the urban environment (specifically vegetation density and altitudinal range) that influence the deposition of Pb-rich dust in parks within Isfahan's central core. To achieve this, a robust Generalized Linear Regression model was employed to address the study's objective.

2. Materials and Methods

2.1 Study area and surface dust sampling stations

This study was conducted in the historical heart of Isfahan, a region characterized by dense urbanization and a complex mix of residential, commercial, and public spaces, centrally located at 32° 40' 15" N latitude and 51° 40' 14" E longitude. The region experiences an arid to semi-arid climate, with summer temperatures often exceeding 40°C and receiving less than 150 mm of annual precipitation (Asgarian et al., 2018). Despite the urban intensity, a network of small public parks is uniformly distributed throughout this area, providing vital green spaces within the densely built environment. For this study, 45 small parks (Figure 1) were selected, each with an approximate area of 1053 ± 507 m², ensuring consistency in park size and physical structure across our analysis. While these parks are all designed for public use, they vary significantly in terms of vegetation design, species composition, and maintenance levels. These differences reflect diverse management approaches aimed at meeting public and environmental needs in an urban context. One common feature shared by all the parks is the presence of paved walking paths, which offer easy access for visitors but also create distinct surfaces where dust can accumulate. The accumulation of dust on these impervious pavements, as opposed to the adjacent soil, is a key focus of this study. Pavements are more prone to capturing airborne dust and pollutants due to their impervious nature, making them an ideal subject for investigating how urban infrastructure affects dust dynamics. Figure 1 illustrates the locations of the selected parks, showcasing their distribution within Isfahan's varied land use zones.

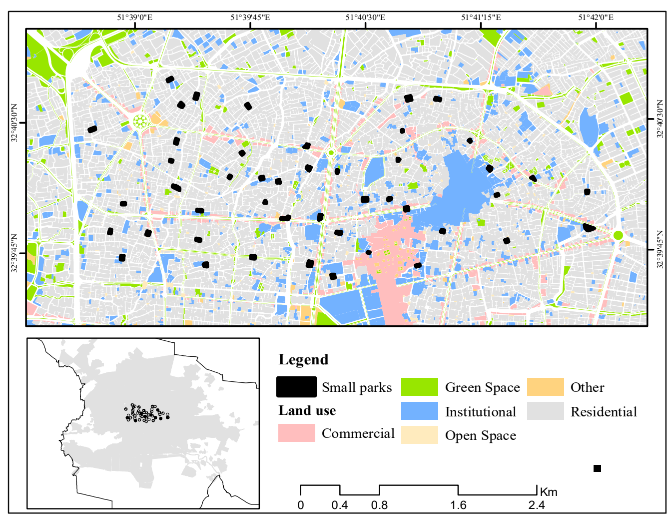

Figure 1. Distribution of small urban parks in the central part of Isfahan City, an arid part of Iran

2.2 Park surface dust sampling and analysis

Dust samples were gathered from the edges of the concrete surfaces near the center of each park, with additional samples taken from locations up to 30 meters away from the central point. These samples were combined to create a composite weighing less than 0.5 kg, using plastic brushes and dustpans, and then sealed in polyethylene zip-lock bags for storage. The samples were air-dried at ambient spring temperatures (20-30°C), after which they were ground into fine particles using a mortar and pestle and passed through a 0.100 mm mesh sieve. Once prepared, the samples were stored at 4°C until they were ready for further analysis. For the digestion process, a mixture of nitric acid, hydrogen peroxide, and hydrochloric acid was used. A 1.0 gram portion of the dust sample was added to 5.0 mL of HNO_3 in a 50 mL digestion tube and heated on a hot plate at 95°C for 15 min. After cooling, another 5.0 mL of HNO_3 was added, and the solution was reheated for two additional 30-minute intervals at the same temperature. Once cooled again, 2.0 mL of distilled water and 3.0 mL of 30% H_2O_2 were introduced, and the mixture was heated at 75°C for 5 min. Following this, 10 mL of concentrated HCl was added, and the solution was further heated at 95°C for 10 min to complete the digestion. The resulting mixture was then filtered through Whatman no. 42 filter paper, transferred to vials, and diluted to a total volume of 100 mL with deionized water for subsequent analysis. The concentration of Pb (mg/kg) was calculated using the inductively coupled plasma mass spectrometry (ICP-MS) with a detection limit of 1 ppm. To ensure the accuracy and reliability of Pb concentration analysis, quality control protocols were strictly followed. Certified reference materials (CRM) relevant to soil and dust matrices were analyzed alongside the samples to validate the accuracy of the ICP-MS results. The instrument was calibrated using a multi-element standard solution prepared in the same acid matrix as the samples, with calibration curves achieving a correlation coefficient (R^2) of ≥ 0.999. Procedural blanks were included to monitor potential contamination during sample preparation and analysis. Replicate analyses of selected samples were performed to assess analytical precision, which showed a relative standard deviation (RSD) of less than 5%.

2.3 Modeling Pb Concentration in Park Surface Dust

2.3.1 Preparation of Independent Variables

The spatial factors influencing the concentration of Pb in park surface dust were evaluated using a modeling approach. The selection of spatial drivers was grounded in their potential impact on dust composition, particularly in urban environments where traffic emissions, landscape features, and vegetation patterns are known to contribute to variations in pollutant levels (Aguilera et al., 2021; Budai & Clement, 2018). These factors were categorized into three primary groups: road density, urban topography, and vegetation. Road networks are recognized as significant sources of heavy metals in urban areas, largely due to vehicle emissions and the wear of tires and brakes, making road density a critical variable in this analysis (Jeong et al., 2022). To assess road density, the regional road network (Figure 2) was analyzed using a kernel density method with a search radius of 250 m, which provided the most significant results in the Pb concentration model. Topographical features such as slopes, low-lying areas, and natural barriers can create conditions conducive to the accumulation of dust and associated contaminants (Xie et al., 2024; Yang et al., 2024). To capture this effect, a highly detailed digital elevation model (DEM) of the region (Figure 2) was employed, with a spatial resolution of 1 meter. The elevation across the study parks ranged from 1565.99 to 1577.47 m above sea level (Table 1). Vegetation plays a dual role in dust dynamics: it can act as a barrier, reducing airborne particle movement, while also contributing organic material to the soil, affecting how contaminants, such as Pb, bind to dust particles (Hrotkó et al., 2021; Pace et al., 2020). To quantify this, the mean Normalized Difference Vegetation Index (NDVI) of the Isfahan region was utilized. The NDVI layer (with an average value of 0.15 ± 0.09; Table 1) was created by averaging all cloud-free Sentinel-2 optical images captured during the summer of 2024 (Figure 2). All spatial layers were standardized to a 10-meter resolution by upscaling the DEM and applying the same resolution to the kernel density analysis. This ensured uniformity across the model inputs. The mean values for road density, topography, and NDVI were calculated and used as independent variables to explain the variability in Pb concentrations observed in the park surface dust.

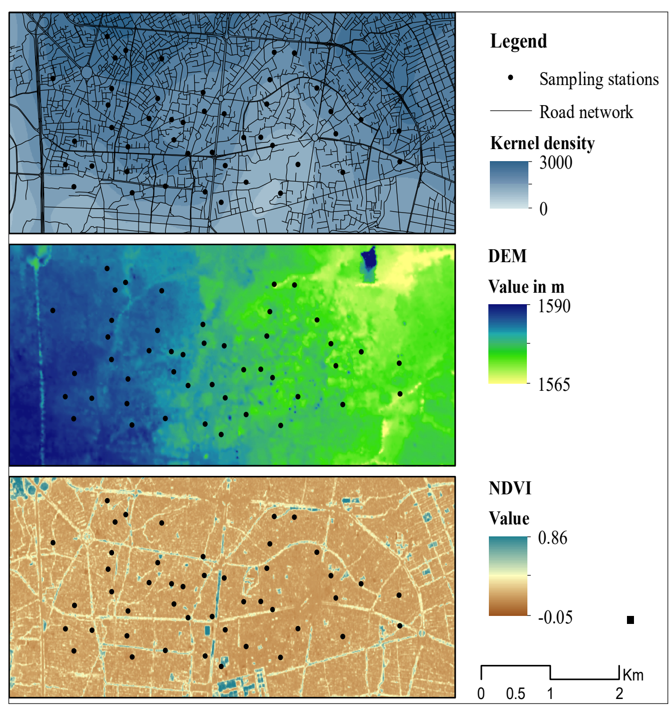

Figure 2. Spatial layers representing the independent variables used for Pb modeling including road density kernel analysis with a 250 m search radius, 1-m resolution DEM layer, and mean NDVI composite created from cloud-free Sentinel-2 images of the summer of 2024

Table 1. Descriptive statistics for the independent variables used in Pb modeling, including road density (Road-K), topography (elevation in m), and mean NDVI values across the study area

Statistic	Variable		
	Road-K	DEM	NDVI
Count	45	45	45
Mean	1997.84	1572.59	0.15
Standard Deviation	389.60	2.99	0.09
Minimum	1084.26	1565.99	0.04
25th Percentile	1814.33	1570.40	0.07
Median	2020.13	1572.60	0.12
75th Percentile	2183.22	1575.38	0.19
Maximum	2851.47	1577.47	0.43

2.3.2 Statistical modeling

Pb concentration in park surface dust was treated as the dependent variable, while the spatial drivers-road density, urban topography, and vegetation (NDVI)-were used as independent variables. To analyze the relationship between them, a Generalized Linear Model (GLM) was implemented using the Stats package in R (Core, 2021). The GLM approach was chosen for its simplicity, interpretability, and ability to examine linear relationships between Pb concentrations and spatial drivers. However, GLMs rely on specific assumptions, such as the linearity of relationships, independence of residuals, and appropriate error distributions. Before implementing the GLMs, key assumptions were tested to ensure the reliability of the results. Multicollinearity among the independent variables was assessed using Variance Inflation Factors (VIF), with all values below 2, indicating minimal correlation among predictors. The normality of residuals was tested using the Kolmogorov-Smirnov (KS) test, and visual inspection of residual plots confirmed no significant deviation from normality. The potential for overfitting was mitigated by using the Akaike Information Criterion (AIC) for model selection, ensuring a balance between model complexity and predictive power. Additionally, diagnostic checks were conducted on the residuals to identify potential outliers or patterns indicative of model misspecification. The significance of the independent variables was determined based on the results of the t-test, allowing us to identify which spatial drivers had the most substantial influence on Pb concentration. The performance of the GLM was evaluated using the coefficient of determination (R^2), which quantified how well the independent variables explained the variability in Pb concentrations. Additionally, the distribution of the residuals was analyzed to assess model accuracy and to ensure that no significant patterns or biases remained unexplained by the model.

3. Results and Discussion

The concentration of Pb in surface dust from small parks in central Isfahan ranged from 28.7 to 36.7 mg/kg, with a total range of 8.0 mg/kg. The mean concentration was 31.80 ± 2.03 mg/kg, indicating moderate variability across the sampled parks. This range is comparable to the findings reported in similar urban environments, such as 28.2-36.1 mg/kg by Siddiqui et al. (2020), but significantly lower than the range of 134-202 mg/kg observed by Zhao et al. (2020) in a Chinese city. The mean Pb concentration in our study is also slightly below the background level of 34.2 mg/kg reported by Azimzadeh and Khademi (2013). Nevertheless, these values warrant attention for environmental monitoring, particularly due to the cumulative toxicity of Pb because Pb exposure has significant health implications, particularly for vulnerable populations such as children, who are more susceptible due to their developing nervous systems and higher rates of ingestion of dust and soil particles (He et al., 2020). Chronic exposure to Pb has been also linked to neurodevelopmental disorders, reduced cognitive function, behavioral issues, and increased risks of cardiovascular diseases in adults (Gundacker et al., 2021). The scatterplots in Figure 3 show the relationship between Pb concentration (mg/kg) in surface dust and three environmental variables: NDVI, DEM, and Road K. The Pb concentrations exhibit a negative correlation with NDVI, where higher vegetation indices correspond to lower Pb levels. In contrast, the relationship between Pb concentration and DEM appears weak, with no clear trend observable. For road density (Road K), a positive correlation is observed, suggesting that areas with a higher density of roads might tend to have higher Pb concentrations.

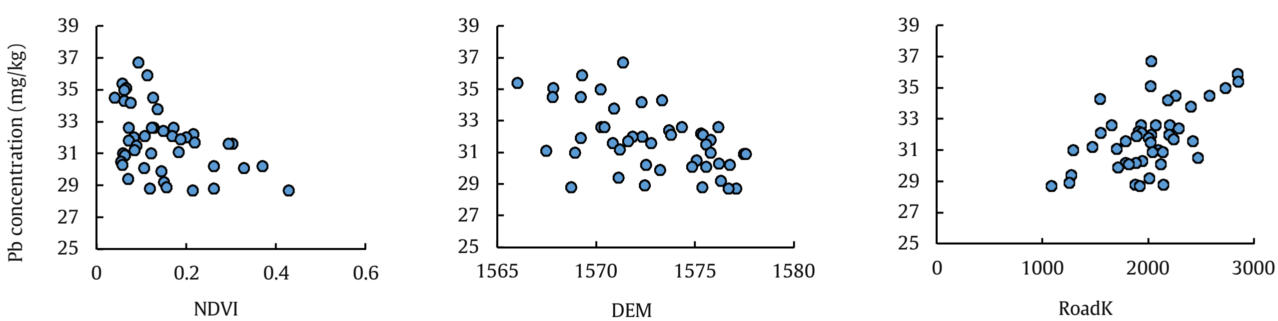

Figure 3. Scatterplots illustrating the relationships between Pb concentration (mg/kg) in surface dust and three variables: NDVI, DEM, and road density (Road K)

Based on the KS normality test (Table 2), the independent variables were found to be normally distributed, with *p-values* for RoadK and DEM well above the threshold of 0.05, indicating no significant deviation from normality. Despite the KS *p-value* of 0.013 for NDVI being slightly below the 0.05 threshold, it is still considered within an acceptable range for analysis in environmental modeling, especially given the robustness of GLM to minor deviations from normality. The VIF values were all below 2 (ranging from 1.316 for NDVI to 1.475 for RoadK), confirming that no significant interrelationships exist between these predictors, and each plays a distinct role in influencing Pb concentrations. These two analyses ensured that the assumptions of the GLM were met, allowing for accurate model estimation. The final model achieved an R^2 of 0.500 (Akaike information criterion = 173.74), indicating that it explained 50% of the variance in Pb concentrations in urban park dust (Table 3). While the model accounts for a significant portion of the variability, a considerable amount of variance remains unexplained, possibly due to factors not included in the analysis. One such factor could be localized traffic emissions, which have been identified as a major source of particulate matter (PM) and associated pollutants in many urban areas (J. M. Wang et al., 2021). Moreover, less common variables, such as the duration of urbanization and the age of the park, may also influence the concentration of potentially toxic elements (PTEs) like Pb in park dust (Liu et al., 2020). Studies such as Zhao et al. (2020) have shown that factors like coal combustion, soil parent material, and fertilizers can surpass traffic sources in contributing to Pb accumulation in urban park dust. This underscores the complex and multifactorial nature of PTE contamination in green spaces, highlighting the need to consider a broad range of local-specific determinants when analyzing pollution levels in urban environments. The model deviance residuals ranged from -3.244 to 3.382, with a median of -0.239 (Figure 4 and Table 2). The relatively symmetrical distribution of residuals around zero indicates that the model provided a good fit to the data, with most predictions closely aligning with the observed values. However, the presence of some outliers, as indicated by the extremes in residuals, suggests that there are specific locations where Pb concentrations were either over- or under-predicted by the model. As demonstrated by Denny et al. (2022), these outliers may be attributed to localized sources of contamination not accounted for, such as nearby industrial emissions, highlighting areas that warrant further investigation.

Table 2. Statistics of the residuals, AIC, and coefficient of determination (R^2) of the best performing model

Deviance Residuals					AIC	R^2
Min	1Q	Median	3Q	Max		
-3.244	-1.087	-0.239	0.977	3.382	173.74	0.500

The intercept of the model was 425.700 (SE = 121.900, *t* = 3.491, *p* = 0.001), representing the baseline Pb concentration when all independent variables are set to zero. The positive intercept is expected given that background levels of Pb are present in most urban environments, even in areas with minimal anthropogenic activity (Kelepertzis et al., 2020; J. Wang et al., 2021). Road density (RoadK) had a positive significant effect on Pb concentrations, with a coefficient of 0.022 (SE = 0.001, *t* = 2.560, *p* = 0.014). This result suggests that as road density increases, Pb concentrations in surface dust rise. This finding is consistent with Marín-Sanleandro et al. (2023), who reported that Pb concentrations are higher on high-traffic streets due to vehicle-related factors such as fuel combustion, oil burning, and brake wear. A multi-sample analysis of PTE concentrations in green open spaces by Sultan et al. (2022) also produced similar results, identifying vehicle emissions as the major source of Pb and predicting higher concentrations in areas with greater vehicular emissions. Thus, the continued presence of Pb near roads underscores the persistent legacy of past pollution and ongoing contamination from vehicular activity in areas with dense road networks. The altitudinal range had a significant negative effect on Pb concentrations, with a coefficient of -0.253 (SE = 0.077, t = -3.277, *p* = 0.002). This suggests that Pb contamination is more concentrated in low-lying areas, where dust is more likely to settle, exacerbated by higher vehicular emissions and industrial activity. The effect of this atmospheric deposition pattern is also acknowledged in the literature. For instance, Xie et al. (2024) found that PTEs tend to be deposited and enriched on hillsides at lower elevations. Similarly, Yang et al. (2024) reported that areas with lower elevations face a greater risk of PTE pollution. Although the study region exhibits only minor altitudinal variation, the negative association between Pb concentration and elevation suggests that urban planners should consider topographical factors when assessing pollution risks and implementing control measures in low-lying areas.

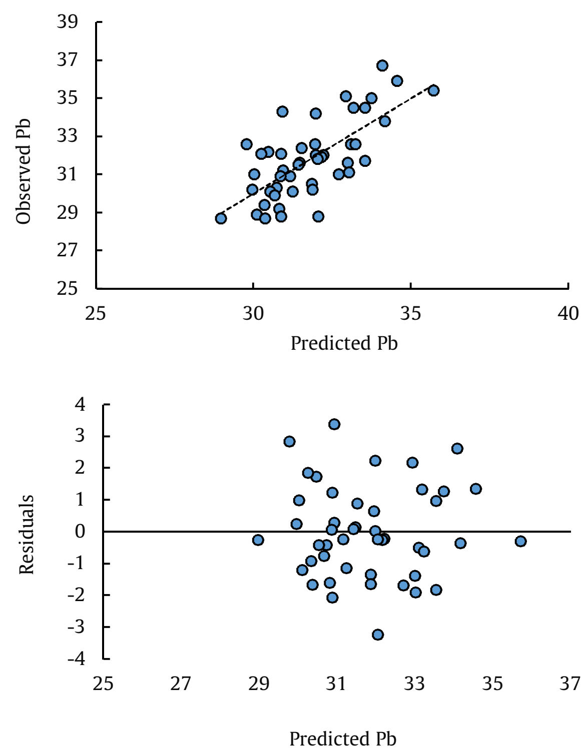

Figure 4. Left: Scatter plot of predicted versus observed Pb concentrations, illustrating the model's overall fit. Right: Residual plot displaying the distribution of the GLM deviance residuals

Table 3. Results of normality test, colinearity using Variance Inflation Factor, and coefficients estimates for variables in the GLM model. Pr (>|t|) values significant at the 0.010 level are presented in bold and underlined, while those significant at the 0.050 level are presented in bold

Variable	Model paramteres				KS normality test		VIF
	Estimate	Std. Error	t value	Pr (>|t|)	Stat.	*p-value*	
β	425.700	121.900	3.491	0.001			
RoadK	0.022	0.001	2.560	0.014	0.099	0.200	1.475
DEM	-0.253	0.077	-3.277	0.002	0.121	0.090	1.417
NDVI	-6.583	2.608	-2.524	0.015	0.148	0.013	1.316

The significant negative effect of NDVI on Pb concentrations, with a coefficient of -6.583 (SE = 2.608, t = -2.524, p = 0.015), indicates that higher NDVI values, which represent parks with denser vegetation, are associated with lower Pb levels. This suggests that vegetation plays a protective role by trapping vehicular dust particles and reducing the dispersion of pollutants. The study on foliar dust by Hrotkó et al. (2021) illustrates this role effectively, showing that PTEs, particularly Pb, can be trapped in higher concentrations on autumn leaves. This finding further underscores the importance of urban green spaces in mitigating pollution and enhancing air quality. It should also be noted that in areas with substantial vegetation, the potential for Pb phytoremediation increases, aiding in the removal of PTEs from urban environments (Pace et al., 2020). Therefore, increasing vegetation cover, especially in areas with high road density, could serve as an effective strategy for reducing Pb exposure in urban environments. Overall, the complex interactions found between urban infrastructure, topography, and green spaces in influencing Pb contamination suggest that targeted urban planning strategies, which prioritize the expansion of green spaces, particularly in densely trafficked and low-lying areas, could effectively reduce Pb exposure and improve overall environmental quality in cities.

4. Conclusion

The results of this study reveal significant relationships between environmental factors and Pb concentration in surface dust, modeled using road density, elevation, and vegetation cover. All variables underwent normality testing and collinearity checks to ensure the model's reliability and the validity of the findings. The analysis underscores the need for targeted pollution control measures in high-traffic areas, where residents are more likely to be exposed to harmful Pb levels. Additionally, pollution risks may be elevated in low-lying areas, where dust tends to settle more easily. The negative correlation between NDVI and Pb concentration yielded promising results, suggesting that increasing urban vegetation could not only enhance aesthetics and recreational opportunities but also serve as an effective strategy for reducing Pb levels in surface dust. To mitigate Pb contamination in urban parks, we recommend increasing vegetation density in high-traffic areas, implementing stricter vehicular emission controls, and establishing regular monitoring programs for heavy metals. Additionally, urban design strategies, such as vegetative buffer zones, and public education initiatives can help reduce exposure risks and enhance environmental health. While this study provides valuable insights, there are several areas open for improvement in future research. First, the analysis was confined to the urban core, limiting the generalizability of the findings to other parts of the city. Future studies should aim to examine the entire urban area, including peripheral regions, to obtain a more comprehensive understanding of Pb distribution across diverse urban landscapes. Additionally, although the study focused on a limited set of variables, the inclusion of a broader range-such as industrial activity, land use types, wind patterns, and soil properties-could provide a more complete picture of the factors influencing Pb contamination. This study's cross-sectional design, based on a single set of dust samples collected during one season, also limited our ability to assess temporal trends in Pb contamination. Expanding the range of explanatory variables, together with testing alternative modeling approaches, such as machine learning algorithms or spatial regression models, may help identify additional sources of Pb and more accurately predict pollution patterns. Moreover, the role of seasonal variations in vegetation density and Pb trapping capacity should also be considered in future research, offering a more holistic understanding of urban Pb pollution and contributing to the development of more effective strategies for pollution mitigation and urban planning.

Authors' Contributions

Mahdi Jalalpour: Data curation; Formal analysis; Investigation; Methodology; Software; Visualization; Writing-original draft. **Atefeh Chamani:** Conceptualization; Formal analysis; Funding acquisition; Project administration; Resources; Supervision; Validation; Writing-review & editing. **Soheil Sobhanardakani:** Conceptualization; Resources; Supervision; Writing-review & editing. **Bahareh Lorestani:** Software; Writing-review & editing.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article. All co-authors have disclosed any potential conflicts, and none have influenced the outcomes or conclusions of this study.

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Ethical considerations

The proposal for the present study was reviewed and approved by the Research Committee of Isfahan (Khorasgan) Branch, Islamic Azad University. (Research code: 162942328).

Using artificial intelligence

The authors used the free version of ChatGPT-4 in early October with the prompt 'check grammar' to enhance the readability of the English language. No additional content was generated or analyzed using this platform.

References

1. Aguilera, A., Bautista-Hernández, D., Bautista, F., Goguitchaichvili, A., & Cejudo, R. (2021). Is the urban form a driver of heavy metal pollution in road dust? evidence from Mexico city. *Atmosphere*, *12*(2), 266.

2. Angel, S., Lamson-Hall, P., Blei, A., Shingade, S., & Kumar, S. (2021). Densify and expand: a global analysis of recent urban growth. *Sustainability*, *13*(7), 3835.

3. Aronson, M. F., Lepczyk, C. A., Evans, K. L., Goddard, M. A., Lerman, S. B., MacIvor, J. S., . . . & Vargo, T. (2017). Biodiversity in the city: key challenges for urban green space management. *Frontiers in Ecology and the Environment*, *15*(4), 189-196.

4. Asgarian, A., Amiri, B. J., & Sakieh, Y. (2015). Assessing the effect of green cover spatial patterns on urban land surface temperature using landscape metrics approach. *Urban Ecosystems*, *18*, 209-222.

5. Asgarian, A., Soffianian, A., Pourmanafi, S., & Bodaghabad, M. B. (2018). Evaluating the spatial effectiveness of alternative urban growth scenarios in protecting cropland resources: a case of mixed agricultural-urbanized landscape in central Iran. *Sustainable Cities and Society*, *43*, 197-207.

6. Azimzadeh, B., & Khademi, H. (2013). Estimation of background concentration of selected heavy metals for pollution assessment of surface soils of Mazandaran province, Iran. *Water and Soil*, *27*(3), 548-559.

7. Budai, P., & Clement, A. (2018). Spatial distribution patterns of four traffic-emitted heavy metals in urban road dust and the resuspension of brake-emitted particles: findings of a field study. *Transportation Research Part D: Transport and Environment*, *62*, 179-185.

8. Core Team, R. (2021). *R: a language and environment for statistical computing. R foundation for statistical computing, Vienna.* https://www.scirp.org/reference/referencespapers?referenceid=3131254

9. Denny, M., Baskaran, M., Burdick, S., Tummala, C., & Dittrich, T. (2022). Investigation of pollutant metals in road dust in a post-industrial city: a case study from Detroit, Michigan. *Frontiers in Environmental Science*, *10*, 974237.

10. Gundacker, C., Forsthuber, M., Szigeti, T., Kakucs, R., Mustieles, V., Fernandez, M. F., . . . & Saber, A. T. (2021). Lead (Pb) and neurodevelopment: a review on exposure and biomarkers of effect (BDNF, HDL) and susceptibility. *International Journal of Hygiene and Environmental Health*, *238*, 113855.

11. He, A., Li, X., Ai, Y., Li, X., Li, X., Zhang, Y., . . . & Yu H. (2020). Potentially toxic metals and the risk to children′s health in a coal mining city: an investigation of soil and dust levels, bioaccessibility and blood lead levels. *Environment International*, *141*, 105788.

12. Hrotkó, K., Gyeviki, M., Sütöriné, D. M., Magyar, L., Mészáros, R., Honfi, P., & Kardos, L. (2021). Foliar dust and heavy metal deposit on leaves of urban trees in Budapest (Hungary). *Environmental Geochemistry and Health*, *43*, 1927-1940.

13. Huang, W., Shi, X., & Wu, K. (2021). Human body burden of heavy metals and health consequences of Pb exposure in Guiyu, an E-waste recycling town in China. *International Journal of Environmental Research and Public Health*, *18*(23), 12428.

14. Hwang, H. M., Fiala, M. J., Park, D., & Wade, T. L. (2016). Review of pollutants in urban road dust and stormwater runoff: part 1. Heavy metals released from vehicles. *International Journal of Urban Sciences*, *20*(3), 334-360.

15. Jeong, H., Ryu, J. S., & Ra, K. (2022). Characteristics of potentially toxic elements and multi-isotope signatures (Cu, Zn, Pb) in non-exhaust traffic emission sources. *Environmental Pollution*, *292*, 118339.

16. Kelepertzis, E., Argyraki, A., Chrastný, V., Botsou, F., Skordas, K., Komárek, M., & Fouskas, A. (2020). Metal (loid) and isotopic tracing of Pb in soils, road and house dust from the industrial area of Volos (central Greece). *Science of the Total Environment*, *725*, 138300.

17. Kumar, P. G., Lekhana, P., Tejaswi, M., & Chandrakala, S. (2021). Effects of vehicular emissions on the urban environment-a state of the art. *Materials Today: Proceedings*, *45*(7), 6314-6320.

18. Lin, J., Deng, Y., Chen, S., Li, K., Ji, W., & Li, W. (2023). Research progress of urban park microclimate based on quantitative statistical software. *Buildings*, *13*(9), 2335.

19. Liu, L., Liu, Q., Ma, J., Wu, H., Qu, Y., Gong, Y., . . . & Zhou, Y. (2020). Heavy metal (loid) s in the topsoil of urban parks in Beijing, China: concentrations, potential sources, and risk assessment. *Environmental Pollution*, *260*, 114083.

20. Marija, P., Dragana, P., Olga, K., Snežana, J., Dragan, Č., Pavle, P., & Miroslava, M. (2017). Evaluation of urban contamination with trace elements in city parks in Serbia using pine (Pinus nigra Arnold) needles, bark and urban topsoil. *International Journal of Environmental Research*, *11*(5-6), 625-639.

21. Marín-Sanleandro, P., Delgado-Iniesta, M. J., Sáenz-Segovia, A. F., & Sánchez-Navarro, A. (2023). Spatial identification and hotspots of ecological risk from heavy metals in urban dust in the city of Cartagena, SE Spain. *Sustainability*, *16*(1), 307.

22. Pace, R., Liberati, D., Sconocchia, P., & De Angelis, P. (2020). Lead transfer into the vegetation layer growing naturally in a Pb-contaminated site. *Environmental Geochemistry and Health*, *42*(8), 2321-2329.

23. Siddiqui, Z., Khillare, P., Jyethi, D. S., Aithani, D., & Yadav, A. K. (2020). Pollution characteristics and human health risk from trace metals in roadside soil and road dust around major urban parks in Delhi city. *Air Quality, Atmosphere & Health*, *13*, 1271-1286.

24. Sultan, M. B., Choudhury, T. R., Alam, M. N. E., Doza, M. B., & Rahmana, M. M. (2022). Soil, dust, and leaf-based novel multi-sample approach for urban heavy metal contamination appraisals in a megacity, Dhaka, Bangladesh. *Environmental Advances*, *7*, 100154.

25. UNDESA. (2018). *World urbanization prospects: the 2018 revision.* https://population.un.org/wup/assets/WUP2018-Report.pdf

26. Wang, J., Yu, J., Gong, Y., Wu, L., Yu, Z., Wang, J., . . . & Liu, W. (2021). Pollution characteristics, sources and health risk of metals in urban dust from different functional areas in Nanjing, China. *Environmental Research*, *201*, 111607.

27. Wang, J. M., Jeong, C. H., Hilker, N., Healy, R. M., Sofowote, U., Debosz, J., . . . & Evans, G. J. (2021). Quantifying metal emissions from vehicular traffic using real-world emission factors. *Environmental Pollution*, *268*, 115805.

28. Xie, N., Kang, C., Feng, B., & Zhang, B. (2024). Insight of heavy metal contamination of soil in high background area: field investigation and laboratory test. *International Journal of Environmental Science and Technology, 22*, 1-16.

29. Yang, J., Han, Z., Yan, Y., Guo, G., Wang, L., Shi, H., & Liao, X. (2024). Neglected pathways of heavy metal input into agricultural soil: water-land migration of heavy metals due to flooding events. *Water Research*, *267*, 122469.

30. Yu, Z., Zhang, H., Tao, Z., & Liang, J. (2019). Amenities, economic opportunities and patterns of migration at the city level in China. *Asian and Pacific Migration Journal*, *28*(1), 3-27.

31. Zhao, L., Yu, R., Yan, Y., Cheng, Y., Hu, G., & Huang, H. (2020). Bioaccessibility and provenance of heavy metals in the park dust in a coastal city of southeast China. *Applied Geochemistry*, *123*, 104798.