

Article

Heavy Metals in Urban Street Dust in Mexico City: A Spatial Analysis by Zones, Districts, and Sites

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Abstract

Heavy metal contamination in urban street dust is often highly heterogeneous, limiting the effectiveness of conventional geostatistical mapping approaches. In Mexico City, previous studies have reported very low spatial autocorrelation for key elements, making interpolation-based methods unsuitable for representing contamination patterns. This study proposes a multiscale cartographic framework to analyze and visualize heavy metal contamination in street dust from 482 sampling sites using the contamination factor (CF) and pollution load index (PLI) at three levels of spatial analysis: (i) city-scale patterns identified through hierarchical clustering of districts based on median CF values, (ii) district-scale variability assessed through statistical comparisons of PLI distributions, and (iii) site-scale identification of contamination hotspots using observed PLI values. Results revealed five contamination clusters and significant differences in pollution load among districts (Kruskal–Wallis, $p < 0.05$); PLI values in Xochimilco and Tláhuac are significantly lower than in Cuauhtémoc, Gustavo A. Madero, and Magdalena Contreras. Higher contamination levels were concentrated in northern and central districts, whereas lower levels predominated in the south. Site-scale analysis identified localized hotspots associated with transportation infrastructure, industrial areas, and commercial corridors, reflecting the influence of local emission sources. The results demonstrate that contamination patterns operate simultaneously at city, district, and site scales and cannot be adequately represented through interpolation alone. The proposed framework provides a practical approach for visualizing heterogeneous contamination datasets, supporting environmental decision-making, and may apply to other metropolitan regions characterized by weak spatial autocorrelation and localized pollution processes.

Keywords: contamination patterns; megacity environmental pollution; contamination factor; multiscale analysis



Academic Editor: Gregorio García-Fernández

Received: 5 June 2026

Revised: 3 July 2026

Accepted: 7 July 2026

Published: 12 July 2026

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1. Introduction

Environmental contamination by heavy metals in large metropolitan areas represents a persistent challenge for urban management and public health. Urban street dust is widely

recognized as an effective indicator of environmental quality because it integrates particles derived from traffic emissions, industrial activity, soil resuspension, construction, and long-range atmospheric transport [1–4]. Elevated concentrations of heavy metals have been reported in urban dust from cities in Europe, Asia, the Middle East, Africa, and Latin America, where exposure through inhalation, ingestion, and dermal contact has been associated with environmental and human health risks [1–5]. As a result, urban street dust has become an important matrix for evaluating contamination patterns and identifying areas requiring environmental intervention.

Studies conducted in cities such as Moscow [6], Harbin [7], Guangzhou [8], Suwałki [4], Istanbul [9,10], Cairo [5], Asaluyeh [2], Yenimahalle [11], Gazipur [12], Barranquilla [1,13], and Hermosillo [3] have shown that higher contamination is commonly associated with major roads, industrial areas, commercial and city centers, and densely urbanized areas. Consequently, the spatial distribution of heavy metals and other urban pollutants reflects the combined influence of local emission sources, urban morphology, geogenic factors, land use, and atmospheric deposition. Cartographic representation has therefore been used to visualize contamination patterns, identify priority intervention areas, and communicate results to decision-makers.

Heavy metal concentrations, and sometimes quantitative indices of contamination, are represented in spatial urban studies through interpolated surfaces generated using interpolation techniques, like Kriging or Inverse Distance Weighting [4,5,9,10,12,14,15]. However, the effectiveness of interpolation depends on the presence of sufficient spatial autocorrelation and stationarity within the dataset, assumptions that are poorly evaluated or reported in environmental contamination studies [7,16].

Although spatial heterogeneity has received less attention than contamination levels themselves, many studies have identified localized hotspots associated with specific emission sources, traffic corridors, industrial areas, and urban infrastructure [6,7,15]. These findings suggest that contamination patterns are frequently governed by local processes rather than by continuous spatial gradients, limiting the reliability of conventional interpolation methods in some metropolitan settings and highlighting the need for alternative cartographic approaches.

Research Gaps and Innovation

The use of geostatistical interpolation [4,5,9,10,12,14,15], land-use regression (LUR) [13,17,18], or geographically weighted regression (GWR) [19,20] techniques has substantially improved the understanding of contamination sources, spatial variability, and the influence of urban characteristics on pollutant distributions. However, their primary objective is generally to predict contamination levels at unsampled locations or to identify statistical relationships between contaminants and environmental drivers. However, how contamination datasets characterized by weak spatial autocorrelation and strong spatial non-stationarity can be effectively represented cartographically has barely been addressed [6,21]. In such cases, interpolation-based methods may generate misleading spatial surfaces because contamination is organized as localized hotspots rather than continuous gradients. Likewise, although LUR and GWR models are valuable for identifying contamination drivers [13,17–20], they do not necessarily provide a clear framework for communicating contamination patterns across the spatial scales at which environmental decisions are made.

The metropolitan area of Mexico City provides a suitable case study for this type of analysis because it is one of the largest megacities in the world with significant heavy metal contamination in urban street dust [22] and presents strong contrasts in land use, traffic intensity, industrial activity, and socio-environmental conditions. Previous investigations have identified the limitations of interpolation-based approaches and demonstrated

that heavy metal contamination in urban street dust is predominantly controlled by local processes, with Moran's I values close to zero for several elements [16]. Geographically weighted regression analyses further revealed that the influence of traffic density, land use, population characteristics, and urban morphology varies locally, and different metals respond to different drivers in different parts of the city, highlighting strong spatial non-stationarity in contamination drivers [19]. Despite these advances, a cartographic framework capable of integrating city-scale patterns, district-scale variability, and site-scale hotspots has not been developed.

The main innovation of this study is the development of a multiscale cartographic framework that represents observed contamination patterns without relying on spatial interpolation. Rather than predicting contamination at unsampled locations, the proposed approach focuses on visualizing contamination at three complementary spatial levels: city-scale clusters that reveal broad contamination patterns, district-scale comparisons that correspond to administrative units where environmental management decisions are implemented, and site-scale hotspots that identify localized areas requiring intervention. By integrating hierarchical clustering, district-level variability, and hotspot identification, the framework complements predictive approaches such as LUR and GWR by emphasizing where contamination occurs and at which spatial scale mitigation actions can be prioritized. Beyond the case of Mexico City, this approach may apply to other metropolitan regions where localized processes and conventional interpolation methods dominate, and contamination are not appropriate.

Accordingly, the objective of this study was to develop and evaluate a multiscale cartographic representation of heavy metal contamination in urban street dust across Mexico City. Specifically, the study aimed to (i) identify city-scale contamination patterns through district clustering, (ii) examine variability among administrative districts, and (iii) locate site-scale hotspots associated with localized contamination processes.

2. Materials and Methods

2.1. Dataset and Sampling Design

The dataset used for the cartographic analysis integrates information from 482 sampling sites distributed across the urban area of Mexico City, collected during April to mid-May 2017, before the rainy season started, and originally reported by Aguilera et al. (2021) [22] (Figure 1). Although the dataset represents conditions in 2017, the objective of the present study is to evaluate and compare cartographic approaches for representing urban contamination patterns rather than to characterize current contamination levels.

Mexico City is in a basin at an altitude of approximately 2240 m above sea level and covers an area of 1485 km². The city experiences two main climatic seasons: a dry season extending from November to mid-May and a rainy season from June to October. Prevailing winds generally flow from northeast to southwest, although local topography ("Sierra del Ajusco") limits the pollutant dispersion [23]. Mexico City exhibits a heterogeneous urban structure, with industrial and densely populated zones concentrated in the north, the historical and commercial core located in the central area, and predominantly residential and commercial land uses occupying the southern sector [24].

Sampling locations were selected using a systematic sampling strategy designed to ensure spatial coverage of the city and to include districts with different land-use characteristics, traffic intensity, and urban morphology. At each site, dust accumulated within a 1 m² area of the street surface was swept and collected. Samples were subsequently air-dried at room temperature in the laboratory and sieved to <250 µm before chemical analysis. For each sampling site, the dataset includes geographic coordinates, district

membership, road type, land-use description, and concentrations of heavy metals measured in urban street dust (mg/kg) [22].

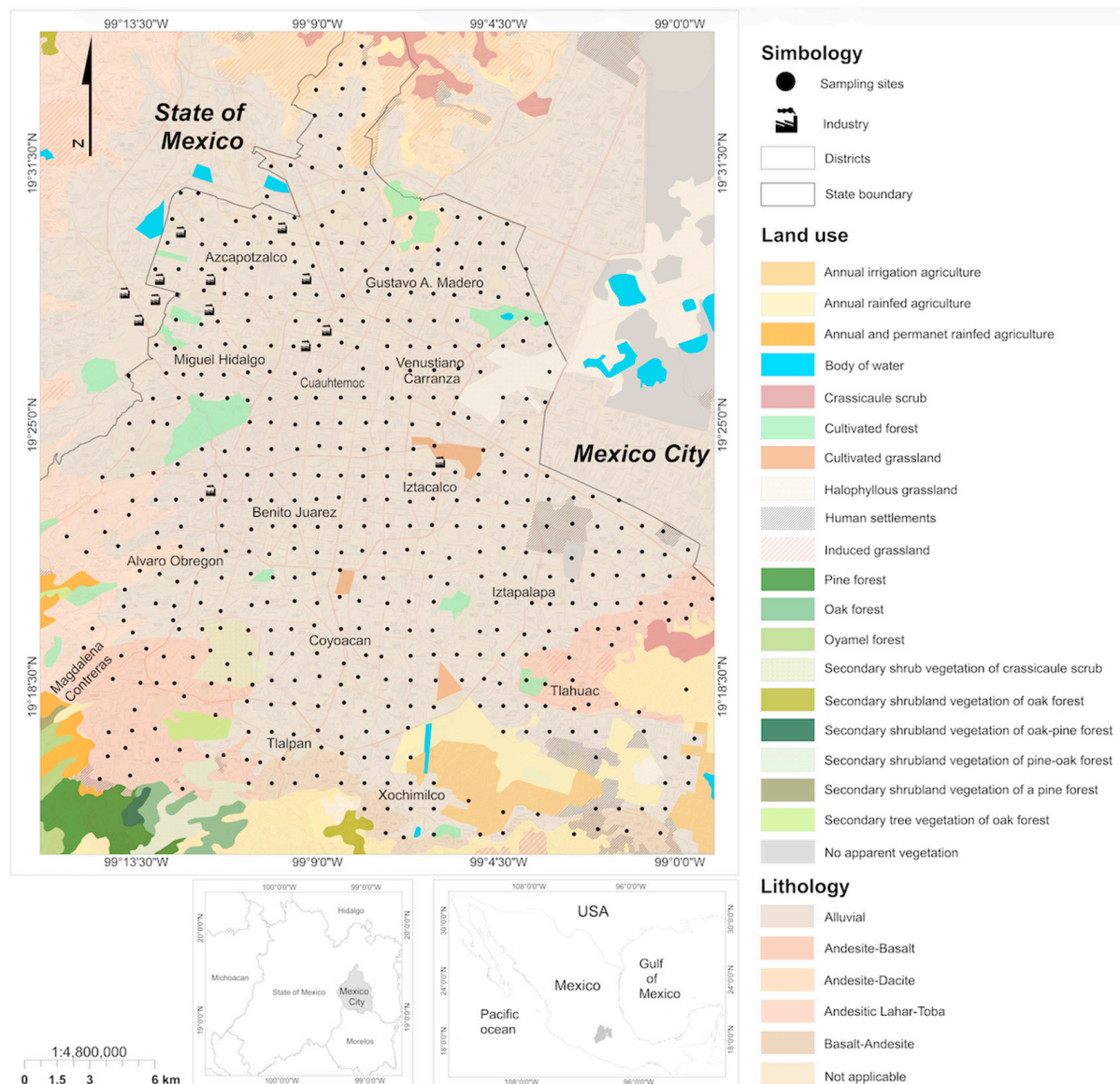


Figure 1. Location map of Mexico City showing the sampling sites (black dots) superimposed on land-use and lithological units. A factory symbol indicates industrial areas.

Heavy metal concentrations were determined following U.S. EPA methods 3051A and 6010C. Briefly, 0.4 g of each street dust sample was subjected to microwave-assisted acid digestion with concentrated HNO_3 and subsequently analyzed by inductively coupled plasma optical emission spectrometry (ICP-OES; Agilent 5100, Santa Clara, CA, USA). Quality assurance and quality control procedures included reagent blanks, sample duplicates, and triplicate analyses, with no evidence of contamination or analyte loss. Calibration was performed using certified multi-element reference materials, and detection and quantification limits were established during method validation.

Urban street dust was selected as the target matrix because it accumulates particles derived from multiple emission sources, including traffic, industrial activity, soil resuspension, and atmospheric deposition, and therefore provides an integrated indicator of environmental contamination in urban environments [2,3]. In addition, street dust can be sampled at high spatial density, which allows detailed spatial analysis in large cities.

2.2. CF and PLI Calculation

Quantitative indices such as the contamination factor (CF) and pollution load index (PLI) are commonly used to summarize multi-element contamination and facilitate comparisons among urban sites [1,12,14,15]. The CF and the pollution load index PLI were calculated for each site using previously established procedures [4,22]. These indices allow multi-element contamination to be summarized into comparable values that can be mapped and statistically analyzed.

The CF was calculated using Equation (1), and the PLI using Equation (2). These indices were computed using local background values derived from the first decile of the data distribution, which can be interpreted as a city-specific background value.

$$CF = C_n/B_n \quad (1)$$

where C_n is the element concentration and B_n is the background value. Background values are intended to represent natural concentrations or baseline conditions before substantial anthropogenic influence. However, defining such values in urban environments is often difficult because most locations have been affected by long-term human activities. As a result, different approaches have been adopted in the literature, including the use of global soil background values [25] or the minimum concentration observed within the study dataset [10,26]. Since no established background values exist for street dust in Mexico City, the first decile of the concentration distribution was used as a local baseline. This approach was selected instead of the minimum value to provide greater robustness against outliers and analytical uncertainty while preserving a conservative estimate of background conditions.

$CF < 1$ indicates negligible contamination, 1–3 indicates moderate contamination, 3–6 indicates considerable contamination, and a value > 6 indicates high contamination.

$$PLI = \sqrt[n]{FC_1 * FC_2 * \dots * FC_n} \quad (2)$$

where n is the number of metals and CF is the contamination factor for each heavy metal. $PLI > 1$ indicates heavy metal contamination.

Here, B_n is the local background calculated with Equation (3), K is the decile number, and n is the number of data points. The result indicates the position where the decile can be found. If the result is a decimal number Equation (4) is used.

$$B_n = \frac{K(n+1)}{10} \quad (3)$$

$$B_n = X_i + d(X_{i+1} - X_i) \quad (4)$$

2.3. Spatial Analysis Framework and Cartographic Approach

Previous studies on heavy metals in urban street dust in Mexico City demonstrated that the spatial autocorrelation of several elements, including Cr, Cu, Ni, Pb, and Zn, is very low, with Moran's I values close to zero [16]. Under these conditions, conventional geostatistical interpolation methods such as ordinary kriging are not appropriate because they assume spatial stationarity and significant spatial autocorrelation. When these assumptions are not met, interpolated surfaces may generate misleading spatial patterns and artificial gradients.

Based on these characteristics, the present study adopted a multiscale cartographic framework focused on the direct representation of observed contamination data and the identification of spatial groupings with similar contamination profiles. The analysis was structured at three complementary spatial levels: (1) city scale, to identify broad spatial patterns of contamination through cluster-based zoning; (2) district scale, corresponding

to political-administrative units where environmental management decisions are implemented, evaluated through statistical comparison of pollution load distributions; and (3) site scale, to identify local hotspots and intra-district variability using observed PLI values at individual sampling locations.

To identify areas with similar contamination characteristics, districts were grouped using hierarchical clustering based on the median CF values of the analyzed metals. Euclidean distance was used as a similarity metric, and Ward's minimum variance method was applied to obtain compact and internally homogeneous groups. Cluster membership was defined by cutting the hierarchical dendrogram into five groups using the *cutree* function in the R statistical environment, version 4.5.2 (31 October 2025). The selected number of clusters was informed by visual inspection of the dendrogram and supported by silhouette analysis (Supplementary Figures S1 and S2). Although solutions with two to four clusters exhibited higher average silhouette widths, they produced broader groups that obscured differences among contamination profiles. The five-cluster solution was retained because it provided a balance between statistical cohesion and environmental interpretation, allowing meaningful spatial differentiation while maintaining a parsimonious classification scheme.

Because one cluster corresponded exclusively to Magdalena Contreras, which was represented by only six sampling sites, an additional sensitivity analysis was performed excluding this district. The resulting cluster structure remained essentially unchanged, indicating that the overall grouping was robust and not driven by a single low-sample district.

Differences in pollution load among districts were evaluated using nonparametric analyses of variance (Kruskal–Wallis tests), followed by Bonferroni post hoc comparisons. All districts were included in the statistical analyses. However, sample sizes differed substantially among some districts, the Kruskal–Wallis test was considered appropriate because it is based on ranked observations and does not require equal sample sizes among groups. Nevertheless, results involving districts with very small sample sizes, like Magdalena Contrera ($n = 6$), should be interpreted with caution because of the greater uncertainty associated with their estimated distributions. These analyses were applied to PLI values to determine statistically significant differences among districts. Nonparametric methods were selected because CF and PLI values exhibit strongly right-skewed and non-normal distributions, which are common characteristics of urban environmental contamination datasets.

The map was structured using five data frames representing the study results at the district, zone, and site levels, and two smaller data frames used to show location references for the study area, the first at the state level and the second at the national level.

For the central map (zonal-scale and district-scale patterns), the territorial division by districts was used as the base spatial layer [27]. Each borough on the central map was colored according to district-scale cluster zoning, using qualitative color schemes to distinguish categorical groups, calculated with the ArcPy library in Visual Studio Code version 1.121 [28]. Based on the clustering results, the most polluted area was represented in dark red, and the least polluted in light green. The CF values were presented using pie charts, in which each slice corresponds to a different element, the size of which is directly proportional to its pollution level, and the overall size of the chart increases according to the PLI value. Furthermore, the central map includes environmental context for the study area by integrating spatial information on agricultural zones [29], bodies of water [30], protected natural areas [31], state boundaries [32], and the spatial distribution of the 482 sampling sites.

Additionally, the maps at the edges (site-scale patterns) provide a closer look at each zone, highlighting the most polluted sites and the variability in pollutant load contributed by each element through pie charts. Black circumferences highlight the ten sites with the highest PLI. The zone labels indicate the dominant metals within each cluster.

Statistical analyses, including hierarchical clustering, Kruskal–Wallis tests, and Bonferroni comparisons, were performed using the R software environment. Spatial data processing and map construction were carried out using ArcGIS Professional Plus version 10.5 [28], and final graphical editing was completed in Adobe Photoshop 2026.

3. Results

The spatial distribution of heavy metal contamination in urban street dust in Mexico City was analyzed using a multiscale cartographic framework combining cluster-based zoning at the city scale, statistical comparison at the district scale, and site-level identification of contamination hotspots. The results are presented in the accompanying map and statistical diagrams, which allow the visualization of contamination patterns at different spatial resolutions.

The absence of strong spatial autocorrelation in individual metal concentrations made it inappropriate to generate interpolated surfaces. Instead, spatial interpretation was based on the direct representation of observed values, hierarchical clustering of districts according to contamination profiles, and statistical comparison of pollution load among administrative districts.

3.1. City-Scale Patterns: Cluster-Based Zoning of Contamination Profiles

Hierarchical clustering based on median CF values grouped the districts of Mexico City into five clusters with similar contamination characteristics (Figure 2). These clusters define spatial zones that emerge from the similarity of the contamination profiles. The cluster with the highest contamination levels includes the districts of Gustavo A. Madero, Venustiano Carranza, Iztacalco, and Cuauhtémoc. These districts are in the northern and central parts of the city and are characterized by heavy traffic, high population density, and the presence of industrial and commercial activities. The CF values in this cluster are dominated by Pb, Zn, Cu, and Fe, resulting in the highest PLI values in the study area.

A second cluster with high but slightly lower contamination includes Azcapotzalco, Benito Juárez, and Miguel Hidalgo. These districts are located near the northwestern sector of the city and are influenced by both local emission sources and proximity to industrial areas located outside the metropolitan boundary. A third cluster corresponds to the Magdalena Contreras district, which appears as an isolated group with high median CF values for several metals but a very small number of sampling sites. Because of the limited sample size, this cluster must be interpreted with caution, although it suggests the presence of localized contamination conditions different from those observed in the rest of the city.

A fourth cluster includes Álvaro Obregón, Coyoacán, and Iztapalapa, which show intermediate contamination levels. These districts correspond mainly to residential areas with moderate traffic intensity and limited industrial activity, although local hotspots are present. The fifth cluster, with the lowest contamination, includes Xochimilco, Tlalpan, and Tláhuac, located in the southern part of the city. These districts have lower population density, larger green areas, and agricultural land use, which is consistent with the lower CF and PLI values observed.

The spatial distribution of these clusters reveals a general gradient of decreasing contamination from the northern sector toward the southern part of the city, although this gradient is irregular and interrupted by local anomalies, reflecting the strong influence of local emission sources.

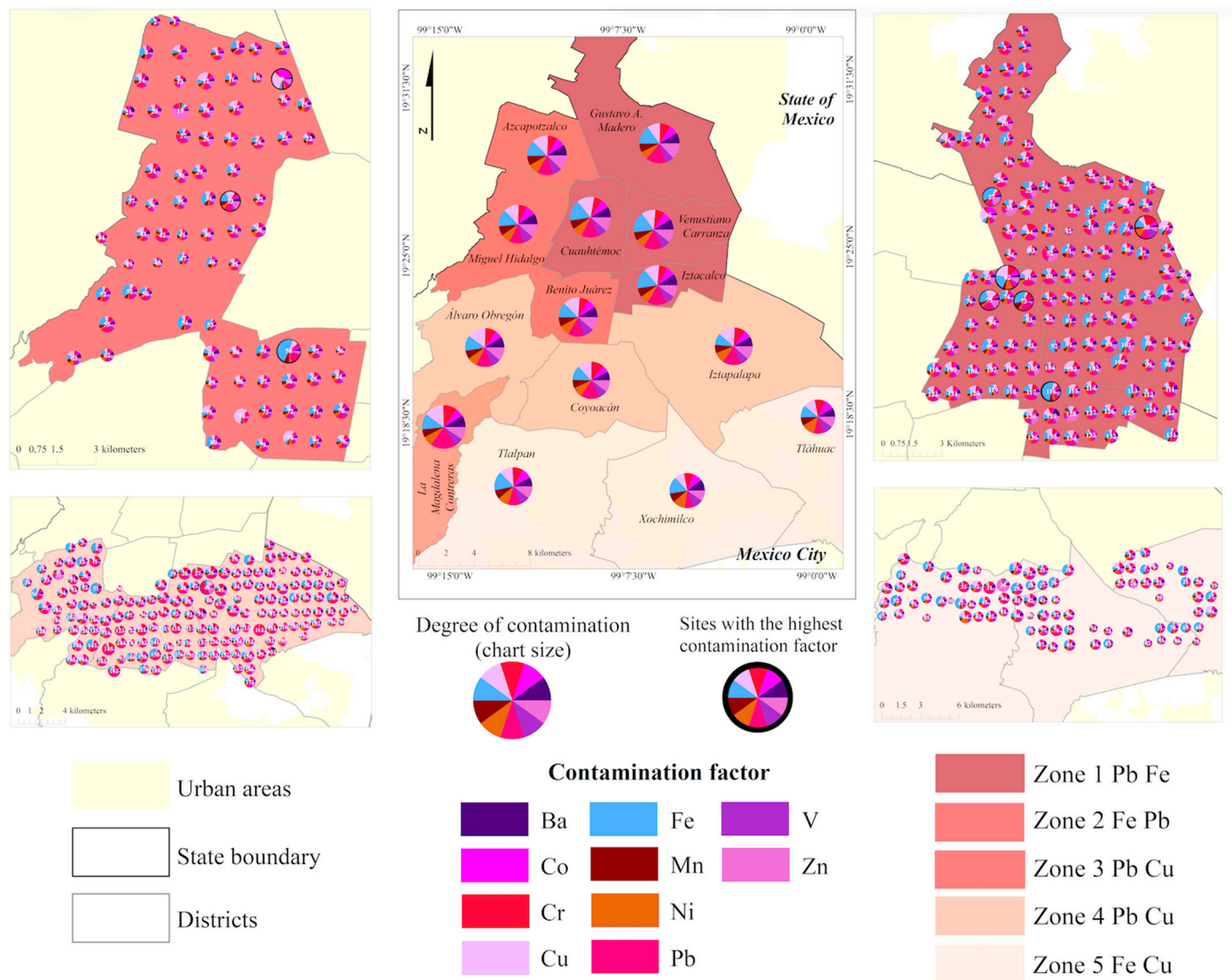


Figure 2. Spatial distribution of heavy metal contamination in urban street dust across Mexico City. Pie chart size represents the degree of contamination; black circumferences highlight the ten sites with the highest Pollution Load Index. Zoning delineates hierarchical median Contamination Factors (CF) clusters defined by median contamination factors, while labels indicate the dominant metals within each cluster.

3.2. District-Scale Variability of Pollution Load

Differences in overall contamination among districts were evaluated using PLI values. Violin plots ranked by decreasing median PLI show strong variability among districts (Figure 3). According to the median value of the PLI, the pollution by districts is Contreras > Cuauhtémoc > G. A. Madero > V. Carranza > Iztacalco > Azcapotzalco > A. Obregón > B. Juárez > M. Hidalgo > Tlalpan > Iztapalapa > Coyoacán > Xochimilco > Tlahuac, but if we consider the sum of the pollution factors, the sequence changes to Contreras > Cuauhtémoc > V. Carranza > Iztacalco > G. A. Madero > Azcapotzalco > A. Obregón > B. Juárez > Coyoacán > Iztapalapa > M. Hidalgo > Tlalpan > Xochimilco > Tlahuac (Table 1).

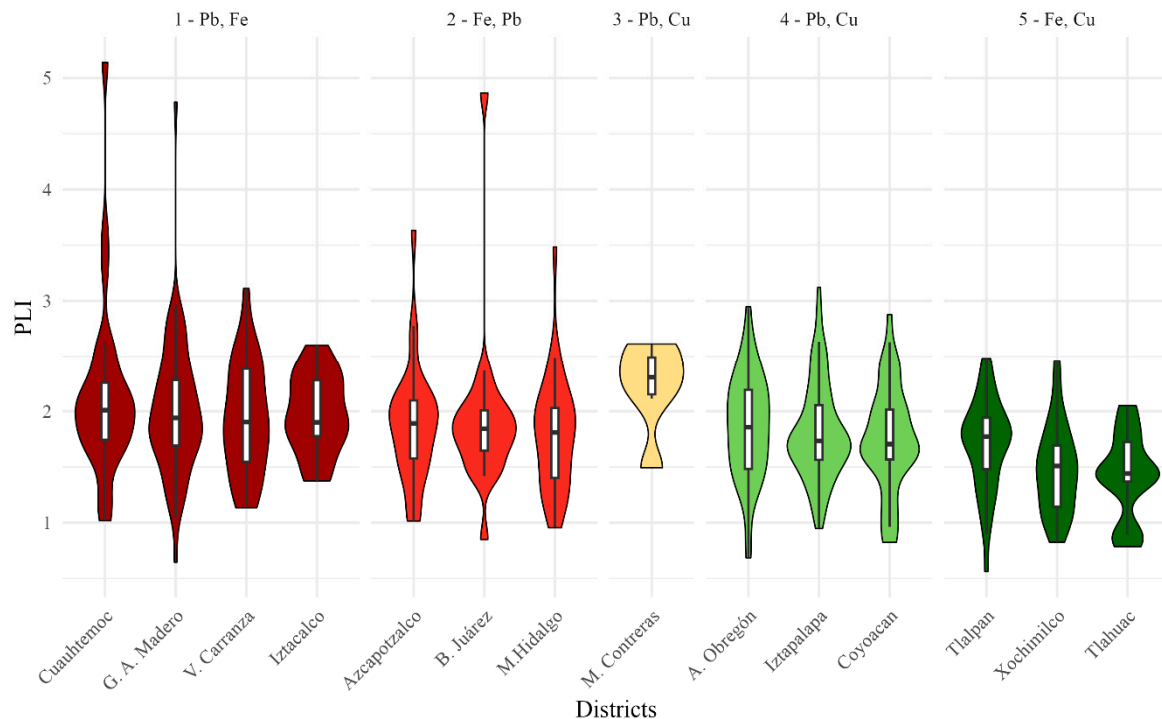


Figure 3. Violin plots of the Pollution Load Index (PLI) ranked by decreasing median PLI. The metals found at the top of the violin plots are the ones that dominate the cluster. The PLIs in Tláhuac and Xochimilco are significantly smaller than in Cuauhtémoc, G. A. Madero, and M. Contreras. PLI in Xochimilco is also smaller than in Iztapalapa, according to Kruskal–Wallis and Bonferroni tests. The colors correspond to the cluster assignment of each district.

Magdalena Contreras, Cuauhtémoc, and Gustavo A. Madero have the highest median PLI values. Cuauhtémoc and Gustavo A. Madero also show wide distributions, indicating large internal variability and the presence of highly contaminated sites within the same district. In contrast, Xochimilco and Tláhuac show the lowest PLI values and narrow distributions, indicating relatively homogeneous and low contamination levels. The Kruskal–Wallis test showed significant differences among districts ($H = 54.48$, $df = 13$, $p = 7.44 \times 10^{-7}$). Statistical comparison using the Bonferroni correction confirms that PLI values in Xochimilco and Tláhuac are significantly lower than in Cuauhtémoc, Gustavo A. Madero, and Magdalena Contreras. Xochimilco also shows significantly lower values than Iztapalapa (Table S1), despite belonging to the same general sector of the city.

Even when Magdalena Contreras exhibited some of the highest median PLI and CF values in the dataset, this district was represented by only six sampling sites (Table 1); therefore, the observed values should be interpreted as indicative of localized contamination conditions rather than as robust estimates of district-wide contamination levels.

Analysis of CF values for individual metals shows that different districts are dominated by different elements. Magdalena Contreras (PLI = 2.31) has the highest median CF values for Pb, Cu, Cr, Ba, Ni, and V, whereas Cuauhtémoc (PLI = 2.01) shows high values for Fe, Cu, Mn, and V, and Gustavo A. Madero (PLI = 1.94) is characterized by high CF values for Pb and Zn. These differences indicate that districts with similar PLI values may have different contamination profiles (Table 1).

The district-scale analysis demonstrates that spatial heterogeneity in contamination cannot be fully described by a simple north–south gradient, and that administrative boundaries provide a useful level of aggregation for identifying priority and reference areas for environmental management.

Table 1. Median Contamination Factors (CF) and Pollution Load Index (PLI) of heavy metals in Mexico City by Districts and Zones. The highest values are shown in bold and red.

District	n	Density *	Ba		Co		Cr		Cu		Mn		Ni		Pb		V		Zn		Fe		PLI	
			Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR
Cuauhtemoc	28	1.2	1.8	0.7	1.5	0.3	1.4	0.7	2.9	2.3	1.5	0.6	1.7	0.6	2.9	1.8	1.5	0.5	2.4	1.5	3.4	2.8	2.0	0.5
G. A. Madero	64	1.5	1.7	0.5	1.5	0.5	1.7	1.0	2.1	1.7	1.4	0.4	1.3	0.5	3.3	3.0	1.4	0.3	2.6	1.7	3.0	3.3	1.9	0.6
V. Carranza	25	1.3	1.8	0.5	1.5	0.5	1.5	1.0	2.3	2.1	1.4	0.5	1.5	0.7	3.1	1.3	1.5	0.3	2.2	1.9	3.4	8.3	1.9	0.8
Iztacalco	19	1.2	1.9	0.8	1.5	0.5	1.4	0.6	2.5	1.8	1.5	0.2	1.4	0.3	3.2	1.7	1.5	0.4	2.0	1.9	3.2	3.3	1.9	0.5
Zone 1	136	1.3	1.8	0.6	1.5	0.5	1.5	0.8	2.4	2.0	1.5	0.4	1.5	0.5	3.1	2.0	1.5	0.4	2.3	1.8	3.3	4.4	1.9	0.6
Azcapotzalco	28	1.2	1.7	0.4	1.5	0.5	1.4	0.6	2.5	1.5	1.5	0.4	1.6	0.7	2.5	1.9	1.4	0.4	2.3	2.0	2.4	1.1	1.9	0.5
B. Juarez	22	1.2	1.6	0.5	1.5	0.4	1.3	0.4	2.5	1.0	1.4	0.4	1.6	0.6	2.5	0.9	1.5	0.6	2.1	0.7	2.3	2.3	1.8	0.4
M. Hidalgo	30	1.6	1.6	0.6	1.5	0.3	1.2	0.6	2.2	1.9	1.4	0.4	1.3	0.8	2.2	1.8	1.5	0.5	2.0	1.3	2.5	4.1	1.8	0.6
Zone 2	80	1.3	1.6	0.5	1.5	0.4	1.3	0.5	2.4	1.5	1.4	0.4	1.5	0.7	2.4	1.5	1.5	0.5	2.1	1.3	2.4	2.5	1.8	0.5
Contreras	6	12.4	2.2	0.5	1.5	0.2	2.5	1.1	3.5	0.5	1.5	0.2	1.8	0.7	4.7	2.0	1.5	0.2	2.3	0.5	2.8	0.6	2.3	0.3
A. Obregón	39	2.5	1.6	0.7	1.3	0.5	1.6	0.7	2.8	2.2	1.3	0.3	1.5	0.7	2.5	2.0	1.4	0.3	2.1	1.0	2.3	4.4	1.9	0.7
Iztapalapa	86	1.4	1.5	0.5	1.3	0.3	1.6	0.7	2.6	1.6	1.3	0.4	1.7	0.7	2.9	2.3	1.3	0.4	2.1	1.4	1.8	1.7	1.7	0.5
Coyoacan	48	1.1	1.4	0.5	1.3	0.3	1.9	0.9	2.2	2.0	1.3	0.4	1.6	0.8	3.0	2.2	1.4	0.5	1.9	0.9	2.3	2.7	1.7	0.5
Zone 4	173	1.7	1.5	0.6	1.3	0.3	1.7	0.7	2.5	1.9	1.3	0.4	1.6	0.7	2.8	2.1	1.3	0.4	2.0	1.1	2.1	2.9	1.8	0.6
Tlalpan	39	8.0	1.2	0.6	1.5	0.3	1.4	0.7	1.8	2.1	1.2	0.3	1.6	0.8	1.9	1.7	1.3	0.4	1.7	0.9	2.6	6.6	1.8	0.5
Tlahuac	21	1.7	1.2	0.5	1.3	0.3	1.4	0.7	1.5	1.2	1.1	0.2	1.7	0.6	1.3	1.5	1.3	0.3	1.4	1.3	1.5	1.9	1.4	0.4
Xochimilco	27	4.6	1.5	0.7	1.3	0.5	1.2	0.6	1.2	1.1	1.2	0.3	1.6	0.6	1.2	1.4	1.3	0.4	1.3	0.8	2.1	3.4	1.5	0.6
Zone 5	87	4.8	1.3	0.6	1.3	0.3	1.3	0.6	1.5	1.5	1.2	0.3	1.6	0.6	1.5	1.5	1.3	0.4	1.5	1.0	2.1	3.9	1.6	0.5

* Note: Sampling density (km²/n) was calculated using the total administrative area of each district. For peripheral districts such as Magdalena Contreras, Álvaro Obregón, Tlalpan, and Xochimilco, sampling was restricted to urbanized areas and did not include conservation land, forests, agricultural land, or protected natural areas. Therefore, sampling densities for these districts may underestimate the effective sampling intensity within the urbanized area.

3.3. Site-Scale Patterns and Contamination Hotspots

At the sampling-site scale, the distribution of PLI values shows strong local variability, with several sites presenting contamination levels much higher than the district average. The ten highest PLI values are highlighted in the map to identify local hotspots. Nine of these sites are in the northern part of the city, within the clusters with the highest contamination levels, while one site is in the central sector, in the Iztapalapa district, which belongs to the intermediate contamination cluster.

The site with the highest PLI value (PLI = 5.14) is in the Cuauhtémoc district, in an area characterized by heavy traffic and mixed commercial activity. The second highest value (PLI = 4.87) occurs in Benito Juárez, and the third (PLI = 4.78) in Gustavo A. Madero. All remaining high-PLI sites are associated with road intersections, transport corridors, industrial facilities, railway areas, or commercial zones.

Several of the most contaminated sites are located near major transportation infrastructure, including subway lines, bus terminals, distribution centers, and arterial roads. Other hotspots occur near warehouses, railway tracks, or areas with intense commercial activity. These observations indicate that local urban features strongly control contamination patterns at short spatial scales. The presence of isolated hotspots within districts with moderate average contamination confirms that mapping only district averages would underestimate the spatial complexity of pollution.

4. Discussion

The cluster-based zoning obtained from hierarchical analysis revealed a general spatial organization of contamination levels across the city, with the highest pollution in northern and central districts and lower values toward the south. This pattern is consistent with previous studies that reported spatial gradients in dust load and heavy metal concentrations associated with differences in urban structure, land use, and the historical development of the metropolitan area [16,19]. The elevated contamination levels observed in northern and central districts are likely the result of a combination of historical industrial development and contemporary urban activities. Northern Mexico City has traditionally functioned as the principal industrial sector of the metropolitan area, characterized by high population density, intense commercial activity, and extensive transportation infrastructure [23,33] (Figure 1). Although economic restructuring during the 1980s led to the relocation of many large industrial facilities outside the city limits, these districts continue to host numerous small- and medium-sized industries and some of the highest traffic densities in the city [34].

Consequently, present-day contamination patterns likely reflect the combined influence of legacy industrial development, ongoing industrial activities, and sustained vehicular emissions. Source apportionment, previously addressed for the same dataset using PCA [22], identified both geogenic (Fe, Mn, V, Al) and anthropogenic (Pb, Cr, Zn, Cu) factors. The latter were strongly associated with traffic-related emissions and urban activities, including brake and tire wear, fuel combustion, and road paint deterioration.

Regional atmospheric processes may also contribute to the spatial organization of contamination. Previous studies have suggested that the prevailing north–south wind regime in the Valley of Mexico can transport particles from industrial sources located outside the metropolitan area, particularly from the northwestern industrial corridor that includes the Tula refinery and thermoelectric complex [19,35]. This regional influence may partly explain the higher contamination observed in the northern districts. However, the relative contribution of regional transport cannot be quantified using the present dataset.

The spatial patterns identified in urban street dust are consistent with previous studies conducted in other environmental matrices within Mexico City. Investigations of urban topsoils reported elevated concentrations of Cu, Zn, and Pb associated with anthropogenic

activities, with contamination extending from the city center toward northern sectors of the metropolitan area, while Pb was more widely distributed throughout the urbanized region [35]. Similarly, analyses of atmospheric pollutants identified persistent pollution hotspots in central districts and areas characterized by intense traffic activity and industrial influence [36]. Although direct comparisons among street dust, soils, and atmospheric particles should be made cautiously because each matrix reflects different transport, accumulation, and exposure processes, the convergence of these studies suggests that the northern and central sectors of Mexico City have consistently functioned as areas of elevated environmental contamination. This agreement provides additional support for the spatial patterns identified by the multiscale cartographic framework.

Heavy metal contamination in urban street dust exhibits similar spatial organization in many metropolitan regions worldwide. Studies conducted in Moscow, Suwałki, Barranquilla, Cairo, Guangzhou, Harbin, and Istanbul consistently report higher contamination levels in densely urbanized sectors characterized by intense traffic activity, commercial functions, industrial land use, and transportation infrastructure [1,4–8,14]. In Moscow, contamination hotspots were concentrated in the city center, major ring roads, and industrial districts [6], whereas in Suwałki elevated concentrations of Cr, Cu, Ni, Pb, and Zn were associated with commercial centers, bus terminals, and heavily trafficked roads [4]. Similar patterns were identified in Harbin, where Cd and Pb accumulated preferentially in areas containing dense transportation networks and industrial facilities [7], and in Barranquilla, where Cu, Zn, and Cd formed distinct district-scale hotspots linked to vehicular and industrial activities [1].

Some studies specifically identify the city center as an area of elevated contamination [3,4,6,36], while others report mining activities, metallurgical facilities, or metal-processing industries as significant sources of pollution in their cities [1,6,11,12,21]. Additionally, some studies highlight construction activities as important contributors to contamination [4,5,8,12,37]. Despite differences in climate, urban form, and socioeconomic context, these studies consistently indicate that urban contamination is spatially heterogeneous and controlled by the interaction of local emission sources and urban infrastructure. The spatial organization observed in Mexico City, therefore, appears consistent with a broader international pattern in which contamination is concentrated within specific functional zones rather than distributed uniformly across metropolitan areas.

Although city-scale clusters reveal general trends, statistical comparison among districts shows that pollution levels vary within each cluster and that some districts contain both highly contaminated and relatively clean sites. This result highlights the importance of representing data at more than one spatial scale, because conclusions based only on city-wide averages or on large spatial zones may obscure important local differences [36,37]. Since environmental management actions are usually implemented at the district or municipal level, maps structured according to administrative boundaries are particularly useful for decision-making.

At the sampling-site scale, the distribution of PLI values showed strong local variability, with several hotspots associated with specific urban features such as major roads, transport terminals, railway areas, commercial corridors, and industrial facilities. Although statistical analyses frequently identify vehicular traffic as one of the principal sources of heavy metals in urban environments [2–6,8,10–12,14], spatial analyses often associate highly contaminated areas with broader urban features such as industrial districts, densely populated neighborhoods, commercial centers, or city centers [2–5,8,11,12]. This occurs because traffic-related emissions are generated along road networks that consist of interconnected but spatially discontinuous linear features rather than continuous surfaces. As a result, interpolation-based maps tend to emphasize generalized contamination gradients

while obscuring the specific road segments and transportation corridors or intersections where contamination accumulates.

These observations are consistent with previous studies indicating that heavy metal accumulation in urban street dust is strongly influenced by short-range processes, including vehicle emissions, tire and brake wear, resuspension of contaminated soil, and particle deposition in areas with complex road geometry [16,19]. This interpretation is supported by the very low spatial autocorrelation previously reported for Cr, Cu, Ni, Pb, and Zn (Moran's I values close to zero), indicating that contamination is not distributed as a continuous regional gradient but rather as a series of localized hotspots [16].

Similarly, geographically weighted regression analyses have shown that the influence of traffic, land use, and urban morphology varies substantially across the city, reflecting strong spatial non-stationarity in contamination drivers [19]. Therefore, although regional atmospheric transport may contribute to background contamination levels, the spatial patterns identified in this study appear to be controlled predominantly by local emission sources and site-specific urban characteristics. The occurrence of isolated hotspots within districts exhibiting moderate average contamination further demonstrates that exposure risk cannot be adequately assessed using district-level averages alone and requires site-scale information.

The importance of site-scale analysis has also been reported in Moscow, Wuhan, Tianjin, and Harbin where hotspots are site-specific, localized and not adequately represented by city-wide averages [6,7,20,38]. These findings reinforce the need for spatial frameworks capable of simultaneously representing broad contamination patterns and localized anomalies.

Management Implications and Future Perspectives

The multiscale framework developed in this study provides information relevant to environmental management at different spatial levels. At the city scale, the cluster analysis revealed broad contamination gradients that can support strategic monitoring and prioritization efforts across Mexico City. The concentration of higher contamination levels in northern and central districts may therefore represent priority zones for city-wide pollution mitigation programs and long-term environmental monitoring.

At the district scale, differences in PLI distributions indicate that contamination burdens are not evenly distributed among administrative units. Because environmental management actions are commonly implemented at the borough level, district-scale information may assist local authorities in prioritizing cleaning programs, road maintenance, dust control measures, and environmental surveillance according to the predominant contamination patterns identified in each district.

At the site scale, the identification of localized hotspots highlights areas where direct intervention may be most effective. Localized management actions such as targeted street sweeping, dust suppression, vegetation barriers, pavement maintenance, and source-specific monitoring may reduce potential exposure in highly contaminated locations.

Although the present study does not include a formal health risk assessment, the elevated Pb and Zn contamination observed in several central and northern districts may increase exposure risks in densely populated areas where street dust can be readily resuspended and inhaled or ingested. Previous studies conducted in Mexico City have demonstrated that urban dust constitutes a relevant exposure pathway for heavy metals, outdoors and even higher indoors [22,39]. Therefore, the contamination patterns identified here may help prioritize areas for future exposure and health risk assessments.

A valuable future direction for urban pollution research in Mexico City would be to integrate local knowledge and community perceptions of urban pollution and dust

deposition into critical cartographic approaches. Incorporating residents' experiences and environmental awareness could provide a more comprehensive understanding of spatial pollution patterns and their social implications [40].

Another important improvement would be the standardization of color scales used in urban pollution mapping, similar to the approach adopted for light pollution maps. Standardized visualization frameworks would facilitate comparisons among studies, enhance scientific communication, and improve the accessibility and interpretation of pollution data by both researchers and decision-makers [41].

The integration of city-scale clusters, district-scale statistical diagrams, and site-scale symbols allows both general patterns and local anomalies to be visualized simultaneously, improving the interpretability of complex environmental data like heavy metal contamination in urban street dust in highly heterogeneous cities. This approach avoids the limitations of interpolation under low spatial autocorrelation, highlights spatial variability relevant for environmental management, and produces maps that are more consistent with the complex spatial structure of urban pollution and can be used as a reference to make management decisions.

5. Conclusions

This study developed a multiscale cartographic framework to represent heavy metal contamination in urban street dust across Mexico City using contamination factor (CF) and pollution load index (PLI) data. The approach was designed for environmental datasets characterized by weak spatial autocorrelation, where conventional interpolation methods may not provide reliable representations of spatial patterns.

The results revealed a heterogeneous contamination structure operating at multiple spatial scales. At the city scale, hierarchical clustering identified broad contamination patterns, with higher pollution levels concentrated in northern and central districts and lower levels toward the south. At the district scale, significant differences in contamination load and composition were observed among administrative units. At the site scale, localized hotspots were associated with transportation infrastructure, industrial areas, and commercial corridors, highlighting the importance of local emission sources.

These findings demonstrate that contamination patterns cannot be adequately represented by a single spatial scale. The integration of city-scale clusters, district-scale variability, and site-scale hotspots provides a more comprehensive cartographical representation of contamination patterns and facilitates the interpretation of spatial heterogeneity in complex urban environments.

The proposed framework offers a practical alternative for mapping environmental contamination when spatial autocorrelation is weak and contamination is controlled by localized processes. By linking contamination patterns to spatial scales relevant for environmental management, this approach may also apply to other metropolitan regions facing similar challenges of spatial heterogeneity and urban pollution.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15071249/s1>, Figure S1: Hierarchical clustering of districts based on median Contamination Factors; Figure S2: Silhouette analysis identified two to four clusters as the statistically optimal solution, but the five-cluster solution was retained because it provided greater environmental and cartographic interpretability, and the overall structure proved robust when Magdalena Contreras ($n = 6$) was removed; Table S1: Pairwise comparisons using Dunn's test with Holm (or Bonferroni) correction for multiple testing.

Author Contributions: Conceptualization, F.B.; methodology, A.A., Á.G. and R.C.; software, A.A., Á.G. and M.M.; validation, F.B.; formal analysis, A.A., Á.G. and M.M.; investigation, A.A.; resources, A.G. and F.B.; data curation, A.A. and A.G.; writing—original draft preparation, A.A.; writing—review and editing, F.B.; visualization, A.A., Á.G. and M.M.; supervision, F.B.; project administration, A.G. and F.B.; funding acquisition, A.G. and F.B. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Secretaría de Ciencias, Tecnología e Innovación de la Ciudad de México, under Grant “Sistema de monitoreo de la contaminación por metales pesados en polvos urbanos de la CDMX” [number SECITI/051/2016].

Data Availability Statement: The datasets used and analyzed during the current study are available from the corresponding authors on reasonable request.

Acknowledgments: Anahi Aguilera gratefully acknowledges the Dirección General de Asuntos del Personal Académico of the Universidad Nacional Autónoma de México for the postdoctoral fellowship. Ángeles Gallegos is grateful for the Postdoctoral Stay grant for Mexico, awarded by the Secretaría de Ciencia, Humanidades, Tecnología e Innovación (SECIHTI) of the Government of Mexico, CVU number 483497.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

CF Contamination Factor
PLI Pollution Load Index

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