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Meta-analysis of source identification and apportionment in soil: A systematic review of analytical procedures, receptor modeling, and environmental applications

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ABSTRACT

Soil pollution poses significant risks to ecosystems and human health, necessitating accurate source identification and apportionment to guide mitigation strategies. This systematic review evaluates the application of Positive Matrix Factorization (PMF) and other receptor models in soil pollution studies, focusing on analytical procedures, tracer indicators, and environmental applications. This review aims to provide a comprehensive framework for conducting soil source apportionment studies, aiding policymakers in designing effective, region-specific environmental management strategies by compiling global trends and methodological insights. The study addresses sampling protocols, emphasizing representativeness and quality control. Data from 500 peer-reviewed publications highlight the dominance of research in China, Eastern Europe, and South Asia, with agricultural soils being the most frequently studied. Key findings reveal that traffic emissions (20.8 %) and industrial activities (19.4 %) are the primary global contributors to soil contamination, with regional variations such as coal combustion in cold climates and agricultural inputs in developing regions. Policy recommendations include stricter industrial regulations, sustainable agricultural practices, and targeted remediation efforts based on source-specific risks.

1. Introduction

The growing global concern regarding soil health is driven by its critical role in sustaining ecosystems and human well-being (Bilyera et al., 2025). Healthy soils are fundamental for preserving water quality, mitigating climate change, maintaining biodiversity, and safeguarding both plant and human health (Lehmann et al., 2020). Moreover, soil conditions impact cultural and societal values, influencing community-derived benefits from the land resources (Shokri et al., 2025).

Receptor modeling constitutes a critical component of environmental assessment and management (Viana et al., 2008). It identifies and evaluates the relationships among contamination sources, environmental pathways, and receptors, including humans, wildlife, and plants, that may be affected by pollutants. By incorporating receptor modeling into legislation, authorities can systematically evaluate environmental risks, prioritize remediation efforts, and implement land management policies that protect ecological and human health (Ministry of Environment, 2021; IEPA, 2013).

Shi et al. (2024a) provided a detailed review of the development and perspectives of receptor models for source apportionment (SA) for soil pollution. Approaches for estimating pollution source contributions in soil management vary according to existing knowledge prior to receptor modeling. Basics of multivariate statistical techniques, including principal component analysis (PCA) and factor analysis (FA), are widely utilized to quantify pollutant sources based on the similarities among soil quality indicators, represented by potential interactions between different chemicals through pairwise variable comparisons. PCA and FA are used to identify the most significant statistical parameters contributing to overall contamination (Zuber et al., 2017). The core step involves extracting principal components (PCs) with distinct factor loadings using an orthogonal transformation method, subsequently assigning each PC to a plausible pollution source based on specific source markers or profiles.

While PCA and FA originated in the social sciences, the U.S. Environmental Protection Agency's (EPA) Positive Matrix Factorization (PMF) model was specifically developed to facilitate the science-based

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development and implementation of environmental standards and to support environmental forensics (Brown et al., 2015; Paatero and Tapper, 1994). Vaccaro et al. (2007) conducted one of the earliest PMF applications, partitioning soil variance into distinct sources, including background geochemistry, organic influences, and anthropogenic contamination.

Recent advances in receptor modeling have improved the resolution and reliability of source apportionment. Complementary models such as Chemical Mass Balance (CMB) and UNMIX present distinct strengths. While PMF excels at managing datasets with significant uncertainty, CMB offers advantages when source profiles are well-defined (Hopke, 2016). The CMB model assumes that emission compositions of all relevant sources are known; when variations in source profiles between the emitter and the receptor are negligible, CMB serves as an ideal receptor model. However, these conditions are rarely fully met in practice, making purely CMB-based approaches often challenging (Hopke and Cohen, 2011). In contrast, UNMIX, which shares characteristics with PMF, automatically identifies the number of sources and contributors when the source quantities are uncertain (Li et al., 2021). This approach depends on large datasets and linear mixing of parameter assumptions, constraining its wide applicability.

Given the limitations of individual methods, practical cases often require hybrid approaches that combine multiple methods, allowing them to complement and verify each other. Integrating machine learning (ML) algorithms with receptor models can explain complex relationships between target variables and environmental factors, enhancing predictive accuracy (Xu et al., 2023; Yang et al., 2021; Zhang et al., 2021). Examples of the application of machine learning with receptor models are presented in **Appendix A Text S1**. Geostatistical techniques further enhance the reliability and interpretability of PMF outputs by capturing spatial heterogeneity and validating source apportionment results (Wang et al., 2022a).

SA has become critical in identifying pollutant origins, enabling evidence-based land management strategies (Duckworth et al., 2022). Quantifying contamination sources can support policymakers in designing targeted interventions to mitigate environmental risks. Regional disparities in pollution sources emphasize the need for tailored, location-specific policy measures. For example, the prevalence of coal combustion and industrial emissions in some regions calls for stricter regulations and the adoption of cleaner energy (Jianfei et al., 2020), while traffic-related emissions point to the need for improved urban transportation planning. Biomass burning, significant in certain regions, suggests the importance of alternative energy and land management policies. Agricultural activities, such as fertilizer use, substantially contribute to water and soil pollution, and SA studies guide interventions such as using buffer strips and sustainable practices (Ren et al., 2022). Urban environments face challenges related to construction and road dust, which should be addressed through receptor-based management (Chakraborty et al., 2023). Recognizing and accounting for these spatial variations via receptor modeling is vital for devising effective mitigation strategies that align with local socio-economic and environmental conditions. However, there are no reviews dedicated to SA studies on a global scale, but existing reviews focus only on the numerical tools only (Mostert et al., 2010; Shi et al., 2024a), limited to local conditions (Agyeman et al., 2021a), focused on particular indicators only (Wilcke, 2000), or limited to bibliometric overview (Shi et al., 2024b).

This study aims to develop comprehensive guidelines for conducting soil source apportionment with a specific focus on the application of PMF. The objectives of the study are (i) to systematically review established approaches for soil sampling procedures, protocols, and chemical analysis techniques for source apportionment; (ii) to compile and evaluate tracer indicators and their associated contamination sources in soils; and (iii) to quantitatively synthesize the existing literature across diverse geographical and occupational contexts, identifying trends in PMF applications.

2. Principles and methods for the identification of soil contaminants

Effective identification of soil contaminants requires a systematic approach that includes appropriate sampling strategies, thorough sample preparation, and rigorous instrumental analysis (Fig. 1).

Soil sampling principles ensure the representative and uncontaminated collection of samples critical for accurate assessment. Subsequent sample preparation procedures vary depending on the target analytes, with distinct protocols for elemental analysis and organic contaminant (e.g., polycyclic aromatic hydrocarbons, PAHs) analysis. The instrumental techniques employed for elemental analysis and PAHs detection use advanced analytical platforms to provide precise qualitative and quantitative data.

2.1. Soil sampling principles for source apportionment

Soil functions as a crucial environmental matrix, accumulating various pollutants from multiple sources over time (Khan et al., 2021). Consequently, soil analysis is invaluable for understanding patterns of environmental pollution and tracing its origins through SA studies. The accuracy of these studies, which aim to identify and quantify the contributions from different pollution sources, depends fundamentally on the quality and representativeness of the initial soil sample collection (Boone et al., 1999). Therefore, establishing and adhering to best practices in soil sampling is essential for ensuring the reliability and validity of conclusions drawn from SA investigations.

Effective soil sample collection requires consideration of the study's objectives, soil matrix properties, and the potential contamination sources within the area of interest (Fisher et al., 2015; Öhlinger, 1996). The primary principle involves obtaining samples that accurately reflect the spatial variability of soil and contaminants within the target area, especially in heterogeneous environments such as urban and industrial zones, where pollution can be highly localized (Agyeman et al., 2023). Therefore, both spatial and temporal variability must be addressed during sampling design. For example, seasonal crop rotation in agricultural areas can significantly influence soil composition, and sampling is often conducted prior to agricultural activities to capture baseline soil conditions (Campbell et al., 1999).

Spatial variability heterogeneity is managed by selecting an appropriate number and distribution of sampling points, employing designs such as random, systematic, or stratified sampling (Wang et al., 2012). While random sampling is the most straightforward approach and provides unbiased averages, systematic grid sampling yields uniform area coverage and improved spatial interpolation. Stratified sampling, which divides the study area into distinct subgroups based on known characteristics (e.g., land use, soil type), is advantageous in SA of large, heterogeneous regions (Su et al., 2022), but its effectiveness may be less pronounced in smaller, homogeneous sites. Sample quantity depends on soil heterogeneity and the desired confidence levels, with some large-scale studies requiring up to thousands of sampling points (Fei et al., 2019). Additionally, topographic features, such as slopes and depressions, should be considered since low-lying areas may accumulate higher contaminant loads due to runoff (Anaman et al., 2022). Since source identification often relies on spatially determined receptor patterns for labeling, non-representative sampling locations can lead to misattribution of pollutants, invalidating the results of SA studies. Additionally, insufficient sampling density produces skewed source profiles, which increases not only the risk of misattribution but also the risk of biased source contributions.

Topsoil (0–20 cm) is the most sampled layer in SA studies (Bai et al., 2023; Fei et al., 2020; Guo et al., 2022), as it is directly affected by immediate anthropogenic activities and is accessible for human health and ecological risk assessments. However, deeper soil layers (up to

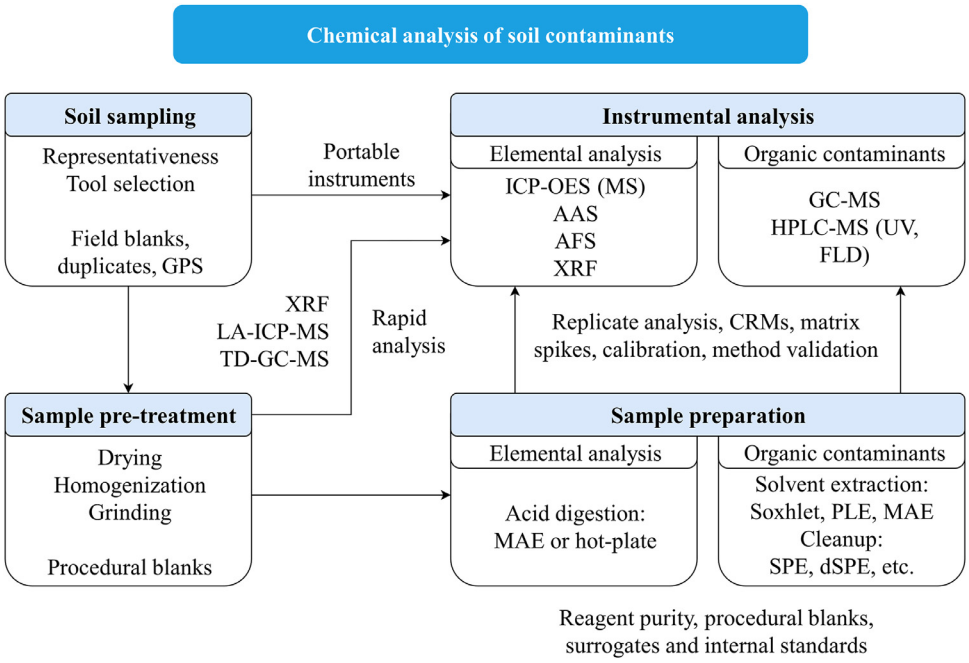


Fig. 1 – Sampling strategies and analytical methods for soil contaminants.

1 m, with 10–20 cm resolution) are sampled to investigate the vertical contaminant distribution (Liu et al., 2021a; Wu et al., 2021), providing insights into the soil formation process and historical pollution trends.

Sampling tool selection depends on the soil's hardness, contaminant type, and sampling depth (ITRC, 2026). Steel shovels and trowels are typical for surface sampling (Guo et al., 2022), while augers or corers are used for deeper sampling of heavy metals and other persistent contaminants (Kang et al., 2019; Huang et al., 2018). For volatile organic compounds (VOCs), specialized techniques that minimize volatilization, such as direct transfer into sampling containers or specialized coring devices (e.g., EnCore^{TM}), are preferred (USEPA, 2023), coupled with minimizing headspace in containers and refrigerated preservation post-collection.

Composite sampling is prevalent in SA studies, in which multiple sub-samples (5–10) from a specific area are mixed to form a single sample. The composite areas may range from 5 m^2 (Wu et al., 2021) to 100 m^2 (Bai et al., 2023; Qu et al., 2021), depending on the study aims. Cross-pattern sampling, with four sub-samples at the square corners and one from the center, represents a common composite sampling approach. Plastic bags (Agyeman et al., 2021b; Ma et al., 2023a) and glass jars (Hu et al., 2021; Wu et al., 2020a) are standard sample containers, and composite sample masses typically varied from 1 to 2 kg, ensuring sufficient volume for all required analyses. However, composite sampling has limitations for VOC loss, including low-molecular-weight polycyclic aromatic hydrocarbons (PAHs), particularly naphthalene (ASTM D4547-20), which may be lost during mixing.

Due to the fundamental importance of soil sampling for SA studies, stringent quality assurance and quality control (QA/QC) measures should be implemented (Boone et al., 1999), including field blanks, field duplicates, proper tool decontamination (or single-use tools), as well as detailed documentation of sampling location (GPS), time, and environmental conditions. Additionally, the increasing availability of real-time or in-situ soil analysis techniques offers the potential to guide sampling strategies in the field, enabling on-the-spot quantification of contamination levels. Portable instruments, including X-ray fluorescence (XRF) analyzers, provide rapid results, reducing uncertainties associated with sampling handling (Archbold et al., 2023).

2.2. Sample preparation of soil

When conducting SA, soil samples are analyzed for a range of contaminants, including heavy metals, organic pollutants, and diverse soil properties (pH, organic matter content, etc.). Although the specific analytical techniques vary depending on the target contaminants, the general sample preparation steps remain consistent, including drying, cleaning, and homogenization. These procedures significantly enhance the analytical accuracy and precision. However, sample alterations during preparation should be minimized to ensure the results accurately represent the original sample (Even et al., 2025). Receptor models employed in SA studies are sensitive to input data quality, and selective component depletion or enrichment during sample preparation can lead to biased results.

Drying constitutes the initial step in sample preparation. Moisture removal prevents microbial activity and ensures the stability of analytes. Air drying at room temperature for up to a week is the most common approach, as it is straightforward and requires minimal equipment (Ma et al., 2023b; Anaman et al., 2022). Alternatively, oven drying at temperatures up to 105 °C, desiccation, or freeze-drying completely removes moisture (Boone et al., 1999; Schaefer and Einax, 2016). Freeze-drying is widely regarded as the most effective method for preserving sample integrity and minimizing the loss of volatile compounds, such as mercury and PAHs (Berriro et al., 2014; Hojdová et al., 2015). Hojdová et al. (2015) reported a 24 % decrease in total Hg detected by air-drying and a 3 % decrease by oven-drying compared to freeze-drying. Similarly, Berriro et al. (2014) showed that low-molecular-weight PAHs are highly affected by drying procedure, with lower recoveries even at room temperature. Nevertheless, freeze-drying requires specialized equipment and is less practical for large-scale studies, such as SA, where high sample throughput is often necessary (Luo et al., 2022). As a result, air-drying remains the prevalent technique for sample preparation in SA studies, despite the potential for significant analytical inaccuracies.

After drying, samples undergo debris removal to eliminate large particles, such as stones, plant material, and other interferences, using either manual picking (Kim et al., 2009) or sieving with a coarse mesh (2–5 mm) (Wang et al., 2019a). After debris removal, the samples are homogenized by grinding or ball milling to ensure a uniform analyte distribution. Studies further sieve the soil sample to obtain a specific

particle size fraction (e.g., 75–100 μm) for analysis, depending on the requirements of the downstream analytical techniques (Wang et al., 2007; Humbert et al., 2022; Płotka-Wasylka et al., 2015).

2.2.1. Sampling preparation of elements in soils

The samples undergo digestion to analyze heavy metals and other inorganic contaminants, which extracts analytes from the soil matrix into a liquid phase. Acid digestion is a generally employed method in which samples are treated with a mixture of strong acids, including nitric acid (HNO_3), hydrochloric acid (HCl), and perchloric acid ($HClO_4$). Hydrogen peroxide (H_2O_2) can also be added to oxidize organic matter and enhance metal extraction (Mikutta et al., 2005; Anaman et al., 2022). Aqua Regia (HCl:HNO_3 = 3:1, *V/V*) is a widely used mixture for soil digestion that effectively extracts a broad range of metals, excluding those strongly bound to the silicate matrix (Su et al., 2022; Wang et al., 2019a). This method yields "pseudo-total" metal concentrations, offering insights into the fraction of the metals that could become bioavailable to plants and microorganisms (Saleem et al., 2014; Sungur et al., 2021). To achieve "true total" concentrations, more aggressive digestion methods that incorporate hydrofluoric acid (HF) are required to dissolve the silicate matrix (Shao et al., 2024). Growing interest exists in sequential extraction mixtures to characterize distinct metal fractions in soil (water-soluble, exchangeable, carbonate-bound, Fe-Mn oxide-bound, residual forms, etc.), providing valuable insights into their mobility and bioavailability for understanding environmental impact behavior. Although such fractionation methods are not yet prevalent in SA, they can enhance a comprehensive understanding of the metal sources and their environmental interactions.

Digestion is accelerated by heating the acid-sample mixture using hot plates, electric heating blocks, and microwave-assisted acid digestion (MW-AD) techniques. MW-AD offers advantages, such as a more complete sample breakdown, improved analyte recoveries, enhanced reproducibility (Sandroni et al., 2003), reduced reagent consumption, less contamination risk, and faster processing times, benefiting SA studies involving large numbers of samples.

QA/QC in soil sample preparation requires high-purity reagents and meticulously cleaned glassware, often achieved through acid-washing procedures. Due to the complexity of the soil matrix and the potential for aerosol formation, cross-contamination poses a significant challenge during soil sample preparation. To mitigate these risks, laboratories should implement strict decontamination protocols for equipment and workspaces, including procedural blanks during analysis, and conduct duplicate digestions on at least 20 % of samples to verify data reliability and reproducibility.

A key issue for SA is that digestion protocols produce different forms of metal concentrations, yet most studies treat these data as interchangeable. Limited comparative research evaluates how pseudo-total, total, and fractionated digests influence receptor-model outputs, leaving uncertainties about the robustness of inferred source profiles. Future research should systematically assess variability in digestion, develop harmonized protocols suitable for large SA datasets, and determine whether integrating fractionation data can improve discrimination between geogenic and anthropogenic contributions.

2.2.2. Sampling preparation of PAHs in soils

PAHs are persistent organic pollutants generated through the incomplete combustion of organic materials (Wickliffe et al., 2014) and include hydrocarbon PAHs and their derivatives, such as nitro-PAHs, oxy-PAHs, and hydroxy-PAHs, exhibiting a broad range of toxicities, volatilities, and environmental behaviors. Most SA studies target the 16 U.S. EPA priority PAHs, defined by their high toxicity, hydrophobicity, and persistence (Liu et al., 2024a; Zhou et al., 2024a). Accurate determination of PAHs in soil samples is complicated by the complex soil matrix, requiring critical sample preparation steps, including extraction and clean-up (Lau et al., 2010; Wu et al., 2019). Techniques ranging from traditional to advanced automated approaches are applied to extract PAHs from the soil matrix (Mogashane et al., 2024). The selected extraction method significantly effects the analytical results, analysis time, and solvent consumption. Traditional bulk extraction methods encompass Soxhlet extraction (USEPA Method 3540C) and sonication (USEPA Method 3550C).

Soxhlet extraction remains a benchmark method for extracting organic compounds from solid matrices (Wang et al., 2007). A continuous cycle of solvent evaporation and condensation (commonly n-hexane/acetone (1:1, *V/V*), dichloromethane (DCM)/acetone, toluene/methanol, DCM/toluene) (Khan et al., 2005) enables near-exhaustive analyte recovery, but requires time-intensive extraction (up to 24 h for complete extraction) and consumes large solvent volumes (~300 mL per sample). Automated Soxhlet systems (USEPA Method 3541) can reduce both time and solvent use, though large solvent volumes still necessitate concentration steps, risking loss of volatile PAHs (Płotka-Wasylka et al., 2015). Sonication extraction (10–30 min) utilizes high-frequency sound waves in standard glassware, providing rapid throughput without specialized equipment, but extraction efficiency can be inconsistent, and analytes may degrade (Lau et al., 2010; Lawal, 2017).

Several more advanced bulk extraction techniques have been developed to enhance the sample throughput and reduce solvent consumption, including pressurized liquid extraction (PLE) (USEPA Method 3545A), microwave-assisted extraction (MAE) (USEPA Method 3546), and supercritical fluid extraction (SFE) (USEPA Method 3561).

PLE employs conventional solvents under high pressure (1500–2000 psi) and temperature (50–200 °C), enabling rapid analyte extraction from solid matrices. This method substantially decreases extraction time (10–30 min) and solvent consumption (15–40 mL) compared to Soxhlet extraction, while achieving comparable or superior recoveries (Mogashane et al., 2024; USEPA Method 3545A). Additionally, PLE offers reduced labor intensity and compatibility with automation. However, its main limitations include the need for specialized equipment and the potential for co-extracting higher levels of matrix interferences. MAE operates similarly to PLE by increasing temperature and pressure but utilizes microwave energy to rapidly heat the solvent in a closed vessel (USEPA Method 3545A). This method can reach very short extraction times (5–20 min) and allows simultaneous extraction of multiple samples, thereby substantially improving throughput. An additional advantage of MAE is its capability to process wet samples directly, eliminating pre-drying steps, which is particularly beneficial for soil samples. Nevertheless, MAE demonstrates reduced efficiency for certain PAHs compared to PLE and necessitates dedicated equipment (USEPA Method 3546; Wang et al., 2007).

Post-extraction, clean-up of the sample extracts is essential for eliminating matrix interferences, such as humic and fulvic acids, lipids, waxes, and other co-extracted organic compounds from soil (Temerdashev et al., 2022). The interferences compromise analytical techniques used for PAH quantification and can affect measurement accuracy or complicate the instrumental analysis.

Standard cleanup methods include silica gel chromatography (USEPA Method 3630C), size exclusion chromatography (SEC) (USEPA Method 3640A), and solid-phase extraction (SPE). Silica gel chromatography effectively removes polar interferences from organic extracts by retaining polar compounds while allowing non-polar PAHs to elute (Bertoz et al., 2021). SEC separates molecules based on their hydrodynamic size in solution, effectively removing high-molecular-weight interferences (lipids, polymers, and humic substances), but is less effective for compounds with molecular dimensions similar to those of the target analytes. Alternative sorbents, including alumina, Florisil, C18, and polymeric resins, have been used for PAH extract cleanup, allowing selective removal of specific interferents while requiring optimization for each application (Płotka-Wasylka et al., 2015). Contemporary cleanup strategies emphasize simplified, miniaturized methods, such as dispersive SPE (dSPE). This technique directly incorporates the sorbent into the extract, followed by centrifugal separation of the sor-

bent, resulting in significantly faster extraction speeds and greater simplicity compared to cartridge-based methods (Drábová et al., 2022). Primary secondary amine (PSA) represents a frequently used dSPE sorbent for organic extracts, adapted for PAHs analysis. PSA effectively removes organic and fatty acids and carbohydrates through weak anion exchange and polar interactions (Chiaia-Hernandez et al., 2017). Anhydrous salts (e.g., magnesium sulfate) added to dSPE facilitate the removal of residual water. However, due to a lack of standardized protocols, dSPE methods must be used cautiously and validated for specific applications (Richardson, 2012).

Method-dependent recovery patterns, particularly losses of volatile PAHs during bulk extraction or variable removal of matrix interferences during cleanup, introduce uncertainties that are rarely quantified in SA applications. There is limited research evaluating how these sample preparation selections influence diagnostic ratios, multivariate profiles, or receptor-model outcomes. Future work should establish recovery-corrected or method-harmonized workflows, evaluate the effectiveness of miniaturized cleanup approaches for large datasets, and determine whether integrating PAH derivative classes (e.g., nitro-PAHs, oxy-PAHs) improves source differentiation.

2.3. Soil contaminants instrumental analysis

2.3.1. Elements analysis in soils

Multiple instrumental techniques are available for analyzing inorganic components in soil, either directly or after sample digestion. In SA studies, the most widely used methods include X-ray fluorescence (XRF), atomic absorption spectrometry (AAS), inductively coupled plasma optical emission spectrometry (ICP-OES), and inductively coupled plasma mass spectrometry (ICP-MS). **Appendix A Table S1** provides a comparison of the analytical performance of these methods.

AAS quantifies metal concentrations by measuring the light absorbed by atomized analytes, introduced into a flame or graphite furnace. Its advantages include relatively low cost, straightforward operation, and maintenance, making it suitable for routine metal analysis (Fernández García et al., 2019). Its sensitivity reaches low parts-per-million (ppm) detection limits (LOD), which are sufficient for most soil components, although sensitivity can be improved by using various oxidizers or a graphite furnace (Butcher, 2005). However, the technique is inherently limited for single-element analysis, restricting throughput, especially in multi-element SA studies (Ferreira et al., 2018). Furthermore, AAS may lack sufficient sensitivity for trace-element determination and be susceptible to matrix interferences.

ICP-OES measures the spectral line intensity emitted by excited atoms in a plasma and does not require a specific wavelength light source, enabling simultaneous multi-element determination (Khan et al., 2022). ICP-OES offers greater versatility and sensitivity than AAS, with LODs ranging from ppm to parts-per-billion (ppb) and an extended dynamic range for analyzing both trace and major elements in a single run (Douvris et al., 2023). It is also less prone to matrix interferences, making it well-suited for complex soil digestates (Ferreira et al., 2024). The majority of spectral interferences can be resolved using inter-element correction (IEC) protocols, while matrix interferences require internal standards or matrix-matched calibration. Despite these advantages, its high capital and operating costs, particularly due to argon consumption, require a thorough wavelength selection to minimize spectral interferences, and incompatibility for elements at ultra-trace levels may limit its accessibility.

ICP-MS addresses the limitations of AAS and ICP-OES by detecting ions resulting from plasma via mass spectrometry instead of optical emission. It offers exceptional sensitivity with LOD in ppb and sub-ppb range, higher precision, and multi-element capabilities within a single run (Adesina et al., 2025). ICP-MS also provides isotopic composition data, which is invaluable for SA studies that rely on isotopic signatures in addition to elemental concentrations (Dowell et al., 2023). Instrumental challenges, such as polyatomic interference (e.g., AgCl overlapping As signals), can be resolved by sample preparation, internal standards, or by utilizing additional instrumentation, such as collision/reaction cells. For the most demanding applications, especially those involving isotopic analysis or ultra-trace quantification in complex matrices, isotope dilution is a powerful calibration technique. This method involves adding a known amount of a stable isotope of the analyte to the sample, allowing for highly accurate quantification by measuring the change in the isotopic ratio (Nolan et al., 2004). Advanced mass analyzers (e.g., sector field or time-of-flight mass spectrometers) further improve mass resolution and sensitivity, resolving interferences in ICP-MS, albeit at increased cost and operational complexity (Ferreira et al., 2024). However, ICP-MS challenges include the high acquisition and maintenance costs, the need for skilled operators, sensitivity to dissolved solids (necessitating dilution for saline samples), and vulnerability to contamination and memory effects due to its high sensitivity.

Laser ablation inductively coupled plasma mass spectrometry (LA-ICP-MS) extends ICP-MS capabilities for direct solid-sample analysis without prior digestion. A highly focused UV laser beam ablates a small sample volume, generating an aerosol transported into the ICP-MS analysis (Pasilis and Van Berkel, 2010). The minimal or nonextensive sample preparation and rapid analysis time, coupled with spatially resolved elemental mapping, make LA-ICP-MS a powerful tool (Limbeck et al., 2015). Although the heterogeneity of analytes within the sample is not the focus of SA studies, it can be useful for understanding the variance of contaminants across the soil particles (Arroyo Mora et al., 2010). However, limitations of LA-ICP-MS include pronounced matrix effects, influencing both the ablation process and the ionization efficiency in the plasma, reduced sensitivity compared to solution-based ICP-MS, challenges in achieving reproducibility, and insufficient detection limits for ultra-trace elements (Miliszkiewicz et al., 2015).

X-ray fluorescence (XRF) is another technique for element determination, which is a non-destructive analytical alternative with minimal sample preparation, can be deployed in portable configurations, and provides rapid results. It operates by exciting sample atoms with incident X-rays, thereby prompting the emission of characteristic fluorescent X-rays that are detected by the instrument (Sharpe, 2024). Portable, handheld energy-dispersive XRF (EDXRF) analyzers have gained increasing popularity for field analysis of soil samples, allowing real-time data acquisition and immediate decision-making. In-situ XRF analysis eliminates surface debris and places the instrument probe directly into the soil (Fedeli et al., 2024). A brief period of air-drying the soil in the sun has been reported to enhance analytical performance (Melquiades et al., 2011). Ex-situ XRF typically involves conventional sample preparation. The uniformity and smoothness of the sample significantly influence analytical accuracy; consequently, the sample is ground into a fine powder and pressed into a pellet, sometimes with the addition of a binding agent (such as wax or cellulose) (Croffie et al., 2020). XRF provides multi-element capabilities, which are beneficial for analyzing heavy metals in soil samples. However, XRF shows reduced sensitivity for light elements (e.g., Na, Mg, Al) and can also be influenced by factors such as particle size, mineralogy, moisture content, and organic matter content (Sharpe, 2024). Additionally, XRF primarily characterizes surface composition, with penetration limited to several millimeters, potentially resulting in unrepresentative assessments of bulk soil composition (Weindorf and Chakraborty, 2020).

ICP-OES and, especially, ICP-MS are the prevailing analytical methods, providing data quality compatible with receptor models and isotopic approaches. By neglecting these techniques, measurement uncertainty can extend into source-contribution estimates. Portable XRF devices offer promising, rapid, or on-site alternatives for analyzing high-concentration elements or for preliminary screening; however, their performance in detecting trace levels and within heterogeneous matrices remains limited. Future work should explore the potential of hybrid workflows, integrating field screening with targeted ICP-based analysis, to support large-scale SA studies without compromising analytical robustness.

2.3.2. PAHs analysis in soils

Gas chromatography (GC) stands as a highly effective method for analyzing VOCs and semi-VOCs (SVOCs), making it the predominant technique for the determination of PAHs in environmental samples (Soursou et al., 2023; USEPA Method 8270E, USEPA Method 8275A). In GC, PAHs are separated based on their volatility and interaction with the stationary phase in the capillary column, typically coated with a non-polar or mid-polar phase such as polydimethylsiloxane (PDMS) or 5 % phenyl methylpolysiloxane. Detection is achieved through various detectors, including flame ionization (FID) and mass spectrometry (MS) (Lawal, 2017; Song et al., 2022). FID is a robust, cost-effective option for detecting carbon-containing compounds and provides simple, reliable operation. However, FID lacks qualitative information, relying solely on retention time for identification, which leads to ambiguities when identifying co-eluting compounds and is less suitable for complex mixtures (Song et al., 2022).

On the other hand, MS is the most widely used detector for GC, providing exceptional sensitivity, selectivity, and structural information, with LODs for PAHs in low ppb or sub-ppb levels (Shang et al., 2014; Wickliffe et al., 2014). Additionally, GC–MS separates co-eluting compounds based on their mass-to-charge ratio, providing a powerful tool for decreasing ambiguity in identification and facilitating accurate quantification of PAHs in complex mixtures. Advanced MS techniques, such as tandem mass spectrometry (MS/MS) (Sei et al., 2021; Wang et al., 2019b) and high-resolution mass spectrometry (HRMS) (Astudillo-Pascual et al., 2023; Sei et al., 2021), can further enhance the sensitivity and specificity of PAH analysis.

While most GC–MS methods detect PAHs in liquid soil extracts, thermal desorption (TD) GC–MS has been applied for direct soil analysis (Ding et al., 2009; USEPA Method 8275A). This method involves heating the soil sample in a closed chamber to vaporize VOC and SVOC, then purging the headspace into the GC–MS system for analysis. TD-GC–MS is a rapid and sensitive method that allows analysis of a wide range of PAHs without extensive sample preparation (Portet-Koltalo et al., 2024). However, it exhibits limited sensitivity to heavier PAHs (Humbert et al., 2022) and shows lower recovery rates and reproducibility compared to analysis of liquid extracts (Portet-Koltalo et al., 2024).

High-performance liquid chromatography (HPLC) complements GC for PAH analysis, especially for less volatile, thermally labile, or high-molecular-weight PAHs (Bertoz et al., 2021). Separation in HPLC is achieved on a reverse-phase column (e.g., C18) using mobile phases such as acetonitrile/water or methanol/water (Bertoz et al., 2021; Soursou et al., 2023). Detector options include UV/Diode array detector (DAD) (Mansouri et al., 2020), fluorescence detector (FLD) (Huang et al., 2013), and MS (Song et al., 2022). UV/DAD is commonly used for PAH analysis due to its strong UV light absorption (Lawal, 2017), and provides qualitative information by acquiring the full UV spectrum during analysis (Papadoyannis and Gika, 2004). Additionally, DAD acquires the entire spectrum during analysis, providing qualitative information to aid identification (Papadoyannis and Gika, 2004). However, UV/DAD offers lower sensitivity and selectivity than fluorescence or MS detectors for PAHs but remains a cost-effective and widely available option (Vistnes et al., 2022). FLD leverages the natural fluorescence of PAHs, which contain conjugated double bonds, making it highly sensitive and selective for these compounds (Qazi et al., 2021). HPLC-FLD is a standard method for analyzing the EPA 16 priority PAHs in environmental samples (e.g., USEPA Method 8310) and hence is widely adopted. HLPC-MS offers advantages similar to GC, enabling compound identification, high sensitivity, and selectivity. Advanced techniques such as HPLC-MS/MS and HPLC-HRMS are increasingly crucial for the determination of PAH derivatives (e.g., nitro-PAHs, hydroxy-PAHs), which are not amenable to GC analysis (Nakken et al., 2025; Soursou et al., 2023). Atmospheric pressure chemical ionization (APCI) and atmospheric pressure photoionization (APPI) are often more effective ionization sources for parent PAHs than electrospray ionization (ESI), due to a lack of ionization in solvents (Bertoz et al., 2021).

In SA studies, thorough validation of analytical methods is important for PAH analysis, demonstrating their fitness for purpose, unless standardized methods are used. Key performance characteristics include LOD and limits of quantification (LOQ), linearity, and precision (Poster et al., 2006). Routine quality control measures should include procedural blanks, matrix spikes, duplicates, and certified reference materials (CRMs) (Poster et al., 2006). Using surrogates (added before extraction) and internal standards (added before analysis) is critical for PAH analysis. Deuterated PAHs are used as surrogates and internal standards, as they behave similarly to the target analytes (Boden and Reiner, 2004).

For SA applications, the determination of EPA priority PAHs in soils is well-established, primarily relying on GC–MS, which provides sufficient selectivity when combined with strict QA/QC protocols. Most uncertainties in current SA datasets arise not only from instrumental limitations but also from inconsistent use of surrogates, internal standards, or cleanup procedures, which can slightly distort the compositional patterns used in receptor models. While advanced MS platforms and non-targeted workflows offer the potential to expand PAH profiles to include derivatives and transformation products, their practical relevance for SA remains unexplored, mainly due to methodological complexities.

3. Source apportionment markers and indicators in soils

The foundation of the SA lies in the selection and use of tracers, which are distinct, measurable soil properties that serve as unique identifiers or “fingerprints” of different contamination sources (Chen et al., 2021; Fei et al., 2020). An ideal tracer should possess several key characteristics: significant concentration variation between different sources; conservative environmental behavior (i.e., neither accumulating nor diluting in soil); and compatibility with standard analytical techniques (Guzmán et al., 2013). In practice, however, tracer selection often compromises these ideal characteristics, constraining the practical analytical methods. The following element-specific discussion focuses on mobility and environmental behavior to characterize when and how these factors either facilitate or hinder the interpretability of SA results.

3.1. Heavy metals as tracers

In SA studies, heavy metal tracers are generally classified according to their primary sources. The combinations of Pb, Zn, and Cu indicate urban and traffic-related sources, including atmospheric deposition, vehicle emissions, tire wear, and brake abrasion (Liang and Mao, 2015; Hwang et al., 2016; Morse et al., 2016), whereas Cd predominantly traces agricultural inputs derived from phosphate fertilizers and wastewater irrigation (Suciu et al., 2022; Alhaj Hamoud et al., 2024). Coal-combustion markers, including elements such as Hg, arise from the burning of coal and other fossil fuels in power generation and heating systems (Wu et al., 2024). High-temperature industrial processes, such as fossil fuel combustion, smelting, and cement production, are characterized by the presence of Hg and Co (Daripa et al., 2023). Conversely, elements such as Ni, Cr, Mn, and Co serve as geological background indicators, reflecting parent material signatures and natural soil-forming processes (Kumar et al., 2023; Vincent, 2023; Uren, 2012). In practice, attribution of these tracers relies on analyzing their co-varying concentrations in different sources (Guo et al., 2024; Zhang et al., 2024a; Kazapoe et al., 2025). Therefore, effective source discrimination requires a multi-element approach, ideally integrated isotopic tracers (particularly Pb and Hg isotopes), to resolve overlapping natural and anthropogenic sources (Liang et al., 2021; Zhang et al., 2023a).

Heavy metal sources in soil primarily fall into geogenic and anthropogenic categories (Soltani-Gerdefaramarzi et al., 2021). Geogenic sources comprise naturally occurring metals in the soil due to geological processes, including weathering, erosion, and volcanic activity. These metals exhibit uniform soil concentrations across relatively large areas (Hošek et al., 2024). Anthropogenic sources derive from human

activities, such as mining, smelting, industrial activities, and agriculture. Often localized and not associated with rock materials, anthropogenic sources can produce bioavailable heavy metal hotspots and pose a greater risk to human health and ecosystems (Li et al., 2024a; Wang et al., 2025). Studies have shown that anthropogenic sources contributed up to 80.2 % of the total heavy metal content in soil samples in the industrial area of Tangshan, China (Sun et al., 2019). **Appendix A Table S2** summarizes the source apportionment based on heavy metals as tracers, with the corresponding description provided in the Supplementary Materials (**Appendix A Text S2**).

3.2. PAHs as tracers

PAHs, persistent organic pollutants primarily derived from incomplete combustion of organic materials (e.g., fossil fuels, biomass) and petroleum-related sources, provide effective tracers for pollution origin identification due to their source-distinctive molecular fingerprints (Harvey, 1991). Urban soils exhibit PAH concentrations an order of magnitude higher than those in natural soils, peaking at high-traffic sites, followed by park/residential and suburban locations (Wang et al., 2017; Wilcke, 2000). Diagnostic ratios enable preliminary source discrimination between petrogenic (e.g., spilled oil, petroleum products) and pyrogenic (e.g., combustion of fuels, biomass, or coal) sources (**Appendix A Table S3**). For example, the ratio of low-molecular-weight (LMW) (2–3 rings) to high-molecular-weight (HMW) (4–6 rings) PAHs <1 indicates pyrogenic sources (incomplete combustion of fossil fuels or wood); ratios higher than 1 suggest petrogenic sources (spilled oil or petroleum products). The Fluoranthene/Fluoranthene + Pyrene (Flu/Flu + Pyr) ratio boundary lies for petroleum near 0.4, where values 0.4–0.5 correspond to liquid fossil fuel (vehicle and crude oil) combustion, and greater than 0.5 to grass, wood, or coal burning (Yunker et al., 2002). Similarly, Ravindra et al. (2008) associated Flu/(Flu + Pyr) > 0.5 with diesel emissions and < 0.5 with gasoline emissions. Other ratios include BaA/(BaA + Chr), with < 0.2 implying petroleum, 0.2–0.35 mixed petroleum/combustion, and > 0.35 combustion; InP/(InP + BghiP) ratio < 0.2 for petroleum, 0.2–0.5 for liquid fossil fuel (vehicle and crude oil) combustion, and > 0.5 for grass, wood, and coal combustion; Ant/(Ant + Phe) ⟨ 0.1 indicator of petroleum, while ⟩ 0.1 combustion dominance (Budzinski et al., 1997); and BaP/BghiP ratio > 0.6 signifies traffic and < 0.6 non-traffic emissions.

Nevertheless, diagnostic ratios of PAHs should be used with utmost care. Due to environmental and biological transformation and transport of parent PAHs, the raw concentration ratios typically do not reflect the composition of emissions (Tobiszewski and Namieśnik, 2012). Selective sorption processes (differences in the rates of photo- and biodegradation) can significantly affect values in environmental compartments. Various correction factors were developed to improve the accuracy of diagnostic ratios; however, the accuracy of these models remains under investigation. Additionally, diagnostic ratios of HMW PAHs are more conservative, due to their chemical stability (Wang et al., 2017).

PMF offers significant advantages for PAH source identification by robustly decomposing a matrix of complex sample data into factor contributions and factor profiles while incorporating measurement uncertainties (Paatero and Tapper, 1994; USEPA, 2025). PAH profiles differ by emission type, with petrogenic sources (e.g., crude oil spills, unburned fuels) dominated by LMW PAHs (Yunker et al., 2002) and pyrogenic sources (e.g., combustion of coal, gasoline, diesel, biomass) enriched in HMW PAHs (Manoli et al., 2004; Wang et al., 2010). The PMF application benefits from emphasizing HMW PAHs due to their transport stability (Zhang et al., 2005) and interpreting factors with literature source profiles to local emission inventories and documented source profiles (Wang et al., 2013). The incorporation of spatial analysis further enhances source identification accuracy, as demonstrated by mapping the urban-to-rural distribution of PAHs (Wang et al., 2015a).

4. Source apportionment applications in different environmental contexts

PMF is a receptor modeling approach that resolves chemical mass balance by decomposing contaminant concentration matrices in soil samples into source contributions and source profiles (Comero et al., 2009). The data matrix is modeled as the sum of factor contributions, profiles, and residuals. PMF minimizes an objective function weighted by measurement uncertainties derived from chemical concentrations, relative standard deviations, and method detection limits. Values below the detection limit are substituted with corresponding adjusted uncertainties, half the LOD. The model enforces non-negativity constraints on factor contributions and employs a multilinear engine algorithm that iterates from multiple starting points to avoid local minima, thereby ensuring convergence to the global minimum and yielding robust source apportionment results. A detailed description of PMF fundamentals is provided in the Supplementary Materials (**Appendix A Text S3**).

A comprehensive bibliometric analysis was conducted in the Scopus database to identify peer-reviewed soil SA studies that employ PMF. The initial query, combining the keywords “soils”, “source apportionment”, and “positive matrix factorization”, resulted in 1288 publications. After systematic exclusion of studies focused on non-soil environmental media (e.g., air, water, sediments, dust), 500 publications (as of January 31st, 2025) were selected for analysis (**Appendix A Table S4**). The global distribution of these studies (**Appendix A Fig. S1**) reveals a predominance of research conducted in China, followed by notable contributions from Eastern Europe and South Asia.

Categorization by land-use type indicates that agricultural soils constitute the largest share of investigations (218 locations; 42.6 %), followed by regional-scale assessments (81 locations; 15.8 %), and residential areas (75 locations; 14.6 %). Industrial impact zones (48 locations; 9.4 %) and extraction/mining areas (44 locations; 8.6 %) form the next tier of research intensity, while urban-industrial complexes (27 locations; 5.3 %), recreational areas (14 locations; 2.7 %), and landfill-impacted soils (5 locations; 1.0 %) represent less frequently studied contexts. The spatial distribution of SA studies using different analytes as indicators (**Appendix A Fig. S2**) demonstrates that most studies (413; 82.6 %) used metals as indicators for PMF performance, followed by PAHs (99; 19.8 %), with a smaller investigation (23; 4.6 %) dedicated to non-trivial indicator compounds for receptor modeling. The findings of pollution source contributions to soils in different environmental contexts worldwide are summarized in Fig. 2.

Based on the comprehensive review of published studies, the identified pollution sources were systematically classified into major categories, including: natural (geogenic) contributions related to local lithological features; coal combustion signatures; agricultural sources; traffic-related emissions from both fuel burning and tire and brake wear; industrial sources associated with metallurgical, petrochemical, cement, and other manufacturing processes, as well as mineral and fossil fuel extraction; biomass burning; and other site-specific or less frequently reported sources documented in individual studies.

4.1. Regional level

Although regional-scale studies represent a minority within soil SA research, they possess substantial scientific interest by providing a comprehensive assessment across extensive geographical areas. These studies systematically evaluate soil quality issues across diverse landscapes and geographic, economic, and industrial contexts (Fig. 3**a**). Globally, traffic emissions are the predominant contributor, accounting for 20.8 % of total pollution. This source is especially significant in urbanized regions such as Europe (51.7 %), where high traffic density remains the primary source of pollution even in compact cities (Qi et al., 2020; Sakizadeh and Zhang, 2021). Similar patterns are observed in densely populated residential areas (26.2 %), such as those in South China (Guo et al., 2021). Examples from the Caspian and Central Asian re-

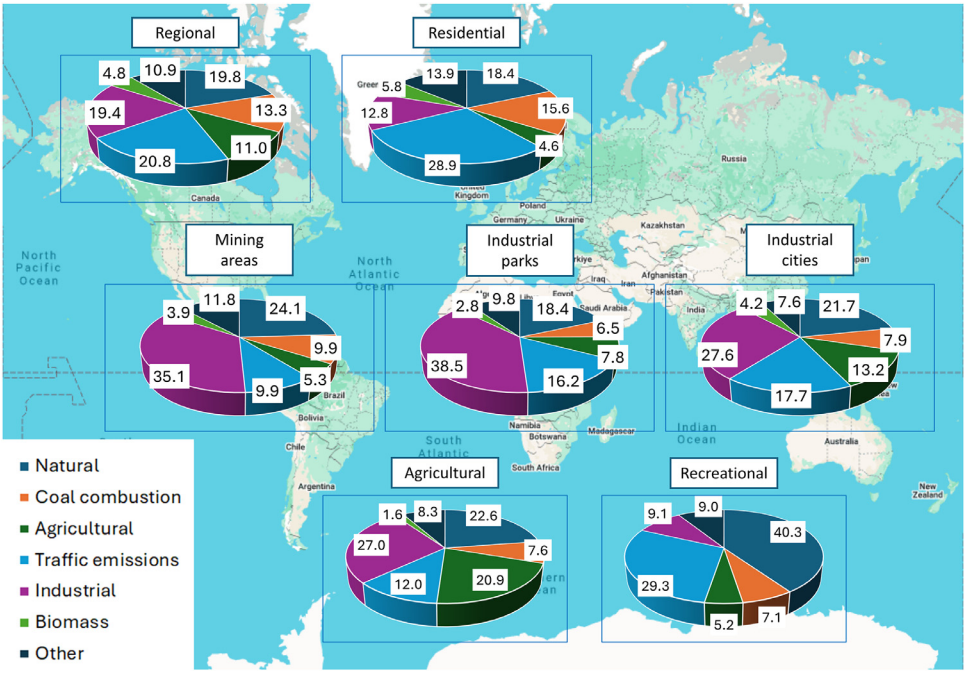
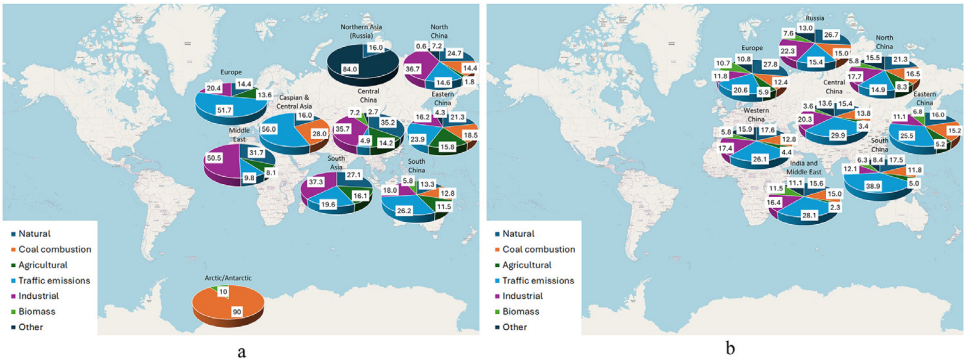


Fig. 2 – Pollution source contributions to soils in different environmental contexts worldwide.



a b

Fig. 3 – The contributions of pollution sources to soils (a) at the regional scale and (b) in residential areas.

gions indicate that gasoline and diesel combustion products (56 %) can be transported over moderate distances from both large metropolitan areas and local transportation hubs to mountainous regions (Li et al., 2020a). River transportation in riparian zones is a frequently overlooked but substantial pollution source, contributing 23.8 %–50.2 % of contamination. Notable examples include Chongming Island (Sun et al., 2020) and the Danjiangkou Reservoir (Sheng et al., 2023), where oil leakage and emissions from waterway traffic have markedly affected aquatic ecosystems and adjacent soils.

Industrial activities are the second most significant pollution source, accounting for an average of 19.4 % of soil contamination, with contributions ranging from 16.1 % to 50.2 % across the studied regions. North and Central China (Xu et al., 2022; Zhang et al., 2024b) are particularly affected by the extensive metal processing and manufacturing industries, which substantially elevate contamination levels via the migration and deposition of atmospheric particulate matter under wind, thereby triggering heavy metal contamination in semi-arid areas. Mining operations also demonstrate considerable environmental threats, especially in ecologically sensitive areas such as the Qinghai-Tibet Plateau (Du et al., 2023) and Altay Mountains (Luo et al., 2023), where metal and mineral extraction result in widespread soil and water pollution reflecting records in considerable growth in trace elements concentrations from 1970 to 1990 with the future the environmental protection policies implemented since 2010 and following decrease. Polymers-related pollution remains a major industrial contributor (20.6 %–31.0 %) in Shandong Province (Wang et al., 2020) and the Liaohe Delta (Li et al., 2016), where contaminated sludge and waste from chlor-alkali and petrochemical operations serve as point sources and have substantially degraded ecosystems within these regions. Industrial activities also dominate source profiles in the Middle East, accounting for 50.5 % in the largest industrial Province in Iran, which is renowned as the center of the steel industry and many major mining activities. A total of 40 active industrial towns caused alarmingly high levels of total soil pollution, posing significant public health risks (Rastegari Mehr et al., 2017).

Coal combustion, a major global energy source, accounts for 13.3 % of global pollution, lower than industrial emissions (19.4 %) or traffic emissions (20.8 %), yet it has disproportionate environmental impacts. While traffic pollution predominates in urbanized regions, coal-derived contamination is particularly severe in cold ecosystems. Arctic and Antarctic stations exemplify this pattern as they mainly rely on fossil fuel combustion for energy generation (Wei et al., 2024). Agricultural pollution (10.2 %–33.7 %) displays pronounced regional variations, with nearly double the global average observed in Southwestern China provinces, including Guizhou (Lu et al., 2021) and Yunnan (Guo et al., 2022), compared to European farmlands (< 15.0 %), revealing the junction to large rivers, the Yangtze River Basin and extensive cropland practices. This disparity reflects both intensive fertilizer application practices and geological factors, such as karst topography, which enhance contaminant mobility. Domestic waste impacts (10.2 %–24.15 %) are inversely related to development status. Remote locations, such as the

Altay Mountains, serve as examples of the accumulation of organic pollutants and heavy metals due to insufficient waste management, further compromising ecosystem health (Zhou et al., 2023).

While biomass combustion ranks as the least significant pollution source globally (4.8 %), its impact varies across regions, reflecting disparities in energy infrastructure. In developing rural areas like China's Yangtze River Delta (Li et al., 2020b) and Kyrgyzstan (Li et al., 2020a), reliance on traditional biomass fuels creates localized pollution hotspots. Wood combustion contributes 20 %–22 % to pollution and exacerbation of soil degradation in Yulin (Liu et al., 2019) and the Liaohe Delta (Lang et al., 2015), where it is a primary source due to its role in traditional heating and cooking. A non-trivial example of Northern Asia exhibits distinctive pollution patterns in Arctic soils, where legacy oil dumping, atmospheric deposition, and seabird colonies (Yushin et al., 2024) all contribute to unique regional contamination profiles.

4.2. Residential soils

A critical area of investigation involves examining studies on soil pollution in residential areas (Fig. 3**b**), encompassing both urban and rural environments. Urban zones, particularly megacities, constitute the predominant residential landscape, though rural areas are also subject to diverse forms of contamination. This evaluation examines the primary sources of pollution in residential areas while excluding heavily industrialized cities, which are evaluated separately (Section 4.3).

Residential soil pollution is predominantly caused by traffic emissions, accounting for 28.9 % globally, particularly in densely populated urban centers like Macau, China (Xie et al., 2021), and Lucknow, India, which has a notably high rate of 49 % (Shukla et al., 2022). Such examples show the significant distribution of the pollution levels, which suffer from high pollution levels due to long histories of urbanization with much larger populations and traffic densities. Non-exhaust emissions, including tire and brake wear, were identified as contributors to soil pollution via fine dust and air pollution in Southern China, where such sources account for over 38 % of contamination (Lu et al., 2023; Xu et al., 2023).

Some regions, such as Europe (Dreij et al., 2020; Pilková et al., 2024), show reduced vehicular impact, while natural sources dominate more prominently. Natural sources account for 18.4 % of residential pollution worldwide, resulting from geological processes like rock weathering and the breakdown of soil parent material. Hydrous systems may also play a role in enhancing the distribution of natural factors in regions with significant groundwater activity. Northern China showcases higher natural contributions at 21.3 %, with sites such as Harbin (Weng et al., 2024a) and Xilinhot (Qin et al., 2023) displaying notably high levels attributed to their geological composition, reflecting low human impact and the implementation of the control policy on soil in China. Similarly, Europe displays considerable contributions from soil parent material (27.8 %) and applies similar regulations for sustainable land use in residential areas (Pilková et al., 2024).

Although the combustion of coal represents a relatively small proportion globally (15.7 %), it continues to be a significant source of pollution in particular regions, notably Northern China, where it can account for up to 65 % in localized areas, reflecting high reliance on the solid fossil fuel as the energy source (Sun et al., 2023). It aligns with rural zones that are intensively impacted, with domestic coal used for heating accounting for up to 43.3 % of total contamination (Li et al., 2022). Additionally, in India, the demand for not only residential but also industrial energy generation exacerbates soil pollution caused by coal (Shukla et al., 2022). While industrial activities account for 12.9 % of residential soil pollution worldwide, some examples show that a single point source in an industrial park may affect the entire city. Industrial sources contributed 42 % of the overall pollution in Zhangqiu District, China (Wang et al., 2022b). Additional sources, categorized as "Other" collectively contribute 13.4 % to global soil pollution and include petrogenic sources (e.g., oil spills, petroleum combustion) (Wang et al., 2015b), coke oven emissions (Li et al., 2022), atmospheric deposition (Li et al., 2024b), waste incineration (Liu et al., 2018), and construction materials (Guo et al., 2024). While agricultural activities and biomass burning account for a smaller share globally (4.7 % and 5.9 %, respectively), they play a crucial role in specific rural regions. Intensive farming practices, including the use of pesticides and fertilizers, drive pollution in agricultural areas such as South China's Hutou Village (25 %) (Chen et al., 2022), while biomass combustion largely stem from wood burning for domestic heating and crop residue burning in agricultural zones near residential areas (Cao et al., 2017; Shukla et al., 2022).

4.3. Agricultural soils

Agricultural soils carry the cumulative burden of anthropogenic pollution while sustaining ecosystems and human populations. This section highlights these vital yet vulnerable systems, where industrial, vehicular, and geogenic contaminants accumulate, leading to serious implications for crop safety, soil biodiversity, and long-term fertility (Fig. 4**a**).

Industrial activities are the primary source of global soil pollution, causing about 27.0 % of total contamination, the majority of which originates from smelting and metal processing (Ding et al., 2024; Gao et al., 2024; Shi et al., 2024c; Xie et al., 2023), and large manufacturing clusters (Deng et al., 2020). For example, over 65 % of soil pollution in Tielong, China, was attributable to mining and manufacturing activities, in which old mining, non-ferrous metal, and cement plants generated large amounts of tailings that were transported from upstream to farmland (Xie et al., 2018). The same pattern was observed in Western China, where over 80 % of the ore mining site's waste was transferred via stream and sedimentation to agricultural fields (Zhao et al., 2024a). The long-term legacy of industrial activity is evident in agricultural soils near a gold mining and smelting facility in Nanjing, China, where mining-related sources constitute over 60 % of contamination (Zhou et al., 2024b). The large proportion of industrial activities (75.6 %) was observed in Eastern China's rice-producing regions (Ding et al., 2024), while the authors highlighted this fact as may have been caused by the local economic mode of development and industrial production. The work by Su et al. (2023a) raised the issue of pharmaceutical industry wastewater traffic, which exceeded 50.0 % of the identified pollutants in Wuhan's agricultural soils.

Regional patterns highlight industrial dominance in Central China, with a 36.5 % contribution, particularly in Hunan (Yu et al., 2021), Hubei (Li et al., 2023c), and Anhui (Yin et al., 2018), reflecting the region's intensive industrialization. Eastern China shows similar trends due to concentrated manufacturing (Huang et al., 2022; Zhou et al., 2022). The only North American study available reported a 39.0 % industrial contribution to agricultural soils around the Cerrito Blanco in Matehuala, Mexico, reflecting high loading from the dissolution of metallurgical wastes from an abandoned smelter upstream (Saha et al., 2022).

Traffic emissions consistently show regional contributions, peaking in North China. European studies confirm significant shares (Agyeman et al., 2022; Škrbić et al., 2021), matching those in Beijing (Li et al., 2023a) and Tianjin (Wang et al., 2021) at 19.9 %, which ranks among the highest recorded values worldwide. Despite efforts to implement policies, traffic pollution continues to impact even agricultural systems, stemming from gasoline and diesel combustion, tire wear, and road dust, contributing an average of 12.0 % globally.

Natural sources contribute 22.6 %, with extreme concentrations found in the distinct geological regions of Central China. Chongqing (Jiang et al., 2023a), Guizhou (Zhang et al., 2023b), and Tibet (Ning et al., 2023) experience a natural-source contribution of around 40 %, whereas Hezem exceeds 80 % (Zhao et al., 2023). Globally, coal combustion averages 7.6 %, with rare local exceptions. For instance, China's Wuwei remote mountainous region has a typical continental temperate climate with strong solar radiation, where the contribution of coal combustion exceeds 40 % (Tian et al., 2021).

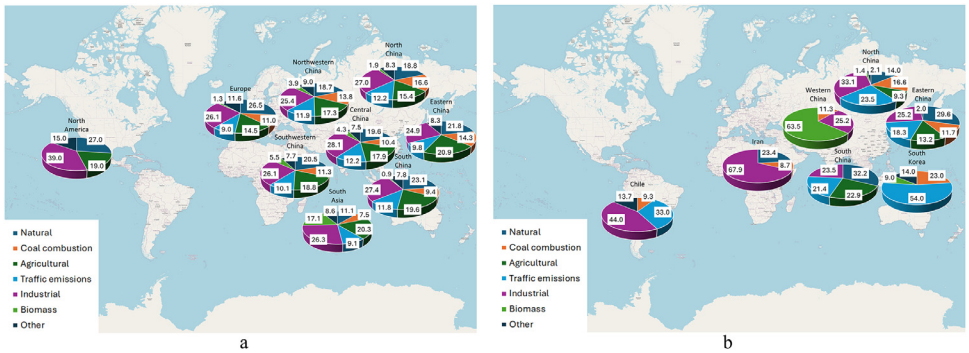


Fig. 4 – The contributions of pollution sources to soils (a) in farmlands, and (b) in industrial cities.

4.4. Industrial cities' soil

Assessing soil pollution sources in heavily industrialized urban areas reveals pronounced variability in emission contributions, with industrial activities being the dominant anthropogenic source at 27.6 %, followed by traffic emissions (17.7 %) and agricultural inputs (13.2 %). Regional analysis demonstrates distinct patterns (Fig. 4**b**), with Eastern China displaying a balanced mix of contributions: natural processes (29.6 %), industrial emissions (25.2 %), traffic (18.3 %), and agriculture (13.2 %). In contrast, Northern and Central China, which are dominated by large manufacturing, exhibit stronger industrial dominance (33.1 %) and considerable traffic contributions (23.5 %), collectively accounting for more than half of the regional soil pollution. For example, Anqing in Central China is a highly industrialized city with petrochemical plants, electroplating plants, steel plants, and many other chemical factories. Experiences a contribution of 64.1 % of industrial activities (Sun et al., 2022). Extreme cases of soil degradation are noted in Qingzhou City, Shandong Province, China, where iron ore mining combined with building material processing has led to 77.0 % of total soil contamination (Zhang et al., 2024a). Shanghai's industrial districts, known for metal production, electrical manufacturing, and integrated circuit fabrication, account for over 50.0 % of local soil pollution (Shen et al., 2024). A similar trend of industrial predominance is observed in global manufacturing centers, including Iran (Keshavarzi et al., 2019) and Chile (Maurelia et al., 2022), where industrial activities are major sources of pollution. The location of agricultural lands adjacent to industrial clusters raises significant concerns about the safety of the food supply chain. However, agricultural activities themselves represent measurable pollution sources, as evidenced by Ningbo City (26.0 %) (Shiyi et al., 2023) and the vicinity of Tangshan's industrial harbor (22.0 %) (Jiang et al., 2023b).

Several deviations from global trends emerge in certain urban contexts. Ulsan, South Korea, shows exceptional dependence on vehicular sources, accounting for 50.0 % of soil contamination factors (Kwon and Choi, 2014), whereas China's Chengdu Economic Region exhibits an unusual predominance of biomass-burning tracers at 63.0 % (Zheng et al., 2018). Such localized patterns emphasize the importance of pollution mitigation strategies tailored to regions and their unique industrial and infrastructural characteristics.

4.5. Industrial parks soils

Industrial zones and parks are areas of special interest for soil investigation, as anthropogenic activities intersect with local ecosystems despite the absence of residential populations (Fig. 5**a**). Industrial emissions dominate soil contamination globally, with smelting and petrochemical activities as major contributors. SA studies show industrial sources account for 38.5 % of global soil pollution, followed by natural processes (18.4 %), traffic emissions (16.2 %), and agriculture (7.8 %), while biomass burning and localized emissions play secondary roles. Many researchers focus on legacy contamination from abandoned industrial sites, revealing persistent impacts on soil health (Jin et al., 2023; Liu et al., 2021b; Zhang et al., 2023c). In Serbia, former steel production plants and lead-acid battery recycling facilities demonstrate extreme industrial contributions (61.8 %), primarily from historical particulate emissions, with additional degradation from traffic (18.5 %) and mixed anthropogenic sources (16.6 %) (Miletić et al., 2024). Advanced tracer techniques now enable precise source apportionment at petrochemical sites: VOCs differentiate petroleum, solvent, and coal sources using PAH and BTEX profiles (Ma et al., 2023c), while chlorinated/brominated hydrocarbons identify the impacts of synthetic rubber and resin manufacturing (Zhao et al., 2024b).

While establishing farmlands was questionable even in the industrial cities, agricultural activities contribute measurably to pollution even in industrial peripheries (Su et al., 2023b; Tarighat et al., 2024; Wang et al., 2022c). In Ningdong (Zhou et al., 2024c) and Changxing (Xue et al., 2014), agricultural runoff and pesticide degradation contribute to 22.0 % and 21.7 % of soil contamination, respectively. The "Other" source category often indicates industrial waste field impacts, highlighting extensive contamination vectors in remote areas (Jin et al., 2023; Li et al., 2023b; Liu et al., 2021b).

4.6. Mining areas' soils

Mining regions (Fig. 5**b**) are critical hotspots of environmental contamination, with industrial activities contributing ~35.1 % to global pollution profiles. The Taoyuan coal mine in Anhui Province illustrates a trend in which mining operations account for 48.4 % of local soil contamination, mainly due to heavy metal deposition (Xu et al., 2021). Similarly, Huangshi in Southeastern Hubei displays combined industrial (34.7 %) and mining-related (28.2 %) pollution, reflecting its polymetallic mining economy (Li et al., 2023c). Majdanpek (Serbia) shows 42.3 % industrial contamination from copper mining, exacerbated by heavy transport emissions (35.3 %) (Vesković and Onjia, 2024), while Ahvaz (Iran) reveals 51.5 % oil-derived pollution, predominantly from petroleum hydrocarbons (Kazemi et al., 2024). Natural sources account for a substantial secondary influence (~24.1 %) of global contamination. Xilinguole League (Inner Mongolia) exemplifies this contribution, with 37.2 % of pollution originating from soil parent materials and weathering (Cheng et al., 2020). Comparable patterns emerge in Wanshan District, Guizhou Province (28.2 % natural sources), where mercury smelting and coal combustion amplify baseline geogenic pollution (Wu et al., 2020b). The Yamal-Nenets region of Russia demonstrates the complex interaction between natural processes and industrial contamination, where permafrost dynamics mediate pollutant distribution (Ji et al., 2019). These cases explain the necessity of considering geological and climatic factors in pollution assessments, especially in mineral-rich terrains.

Diverse regions exhibit unique pollution profiles that reflect local industrial, agricultural, and climatic conditions. The Brahmaputra Valley (India) shows biomass-burning dominance (47.0 % of PAHs) from residential fuel use (Deka et al., 2016), while the North Karanpura Basin (India) demonstrates seasonal shifts between coal combustion and mixed sources (Chakraborty et al., 2024). Ulaanbaatar, Mongolia's urban cen-

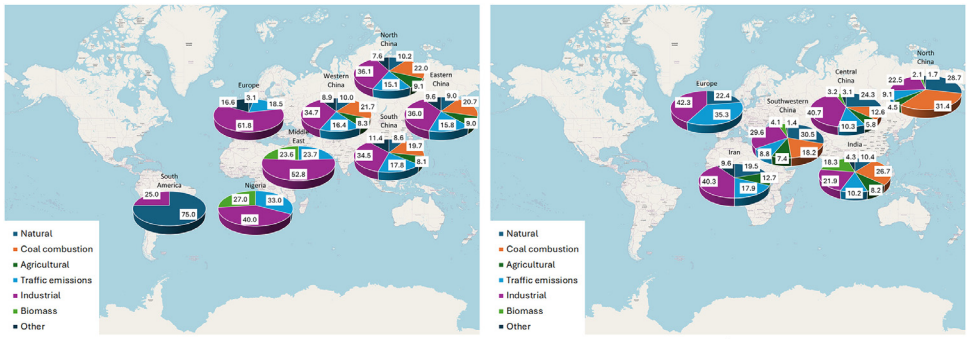


Fig. 5 – Pollution source contributions to soils (a) in industrial zones, and (b) in mining areas.

ter, struggles with coal-driven pollution (45.3 %), exacerbated by mining activities (Yoon et al., 2023), whereas Shazand (Iran) reflects a balanced contribution from industrial (29.2 %) and agricultural sources (25.4 %) (Tarighat et al., 2024). These regional variations highlight the imperative for context-specific remediation strategies that address dominant local pollution drivers.

4.7. Soils at recreational areas, dumpsites, and non-trivials

Soils classified as recreational are found in urban parks, playgrounds, and tourist areas, including remote locations. These soils experience distinct contamination profiles. European and Central/Eastern Chinese studies indicate that natural factors dominate recreational soil quality (40.3 % average contribution), followed by traffic-related pollution (29.3 % average). In Bratislava, Slovakia, playground soils show 28.4 % contamination from mixed traffic sources, supplemented by industrial activities and atmospheric deposition (Pilková et al., 2024). Similarly, in Zakopane, Poland's tourist area, soils contain elevated levels of PAHs and heavy metals caused by vehicular emissions (Ciarkowska et al., 2019). Contrasting patterns emerge in Guiyang (China), where biomass burning dominates (31.9 %) (Liang et al., 2023), and in Kruševac (Serbia), where a combination of coal/firewood and traffic emissions is the primary source (Tanić et al., 2023). Several studies report high fertilizer loading used to enhance the decorative effect of vegetation in domestic recreational areas, such as the assessment in urban parks in Wuhan, Central China (Li et al., 2023d).

Only five published studies examine soil pollution near dumpsites and landfills, all of which confirm the impacts of electronic waste. Key cases include Nigeria (Owoade et al., 2020), multiple sites in India (Chakraborty et al., 2018), the rebuilt e-waste site in Hangzhou, China (Wang et al., 2024), and legacy landfills in Eastern Europe (Ilić et al., 2024; Kudryavtseva et al., 2021). These complex environments require innovative source apportionment methods, as demonstrated by Chinese studies using bisphenols (BPA, BPS, BPF) as plastic industry tracers (Weng et al., 2024b) and Vietnamese/Taiwanese research employing dioxin fingerprinting to identify sources of open burning and atmospheric deposition (Kudryavtseva et al., 2022; Ngo et al., 2018). Studies indicate that dismantling electronic waste substantially affects nearby croplands through heavy metal contamination (Dong et al., 2014; Fang et al., 2023; Liang et al., 2022). Recent emerging research uncovers further industrial consequences, including the transport of PFAS from fluorochemical manufacturing (Liu et al., 2023), the accumulation of microplastics in Qinghai-Tibetan soils (Liu et al., 2024b), and contamination linked to the production of consumer goods such as food packaging, textiles, and emulsifiers (Cheng et al., 2023).

5. Policy recommendations and conclusions

Unregulated soil use increases soil pollution, resulting in severe consequences, including reduced agricultural productivity, food insecurity, soil degradation, and economic instability. Policy recommendations are usually based on risk screening and intervention thresholds for the chemicals monitored and largely serve as post-contamination tools for assessing land status and guiding land-use decisions (MEE, 2018). In contrast, source apportionment studies provide proactive, process-oriented insights by identifying pollution sources, quantifying their contributions, and revealing contamination pathways before exceedances occur. A comprehensive analysis of reviewed studies on SA associated with PAHs and heavy metals across diverse environments may yield several recommendations for developing advanced measures to mitigate soil pollution.

Mitigating soil pollution from industrial and mining operations requires stringent regulation of emissions from mining equipment, particularly in permafrost regions, where mining is a dominant source of PAHs. Transfer of industrial emissions via atmospheric depositions from coal combustion, smelting, and vehicle exhaust should be targeted for intervention as major contributors to subsequent PAHs and heavy metal soil contamination (Anaman et al., 2024; Yang et al., 2024; Huang et al., 2023). Adopting cleaner production technologies in the mining and industrial sectors should be prioritized, despite the economic burdens it imposes on local governments. Additionally, authorities should prevent untreated smelter wastewater and slag pile runoff from entering drainage systems and implement composite remediation methods (physical, chemical, and biological) to mitigate heavy metal impacts on agricultural environments (Anaman et al., 2024; Liu et al., 2025). Specific focus should be placed on regulating the non-ferrous mining and smelting industries to reduce cadmium (Cd) emissions and remediate arsenic (As)-polluted farmlands using phytoextraction technologies (Zhou et al., 2022).

Additionally, sustainable agricultural practices should be promoted to reduce heavy metal accumulation from atmospheric deposition and fertilization, thereby decreasing dependence on chemical fertilizers and pesticides (Shi et al., 2024b; Xu et al., 2024; Yang et al., 2024). However, a significant threat arises from the use of calcium superphosphate fertilizers, which often contain impurities such as Cd, Co, Cu, and Zn that can lead to dangerous accumulation (Gimeno-García et al., 1996). The necessary nutrients can be supplied through alternative fertilizers. Appropriate fertilizer application aims to enhance soil health by increasing the sequestration of soil organic carbon and total nitrogen, though outcomes may vary by fertilizer type. A meta-analysis by Bohoussou et al. (2023) showed that the integrated application of organic and mineral fertilizers led to a threefold increase in total soil nitrogen content compared to mineral fertilizers alone, significantly reducing anthropogenic pressure on soils.

Urban and vehicular emissions need to be controlled through stricter regulatory frameworks and the adoption of catalyst converters to reduce PAH emissions (Xu et al., 2024; Li et al., 2023d). Zoning policies should be enforced to establish a distance between residential areas and high-pollution industries, especially in agricultural areas, and minimize exposure risks, and prevent pollution spread (Li et al., 2024c; Qin et al., 2023). Integrated environmental management strategies that combine pollution control, monitoring, and public health interventions are essen-

tial for sustainable development (Chen et al., 2024; Liang et al., 2022). National plans for eco-economic development should focus on reducing pollution and ensuring sustainable land use.

Urban farmers frequently cultivate diverse crops in soils that may contain residual pollutants from manufacturing and mining activities. Multiple studies consistently reveal high levels of contaminants in urban agricultural soils, revealing a critical environmental and public health concern. This finding highlights the urgent need for advanced technical support in soil assessment and remediation. While efforts in this area are still in their early stages, receptor modeling has emerged as a valuable tool to address these challenges.

In the PMF model, the clarity of data uncertainty and the processing of data may inevitably influence the robustness and interpretation of results in PMF analysis (Brown et al., 2015). Incorporating uncertainty into anthropogenic background values can yield a wide range of error estimates for individual sources. The contaminants usually span several orders of magnitude, so it is challenging to compare errors across different reasoned solutions or across different contaminants within one solution when using different concentration units. Integrating multiple SA models, such as GPCA/APCS, PMF, and UNMIX, can improve the accuracy of pollution source identification and management. Spatial analysis should be employed to identify pollution hotspots and prioritize remediation efforts in high-risk areas. Temporal variations of pollutant levels should also be monitored to assess the effectiveness of implemented policies and regulations.

Addressing human health risks is critical, particularly for vulnerable populations such as children (Wu et al., 2024; Zhou et al., 2024a; Ma et al., 2023c). Carcinogenic risks from PAHs and heavy metals necessitate targeted interventions and public health awareness campaigns based on receptor modeling outcomes (Zhou et al., 2024a; Liang et al., 2023; Chakraborty et al., 2024). These interventions should focus on mitigating exposure pathways, such as soil ingestion and dermal contact. Remediation strategies should prioritize areas with elevated heavy metal levels, such as cadmium and mercury, which pose significant ecological and human health risks.

This study provides insights into pollution source attribution, offering a foundation for targeted mitigation strategies. However, several limitations warrant acknowledgement. The reviewed literature includes fragmented data, requiring further consolidation of similar sources for clearer regional summaries. Additionally, some studies' lack of precise percentage distributions of pollution sources led to the exclusion of meta-analytical averaging results. Despite these limitations, the findings provide a robust overview of global soil quality studies, emphasizing the need for continued research to address knowledge gaps and refine pollution management practices.

CRediT authorship contribution statement

Ivan Radelyuk: Writing – original draft, Visualization, Project administration, Investigation, Formal analysis, Data curation, Conceptualization. **Aset Muratuly:** Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Dmitriy Snopkov:** Investigation, Formal analysis, Data curation. **Nassiba Baimatova:** Writing – review & editing, Visualization, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A Supplementary data

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.jes.2026.01.077.

References

Adesina, K.E., Burgos, C.J., Grier, T.R., Sayam, A.S., Specht, A.J., 2025. Ways to measure metals: from ICP-MS to XRF. Curr. Environ. Health Rep. 12 (1), 7–16.

Agyeman, P.C., Ahado, S.K., John, K., Kebonye, N.M., Vašát, R., Borůvka, L., et al., 2021a. Health risk assessment and the application of CF-PMF: a pollution assessment–based receptor model in an urban soil. J. Soil. Sediment. 21 (9), 3117–3136.

Agyeman, P.C., Ahado, S.K., Kingsley, J., Kebonye, N.M., Biney, J.K.M., Borůvka, L., et al., 2021b. Source apportionment, contamination levels, and spatial prediction of potentially toxic elements in selected soils of the Czech Republic. Environ. Geochem. Health 43 (1), 601–620.

Agyeman, P.C., Kingsley, J., Kebonye, N.M., Ofori, S., Borůvka, L., Vašát, R., et al., 2022. Ecological risk source distribution, uncertainty analysis, and application of geographically weighted regression cokriging for prediction of potentially toxic elements in agricultural soils. Process Saf. Environ. 164, 729–746.

Agyeman, P.C., Kebonye, N.M., John, K., Haghnazar, H., Borůvka, L., Vašát, R., 2023. Compositional mapping, uncertainty assessment, and source apportionment via pollution assessment-based receptor models in urban and peri-urban agricultural soils. J. Soil. Sediment. 23 (3), 1451–1472.

Alhaj Hamoud, Y., Shaghaleh, H., Zia-ur-Rehman, M., Rizwan, M., Umair, M., Usman, M., et al., 2024. Cadmium and lead accumulation in important food crops due to wastewater irrigation: pollution index and health risks assessment. Heliyon 10 (3), e24712.

Anaman, R., Peng, C., Jiang, Z., Liu, X., Zhou, Z., Guo, Z., et al., 2022. Identifying sources and transport routes of heavy metals in soil with different land uses around a smelting site by GIS based PCA and PMF. Sci. Total Environ. 823, 153759.

Anaman, R., Peng, C., Jiang, Z., Amanze, C., Fosua, B.A., 2024. Distinguishing the contributions of different smelting emissions to the spatial risk footprints of toxic elements in soil using PMF, Bayesian isotope mixing models, and distance-based regression. Sci. Total Environ. 933, 173153.

Archbold, G., Parra, C., Carrillo, H., Mouazen, A.M., 2023. Towards the implementation of ISFET sensors for in-situ and real-time chemical analyses in soils: a practical review. Comput. Electron. Agric. 209, 107828.

Arroyo Mora, L.E., Trejos, T., Hosick, T., Machemer, S., Almirall, J.R., Gardinali, P.R., 2010. Analysis of soils and sediments by laser ablation inductively coupled plasma mass spectrometry (LA-ICP-MS): an innovative tool for environmental forensics. Environ. Forensics 11 (4), 315–327.

Astudillo-Pascual, M., Tudor, R., Domínguez, I., Aguilera, P.A., Frenich, A.G., 2023. Determination of PAHs, PAH-derivatives and other concerning substances in Posidonia oceanica seagrass and marine sediments by high resolution mass spectrometry. J. Mar. Sci. Eng. 11 (2), 369.

Bai, Y., Zhang, Y., Liu, X., Wang, Y., 2023. The spatial distribution and source apportionment of heavy metals in soil of Shizuishan, China. Environ. Earth Sci. 82 (21), 494.

Beriro, D.J., Vane, C.H., Cave, M.R., Nathanail, C.P., 2014. Effects of drying and comminution type on the quantification of polycyclic aromatic hydrocarbons (PAH) in a homogenised gasworks soil and the implications for human health risk assessment. Chemosphere 111, 396–404.

Bertoz, V., Purcaro, G., Conchione, C., Moret, S., 2021. A review on the occurrence and analytical determination of PAHs in olive oils. Foods 10 (2), 324.

Bilyera, N., Turner, B.L., Zhang, X., Zang, H., Dorodnikov, M., Kuzyakov, Y., 2025. Soil health under global change and human impact. Land Degrad. Dev. 36 (3), 683–688.

Boden, A.R., Reiner, E.J., 2004. Development of an isotope-dilution gas chromatographic-mass spectrometric method for the analysis of polycyclic aromatic compounds in environmental matrices. Polycycl. Aromat. Comp. 24 (4–5), 309–323.

Bohoussou, N.D.Y., Han, S.W., Li, H.R., Kouadio, Y.D., Ejaz, I., Virk, A.L., et al., 2023. Effects of fertilizer application strategies on soil organic carbon and total nitrogen storage under different agronomic practices: a meta-analysis. Land Degrad. Dev. 34 (18), 5889–5904.

Boone, R.D., Grigal, D.F., Sollins, P., Ahrens, R.J., Armstrong, D.E., 1999. Soil sampling, preparation, archiving, and quality control. In: Robertson, G.P., Coleman, D.C., Bledsoe, C.S., et al. (Eds.), Standard Soil Methods for Long-term Ecological Research. Oxford University Press, New York, pp. 3–28.

Brown, S.G., Eberly, S., Paatero, P., Norris, G.A., 2015. Methods for estimating uncertainty in PMF solutions: examples with ambient air and water quality data and guidance on reporting PMF results. Sci. Total Environ. 518, 626–635.

Budzinski, H., Jones, I., Bellocq, J., Pierard, C., Garrigues, P.H., 1997. Evaluation of sediment contamination by polycyclic aromatic hydrocarbons in the Gironde estuary. Mar. Chem. 58 (1), 85–97.

Butcher, D.J., 2005. Atomic absorption spectrometry: interferences and background correction. In: Worsfold, P., Townshend, A., Poole, C. (Eds.), Encyclopedia of Analytical Science. Elsevier, Amsterdam, pp. 157–163.

Campbell, C.A., Biederbeck, V.O., Wen, G., Zentner, R.P., Schoenau, J., Hahn, D., 1999. Seasonal trends in selected soil biochemical attributes: effects of crop rotation in the semiarid prairie. Can. J. Soil Sci. 79 (1), 73–84.
Cao, H., Chao, S., Qiao, L., Jiang, Y., Zeng, X., Fan, X., 2017. Urbanization-related changes in soil PAHs and potential health risks of emission sources in a township in Southern Jiangsu, China. Sci. Total Environ. 575, 692–700.
Chakraborty, P., Selvaraj, S., Nakamura, M., Prithiviraj, B., Cincinelli, A., Bang, J.J., 2018. PCBs and PCDD/fs in soil from informal e-waste recycling sites and open dumpsites in India: levels, congener profiles and health risk assessment. Sci. Total Environ. 621, 930–938.
Chakraborty, P., Singh, S., Hazra, B., Majumdar, A.S., Kumari, J., 2024. Spatial distribution, source apportionment, and health risks assessment of trace elements in pre- and post-monsoon soils in the coal-mining region of North Karanpura basin, India. Sci. Total Environ. 955, 177173.
Chakraborty, T.K., Islam, M.S., Ghosh, G.C., Ghosh, P., Zaman, S., Hossain, M.R., et al., 2023. Receptor model-based sources and risks appraisal of potentially toxic elements in the urban soils of Bangladesh. Toxicol. Rep. 10, 308–319.
Chen, R., Zhang, Q., Chen, H., Yue, W., Teng, Y., 2021. Source apportionment of heavy metals in sediments and soils in an interconnected river-soil system based on a composite fingerprint screening approach. J. Hazard. Mater. 411, 125125.
Chen, Z., Shi, Z., Ni, S., Cheng, L., 2022. Characteristics of soil pollution and element migration associated with the use of coal in Hutou Village, Yunnan Province, China. Ecol. Indic. 139, 108976.
Chen, T., Zhang, R., Wang, H., Dong, X., Zheng, S., Chang, Q., 2024. Source governance-oriented zoning for heavy metal pollution in farmland soil: a case study of an industrial park in mid-western Shaanxi Province, China. Water Air Soil Pollut. 235 (6), 330.
Cheng, W., Lei, S., Bian, Z., Zhao, Y., Li, Y., Gan, Y., 2020. Geographic distribution of heavy metals and identification of their sources in soils near large, open-pit coal mines using positive matrix factorization. J. Hazard. Mater. 387, 121666.
Cheng, Y., An, Q., Qi, H., Li, R., Liu, W., Gu, B., et al., 2023. Temporal trends of legacy and emerging PFASs from 2011 to 2021 in agricultural soils of Eastern China: impacts of the Stockholm Convention. Environ. Sci. Technol. 57 (25), 9277–9286.
Chiaia-Hernandez, A.C., Keller, A., Wächter, D., Steinlin, C., Camenzuli, L., Hollender, J., et al., 2017. Long-term persistence of pesticides and TPs in archived agricultural soil samples and comparison with pesticide application. Environ. Sci. Technol. 51 (18), 10642–10651.
Ciarkowska, K., Gambus, F., Antonkiewicz, J., Koliopoulos, T., 2019. Polycyclic aromatic hydrocarbon and heavy metal contents in the urban soils in southern Poland. Chemosphere 229, 214–226.
Comero, S., Capitani, L., Gawlik, B.M., 2009. Positive matrix factorisation (PMF). An Introduction to the Chemometric Evaluation of Environmental Monitoring Data Using PMF. European Commission Joint Research Centre, Office for Official Publications of the European Communities, Luxembourg.
Croffie, M.E., Williams, P.N., Fenton, O., Fenelon, A., Metzger, K., Daly, K., 2020. Optimising sample preparation and calibrations in EDXRF for quantitative soil analysis. Agronomy 10 (9), 1309.
Daripa, A., Chattaraj, S., Malav, L., Ray, P., Sharma, R., Mohekar, D.S., et al., 2023. Risk assessment of agricultural soils surrounding an iron ore mine: a field study from Western Ghat of Goa, India. Soil Sediment Contam. 32 (5), 570–590.
Deka, J., Sarma, K.P., Hoque, R.R., 2016. Source contributions of polycyclic aromatic hydrocarbons in soils around oilfield in the Brahmaputra Valley. Ecotox. Environ. Saf. 133, 281–289.
Deng, M., Zhu, Y., Shao, K., Zhang, Q., Ye, G., Shen, J., 2020. Metals source apportionment in farmland soil and the prediction of metal transfer in the soil-rice-human chain. J. Environ. Manage. 260, 110092.
Ding, H., Liu, J., Liu, Q., Guo, L., Hang, Q., Zhang, Y., et al., 2024. Risk assessment and source tracing of heavy metals in major rice-producing provinces of Yangtze River Basin. J. Hazard. Mater. 480, 136206.
Ding, L.C., Ke, F., Wang, D.K., Dann, T., Austin, C.C., 2009. A new direct thermal desorption-GC/MS method: organic speciation of ambient particulate matter collected in Golden, BC. Atmos. Environ. 43 (32), 4894–4902.
Dong, Y., Li, L., Bie, P., Jia, S., Wang, Q., Huang, Z., et al., 2014. Polybrominated diphenyl ethers in farmland soils: source characterization, deposition contribution and apportionment. Sci. Total Environ. 466, 524–532.
Douvris, C., Vaughan, T., Bussan, D., Bartzas, G., Thomas, R., 2023. How ICP-OES changed the face of trace element analysis: review of the global application landscape. Sci. Total Environ. 905, 167242.
Dowell, S.M., Humphrey, O.S., Blake, W.H., Osano, O., Chenery, S., Watts, M.J., 2023. Ultra-trace analysis of fallout plutonium isotopes in soil: emerging trends and future perspectives. Chem. Afr. 6 (5), 2429–2444.
Drábová, L., Dvořáková, D., Urbancová, K., Gramblička, T., Hajšlová, J., Pulkrabová, J., 2022. Critical assessment of clean-up techniques employed in simultaneous analysis of persistent organic pollutants and polycyclic aromatic hydrocarbons in fatty samples. Toxics 10 (1), 12.
Dreij, K., Lundin, L., Le Bihanic, F., Lundstedt, S., 2020. Polycyclic aromatic compounds in urban soils of Stockholm City: occurrence, sources and human health risk assessment. Environ. Res. 182, 108989.
Du, H., Wang, J., Wang, Y., Yao, Y., Liu, X., Zhou, Y., 2023. Contamination characteristics, source analysis, and spatial prediction of soil heavy metal concentrations on the Qinghai-Tibet Plateau. J. Soil. Sediment. 23 (5), 2202–2215.
Duckworth, O.W., Polizzotto, M.L., Thompson, A., 2022. Bringing soil chemistry to environmental health science to tackle soil contaminants. Front. Environ. Sci. 10, 981607.
Even, R.J., Machmuller, M.B., Lavallee, J.M., Zelikova, T.J., Cotrufo, M.F., 2025. Large errors in soil carbon measurements attributed to inconsistent sample processing. Soil 11 (1), 17–34.
Fang, J., He, Y., Huang, N.T., Zhi, Y.Y., Fu, W.J., 2023. Integrated analysis on source-exposure risk of heavy metals in farmland soil based on PMF Model: a case study in the e-waste dismantling area in Zhejiang Province. Environ. Sci. 44 (7), 4027–4038.
Fedeli, R., Di Lella, L.A., Loppi, S., 2024. Suitability of XRF for routine analysis of multi-elemental composition: a multi-standard verification. Methods Protoc. 7 (4), 53.
Fei, X., Lou, Z., Xiao, R., Ren, Z., Lv, X., 2020. Contamination assessment and source apportionment of heavy metals in agricultural soil through the synthesis of PMF and GeogDetector models. Sci. Total Environ. 747, 141293.
Fei, X., Xiao, R., Christakos, G., Langousis, A., Ren, Z., Tian, Y., et al., 2019. Comprehensive assessment and source apportionment of heavy metals in Shanghai agricultural soils with different fertility levels. Ecol. Indic. 106, 105508.
Fernández García, B., Lobo, L., Pereiro, R., 2019. Atomic absorpton spectrometry | fundamentals, instrumentation and capabilities. In: Worsfold, P. (Ed.), Encyclopedia of Analytical Science. Academic Press, Oxford, pp. 137–143.
Ferreira, S.L.C., Bezerra, M.A., Santos, A.S., dos Santos, W.N., Novaes, C.G., de Oliveira, O.M., et al., 2018. Atomic absorption spectrometry: a multi-element technique. Trends Anal. Chem. 100, 1–6.
Ferreira, S.L.C., Teixeira, L.S., Ferreira, W.Q., Dantas, S.V., Lima, A.S., Korn, M.G., et al., 2024. Determination and assessment of contamination of toxic chemical elements in soils – review. Trends Anal. Chem. 181, 118055.
Fisher, S.C., Reilly, T.J., Jones, D.K., Benzel, W., Griffin, D.W., Loftin, K.A., et al., 2015. Standard Operating Procedures for Collection of Soil and Sediment Samples for the Sediment-bound Contaminant Resiliency and Response (SCoRR) Strategy Pilot Study 2015-1188B, Reston, VA.
Gao, Z., Sheng, H., Jiang, B., Zhang, Y., Dong, H., Niu, Y., et al., 2024. High-density sampling of soil heavy metals in the upper Bailang River basin: contamination characteristics, sources, and source-oriented health risk assessment. Environ. Geochem. Health 46 (9), 346.
Gimeno-García, E., Andreu, V., Boluda, R., 1996. Heavy metals incidence in the application of inorganic fertilizers and pesticides to rice farming soils. Environ. Pollut. 92 (1), 19–25.
Guo, G., Chen, S., Li, K., Lei, M., Ju, T., Tian, L., 2024. Determining the priority control sources of heavy metals in the roadside soils in a typical industrial city of North China. J. Hazard. Mater. 480, 136347.
Guo, G., Li, K., Zhang, D., Lei, M., 2022. Quantitative source apportionment and associated driving factor identification for soil potential toxicity elements via combining receptor models, SOM, and geo-detector method. Sci. Total Environ. 830, 154721.
Guo, G., Wang, Y., Zhang, D., Lei, M., 2021. Source-specific ecological and health risks of potentially toxic elements in agricultural soils in Southern Yunnan Province and associated uncertainty analysis. J. Hazard. Mater. 417, 126144.
Guzmán, G., Quinton, J.N., Nearing, M.A., Mabit, L., Gómez, J.A., 2013. Sediment tracers in water erosion studies: current approaches and challenges. J. Soils Sediments 13 (4), 816–833.
Harvey, R.G., 1991. Polycyclic Aromatic Hydrocarbons: Chemistry And Carcinogenicity. Cambridge University Press, Cambridge.
Hojdová, M., Rohovec, J., Chrastný, V., Penížek, V., Navrátil, T., 2015. The influence of sample drying procedures on mercury concentrations analyzed in soils. Bull. Environ. Contam. Toxicol. 94, 570–576.
Hopke, P.K., 2016. Review of receptor modeling methods for source apportionment. J. Air Waste. Manage. 66 (3), 237–259.
Hopke, P.K., Cohen, D.D., 2011. Application of receptor modeling methods. Atmos. Pollut. Res. 2 (2), 122–125.
Hošek, M., Pavlíková, P., Šoltýs, M., Tůmová, Š., Matys Grygar, T., 2024. Distinguishing geogenic load and anthropogenic contribution to soil contamination in mineralised mountain landscape of ore mountains (Czech Republic) using cumulative distribution functions. Land 13 (2), 218.
Hu, J., Xie, C., Xu, L., Qi, X., Zhu, S., Zhu, H., et al., 2021. Direct analysis of soil composition for source apportionment by laser ablation single-particle aerosol mass spectrometry. Environ. Sci. Technol. 55 (14), 9721–9729.
Huang, C.C., Cai, L.M., Xu, Y.H., Wen, H.H., Jie, L., Hu, G.C., et al., 2022. Quantitative analysis of ecological risk and human health risk of potentially toxic elements in farmland soil using the PMF model. Land Degrad. Dev. 33 (11), 1954–1967.
Huang, Y., Wei, J., Song, J., Chen, M., Luo, Y., 2013. Determination of low levels of polycyclic aromatic hydrocarbons in soil by high performance liquid chromatography with tandem fluorescence and diode-array detectors. Chemosphere 92 (8), 1010–1016.
Huang, Y., Deng, M., Wu, S., Japenga, J., Li, T., Yang, X., et al., 2018. A modified receptor model for source apportionment of heavy metal pollution in soil. J. Hazard. Mater. 354, 161–169.
Huang, W., Wang, S., Wang, L., Song, Y., Zhu, Y., Yang, H., et al., 2023. Source apportionment of soil heavy metal (loid) s in farmland using diverse models: a comparative assessment in the yellow river delta. J. Mar. Sci. Eng. 11 (5), 1069.
Humbert, K., Debret, M., Morin, C., Cosme, J., Portet-Koltalo, F., 2022. Direct thermal desorption-gas chromatography-tandem mass spectrometry versus microwave assisted extraction and GC-MS for the simultaneous analysis of polyaromatic hydrocarbons (PAHs, PCBs) from sediments. Talanta 250, 123735.
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. Int. J. Urban Sci. 20 (3), 334–360.
IEPA, 2013. Guidance On the Management of Contaminated Land and Groundwater at EPA Licensed Sites County Wexford, Ireland.
Ilić, P., Ilić, S., Rashid, A., Mushtaq, Z., Mrazovac Kurilić, S., Stojanović Bjelić, L., et al., 2024. Exposure levels, health risks, spatially distribution, multivariate statistics and positive matrix factorization model of heavy metals from wild solid waste dumpsites. Water Air Soil Pollut. 235 (10), 648.
ITRC (Interstate Technology & Regulatory Council), 2026. PFAS Technical and Regulatory Guidance Document and Fact Sheets, 11 Sampling and Analysis. Interstate

Technology & Regulatory Council, PFAS Team, Washington, D.C. Available at:. https://pfas-1.itrcweb.org/11-sampling-and-analytical-methods/ Accessed January 22, 2026.
Ji, X., Abakumov, E., Polyako, V., Xie, X., Dongyang, W., 2019. The ecological impact of mineral exploitation in the Russian Arctic: a field-scale study of polycyclic aromatic hydrocarbons (PAHs) in permafrost-affected soils and lichens of the Yamal-Nenets autonomous region. Environ. Pollut. 255, 113239.
Jianfei, C., Chunfang, L., Lixia, Z., Quanyuan, W., Jianshu, L., 2020. Source apportionment of potentially toxic elements in soils using APCS/MLR, PMF and geostatistics in a typical industrial and mining city in Eastern China. PLoS One 15 (9), e0238513.
Jiang, Y.L., Yu, J., Wang, R., Wang, J.B., Li, Y., Yu, F., et al., 2023a. Source analysis and pollution assessment of soil heavy metals in typical geological high background area in Southeastern Chongqing. Environ. Sci. 44 (7), 4017–4026.
Jiang, W., Chu, H., Liu, Y., Chen, B., Feng, Y., Lyu, J., et al., 2023b. Distribution of heavy metals in coastal sediments under the influence of multiple factors: a case study from the south coast of an industrialized harbor city (Tangshan, China). Sci. Total Environ. 889, 164208.
Jin, H., Zhihong, P., Jiaqing, Z., Chuxuan, L., Lu, T., Jun, J., et al., 2023. Source apportionment and quantitative risk assessment of heavy metals at an abandoned zinc smelting site based on GIS and PMF models. J. Environ. Manage. 336, 117565.
Kang, M.J., Kwon, Y.K., Yu, S., Lee, P.K., Park, H.S., Song, N., 2019. Assessment of Zn pollution sources and apportionment in agricultural soils impacted by a Zn smelter in South Korea. J. Hazard. Mater. 364, 475–487.
Kazapoe, R.W., Kwayisi, D., Alidu, S., Fynn, O.F., Sagoe, S.D., Amuah, E.E.Y., et al., 2025. Patterns and source apportionment of potentially toxic elements distribution in the soils of the Nangodi area, Northeast Ghana: a multivariate and machine learning approach. J. Hazard. Mater. Adv. 18, 100688.
Kazemi, A., Parvaresh, H., Ghanatghestani, M.D., Ghasemi, S., 2024. A study on source identification of contaminated soil with total petroleum hydrocarbons (aromatic and aliphatic) in the Ahvaz oil field. Environ. Monit. Assess. 196 (9), 776.
Keshavarzi, B., Najmeddin, A., Moore, F., Moghaddam, P.A., 2019. Risk-based assessment of soil pollution by potentially toxic elements in the industrialized urban and peri-urban areas of Ahvaz metropolis, southwest of Iran. Ecotox. Environ. Saf. 167, 365–375.
Khan, S., Naushad, M., Lima, E.C., Zhang, S., Shaheen, S.M., Rinklebe, J., 2021. Global soil pollution by toxic elements: current status and future perspectives on the risk assessment and remediation strategies – a review. J. Hazard. Mater. 417, 126039.
Khan, S.R., Sharma, B., Chawla, P.A., Bhatia, R., 2022. Inductively coupled plasma optical emission spectrometry (ICP-OES): a powerful analytical technique for elemental analysis. Food Anal. Methods 15 (3), 666–688.
Khan, Z., Troquet, J., Vachelard, C., 2005. Sample preparation and analytical techniques for determination of polyaromatic hydrocarbons in soils. Intl. J. Environ. Sci. Technol. 2 (3), 275–286.
Kim, J.S., Kim, J.G., Kim, K.S., 2009. Source apportionment of polychlorinated dibenzo-p–dioxins (PCDDs) and polychlorinated dibenzofurans (PCDFs) in soil around a hazardous waste incinerator in multi-sources region. Environ. Forensics 10 (2), 132–143.
Kudryavtseva, A.D., Mir-Kadyrova, E.Y., Kalinkevich, G.A., Brodskii, E.S., 2021. Dioxin soil contamination near former landfills. Eurasian Soil Sci. 54 (8), 1241–1251.
Kudryavtseva, A.D., Shelepchikov, A.A., Brodsky, E.S., 2022. Fingerprinting and source apportionment of dioxin contamination of soils and chicken eggs in Southeast and Central Vietnam. Environ. Sci. Pollut. Res. 29 (31), 47137–47147.
Kumar, A., Kumar, V., Thakur, M., Bakshi, P., Koul, A., Javaid, A., et al., 2023. Comprehensive review of nickel biogeochemistry, bioavailability, and health risks in the environment. Land Degrad. Dev. 34 (14), 4141–4156.
Kwon, H.-O., Choi, S.-D., 2014. Polycyclic aromatic hydrocarbons (PAHs) in soils from a multi-industrial city, South Korea. Sci. Total Environ. 470, 1494–1501.
Lang, Y.H., Li, G.L., Wang, X.M., Peng, P., Bai, J., 2015. Combination of Unmix and positive matrix factorization model identifying contributions to carcinogenicity and mutagenicity for polycyclic aromatic hydrocarbons sources in Liaohe delta reed wetland soils, China. Chemosphere 120, 431–437.
Lau, E.V., Gan, S., Ng, H.K., 2010. Extraction techniques for polycyclic aromatic hydrocarbons in soils. Int. J. Anal. Chem. 2010 (1), 398381.
Lawal, A.T., 2017. Polycyclic aromatic hydrocarbons. A review. Cogent Environ. Sci. 3 (1), 1339841.
Lehmann, J., Bossio, D.A., Kögel-Knabner, I., Rillig, M.C., 2020. The concept and future prospects of soil health. Nat. Rev. Earth Environ. 1 (10), 544–553.
Li, F., Jin, J., Gao, Y., Geng, N., Tan, D., Zhang, H., et al., 2016. Occurrence, distribution and source apportionment of polychlorinated naphthalenes (PCNs) in sediments and soils from the Liaohe River Basin, China. Environ. Pollut. 211, 226–232.
Li, Q., Wu, J., Zhou, J., Sakiev, K., Hofmann, D., 2020a. Occurrence of polycyclic aromatic hydrocarbon (PAH) in soils around two typical lakes in the western Tian Shan Mountains (Kyrgyzstan, Central Asia): local burden or global distillation? Ecol. Indic. 108, 105749.
Li, Y., Liu, M., Li, R., Sun, P., Xia, H., He, T., 2020b. Polycyclic aromatic hydrocarbons in the soils of the Yangtze River Delta Urban Agglomeration, China: influence of land cover types and urbanization. Sci. Total Environ. 715, 137011.
Li, Y., Kuang, H., Hu, C., Ge, G., 2021. Source apportionment of heavy metal pollution in agricultural soils around the Poyang Lake region using UNMIX model. Sustainability 13 (9), 5272.
Li, Y.J., Wang, B.B., Cao, S.Z., Gao, F., Zhang, L.W., Duan, X.L., 2022. Quantitative source analysis method of carcinogenic risk of polycyclic aromatic hydrocarbons in soil based on PMF model: a case study of Taiyuan. Res. Environ. Sci. 35 (8), 1996–2005.
Li, B., Zhao, L., Zhong, S., An, R., Ma, R., Xu, X., et al., 2023a. Occurrence, distribution and risk assessment of polycyclic aromatic hydrocarbons in soils around main water source areas of Beijing, China. Environ. Geochem. Health 45 (11), 7569–7584.
Li, Q., Cao, Y., Meng, T., He, L., Zhang, S., 2023b. Biogeochemical behavior, health risk assessment and source identification of antimony and arsenic in soil from a legacy antimony smelter in Gansu, Northwest China. Env. Sci. Eur. 35 (1), 114.
Li, Y., Liu, S., Zhan, C., Liu, H., Zhang, J., Guo, J., et al., 2023c. Source-based health risk assessment of heavy metal contamination in soil: a case study from a polymetallic mining region in Southeastern Hubei, Central China. Environ. Geochem. Health 46 (1), 12.
Li, D., Lu, Q., Cai, L., Chen, L., Wang, H., 2023d. Characteristics of soil heavy metal pollution and health risk assessment in urban parks at a megacity of Central China. Toxics 11 (3), 257.
Li, W., Cao, X., Hu, Y., Cheng, H., 2024a. Source apportionment and risk assessment of heavy metals in agricultural soils in a typical mining and smelting industrial area. Sustainability 16 (4), 1673.
Li, J., Liu, J.Z., Tai, X.S., Jiao, L., Zhang, M., Zang, F., 2024b. Pollution and source-specific risk analysis of potentially toxic metals in urban soils of an oasis-tourist city in northwest China. Environ. Geochem. Health 46 (2), 55.
Li, X., Ding, D., Xie, W., Zhang, Y., Kong, L., Li, M., et al., 2024c. Risk assessment and source analysis of heavy metals in soil around an asbestos mine in an arid plateau region, China. Sci. Rep. 14 (1), 7552.
Liang, J., Mao, J., 2015. Source analysis of global anthropogenic lead emissions: their quantities and species. Environ. Sci. Pollut. Res. 22 (9), 7129–7138.
Liang, L., Zhu, Y., Xu, X., Hao, W., Han, J., Chen, Z., et al., 2023. Integrated insights into source apportionment and source-specific health risks of potential pollutants in urban park soils on the Karst Plateau, SW China. Expos. Health. 15 (4), 933–950.
Liang, Q., Tian, K., Li, L., He, Y., Zhao, T., Liu, B., et al., 2022. Ecological and human health risk assessment of heavy metals based on their source apportionment in cropland soils around an e-waste dismantling site, Southeast China. Ecotox. Environ. Saf. 242, 113929.
Liang, X., Wang, C., Song, Z., Yang, S., Bi, X., Li, Z., et al., 2021. Soil metal(loid)s pollution around a lead/zinc smelter and source apportionment using isotope fingerprints and receptor models. Appl. Geochem. 135, 105118.
Limbeck, A., Galler, P., Bonta, M., Bauer, G., Nischkauer, W., Vanhaecke, F., 2015. Recent advances in quantitative LA-ICP-MS analysis: challenges and solutions in the life sciences and environmental chemistry. Anal. Bioanal. Chem. 407 (22), 6593–6617.
Liu, H., Yu, X., Liu, Z., Sun, Y., 2018. Occurrence, characteristics and sources of polycyclic aromatic hydrocarbons in arable soils of Beijing, China. Ecotox. Environ. Saf. 159, 120–126.
Liu, J., Liu, Y.J., Liu, Z., Zhang, A., Liu, Y., 2019. Source apportionment of soil PAHs and human health exposure risks quantification from sources: the Yulin National Energy and Chemical Industry Base, China as case study. Environ. Geochem. Health 41 (2), 617–632.
Liu, H., Zhang, Y., Yang, J., Wang, H., Li, Y., Shi, Y., et al., 2021a. Quantitative source apportionment, risk assessment and distribution of heavy metals in agricultural soils from southern Shandong Peninsula of China. Sci. Total Environ. 767, 144879.
Liu, C., Yi, L., Lu, A., Xie, B., Peng, H., 2021b. Evaluating metal(loid)s contamination in soil of a typical industry smelting site in South Central China: levels, possible sources and human health risk analysis. Sustainability 13 (20), 11294.
Liu, S., Liu, Z., Tan, W., Johnson, A.C., Sweetman, A.J., Sun, X., et al., 2023. Transport and transformation of perfluoroalkyl acids, isomer profiles, novel alternatives and unknown precursors from factories to dinner plates in China: new insights into crop bioaccumulation prediction and risk assessment. Environ. Int. 172, 107795.
Liu, Z., Zheng, T., Chen, Q., Chen, X., Xie, Y., Wang, Y., et al., 2024a. Identification and health risk evaluation of soil contaminated by polycyclic aromatic hydrocarbons at shale gas extraction sites based on positive matrix factorization. Chemosphere 356, 141962.
Liu, M., Shao, T., Han, S., Nan, W., Wang, R., Xiao, F., et al., 2024b. Accumulation characteristics and source analysis of microplastics derived traffic of soil in the Tibetan Plateau. J. Hazard. Mater. 480, 136191.
Liu, L., Li, Y., Gu, X., Tulcan, R.X.S., Yan, L., Lin, C., et al., 2025. Priority sources identification and risks assessment of heavy metal (loid)s in agricultural soils of a typical antimony mining watershed. J. Environ. Sci. 147, 153–164.
Lu, Q., Wang, S., Bai, X., Liu, F., Li, C., Deng, Y., et al., 2021. Quantitative assessment of human health risks under different land uses based on soil heavy metal pollution sources. Hum. Ecol. Risk Assess. 27 (2), 327–343.
Lu, X., Wang, Z., Chen, Y., Yang, Y., Fan, X., Wang, L., et al., 2023. Source–specific probabilistic risk evaluation of potentially toxic metal(loid)s in fine dust of college campuses based on positive matrix factorization and Monte Carlo simulation. J. Environ. Manage. 347, 119056.
Luo, C., Mi, S., Zhou, N., Liu, Z., Cai, L., 2022. Modelling the primary drying stage of the spray freeze drying process based on the non-equilibrium formulation. Int. J. Heat Mass Transf. 188, 122659.
Luo, N., Yu, R., Wen, B., Li, X., Liu, X., Li, X., 2023. Identifying anthropogenic sources of heavy metals in alpine peatlands over the past 150 years: examples from typical peatlands in Altay Mountains, Northwest China. Int. J. Env. Res. Public Health 20 (6), 5013.
Ma, J., Lanwang, K., Liao, S., Zhong, B., Chen, Z., Ye, Z., et al., 2023a. Source apportionment and model applicability of heavy metal pollution in farmland soil based on three receptor models. Toxics 11 (3), 265.
Ma, J., Shen, Z.J., Wang, S.L., Deng, L., Sun, J., Liu, P., et al., 2023b. Source apportionment of heavy metals in soils around a coal gangue heap with the APCS-MLR and PMF receptor models in Chongqing, southwest China. J. Mountain Sci. 20, 1061–1073.
Ma, W., Hu, J., Li, J., Gao, P., Okoli, C.P., Wang, P., 2023c. Distribution, sources, and health risk assessment of VOCs/SVOCs in soils obtained from petrochemical-contaminated sites in Guangzhou, a subtropical coastal megacity in southern China. J. Cleaner Prod. 426, 139198.

Manoli, E., Kouras, A., Samara, C., 2004. Profile analysis of ambient and source emitted particle-bound polycyclic aromatic hydrocarbons from three sites in northern Greece. Chemosphere 56 (9), 867–878.
Mansouri, E., Yousefi, V., Ebrahimi, V., Eyvazi, S., Hejazi, M.S., Mahdavi, M., et al., 2020. Overview of ultraviolet-based methods used in polycyclic aromatic hydrocarbons analysis and measurement. Sep. Sci. Plus 3 (4), 112–120.
Maurelia, J., Cornejo, O., Tume, P., Roca, N., 2022. Distribution of heavy metals in the commune of Coronel, Chile. Minerals 12 (3), 320.
MEE, 2018. Soil Environmental Quality Risk control Standard For Soil Contamination of Agricultural Land (GB 15618—2018). Ministry of Ecology and Environment, PRC, Beijing, China.
Melquiades, F.L., Bastos, R.O., Biasi, G.E., Parreira, P.S., Appoloni, C.R., 2011. Granulometry and moisture influence for in situ soil analysis by portable EDXRF. AIP Conf. Proc. 1351, 317–320.
Mikutta, R., Kleber, M., Kaiser, K., Jahn, R., 2005. Organic matter removal from soils using hydrogen peroxide, sodium hypochlorite, and disodium peroxodisulfate. Soil Sci. Soc. Am. J. 69 (1), 120–135.
Miletić, A., Vesković, J., Lučić, M., Onjia, A., 2024. Monte Carlo simulation of source-specific risks of soil at an abandoned lead-acid battery recycling site. Stoch. Environ. Res. Risk Assess. 38 (8), 3313–3329.
Miliszkiewicz, N., Walas, S., Tobiasz, A., 2015. Current approaches to calibration of LA-ICP-MS analysis. J. Anal. At. Spectrom. 30 (2), 327–338.
Ministry of Environment, 2021. Contaminated Land Management Guidelines No. 5: Site investigation and Analysis of Soils. Ministry for the Environment, Wellington.
Mogashane, T.M., Mokoena, L., Tshilongo, J., 2024. A review on recent developments in the extraction and identification of polycyclic aromatic hydrocarbons from environmental samples. Water 16 (17), 2520.
Morse, N., Walter, M.T., Osmond, D., Hunt, W., 2016. Roadside soils show low plant available zinc and copper concentrations. Environ. Pollut. 209, 30–37.
Mostert, M.M., Ayoko, G.A., Kokot, S., 2010. Application of chemometrics to analysis of soil pollutants. Trends Anal. Chem. 29 (5), 430–445.
Nakken, C.L., Sørhus, E., Holmelid, B., Meier, S., Mjøs, S.A., Donald, C.E., 2025. Transformative knowledge of polar polycyclic aromatic hydrocarbons via high-resolution mass spectrometry. Sci. Total Environ. 960, 178349.
Ngo, T.H., Tsou, H.H., Chen, Y.F., Chen, Y.W., Chi, K.H., 2018. Sources identification of PCDD/Fs in soil and atmospheric deposition in Taiwan. Chemosphere 208, 374–381.
Ning, W., Hu, Y., Feng, S., Cao, M., Luo, J., 2023. Ecological risk assessment and transmission of soil heavy metals in pastoral areas of the Tibetan plateau based on network environment analysis. Sci. Total Environ. 905, 167197.
Nolan, A.L., Ma, Y., Lombi, E., McLaughlin, M.J., 2004. Measurement of labile Cu in soil using stable isotope dilution and isotope ratio analysis by ICP-MS. Anal. Bioanal. Chem. 380 (5), 789–797.
Öhlinger, R., 1996. Soil sampling and sample preparation. In: Schinner, F., Öhlinger, R., Kandeler, E., Margesin, R. (Eds.), Methods in Soil Biology. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 7–11.
Owoade, O.K., Tunde, O.L., Olise, F.S., Odekunle, A.T., Abiodun, P.O., Ezeh, G.C., et al., 2020. Contamination and source identification of the elemental contents of soil samples from municipal and medical waste dumpsites in Ile-Ife, Nigeria. EQA 40, 31–41.
Paatero, P., Tapper, U., 1994. Positive matrix factorization: a non-negative factor model with optimal utilization of error estimates of data values. Environmetrics 5 (2), 111–126.
Pasilis, S.P., Van Berkel, G.J., 2010. Modern atmospheric pressure surface sampling/ionization techniques in mass spectrometry. In: Gross, M.L., Caprioli, R.M. (Eds.), Encyclopedia of Analytical Chemistry. Elsevier, Amsterdam, pp. 1544–1555.
Papadoyannis, I.N., Gika, H.G., 2004. Peak purity determination with a diode array detector. J. Liq. Chromatogr. Relat. Technol. 27 (6), 1083–1092.
Pilková, Z., Filová, L., Hiller, E., Mihaljevič, M., 2024. Re-interpretation of metal(loid) concentrations in urban soils of two different land uses by Positive Matrix Factorisation. Environ. Forensics 25 (6), 626–644.
Płotka-Wasylka, J., Szczepańska, N., de la Guardia, M., Namieśnik, J., 2015. Miniaturized solid-phase extraction techniques. Trends Anal. Chem. 73, 19–38.
Portet-Koltalo, F., Humbert, K., Cosme, J., Debret, M., Morin, C., Le Gohlisse, S., 2024. Measuring aliphatic hydrocarbons in sediments by direct thermal desorption-gas chromatography-mass spectrometry: matrix effects and quantification challenges. J. Chromatogr. A 1722, 464895.
Poster, D.L., Schantz, M.M., Sander, L.C., Wise, S.A., 2006. Analysis of polycyclic aromatic hydrocarbons (PAHs) in environmental samples: a critical review of gas chromatographic (GC) methods. Anal. Bioanal. Chem. 386 (4), 859–881.
Qazi, F., Shahsavari, E., Prawer, S., Ball, A.S., Tomljenovic-Hanic, S., 2021. Detection and identification of polyaromatic hydrocarbons (PAHs) contamination in soil using intrinsic fluorescence. Environ. Pollut. 272, 116010.
Qi, P., Qu, C., Albanese, S., Lima, A., Cicchella, D., Hope, D., et al., 2020. Investigation of polycyclic aromatic hydrocarbons in soils from Caserta provincial territory, southern Italy: spatial distribution, source apportionment, and risk assessment. J. Hazard. Mater. 383, 121158.
Qin, M., Jin, Y., Peng, T., Zhao, B., Hou, D., 2023. Heavy metal pollution in Mongolian–Manchurian grassland soil and effect of long-range dust transport by wind. Environ. Int. 177, 108019.
Qu, M., Chen, J., Huang, B., Zhao, Y., 2021. Source apportionment of soil heavy metals using robust spatial receptor model with categorical land-use types and RGWR-corrected in-situ FPXRF data. Environ. Pollut. 270, 116220.
Rastegari Mehr, M., Keshavarzi, B., Moore, F., Sharifi, R., Lahijanzadeh, A., Kermani, M., 2017. Distribution, source identification and health risk assessment of soil heavy metals in urban areas of Isfahan province, Iran. J. Afr. Earth Sci. 132, 16–26.
Ravindra, K., Wauters, E., Van Grieken, R., 2008. Variation in particulate PAHs levels and their relation with the transboundary movement of the air masses. Sci. Total Environ. 396 (2), 100–110.
Ren, Z., Christakos, G., Lou, Z., Xu, H., Lv, X., Fei, X., 2022. Contamination assessment and source apportionment of metals and metalloids pollution in agricultural soil: a comparison of the APCA-MLR and APCA-GWR models. Sustainability 14 (2), 783.
Richardson, S.D., 2012. Environmental mass spectrometry: emerging contaminants and current issues. Anal. Chem. 84 (2), 747–778.
Saha, A., Gupta, B.S., Patidar, S., Martínez-Villegas, N., 2022. Spatial distribution and source identification of metal contaminants in the surface soil of Matehuala, Mexico based on positive matrix factorization model and GIS techniques. Front. Soil Sci. 2, 1041377.
Sakizadeh, M., Zhang, C., 2021. Source identification and contribution of land uses to the observed values of heavy metals in soil samples of the border between the Northern Ireland and Republic of Ireland by receptor models and redundancy analysis. Geoderma 404, 115313.
Saleem, M., Iqbal, J., Shah, M.H., 2014. Non-carcinogenic and carcinogenic health risk assessment of selected metals in soil around a natural water reservoir, Pakistan. Ecotox. Environ. Saf. 108, 42–51.
Sandroni, V., Smith, C.M., Donovan, A., 2003. Microwave digestion of sediment, soils and urban particulate matter for trace metal analysis. Talanta 60 (4), 715–723.
Schaefer, K., Einax, J.W., 2016. Source apportionment and geostatistics: an outstanding combination for describing metals distribution in soil. CLEAN–Soil Air Water 44 (7), 877–884.
Sei, K., Wang, Q., Tokumura, M., Miyake, Y., Amagai, T., 2021. Accurate and ultrasensitive determination of 72 parent and halogenated polycyclic aromatic hydrocarbons in a variety of environmental samples via gas chromatography–triple quadrupole mass spectrometry. Chemosphere 271, 129535.
Shang, D., Kim, M., Haberl, M., 2014. Rapid and sensitive method for the determination of polycyclic aromatic hydrocarbons in soils using pseudo multiple reaction monitoring gas chromatography/tandem mass spectrometry. J. Chromatogr. A 1334, 118–125.
Shao, F., Li, K., Ouyang, D., Zhou, J., Luo, Y., Zhang, H., 2024. Sources apportionments of heavy metal(loid)s in the farmland soils close to industrial parks: integrated application of positive matrix factorization (PMF) and cadmium isotopic fractionation. Sci. Total Environ. 924, 171598.
Sharpe, L.R., 2024. Exploring matrix effects on the determination of iron in soil using X-ray fluorescence. J. Chem. Educ. 101 (3), 1081–1086.
Shen, C., Huang, S., Wang, M., Wu, J., Su, J., Lin, K., et al., 2024. Source-oriented health risk assessment and priority control factor analysis of heavy metals in urban soil of Shanghai. J. Hazard. Mater. 480, 135859.
Sheng, Y., Wang, Z., Feng, X., 2023. Potential ecological risk and zoning control strategies for heavy metals in soils surrounding core water sources: a case study from Danjiangkou Reservoir, China. Ecotox. Environ. Saf. 252, 114610.
Shi, B., Meng, J., Wang, T., Li, Q., Zhang, Q., Su, G., 2024a. The main strategies for soil pollution apportionment: a review of the numerical methods. J. Environ. Sci. 136, 95–109.
Shi, H., He, Z., Deng, C., Liu, A., Feng, Y., Li, L., et al., 2024b. How has the source apportionment of heavy metals in soil and water evolved over the past 20 years? A bibliometric perspective. Water 16 (22), 3171.
Shi, J., Yang, Y., Shen, Z., Lin, Y., Mei, N., Luo, C., et al., 2024c. Identifying heavy metal sources and health risks in soil-vegetable systems of fragmented vegetable fields based on machine learning, positive matrix factorization model and Monte Carlo simulation. J. Hazard. Mater. 478, 135481.
Shiyi, Y., Xiaonuo, L., Weiping, C., 2023. High-resolution risk mapping of heavy metals in soil with an integrated static-dynamic interaction model: a case study in an industrial agglomeration area in China. J. Hazard. Mater. 455, 131650.
Shokri, N., Aminzadeh, M., Flury, M., Jin, Y., Matin, M.A., Panagos, P., et al., 2025. Sustainability Nexus AID: soil health. Sustain. Nexus Forum 33 (1), 3.
Shukla, S., Khan, R., Bhattacharya, P., Devanesan, S., AlSalhi, M.S., 2022. Concentration, source apportionment and potential carcinogenic risks of polycyclic aromatic hydrocarbons (PAHs) in roadside soils. Chemosphere 292, 133413.
Škrbić, B.D., Antić, I., Živančev, J., Vágvölgyi, C., 2021. Comprehensive characterization of PAHs profile in Serbian soils for conventional and organic production: potential sources and risk assessment. Environ. Geochem. Health 43 (10), 4201–4218.
Soltani-Gerdefaramarzi, S., Ghasemi, M., Ghanbarian, B., 2021. Geogenic and anthropogenic sources identification and ecological risk assessment of heavy metals in the urban soil of Yazd, central Iran. PLoS One 16 (11), e0260418.
Song, N., Tian, Y., Luo, Z., Dai, J., Liu, Y., Duan, Y., 2022. Advances in pretreatment and analysis methods of aromatic hydrocarbons in soil. RSC Adv. 12 (10), 6099–6113.
Soursou, V., Campo, J., Picó, Y., 2023. Revisiting the analytical determination of PAHs in environmental samples: an update on recent advances. Trends Environ. Anal. Chem. 37, e00195.
Su, C., Meng, J., Zhou, Y., Bi, R., Chen, Z., Diao, J., et al., 2022. Heavy metals in soils from intense industrial areas in South China: spatial distribution, source apportionment, and risk assessment. Front. Environ. Sci. 10, 820536.
Su, Q., Zhang, X., Zhang, Y., Sun, G., Li, Z., Xiang, L., et al., 2023a. Risk assessment of heavy metal pollution in agricultural soil surrounding a typical pharmaceutical manufacturing complex. Front. Environ. Sci. 10, 1105910.
Su, C., Wang, J., Chen, Z., Meng, J., Yin, G., Zhou, Y., et al., 2023b. Sources and health risks of heavy metals in soils and vegetables from intensive human intervention areas in South China. Sci. Total Environ. 857, 159389.
Suciu, N.A., De Vivo, R., Rizzati, N., Capri, E., 2022. Cd content in phosphate fertilizer: which potential risk for the environment and human health? Curr. Opin. Environ. Sci. Health 30, 100392.

Sun, J., Zhao, M., Huang, J., Liu, Y., Wu, Y., Cai, B., et al., 2022. Determination of priority control factors for the management of soil trace metal(loid)s based on source-oriented health risk assessment. J. Hazard. Mater. 423, 127116.
Sun, L., Guo, D., Liu, K., Meng, H., Zheng, Y., Yuan, F., et al., 2019. Levels, sources, and spatial distribution of heavy metals in soils from a typical coal industrial city of Tangshan, China. Catena 175, 101–109.
Sun, P., Yang, J., Wu, Y., Liu, X., Huang, Y., He, E.K., et al., 2023. Spatial modeling and source identification of PAHs in soils and roadside dusts from Hangzhou, a new first-tier megcity of China. J. Hazard. Mater. 460, 132366.
Sun, T., Huang, J., Wu, Y., Yuan, Y., Xie, Y., Fan, Z., et al., 2020. Risk assessment and source apportionment of soil heavy metals under different land use in a typical estuary alluvial island. Int. J. Env. Res. Public Health 17 (13), 4841.
Sungur, A., Kavdir, Y., Özcan, H., İlay, R., Soylak, M., 2021. Geochemical fractions of trace metals in surface and core sections of aggregates in agricultural soils. Catena 197, 104995.
Tanić, M.N., Dinić, D., Kartalović, B., Mihaljev, Ž., Stupar, S., Ćujić, M., et al., 2023. Occurrence, source apportionment, and health risk assessment of polycyclic aromatic hydrocarbons in soil of urban parks in a mid-sized city. Water Air Soil Pollut. 234 (7), 484.
Tarighat, H., Taati, A., Baghdadi, M., 2024. Quantitative source apportionment and health risk assessment of trace elements in surface soils around the Shazand chemical industrial district, northwestern of Iran. Hum. Ecol. Risk Assess. 30 (5–6), 419–435.
Temerdashev, Z.A., Musorina, T.N., Ovsepyan, S.K., Korpakova, I.G., 2022. Determination of polycyclic aromatic hydrocarbons in soils and bottom sediments by gas chromatography–mass spectrometry with QuEChERS sample preparation. J. Anal. Chem. 77 (5), 595–603.
Tian, J., Guan, Q., Shao, W., Liu, Z., Ma, Y., Li, H., et al., 2021. A joint method to quantify source contributions of heavy metals to ecological and human health risks in oasis farmland soil. Soil Sci. Soc. Am. J. 85 (5), 1600–1619.
Tobiszewski, M., Namieśnik, J., 2012. PAH diagnostic ratios for the identification of pollution emission sources. Environ. Pollut. 162, 110–119.
Uren, N.C., 2012. Cobalt and manganese. In: Heavy Metals in Soils: Trace metals and Metalloids in Soils and Their Bioavailability. Springer Netherlands, Dordrecht, pp. 335–366.
USEPA, 2023. Soil Sampling. U.S. Environmental Protection Agency.
USEPA, 2025. Positive matrix factorization model for environmental data analyses. Environmental Protection Agency, U.S..
Vaccaro, S., Sobiecka, E., Contini, S., Locoro, G., Free, G., Gawlik, B.M., 2007. The application of positive matrix factorization in the analysis, characterisation and detection of contaminated soils. Chemosphere 69 (7), 1055–1063.
Vesković, J., Onjia, A., 2024. Environmental implications of the soil-to-groundwater migration of heavy metals in mining area hotspots. Metals 14 (6), 719.
Viana, M., Kuhlbusch, T.A., Querol, X., Alastuey, A., Harrison, R.M., Hopke, P.K., et al., 2008. Source apportionment of particulate matter in Europe: a review of methods and results. J. Aerosol Sci. 39 (10), 827–849.
Vincent, J.B., 2023. Chromium: sources, speciation, toxicity, and chemistry. In: Kumar, N., Walther, C., Gupta, D.K. (Eds.), Chromium in Plants and Environment. Springer Nature Switzerland, Cham, pp. 43–62.
Vistnes, H., Sossalla, N.A., Røsvik, A., Gonzalez, S.V., Zhang, J., Meyn, T., et al., 2022. The determination of polycyclic aromatic hydrocarbons (PAHs) with HPLC-DAD-FLD and GC-MS techniques in the dissolved and particulate phase of road-tunnel wash water: a case study for cross-array comparisons and applications. Toxics 10 (7), 399.
Wang, W., Meng, B., Lu, X., Liu, Y., Tao, S., 2007. Extraction of polycyclic aromatic hydrocarbons and organochlorine pesticides from soils: a comparison between Soxhlet extraction, microwave-assisted extraction and accelerated solvent extraction techniques. Anal. Chim. Acta 602 (2), 211–222.
Wang, W., Simonich, S.L.M., Xue, M., Zhao, J., Zhang, N., Wang, R., et al., 2010. Concentrations, sources and spatial distribution of polycyclic aromatic hydrocarbons in soils from Beijing, Tianjin and surrounding areas, North China. Environ. Pollut. 158 (5), 1245–1251.
Wang, J.F., Stein, A., Gao, B.B., Ge, Y., 2012. A review of spatial sampling. Spat. Stat. 2, 1–14.
Wang, X.T., Miao, Y., Zhang, Y., Li, Y.C., Wu, M.H., Yu, G., 2013. Polycyclic aromatic hydrocarbons (PAHs) in urban soils of the megacity Shanghai: occurrence, source apportionment and potential human health risk. Sci. Total Environ. 447, 80–89.
Wang, C., Wu, S., Zhou, S., Wang, H., Li, B., Chen, H., et al., 2015a. Polycyclic aromatic hydrocarbons in soils from urban to rural areas in Nanjing: concentration, source, spatial distribution, and potential human health risk. Sci. Total Environ. 527, 375–383.
Wang, X.T., Chen, L., Wang, X.K., Lei, B.L., Sun, Y.F., Zhou, J., et al., 2015b. Occurrence, sources and health risk assessment of polycyclic aromatic hydrocarbons in urban (Pudong) and suburban soils from Shanghai in China. Chemosphere 119, 1224–1232.
Wang, C., Wu, S., Zhou, S., Shi, Y., Song, J., 2017. Characteristics and source identification of polycyclic aromatic hydrocarbons (PAHs) in urban soils: a review. Pedosphere 27 (1), 17–26.
Wang, S., Cai, L.M., Wen, H.H., Luo, J., Wang, Q.S., Liu, X., 2019a. Spatial distribution and source apportionment of heavy metals in soil from a typical county-level city of Guangdong Province, China. Sci. Total Environ. 655, 92–101.
Wang, S.W., Hsu, K.H., Huang, S.C., Tseng, S.H., Wang, D.Y., Cheng, H.F., 2019b. Determination of polycyclic aromatic hydrocarbons (PAHs) in cosmetic products by gas chromatography-tandem mass spectrometry. J. Food Drug Anal. 27 (3), 815–824.
Wang, Y., Zhang, L., Wang, J., Lv, J., 2020. Identifying quantitative sources and spatial distributions of potentially toxic elements in soils by using three receptor models and sequential indicator simulation. Chemosphere 242, 125266.
Wang, J., Yu, D., Wang, Y., Du, X., Li, G., Li, B., et al., 2021. Source analysis of heavy metal pollution in agricultural soil irrigated with sewage in Wuqing, Tianjin. Sci. Rep. 11 (1), 17816.
Wang, J., Yang, J., Chen, T., 2022a. Source appointment of potentially toxic elements (PTEs) at an abandoned realgar mine: combination of multivariate statistical analysis and three common receptor models. Chemosphere 307, 135923.
Wang, W., Xu, X., Zhou, Z., Dong, X., Tian, T., 2022b. A joint method to assess pollution status and source-specific human health risks of potential toxic elements in soils. Environ. Monit. Assess. 194 (10), 685.
Wang, X., Wang, L., Zhang, Q., Liang, T., Li, J., Hansen, H.C.B., et al., 2022c. Integrated assessment of the impact of land use types on soil pollution by potentially toxic elements and the associated ecological and human health risk. Environ. Pollut. 299, 118911.
Wang, X., Chen, Y., Chen, T., Guo, L., Yang, Z., Chen, Y., et al., 2024. Lagging pollution of polycyclic aromatic hydrocarbons in the rebuilt e-waste site: from the perspective of characteristics, sources, and risk assessment. Sci. Total Environ. 929, 172406.
Wang, P., Yu, F., Lv, H., Wu, L., Zhou, H., 2025. Potential risk of heavy metals release in sediments and soils of the Yellow River Basin (Henan section): a perspective on bioavailability and bioaccessibility. Ecotox. Environ. Saf. 291, 117799.
Wei, L., Lv, J., Zuo, P., Li, Y., Yang, R., Zhang, Q., et al., 2024. The occurrence and sources of PAHs, oxygenated PAHs (OPAHs), and nitrated PAHs (NPAHs) in soil and vegetation from the Antarctic, Arctic, and Tibetan Plateau. Sci. Total Environ. 912, 169394.
Weindorf, D.C., Chakraborty, S., 2020. Portable X-ray fluorescence spectrometry analysis of soils. Soil Sci. Soc. Am. J. 84 (5), 1384–1392.
Weng, C.Y., Jia, S.M., Wang, D.Q., Ma, W.L., 2024a. Pollution characteristics of heavy metal(loid)s in soil in China: implications for health risk assessment and temporal trend analysis. Environ. Chem. Ecotox. 6, 248–258.
Weng, C.Y., Zhang, Y.Y., Zhu, F.J., Jia, S.M., Ma, W.L., 2024b. National investigation of bisphenols in the surface soil in China. Sci. Total Environ. 956, 177319.
Wickliffe, J., Overton, E., Frickel, S., Howard, J., Wilson, M., Simon, B., et al., 2014. Evaluation of polycyclic aromatic hydrocarbons using analytical methods, toxicology, and risk assessment research: seafood safety after a petroleum spill as an example. Environ. Health Persp. 122 (1), 6–9.
Wilcke, W., 2000. SYNOPSIS polycyclic aromatic hydrocarbons (PAHs) in soil — a review. J. Plant Nutr. Soil Sci. 163 (3), 229–248.
Wu, L., Sun, R., Li, Y., Sun, C., 2019. Sample preparation and analytical methods for polycyclic aromatic hydrocarbons in sediment. Trends Environ. Anal. Chem. 24, e00074.
Wu, J., Li, J., Ma, M., Zhang, D., 2020a. Source apportionment of soil PAH concentration and associated carcinogenic and mutagenic potencies by combined utilization of PMF and toxic assessment: a case study in North China. Soil Sediment Contam. 29 (4), 421–437.
Wu, Z., Zhang, L., Xia, T., Jia, X., Wang, S., 2020b. Heavy metal pollution and human health risk assessment at mercury smelting sites in Wanshan district of Guizhou Province, China. RSC Adv. 10 (39), 23066–23079.
Wu, Q., Hu, W., Wang, H., Liu, P., Wang, X., Huang, B., 2021. Spatial distribution, ecological risk and sources of heavy metals in soils from a typical economic development area, Southeastern China. Sci. Total Environ. 780, 146557.
Wu, Y.S., Osman, A.I., Hosny, M., Elgarahy, A.M., Eltaweil, A.S., Rooney, D.W., et al., 2024. The toxicity of mercury and its chemical compounds: molecular mechanisms and environmental and human health implications: a comprehensive review. ACS Omega 9 (5), 5100–5126.
Xie, Q., Ren, B., Deng, X., Yin, W., Lu, Y., 2023. Quantitative source identification, risk assessment and pollution of heavy metals in soils around a typical Sb smelter in central and southern China. Stoch. Environ. Res. Risk Assess. 37 (7), 2495–2511.
Xie, T., Lu, F., Wang, M., Zhang, Y., Liu, C., Chen, W., 2021. The application of urban anthropogenic background to pollution evaluation and source identification of soil contaminants in Macau, China. Sci. Total Environ. 778, 146263.
Xie, W., Peng, C., Wang, H., Chen, W., 2018. Bioaccessibility and source identification of heavy metals in agricultural soils contaminated by mining activities. Environ. Earth Sci. 77 (17), 606.
Xu, J., Gui, H., Chen, J., Li, C., Li, Y., Zhao, C., et al., 2021. A combined model to quantitatively assess human health risk from different sources of heavy metals in soils around coal waste pile. Hum. Ecol. Risk Assess. 27 (9–10), 2235–2253.
Xu, X., Liu, W., Jia, T., Shi, Z., He, Y., Mao, T., et al., 2023. Investigation of relationship between polycyclic aromatic hydrocarbons and human activities in urban soils of China using machine learning methods. J. Cleaner Prod. 404, 136839.
Xu, Y., Wang, X., Cui, G., Li, K., Liu, Y., Li, B., et al., 2022. Source apportionment and ecological and health risk mapping of soil heavy metals based on PMF, SOM, and GIS methods in Hulan River Watershed, Northeastern China. Environ. Monit. Assess. 194 (3), 181.
Xu, X., Xu, Z., Liang, L., Han, J., Wu, G., Lu, Q., et al., 2024. Risk hotspots and influencing factors identification of heavy metal (loid) s in agricultural soils using spatial bivariate analysis and random forest. Sci. Total Environ. 954, 176359.
Xue, J.L., Zhi, Y.Y., Yang, L.P., Shi, J.C., Zeng, L.Z., Wu, L.S., 2014. Positive matrix factorization as source apportionment of soil lead and cadmium around a battery plant (Changxing County, China). Environ. Sci. Pollut. Res. 21 (12), 7698–7707.
Yang, S., Taylor, D., Yang, D., He, M., Liu, X., Xu, J., 2021. A synthesis framework using machine learning and spatial bivariate analysis to identify drivers and hotspots of heavy metal pollution of agricultural soils. Environ. Pollut. 287, 117611.
Yang, Z., Yu, J., Yang, K., Zhang, Q., Chen, Y., Qiao, S., 2024. Source apportionment and risk assessment of potentially toxic elements based on PCA and PMF model in black soil area of Hailun City, Northeast China. Toxics 12 (9), 683.
Yin, G.Q., Jiang, H., Wang, Q., Nie, J., Ma, Y., Hu, H., 2018. Analysis of the sources and characteristics of heavy metals in farmland soil from a typical district in Anhui Province. J. Agro-environment Sci. 37 (1), 96–104.
Yoon, S., Kim, D.M., Yu, S., Batsaikhan, B., Kim, T., Yun, S.T., 2023. Characteristics of soil contamination by potentially toxic elements in mine areas of Mongolia. Environ. Geochem. Health 46 (1), 15.

Yu, D., Wang, J., Wang, Y., Du, X., Li, G., Li, B., 2021. Identifying the source of heavy metal pollution and apportionment in agricultural soils impacted by different smelters in China by the Positive Matrix Factorization Model and the Pb isotope ratio method. Sustainability 13 (12), 6526.

Yunker, M.B., Macdonald, R.W., Vingarzan, R., Mitchell, R.H., Goyette, D., Sylvestre, S., 2002. PAHs in the Fraser River basin: a critical appraisal of PAH ratios as indicators of PAH source and composition. Org. Geochem. 33 (4), 489–515.

Yushin, N., Jakhu, R., Chaligava, O., Grozdov, D., Zinicovscaia, I., 2024. Evaluation of the potentially toxic elements and radionuclides in the soil sample of Novaya Zemlya in the Arctic Circle. Environ. Pollut. 361, 124871.

Zhang, H., Yin, A., Yang, X., Fan, M., Shao, S., Wu, J., et al., 2021. Use of machine-learning and receptor models for prediction and source apportionment of heavy metals in coastal reclaimed soils. Ecol. Indic. 122, 107233.

Zhang, X.L., Tao, S., Liu, W.X., Yang, Y., Zuo, Q., Liu, S.Z., 2005. Source diagnostics of polycyclic aromatic hydrocarbons based on species ratios: a multimedia approach. Environ. Sci. Technol. 39 (23), 9109–9114.

Zhang, K., Liao, L., Li, Z., Lin, Y., Meng, B., Feng, X., 2023a. Mercury isotopes trace historical mercury pollution from PbZn smelter in China. Chem. Geol. 635, 121622.

Zhang, X., Tian, K., Wang, Y., Hu, W., Liu, B., Yuan, X., et al., 2023b. Identification of sources and their potential health risk of potential toxic elements in soils from a mercury-thallium polymetallic mining area in Southwest China: insight from mercury isotopes and PMF model. Sci. Total Environ. 869, 161774.

Zhang, Y., Zhang, Q., Chen, W., Shi, W., Cui, Y., Chen, L., et al., 2023c. Source apportionment and migration characteristics of heavy metal(loid)s in soil and groundwater of contaminated site. Environ. Pollut. 338, 122584.

Zhang, Y., Jiang, B., Gao, Z., Wang, M., Feng, J., Xia, L., et al., 2024a. Health risk assessment of soil heavy metals in a typical mining town in north China based on Monte Carlo simulation coupled with positive matrix factorization model. Environ. Res. 251, 118696.

Zhang, X., Zhang, S., Wei, X., Liu, Z., Wang, C., Mu, H., et al., 2024b. Identification of sources and analysis of spatial distribution of soil heavy metals in northern China coal mining areas. Environ. Geochem. Health 46 (3), 94.

Zhao, Q.L., Li, Q.C., An, M.G., Yu, L.S., Wan, X., Cao, F.H., et al., 2023. Potential source identification and ecological risk assessment of heavy metals in surface soil of Heze Oil Peony Planting Area based on PMF-PCA/APCS and PERI. Environ. Sci. 44 (9), 5253–5263.

Zhao, B., O'Connor, D., Huang, Y., Hou, R., Cai, L., Jin, Y., et al., 2024a. An integrated framework for source apportionment and spatial distribution of mercury in agricultural soil near a primary ore mining site. Chemosphere 353, 141556.

Zhao, X., Meng, J., Li, Q., Su, G., Zhang, Q., Shi, B., et al., 2024b. Source apportionment and suitability evaluation of seasonal VOCs contaminants in the soil around a typical refining-chemical integration park in China. J. Environ. Sci 137, 651–663.

Zheng, H., Xing, X., Hu, T., Zhang, Y., Zhang, J., Zhu, G., et al., 2018. Biomass burning contributed most to the human cancer risk exposed to the soil-bound PAHs from Chengdu Economic Region, western China. Ecotox. Environ. Saf. 159, 63–70.

Zhou, Y., Jiang, D., Ding, D., Wu, Y., Wei, J., Kong, L., et al., 2022. Ecological-health risks assessment and source apportionment of heavy metals in agricultural soils around a super-sized lead-zinc smelter with a long production history, in China. Environ. Pollut. 307, 119487.

Zhou, W., Dan, Z., Meng, D., Zhou, P., Chang, K., Zhuoma, Q., et al., 2023. Distribution characteristics and potential ecological risk assessment of heavy metals in soils around Shannan landfill site, Tibet. Environ. Geochem. Health 45 (2), 393–407.

Zhou, S., Wang, X., Yang, Y., Wang, R., Liao, J., Zhang, P., et al., 2024a. Distribution and source identification of polycyclic aromatic hydrocarbons (PAHs) with PCA-MLR and PMF methods in the topsoil of Chengdu at SW, China. Sci. Total Environ. 908, 168263.

Zhou, Y., Ding, D., Zhao, Y., Li, Q., Jiang, D., Lv, Z., et al., 2024b. Determining priority control toxic metal for different protection targets based on source-oriented ecological and human health risk assessment around gold smelting area. J. Hazard. Mater. 468, 133782.

Zhou, Y., Feng, F., Sun, J., Shan, Y., Su, W., Shang, W., et al., 2024c. Distribution and source analysis of soil toxic organic compounds of coal-electricity production base in arid and semi-arid region of China. J. Hazard. Mater. 477, 135317.

Zuber, S.M., Behnke, G.D., Nafziger, E.D., Villamil, M.B., 2017. Multivariate assessment of soil quality indicators for crop rotation and tillage in Illinois. Soil Tillage Res. 174, 147–155.