

Soil and Sediment Contamination: An International Journal

ISSN: 1532-0383 (Print) 1549-7887 (Online) Journal homepage: www.tandfonline.com/journals/bssc20

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To cite this article: Benjamin Darko Asamoah, Barnabas Awortwe, Lawrence Sheringham Borquaye, Matt Dodd & Godfred Darko (13 Oct 2025): Source Apportionment of Potentially Toxic Elements in Topsoils Across Some Mining-Impacted Communities in Ghana Using the Positive Matrix Factorization Model, Soil and Sediment Contamination: An International Journal, DOI: 10.1080/15320383.2025.2574273

To link to this article: https://doi.org/10.1080/15320383.2025.2574273

Published online: 13 Oct 2025.

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https://doi.org/10.1080/15320383.2025.2574273

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Source Apportionment of Potentially Toxic Elements in Topsoils Across Some Mining-Impacted Communities in Ghana Using the Positive Matrix Factorization Model

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ABSTRACT

In this study, we employed the positive matrix factorization receptor model to ascertain whether the prevalence of potentially toxic elements in surface soils of two mining communities in Ghana is exclusive to mining. At the two mining communities (Kenyasi and Obuasi), 49 samples were taken at each location, whereas 90 soil samples were collected from Sunyani, the non-mining community. All the soil samples were screened for elemental concentrations using the Niton XL3t GOLDD+ field portable X-ray fluorescence spectrometer. The positive matrix factorization model was set to three factors in the base model for the analyses, and the receptor model revealed three major contributing factors to the metal pollution in the study areas. Although mining activities contributed to As, Cd, Cu, Ni, and Pb in Kenyasi, a typical mining community, farming activities also contributed significantly to the presence of Zn and Cd in the surface soils. At Obuasi, construction works and geogenic factors were responsible for the enrichment of Cr and Cu in the surface soils, farming activities accounted for the Mn, Pb, and Zn contamination, and As, Cd, and Ni contamination by mining activities. In Sunyani, the non-mining community, the model revealed that the contamination of the soil by Cd, Mn, Ni, and Pb was primarily from multiple sources, such as the mass burning of wastes, farming, and construction works within the municipality. The prevalence of Zn in the municipality was attributed to natural origin since the pollution indices showed low contamination of the metal. This study will serve as a scientific reference for the holistic mitigation of soil heavy metal contamination in the study areas.

KEYWORDS

Soil contamination; geogenic factors; source profiles; farming activities; receptor modeling

1. Introduction

Metal contamination in soils, particularly in mining-impacted areas, is a significant global environmental issue due to its high toxicity, persistence, and inability to biodegrade (Dodd et al. 2023). The accumulation of these element concentrations in surface soils can affect surface and groundwater, eventually entering the food chain and posing risks to human health (Angon et al. 2024). The negative health effects of potentially toxic metals are significant, especially for children and other vulnerable groups in the community. For

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instance, long-term mercury exposure can result in neurological harm, cognitive impairments, and developmental delays in children (Gao et al. 2018). Extended lead exposure can impede cognitive development, reduce IQ, and lead to behavioral problems in children (Kyene et al. 2023). In adults, lead exposure is linked to high blood pressure, kidney damage, and reproductive issues (Assi et al. 2016). There is compelling evidence suggesting that cadmium exposure, often from smoking or industrial activities, is associated with kidney damage, bone loss, and an increased risk of osteoporosis (Tellez-Plaza et al. 2013).

Human activities like mining, urbanization, and agriculture play a pivotal role in releasing toxic metals into the environment. Mining often extracts metals like As, Hg, and Pb, which can pollute nearby soil, water, and air (Karn et al. 2021). Urbanization adds to pollution through industrial processes, vehicle emissions, and improper waste disposal, introducing harmful metals like cadmium and chromium into ecosystems (Sun et al. 2019). Similarly, excessive use of fertilizers and pesticides in farming leads to the buildup of metals such as copper, zinc, and nickel in soil and water (Aradhi et al. 2023). These toxic metals can contaminate food chains, harm ecosystems, and cause long-term damage to natural resources, posing serious risks to both human health and the environment.

In Ghana, severe soil pollution from mining has been noted, largely due to rapid industrialization, urbanization, and the high cost of living over recent decades (Adjei et al. 2024). It is estimated that 90% of Ghana's mineral exports are associated with gold mining, positioning gold as the central element of the mining and mineral sector. This industry supports over 200,000 gold workers and approximately one million family members who rely on their income (Ros-Tonen et al. 2021). Mining and related activities have led to the exponential rise of potentially toxic element concentrations in the top soils of the mining-impacted vicinities. For example, Bempah and Ewusi (2016), recorded As and Cd mean levels of 6.83 ± 2.42 mg/kg and 0.19 ± 0.09 mg/kg, respectively, in the Obuasi municipality of Ghana. In less than ten years, the levels of these two metals in the same municipality had risen to 175.14 ± 30.19 6.30 mg/kg in arsenic and 6.30 ± 1.32 mg/kg in cadmium (Darko Asamoah et al. 2024). Due to the detrimental effects caused by mining, particularly artisanal and small-scale (galamsey), the government of Ghana has made pragmatic efforts to halt the activities of the galamsey, but to no avail (Ofori 2023). Some recognized unions in Ghana, such as the University Teachers Association of Ghana (UTAG), embarked on a strike action to compel the government to put a stop to the galamsey menace in Ghana. This research used the positive matrix factorization receptor model to ascertain whether the elevation of elemental levels in soils of mining-impacted areas is exclusively due to mining. Because many environmental studies fail to clearly identify the main sources of pollution and quantify each source's contribution to overall pollution levels, this research utilized the positive matrix factorization technique to bridge that gap.

Positive matrix factorization (PMF) is a widely recognized receptor model extensively utilized for determining the sources contributing to ambient particulate matter mass concentrations (Jain et al. 2020; Li et al. 2020; Song et al. 2021). In recent times, few studies have shifted attention to reporting the source apportionment of metal pollutants using the PMF model, to elucidate the possible sources that contribute to soil pollution rather than particulate matter (Yuan et al. 2020; Zheng et al. 2023). It is important to note that most of the source apportionment studies have been conducted in developed countries (Reff et al. 2007; Song et al. 2019; Gu et al. 2020). However, such studies are crucial in developing countries, including Ghana, due to the rapid growth and related environmental issues.

While traditional methods like principal component analysis (Podlasek et al. 2024) and chemical mass balance (Rejivas et al. 2024) have been employed to identify pollution sources, the positive matrix factorization (PMF) receptor model offers more precise and realistic factors and contribution rates for metal pollutants. PMF is especially advantageous for environmental data analysis as it accounts for the varying uncertainties often found in environmental sample measurements (Gu et al. 2020). Additionally, PMF ensures that all values in the solution profiles and contributions are nonnegative, making it more realistic compared to older methods like principal component analysis (Reff et al. 2007). Therefore, this study aimed to employ the positive matrix factorization model to identify the possible sources of potentially toxic element contamination in surface soils at three different communities in Ghana: two mining areas and one commercial city. The specific objectives of the study are: to identify the possible sources of potentially toxic metal contamination in topsoils of two major mining areas and a commercial city in Ghana, determine the contribution rates of the potentially toxic metal at the three study locations, and compare the results from the PMF receptor model to a spatial distribution pattern at the study areas. The findings of this study can serve as a valuable database for African researchers in estimating the different sources of elemental pollution in different parts of the continent. Additionally, the findings can also aid policymakers in addressing the most harmful sources with the greatest impact, especially in Africa, where literature on the use of the PMF model is scanty.

2. Methodology

2.1. Study areas

The three study communities and the sampling points for this study are shown in Figure 1. The detailed descriptions for the three study areas have already been reported (Asamoah et al. 2023; Darko Asamoah et al. 2024). Briefly, Kenyasi (latitude 6.98° and longitude −2.39°) is a mining community in the Asutifi North District in the Ahafo Region of Ghana. The town is known for Newmont Ghana Ahafo mines and other artisanal small-scale gold mining activities. Farming is the main occupation of the locals, where they primarily cultivate plantain and cassava for their use, with cocoa being the chief cash crop.

Obuasi (latitude 6.2073° and longitude 1.6636°) is also a mining community in the Ashanti Region of Ghana. It is an ancient city due to the several decades of operation of

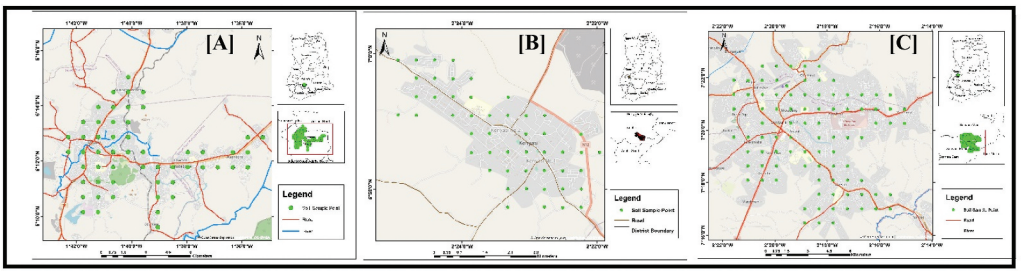


Figure 1. Map showing the sampling points at Obuasi – a mining town [A], Kenyasi – a mining town [B], and Sunyani – a non-mining community [C].

the AngloGold Ashanti mines. The municipality has records of artisanal small-scale gold mining activities, most of which are done illegally, called galamsey. Besides mining, a smaller portion of the Obuasi population engages in petty trading, often selling produce from their farms. Conversely, Sunyani (latitude 7.34° and longitude −2.33°), the capital town of the Bono region of Ghana, has no evidence of large-scale and small-scale mining activities. The town is one of the well-known hubs for commercial activities, including clothing shops, supermarkets, banking and healthcare services, restaurants, and automobile services. Most Ghanaians refer to Sunyani and its environs as the food basket of the nation due to the locals' involvement in farming activities, yielding a great harvest of crops. Almost all the edible foods sold at the marketplaces in Sunyani are directly obtained from the farms of the indigenes.

2.2. Soil sampling

Kenyasi and Sunyani study areas were mapped on a $0.5 \times 0.5\ km^2$ grid net, and Obuasi on a $2 \times 2\ km^2$ grid. Soil samples were taken at coordinate intersections as shown in Figure 1. When original sampling points were inaccessible due to tarred roads or buildings, they were shifted 3 m to the left or right within the same cluster (Akanchise et al. 2020).

A clean, dry shovel was used to collect about 500 g of topsoil (0–15 cm). This depth is assumed to represent the layer most likely to come into contact with humans during daily activities, thereby enhancing the accuracy of human risk assessment (Dodd et al. 2017). The digging implements were scrubbed with detergents and rinsed with deionized water after each sample point to minimize cross-contamination during sampling. At both Kenyasi and Obuasi, 49 soil samples were taken, and 90 from Sunyani. All soil samples were transported to the laboratory and air-dried in a fume hood at room temperature. The dried samples were thoroughly cleaned of debris, stones, and pebbles before being powdered and sieved.

2.3. X-ray fluorescence analysis

Metal concentrations in the samples were initially screened using a Niton XL3t GOLDD+ field-portable X-ray fluorescence (FP-XRF) spectrometer, with results subsequently validated using inductively coupled plasma mass spectrometry (ICP-MS). Quality control during the XRF analysis included the use of NIST 2709a standard reference materials (SRMs), procedural blanks, and recovery tests. Satisfactory recoveries were obtained for As (88 ± 7%), Cd (57 ± 5%), Cr (78 ± 6%), Cu (102 ± 14%), Mn (120 ± 16%), Ni (91 ± 12%), Pb (89 ± 8%), and Zn (107 ± 15%). The repeatability of the analysis, and the variability in the measurement system caused by the measurement device, was assessed using 5 replicates of the reference material and was found to be 4–5%, indicating a high level of reliability (Huang et al. 2023).

2.4. The positive matrix factorization model

The PMF model is a source analysis method grounded in factor analysis technology, initially proposed by Paatero and Tapper (1994). In this study, the EPA PMF 5.0 software (EPA, USA, No: EP-D-09–097) was employed to identify the possible sources of the potentially

toxic elements. This multivariate receptor model was used to solve the chemical mass balance (CMB) Equation 1:

$$X_{ij} = \sum_{k=}^{P} \left(G_{ik} x F_{kj}\right) + E_{ij} \tag{1}$$

X_{ij} represents the level of the jth element in the ith sample, G_{ik} denotes the relative contribution of the ith sample to the contribution rate of the kth contamination source, F_{kj} is the characteristic value of the Kth pollution source for the ith concentration of elements, E_{ij} is the residuals, and P is the number of factors. Here, i, j, and k, can be 1, 2, 3, etc. The PMF receptor model aims to determine the most suitable factor profile and contribution by minimizing the objective function, Q using Equation 2:

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{m} \left(\frac{E_{ij}}{U_{ij}}\right)^2 \tag{2}$$

Here, *n* denotes the number of samples, *m* represents the number of species, and Uij indicates the uncertainty in the measured concentration for the ith sample and the jth species. The minimization is conducted under the constraint that source profiles and contributions must be non-negative (Brown et al. 2015). The uncertainty is determined using Equation 3:

$$U_{ij} = \sqrt{(\delta xc)^2 + (0.5 x MDL)^2} \tag{3}$$

where δ signifies the error fraction, c indicates the concentration of the metal, and MDL refers to the method detection limit (Liu et al. 2022). The PMF model can utilize user-supplied uncertainty for each measured sample, giving the model insight into the confidence level of the environmental measurements (Song et al. 2019).

2.5. Q-value

The Q-value in the EPA PMF model quantifies the model's fit to the data. It was used to evaluate the model's quality by showing how well it explains the observed data. Typically, a lower Q value signifies a better model fit. Table 1 shows the lowest Q-value of each potentially toxic element in the study areas.

Table 1. The Q-value of each metal in the study locations.

	Q-value		
Element	Kenyasi	Obuasi	Sunyani
As	0.00	0.14	0.78
Cd	1.74	0.68	0.86
Cr	0.87	0.00	6.74
Cu	0.84	3.40	4.78
Mn	0.00	2.87	20.69
Ni	0.00	0.00	0.08
Pb	0.84	1.13	0.66
Zn	0.00	0.03	0.00

2.6. Quality control and quality assurance

The input data was reviewed and cross-checked for errors and inconsistencies before loading it into the software. The model was set up correctly and with all parameters and inputs entered as intended. The optimal number of factors was identified by evaluating the Q/Qexp value and the interpretability of the factors. The model's validity was supported by signal-to-noise ratios (S/N) classified as strong, exceeding 8. Additionally, with coefficients of determination (r^2) greater than 0.80, the model effectively predicted the high measured data for each potentially toxic element. This indicates that the results are reliable and the PMF model parameters are appropriately selected. Thus, this model is suitable for explaining the origins of the potentially toxic elements in the soil within the study areas.

3. Results

The descriptive statistics for each potentially toxic element at the three study areas are presented in Table 2. To determine the source contributions of the potentially toxic elements and associated risks, the PMF method was employed. For each study area, a three-factor solution provided the most coherent source profiles for the identification of the possible sources of elemental contamination.

3.1. The positive matrix factorization model for Kenyasi

The PMF model was set to three factors in the base model for the analysis. Figures 2 and 3 are the source profiles and factor fingerprints for the potentially toxic elements at Kenyasi, respectively. Table 3 also represents the contribution rates for the identified sources of the potentially toxic elements.

Table 2. Descriptive statistics of potentially toxic elements (mg/kg) across the three study locations.

		As	Cd	Cr	Cu	Mn	Ni	Pb	Zn
Kenyasi,	Minimum	≤2.40	≤4.48	14.07	≤9.23	43.22	15.74	3.10	12.27
mining community	Maximum	20.24	37.75	278.97	179.75	1422.10	255.48	19.19	918.35
n = 49	Mean	7.31	17.32	55.48	33.09	507.30	52.25	6.09	159.19
	Standard deviation	4.48	8.86	49.14	29.66	47.21	45.89	3.35	33.82
Obuasi,	Minimum	11.16	4.57	10.15	8.77	36.92	15.28	2.92	13.84
mining community	Maximum	1360.58	11.43	249.18	361.01	958.97	112.48	739.48	2814.75
n = 49	Mean	175.1	6.30	75.45	36.22	228.19	33.05	24.22	124.06
	Standard deviation	30.19	1.32	4.72	5.10	20.93	1.99	10.69	40.03
Sunyani,	Minimum	≤2.21	≤4.98	8.26	8.80	134.11	16.13	2.83	13.06
non-mining community	Maximum	13.12	19.77	325.38	82.29	1573.93	81.14	110.67	229.20
n = 90	Mean	4.31	7.04	71.24	24.52	571.05	28.79	5.61	57.45
	Standard deviation	2.25	4.19	46.19	13.63	26.93	14.75	1.52	17.74
CCME (2007)		12	10	64	63	–	45	70	200
Control sample		0.02	0.01	5.61	1.02	34.03	1.78	1.16	1.76
T		5.263	10.152	−1.880	2.331	−1.122	4.457	0.284	3.990
p-value		0.000	0.000	0.062	0.021	0.060	0.000	0.777	0.000

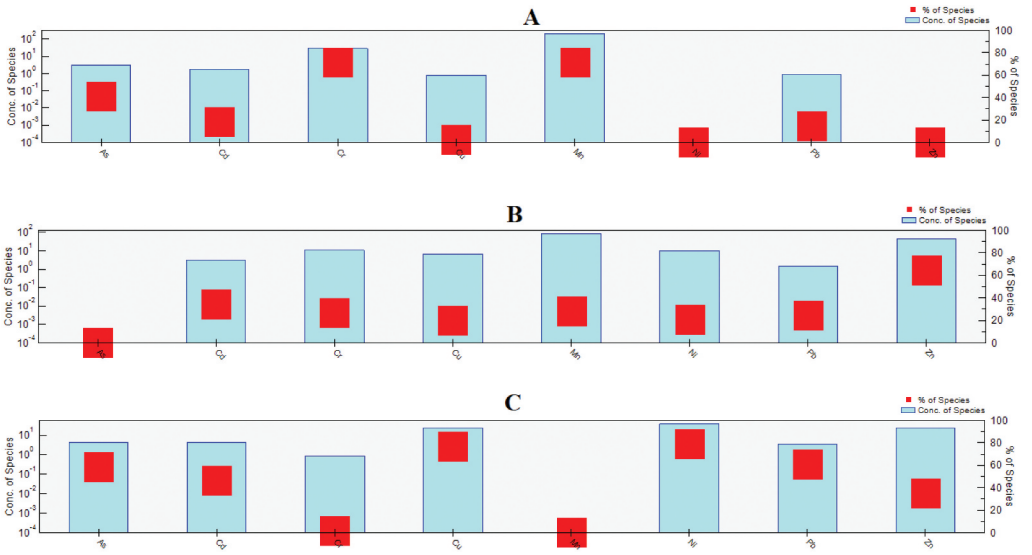


Figure 2. Source profiles of the potentially toxic metals in Kenyasi, showing Factor 1 [A], Factor 2 [B], and Factor 3 [C].

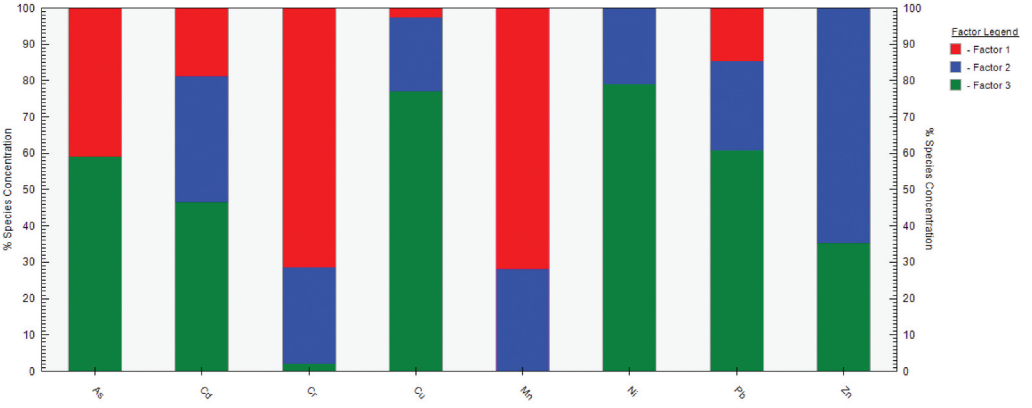


Figure 3. Factor fingerprints of the potentially toxic metals in the Kenyasi surface soils.

Table 3. Contribution rates of potentially toxic metals in Kenyasi.

Metal	Factor (1%)	Factor (2%)	Factor (3%)
As	41.0	0	59.0
Cd	18.8	34.7	46.4
Cr	71.3	26.6	2.1
Cu	2.6	20.3	77.1
Mn	71.8	28.2	0
Ni	20.9	0.0	79.1
Pb	14.7	24.5	60.8
Zn	0	64.6	35.4

Mn and Cr showed contribution rates of 71.8% and 71.3%, respectively, making them the dominating metals of Factor 1. Factor 2 was, however, linked to Zn and Cd with contribution rates of 64.6% and 34.7%, respectively, making them the primary contributors to this source component compared to the other six potentially toxic metals. Factor 3 showed higher contributions of As, Cu, Ni, Pb, and Cd compared to the other two sources, with respective contribution rates of 59.0%, 77.1%, 79.1%, 60.8%, and 46.4%.

3.2. The positive matrix factorization model at Obuasi

Figures 4 and 5 show the source profiles and factor fingerprints for the potentially toxic metals at Obuasi, respectively. Table 4 also shows the contribution rates for the identified sources of the potentially toxic metals.

The PMF receptor model identified Cr and Cu as the major contributors to factor 1, contributing 77.5% and 45.2%, respectively. As, Ni and Cd dominated Factor 2 with contribution rates of 75.3%, 70.7%, and 48.4%, respectively. Factor 3 was associated with Mn, Pb, and Zn, contributing 68.4%, 54.0%, and 71.7%, respectively, making them the prime contributors to this source component relative to the other five potentially toxic metals.

3.3. The positive matrix factorization model at Sunyani

The source profiles and factor fingerprints for the potentially toxic metals at Sunyani are shown in Figures 6 and 7, respectively. The factor contribution rates for each potentially toxic metal are also summarized in Table 5.

For the commercial city, Cd, Mn, Ni, and Pb made significant contributions to factor 1 with 61.3%, 85.9%, 76.5%, and 49.2% rates, respectively. Four out of the eight potentially

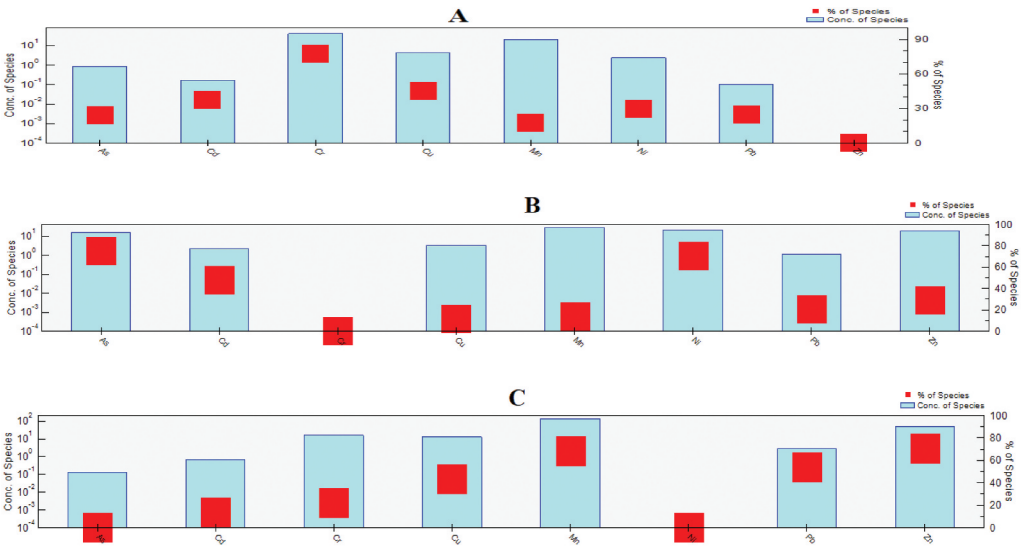


Figure 4. Source profiles of the potentially toxic metals in Obuasi, showing Factor 1 [A], Factor 2 [B] and Factor 3 [C].

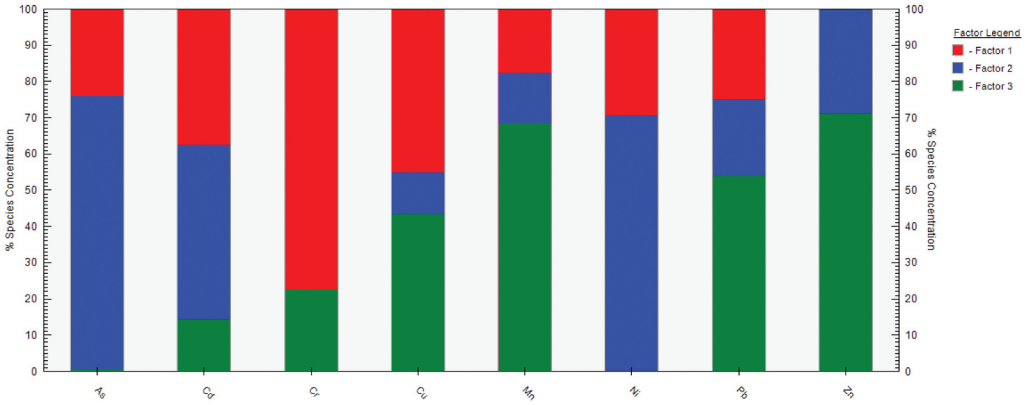


Figure 5. Factor fingerprints of the potentially toxic metals in the Obuasi surface soils.

Table 4. Contribution rates of the potentially toxic metals in Obuasi.

Metal	Factor (1%)	Factor (2%)	Factor (3%)
As	24.0	75.3	0.7
Cd	37.4	48.4	14.3
Cr	77.5	0.0	22.5
Cu	45.2	11.4	43.5
Mn	17.5	14.1	68.4
Ni	29.3	70.7	0.0
Pb	24.9	21.1	54.0
Zn	0.0	28.9	71.7

toxic metals linked to factor 1 are the highest among the three factors. This means that the PMF model has identified factor 1 as the most contributing source to the contamination of the Sunyani surface soil. Factor 2, on the other hand, identified only Zn as the major contributor by the PMF receptor model, recording the highest contribution rate of 75.4%. In contrast, As, Cr, and Cu were linked with the considerable contributors of factor 3, contributing 68.7%, 69.9% and 64.4% respectively.

4. Discussions

4.1. Factor analyses for the metals at Kenyasi

Factor 1 was dominated by Mn and Cr, and this can be attributed to geogenic sources. Manganese is a naturally occurring element that is commonly found in rocks, water, and soil. Emissions from industries, fossil fuel combustion, and soil erosion release manganese into the environment (Kostova 2023). Mn is a reliable tracer and marker of vehicular emissions, as noted by Taghvaee et al. (2018). In a previous study by Asamoah et al. (2023) at Kenyasi, the pollution and ecological risk indices indicated that Cr and Mn pose low pollution and ecological risks, suggesting minimal impact from anthropogenic activities across the study area. In that same research, the average concentrations of Cr and Mn in soils were below their respective CCME guidelines (CCME 2007), indicating a natural background source. Additionally, spatial analysis of Mn did not show a clear point source

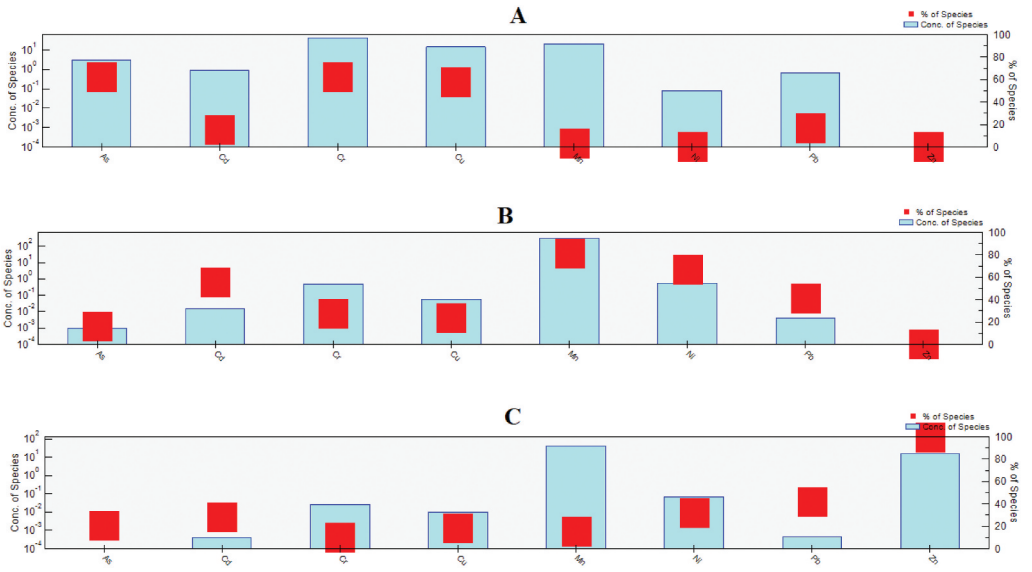


Figure 6. Source profiles of the potentially toxic metals in Sunyani. A – Factor 1, B – Factor 2, and C – Factor 3.

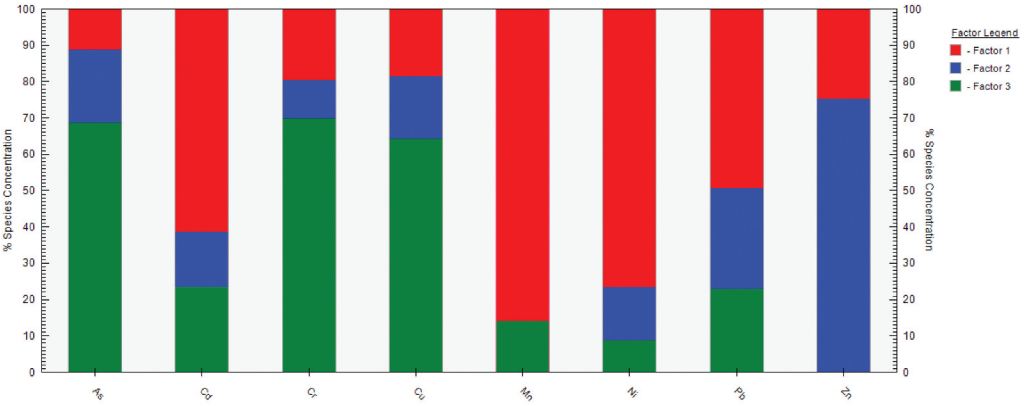


Figure 7. Factor fingerprints of the potentially toxic metals in the Sunyani surface soils.

Table 5. Contribution rates of the potentially toxic metals in Sunyani.

Metal	Factor (1%)	Factor (2%)	Factor (3%)
As	11.1	20.3	68.7
Cd	61.3	15.1	23.6
Cr	19.6	10.5	69.9
Cu	18.6	17.0	64.4
Mn	85.9	0.0	14.1
Ni	76.5	14.8	8.8
Pb	49.2	27.7	23.1
Zn	24.6	75.4	0.0

contamination, implying a natural origin of the metal (Asamoah et al. 2023). The low PMF contributions of other metals suggest they are less affected by human activities. For instance, zinc's 0% contribution to Factor 1 indicates its concentration is too low to be significant. Overall, the majority of the Cr and Mn elements appear to originate from natural sources influenced by the parent material of the soil. Thus, Factor 1 is identified as the geogenic source.

Factor 2 was characterized by high contributions of zinc (Zn, 64.6%) and cadmium (Cd, 34.7%). Accumulation of zinc in soils has been attributed to the application of fertilizers, especially those that contain zinc as a micronutrient (Li et al. 2019). Additionally, some pesticides, herbicides, and animal manure contain zinc as an active ingredient or additive. Constant use can lead to elevated levels of zinc in the soil (Huang et al. 2019). In a previous study at Kenyasi (Asamoah et al. 2023), the average zinc concentration (159.19 mg/kg) was about twice as high as the Clarke value of 71 mg/kg (Burchfiel 1983), but slightly lower than the CCME soil quality guidelines of 200 mg/kg (CCME 2007), indicating anthropogenic influence. The Spatial distribution map of the potentially toxic metals in the study area showed higher zinc concentrations in the middle belt of Kenyasi, where more residents live and undertake their farming activities (Asamoah et al. 2023). Similar to zinc, cadmium can infiltrate the soil when animal manure or biosolids (treated sewage sludge) containing cadmium are applied, and the use of phosphate fertilizers containing cadmium (Haider et al. 2021). This could explain the 34.7% contribution of cadmium to factor 2. Due to the agricultural activities in Kenyasi contributing to the elevated levels of Zn and slightly Cd, farming is primarily responsible for factor 2.

Factor 3 involves higher levels of As, Cu, Ni, Pb, and Cd compared to the other two sources. These values are consistent with a previous study conducted on Kenyasi surface soils, which revealed high contamination of Cd and moderate contamination of As, Ni, and Pb (Asamoah et al. 2023), indicating an influence of anthropogenic stress. The spatial distribution map also showed higher concentrations of Cd, Cu, Ni, and Pb in the south-eastern corridor, near the main road where miners use and have ongoing building projects (Asamoah et al. 2023). Within this zone is an auto mechanic shop highly patronized by the miners. This may explain the elevated levels of the metals as indicated by the positive matrix factorization model due to auto-electrical and mechanical activities like soldering and welding (Nna Orji et al. 2018). Lead (Pb) pollution in various environmental media, including dust and soil, is primarily caused by transport emissions, as Pb is used in automobile parts and was previously added to gasoline (Deng et al. 2022). Therefore, factor 3 is identified as mining and related activities.

4.2. Factor analyses for the metals at Obuasi

The PMF receptor model identified Cr and Cu as the dominant metals and major contributors to factor 1. Chromium is commonly present in construction materials, especially stainless steel, cement, and paints (Gardner 2010). When chromium-containing materials are used in building and infrastructure projects, there is a risk of environmental release, particularly during demolition activities (Gardner 2010). In contrast, copper is extensively utilized in construction for electrical wiring, plumbing pipes, and roofing (Agrawal and Verma 2021). The processes of installing, cutting, or removing these materials can result in copper particles being released into the soil. A previous study at the Obuasi municipality

(Darko Asamoah et al. 2024), revealed low contamination and enrichment of Cr and Cu in the surface soils with geoaccumulation values of −0.35 and −0.21, respectively. The spatial distribution pattern from the study also showed significant concentrations of Cr and Cu in the northern zone of the municipality, where lots of construction works have been carried out. Therefore, the presence of Cr and Cu could be from a natural origin with minimal anthropogenic inputs. Factor 1 is therefore attributed to geogenic contribution and construction works.

The dominant contributors to Factor 2 were As, Ni, and Cd, accounting for 75.3%, 70.7%, and 48.4% of the total contribution, respectively. These are metals commonly associated with artisanal and small-scale mining (Hilson and Pardie 2006). This assertion is consistent with the extremely high contamination of As and Cd, as reported by (Darko Asamoah et al. 2024), with enrichment factor values of 216.70 and 38.94, respectively. In that study, the As and Cd mean levels (175.14 ± 30.19 and 6.30 ± 1.32) mg/kg were about 5000 and 300 times higher than those of the reference site (0.03 and 0.02) mg/kg, respectively, indicating a strong influence by human activities. The previous study also found that As, Cd and Ni were concentrated around the southern and eastern corridors of the municipality, where some illegal miners were spotted on site (Darko Asamoah et al. 2024). The above observations are consistent with other works carried out in mining-impacted areas in Ghana (Gyam et al. 2019; Opoku et al. 2020). Thus, factor 2 reflects mining sources.

Factor 3 showed a strong association with Mn, Pb, and Zn, highlighting these elements as the key contributors to this source component compared to the other five potentially toxic metals. Although Mn and Zn are essential micronutrients for plant growth, excessive levels can occur as a result of the use of some fertilizers that contain these metals, impeding plant growth (Francová et al. 2020; Zhao et al. 2023). Lead accumulation in topsoil usually results from historical use of lead-based pesticides, industrial activities, and urban runoff (Nezat et al. 2017). Previous research by Bempah and Ewusi (2016), indicated high levels of the metals in groundwater samples in Obuasi, which may have entered the topsoil through irrigation practices (Abedi et al. 2023). Factor 3, therefore, is identified as a farming source from the PMF model.

4.3. Factor analyses of the metals at Sunyani

Factor 1 is the primary source contributing to surface soil contamination in the commercial city of Sunyani. Factor 1 showed significant contributions from Cadmium (Cd), Manganese (Mn), Nickel (Ni), and Lead (Pb), with contribution rates of 61.3%, 85.9%, 76.5%, and 49.2%, respectively. Notably, Cd, Mn, Ni, and Pb, out of the eight potentially toxic metals, recorded the highest values across all three factors. This could be due to many anthropogenic activities, such as farming, construction, and the mass burning of waste within the municipality (Agbeshie et al. 2020). This assertion is consistent with the spatial distribution map of the potentially toxic metals across the municipality, as reported by Asamoah et al. (2023). The distribution pattern showed considerable concentrations of Cd, Mn, Ni, and Pb in the southern sector of the city, where the above-mentioned activities are prevalent. Thus, factor 1 for this area can be attributed to mixed sources of contamination.

In contrast, the PMF model revealed only Zn as the prime contributor to factor 2. Even with the highest contribution rate of 75.4% for factor 2, zinc's average concentration of

159.19 mg/kg as reported by Asamoah et al. (2023), was lower than the Canadian soil quality guideline value of 200 mg/kg (CCME 2007), indicating background levels of Zn metal. With the minimal contributing rates of the other metals, such as 0.0% of Mn, 10.5% of Cr, and 14.8% of Ni, it can be concluded that these metals are of natural origin. Therefore, factor 2 is identified with a geogenic source.

Conversely, As, Cr, and Cu were the major contributors to factor 3. A spatial distribution map showed a significant concentration of these potentially toxic metals in the middle zone of the municipality, where vehicular emissions are prevalent (Asamoah et al. 2023). Road traffic can introduce various metal sources into the environment. These include combustion byproducts from fuel and oil, wear particles from tyres, brake linings, bearings, and clutches, corrosion of vehicle parts and road construction materials, as well as the resuspension of soil and road dust (Hui et al. 2017). Furthermore, around the middle belt of the Sunyani municipality are the main 200-acre auto-mechanic workshops of the municipality. Tyre and brake wear, oil spills, engine repairs, car straightening, and erosion of roads may have contributed to the high levels of these metals (Asamoah et al. 2021). Due to the above-mentioned activities, vehicular emissions are solely responsible for factor 3.

4.4. Remediation techniques for potentially toxic elements contamination

The primary goal of remediation strategies is to restore a healthy ecosystem that supports both human and animal life. The choice of treatment method depends on the chemical and physical characteristics of the potentially toxic elements involved (Wuana and Okieimen 2011). To prevent the spread of heavy metal contaminants in soil and water, a variety of treatment approaches are used. These include physical, chemical, and biological processes to effectively remove or stabilize metals.

Physical remediation techniques include: soil replacement, ion exchange, membrane filtration, and thermal desorption (Karn et al. 2021). Examples of chemical remediation processes are: chemical precipitation, chemical leaching, immobilization, and chemical fixation (Haider et al. 2021). Biological remediation techniques involve the use of fungi, bacteria, and plant species (phytoremediation) in bioremediation (Ali 2023).

5. Conclusion

This study efficiently employed the positive matrix factorization model to ascertain the possible sources and contribution rates of eight potentially toxic metal contaminants in the surface soils of two mining communities and a commercial city in Ghana. At Kenyasi, a mining community, the PMF model confirmed mining activities as the major contributing source to As, Cu, Ni, Pb, and Cd. Farming activities contributed significantly to Zn metal, whereas geogenic factors were responsible for Mn and Cr metals. Again, the model showed mining and its related activities as the prime contamination source of As, Ni, and Cd, in Obuasi, whereas farming and geogenic factors contributed significantly to the remaining metals. In the commercial city, the receptor model identified vehicular emissions as the source of As, Cr, and Cu contamination whereas burning of wastes and construction works were linked with Cd, Mn, Ni, and Pb enrichment, with Zn associated with geogenic contributions. Comparing the PMF receptor model results from this study to the spatial distribution patterns of the potentially toxic metals from previous research conducted

within the study areas, the different factors were confirmed as the contributing sources of the potentially toxic elements. It is recommended that other multivariate analytical tools be used to confirm the source apportionment of these potentially toxic elements at the three study locations.

Acknowledgments

We thank the Sheathe project team for providing us with laboratory space and instrumentation.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The authors did not receive any direct funding for this research.

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