



# Analysis of heavy metal concentrations in soil using Kriging technique using remote sensing data

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## Abstract

The study addresses the challenging task of estimating toxic concentration in soils, focusing on Tirupur District, Tamilnadu, India, utilizing Landsat 8 imagery. Acknowledging the potential environmental repercussions, the research emphasizes the increase in pollution—air, water, and soil—due to toxic concentrations, particularly heavy metals resulting from industrial activities. Soil pollution, a consequence of rapid industrial development near water sources, is a key concern, exacerbated by improper waste disposal. Utilizing Landsat 8 OLI images and relevant soil standards, the study employs Kriging and regression analysis for mapping heavy metal concentrations in the soil, both through remote sensing and field data. The correlation between remote sensing and in-situ data enhances result reliability. The findings categorize soil samples from 17 locations in Tirupur District based on pollution levels, distinguishing regions as highly polluted, not polluted, or moderately polluted. This research contributes valuable insights into the spatial distribution of heavy metal pollution, offering a foundation for targeted environmental management strategies in the identified regions.

**Keywords** Heavy metal concentration · Kriging · Regression analysis · Remote sensing

## 1 Introduction

The increasing concern over environmental pollution, specifically toxic concentrations in soil, necessitates precise estimation methods. This study delves into the challenging task of evaluating toxic concentration, focusing on Tirupur District, Tamilnadu, India. Leveraging Landsat 8 imagery, we explore the repercussions of heightened pollution in soil. Of particular interest is the impact of heavy metal concentrations, often associated with industrial activities. Soil pollution, exacerbated by the rapid growth of industries near water sources, poses a significant threat. Accumulation of heavy metals in agricultural soils poses a threat to crop growth and poses potential risks to human health [1–3]. This phenomenon

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is primarily attributed to industrial waste, discharge from dyeing outlets, and the presence of sewage sludge [4–6]. Kachenko and Singh (2006) [4] employed field sampling in urban and metal smelter-contaminated sites in Australia. Vegetable samples were collected and analyzed for heavy metal concentrations, possibly using methods like atomic absorption spectroscopy. The study concluded with insights into heavy metal contamination levels in vegetables, providing valuable information on potential risks to human health in urban and metal smelter-contaminated areas in Australia. Atafar et al. (2010) [5] implemented a field study to investigate the impact of fertilizer application on soil heavy metal concentrations. The methodology could involve soil sampling pre and post-fertilizer application. Analytical techniques, such as atomic absorption spectroscopy, may have been utilized to assess changes in heavy metal concentrations. The study concluded with findings detailing the effects of fertilizer application on soil heavy metal concentrations, contributing insights into agricultural practices and environmental implications.

Copper and zinc, though present in soil at trace levels, significantly impact human metabolism [7, 8]. Lamsayah et al. (2016) [7] employed liquid–liquid extraction to investigate the selectivity of Fe(II) and Pb(II) using long-chain acid pyrazole- and triazole-based ligands. The study might have involved experimental extraction processes to assess the efficiency and selectivity of the ligands. Theoretical calculations with TD-DFT (Time-Dependent Density Functional Theory) may have complemented the experimental work. The study concluded with insights into the liquid–liquid extraction selectivity of Fe(II) and Pb(II) and supported by theoretical calculations, offering valuable information for metal separation processes. Even trace concentrations of other heavy metals such as Cd, Hg, and Pb in soil can be toxic to humans. Numerous studies have explored heavy metal concentrations in urban waste [9, 10], shedding light on the environmental implications of such pollutants. Umsan et al. (2006) [9] conducted a study on remediating heavy metal-contaminated soil using immobilizing compounds. The methodology have involved applying these compounds to the soil and assessing their effectiveness in reducing heavy metal mobility. Techniques such as soil sampling and analysis, possibly using methods like atomic absorption spectroscopy, may have been employed. It was concluded with insights into the efficacy of immobilizing compounds for remediating heavy metal-contaminated soil.

Additionally, there is a body of research focused on detecting heavy metals in sediment samples [11, 12]. These investigations collectively contribute to our understanding of the widespread impact of heavy metal accumulation in various environmental matrices, emphasizing the need for effective management strategies to mitigate potential hazards to both agricultural productivity and human well-being. Ulrich (2004) [11] adopted an interdisciplinary approach to study sediment dynamics and pollutant mobility in rivers. The methodology probably involved field measurements, sediment sampling, and possibly laboratory analyses. Techniques like sediment coring and analytical methods such as spectrophotometry may have been utilized. It was concluded with interdisciplinary insights into sediment dynamics and pollutant mobility in rivers, contributing valuable information for environmental management and aquatic ecosystem health. Guo et al. (2013) [13] conducted field sampling in the industrial district, collecting soil and agricultural product samples. Laboratory analyses, possibly using techniques like atomic absorption spectroscopy, were employed to determine heavy metal concentrations. This comprehensive approach aimed to assess the impact of industrial activities on both soil and crops. They concluded that it would have highlighted the spatial distribution of heavy metals, potential bioaccumulation, and implications for environmental and food safety in the vicinity of the industrial district.

Fernandez, Seoane, and Merino (1999) [14] employed field sampling in agricultural serpentine soils, assessing plant heavy metal concentrations and soil biological properties. Analytical methods, such as atomic absorption spectroscopy, may have been used. Soil biological properties may have been evaluated through measures like microbial biomass or enzyme activities. It was concluded with insights into the relationships between plant heavy metal concentrations and soil biological properties in serpentine soils, providing valuable information for understanding ecological dynamics. It was observed that there was a decrease in heavy metal concentration in plants and also higher soil microbial activity will lower metal availability in the soil. Tumuklu et al. (2007) [15] employed field assessments to detect heavy metal concentrations in soil impacted by the Nigde City Garbage Dump. Soil samples have been collected and analyzed using techniques such as atomic absorption spectroscopy. It was concluded with findings on the levels of heavy metal contamination in the soil near the Nigde City Garbage Dump, contributing insights into the environmental impact of waste disposal practices. They reported that a modern, organized storage system must be used instead of wild storage system in storing the urban wastes, and recyclable products. Yan et al. (2012) [16] conducted field studies in roadside farmland in Nepal, collecting soil and grass samples. Analytical methods, such as atomic absorption spectroscopy, may have been used to determine heavy metal concentrations. This study concluded with insights into the relationship between heavy metal concentrations in soils and grasses in roadside farmland in Nepal, providing valuable information on potential environmental and health implications.

Yan et al. (2013) [17] conducted field observations in the Qinghai-Tibet Plateau, China, collecting topsoil samples at varying distances from road edges. The regression results revealed that there is a decrease of heavy metals' concentrations with an increase of roadside distance, and the R square values for most of the exponential regression models were larger than 0.9, except for Cr and Co. Analytical methods, potentially including techniques like atomic absorption spectroscopy, were likely employed to determine heavy metal concentrations. The study concluded with insights into the relationships between heavy metal concentrations in roadside topsoil and distance to road edges in the Qinghai-Tibet Plateau, contributing to understanding environmental impacts. Gabarrón et al. (2017) [18] conducted field studies assessing heavy metal concentrations in topsoil and road dust influenced by various industrial activities. Soil and dust samples were probably collected and analysed using techniques like atomic absorption spectroscopy. It was shown that the physicochemical properties of soil and road dust and the bioavailability of all metals had been influenced by the industrial activity. Due to industrial activity, Pb, Zn, Cu and Cr distribution in the different solid phases were affected while Co and Ni distribution were not affected. The study concluded with insights into the impact of diverse industrial activities on heavy metal concentrations and chemical distribution in topsoil and road dust, contributing to understanding environmental implications associated with these industrial processes.

Oluyemi et al. (2008) [19] conducted a study on a Nigerian landfill, analyzing seasonal variations in heavy metal concentrations in soil and selected crops. They examined soil from landfill during the wet and dry seasons and observed that values for Cd, Cu, Fe, Ni, Cr, Zn, Co and Pb were higher than normal levels of a typical agricultural soil and also noted that As (3.20 and 4.13 mg/kg) values were found to be within the acceptable range. Mn values of 597.00–828.37 mgkg<sup>-1</sup> were somewhat above the usual background levels. The study concluded with findings on the seasonal dynamics of heavy metal concentrations in soil and crops at the landfill, providing insights into the environmental impact of waste disposal practices.

Jung (2008) [20] conducted a study near a Korean Cu-W mine, investigating heavy metal concentrations in soils and factors influencing metal uptake by plants stated that the ingredient of plants mainly depends on the total metal concentrations in soils. Soil pH was also considered as an important factor. To identify the metal uptake by the plants, linear multiple regression analysis was executed. The study likely concluded with insights into heavy metal concentrations in soils and the factors influencing metal uptake by plants in the proximity of a Korean Cu-W mine, contributing to understanding the environmental impact of mining activities.

Jung (2008) [20] conducted a study near a Korean Cu-W mine, investigating heavy metal concentrations in soils and factors influencing metal uptake by plants. To identify the metal uptake by the plants, linear multiple regression analysis was executed. The study concluded with insights into heavy metal concentrations in soils and the factors influencing metal uptake by plants in the proximity of a Korean Cu-W mine, contributing to understanding the environmental impact of mining activities. Song et al. (2016) [21] conducted spatio-temporal assessments of heavy metal concentrations in a soil-rice system. This study implies a variation of 43.3% in metal concentrations in soil. This study demonstrated heavy metal concentrations in a soil-rice system due to human intervention in Wenling County. The research concluded with insights into the spatio-temporal variability of heavy metals in the soil-rice system, incorporating socio-environmental analyses for a comprehensive understanding of the dynamics. Song et al. (2016) [21] conducted spatio-temporal assessments of heavy metal concentrations in a soil-rice system. The study probably involved field sampling over time, with soil and rice samples analyzed using techniques such as atomic absorption spectroscopy. This implies a variation of 43.3% in metal concentrations in soil. This study demonstrated heavy metal concentrations in a soil-rice system due to human intervention in Wenling County. The research concluded with insights into the spatio-temporal variability of heavy metals in the soil-rice system, incorporating socio-environmental analyses for a comprehensive understanding of the dynamics.

El Behairy et al. (2022) [22] combined GIS and multivariate analysis to assess soil heavy metal contamination in arid zones. The methodology includes spatial data analysis, field sampling, and the application of statistical methods for multivariate analysis. This study concluded with insights into soil heavy metal contamination in arid zones, utilizing a combination of GIS and multivariate analysis. The research contributed to a comprehensive understanding of the spatial distribution and factors influencing heavy metal contamination in these regions. Wang et al. (2022) [23] conducted environmental risk assessments on municipal solid waste landfills, analyzing factors influencing heavy metal concentrations in the soil. The methodology may involve field sampling, laboratory analyses using techniques like atomic absorption spectroscopy, and a comprehensive assessment of environmental risk factors. The study concluded with insights into the environmental risk associated with heavy metal concentrations in landfill soil, contributing to waste management strategies and understanding factors influencing soil contamination. Jiji G. Wiselin [24] conducted a study on heavy metal concentration analysis in Tirupur, India, using a spectral mixture modelling approach and regression. The research employed these techniques to assess the distribution of heavy metals. The combined use of spectral mixture modelling and regression provides a robust methodology for understanding and mapping heavy metal pollution in the region. In the study, Fan et al. (2021) [25] developed a hybrid approach for short-term electricity load forecasting. They employed a combination of Support Vector Regression (SVR) with grey catastrophe modeling and Random Forest. The SVR captures non-linear patterns, while grey catastrophe modeling accounts for uncertain factors. Random Forest enhances predictive accuracy. The hybrid model showcases improved performance, demonstrating its

potential for enhancing short-term electricity load forecasting in utility contexts. The study by Akkem et al. [26] explores smart farming's integration with artificial intelligence (AI). Their methodology involves a comprehensive review of existing literature on AI applications in agriculture. They analyze key findings to draw conclusions about the current state of smart farming, emphasizing its potential benefits. This article contributes insights that can inform the ongoing development of AI technologies in agriculture, fostering sustainable and efficient practices. Akkem et al. presented [27] a study on smart farming monitoring employing Machine Learning (ML) and MLOps. Their methodology involves the application of ML algorithms for data analysis in agricultural settings. They highlight the integration of MLOps for efficient model deployment and management. The conclusions underscore the effectiveness of ML and MLOps in enhancing smart farming practices, emphasizing the potential for improved monitoring and decision-making in agriculture.

Urbanization poses a significant threat to the delicate balance between human activities and land in Tirupur district, Tamilnadu. Agricultural lands along rivers have become highly contaminated with heavy metals, necessitating urgent and precise estimation. Employing Remote Sensing Data for heavy metal concentration estimation proves time and cost-effective compared to traditional laboratory analyses. However, previous attempts using remote sensing data for heavy metal inversion have fallen short of expectations. In this study, we utilize the kriging and regression analysis methods to enhance the accuracy of estimating and classifying various heavy metal concentrations in soil. Notably, improvements in accuracy are evident, particularly in cultivated areas, offering a promising step toward effective environmental monitoring.

The current level of GIS-based classification methods for heavy metal pollution reflects a sophisticated integration of spatial analysis, statistical techniques, and remote sensing technologies. Advanced GIS tools and modeling approaches contribute to the ongoing refinement of these methods, allowing for more accurate and detailed assessments of heavy metal pollution across different spatial scales. The application of machine learning algorithms within GIS is also emerging as a promising direction for future research in this field. The objective of this study is to assess and estimate the concentration of toxic elements, particularly heavy metals, in the soil of Tirupur District, Tamilnadu, India, using Landsat 8 imagery. The study aims to investigate soil pollution, particularly in areas with rapid industrial development near water sources, exacerbated by improper waste disposal practices. By utilizing Landsat 8 OLI images and relevant soil standards, the research employs Kriging and regression analysis for mapping heavy metal concentrations, both through remote sensing and field data. The goal is to enhance the accuracy of estimation and provide valuable insights into the spatial distribution of heavy metal pollution in order to inform targeted environmental management strategies in the identified regions.

Section 2 details the Methodology, outlining the approaches and procedures used in the study. Section 3 encompasses the Results and Discussion, presenting empirical findings and engaging in analytical discourse. Finally, Section 4 encapsulates the Conclusion, summarizing key insights drawn from the research.

## 2 Methodology

In this research, aimed to categorize the concentration of heavy metal pollutants as high, medium, and normal. To achieve this goal, gathered in-situ data and obtained Landsat 8 OLI satellite images from the study area. These datasets

are then compiled and subjected to analysis through both statistical methods and machine learning approaches. The structural design of the proposed work is illustrated in Fig. 1.

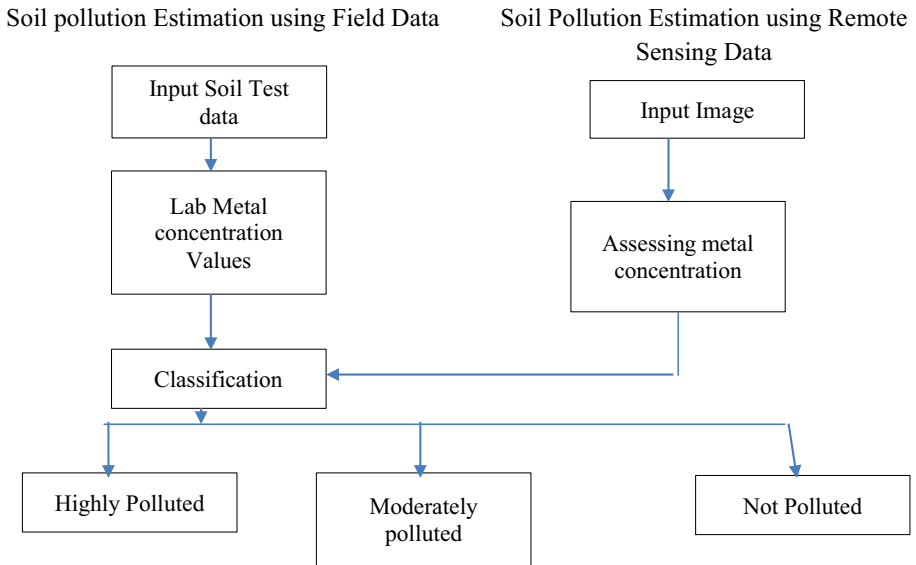


Fig. 1 Block diagram of the methodology

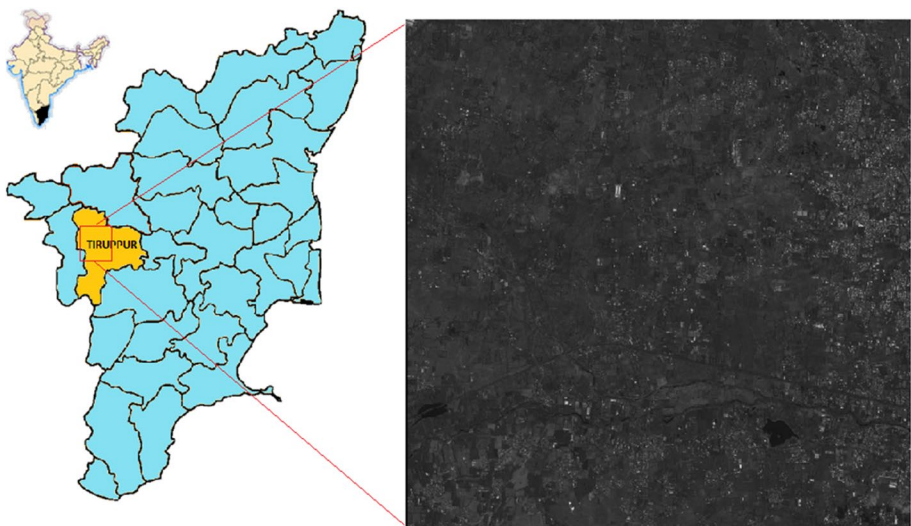


Fig. 2 Study area map showing Pan image acquired on 20.<sup>th</sup>August, 2016

## 2.1 Study area

The study area selected for investigation is Tirupur District in Tamilnadu, India, as illustrated in Fig. 2. A total of 17 soil samples were collected from various locations within this district. The notable presence of dyeing industries situated near the river is identified as a significant contributor to pollution, manifesting in the observed soil pollution in the study area.

### 2.1.1 Input images and data

A total of 17 soil samples were gathered from various locations in Tirupur, and corresponding remote sensing satellite images (Cartosat 2—panchromatic image) for the same region were obtained through the assistance of the National Remote Sensing Centre (NRSC) in Hyderabad. Additionally, standard international values for heavy metals were collected for reference. To determine the heavy metal concentration in the samples, ICP OES tests were conducted at IIT Madras. In our study, the kriging technique is employed for extracting feature descriptors to categorize the region (Table 1).

**Estimation (Kriging)** Geostatistical methods play a crucial role in evaluating and mapping the characteristics of objects in areas where direct sampling may not be available. One such prominent geostatistical technique is Kriging, a statistical interpolation method widely employed in spatial analysis [14, 15]. Kriging aims to provide optimal estimations by leveraging the structural information derived from the reflectance of sampled data and the spatial relationships between sample points. The implementation of Kriging involves assessing

**Table 1** List of 17 soil samples collected locations and their latitude and longitude positions

S.NO	Locations	Latitude	Longitude
S1	Gsnapathipalayam, Palladam- Dharapuram Road, TirupurDist	10° 51' 52.34" N	77° 24' 58.10" E
S2	Meddukatai, Palladam- Dharapuram Road, TirupurDist	10° 52' 38.32" N	77° 23' 7.82" E
S3	Kallakinar, Palladam- Dharapuram Road, TirupurDist	10° 57' 11.26" N	77° 19' 14.63" E
S4	Panapalayam, Palladam, TirupurDist	10° 59' 13.77" N	77° 17' 51.73" E
S5	Mullai Nagar, Palladam, TirupurDist	10° 59' 28.80" N	77° 17' 0.56" E
S6	Karanampettai, Tiruchi Road NH67, TirupurDist	11° 0' 51.57" N	77° 11' 16.31" E
S7	Sulur, TirupurDist	11° 2' 7.43" N	77° 8' 31.51" E
S8	Sulur, TirupurDist	11° 2' 3.65" N	77° 8' 31.37" E
S9	Samalapuram, TirupurDist	11° 4' 33.57" N	77° 11' 52.75" E
S10	Pallapalayam, TirupurDist	11° 5' 2.32" N	77° 12' 52.48" E
S11	Noyyal River, Sammandampalayampudur, TirupurDist	11° 6' 23.27" N	77° 14' 49.28" E
S12	Sammandampalayampudur, TirupurDist	11° 6' 21.72" N	77° 13' 59.08" E
S13	Kousika, TirupurDist	11° 6' 43.83" N	77° 15' 46.45" E
S14	Kulathupudur, Tirupur	11° 6' 12.09" N	77° 17' 53.99" E
S15	ChinnandipalayamKulam, Tirupur	11° 6' 13.06" N	77° 17' 50.05" E
S16	ChinnandipalayamKulam, SulthanPeetai, Tirupur	11° 6' 31.86" N	77° 17' 16.64" E
S17	Murugampalayam, Tirupur	11° 4' 23.40" N	77° 19' 11.51" E

the spatial variability of the phenomenon of interest based on the sampled data points. The method considers not only the values at the sampled locations but also the correlations and variations in these values across space. This information is then used to generate predictions for unsampled areas, resulting in a spatially continuous estimation surface. Kriging is used for classifying heavy metal pollution lies in its ability to account for spatial correlation, quantify uncertainty, incorporate variability, adapt to non-linear patterns, and provide optimal estimates. Kriging's unique strengths in handling spatial relationships and uncertainty make it a robust choice for accurately classifying the degree of heavy metal pollution in a given area.

In this specific study, linear Kriging methods, including Ordinary Kriging (OK), Co-Kriging (CK), and Radial Basis Function Kriging (RK), have been employed to estimate soil heavy metal concentrations. These techniques take into account the spatial dependence and covariance structures observed in the sampled data, allowing for a more accurate and detailed prediction of heavy metal concentrations across the entire study area. By utilizing Kriging, this research enhances the precision of estimations and provides a spatially explicit representation of soil pollution, contributing valuable insights for environmental management strategies.

**Ordinary Kriging (OK)** OK is the technique which is calculated based on the assumption that the mean is not known. We calculated the unsampled value  $z(v)$  by considering the linear combination of the neighboring observations:

$$Z_{OK}^*(v) = \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(v) Z(v_{\alpha}) \quad (1)$$

where  $v$  is a vector of spatial coordinates,  $n(v)$  is the number of neighboring sampled values and  $z(v_{\alpha})$  is the observed value at  $v_{\alpha}$ . Ensuring the estimated value to be unbiased and to minimize the estimated variance,  $\lambda_{\alpha}$  that is the weight of the neighboring sampled values, which is obtained by the below equations:

$$\begin{cases} \sum_{\beta=1}^{n(v)} \lambda_{\beta}(v) \gamma(v_{\alpha} - v_{\beta}) - \mu(v) = \gamma(v_{\alpha} - v) \alpha = 1, \dots, n(v) \\ \sum_{\beta=1}^{n(u)} \lambda_{\beta}(uv) = 1 \end{cases} \quad (2)$$

where  $\mu(v)$  is the Lagrange parameter and  $\gamma$  is the semi-variogram and  $\gamma$  is calculated by:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(v) - z(v_{\alpha} + h)]^2 \quad (3)$$

where  $N(h)$  is the number of data pairs for a given distance  $h$ . The estimate variance  $\sigma_{OK}^2(v)$  is given by:

$$\sigma_{OK}^2(v) = \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(v) \gamma(v_{\alpha} - v) - \mu(v) \quad (4)$$

**Cokriging (CK)** CK, derived from ordinary kriging, gives an additional correlated information in the subsidiary variables. The CK estimator of  $z(v)$  with a single auxiliary variable ( $y$ ) is expressed as:

$$Z_{CK}^*(v) = \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(v) Z(v_{\alpha}) + \sum_{\beta=1}^{n(y)} \lambda_{\beta}(v) y(v_{\beta}) \quad (5)$$

where  $\lambda_{\alpha}$  and  $\lambda_{\beta}$  are the weights of the primary and auxiliary variables, and  $n(v)$  and  $n(y)$  are the numbers of neighboring  $y$  samples of the primary and auxiliary variables. The cross variograms are calculated as:



$$\gamma_{z,y}(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(v_{\alpha}) - z(v_{\alpha} + h)] [y(v_{\alpha}) - y(v_{\alpha} + h)] \tag{6}$$

where  $N(h)$  is the number of pairs of  $z(v)$  and  $y(v)$  at a separate distance  $h$ .

**Regression Kriging (RK)** RK, is useful for varying local means that combines regression results of the dependent variable with kriging results of the regression residuals. It uses regression on auxiliary information along with simple kriging with known mean (0) to interpolate the residuals from the regression model. The RK estimation can be described as:

$$Z^*_{RK}(v) = m^*_{RK}(v) + \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(v)Z(v_{\alpha}) \text{ with } R(v_{\alpha}) = Z(v_{\alpha}) - m^*_{RK}(v) \tag{7}$$

where  $m^*_{RK}(v)$  is theregressionresult;  $\lambda_{\alpha}(v)$  is theweight of the primary variable, and  $R(v_{\alpha})$  is the residual of regression.  $m^*_{RK}(v)$  is usually modeled by linear regression of the auxiliary variable.

### 2.1.2 Pollution classification

Pollution classification step is mainly useful for grouping land cover soil area based on features. In this study, to classify the soil pollution level unsupervised classification is used.

In the unsupervised classification, each feature value is grouped based on the reflectance properties of the soil samples. In this study, we considered the soil pollution into three groups: highly polluted, moderately polluted and not polluted: C1-Heavily polluted, C2-Moderately polluted and C3-Not polluted and mapped using Fuzzy-logic. We have considered the concentration of heavy metals [16] in soil as feature vector. The formula used to group into Three classes C1-Heavily polluted, C2- moderately polluted and C3-Not polluted are given in Eqs. 8–11.

$$Input, I = \{\emptyset, f1, f2, f3, f4, f5, \neg f1, \neg f2, \neg f3, \neg f4, \neg f5\} \tag{8}$$

$$C1 = (\forall f1, f2, f3, f4, f5 \in I) f1 \cap f2 \cap f3 \cap f4 \cap f5 \tag{9}$$

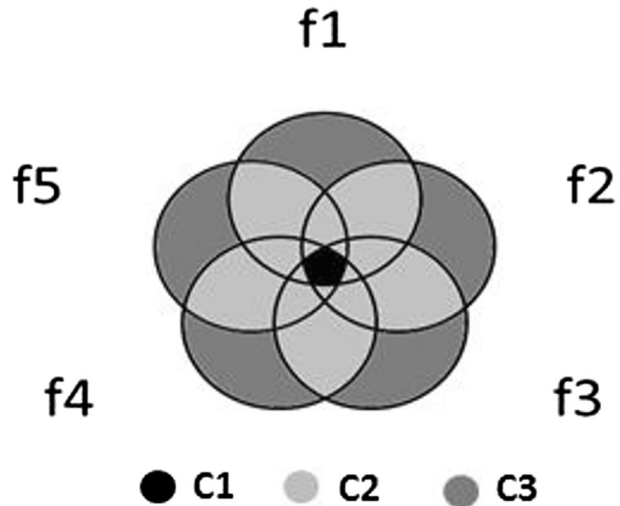
$$C3 = (\forall \neg f1, \neg f2, \neg f3, \neg f4, \neg f5 \in I) \{ \neg f1 \cup \neg f2 \cup \neg f3 \cup \neg f4 \cup \neg f5 \} \cup \emptyset \tag{10}$$

$$C2 = I - \{ C1 \cup C3 \}, C1, C2, C3 \in I \tag{11}$$

where  $f1, f2, f3, f4$  and  $f5$  are the five features of the soil based on the concentration of heavy metals(Arsenic, Mercury, Zinc, Lead and chromium) and  $C1, C2,$  and  $C3$  are classified classes. Figure 3 indicates the three classes of pollution level.

## 3 Results and discussions

The implementation was done using the programming tool MATLAB in HP z600 workstation. In this work, we have focused five metal concentration: Arsenic, Mercury, Zinc, Lead and Chromium in 17 locations. Table 2 implies the metal concentrations assessed by ICP-OES. Moreover, the extracted concentration using remote sensing images are given in Table 3. The standard measures of minerals are shown in Table 4.

**Fig. 3** Soil pollution level classification**Table 2** Mineral extraction results for the surface soil regions in Tirupur District using ICP-OES analysis result (Unit: mg/l, BDL- Bellow Detection Level)

Sample ID	As(mg/lit)	Cd(mg/lit)	Hg(mg/lit)	Zn(mg/lit)	Pb(mg/lit)	Cr(mg/lit)
S1	-0.171	0.002	-2.054	3.997	0.068	0
S2	-0.232	0.000	-2.903	4.849	0.374	0
S3	-0.184	0.001	-2.833	3.281	0.263	0
S4	-0.227	0.004	-6.689	4.281	0.453	0
S5	-0.191	-0.005	-5.332	4.183	0.202	0
S6	-0.150	0.001	-16.66	29.38	0	2.157
S7	-0.071	0.002	-8.391	38.72	0	1.258
S8	-0.023	-0.001(BDL)	-6.362	0.174	0	1.008
S9	-0.063	0.010	-6.583	0.402	0	0.703
S10	-0.131	-0.002(BDL)	-7.188	33.67	0	0.988
S11	(BDL)	(BDL)	(BDL)	1.482	0.113	0
S12	(BDL)	0.008	(BDL)	4.770	0.169	0
S13	(BDL)	0.057	(BDL)	0.841	0.358	0
S14	(BDL)	0.066	(BDL)	1.198	0.505	0
S15	(BDL)	0.029	(BDL)	0.602	0.642	0
S16	(BDL)	0.008	(BDL)	0.402	0.198	0
S17	(BDL)	(BDL)	(BDL)	1.262	0.220	0

The relationship between in-situ samples and remote sensing samples for elements such as arsenic, cadmium, mercury, lead, and zinc is illustrated in Fig. 4(a)-(e). The standard limits for heavy metal concentrations in soil samples for various elements are as follows: Cd (-0.005 to 0.010 mg/lit), Pb (0.068 to 0.453 mg/lit), Hg (-2.054 to -16.66 mg/lit), Cr

**Table 3** Mineral extraction results for the surface soil regions in Tirupur District using mineral extraction using reflectance from remote sensing image (Unit: mg/l)

Sample number	As(188.979)	Cd(228.802)	Hg(253.652)	Pb(220.353)	Zn(206.200)
S1	-0.1711	0.0030	-2.0541	0.0690	3.9980
S2	-0.2321	0.0003	-2.9031	0.3750	4.8491
S3	-0.1842	0.0013	-2.8332	0.2640	3.2811
S4	-0.2280	0.0042	-6.6891	0.4531	4.2811
S5	-0.1920	-0.0060	-5.3330	0.2021	4.1840
S6	-0.1510	0.0110	-16.6601	0.0000	29.3810
S7	-0.0711	0.0030	-8.3911	0.0000	38.7210
S8	-0.0232	-0.0010	-6.372	0.0000	0.1750
S9	-0.0632	0.0101	-6.5840	0.0000	0.4030
S10	-0.1313	-0.0120	-7.189	0.0000	33.6710
S11	0.0010	0.0010	0.0000	0.1131	1.4830
S12	0.0001	0.0081	0.0001	0.1691	4.7710
S13	0.0001	0.0572	0.0001	0.3582	0.8420
S14	0.0001	0.0661	0.0001	0.5051	1.1990
S15	0.0001	0.0291	0.0001	0.6421	0.6030
S16	0.0001	0.0180	0.0001	0.1981	0.4021
S17	0.0100	0.0000	0.0100	0.2210	1.2621

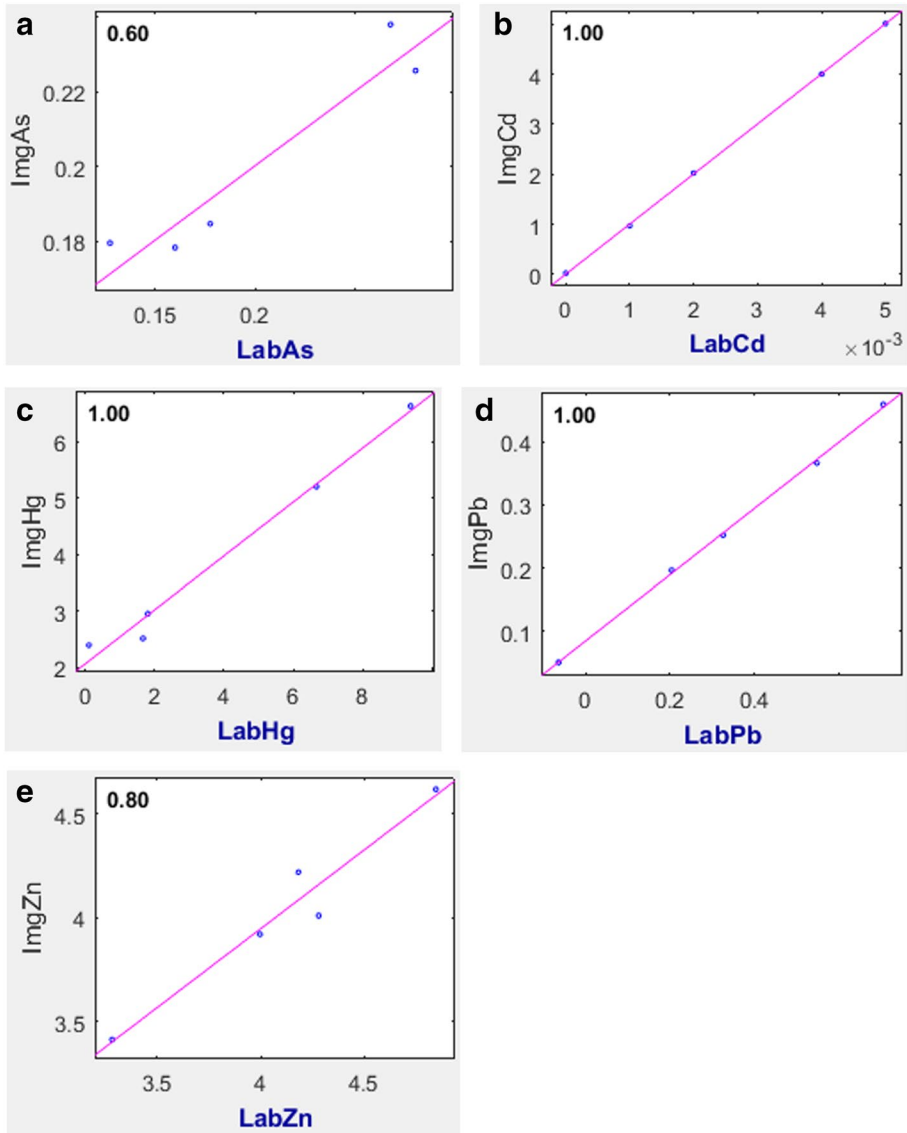
**Table 4** National standard for heavy metal

Heavy Metals	Concentration in mg/kg
Arsenic	4.5
Cadmium	0.76
Mercury	1.9
Lead	55
Zinc	16

(0.703 to 2.157 mg/lit), As (-0.023 to -0.232 mg/lit) [18], and Zn (0.174 to 38.72 mg/lit). A comparison with recent work [16] is presented in Table 5 and Fig. 5. The results indicate that the proposed method exhibits a significant ability to extract mineral concentrations compared to earlier work.

Table 6 offers a detailed overview of soil sample locations classified according to varying pollution levels across distinct regions. The accompanying classification map visually illustrates the pollution levels across the 17 selected locations in our study area. Highly polluted regions are highlighted in red, areas exhibiting no pollution are depicted in green, and moderately polluted regions are represented in yellow. This visual representation significantly enhances our comprehension of the distribution of pollution within the examined locations.

This study extensively examined the relationship between in-situ and remote sensing samples for key elements, including arsenic, cadmium, mercury, lead, and zinc.

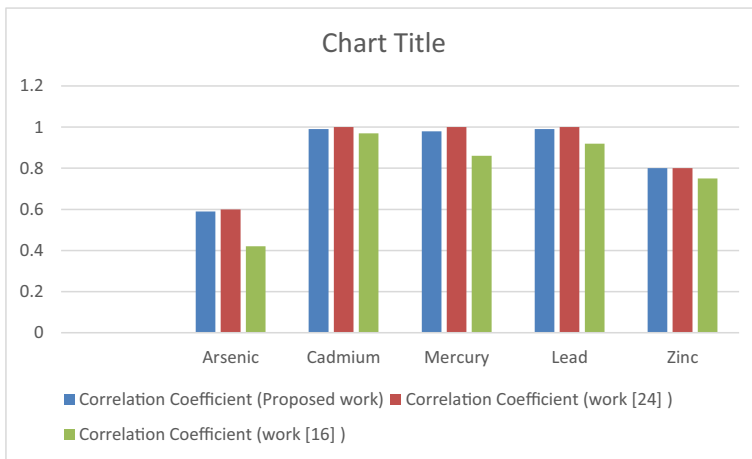


**Fig. 4** **a** Results of correlation of lab value with mixture analysis for Arsenic (As). **b** Results of correlation of lab value with mixture analysis for Cadmium (Cd). **c** Results of correlation of lab value with mixture analysis for Mercury (Hg). **d** Results of correlation of lab value with mixture analysis for Lead (Pb). **e** Results of correlation of lab value with mixture analysis for Zinc (Zn)

Figure 4(a)–(e) visually represents this relationship. The heavy metal concentrations in soil samples adhered to standard limits: Cd (−0.005 to 0.010 mg/lit), Pb (0.068 to 0.453 mg/lit), Hg (−2.054 to −16.66 mg/lit), Cr (0.703 to 2.157 mg/lit), As (−0.023 to −0.232 mg/lit) [18], and Zn (0.174 to 38.72 mg/lit).

**Table 5** Correlation coefficient for the elements using spectral mixture analysis

Elements	Correlation coefficient (Proposed work)	Correlation coefficient (work [24])	Correlation coefficient (work [16])
Arsenic	0.59	0.6	0.42
Cadmium	0.99	1.0	0.97
Mercury	0.98	1.0	0.86
Lead	0.99	1.0	0.92
Zinc	0.8	0.8	0.75

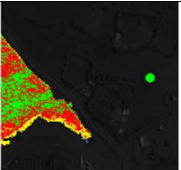
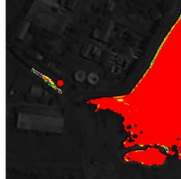
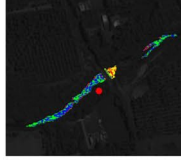
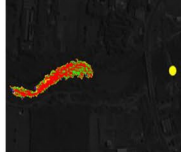

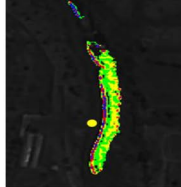


**Fig. 5** Analysis for spectral mixture analysis and earlier works

Comparing our proposed methodology with a recent study [16], as shown in Table 5 and Fig. 5, reveals the significant capability of our approach in accurately extracting mineral concentrations. These findings underscore the efficacy of our method in providing reliable estimates of heavy metal concentrations in soil, showcasing its advancement compared to previous work. This research contributes valuable insights into environmental monitoring and management, offering a robust foundation for future studies in this field.

## 4 Conclusion

This paper presents an analysis of pollution concentrations in the selected area of Tirupur district. The study utilizes field samples and remote sensing data, employing statistical data analysis. The proposed Kriging technique demonstrated excellence in accurately analyzing pollution in various selected soil regions. The study establishes a robust model for soil pollution, revealing high-pollution areas near water pollutant regions. Notably, the heavy

**Table 6** Output results

Latitude Longitude	Soil & Water Samples Result	Descriptions
(11°06'20.38" N, 77°17'46.97"E ) )-(11°06'04.81" N, 77°17'52.82"E )		S17, Kulathupudur, Tirupur This green color dot indicates this location is not polluted.
(11°06'19.91" N,77°17'27.29 "E)- (11°06'10.14" N,77°17'32.49 "E)		S8, Chinnandi palayamKulam, Tirupur. This red color dot indicates this location is highly polluted.
(11°06'25.58" N,77°14'49.09 "E)- (11°06'21.24" N,77°14'54.8 9"E)		S4, Noyyal River, Semmandampalayampudur, TirupurDist. This red color dot indicates this location is highly polluted.
(11°06'27.88" N,77°16'01.27 "E)- (11°06'20.86" N,77°16'18.73 "E)		S10, Noyyal River, Palladam-Avinasi Rd, Tirupur. This yellow color dot indicates this location is moderately polluted.
(11°06'00.92" N,77°18'44.76 "E)- (11°05'54.26" N,77°18'49.75 "E)		S16, Kozhipannai, Tirupur. This green color dot indicates that this location is not polluted.
(11°06'48.83" N,77°15'39.03 "E)- (11°06'39.34" N,77°15'50.67 "E)		S7, Kousika, Tiruppur Dist. This yellow color dot indicates that this location is moderately polluted.
(10°59'39.21" N, 77°16'56.94"E ) )-(10°59'28.69" N, 77°17'15.02"E )		S3, THIS LOCATION Mullai Nagar, Palladam, Tirupur Dist. This the green color dot indicates that this location is not polluted.
(10°59'54.44" N, 77°17'12.87"E ) )-(10°59'41.42" N, 77°17' 29.29"E)		S2, Palladam, TirupurDist This yellow color dot indicates that this location is moderately polluted.

metal Mg emerged as a key toxicity element, indicating heightened pollution in all water bodies and subsequently influencing soil pollution. The future directions, the research can contribute to a more comprehensive and holistic understanding of soil pollution dynamics, aiding in the development of effective environmental management strategies.

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**Data availability** Data available on request from the author.

## Declarations

**Conflicts of interest/Competing interests** No conflicts of interest to disclose.

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