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Study on Heavy Metal Concentrations in Soil Using Kriging Technique

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Research Article

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Abstract

The increase of toxic concentration leads environmental pollution. Soil pollution has become the most important problem of current scenario due to the rapid growth of industries. Heavy metal concentration in soil reveals the pollution level in soil. This work emphasis on the study of level of heavy metal concentration in Soil because of water pollution in Tirupur District, Tamilnadu, India, well-known for dying activities. The assessment of heavy metal concentrations has been researched based on soil samples and remote sensing data (Landsat 8 OLI images) with the relevant soil standards. Kriging technique and regression analysis are applied to the field and remote sensing data to map heavy metal contamination in soil. Finally, the obtained concentration element using remote sensing data was correlated with in-situ data and results are analyzed.

Introduction

In biological system, Soil plays a vital role. pollution of soil is a most important problem. Fluid fresh water is important to the mankind. But less than 1% of the total water is supplied. Water bodies as source of water, food, transportation and recreation are utilized by man. The degradation of soil quality near rivers, lakes, tanks and estuaries have been accelerated by the rapid and continuous growth of industries coupled with unregulated discharge of industrial waste and municipal sewage. Conventional in-situ measurements of water quality parameters arc slow, sparse and costly. Remote sensing has significant advantages over in-situ techniques in monitoring the soil quality parameters because of its synoptic and repetitive nature. Remote sensing data cannot sense and measure all soil pollutants.

Contamination of heavy metal in Soil and water resources plays a major hazard regarding human and animal's health. Agricultural activities and Land usage is affected because of spatial and temporal patterns of soil heavy metals. Heavy metals have the atomic mass of over 55.8 g mol − 1 or a density of over 5 g cm − 3. The most hazardous heavy metals i.eArsenic, mercury, zinc, lead, cadmium, chromium, copper, manganese, nickel and vanadium [1] are contaminated into the soil and found in the biosphere which make harmful to mankind.

Arman Nadari [1] reported that analysed the stepwise multiple linear regression (MSLR) and neural network-genetic algorithm model (ANN-GA) had been used for heavy metal distribution and the results were compared and assessed based on satellite imagery. It was evident that the accumulation of industrial wastes in roads and streams were the key factors of pollution, and the concentration of soil heavy metals can be diminished by means of increasing the distance from these sources. Weibo Ma[2] used weighted k-Nearest Neighbor (weighted k-NN) method to estimate the content of heavy metal with hyperspectral data and found that the accuracy of weighted k-NN method was higher than other methods in the inversion of heavy Zinc (Zn), Chromium (Cr) and Plumbum (Pb).

JinchunZhen[3] reported that ANN-GA has higher predicting ability of heavy metal distribution in various resources when compared to MSLR. The local Moran's indextechnique is helpful in analysing remote

sensing imagining and regional hotspots of heavy metal distributions. T.Kemper [4]reported that variable multiple endmember SMA system (VMESMA) was helpful in mapping of residual sludge and sludge derivatives which has greater flexibility and possibilities to get improved performances and more accurate interpretation of the unmixing results. This approach would endmember set of background material andthe delineation of the affected area using the RMS error with the GIS layers of the affected area.

Ali Al Maliki [5] analyzed the Pb concentrations in soils and studies have shown that the characteristics of urban and agricultural soils have heavy metal contaminations.Heavy metals are supplemented through the food chain, which damages the human health. Chronic exposure of Cd reflected the health hazards like lung cancer, prostatic proliferative lesions, bone fractures, kidney dysfunction and hypertension. Chronic oral and inhalation exposure of lead causes skin lesions and lung cancer and Pb causesplumbism, anemia, nephropathy, gastrointestinal colic and central nervous system symptoms.

Żukowska J, BiziukM[6] reported that the high concentrations of heavy metals such as Cd, low pH in soil leads human health risks. The human health risk from heavy metal contamination is not only correlated with the soil metals concentrations but is related to the overall environmental system. The land uses were considered when assessing the heavy metal health risks in this study.

Huarong Zhao, Beicheng Xia [7] stated that the size of the local population should also be considered with larger populations in a residential land since there is a higher chance of adverse human health effects. Manoj Kumar Tiwari [8] et.al reported that the concentrations of heavy metals in soil near to the dumping/disposal site is more and decreases as distance increases. Also in the depth wise analysis, it was observed that the higher concentrations of selected heavy metals are observed near the surface of ground and magnesium which has highest concentration .The higher pH (alkaline) of the disposed industrial solid wastes may reduce the leach ate generation, so suitable industrial solid waste disposal or dumping near populated vicinity has to be used. ChijiokeEmenike[9] et.al reported that the landfilling is one of the ultimate waste disposal option among Asian nations.Disposal sites are influenced by the deposited Leach ate quality waste. The studies revealed that in-site composition is similar even though there is a slight variation among the Asian landfills in leach ate quality. Hence there is an immediate need for refurbishment of existing landfills and dumps.

From the studies carried out by Nalawade P.M et. al[10] revealed that different heavy metals that are available in the fly ash dumping ground and its surrounding area can be recovered, reused and recycled. Based on the availability of metal deposited there is contamination of heavy metal surrounding the thermal power plant. It is life threatening to human. Bioremediation technique is the recent technique adopted to provide remedy of metal pollutants and to create an eco-friendly environment.

Another work to determine the levels of metals like Cu, Fe, Ni, Cd, Pb and Zn deposited on the soil surface in the locality of railway workshop is proposed by Akot[11]. In this work using geo accumulation index and enrichment value the soil pollution is measured. The enrichment value calculated showed the Pb and Cu metals were enriched by 3.47 and 2.26 respectively. Accumulation index value showed that Cd and Ni

concentration are at background level and is moderately polluted by Zn and extremely polluted by Pb and Cu. Anthropogenic sources are the cause for high concentration of Zn, Pb and Cu.

Yet another method to predict the concentration of heavy metals using reflectance spectroscopy is proposed by Peters et al.[12]. The approach lacks to determine the heavy metals that are slightly concentrated in soil. C.M.Pandit et al.[13] proposed a method to estimate the contamination of heavy metals such as Cd, Cr, Pb, AS, Hg and Zn in urban areas and produced promising results using PLSR models.

Due to Urbanization in Tirupur district in Tamil Nadu there is a serious conflict between human and land. The agricultural land neighboring the river is being highly polluted by the heavy metals. Precise estimation of concentration of heavy metals in soil is crucial and vital. Usage of Remote sensing data to estimate the concentration of heavy metals in soilis time and cost effective compared to laboratory analysis. Accuracy of estimation is not as expected using the remote sensing data with the inversion of heavy metals in soil. In the previous works carried on Remote Sensing data the concentration of Pb in soil is alone estimated. In this work various heavy metals inversion in soil is estimated and classified using kriging and regression analysis method. The accuracy of estimation of heavy metal concentration in soil is improved in cultivated areas.

This paper presents the method and results based on the in-situ heavy metal concentrations and remote sensing data. The objectives are: -

- To study the soil pollution level near water bodies in Tirupur District.
- To assess the level of soil pollution by using image processing and statistical methods.

Methodology

In our present study we envisage the level of heavy metal pollutant as High, medium, and Normal. To attain this objective, we have collected in-situ data and acquired Landsat 8 OLI satellite images for the study area and compiled analyzed using statistical and machine learning approaches on both spatial and lab data. The architecture of the proposed work is given in Fig. 1.

Study area

The study area of Tirupur District in Tamilnadu, India was selected and is shown in Fig. 2. We have collected soil samples from 17 locations. The Bleaching units situated near the river is the key reasons for the pollution, which reflected the soil pollution around in the study area.

Input images and data

We have collected soil samples from 17 location in Tirupur and acquired the remote sensing satellite images (cartosat 2 - panchromatic image)for the same region with the help of National Remote Sensing

Centre (NRSC) Hyderabad. Heavy metals normal international standard values also collected. Soil samples are tested to find the heavy metals in those samples. We have to find the heavy metal concentration of the soil using the ICP OES test, that was made at IIT madras. Before the test was made the soil samples are first goes under the digestion process (converts the soil into liquid form). Then the samples are tested at IIT and the result of the heavy metal concentration in that soil was obtained. In our work the kriging technique is used to extract feature descriptor to classify the region.

Table 1
List of 17 samples collected locations and its 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

ESTIMATION (KRIGING)

Geostatistical methods are applied to estimate and map the attributes of objects in unsampled areas. Kriging [14, 15] is an unbiased and optimal estimation based on the structural information of the regionalized variable reflected by the sampled data and the mutual spatial positional relationship of the sample points. In this study, we used linear kriging methods (OK, CK and RK) to estimate soil heavy metals.

ORDINARY KRIGING (OK)

OK is one of the powerful techniques commonly used in finding the assumption that the mean is not known. We have computed the unsampled value z(v) by considering it as a linear combination of the neighboring observations:

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

where v is a vector of spatial coordinates, n(v) is the number of neighboring sampled values that have a significant influence on the estimated. value, and z(v_{α}) is the observed value at v_{α}. To ensure that the estimate was unbiased and to minimize the estimate variance, λ_{α} that is the weight of the neighboring sampled values, using following equations:

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

where μ(v) is the Lagrange parameter and γ is the semi-variogram of the variable to be estimated. γ is calculated by:

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

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

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

COKRIGING (CK):

CK, is an interpolation method derived from ordinary kriging. This method takes full benefit of the added correlated information in the subsidiary variables. The CK estimator of z(v) with a single auxiliary variable (y) is expressed as:

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

where λ_{α} and λ_{β} are the weights of the primary and auxiliary variables, respectively, and n(v) and n(y) are the numbers of neighboring y samples of the primary and auxiliary variables, respectively. The cross variograms are calculated as:

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

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

REGRESSION KRIGING (RK):

RK, also called simple kriging with varying local means, is a technique that combination of regression results of the dependent variable with kriging results of the regression residuals. It first applies regression on auxiliary information and then uses simple kriging with known mean (0) to interpolate the residuals from the regression model. This allows the use of arbitrarily complex regression methods, including generalized linear models. The RK estimation can be described as:

$$Z_{RK}^{*}(v)=m_{RK}^{*}(v)+\sum_{\alpha=1}^{n(u)}\lambda_{\alpha}(v)\,Z(v_{\alpha})\,with\,R(v_{\alpha})=Z(v_{\alpha})-m_{RK}^{*}(v)$$

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.

Pollution Classification

Image classification is a process of grouping a pixels to represent land cover features. In this study, we used unsupervised classification to classify the soil pollution level. In the unsupervised classification, each feature value is grouped based on the reflectance properties of feature values. These groupings are called classes. In this study, we classified the soil pollution as highly polluted, moderately polluted and not polluted: C1-Heavily polluted, C2-Moderately polluted and C3-Not polluted. The fuzzy-logic method is proposed for soil pollution mapping. In this method, the classification is done based on the concentration of heavy metals [16] in soil as features. From the proposed method, three ranges of pollution level were generated. Three classes C1-Heavily polluted, C2- moderately polluted and C3-Not polluted are computed as follows.

$$Input, I=\{\varnothing, f1, f2, f3, f4, f5, \neg f1, \neg f2, \neg f3, \neg f4, \neg f5\}$$

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$C1=(\forall f1, f2, f3, f4, f5\in I)f1\cap f2\cap f3\cap f4\cap f5$ (7)

$C3=(\forall\neg f1, \neg f2, \neg f3, \neg f4, \neg f5\in I)\{\neg f1\cup\neg f2\cup\neg f3\cup\neg f4\cup\neg f5\}\cup\varnothing$ (8)

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

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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 4 shows the three classes of pollution level.

Results And Discussions

We have developed the code segments by using the programming tool MATLAB and done our image processing steps in HP z600 workstation. We have selected 17 locations and analyzed for 5 metal concentrations: Arsenic, Mercury, Zinc, Lead and Chromium. The element concentrations of each field samples are tested at SAIF, IITM, Chennai. The metal concentrations were assessed by ICP-OES and the data are listed in Table 2. Moreover, we have extracted the surface soil minerals using remote sensing images are given in Table 3. The prescribed standard measures of minerals are shown in Table 4.

The performance measure is examined based on the correlative relationship between the in-situ samples and remote sensing samples. Figure 4(a)-(e) shows the correlation analysis for the elements such as arsenic, cadmium, mercury, lead and zinc. We have plotted between the in-situ and Lab results for the metals. The heavy metal concentrations of the soil samples ranges from, Cd (-0.005 to 0.010mg/lit), Pb (0.068 to 0.453mg/lit), Hg(-2.054 to -16.66mg/lit), Cr(0.703 to 2.157mg/lit), As(-0.023 to -0.232 mg/lit) [18] and Zn (0.174 to 38.72mg/lit). For the fair analysis, the result of the proposed work is compared with work [16] and is given in Table 5. The graphical representation of comparative analysis between proposed and work [16] is given in Fig. 5. The results of Table 5 reveal that the proposed method has significant ability to extract the mineral concentration when compared with earlier work.

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

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	-0.1710	0.0020	-2.0540	0.0680	3.9970
S2	-0.2320	0.0000	-2.9030	0.3740	4.8490
S3	-0.1840	0.0010	-2.8330	0.2630	3.2810
S4	-0.2270	0.0040	-6.6890	0.4530	4.2810
S5	-0.1910	-0.0050	-5.3320	0.2020	4.1830
S6	-0.1500	0.0010	-16.6600	0.0000	29.3800
S7	-0.0710	0.0020	-8.3910	0.0000	38.7200
S8	-0.0230	-0.0010	-6.362	0.0000	0.1740
S9	-0.0630	0.0100	-6.5830	0.0000	0.4020
S10	-0.1310	-0.0020	-7.188	0.0000	33.6700
S11	0.0000	0.0000	0.0000	0.1130	1.4820
S12	0.0000	0.0080	0.0000	0.1690	4.7700
S13	0.0000	0.0570	0.0000	0.3580	0.8410
S14	0.0000	0.0660	0.0000	0.5050	1.1980
S15	0.0000	0.0290	0.0000	0.6420	0.6020
S16	0.0000	0.0080	0.0000	0.1980	0.4020
S17	0.0000	0.0000	0.0000	0.2200	1.2620

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

Table 5
Correlation coefficient for the elements using Spectral Mixture Analysis

Elements	Correlation Coefficient (Proposed work)	Correlation Coefficient (work [16])
Arsenic	0.6	0.42
Cadmium	1.0	0.97
Mercury	1.0	0.86
Lead	1.0	0.92
Zinc	0.8	0.75

Average correlation coefficient (proposed work) = 0.88

The Table 6 shows the pollution classification results for the region wise soil sample collected location. However, the elements concentration analysis revealed the toxicity level. The classification map gives a better understanding of pollution level in that region. Red colour shows the region is highly polluted. Green Colour shows Not polluted and yellow colour shows moderately polluted.

Conclusion

This paper deals with the pollution level analysis in the soil in and around the Tirupur district. We have carried out the study by using the field samples and remote sensing data entailing statistical data analysis. The result of this study showed that the proposed Kriging technique which had provided most accurate pollution analysis by analyzing various soil regions. This study exhausted a good base model for soil pollution. As per assessment, it is observed that the high pollutant soil areas are identified near the water pollutant regions. The heavy metal Mg was categorized as the toxicity element which showed increased pollution in all water bodies which increased the soil pollution.

Declarations

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Conflicts of interest/Competing interests: We have **no conflicts of interest** to disclose.

Availability of data and material (data transparency): Data available on request from the authors.

Code availability (software application or custom code): software application.

References

1. Arman Nadari&. (2017). Mohmmad Amir Delavar&BabakKaboudin& Mohammad SagdeghAskari," Assessment of spatial distribution of soil heavy metals using ANN-GA, MSLR and satellite imagery". *Environ Monit Assess*, 189, 214
2. Ma, W., Tan, K., Du, Q., Ding, J., & Yan, Q. (2016). August. Estimating soil heavy metal concentration using hyperspectral data and weighted K-NN method. *In 2016 8th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)* (pp. 1–4). IEEE.
3. Jinchun Zhen, T., Pei, & ShuyunXie (2019). Kriging Methods With Auxiliary Nighttime Lights Data To Detect Potentially Toxic Metals Concentrations In Soil. *Science Of Total Environment*, 659, 363371
4. T.Kemperand S.Sommer"Mapping and monitoring of residual heavy metal contamination and acidification risk after the aznalcóllar mining accident (andalusia, spain) using field and airborne hyperspectral data",international journal of remote sensing, 31: 9,2309–2324),
5. Maliki, A. A., Owens, G., & Bruce, D., "Capabilities of remote sensing hyperspectral images for the detection of lead contamination: A Review", ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume 1–7, 2012, XXII ISPRS Congress, 25 August-01 September 2012, Melbourne, Australia.
6. Żukowska, J., & Biziuk, M. (2008). Methodological evaluation of method for dietary heavy metal intake. *Journal of food science*, 73(2), 21–29
7. Zhao, H., BeichengXia, C., Zhao, F. P., & Shen, S.. "Human health risk from soil heavy metal contamination under different land uses near Dabaoshan Mine,Southern China".
8. Tiwari, M. K., Bajpai, S., & Dewangan, U. K. (2015). An analytical study of heavy metal concentration in soil of an industrial region of Chhattisgarh, central India. *International Journal of Scientific and Research Publications*, 5(7), 1–8
9. Emenike, C. U., Fauziah, S. H., & Agamuthu, P. (2012). Characterization and toxicological evaluation of leachate from closed sanitary landfill. *Waste Management & Research*, 30(9), 888–897
10. Nalawade, P. M., Bholay, A. D., & Mule, M. B. (2012). Assessment of Groundwater and surface water quality indices for heavy metals nearby area of Parli thermal power plant. *Universal Journal of Environmental Research and Technology*, 2(1), 47–51
11. Akot, O., & Abankwa, E. (2014). Heavy metals contamination and speciation in sediments of the Owabi reservoir. *Environmental Research Journal*, 8(1), 10–16
12. Peters, D. C., Hauff, P. L., Peppin, W. A., Prosh, E. C., Borstad, G. A., Henderson Iii, F. B. … Wangerud, K. W. (2001). "Waste identification and characterization for the international smelter area using CASI/SFSI hyperspectral remote sensing data".
13. Pandit, C. M., Filippelli, G. M., & Li, L. (2010). Estimation of heavy-metal contamination in soil using reflectance spectroscopy and partial least-squares regression. *International Journal of Remote Sensing*, 31(15), 4111–4123
14. Jinchun Zhen, T., Pei, S., & Xie (2019). In Soil". *Science Of Total Environment*, 659, 363371"Kriging Methods With Auxiliary Nighttime Lights Data To Detect Potentially Toxic Metals Concentrations
15. Cressie, N. (1988). Spatial prediction and ordinary kriging. *Mathematical geology*, 20(4), 405–421

16. Yan, X., Zhang, F., Zeng, C., Zhang, M., Devkota, L. P., & Yao, T. (2012). Relationship between heavy metal concentrations in soils and grasses of roadside farmland in Nepal. *International journal of environmental research and public health*, 9(9), 3209–3226

Table

Table 6 is available in the Supplementary Files section.

Figures

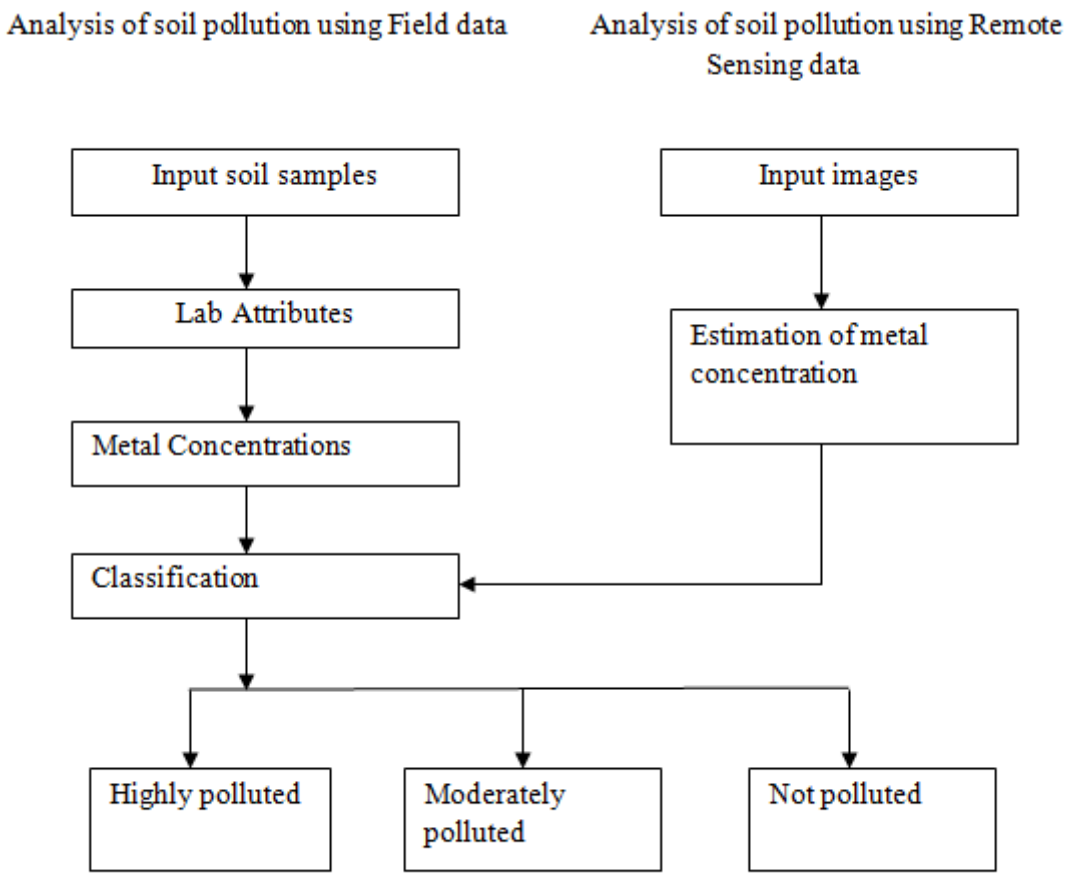

Figure 1

Block diagram of the methodology

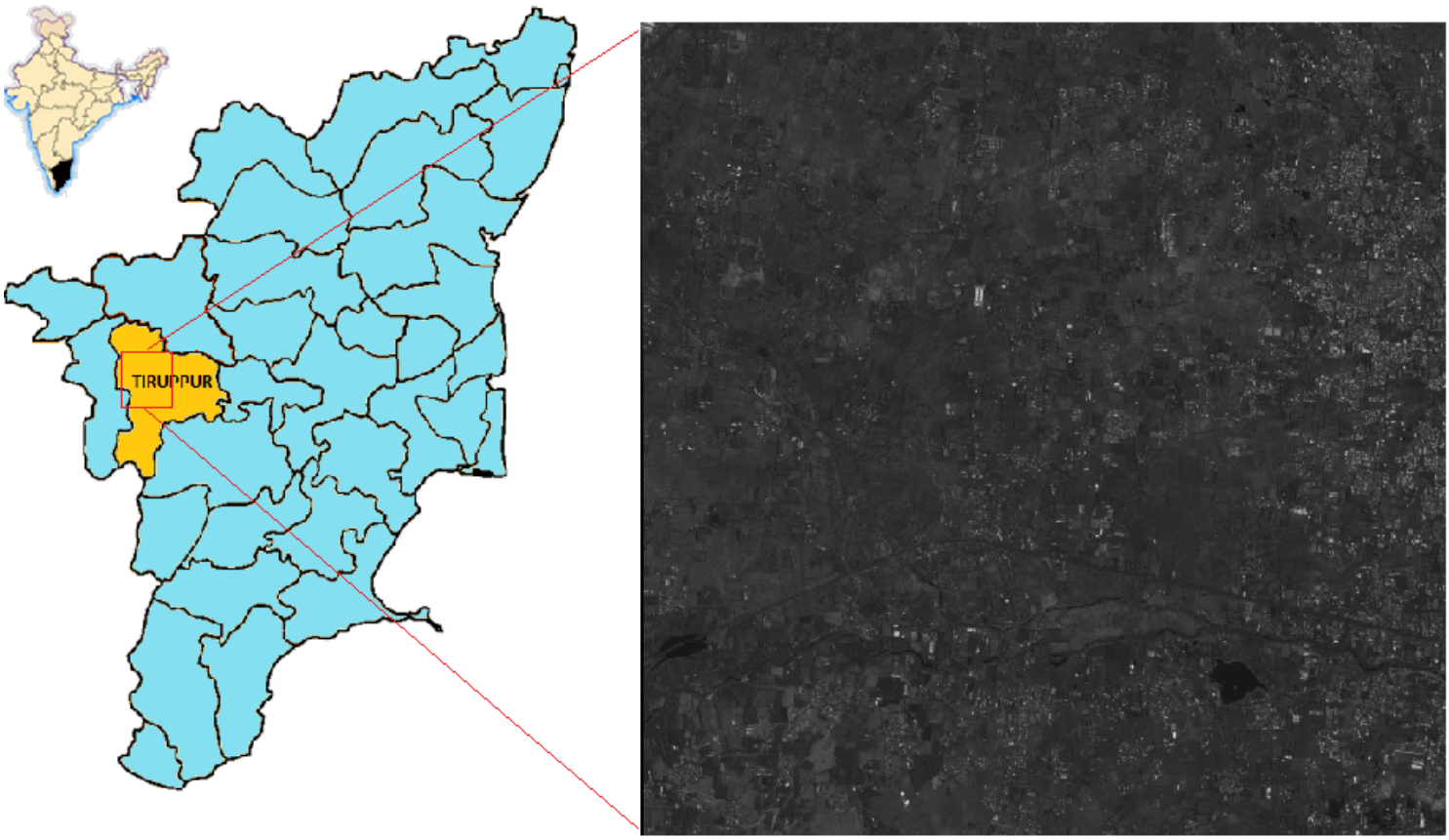

Figure 2

Study Area Map showing Pan Image acquired on 20th August, 2016.

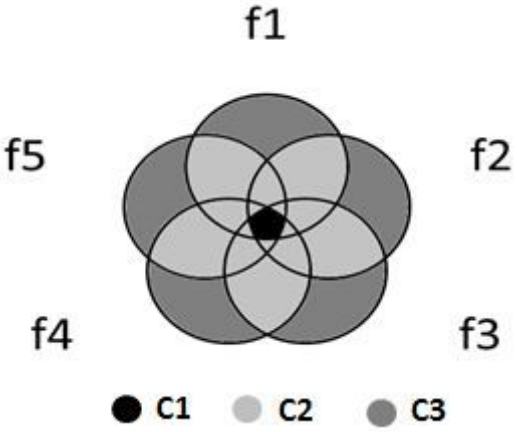

Figure 3

Classification of soil pollution level

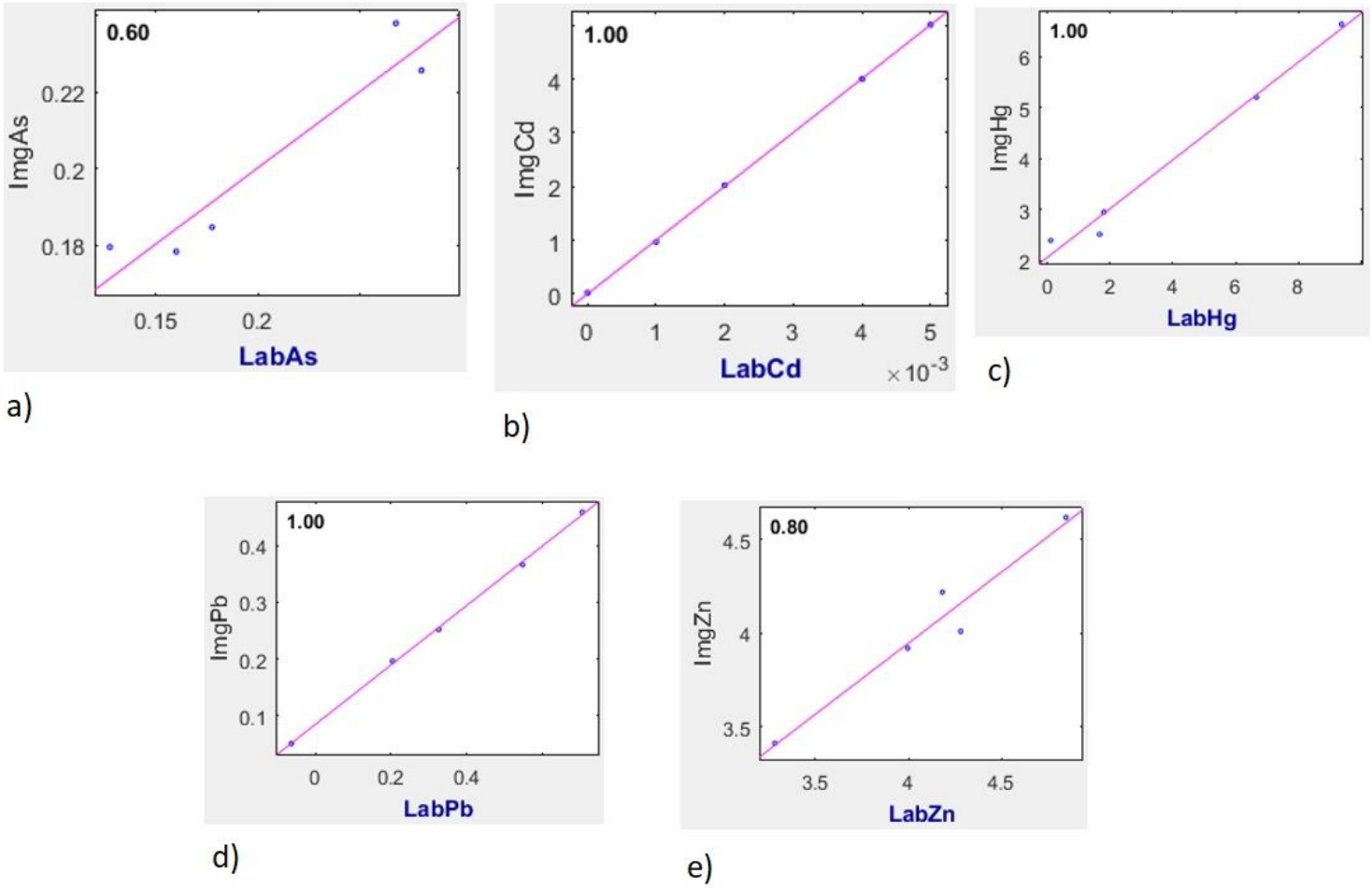

Figure 4

(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)

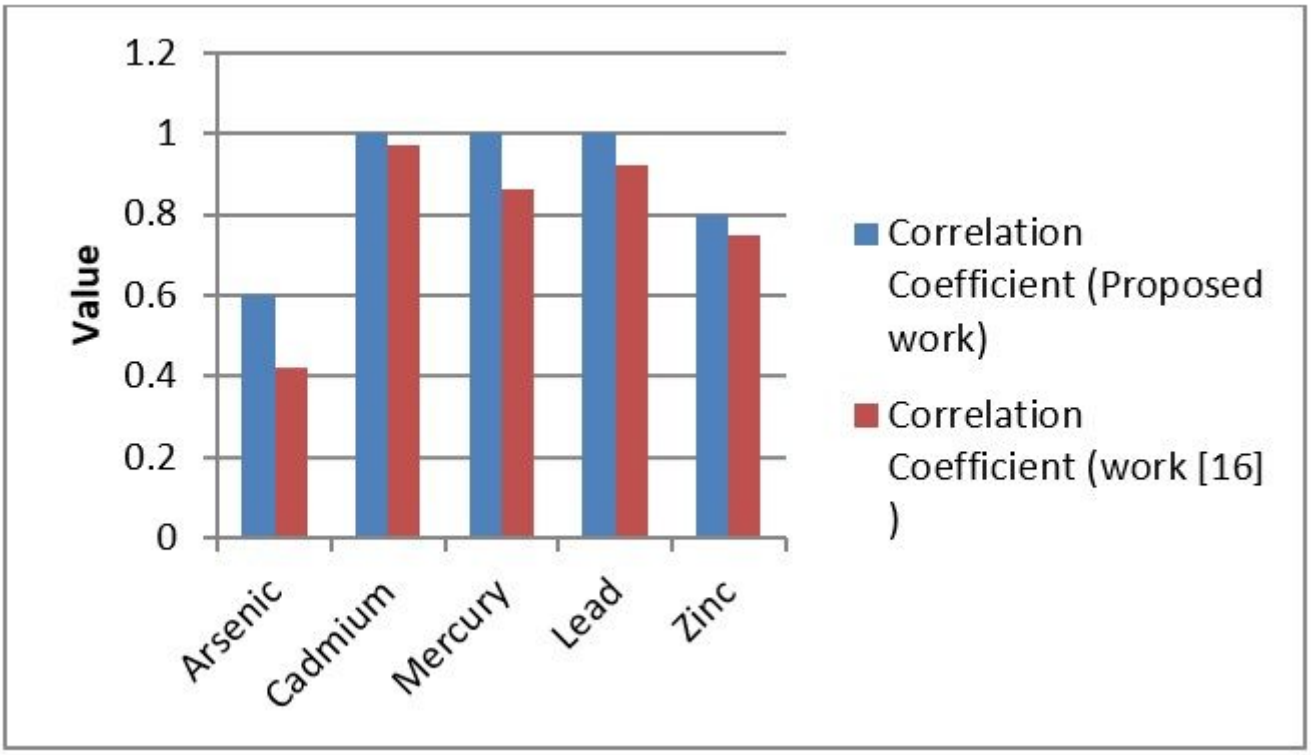

Figure 5

Analysis for Spectral Mixture Analysis and Work [16]

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Table6.docx