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Distribution of heavy metals and their potential pollution prediction using spatial modelling in the floodplain farmland around municipal waste dumpsite in Yola Adamawa State Nigeria

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ABSTRACT

Floodplains are receptors of sediments from upland municipal areas, waste dumpsites, and adjacent rivers polluting floodplain farmlands used for both rainfed and irrigation continuous cropping. This study was therefore undertaken to study the distribution of heavy metals (HMs) and their potential pollution prediction using spatial modelling in the floodplain farmland around municipal waste dumpsite in Yola Adamawa, State Nigeria. Soil samples were collected systematically at 6 points (0, 20, 40, 60, 80 and 100 m) along three traverses from the dumpsite at interval of 20 m. Mean values of iron (Fe) and chromium (Cr) across the study area were significantly higher than at the dumpsite, while Cu and Zn were significantly higher at dumpsite and decreased as spatial distance increased away from dumpsite. Clay significantly influenced spatial distribution of HMs' Fe and Cr, while sand and soil pH had negatively effects on HMs. Increase in total organic carbon, available phosphorus (P), exchangeable calcium (Ca) and magnesium (Mg) increased concentration of manganese (Mn), copper (Cu), lead (Pb), chromium (Cr) and zinc (Zn). Among the HMs, copper had the prediction model with highest r - value and was obtained using the square root of spatial distance {$Cu = 225.397 - 1.5328(SD)^{½}$} with the highest R-Squared value of 40.98%, though less than 50 %. The overall means of contamination factor (CF) indicated a decreasing order of Pb > Zn > Cd > Cu > Mn > Cr > Fe. The enrichment factor (EF) index had moderate risk for all the metals with only Cr having low risk to the floodplain. Assessment of HMs using CF, EF and potential ecological risks (PER) models had similar trend of correlations with spatial distances from dumpsite, hence were considered to be more appropriate models to use for predicting HMs pollution compared to index of geo-accumulation (I_{geo}) model in the study area.

Keywords: Heavy metals; spatial distribution; modelling; floodplain

INTRODUCTION

Soils across the globe are the basic environmental elements constituting ecosystem, and plays critical roles in maintaining ecosystem services, such as food production, biodiversity maintenance, water resources protection, carbon sequestration and regulation of microclimate (Adedeji *et al.,* 2020). However, environmental safety of soils deteriorates severely with the rapid population growth, urbanization and industrialization (Yao *et al.,* 2012; Akinbile *et al.,* 2016; Adedeji *et al.,* 2020). Soils under such situations are increasingly

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polluted by heavy metals. These heavy metals often originate from different anthropogenic activities or other alteration in the natural soil environment (Islam *et al.,* 2015a; Adedeji *et al.,* 2020; Otene and Alfred-Ockiya, 2020). In developing countries such as Nigeria, open dumpsites are common practice due to the low budget for waste disposal. A good amount of the city garbage is dumped in low lying areas which poses serious threat to groundwater resources and soil (Akinbile *et al.,* 2016). The management of municipal solid waste (MSW) is essential for every community; and it is currently a major challenge in most Nigerian cities (Iorhemen *et al.,* 2016; Ike *et al.,* 2018).

Soil pollution and risk assessment indices indicate the effects of overall soil quality of an area. Many authors have used indices for determination of Geo-accumulation index (I_{geo}), Enrichment Factor (EF), Contamination factor (CF), Pollution load index, (PLi) for soil of an area (Qingjie and Jun, 2008; Inengite *et al.,* 2015; Islam *et al.,* 2015a; Liu *et al.,* 2016; Dash *et al.,* 2019; Dhamodharan *et al.,* 2019; Jimoh *et al*., 2020; Shirani *et al.,* 2020; Tong *et al.,* 2022). Muller (1969) made use of the Geo-accumulation formula for calculating the degree of contamination in soil within dumpsite by the background concentration of the continental shale. While Islam *et al.* (2015a) and El Nemr *et al.* (2016) assessed the I_{geo} comparing the heavy metal in concentration in the dumpsite relative to the background level in the soil. The Enrichment factor was another index adopted by researchers to measure the possible impact of anthropogenic activity on the concentration of heavy metals in soils. This identifies the impact of the expected anthropogenesis on the heavy metal concentration in the soil (Islam *et al.,* 2015a). In order to determine contamination level of heavy metals in soil around landfill pollution models such as contamination factor and degree of contamination developed by Hakanson (1980); modified degree of contamination (Abrahim, 2008) and pollution load index (Tomlinson *et al.,* 1980) and Geo-accumulation index (Muller, 1969) were used. Several of these indices as models determining extent of soil pollution have been used in Nigeria along with other models like degree of contamination (CD) and the potential ecological risk (PER) by researcher (Adedeji *et al.,* 2020) to examine the ecological and health risks of potentially toxic metals. Otene and Alfred-Ockiya (2020) used some pollution indices such as contamination factor (CF), pollution load index (PLI), geo-accumulation index (Igeo), toxicity unit analysis (TUA) and potential ecological risk (PER) to determine the pollution status and ecological risk level of the sediment of Elele-Alimini Stream, Port Hacourt Nigeria.

Floodplains are receptors of sediments from upland municipal areas, waste dumpsites, and adjacent rivers. The sediments transport heavy metals causing pollution within floodplain farmlands (Islam *et al*., 2015a). These floodplains in the Savanna zone of Nigeria are where rainfed crop production is sustained in the dry season via irrigation for continuous cropping. Hence, when the spatial distribution of pollutant heavy metals on such agricultural land is not known it is difficult to manage or understand their impact on the environment and human health (Akinbile *et al.,* 2016).

This study, therefore, designed to develop model for predicting spatial distribution of heavy metals and examine pollution indices that more appropriately define influence of waste dumpsite on the pollution of irrigation floodplains in Yola Adamawa State, Nigeria.

MATERIALS AND METHODS

Study Area

The study area is the irrigation farmland along Shinko floodplain of Benue River in Yola, Adamawa State. The study area is geographically situated along Latitude 9º 17' to 14.28″ N and longitude 12º 27' to 04.61″ E at 157 to 162 m above sea level (Figure 1). The Municipal waste dumpsite is situated within residential area/buildings along the busy Mubi road. The dumpsite lay in heaps that span about 500 m along the road adjacent to the river and has been active for more than five decades and takes waste and irrigation water from different parts of the community.

Yola shows typical tropical climate (Zemba, 2010), with average annual rainfall is 872.4 mm with the highest occurrence in July, August and September. The rainy season runs from the months of May through October, while the dry season commences in November and ends in April/May. The area has an average sunshine hour of 7.80 daily, 237.13 monthly and 2845.5 yearly. The temperature of the study area is generally high throughout the year. The seasonal variation in temperature indicated maximum temperature was lowest between August and September (31.3^{0}C) to a highest value of 39.8^{0}C in April. The minimum temperature increases from 16.9^{0}C to 27.0^{0}C in November to April respectively.

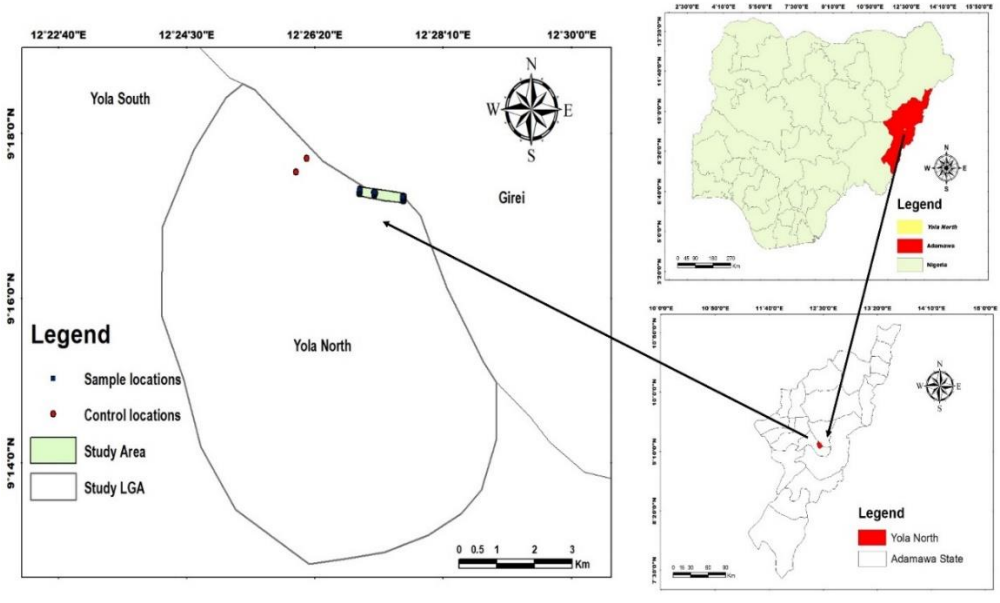

Figure 1: Map of Nigeria showing the Study Area in Yola, Adamawa State

Soil Sampling

Soils samples were collected at two different depths in a single profile at a depth of 0–30 cm and 30–60 cm. The soil was collected at six (6) points (0, 20, 40, 60, 80 and 100 m) along a traverse from the dumpsite at interval of 20 m and it was replicated 3 times along the dumpsite to the farmland (Figure 2) with control point within floodplain over 2 km outside

the farmland. This provided a total of 38 soil samples collected (6 x 3 x 2) +2). The soil samples were air dried, crushed and sieved using 2 mm diameter sieve and the selected soil properties were analyzed in the laboratory.

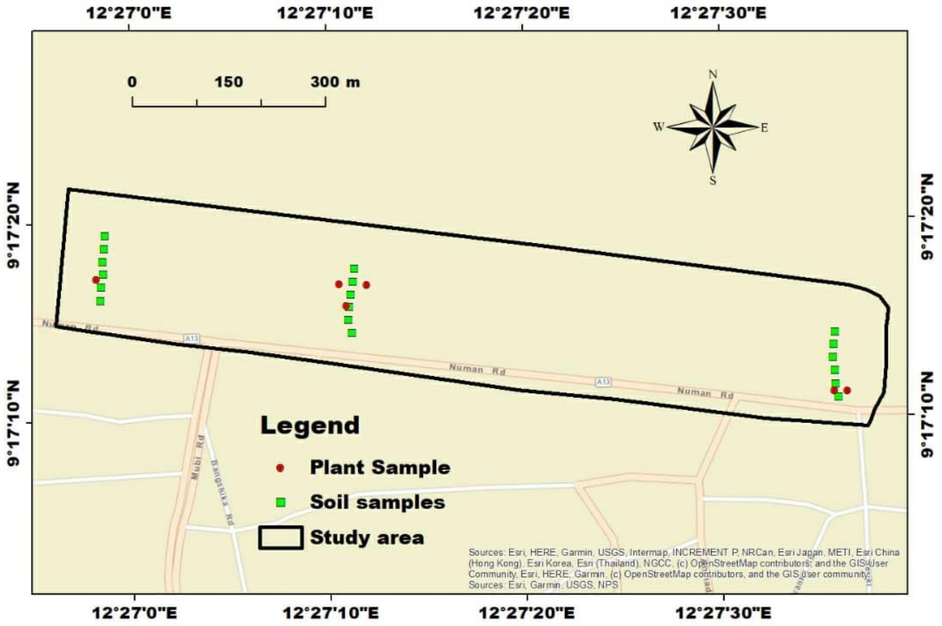

Figure 2: Map of the study area showing the soil sampling points along the traverse

Laboratory Analysis

The bulk density is determined as described by Blake and Hartge (1986). The particle size distribution was determined by the hydrometer method as described by Udo *et al.* (2009). Total porosity was calculated mathematically using equation 1 (Danielson and Sutherland, 1986):

$$TP\ (\%) = \left[\!\left[1 - \left(\frac{\rho b}{\rho p}\right) \right]\!\right] 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

TP =Total porosity

ρ_p = Particle density

ρ_b = Bulk density.

Soil pH was determined in both water and 0.01 M $CaCl_2$ solution at a 1:1 soil/water solution ratio. On equilibration, pH was read with a glass electrode on a pH meter Model PS-3C meter. Electrical conductivity was determined from the soil/water paste using a Wheatstone bridge at 25 ^{0}C. The organic carbon was determined by the Walkley-Black dichromate wet oxidation method as described by Nelson and Sommer (1982). Available phosphorus was extracted using the Bray- 1 method and determined following the procedure described by Uyovbisere *et al.* (2013).

Exchangeable bases (Ca, Mg, K and Na) were extracted using ammonium acetate (NH_4OAc) saturation method and determined as described by Thomas (1982). Potassium and sodium was read from the undiluted extract on a Flame photometer. Calcium and magnesium was read on an atomic absorption spectrophotometer (AAS). Cation exchange capacity (CEC) was determined by the neutral (pH 7.0) NH_4OAc saturation method (Rhoades, 1982).

Heavy metals in the soil sample were extracted using aqua – regia acid (a mixture of 3 parts of HCl to 1 part of HNO_3). The copper (Cu), iron (Fe), manganese (Mn), lead (Pb), cadmium (Cd) and zinc (Zn) were determined from the extract using atomic absorption spectrophotometer 230 Buck science (Udo *et al.,* 2009; Uyovbisere *et al.,* 2013).

Pollution and Risk Assessment of the Soils

Contamination index assesses level of pollution, evaluates the pattern of contamination and determines the potential risk due to exposure to ecological sensitivity in the soils. The analyzed results of the HMs in the soils were subjected to models to assess the extent of pollution and ecological risk. Contamination factor (CF), Enrichment factor (EF), Geo-accumulation index, (I_{geo}), Pollution load index (PLI) and Potential ecological risk (PER).

Contamination factor (CF) was estimated using equation 2.

$$CF = \frac{Cm}{Cb} \qquad (2)$$

Where:

Cm = concentration of an element in the soil sample

Cb = geochemical background value of non-effected soil at the site.

Enrichment factor (EF) was determined by equation 3 (Zhang *et al.,* 2007).

$$EF = \frac{\left\{\frac{C_m}{C_{Fe}}\right\} sample}{\left\{\frac{C_m}{C_{Fe}}\right\} BG} \qquad (3)$$

Where:

C_m = concentration of element *i* in the sample of interest

C_{Fe} = concentration of reference element (Fe)

sample = soil sample of interest

BG = soil sample of background (control site) (Zhang *et al.,* 2007).

Geo accumulation index (I_{geo}) for each of the heavy metals from the dumpsite and farmland was determined mathematically from equation 4 (Islam *et al.,* 2015a; El Nemr *et al.,* 2016).

$$I_{geo} = \log_2 \left(\frac{Cn}{Bn}\right) \qquad (4)$$

Where:

C_n = concentration of an element in the soil sample

B_n = geochemical background value of non-effected soil at the site.

The constant 1.5 allowed us to minimize effect variation in background concentration due to lithogenic impacts. Pollution load index (PLI) is an integrated approach used in assessing the sediment quality of heavy metals (Dash *et al.*, 2019; Dhamodharan *et al.*, 2019). Dhamodharan *et al.* (2019) opined that pollution load index can be assessed using the five hazardous elements, Cd, Cr, Ni, Cu, and Pb (Tomlinson *et. al.,* 1980). Pollution load index (PLI) was determined using the element, Cd, Cr, Cu, Ni and Pb from equation 5 (Liu *et al.*, 2016; Dhamodharan *et al.,* 2019) and categorized by Liu *et al.* (2016):

$$PLI = \sqrt[p]{CF_1 \times CF_2 \times \cdots \times CF_p} \quad \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Where:

CF = contamination factor for each simple metal

p = number of heavy metals

PLI = Pollution load index

Potential ecological risk (PER) of individual metal element was determined using equation 6 (Islam *et al.*, 2015b).

$$E_r^i = C_r^i \times T_r^i = \left(\frac{C_S^i}{C_n^i}\right) \times T_r^i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Where:

C^i_s = concentration of an element in the soil sample

C^i_n = geochemical background value of non-effected soil

T^i_r = toxic response factor for each metal

Toxic response factors were taken 2 for Cr, 5 for Cu and Pb, 10 for As, 40 for Hg and 50 for Cd.

Statistical Analysis

Descriptive statistics and two-way analysis of variance (ANOVA) were used to analyze the variation between the sampling points (0, 20, 40, 60 80, 100 cm and control point) and between the soil depths (surface; 0–30 cm and subsoil; 30–60 cm). The six sampling points, control and horizons (surface and subsurface) were regarded as the treatments, and replicated three times as traverses along the dumpsites. Properties that were significantly varied were ranked using Duncan Multiple Range test (DMRT). Pearson correlation analysis was used to determine the relationship between the parameters that were normally distributed, while Spearman correlation for those soil samples not normally distributed. All the statistical analyses were carried out at 95 % confidence level. To develop models for predicting spatial distribution of heavy metals from dumpsite, regression analysis was used after the data were transformed as were not normally distributed to enabled validation and provide options to obtain the best model. Model that had a highly significant correlation with highest R^2 was chosen as the best for each heavy metal. The statistical analyses were carried out using Statgraphic Centurion XV computer soft-ware packages (StatPoint, 2020).

RESULTS AND DISCUSSION

Status, Spatial Distribution and Relationship of Heavy Metals

The overall range and means across the study area indicated decreasing order of concentration of heavy metals as follow: Fe ranged between 3205.75 and 4080.25 mg kg^{-1} (mean: 3,818.21 mg kg^{-1}) > Mn 267.75 to 1,554.25 mg kg^{-1} (881.49 mg kg^{-1}) > Zn 132.60 and 788.25 mg kg^{-1} (552.73 mg kg^{-1}) > Cu 30.50 to 594.75 mg kg^{-1} (148.76 mg kg^{-1}) > Cr 69.5 and 203.5 mg kg^{-1} (138.88 mg kg^{-1}) > Pb 0 to 114.75 mg kg^{-1} (26.45 mg kg^{-1}) > Cd 0 to 142.25 mg kg^{-1} (7.73 mg kg^{-1}). The overall mean of concentration of heavy metals across the

study area were rated as high for Cu, low for Fe and Mn, low to high for Zn, Cr, Pb and Cd (FAO/WHO, 2001).

The mean values of heavy metals Fe, Cu, Zn and Cr were significantly different between the spatial distances (Table 1). The mean values of Fe and Cr across the study area were significantly higher than at the dumpsite, while Cu and Zn were significantly higher at dumpsite and decreased as spatial distance increased away from dumpsite.

Finer particles silt and clay tend to adsorb Fe, thereby increasing the concentration as indicated by their highly significant and positive correlation ($r = 0.7723^{**}$ and 0.6367^{**} respectively; Table 2). Soil pH had a significant but negative correlation with Fe. These soil physical and chemical properties influenced the adsorption, mobility and availability of Fe as also ascertained by Luo *et al.* (2016).

Spatial distribution of Mn was notably influenced by soil physical and chemical properties as indicated by the significant positive correlation with several parameters (Table 2). Increase in silt, organic carbon and CEC contributed to adsorption of Mn, hence influencing its availability for plant use. The significant relationship between Mn and basic cation (Ca and Mg) as well as heavy metals Cu, Fe and Pb indicated similar factors and processes influenced their distributional trends in form of adsorption, mobility and availability (Alloway, 2001; Yahaya 2009). The distribution of organic carbon influenced adsorption and mobility of Cu and probably with available phosphorus as indicated by their correlation matrix (Table 3), and considered to be resourceful in the land use and management decisions for the study area.

Table 1: Ranking of Means of Heavy Metals of the Study Area (Spatial Distribution)

Properties	Units	Dump	Spatial Sampling Points					Site	SE±	P (Value)	LOS
		0 m	20 m	40 m	60 m	80 m	100 m	Control			
Fe	(mg kg^{-1})	3484b	3966.4a	3979.1a	3964.7a	3754.4ab	3760.7ab	3902ab	137.90	0.004	**
Mn	(mg kg^{-1})	995.5	971.5	878.4	994.5	720.08	729	594.5	199.81	0.402	NS
Cu	(mg kg^{-1})	283.2a	160.5b	119.3b	125.8b	100.6b	103.6b	84.5b	46.03	0.002	**
Zn	(mg kg^{-1})	651.9a	668.8a	577.5ab	559.5ab	434.9bc	423.8bc	266.3c	91.98	0.006	**
Cd	(mg kg^{-1})	38.38	2.79	1.88	1.42	1.04	0.87	6.00	14.272	0.074	NS
Cr	(mg kg^{-1})	94.75b	151.42a	140.54a	164.21a	143.21a	139.14a	141.25a	18.155	0.013	*
Pb	(mg kg^{-1})	33.04	33.58	13.75	19.13	25.17	34.04	10.63	19.974	0.859	NS

NS > 0.05, * ≤ 0.05, ** ≤ 0.01. SE = statndard error. Means followed by the same letters in the rows are not significantly different at 5% level of significance (LOS).

Table 2: Pearson correlation matrix of soil properties verses heavy metals of the study area

	Fe	Mn	Cu	Cd	Cr	Pb	Zn
CLAY	0.637**	0.095	-0.106	-0.226	0.553**	-0.263	0.204
SAND	-0.784**	-0.324	0.065	0.251	-0.664**	0.048	-0.361*
SILT	0.772**	0.535**	0.004	-0.219	0.636**	0.239	0.469**
Av. P	-0.134	0.373*	0.688**	0.207	-0.307	0.400*	0.350*
BD	0.275	-0.247	-0.389*	-0.2541	0.327	-0.163	-0.243
Ca	0.583**	0.496**	0.261	-0.151	0.462**	0.353**	0.722**
CEC	0.156	0.333*	0.354*	0.266	0.159	-0.005	0.669**
ECe	-0.173	-0.291	-0.063	0.196	-0.038	-0.215	-0.200
ESP	-0.285	0.103	0.305	0.584**	-0.202	-0.277	0.372*
K	-0.251	0.081	0.293	0.462**	-0.162	-0.273	0.359*
Mg	0.481**	0.538**	0.412*	0.198	0.360*	0.043	0.727**
Na	-0.258	0.088	0.284	0.490**	-0.166	-0.259	0.380**
TOC	0.128	0.519**	0.539**	0.263	-0.050	0.420*	0.726**
pH $CaCl_2$	-0.016	0.330*	0.183	0.048	-0.217	0.189	0.454**
pH H_20	-0.367*	0.175	0.119	0.296	-0.494**	0.249	0.231
Spoint	0.134	-0.301	-0.556**	-0.373*	0.314	-0.023	-0.551**
TP (%)	-0.059	0.154	0.088	0.009	-0.094	0.102	0.101
Fe		0.506**	-0.012	-0.335*	0.780**	0.225	0.444**
Mn			0.481**	0.046	0.208	0.440**	0.763**
Cu				0.256	-0.060	0.410*	0.615**
Cd					-0.217	-0.067	0.139
Cr						0.043	0.227
Pb							0.463**

BD = Bulk density, TOC = Total organic carbon, Av. P = Available Phosphorus, Spoint = Sampling point, LOS = Level of significance (P): * ≤ 0.05, ** ≤ 0.01.

Concentration of Zinc (Zn) highly and significantly varied with increasing the spatial distance buttressed by the highly significant correlation (r = -0.5506**). Increase in organic carbon, silt and CEC contributed to the adsorption of Zn, (Table 2). Zinc significantly and positively correlated with Av. P, Ca, Mg, K, Na, Cu, Fe, Pb and Mn (Table 2) indicated similarity in distribution trend associated with mobility adsorption and availability Uba *et al.* (2013). The trend of variation and relationship between soil properties are essential to land use, management plan and remediation strategy in the study area.

The concentration of Cd and Cr in the soils significantly correlated with spatial distance (Table 2) and may be attributed to influence of physico-chemical properties that significantly correlated with them (Table 2). The high values of Pb may be attributed to traffic pollution. The significant relationship between available P and total organic carbon implied that Cd and avail. P might have been adsorbed or formed chelate complexes with Pb (Kabata-Pendias, 2011; Wuana *et al.,* 2014).

Modelling Spatial Distribution of Heavy Metals around Dumpsite

From the correlation analysis of concentration of selected heavy metals Fe, Mn, Cu, Zn, Cr, Cd and Pb with the spatial distance from the waste dumpsite (Table 2), only Cd, Cu and Zn were significantly and negatively correlated with the spatial distance. Heavy metal

Cd, Cu and Zn significantly correlated negatively with spatial distance indicating correlation matrix r = -0.3734*, -0.6402** and -0.5493** (Table 3 and Table 4). To develop model for predicting heavy metals based on distance from dumpsite, the data were transformed as were not normally distributed to enabled validation and provide options to obtain the best model (Table 3). For Cd, the model with the highest r - value was the square root-spatial distance model which yields the highest R-Squared value with 22.20 % (Table 4 and Figure 3). Copper highest r – value for the prediction model was obtained using the square root-X (spatial distance) model which yields the highest R-Squared value with 40.98 % (Table 4 and Figure 4). The prediction model that fitted for Zn is the squared-Zn model that yields the highest R-Squared value with 30.43 % (Table 4 and Figure 5). However, Cd had the least coefficient of determination (R^2) and was quite low (Table 3). The prediction models of spatial distribution of Cd and Zn are also considered not good. Copper had the highest R^2 with regression prediction model equation obtained using the square root of spatial distance (SD) {Cu = 225.397 - 1.5328(SD)^{½}} which yields the highest R-Squared value of 40.98 % (coefficient of determination; 0.4098) Tables 3 and 4). All the coefficient of determination (R^2) were less than 50 %, hence considered as weak prediction models for the heavy metals studied in the study area.

Table 3: Comparison of alternative models for Cd, Cu and Zn

	Cd		*Cu*		*Zn*	
Model	*Correlation*	*R^2(%)*	*Correlation*	*R^2(%)*	*Correlation*	*R^2(%)*
Square root-X	-0.4712	22.20	-0.6402	40.98	-0.4932	24.32
Squared-Y	-0.2997	8.98	-0.4418	19.52	-0.5516	30.43
Squared-X	-0.2698	7.28	-0.4105	16.85	-0.5493	30.17
Squared-Y square root-X	-0.3857	14.88	-0.6364	40.50	-0.5040	25.40
Linear	-0.3734	13.94	-0.5558	30.89	-0.5506	30.32
Square root-Y squared-X	-0.3692	13.63	-0.5066	25.67	-0.5466	29.88
Double squared	-0.2113	4.46	-0.3054	9.32	-0.5320	28.30
Logarithmic-Y squared-X	<no fit>		-0.5346	28.58	-0.5367	28.81
Square root-Y	<no fit>		-0.6069	36.83	-0.5380	28.94
Exponential	<no fit>		-0.6059	36.71	-0.5187	26.91
Reciprocal-Y squared-X	<no fit>		0.5022	25.22	0.5069	25.69
Reciprocal-Y	<no fit>		0.5130	26.31	0.4742	22.48
Reciprocal-Y square root-X	<no fit>		0.4850	23.52	0.4030	16.24
Squared-Y square root-X	<no fit>		-0.5007	25.07	<no fit>	
Logarithmic-Y square root-X	<no fit>		<no fit>		-0.4526	20.48
Squared-Y logarithmic-X	<no fit>		<no fit>		<no fit>	

Table 4: Predicting regression models of heavy metals verses spatial distance

Heavy Metal	Regression Model Equation	r	R^2
Cadmium (Cd)	$Cd = 14.7481 - 0.00191463(SD)^{½}$	-0.4712	22.20 %
Copper (Cu)	$Cu = 225.397 - 1.5328(SD)^{½}$	-0.6402	40.98%
Zinc (Zn)	$Zn = \{646.021 - 0.0254464(SD)\}^{½}$	-0.5516	30.43%

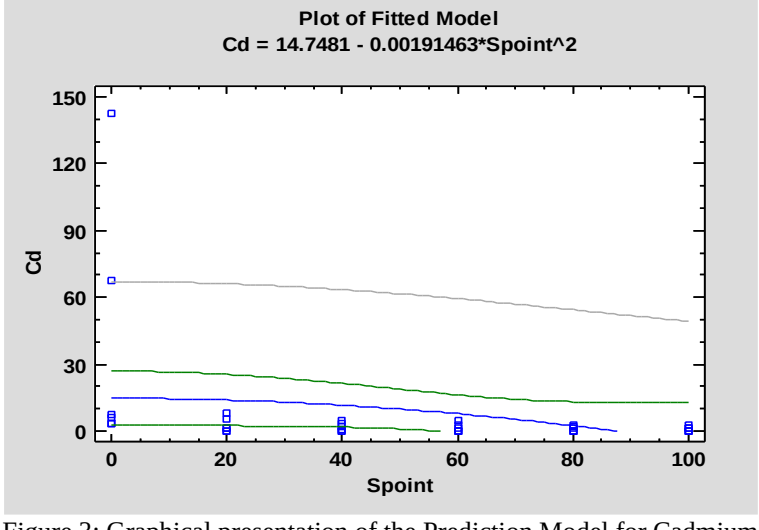

Figure 3: Graphical presentation of the Prediction Model for Cadmium

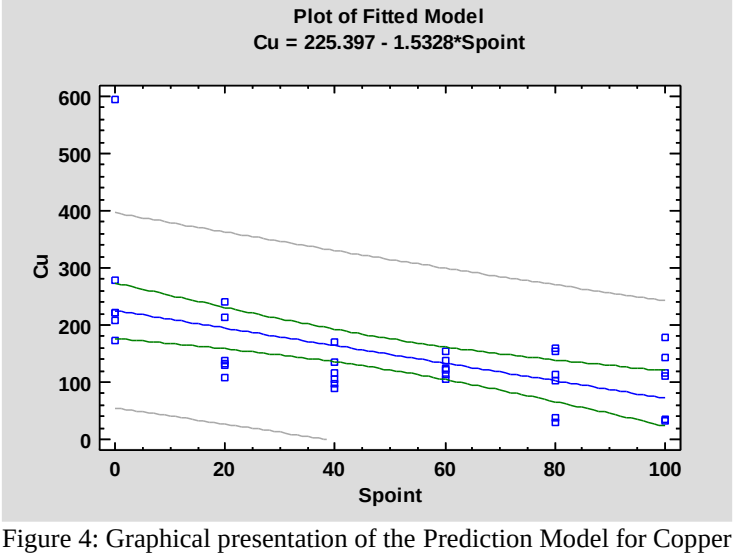

Figure 4: Graphical presentation of the Prediction Model for Copper

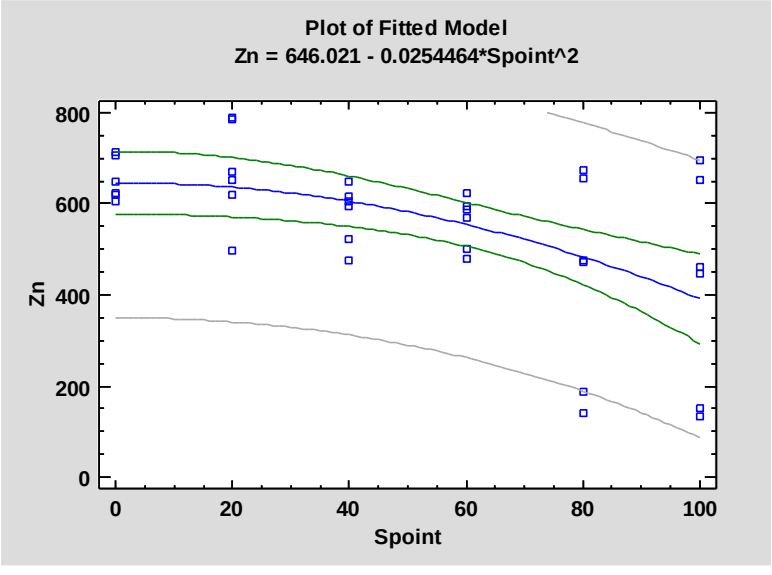

Figure 5: Graphical presentation of the Prediction Model for Zinc

Heavy Metals Pollution and Ecological Risk Assessment of the Soils

Various models were employed to assess the heavy metals pollution and their potential ecological risk. Contamination factor (CF) was assessed as an index of pollution with the results of the overall mean indicated a decreasing order of Pb (2.939) > Zn (2.086) > Cd (1.932) > Cu (1.776) > Mn (1.445) > Cr (1.035) > Fe (0.9799).

The pollution of the soils as indicated by CF index for Fe, Cu, Zn and Cr were significantly influenced by waste dumping (Table 5). However, HMs manganese and Cd were not significant different between the spatial distances. Contamination factor indicated spatial distance correlated significantly but negatively with Cu, Zn and Cd heavy metals (Table 6).

The relationship between spatial distance from waste dump site and pollution and risk indices indicated that contamination factor (CF) for Cu, Zn and Cd were significantly correlated with spatial distance. Similarly, enrichment factor (EF) significantly correlated with spatial distance for Cu, Zn and Cd as well as Mn and Cr (Table 6). The comparisons of the mean values for EF for Cu, Zn, Cd and Cr significantly differ with spatial distance (Table 5), this further affirmed the impact of waste dumping on HMs distribution within the floodplain (Inengite *et al.*, 2015; Adedeji *et al.*, 2020).

Likewise, Pollution Ecological Risk (PER) significantly and negatively correlated only with spatial distance for Cu, Zn and Cd. The significant negative correlation between heavy metals Cu, Zn and Cd with spatial distance implied that pollution and risk indices decrease with increase in spatial distance for CF, EF and PER pollution and risk models.

Table 5: Ranking of means of spatial distribution of pollution and risks indices

Indices	Spatial Sampling Points						SE±	P (Value)	LOS
	0 m (Dump Site)	20 m	40 m	60 m	80 m	100 m			
CF Fe	0.894b	1.017a	1.021a	1.018a	0.964ab	0.965ab	0.0325	0.003	**
CF Mn	1.632	1.593	1.440	1.630	1.181	1.195	0.3076	0.466	NS
CF Cu	3.382a	1.916b	1.424b	1.501b	1.201b	1.233b	0.5272	0.002	**
CF Zn	2.460a	2.524a	2.179ab	2.111ab	1.641b	1.599b	0.3210	0.026	*
CF Cd	9.594	0.698	0.464	0.354	0.260	0.217	3.3519	0.051	NS
CF Cr	0.706b	1.128a	1.047a	1.223a	1.067a	1.036a	0.1264	0.008	**
CF Pb	3.671	3.731	1.528	2.125	2.793	3.782	2.1252	0.843	NS
EF Mn	1.810	1.565	1.406	1.595	1.912	1.203	0.2848	0.238	NS
EF Cu	3.730a	1.883b	1.393b	1.479b	1.210b	1.237b	0.5217	0.000	**
EF Zn	2.752a	2.480a	2.133ab	2.080ab	1.656b	1.606b	0.3039	0.004	**
EF Cd	10.854a	0.686b	0.457b	0.345b	0.285b	0.243b	3.7234	0.044	*
EF Cr	0.787b	1.108a	1.024a	1.202a	1.094a	1.061a	0.1066	0.014	*
EF Pb	3.890	3.670	1.504	2.114	2.778	3.734	2.1266	0.826	NS
PER Cu	16.908a	9.580b	7.122b	7.504b	6.005b	6.164b	2.6360	0.002	**
PER Zn	2.460a	2.524a	2.172ab	2.111ab	1.641b	1.599b	0.3210	0.026	*
PER Cd	287.81	20.94	14.06	10.63	7.81	6.50	100.558	0.051	NS
PER Cr	1.412b	2.256a	2.094a	2.446a	2.133a	2.073a	0.2528	0.008	**
PER Pb	18.36	18.66	7.64	10.63	13.98	18.91	106259	0.843	NS
GAI Fe	0.749a	0.559b	0.555b	0.560b	0.643b	0.640b	0.0502	0.003	**
GAI Mn	0.269	0.220	0.359	0.475	0.611	0.798	0.2745	0.299	NS
GAI Cu	1.039	0.367	0.294	0.157	0.800	0.793	0.3360	0.083	NS
GAI Zn	0.711	0.734	0.531	0.487	0.759	0.813	0.1959	0.490	NS
GAI Cd	1.684	0.746	0.684	0.644	0.801	0.931	0.6966	0.719	NS
GAI Cr	1.120a	0.220b	0.542b	0.318b	0.546b	0.574b	0.1858	0.004	**
GAI Pb	1.017	1.073	0.579	1.089	0.793	0.999	0.6150	0.955	NS

CF = Contamination Factor, EF = Enrichment Factor, PER = Pollution Ecological Risk, GAI = Geo Accumulation Index. LOS (P): NS (Not significant) > 0.05, * ≤ 0.05, ** ≤ 0.01.

Table 6: Correlation matrix of sampling points verses pollution and risk indices

Contamination Factor	Sampling Point	Enrichment Factor	Sampling Point	Pollution Ecological Risk	Sampling Point	Geo Accumulation Index	Sampling Point
CF Fe	0.1337	-	-	-	-	GAI Fe	-0.1316 ^{NS}
CF Mn	-0.3013	EF Mn	-0.3856*	-	-	GAI Mn	0.4010*
CF Cu	-0.5558**	EF Cu	-0.5820**	Cu PER	-0.5558**	GAI Cu	-0.0055 ^{NS}
CF Zn	-0.5506**	EF Zn	-0.6373**	Zn PER	-0.5506**	GAI Zn	0.0795 ^{NS}
CF Cd	-0.3734*	EF Cd	-0.3757*	Cd PER	-0.3734*	GAI Cd	-0.1642 ^{NS}
CF Cr	0.3137 ^{NS}	EF Cr	0.3461*	Cr PER	0.3137 ^{NS}	GAI Cr	-0.3236 ^{NS}
CF Pb	-0.0232 ^{NS}	EF Pb	-0.0399 ^{NS}	Pb PER	-0.0232 ^{NS}	GAI Pb	-0.0207^{NS}

The significant variation for of PER for Cu and Zn (Table 5) also affirmed the impact of waste dumping on HMs distribution. However, geo accumulation index (GAI) did not correlate significantly, similarly most HMs did not vary significantly with spatial distance (Table 5 and Table 6). The similarity in trend of correlations with spatial distances from dumpsite indicated that they were considered to be more appropriate models to use compared to I_{geo} model in the study area. Contamination factor for heavy metal Cd ranged between low and very high. The dumpsite was very highly contaminated with Cd, but the entire farmland was rated to be low. Heavy metal Cd may be immobile in the soils of the study area. It may be conditioned by the effect of the soil physical and chemical properties influence Cd immobilization in soils (Adedeji *et al.,* 2020; Otene and Alfred-Ockiya, 2020). The negative and significant correlation between Cd and spatial distance (-0.3734) indicated influence of dumpsite as a source of distribution Cd pollutant of the soils of the farmland in the study area. It may be transported through surface runoff and deposited along with decrease in contamination. Degefa and Damea (2015) carried out similar research using landfill and indicated cadmium contamination within the dumpsite was as a result of anthropogenic activities. Similarly with the mean values of PER for Cu and Zn indicated that the spatial variability was significantly influenced by waste dumping (Table 5) as an anthropogenic activity Xinjian *et al.* (2020).

CONCLUSION

The study results indicated that clay significantly and positively influenced spatial distribution of concentration of heavy metals iron (Fe) and chromium (Cr), while negatively by sand and soil pH. Concentration of most of manganese (Mn), copper (Cu), lead (Pb), chromium (Cr) and zinc (Zn) increased with increase in total organic carbon (TOC), available phosphorus (P), exchangeable calcium (Ca) and magnesium (Mg) and was attributed to complexation (chelation), thereby influencing their distribution and availability. Copper had the highest coefficient of determination for modelling, but still weak for prediction model, and was obtained using the square root of spatial distance $\{Cu = 225.397 - 1.5328(SD)^{½}\}$ which yields the highest R-Squared value of 40.98 %. The overall means of contamination factor indicated a decreasing order of Pb > Zn > Cd > Cu > Mn > Cr > Fe. The enrichment factor index indicated that all the metals had moderate risk with only Cr had low risk to the environment. Assessment of HMs using contamination factor (CF), enrichment factor (EF) and potential ecological risk (PER) models had similar trend of correlations with spatial distances from dumpsite, hence were considered to be more appropriate models to use compared to I_{geo} model in the study area.

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