

# Statistical Analysis and Spatial Distribution of Metals in Soils of Potash Extraction Site in Matara Uku, Nigeria

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#### Abstract

A survey was carried out in the artisan potash extraction site in Matara uku, Jigawa State, Nigeria and its environs to determine the spatial distribution and possible sources of metals. In the study, samples were collected at different locations of the study area for elemental analysis. The samples were analyzed using Energy Dispersive X-Ray Fluorescence (ED-XRF) Spectroscopy. The quantification of soil pollution was carried out using Enrichment Factor (EF), geo-accumulation index  $(I_{geo})$  and Contamination Factor (CF) in order to determine the metal accumulation, distribution and pollution status. The pollution analysis showed that La has the highest enrichment, while Ti has the highest contamination. The principal component analysis extracted three components with eigen value greater than one. The first principal component (PC1) has high loadings of Al, K, Fe, Ti, Ce and Mn whereas the second component (PC2) has high loadings of Ca and Mg. A lithogenic source is presumed for the first and second components since the metals are generally present in the parent material of the soil. The contour maps of Al, K, Fe, Ti, Ca, Mg, and Mn depicted a similar spatial pattern, with contamination hotspots spontaneously spotted at the Northern and Eastern parts of the study area. These indicate that the elements were from the same source, which is in agreement with principal component analysis.

Keywords: Matara Uku, Birniwa, Energy Dispersive X-Ray fluorescence, Enrichment Factor, Contamination Factor, Principal Component Analysis, Nigeria

### **1.0 Introduction**

Local extraction and mining of metals immensely contribute to the increment of certain metal contaminants in the soil. This increment has an adverse effect on plant life, which consequently affects animals and human health. The demand for metals and minerals continue to increase due to population growth, rapid urbanization, new infrastructural development and the advancement of energy and communication technologies (Maina et al., 2016). It is projected that the demand for minerals will likely increase continuously by approximately 2 - 6 times the current demand, depending on the type of metal or mineral (Watari & Nakajuma, 2021). The mining and artisanal mining of minerals and metals due to their high demands have adversely affected soil and water (Maina et al., 2016; Watari et al., 2021). Soil contamination with heavy metals draws serious attention due to its possible threat to safety and long term effect on the ecosystem (Lu et al., 2012; Krishna & Mohan, 2016). The two main sources of heavy metals in the environment are geochemical reactions and anthropogenic activities. The major anthropogenic sources are individual discharge, agricultural chemicals and municipal sewage discharge (Qishlaqi & Moore, 2007; Yi & Yuan 2022).

The knowledge of heavy metals accumulation in soils, their origin and their effect on the soil has been the main objective of many environmental studies. These studies were conducted using a combination of multivariate statistics and geostatistical analysis to identify pollution characteristics of heavy metals in soil and as well distinguish the natural and anthropogenic inputs (Lu et al., 2012; Chandrasekaran & Ravisankar, 2015; Krishna & Mohan, 2016). Some of these studies were

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conducted near and far from mining and local extraction sites (Maina et al., 2016; Zheng et al., 2020; Kabala et al., 2020). Santos et al., (2014) and Zheng et al., (2020), reported high concentrations of As and Cu from Tungsten and Tin mines, with the later addition of high concentrations of Cd and Pb. Yan et al. (2020), Kabala et al. (2020) and de Araújo et al. (2022) reported high concentrations of Pb, Zn and As in copper mines, with the latter reporting high concentrations of Cu and Ni in addition to the stated metals. Barcelos et al. (2020) and Adewumi & Laniyan (2020) reported high concentration of As, Pb and Hg in gold mining sites with the former reporting high concentration of Cd, Zn and Mn in addition. Kien et al. (2010), A. K. Krishna & Mohan, (2013) and Pattnaik & Equeenuddin (2016) reported high concentration of Cr, Ni and Co in soils near chromite mining sites. Obiora et al. (2016), Liu et al. (2020) and Njoku et al. (2020) reported high concentrations of Cd, Zn, Pb in lead-Zinc mining sites. Mine waste have also been reported to be major sources of soil and water contamination. In Free State Province, South Africa, tailings were observed to contaminate streams and underground water (Belle et al., 2020). The environmental effect of potash mining is poorly understood (Ladrera et al., 2017; Brucet et al., 2019). Potash mining has the potential to significantly alter the biological communities of surrounding rivers and streams (Ladrera et al. 2016; Gorostiza & Sauri, 2019).

According to literature, the environmental effects of mining have been studied years after the operation has started or years after the mining plant is closed (Maina et al., 2016). Basically, it is more pertinent to ascertain the baseline levels of the metal before mining activities begin. This will enable researchers and policy makers to conduct regular audits in order to determine the impact of mining on the environment. Therefore, the objective of this study is to use statistical analysis (univariate and multivariate) and pollution analysis to investigate the current state of metal contamination in the study area and identify the spatial pattern and possible sources of heavy metals. The study will also provide knowledge of the distribution of these metals in soils and then evaluate the environmental impact caused by air emissions from the artisan potash extraction site and agricultural activities near the residential area. Furthermore, it will also provide data on the concentration of heavy metals in the soil before the possible commencement of potash mining (the potash is currently locally extracted in the study area). The result will be used as a follow up study as it will provide the basis for effectively targeting policies to protect soils from the long term accumulation of heavy metals.

# 1.1 The Study Area

Matara uku is located between latitude 12.7° North and longitude 10.3° East and is a rural community in Birniwa Local Government of Jigawa State, Northwest, Nigeria. It is located at an altitude of 325m above sea level. The major occupations of the inhabitants of Matara uku are farming, fishing and artisan mining of potash. The village is located 17 km south east of Hadejia - Nguru Federal Highway. It covered 50 km<sup>2</sup> of cultivable, irrigable land and upland (Omilola, 2009). It has an estimated population of four thousand people, according to 2006 population census (National Population Commission, 2009). It has an annual rainfall of 584.5mm and the average temperature of the area varies from 12°C between December and January and 40°C recorded between March and April (Dauda et al., 2017).

The area falls in the semiarid climatic zone (Ikusemoran & Ezekiel, 2011; Umar et al., 2019). Geologically, the area is covered by the sedimentary Chad Formation. The formation is made up of unconsolidated sediments (Umar et al., 2019). The region has abundant underground water resources due to the unconsolidated sediments.





Figure 1: The Map of River Hadejia showing the study area (based on Umar *et al.*, 2019)

# 2.0 Materials and Methods

The following materials and methods were adopted in this study.

- A. Sample collection and preparation: Soil samples were collected at different locations where potash is locally extracted along the flood wetland of River Hadejia. The samples were collected at a depth of 5 - 15 cm. Before collecting the samples, the top cover soil and grasses were removed. A total of 25 samples were taken and the geographical location of each sampling site was obtained using a portable (handheld) Global Positioning System (GPS). The samples were collected in self-locking polythene bags and sealed in bags. The use of metal tools was avoided, as such plastic spatula was used for sample collection. At the laboratory, the samples were placed inside a desiccator. Later, 1 gram of each fine ground sample was mixed with 0.5 g of boric acid for pellet preparation. The mixture was then pressed into a pellet of 25 mm diameter using a hydraulic press.
- B. XRF Technique: The pellets prepared were analysed using energy dispersive X-ray fluorescence (ED-XRF) at the Centre for Dry Land Agriculture (CDA), Bayero University, Kano. The instrument used for the study is the Bruker S2 Ranger, produced by Bruker AXS GmbH. The instrument is fitted with a side window CX-ray tube (50W) that has a silver anode. It has a silicon drift detector (SDD) with high sensitivity and very high resolution. In addition, it can take 28 samples at a time.

# C. Multivariate Statistical Analysis:

(i). Correlation Analysis: Pearson correlation analysis was adopted in order to quantitatively analyse and confirm the relationship between the metals (Orosun et al., 2005; Qishlaqi & Moore, 2007; Krishna & Mohan, 2016). This analysis is useful in the confirming association between metals. When analysing data from soil samples, a positive correlation between metals indicates that they have the same source or co-contamination, while negative correlation indicates that the metal pairs are derived from different sources or origins (Chandrasekaran et al., 2015). The analysis was carried out using IBM<sup>®</sup> SPSS<sup>®</sup> Statistics version 26.

(ii) Principal Component Analysis (PCA) and Cluster Analysis (CA): These analyses are the most widely used multivariate statistical methods in geochemical studies (Díaz et al., 2003; Dempster et al.,



2013, Tsodoulos et al., 2013; Chandrasekaran et al., 2015). They are performed to identify the relationship among elements in the soil. In this study, PCA is applied to the correlation matrix and each variable is normalized to a unit variance to obtain an equal contribution. This is because the concentrations of the metals evaluated in this study vary by different orders of magnitude. To make the result easily interpretable, PCA with varimax normalized rotation is used in order to maximize the variance of the factor loadings across variables for each factor. Factor loadings of 0.7 are typically regarded as excellent and 0.32 as very poor (Chandrasekaran et al., 2015). In this work, Varimax normalized rotation is performed.

Cluster analysis was used in order to classify elements from different sources on the basis of similarities in their chemical properties. Hierarchical cluster analysis is used to identify relative homogenous groups of variables using an algorithm that begins with each variable in a separate cluster and combines clusters until only one is left. The analysis was carried out using IBM<sup>®</sup> SPSS<sup>®</sup> Statistics version 26.

- D. Descriptive Statistical Analysis: Descriptive statistical analysis deals with the statistical parameters that are generally accepted as indicators of the central tendency and spread of data (Ramzan et al., 2017). This includes a description of the mean, minimum and maximum values, the standard deviation and coefficient of variation. Skewness and kurtosis were also examined to determine whether or not the distribution followed the normal frequency distribution. The coefficient of variation was used to assess the variability of different data sets. In this study, Microsoft Excel 2010 produced by Microsoft <sup>®</sup> Corporation and Origin Pro 8.5, produced by Origin Lab<sup>®</sup> Corporation were used.
- E. Geospatial Distribution: Geospatial methods are used to understand the location of the elements. It provides a comprehensive picture of spatial distribution of an area. In this study, the distribution maps of the elements present in the study area were plotted using Golden Software's Surfer, version 8.0.
- F. Quantification of soil pollution: The essence of quantifying soil pollution is to assess the level of contamination and also detect possible anthropogenic impacts on the soil. In this study, the enrichment factor (EF), geo-accumulation index (Igeo), contamination factor (CF) and pollution load index (PLI) were determined for some selected metals detected in the soil samples obtained from the study area.

(i). Enrichment Factor (EF): The enrichment factor (EF) can be utilized to differentiate between metals originating from human activities and those from natural procedures and to assess the degree of anthropogenic influence (Ghazban et al., 2018). The most common technique used is the normalization of a tested element against a reference one. A reference element is often a conservative one, such as the most commonly used elements: Al, Fe, Mn, Ti, etc. The enrichment factor is calculated using the equation modified by Loska et al., (2004).

$$EF = \frac{(C_n)_{sample}}{(C_{ref})_{sample}} / \frac{(B_n)_{background}}{(B_{ref})_{background}}$$
(1)

where  $(C_n)_{sample}$  is the concentration of the examined element,  $(C_{ref})_{sample}$  is the concentration of the reference element in the examined environment,  $(B_n)_{background}$  is the crustal value of the examined element and  $(B_{ref})_{background}$  is the crustal value of the reference element. (Sutherland, 2000) categorized EF into five groups. They are; EF < 2: deficiency to minimal enrichment; 2 = EF<5: moderate enrichment;  $5 \le EF < 20$ : significant enrichment;  $20 \le EF < 40$ : very high enrichment;  $40 \le \text{EF}$ : extreme high enrichment.

Enrichment factor can also be used to differentiate between elemental concentrations from anthropogenic and natural source. According to Yongming et al. (2006), Ghazban et al. (2018), Chandrasekaran et al. (2015), Alonso-hern (2016) and Ghrefat et al. (2021), EF between 0.5 and 2

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indicates that the soil had no anthropogenic inputs, i.e., it's from crustal materials or natural origin, while those with EF greater than 2 indicate that the sources are likely anthropogenic and EF greater than 10 indicates that the metal has a non crustal source. Due to lack of local reference values for metal concentration, the earth's crust background values reported by Turekian and Wedephol (1961) were used, despite the advantages and disadvantages of their use (Abrahim & Parker, 2008; Pablo et al., 2016).

(ii) Geo-accumulation index  $(I_{geo})$ : This is the quantitative measure of the degree of pollution that has been widely used in heavy metal studies (Maria & Naseem., 2011; Chandrasekaran et al., 2015; Adedeji et al., 2020). It allows for the assessment of contamination by comparing the concentration of elements obtained and the background value in the earth's crust. According to Loska et al., (2004), the geo-accumulation index is calculated using

$$I_{geo} = \log_2\left(\frac{C_n}{kB_n}\right) \tag{2}$$

Forstner (1990), provides the descriptive classification of geo-accumulation index as shown in Table 1.

Class	Range	Index
Class 0	$I_{geo} \leq 0$	Practically uncontaminated
Class 1	$0 < I_{geo} \le 1$	Uncontaminated to Moderately contaminated
Class 2	$1 < I_{geo} \le 2$	Moderately contaminated
Class 3	$2 < I_{geo} \le 3$	Moderately contaminated to heavily contaminated
Class 4	$3 < I_{geo} \le 4$	Heavily contaminated
Class 5	$4 < I_{geo} \le 5$	Heavily contaminated to extremely contaminated
Class 6	$5 < I_{geo} \le 6$	Extremely contaminated

Table 1: Classification of Geo-accumulation ind	ex.
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Due to lack of local reference values for metal concentration, the earth's crust background values reported by Turekian and Wedephol (1961) were used, despite the advantages and disadvantages of their use (Abrahim & Parker, 2008; Pablo et al., 2016).

(iii). Contamination Factor: In an environment, metal contamination is controlled by parameters like physicochemical conditions controlling dissolution and precipitation of metals, nature of the substrate and closeness to pollution sites (Chandrasekaran et al., 2015). The history and degree of contamination can be recorded by the soil (Nobi et al., 2010). Thus, the contamination factor is considered an effective way of monitoring pollution over a period of time. It is obtained using

$$CF = \frac{C_{metal}}{C_{background}}$$
(3)

where  $C_{metal}$  is the concentration of metal in soil sample and  $C_{background}$  is the crustal value of the metal. According to Forstner et al., (1990), contamination factor may be classified based on its intensity ranging from 0 to 6 (0 =none, 1 =none to medium, 2 =moderate, 3 =moderate to strong, 4 = strong, 5 = strong to very strong and 6 = very strong).

# **3.0 Results and Discussions**

Descriptive Statistics: Descriptive data analysis comprising mean, minimum, maximum, standard deviation, skewness and kurtosis were carried out. The standard statistical analysis was carried out to describe the metal content in the soil. The mean concentrations of Al, K, Fe, Ca, Mg, Ti, Zr, La, Ce,

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and Mn are found to be 42115.38, 18200, 15323.08, 11769.23, 7692.31, 610, 390.77, 58.46, 25.38, and 153.04 ppm, respectively (Table 1). Amongst the metals detected, the mean concentrations of Al, K, Fe, Mg, Zr and La are higher, while those of Ca, Ti, Mn and Ce are lower than the crustal value reported by Turekian & Wedephol (1961). The metal Ca showed a higher standard deviation due to its heterogeneity in metal pollution. Skewness is used to identify concentrations with a normal or abnormal distribution (Table 2). The metals with skewness values between -1 and +1 showed a normal distribution and slightly positive skewness values were identified as abnormal. In Matara Uku, Mn showed the highest skewness and as such, it has a slight abnormal distribution.

S/N	Element	No. of	Mean	Minimum	Maximum	Stand.	Skew.	Kurt.	*CV
		Obs.				Dev.			
1	Al	20	42115.38	33600	54800	6076.44	0.56	-0.16	25000
2	Κ	20	18200	11500	25800	4023.47	0.14	-0.24	10700
3	Fe	20	15323.08	8900	27200	5669.83	0.92	0.05	9800
4	Ca	20	11769.23	4300	24300	7099.94	0.89	-0.71	39100
5	Mg	20	7692.31	4000	14000	2529.32	1.03	2.43	7000
6	Ti	20	610	0	770	201.37	-2.59	7.86	1500
7	Zr	20	390.77	240	640	106.81	0.97	1.23	220
8	La	20	58.46	0	120	49.64	-0.33	-1.93	30
9	Ce	20	25.38	0	70	29.04	0.30	-2.03	92
10	Mn	20	153.05	0	800	298.93	1.61	0.96	850

Table 2: Descriptive Statistics of Elements in Matara Uku

\*CV, Crustal value reported by Turekian and Wedephol, (1961)

The concentration of Al is very high due to the sedimentary nature of the environment. The high concentration of Fe is not a major concern because it is not a contaminant. The mean concentrations of the metals in order are Al > K > Fe > Ca > Mg > Ti > Zr > La > Ce > Mn.

# Quantification of soil pollution

The essence of quantifying soil pollution is to access the level of contamination and also to detect whether the source of metal is from crustal material of natural origin or anthropogenic. In this study, enrichment factor, geo-accumulation index, contamination factor and pollution load index.

(i) Enrichment Factor (EF): In this work, Fe is considered the reference element due to its normal distribution. Fe also shows a practically uncontaminated  $I_{geo}$  index. In this study area, the EF of Al, K, Ca, Mg, Zr, La, Ce and Mn are in the range of 0.73-1.73, 0.86-1.59, 0.08-0.31, 0.37-1.4, 0.45-2.01, 0-3.6, 0-0.59 and 0-0.35. The mean value of EF for Matara Uku is given in Table 3.

Table 3:         Values of Enrichment Factor for Matara uku									
		Mean Values							
Element	Al	Κ	Ca	Mg	Ti	Zr	La	Ce	Mn
Enrichment	1.16	1.15	0.19	0.76	0.28	1.25	1.56	0.22	0.08
Factor									

The result of this study area shows that the enrichment factor of all elements is less than two, which indicates that there is minimal enrichment. The result also shows that all elements considered in this study have their source from natural origin. This is because according to Yongming et al. (2006); Ghadimi et al. (2013); Chandrasekaran et al. (2015); Alonso-hernet al., (2016) and Ghrefat et al. (2021), EF values between 0.5 and 2 indicate that the soil had no anthropogenic inputs.

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(ii) Geo Accumulation Index  $(I_{geo})$ : The geo-accumulation index comprises of seven classes ranging from unpolluted to highly polluted soils (Maria & Naseem, 2011). This classification is given in Table 1. The geo-accumulation index of Matara Uku is given in Table 4. The geo accumulation index values belong to class 0 except for Al, K, Zr and La, which belong to class 1. Al has a range of values between -0.33 and 0.55, with a mean value of 0.15. The mean value classifies the soil as uncontaminated to moderately contaminated. K has a minimum value of -0.44, a maximum value of 0.68 and a mean value of 0.14, which also classifies the soil as uncontaminated to moderately contaminated. Zr has a range of values between -0.14 and 0.96, with a mean value of 0.19. The mean value classifies the soil as uncontaminated to moderately contaminated. The Igeo values of La ranged from 0 to 1.4, with a mean value of 0.65. The mean value revealed that the soil is uncontaminated to moderately contaminated.

Table 4:	Geo Accumulation Index for Matara uku	

					Mean Va	lues				
Element	Al	Κ	Fe	Ca	Mg	Ti	Zr	La	Ce	Mn
Mean I <sub>geo</sub>	0.15	0.14	-0.03	-2.55	-0.51	-1.64	0.20	0.65	-0.61	-0.22
Value										

*Correlation Analysis:* According to the values of Pearson correlation coefficients (Table 5), the (iii) following significant relationships were found between the contents of elements in soil from Matara Uku

Table 5: Pearson correlation matrix between elemen	nts in soils from Matara uku
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	Al(pp)	K(ppm)	Fe(pp)	Ca(pp)	Mg(pm)	Ti(ppm)	Zr(ppm)	La(pp)	Ce(pp)	Mn(pm)
Al(ppm)	1									
K(ppm)	0.72694	1								
Fe(ppm)	0.81989	0.88362	1							
Ca(ppm)	0.53479	0.78023	0.78033	1						
				0.53308						
Mg(ppm)	0.14944	0.37996	0.51655	3	1					
				0.28589						
Ti(ppm)	0.35843	0.39208	0.34757	6	0.07035	1				
				-						
Zr(ppm)	-0.1764	0.16212	0.04001	0.01601	0.08115	-0.4839	1			
		-	-	-	-					
La(ppm)	-0.6138	0.33588	0.58375	0.27632	0.56161	-0.1942	0.31303	1		
	0 5750	-	-	0.04200	-	0 2 4 7 7	-	0.01 = 40	1	
Ce(ppm)	-0.5/56	0.12907	0.44056	0.04209	0.14572	-0.3477	0.3/583	0.81542	1	
Mn(nnm)	0 72024	0 7573	0 77400	0.09214	0 20026	0 22671	0 2516	-	-	1
win(ppm)	0.72024	0./5/3	0.77409	1	0.28820	0.520/1	-0.2340	0.57585	0.1314	1

Bold values indicates a strong correlation between metals.

According to the Pearson Correlation Analysis for Matara Uku in Table 5, there is a strong correlation  $(0.5 \le r < 0.7)$  for the following pairs of elements: Al-Ca (r = 0.5348, p < 0.05), Fe-Mg (r = 0.5165, p < 0.05) and Ca-Mg (r = 0.5331, p < 0.05). A very strong correlation ( $0.7 \le r < 1$ ) exists for the 0.7202, p < 0.005), K-Ca (r = 0.7802, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.005), K-Mn (r = 0.7573, p < 0.01), Fe-Ca (r = 0.7803, p < 0.01), Fe-Ca (r = 0.01), Fe-Ca (r0.005), Fe-Mn (r = 07741, p < 0.005), Ca-Mn (r = 0.8921, p < 0.005) and La-Ce (r = 0.8154, p < 0.005) 0.005). The strong positive correlation amongst the metals indicates their common origin, i.e., from parent rock, sulphide minerals and carbonates. In Matara uku, potassium showed a strong positive correlation with Al, Fe and Mn. This indicates that these elements were derived from a common source, i.e., lithogenic source.

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(iv) Principal Component Analysis (PCA): In this work, PCA is used in order to reduce data and extract a small number of latent factors (principal components) so as to easily analyse the relationship between the observed variables. The results of PCA for Matara Uku, are shown in Table 6. Three principal components with Eigen values greater than one were extracted. The components extracted explain 78.913% of the data variation.

Table 6: Total variance explained for the PCA and component matrices for Matara Uku									l	
				Extra	ction Sums	of Squared	<b>Rotation Sums of Squared</b>			
	]	Initial Eiger	nvalues		Loading	gs	Loadings			
		% of	Cumulative		% of	Cumulative		% of	Cumulative	
Comp.	Total	Variance	%	Total	Variance	%	Total	Variance	%	
1	4.366	43.663	43.663	4.366	43.663	43.663	3.876	38.757	38.757	
2	1.879	18.789	62.452	1.879	18.789	62.452	2.161	21.610	60.367	
3	1.646	16.461	78.913	1.646	16.461	78.913	1.855	18.546	78.913	
4	0.801	8.011	86.924							
5	0.612	6.121	93.045							
6	0.341	3.408	96.453							
7	0.191	1.910	98.362							
8	0.109	1.085	99.448							
9	0.032	0.323	99.770							
10	0.023	0.230	100.000							

Extraction Method: Principal Component Analysis.

				R	otated Comp	onent Matrix	X			
		Component	t		Component					
Element	1	2	3	Element	1	2	3			
Al	0.757	0.195	-0.130	Al	0.658	0.436				
Κ	0.853		-0.132	K	0.820	0.247	0.113			
Fe	0.720	-0.253	-0.388	Fe	0.844		-0.143			
Ca	0.614	0.710	0.127	Ca	0.290	0.877	0.209			
Mg	0.252	0.847	-0.106	Mg		0.880	-0.128			
Ti	0.762	-0.497		Ti	0.834	-0.211	0.297			
Zr	0.468	-0.397	0.636	Zr	0.358	-0.207	0.781			
La		0.306	0.925	La	-0.414	0.287	0.836			
Ce	0.758	-0.178	0.385	Ce	0.624		0.596			
Mn	0.856	0.157	-0.154	Mn	0.767	0.433				
				Rotation M	lethod: Varin	nax with Kais	er			

Normalization.

The first component (PC1) matrix shows that Al, K, Fe, Ti, Ce and Mn were associated (Table 6). The component explained 43.66% of the variance. The second component (PC2) has high loadings of Ca and Mg, and it accounts for 18.79% of the variance. Both components PC1 and PC2 explained 62.45% of the variance, indicating that lithogenic factors dominate the distribution of most part of the

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considered elements in the study area. A lithogenic source can be presumed for the first and second components since the metals are generally present in the parent material of the soil. Most of the soil samples were taken from flood plains of River Hadejia, thus, this is considered an alluvial area and the concentration of the metals in the samples is almost in agreement with the concentration ranges present in the parent material. The presence of Ca and Mg in PC2 may be due to the metamorphism of shale due to the massive removal of calcium carbonate and the introduction of Mg to form chlorite. The third component has a high loading of La and it accounts for 16.46% of the variance. The high loading of La, which is a rare earth element may be due to the long-time application of phosphate fertilizer (Ramos et al., 2016). La appeared only in a few sampling locations within the study area.

Spatial Distribution of metals: Spatial distribution using contour maps is an effective tool used in the determination of areas with high concentrations of metals (Saha et al., 2016). It provides a simple and effective means of presenting results in pollution analysis and assesses the possible sources of enrichment (Chandrasekaran et al., 2015). The spatial distribution pattern of twelve (12) metal concentrations in soil samples collected from Matara Uku are presented in Figures 2(a - j). The contour maps were generated using Surfer® software version 9 produced by Golden Software Inc., USA. The method used in generating the maps is the krigging method. The maps clearly indicate the spatial variation in the concentration of different metals.





The contour maps of Al, K, Fe, Ti, Ca, Mg, and Mn evidently support higher concentrations in all sampling locations. These elements also showed a similar spatial pattern, with contamination hotspots spontaneously spotted at the northern and eastern parts of the study area. This indicates that they were from the same source, and it is in agreement with principal component analysis.

### **4.0** Conclusion

The concentration of metals in the soils collected from the Matara Uku potash extraction site and its environs was successfully determined using energy dispersive X-ray fluorescence (ED-XRF) spectrometry. The results obtained showed that Al, K and Fe are the most abundant metals in the study area. This is due to its natural origin, as the area is entirely sedimentary. The skewness values showed that Mn has the highest skewness, and as such, it has the highest abnormal distribution. The pollution analysis showed that La has the highest enrichment, while Ti has the highest contamination. Furthermore, a strong positive correlation amongst Al, K, Fe, TI, Ce and Mn showed that the major sources of these metals are probably related (lithogenic sources). Additionally, it is also found that the result of the principal component analysis is in agreement with the spatial distribution of the metals depicted by the contour maps.

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