

University of Benghazi
Faculty of Science
Department of Chemistry



***CHEMICAL STUDIES FOR AGRICULTURE SOIL
OF BENGHAZI PLAIN***

*A thesis submitted in partial fulfillment of the requirements
of Master Degree in Chemistry*

by

BSc. Mabroka A. M. Atallah

Supervised by:

Prof. Dr. Awad .A. El Hsady

Co- Supervised by:

Dr. Nabil R. Bader

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

{وَسَخَّرَ لَكُمْ مَا فِي السَّمَاوَاتِ وَمَا فِي الْأَرْضِ جَمِيعًا مِنْهُ

إِنَّ فِي ذَلِكَ لآيَاتٍ لِقَوْمٍ يَتَفَكَّرُونَ}

صدق الله العظيم

سورة الجاثية: الآية 13

This thesis is dedicated to...



*My parents for their love, endless
Support and encouragement through
all the difficult times of my study.*

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Abbreviations:

AAS: Atomic Absorption Spectroscopy

XRF: X-Ray Fluorescence

EDXRF: Energy Dispersive X-Ray Fluorescence

ICP-AES: Inductively coupled plasma atomic emission spectroscopy

SSSA: Soil Science Society of America

pH: Power of Hydrogen

EC: Electric Conductivity

TDS: Total Dissolved Solids

ANOVA: Analysis of variance

SD: Standard Deviation

RSD: Relative Standard Deviation

L.S.D: Less Significant Differences

AHA: Agglomerative Hierarchical Analysis

HCA: Hierarchical Cluster Analysis

PC: Principal Components

PCA: Principal Components Analysis

PCR: Partial Least-Squares

BDH: Burrell Durrant Hifle

XLSTAT: Excel Stat Program

EPMA: Electron Probe Micro- Analysis

Conc.: Concentration

Lat.: Latitude

Long.: Longitude

ppm: part per million = $\text{mg kg}^{-1} = \mu\text{g g}^{-1}$

$\mu\text{g/g}$: micro gram per gram

$\mu\text{S/cm}$: microsiemens per centimeter

KW: Kilo Watt

Km^2 : Kilometer square

μm : micrometer

mm: milli meter

cm: centimeter

mL: milliliter

g: gram

$^{\circ}\text{C}$: The degree Celsius

Abstract:

Some analytical and chemometric strategies were used for the comparison of chemical features of soil samples collected from different sites of Benghazi plain. As a preliminary analysis, synchrotron radiation and X-Ray Fluorescence were employed.

For feasibility of using X-ray fluorescence (XRF) spectrometry with chemometric XLSTAT software, beside measurements of pH, EC combined and TDS for each of soil sample collected from the sites of Benghazi plain. On their elemental contents. Both direct non-pre-treatment XRF spectra and elemental concentration were used to achieve discrimination of soil.

The classification of data was carried out on the basis of chemical information obtained from 19 elements (Al, Si, Cl, Ti, S, Rb, Sr, K, Ca, Mn, Fe, Cu, Zn, Cd, Ga, Nb, Sn, Zr and Y) in the studied soil samples using chemometric descriptors for classification purpose of soil sites based on their geographical origin. To differentiate between soil sampling sites in Benghazi plain different pattern recognition techniques such as analysis of variants (ANOVA), hierarchical clustering analysis (HCA) and Principals component analysis (PCA) were applied.

Aim and Importance of the Study

The aim of this project is to analyse soil samples collected from different sites of Benghazi plain by X-Ray fluorescence spectrometry to evaluate the result obtained we used chemometric techniques (HCA, PCA) which enabled us to classify nutrients in the plain.

1. Introduction

1.1. Soil

The word “soil” has a variety of different meanings depending upon its relevance to the society. Farmers consider it as the part of the earth’s surface containing decayed and organic material in sufficient quantity to grow plants and crops ^[1].

Soil is a very complex medium that contains minerals, organic matter, micro-organisms, air and water. Soil is one of the most important factors for agriculture and some soils are deemed more fertile than others. Soil fertility is directly related to factors such as nutrients concentrations or availability, organic matter content, acidity, moisture, etc., as well as to agricultural practice such as till vs. no-till^[2].

According to the Soil Science Society of America (SSSA), soil is a living system that represents a finite resource vital to life on earth. Soil have numerous uses but the most vital is their use for growing crops, without which no human or animal could survive ^[1, 3]. Earlier human civilizations sprung up when man learned how to cultivate the soil and, to this day, agriculture is the most important of all human activities ,since without it neither our society, nor our race, would be able to exist.

Even today, more than 50 % of the world population lives on farms. It is impossible to destroy the whole soil cover of our planet; however, it is possible to degrade the quality of the soil to such an extent that it becomes useless, harmful and even deadly.

In fact, many early civilizations (e.g. Mesopotamia) died out when the soil cover on which they relied was degraded to a point where it was no longer capable of to a decrease in soil fertility.

Ensuring soil fertility is a basic requirement for any form of sustainable agriculture, yet in practice this seemingly trivial goal is very difficult to achieve due not only to the complexity of the soil medium itself, but also due to the complexity of the soil-crop-air interactions and to the fact that some processes require years before having any visible impact.

Various recent studies have shown that soil fertility is declining in many farmlands due mainly either to inadequate farming practices , insufficient fertilization, in which inadequate farming practices^[4, 5] ,insufficient fertilization, in which case the soil reserves are depleted, or over-fertilization that results in pollution to the groundwater or toxic accumulation of chemicals in the soil. Avoiding such under- or e over fertilization is the chief goal of the so-called precision fertilization concept, which aims at delivering exactly the amount of nutrients required to sustain optimal growth of the crop.

One of the main obstacles to the application of the precision fertilization concept, or the more general precision farming concept, is soil heterogeneity^[2, 6].

Hence, although it is technically possible to perform a wide range of analyses and derive a soil fertility or health index such as the one proposed by Idowu (2008), most of the required analyses are time consuming which in practice makes it impossible to map the soil properties of a field with the required spatial and/or

temporal resolution. The need for fast and cheap methods that would enable the analysis of large number of samples has been stressed in numerous studies.

1. 2. Soil quality

There are different views about the soil quality. For people active in production agriculture, it may mean highly productive land, sustaining or enhancing productivity, maximizing profits, or maintaining the soil resource for future generations. For consumers, it may mean plentiful, healthful, and inexpensive food for present and future generations. For naturalists, it may mean soil in harmony with the landscape and its surroundings, and for the environmentalist, it may mean soil functioning at its potential in an ecosystem with respect to maintenance or enhancement of biodiversity, water quality, nutrient cycling, and biomass production. The SSSA defines soil quality as: the capacity of a specific kind of soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation.

Soil quality is therefore related to how well the soil does what we want it to do? This means that we need to have the complete information about the specific kind of soil or the soil characteristics which in fact are always subjected to fluctuations due to changes in management, changing grain fall patterns (including acid rain), changing water table levels and vegetation cover and other environmental factors. These changes in turn disturb the chemical equilibrium pattern in soil. In other words,

soils are not material specific, many of their properties are not single valued, many are transient, and many are not randomly distributed but rather systematically time and spatially dependent [5, 7] .

1.3. Soil Nutrients

Healthy soil is a combination of minerals, rock, water, air, organic matter (plant and animal residue), microorganisms, including bacteria, fungi and protozoa and a variety of insects and worms. This intricate web carries out a process that continually replenishes the soil and maintains long-term soil fertility [8] .

For sustained growth, plants require macro-nutrients and trace elements. Macro-nutrients include, nitrogen (N), phosphorous (P), potassium (K), calcium (Ca), magnesium (Mg) and sulfur (S), while trace elements include, iron (Fe), manganese (Mn), copper (Cu) and zinc (Zn) [9] .

For optimum plant growth, soil must be capable of storing these nutrients and transferring them to the root surface for uptake by plants.

There are 16 elements currently considered necessary for plant growth. Carbon, hydrogen and oxygen which obtained from air and water and through photosynthesis are converted to 90% of a plant's dry matter. Then there are six 'macro' nutrients absorbed in large amounts and seven 'micro' nutrients absorbed in small amounts from the soil or a hydroponic solution.

Under intensive production systems, the nutrient elements of which the soil has the smallest reserve in relation to crop

requirement, are the first to require replenishment. The ratio of nutrients available is important as an excess of one nutrient can result in a deficiency of another element .

1.4. Other Elements

A number of other elements have been found in plant tissue and are most likely required by some plants including sodium, silicon, cobalt, vanadium, iodine, bromine, fluorine, aluminum and nickel.

1.5. Soil Conditioners

A fertile soil is one that contains an adequate supply of all the nutrients required for the successful production of plant life. This is important because the full potential of crops is never realized if a shortage of nutrients occurs at any time during the growth cycle. This is true even- though plants are capable of remarkable recovery from short periods of starvation.

A fertile soil is not necessarily a productive one. The second major requirement is that the soil must provide a satisfactory environment for plant growth. The environmental factors include: texture, structure, soil water supply, pH, temperature, and aeration.

1.6. X-ray fluorescence (XRF)

The XRF technique is a non-destructive technique which can save costs owing to its rapidity and ability to analyse solid environmental samples in situ /on site ^[10-13] .

XRF has the advantage of being a rapid and inexpensive method with a simple sample preparation. Quantitative and qualitative analyses are performed without acid digestion processes and a great number of elements can be determined simultaneously in a short time. The main goal of the present research was to use XRF technique in order to assess the nutrients distribution in some areas and to compare the soil nutrients with the internationally recognized values^[14].

1.6.1. The basics of XRF

The basics of XRF are very similar to those of EPMA—we are dealing with characteristic x-rays and continuum x-rays—with the exception that we are doing secondary fluorescence : x-ray spectroscopy of our samples using x-rays coming out of a sealed tube to excite the atoms in our specimen^[15].

The big difference is that there is NO continuum generated in the sample (x-rays can't generate the Bremsstrahlung), and we are using BOTH characteristic x-rays of the sealed tube target (e.g., Cr, Cu, Mo, Rh) AND continuum x-rays to generate the characteristic x-rays of the atoms in the sample^[12, 15].

XRF has been a bulk analytical tool (grind up 50-100 grams of your rock or sample to analyze), though recently people are developing “micro XRF” to focus the beam on a ~100 mm spot [18].

1.6.2. X-ray Sources

The standard X-ray tube was developed by Coolidge around 1912. It is desirable to produce the maximum intensity of x-rays; a

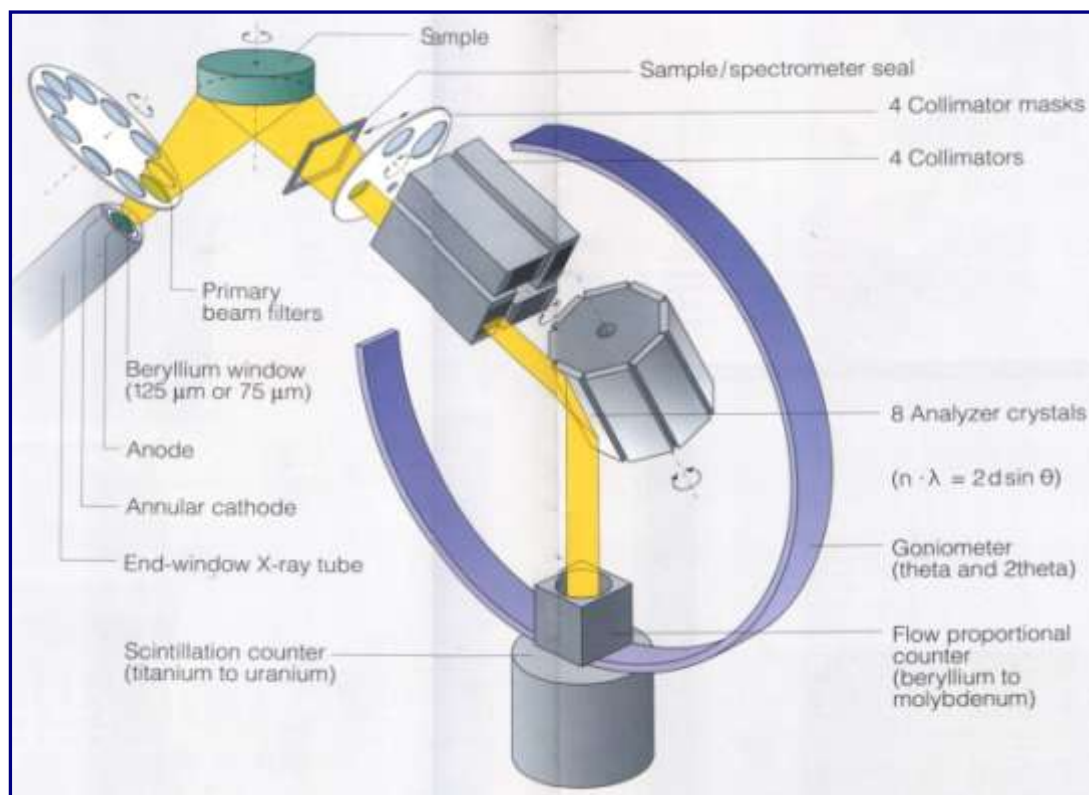
Cu target tube might be able to deliver 2 kW^[15]. The limiting factor is the heat that the target (anode) can handle; cold water is used to remove heat. Higher power can be delivered by dissipating the heat over a larger volume, with a rotating anode. However, this is not normally used for XRF^[13, 14].

1.6.3. A Currently Marketed XRF (WDS version)

This actual model contains additional components. There are probably over a dozen companies building and selling XRFs of various designs. In fact, two are here in Madison:

Bruker-AXS (~Siemens) and

ThermoNORAN (microXRF)



Figure(1.1): From Bruker-AXS brochure

1.6.4. Advantages of XRF

Simplicity ,Lack of moving parts in the excitation and detection components of the spectrometer, Closeness of the detector to the sample result in 100-fold or more in the energy reaching the detector(permits the use of weak sources – radioactive materials or low power X-ray tubes)^[14, 16].

1.6.5. Disadvantages of XRF

Low resolution at wavelengths longer than 1 Å.

1.6.6. Applications

Qualitative and semi quantitative analysis

Elements are identified by the energy or the wavelength of the characteristic line.

Quantitative Analysis

Based on the relation between the net X-ray intensity of the characteristic line and the concentration. Therefore this method belong non-destructive analysis^[15, 16].

1.7. Stasticacal Analysis

1.7.1. Chemometrics

Is a science of multidisciplinary nature which involves multivariate statistics, mathematical modeling and information technology, specifically applied to chemical data. Actually, these methods are useful tool in the quality control of soil quality.

Chemometric is the science of extracting information from chemical systems by data-driven means. It is a highly interfacial discipline, using methods frequently employed in core data-analytic disciplines such as multivariate statistics, applied mathematics, and computer science, in order to address problems in chemistry, biochemistry, medicine, biology and chemical engineering ^[17]. In this way, it mirrors several other interfacial ‘-metrics’ such as psychometrics and econometrics.

Chemometrics is applied to solve both descriptive and predictive problems in experimental life sciences, especially in chemistry. In descriptive applications, properties of chemical systems are modeled with the intent of learning the underlying relationships and structure of the system (i.e., model understanding and identification). In predictive applications, properties of chemical systems are modeled with the intent of predicting new properties or behavior of interest. In both cases, the datasets can be small but are often very large and highly complex, involving hundreds to thousands of variables, and hundreds to thousands of cases or observations. Chemometric techniques are particularly heavily used in analytical

chemistry and metabolomics, and the development of improved chemometric methods of analysis also continues to advance the state of the art in analytical instrumentation and methodology.

It is an application driven discipline, and thus while the standard chemometric methodologies are very widely used industrially, academic groups are dedicated to the continued development of chemometric theory, method and application development. Although one could argue that even the earliest analytical experiments in chemistry involved a form of chemometrics, the field is generally recognized to have emerged in the 1970s as computers became increasingly exploited for scientific investigation.

The term 'chemometrics' was coined by Svante Wold in a grant application 1971^[37], and the International Chemometrics Society was formed shortly thereafter by Svante Wold and Bruce Kowalski, two pioneers in the field. Wold was a professor of organic chemistry at Umeå University, Sweden, and Kowalski was a professor of analytical chemistry at University of Washington, Seattle.

Many early applications involved multivariate classification, numerous quantitative predictive applications followed, and by the late 1970s and early 1980s a wide variety of data- and computer-driven chemical multivariate analysis was a critical facet even in the earliest applications of chemometrics. The data resulting from infrared and UV/visible spectroscopy are often easily numbering in the thousands of measurements per sample. Mass spectrometry, nuclear magnetic resonance, atomic

emission/absorption and chromatography experiments are also all by nature highly multivariate ^[18, 19]. The structure of these data was found to be conducive to use techniques such as; principal components analysis (PCA), and partial least-squares (PLS).

This is primarily because, while the datasets may be highly Multivariate there is strong and often linear low-rank structure present. ^[18] PCA and PLS have been shown over time very effective at empirically modeling the more chemically interesting low-rank structure, exploiting the interrelationships or ‘latent variables’ in the data, and providing alternative compact coordinate systems for further numerical analysis such as regression, clustering, and pattern recognition. ^[25]

Partial least squares in particular was heavily used in chemometric applications for many years before it began to find regular use in other fields ^[21].

1.7.2 Hierarchical Cluster Analysis

The Hierarchical Cluster Analysis (HCA) primary goal is to display the data in such a way as to emphasise their natural clusters and patterns in a two-dimensional space. The results, qualitative in nature, are usually presented as a dendrogram, allowing the visualization of clusters and correlations among samples or variables. In HCA, the Euclidean distances between samples or variables are calculated and transformed into a similarity matrix whose elements are similarity indexes ranging from 0 to 1; a smaller distance means a larger index and therefore, a larger similarity ^[22].

Principal Component Analysis(PCA), on the other hand, is based on the correlation among variables. It maps samples through scores and variables by the loadings in a new space defined by the principal components. The PCs are a simple linear combination of original variables. The score vectors describe the relationship between the samples and allow checking if they are similar or dissimilar, typical or outlier ,while the loadings vectors describe the importance of each variable^[23].

1.7.3 Dendrogram

A dendrogram is a graphical representation of different aggregations made during a cluster analysis. It consists of knots that correspond to groups and branches that represent the associations made at each step.The structure of the dendrogram is determined by the order in which the aggregations are made^[21]. If a scale is added to the dendrogram it is possible to represent the distances over which the aggregations took place. In a more general sense, a dendrogram (from the Greek "dendron", meaning tree) is a tree diagram that illustrates the relations that exist between the members of a set. The first examples of dendrograms were the phylogenetic trees used systematic specialists. The term "dendrogram" seems to have been used for the first time work it in 1953^[21, 24].

2. Experimental

2.1. Sample Sites of the Study:

Sixty soil samples from different twelve sites which cover about (2000) Km² of the Benghazi plain were collected during the autumn 2013 from east Tukra to west Tekah city, the samples were collected from (Tukra, Bograr, Deriana, Sedi Khalifa, Al-Kwefia, Benina, Boatny Al- Hwary, Al- Gwarsha, Al Nwagia, Bodrisa and Tekah) respectively .

In addition from each site 5 samples were collected from depth ranged between (0 to 40)cm, pairing in mind the collection of the samples were collected w-shaped area (zigzag).

2.2. Sampling and Storage:

The soil samples were collected by using Auger and stored in plastic bags and transported to the laboratory for analysis, after each plastic bags was given a number ,site and date of collection, these bags were stored at 4 C° for a period not exceeding 72 hours, fig. (2.1).



Figure (2.1): The Auger which was used for collection of samples

2.3. Labeling of the samples:

For simplicity two letters were chosen to represent the sample site along the Benghazi plain (see the sample sites map, fig. (2.2) and given in table (1.1)) as follows:

TR : Tukra .

BG : Bograr.

DR : Deriana.

SK : Sedi Khalifa .

KF: Al- Kwefia .

BI: Benina .

BA : Boatny .

HO : Al- Hwary .

GO : Al- Gwarsha.

NG : Al Nwagia.

BD : Bodrisa.

TK : Tekah .

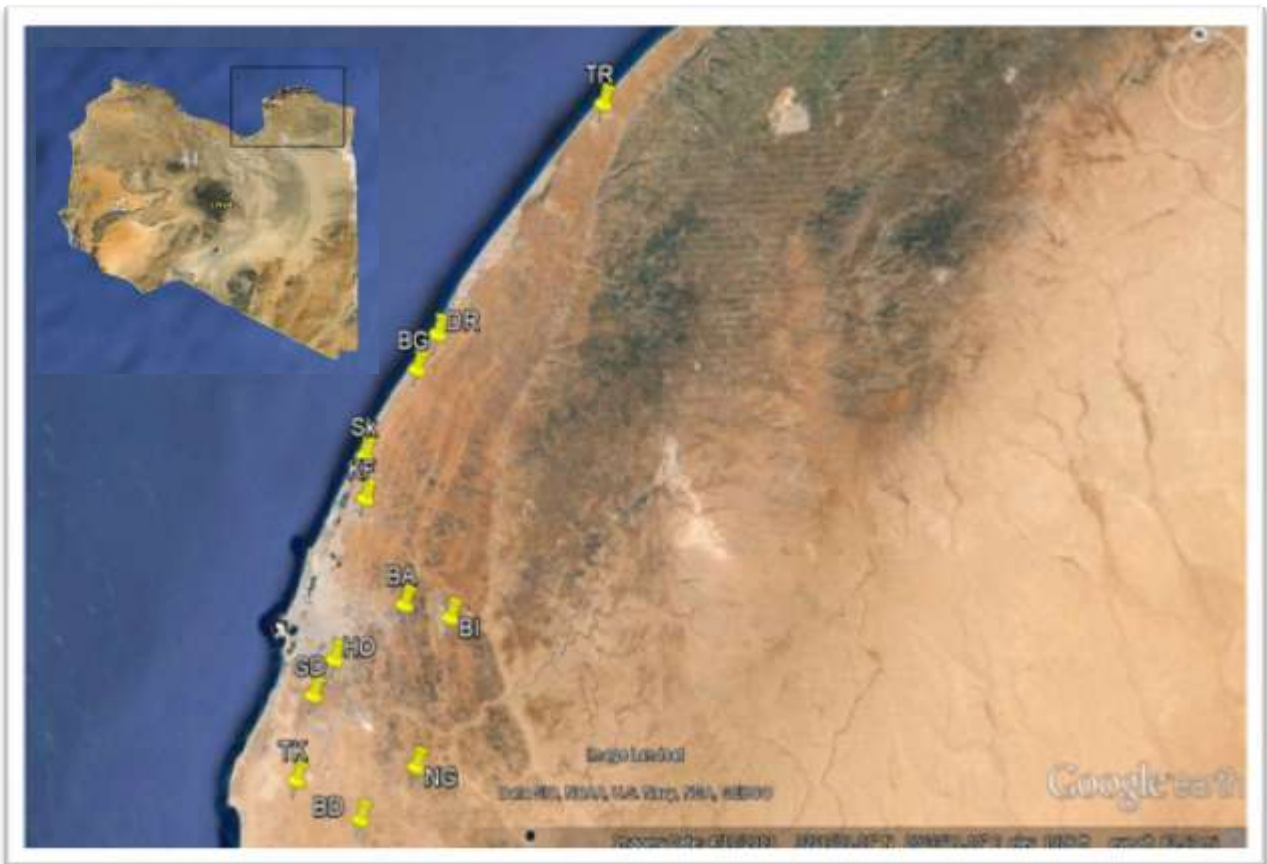


Figure (2.2) : Map of Benghazi plain showing the places of collection

Table (2.1): Electric coordinate of sample sites

Site	Coordinates
TK	Lat 31° 37' 7.73" N Long 20° 3' 6.00" E
NG	Lat 31° 55' 55.15" N Long 20° 11' 4.32" E
BD	Lat 32° 1' 35.28" N Long 20° 6' 1.58" E
GO	Lat 32° 1' 20.97" N Long 20° 3' 58.51" E
HO	Lat 31° 55' 55.15" N Long 20° 11' 4.32" E
BA	Lat 32° 3' 7.73" N Long 20° 12' 19.11" E
BI	Lat 32° 4' 4.43" N Long 20° 15' 42.76" E
KF	Lat 32° 12' 1.64" N Long 20° 10' 38.77" E
SK	Lat 31° 14' 29.57" N Long 20° 11' 9.91" E
DR	Lat 32° 20' 55.15" N Long 20° 18' 30.48" E
BG	Lat 32° 18' 48.79" N Long 20° 16' 24.54" E
TR	Lat 32° 31' 43.74" N Long 20° 34' 36.79" E

2.4. Experimental Procedures:

2.4.1. Drying of soil samples

The collected samples were dried aerobically on sheets of polyethylene after removing leaves and stones fig. (2.3) .



Figure (2.3): Showing air drying of soil samples

2.4.2. Sieving of soil samples

A 2 mm mesh sieve was used to sieve the soil samples so that 2mm granules of soil samples could be opted, which were stored in polyethylene containers for analysis as shown in fig.(2.4), Which can be kept for several years.

The samples can be used for analysis, even after the passage of several years.



Figure (2.4): soil sample containers.

2.4.3. Instrument of Analysis

2.4.3. Materials:

2.4.3.1. Chemicals and Reagents:

All reagents used in this study were analytical reagent grade, including :

- Buffer solution pH (4, 7, 9), BDH.
- Potassium chloride KCl (0.01N), BDH.
- Distilled water.
- Double distilled water.

2.4.3.2 Equipments and glass wares:

- Analytical balance (SARORIUS TE 6101, OHAUS).
- PH meter (JENWAY3150).
- Conductivity meter (METTLER TOLEDO MC 226).
- Centrifuges (HETTICH ZENTAIFUGEN, UNIVERSAL 32).
- Grinding and pressing of samples (HERZO6).
- Drying oven (Gollenhomp).
- Mechanical shaker (STUART SCIENTIFIC, SF1).

2.4.4 Electrochemical measurements

2.4.4.1. PH Measurement

The propose of pH measurement is to Know the type of soil (acidic, neutral or alkaline), the abundance of nutrients in the soil, and the liability of the existence of soluble toxic nutrients.

- **Process:**

Soil solution was prepared by transferring 50g of soil sample into each 150ml conical flask and 100ml double distilled water was added to the each flask. The flasks were closed and then placed in mechanical shaker for an hour, and then were left to rest for 5 minutes. The pH of each solution was measure by using calibrated pH meter as shown in fig. (2.5).



Figure (2.5): Determining pH of Soil.

2.4.4.2 Electrical Conductivity and Total Dissolved Salts Measurements

The aim of measuring conductivity is to determine of total dissolved salts in the soil.

- **Process:**

The soil sample solutions were filtered by using Bochner faunal and to ensure complete separation the filtrates were then placed in centrifuging equipment 10 minuet about 3000 r/min as shown in fig. (2.6). The conductivity of each sample solutions was then measured using a calibrated conductivity meter.



Figure (2.6): filtration and centrifugal of the samples for measuring EC and TDS.

2.5. X-ray fluorescence (XRF) analysis:

The nutrients and heavy metals in all agriculture soil samples were determined using X ray fluorescence spectrometer (Germany, S2 RANGER) as shown in fig. (2.7), [20, 21].

There are atomic spectroscopic methods such as ICP-AES and AAS were used for quantitative analysis of elements in soils . However, these methods are time consuming process because the samples have to be dissolved first before starting the analysis [20].

Therefore XRF spectrometer is used instated for such analysis, because this instrument had been used for various fields, such as material research, environmental research, quality control of products, etc.



Figure (2.7): X ray fluorescence spectrometer RANGER, Burker Germany).

2.5.1. Adjusting of the instrument:

XRF analysis of soil samples were carried out at room temperature ,and to measure the concentrations of metals in soil samples in (ppm) were obtain using by specifying the high voltage and choosing a filter, an element or energy range is selected. In order to analyze lighter elements, the sample chamber is either evacuated by means of an integrated vacuum pump or it is flooded with helium. The X-Flash detects the X-ray fluorescence radiation of the sample. The multi-channel analyzer divides up the different energies and accumulates counts to form intensity vs. energy spectrum^[20]. The measurements were carried in the oxide position as shown in fig.(2.8).



Figure (2.8): XRF spectrometer Screen.

2.5.2. Measurements of nutrients and transition metals

Concentration of nutrients and heavy metals in all agriculture soil samples were measured by X- ray fluorescence spectrometer (S2 RANGER, Burker Germany).

- **Process:**

A bout 25g soil was weighed out from each soil samples, after sieving using (2mm) mesh, In addition for homogeneity and to avoid grain size effect in the quantitative analysis, a vibrating planetary mill was used to obtain to reduce grain size less than $< 70 \mu\text{m}$, in the presence of grinding tablets fig. (2.9).



Figure (2.9): weighting of the samples for XRF analysis.

The a resulting powder (mixture) was thoroughly homogenized once more in a planetary mill and pressed (under 5 tones) into a disc pellet of 32 mm diameter. The pellets were measured using an EDXRF portable analyzer spectrometer (Niton XL3t900s with Geometrically Optimized Large Drift Detector) with Ag x-ray excitation source and several filters as secondary targets for excitation ^[20]. This configuration allows the attainment of improved sensitivity and signal to noise ratio by sequentially selecting appropriate combinations of filters as secondary targets and different groups of elements were carried out depending on element interest. These pellets were placed within the stand lid system. The use of portable analyzer for excitation and the characteristic x-rays emitted by the constituents of the samples were carried out for a period of 200s. The portable XRF uses both quantification techniques: normalization and the full fundamental method for measurements of the concentration of nutrients and heavy metals as shown fig.(2.10).



Figure (2.10):The pressing and resulting pellets of soil sample.

2.6. Chemometric analysis

PCA and HCA were performed with XL Stat 2014 software package, used as a Microsoft Excel plug-in. When concentrations were below the detection limit, a random value between zero and that limit was inserted in order to be able to thoroughly apply PCA and HCA without losing any case and ensure good precision of the analysis.

3. Results and Discussion

3.1 Electrochemical results (pH, EC, and TDS) of soil samples:

3.1.1 pH:

The results of pH for sixty soil samples in different locations in Benghazi plain after Statistical treatment of the average values of pH for each samples collected data using ANOVA are shown in table (3.1) and mean measurements of pH in the soil samples fig. (3.1), we may conclude that all soil samples exhibited a mean pH values higher than background level which is (7.200) in all the studied areas in addition the range was between (7.542-8.116). However for sites (GO, BA, BD, BI) the pH values (7.543, 7.558, 7.626 and 7.654 respectively) which means in these values in proper range of agricultural soil according to the World Organization for Agriculture, while the values for the rest of the samples gave indication of weak alkali level of place i.e (TK:8.116) (HO,BG:8.008) (NG:7.948) (DR:7.884) and (TR:7.704).

Table (3.1): Statistical treatment of pH data using ANOVA:

Sites	No. of samples	pH average	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value (p<0.05)	L.S.D
				Lower Bound	Upper Bound		
TR	5	7.7040	0.1680	7.4952	7.9128	0.0000	NG>DR DR>TR GO>SK BD>KF TR>BI BI>BD KF>BA BA>GO TK>BG,HO BG,HO>NG
BG	5	8.0080	0.2090	7.7475	8.2685		
DR	5	7.8840	0.2680	7.5506	8.2174		
SK	5	7.2000	0.1480	7.0154	7.3846		
KF	5	7.6000	0.2070	7.3430	7.8570		
BI	5	7.6540	0.4250	7.1253	8.1827		
BA	5	7.5580	0.1480	7.3738	7.7423		
HO	5	8.0080	0.2090	7.7475	8.2685		
GO	5	7.5420	0.1880	7.3082	7.7759		
NG	5	7.9480	0.2730	7.6080	8.2880		
BD	5	7.6260	0.1550	7.4335	7.8185		
TK	5	8.1160	0.3000	7.7426	8.4894		

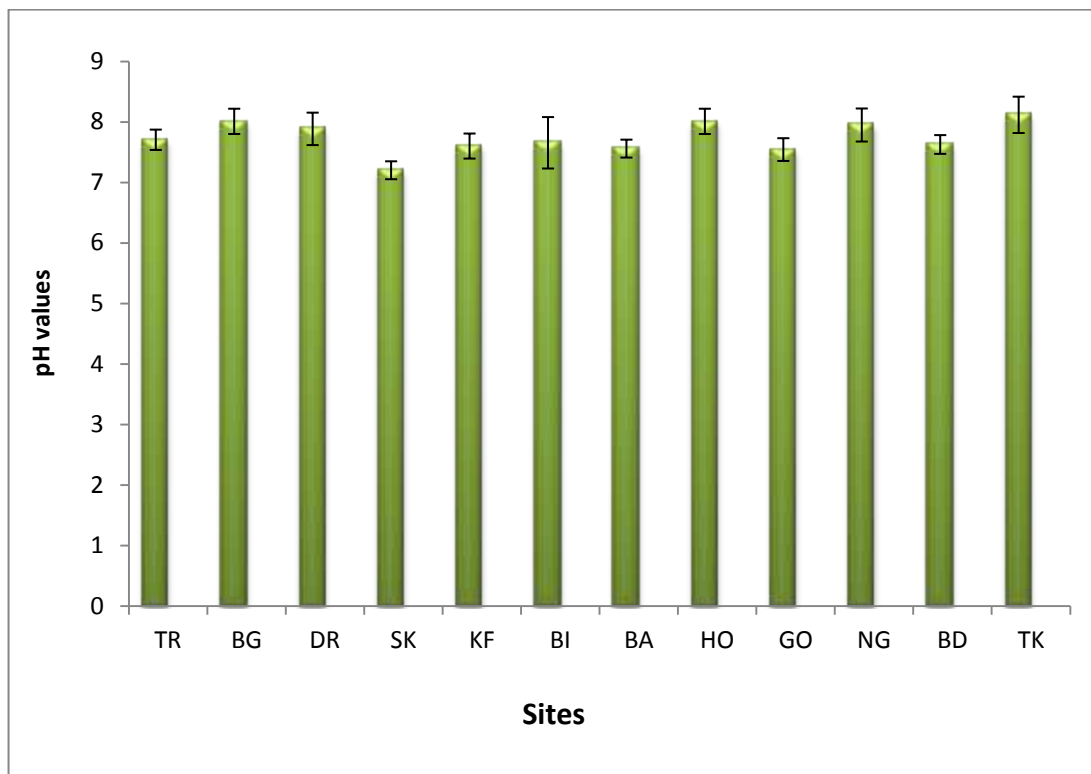


Figure (3.1): Mean measurements of pH average in the soil samples.

3.1.2 Electrical Conductivity (EC):

The results of EC for soil samples for sixty soil samples in different locations in Benghazi plain after Statistical treatment of EC 's data using ANOVA table (3.2) are shown in the figure (3.2).

We may conclude that all soil samples exhibited a mean EC Values higher than background level which is $(0.216) \mu\text{S}/\text{cm}$ in all the studied areas. In addition the electrical conductivity was found to be the highest value in (SK: $3.900 \mu\text{S}/\text{cm}$) which means that SK soil is salty because did not agree well with the permitted value of the World Organization for Agriculture $(0-2 \mu\text{S}/\text{cm})$ ^[58], this may be due to the water used for

irrigation, however the EC value for BA and TK were little bit higher than 2 $\mu\text{S}/\text{cm}$ also .

Table (3.2): Statistical treatment of EC data using ANOVA:

Sites	No. of samples	Mean of EC ($\mu\text{S}/\text{cm}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value (p<0.05)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.2162	0.0390	0.0167	0.2651	0.0750	-
BG	5	0.2376	0.0390	0.0188	0.2864		
DR	5	0.3716	0.2240	0.9272	6.5048		
SK	5	3.9000	4.5210	1.7143	5.9151		
KF	5	0.6192	0.5370	-0.4862	1.2870		
BI	5	0.6272	2.6910	-1.0316	5.6516		
BA	5	2.3100	2.6910	-1.0316	5.6516		
HO	5	0.2376	0.0390	0.1887	0.2864		
GO	5	1.1560	2.0140	-1.3453	3.6576		
NG	5	0.4234	0.1820	0.1968	0.6499		
BD	5	1.4930	2.3100	-1.3762	4.3622		
TK	5	2.1340	2.1710	-0.5626	4.8306		

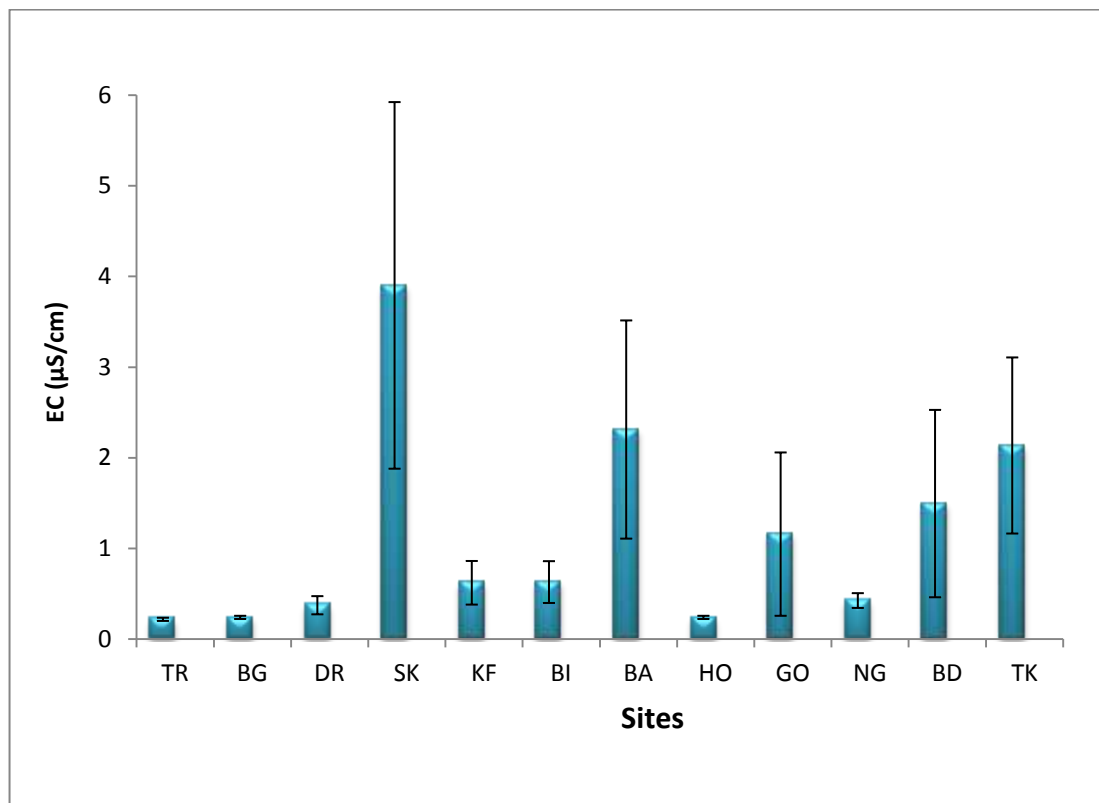


Figure (3.2): Mean measurements of the conductivity values in the soil samples.

3.1.3 Total Dissolved Salts (TDS):

The total dissolved salts $\mu\text{g/g}$ for all samples under study and their statistical treatment using ANOVA are shown in table (3.3) and figure (3.3) consequently, Since,

$$\text{TDS } \mu\text{g/g} = \text{EC } \mu\text{S/cm} * 0.67$$

The value of TDS for SK site is the highest ($1.939 \mu\text{g/g}$) among all samples which means that, this soil is salty other. ^[59]

Table (3.3): Statistical treatment of TDS data using ANOVA:

Sites	No. of samples	Mean of TDS (µg/g)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value (p<0.05)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.1080	0.0192	0.0841	0.1319	0.0940	-
BG	5	0.1180	0.0196	0.0939	0.1428		
DR	5	0.1890	0.1054	0.0587	0.3205		
SK	5	1.9390	2.2473	-0.8506	4.7302		
KF	5	0.3080	0.2689	-0.2510	0.6427		
BI	5	0.3100	0.2579	-0.1024	0.6302		
BA	5	1.1460	1.3323	-0.5081	2.8005		
HO	5	0.1180	0.0196	0.0939	0.1428		
GO	5	0.5800	1.0115	-0.6753	1.8365		
NG	5	0.2110	0.0916	0.0977	0.3254		
BD	5	0.7520	1.1511	-0.6773	2.1813		
TK	5	0.9360	1.1719	-0.5191	2.3911		

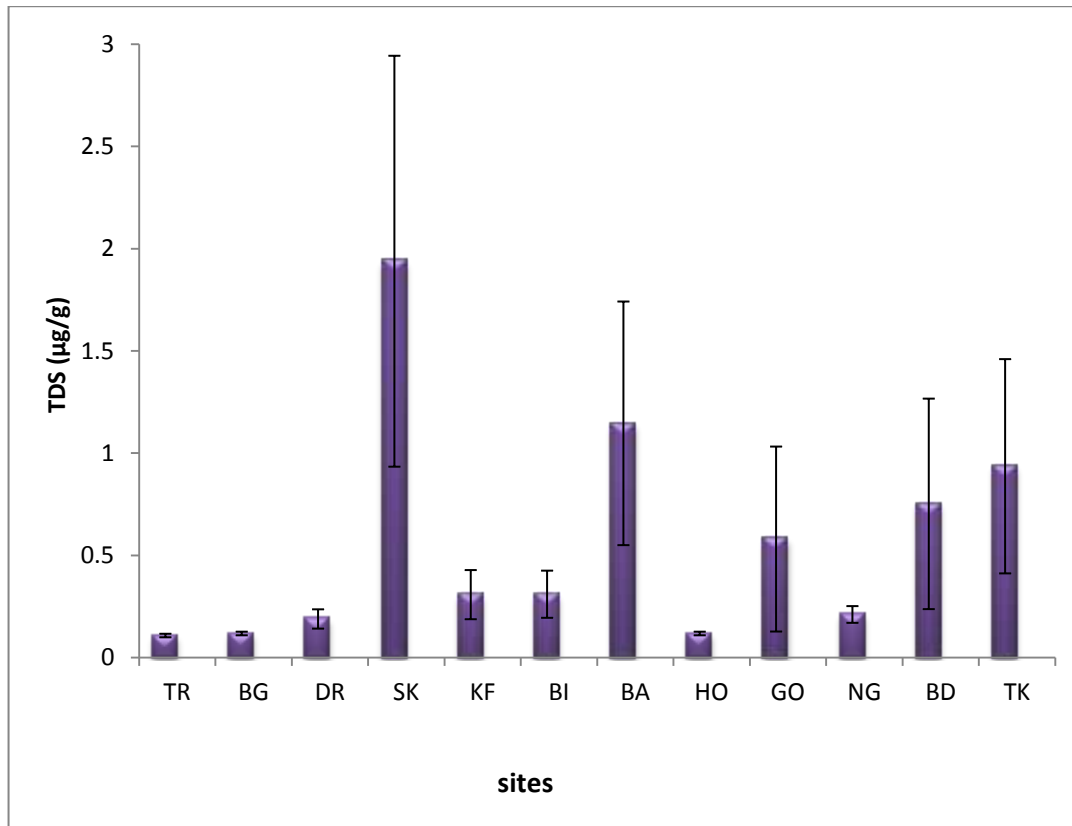


Figure (3. 3): Mean measurements of TDS in the soil samples.

3.2. Concentration of Metal Ions:

The concentration of nineteen ions as nutrients and heavy metals were determined using XRF technique. The concentration of ions Al, Si, Ca, Rb, K, Sr, Sn, Cl and S were determined and showed in table (3.4) and the concentration of ions Ti, Mn, Fe, Cu, Zn, Zr, Y, Nb, Ga and Cd were determined and showed in table (3.5)

Table (3.4): Concentration of ions in soil samples

Sites	Mean of Al ⁺³ conc. ($\mu\text{g/g}$)	Mean of Si ⁺⁴ conc. ($\mu\text{g/g}$)	Mean of Ca ⁺² conc. ($\mu\text{g/g}$)	Mean of K ⁺ conc. ($\mu\text{g/g}$)	Mean of Sr ⁺² conc. ($\mu\text{g/g}$)	Mean of Sn ⁺² conc. ($\mu\text{g/g}$)	Mean of Rb ⁺ conc. ($\mu\text{g/g}$)	Mean of Cl ⁻ conc. ($\mu\text{g/g}$)	Mean of S ⁻² conc. ($\mu\text{g/g}$)
TR	15.3240	55.3050	17.4160	3.0100	0.0700	0.0240	0.0140	0.0440	0.0350
BG	22.6320	60.0940	3.2150	3.2280	0.0280	0.0200	0.0200	0.0900	-----
DR	20.6980	64.3880	2.4950	2.9300	0.0200	0.0200	0.0200	0.0600	0.0650
SK	15.5760	55.7980	16.884	3.3500	0.0380	0.0200	0.0120	0.4150	-----
KF	17.9840	61.3360	6.7980	3.6260	0.0380	0.0200	0.0200	0.5050	0.1033
BI	20.9780	63.3760	2.5025	3.0800	0.0240	0.0200	0.0200	0.5560	0.0533
BA	15.8260	56.7480	15.3160	3.2340	0.0400	0.0240	0.0160	0.0700	0.0833
HO	19.5560	63.4420	4.4960	2.8000	0.0280	0.0200	0.0200	0.0800	0.0433
GO	18.9680	60.0600	8.6180	2.9220	0.0340	0.0200	0.0200	0.0600	0.0600
NG	19.2660	61.3860	6.2800	3.4240	0.0400	0.0200	0.0200	0.1540	0.0800
BD	19.7300	66.4380	2.3575	2.7920	0.0240	0.0200	0.0200	0.0800	-----
TK	19.6580	59.0675	8.2180	2.4380	0.0380	0.0200	0.0200	0.2740	0.0575

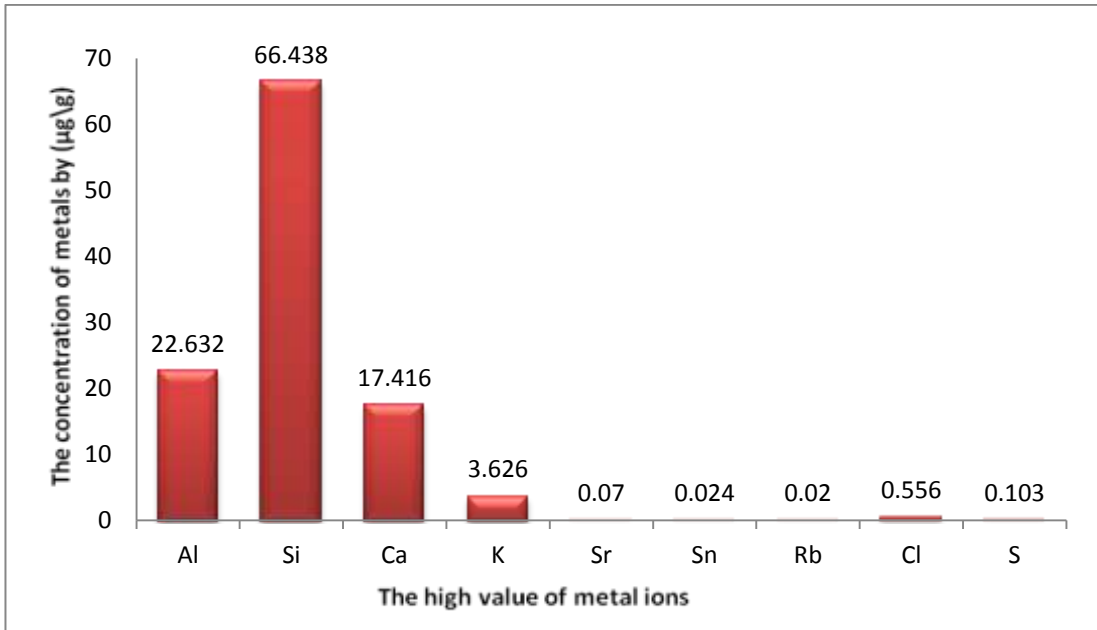


Figure (3.4): The highest concentration of metal ions in soil samples and site

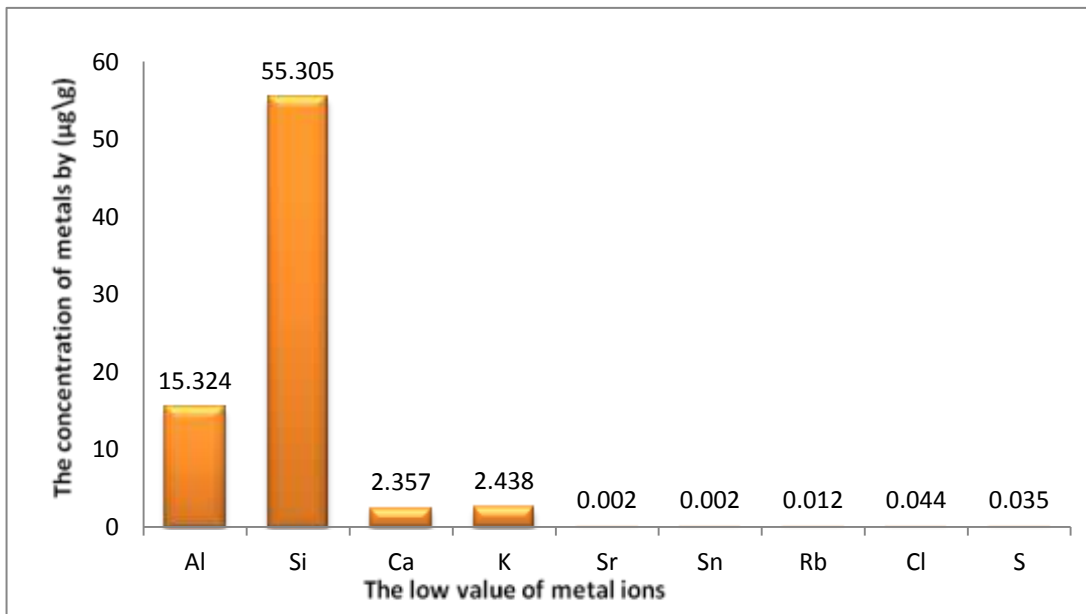


Figure (3.5): The lowest concentration of metal ions in soil samples and site

Table (3.5): Concentration of transition metal ions in soil samples:

Sites	Mean of Ti+ conc. ($\mu\text{g/g}$)	Mean of Mn+2 conc. ($\mu\text{g/g}$)	Mean of Fe+3 conc. ($\mu\text{g/g}$)	Mean of Cu+2 conc. ($\mu\text{g/g}$)	Mean of Zn+2 conc. ($\mu\text{g/g}$)	Mean of Ga+3 conc. ($\mu\text{g/g}$)	Mean of Y+3 conc. ($\mu\text{g/g}$)	Mean of Zr+2 conc. ($\mu\text{g/g}$)	Mean of Nb+5 conc. ($\mu\text{g/g}$)	Mean of Cd+2 conc. ($\mu\text{g/g}$)
TR	0.9380	0.0200	7.1440	0.0100	0.0080	0.0000	0.0060	0.0940	0.0040	0.0100
BG	1.1720	0.0633	9.8780	0.0075	0.0140	0.0040	0.0100	0.0820	0.0020	0.0050
DR	1.0900	0.0700	8.4560	0.0100	0.0140	0.0020	0.0080	0.0920	0.0060	0.0075
SK	0.9725	0.0467	7.0120	-----	0.0100	0.0000	0.0000	0.0780	0.0000	0.0100
KF	1.0560	0.0800	8.3380	0.0075	0.0160	0.0060	0.0040	0.0825	0.0000	0.0033
BI	1.1140	0.0667	8.7320	0.0067	0.0120	0.0020	0.0060	0.0925	0.0050	0.0050
BA	0.8450	0.0275	7.1880	-----	0.0100	0.0000	0.0020	0.0940	0.0020	0.0060
HO	0.9980	0.0525	8.0420	-----	0.0100	0.0000	0.0080	0.0800	0.0060	0.0100
GO	0.9960	0.0320	8.0220	-----	0.0060	0.0000	0.0080	0.0680	0.0060	0.0100
NG	1.0100	0.0760	8.0360	-----	0.0120	0.0000	0.0080	0.0750	0.0075	0.0100
BD	0.9960	0.0600	7.7860	0.0067	0.0120	0.0020	0.0025	0.1075	0.0000	0.0050
TK	0.9580	0.0480	7.8400	-----	0.0120	0.0025	0.0080	0.0860	0.0050	0.0100

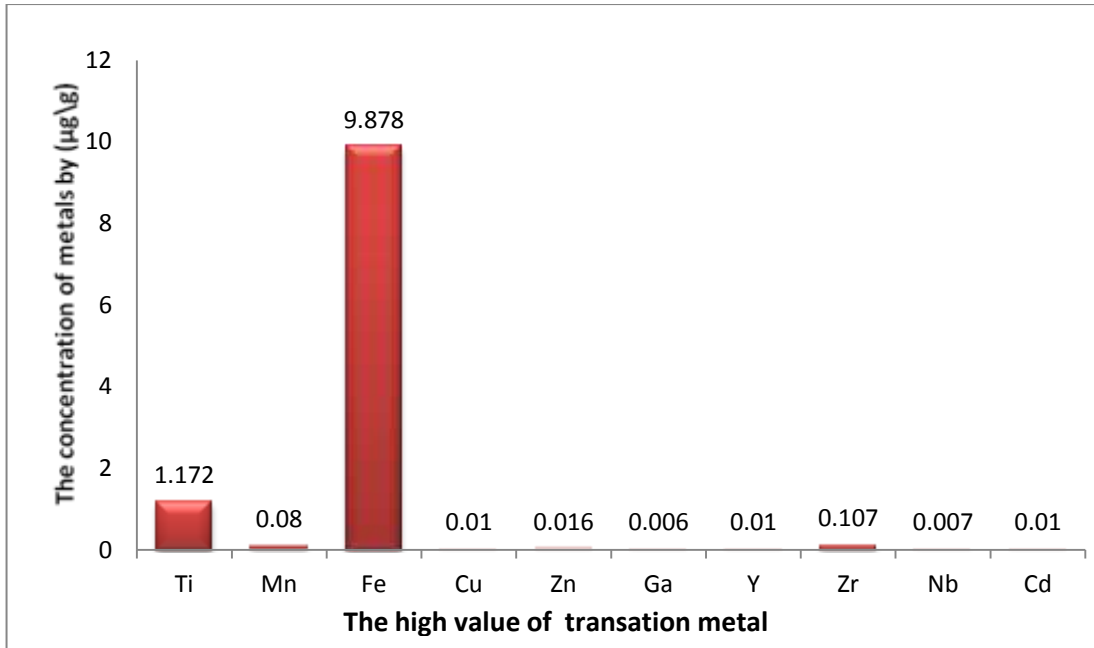


Figure (3.6): The highest concentration of transition metal ions in soil sample and sites

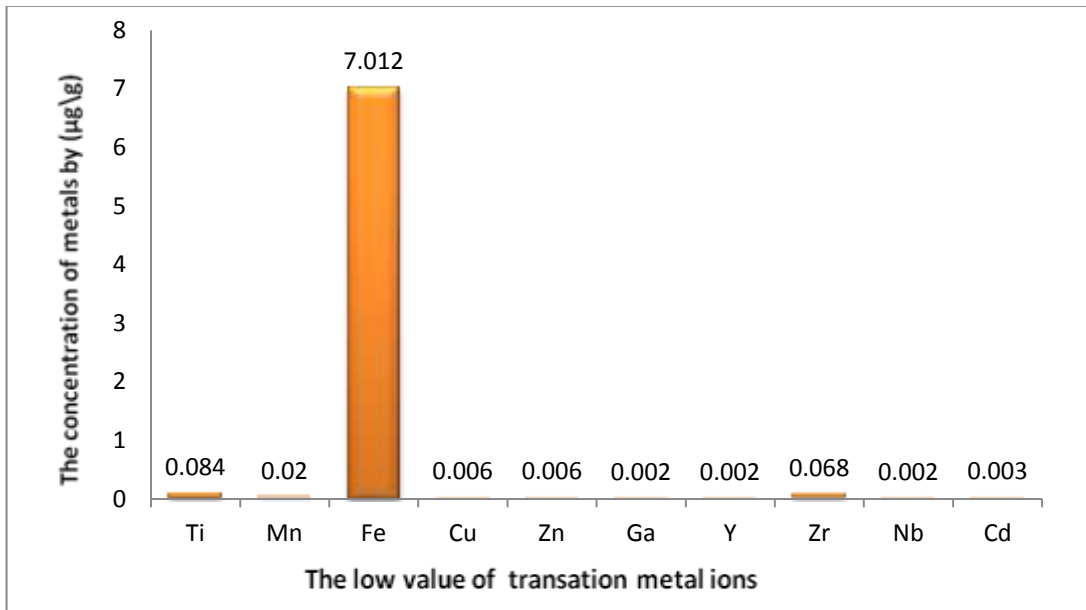


Figure (3.7): The lowest concentration of transition metal ions in soil samples and site

From tables (3.4), (3.5) and figure(3.4), (3.5) we may conclude that the lowest values of concentration for metal ions were found TR as following: (Al:15.324) (Si:55.305) (Cl:0.044) (S:0.035) (Mn:0.020) $\mu\text{g}\backslash\text{g}$,TK (K:2.438) $\mu\text{g}\backslash\text{g}$,DR and BD (Ga:0.002) (Sr:0.020) $\mu\text{g}\backslash\text{g}$, BD (Ca:3.357) (Cu:0.006) ,BA (Y,Nb:0.002)&(Ti:0.845) $\mu\text{g}\backslash\text{g}$, GO(Zn:0.006) (Zr:0.068) $\mu\text{g}\backslash\text{g}$,KF(Cd:0.003) $\mu\text{g}\backslash\text{g}$ and SK (Fe:7.012)&(Rb:0.012))

$\mu\text{g}\backslash\text{g}$. However, the highest metals concentration for Al ,Ti ,Fe ,Y and Cd were (22.632, 1.172,9.878,0.010 and0.01) $\mu\text{g}\backslash\text{g}$ in BG ; K, Zn ,Ga ,Mn and S (3.626,0.016,0.006,0.080 &0.103) $\mu\text{g}\backslash\text{g}$,TR ; Ca,Cu,Rb and Sn were (17.416,0.010,0.020 &0.024)) $\mu\text{g}\backslash\text{g}$ respectively , NG; (Nb:0.007) $\mu\text{g}\backslash\text{g}$ and BI; (Cl:0.556) $\mu\text{g}\backslash\text{g}$.

3.3 Multivariate Analysis

3.3.1 Multivariate Analysis of pH, EC and TDS

The chemical information generated from this work was inherently multivariate meaning that more than one measurement or variable were made on a single sample. Statistical evaluation was done to determine the chemical similarity of the pH, EC and TDS by pattern recognition using cluster analysis.

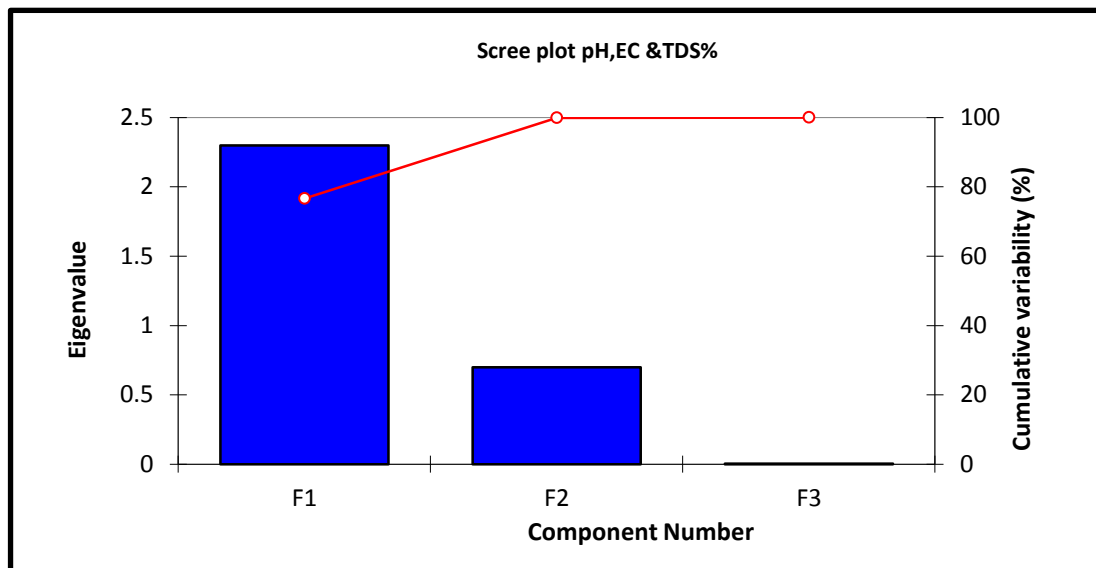
Cluster analysis of observations was the powerful and useful tool adopted to establish the existence of closely related classes. Cluster analysis of pH, EC and TDS was carried out by considering correlated variables ranging from the concentration of the samples to actual identity of the samples.

Cluster observation analysis was applied to all the sample levels using a parameter to assess the chemical similarities and or otherwise of the parameters. XLSTAT software -Eigen value (Scree) plot displayed Eigen value profiles associated with a principal component versus the number of components as seen in fig. (3.8). The aim was to fuse the data into a simple line or plane graph projection, thereby reducing the amount of data or number of dimensions without losing the integrity and relevant information of the samples.^[24]

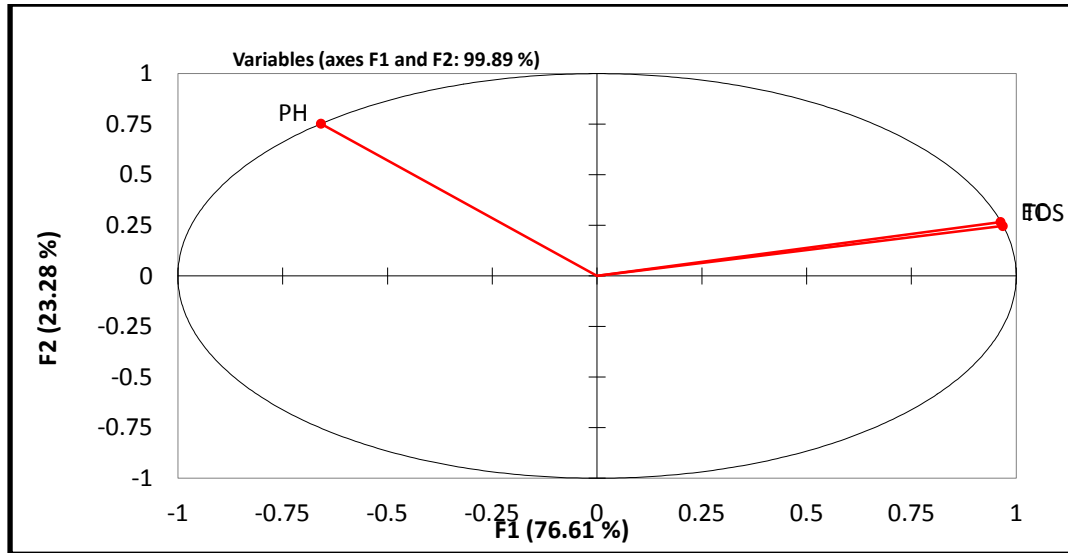
Principal Component Analysis (PCA) used combined concentration and Sample-discrete-identity information while related techniques like Principal Component Factor (PCF) and Partial Least Square (PLS) could only limit its quantification to concentration parameter. Average sample peak areas were normalized and transposed using XLSTAT software. PCA was

used to compute the correlation and covariance matrices to establish the principle components of all samples. Clustering of observations was applied with the complete linkage method, squared Euclidean distance, and standardization to bring out the different clusters Cluster analysis was achieved by using sample information in PC1 and PC2 and plotted in excel.

A score plot was carried out to check the scores for the second principal component (y-axis) versus the scores for the first principal component (x-axis) and values for all samples. 12 samples had 5 dots for the pH ,EC and TDS, middle and bottom levels fig. (3.8 and 3.9). The aim was to identify the pH ,EC and TDS with similar chemical characteristics which were initially unknown. The data was transposed into excel to bring out the individual sample and their depths fig.(3.10).



Figure(3.8) : PCA Scree plots of the Eigen value and the principal components for PH,EC and TDS%



Figure(3.9): XLSTAT - Principal Component Analysis (PCA) - PCA type: Pearson (n) for electrochemical measurements

The samples close or similar to each other were successfully clustered together when they were initially unknown. The choice of final grouping fig.(3.10) was made viewing from the above clustering statistics. Three main clusters were identified as represented with pink (A), green (B) and blue (C) circles.

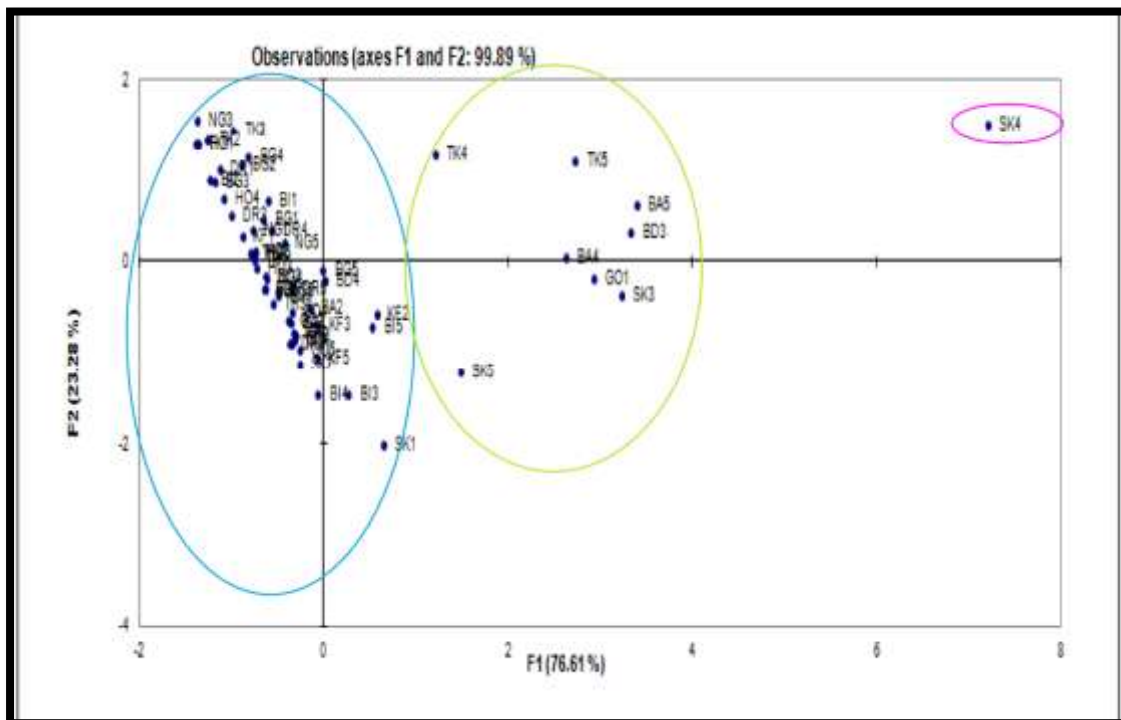


Figure (3.10): Cluster pattern for samples. Three main clusters were identified as represented with pink (A), green (B) blue (C) circles

The clusters attempted to classify the samples into similar chemical characteristics without losing their integrity. Sample C7 in the circle were classified as being non chemically similar. The green circle formed close clusters of samples in C6, C8, C9 and C11 are similarly collected together in group to form similar parameters present in that soil samples. The cluster observation of chemically similar samples is also displayed by group C, the blue circle. In this group, sample C1 C3 and C5 were patterned alike as sample C4, C2 and C10 formed the same cluster.

A dendrogram with cluster observations and cluster variables were produced to confirm the similarity groupings of the sample. The dendrogram cluster analysis of the soil samples was analyzed using pH ,EC and TDS variables to characterize the samples into groups of Chemical similarity. This high resolution dendrogram graph also identified three similar clusters inherent in the samples as seen in fig.(3.11).

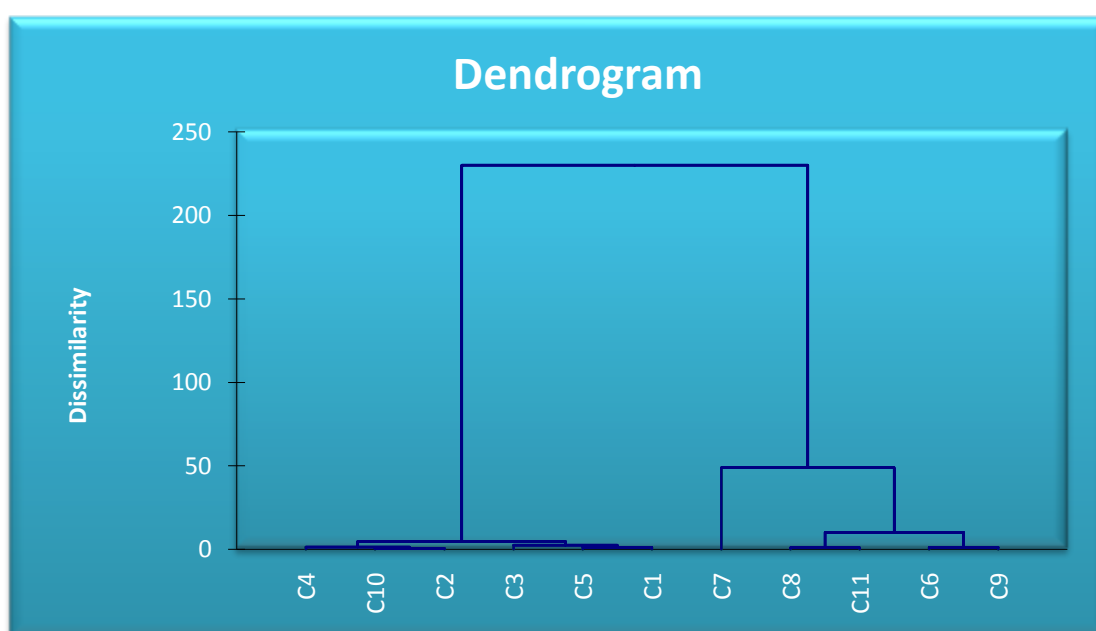


Figure (3.11): Dendrogram analyses of PH,EC&TDS% cluster observations and variables in soil samples

A dendrogram with cluster observations and cluster variables were also produced to show distance observation distribution of the individual samples and plotted using XLSTAT software fig.(3.12). The distribution of samples relative to the distance from the sampling reference point also portrays similar nutrients groupings displayed as a three diagrams below.

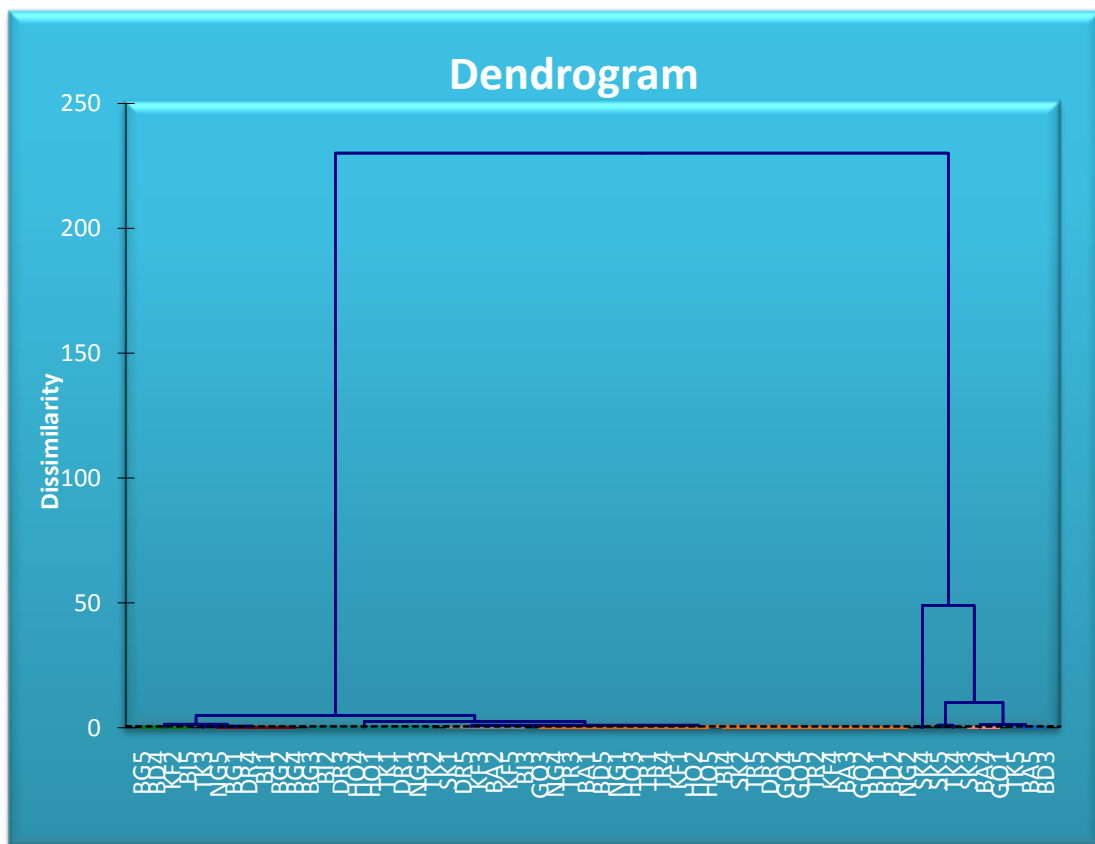


Figure (3.12): Distance - dendrogram analyses of PH,EC&TDS% cluster observations in the site confirms the similarity distribution of the samples relatively.

Table (3.6): XLSTAT k-means clustering - Number of classes 8

Results by class:								
Class	1	2	3	4	5	6	7	8
Objects	7	7	5	15	8	10	4	4
Sum of weights	7	7	5	15	8	10	4	4
Within-class variance	4.283	6.024	2.407	5.666	3.133	3.801	17.129	4.188
Minimum	0.602	0.680	1.013	0.603	0.938	0.780	2.269	0.842
Average distance	1.678	1.985	1.358	2.091	1.543	1.774	3.364	1.626
Maximum	3.454	4.280	1.810	4.865	2.664	2.514	5.374	2.765
	TR1	TR2	TR3	TR5	BG3	DR3	BA1	HO2
	BI1	BG1	TR4	DR4	BG4	BA3	HO1	HO3
	HO4	BG2	GO1	DR5	DR1	HO5	BD3	BD4
	BD1	BG5	BD5	SK3	DR2	GO2	NG1	NG3
	BD2	SK1	TK4	SK5	SK2	GO4	4	3
	NG2	GO3	5	KF1	SK4	GO5		
	NG5	TK5		KF2	KF3	NG4		
	6	7		KF4	BI4	TK1		
				KF5	8	TK2		
				BI2		TK3		
				BI3		10		
				BI5				
				BA2				
				BA4				
				BA5				
				15				

Table (3.7): Agglomeration method: Ward's method Truncation: number of classes 8

Results by class:								
Class	1	2	3	4	5	6	7	8
Objects	6	7	6	15	8	10	5	3
Sum of weights	6	7	6	15	8	10	5	3
Within-class variance	3.857	6.024	3.543	5.666	3.133	3.801	19.325	1.184
Minimum	0.536	0.680	0.679	0.603	0.938	0.780	1.620	0.179
Average distance	1.522	1.985	1.584	2.091	1.543	1.774	3.520	0.780
Maximum	3.384	4.280	2.596	4.865	2.664	2.514	6.431	1.086
	TR1	TR2	TR3	TR5	BG3	DR3	BA1	HO2
	BI1	BG1	TR4	DR4	BG4	BA3	HO1	HO3
	HO4	BG2	GO1	DR5	DR1	HO5	BD3	NG3
	BD1	BG5	BD5	SK3	DR2	GO2	BD4	
	BD2	SK1	NG5	SK5	SK2	GO4	NG1	
	NG2	GO3	TK4	KF1	SK4	GO5		
		TK5		KF2	KF3	NG4		
				KF4	BI4	TK1		
				KF5		TK2		
				BI2		TK3		
				BI3				
				BI5				
				BA2				
				BA4				
				BA5				

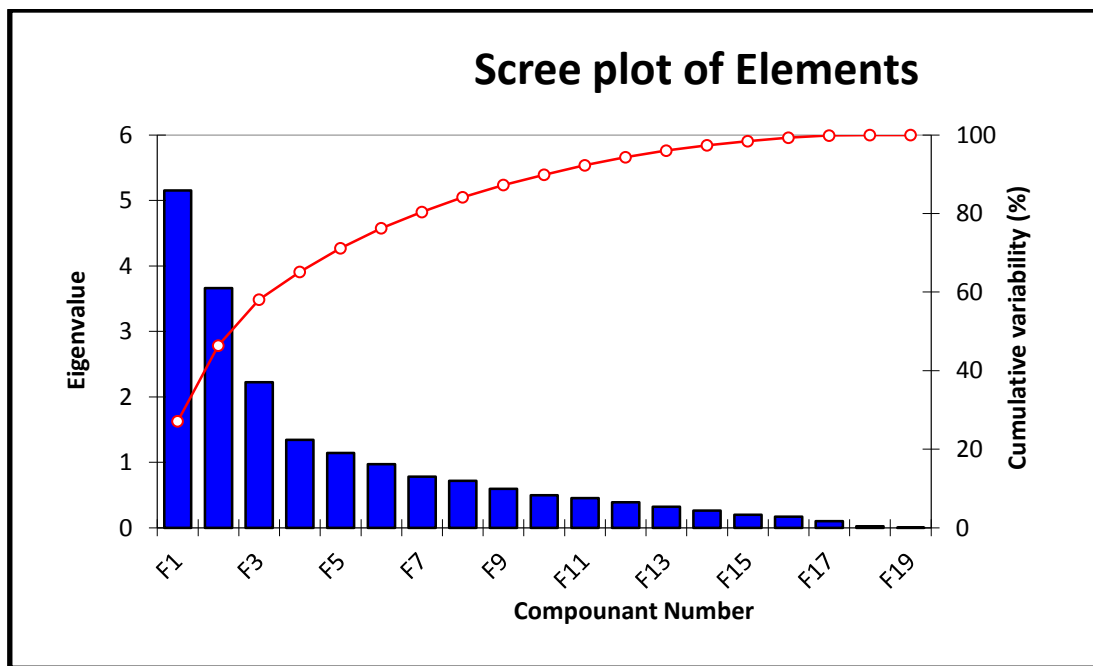
3.3.2 *Multivariate Analysis of nutrients*

The chemical information generated from this work is inherently multivariate because more than one measurement or variable were made on a single sample. Statistical evaluation was done to determine the chemical similarity of the nutrients by pattern recognition using cluster analysis. Cluster analysis of observations is the powerful and useful tool adopted to establish the existence of closely related classes. Cluster analysis of nutrients was carried out by considering correlated variables ranging from the concentration of the samples to actual identity of the samples.

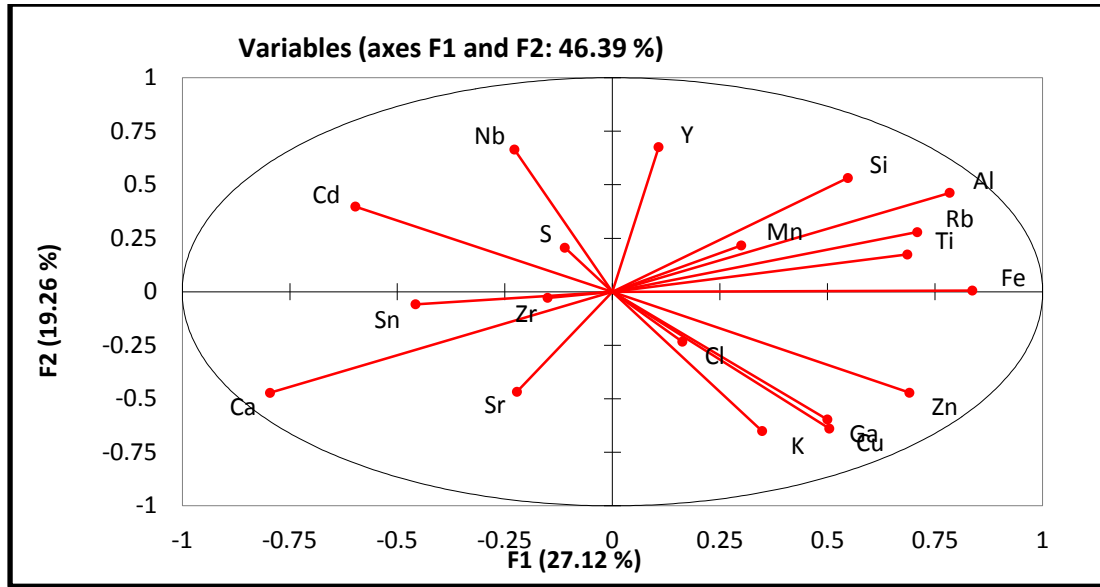
Cluster observation analysis was applied to all the sample levels using as a parameter to assess the chemical similarities and or otherwise of the nutrients .XLSTAT and Minitab software - Eigen value (Scree) plot displayed Eigen value profiles associated with a principal component versus the number of components as seen in fig.(3.13).The aim was to fuse the data into a simple line or plane graph projection, thereby reducing the amount of data or number of dimensions without losing the integrity and relevant information of the samples. ^[24]

Principal Component Analysis (PCA) uses combined concentration and sample-discrete-identity while related techniques like Principal Component Factor (PCF) and Partial Least Square (PLS) could only limit its quantification to concentration parameter. Average sample peak areas were normalized and transposed using XLSTAT software. PCA was used to compute the correlation and covariance matrices to establish the principle components of all samples. Clustering of

observations was applied with the complete linkage method, squared Euclidean distance, and standardization to bring out the different clusters. Cluster analysis was achieved by using sample information in PC1 and PC2 and plotted in excel. A score plot was carried out to check the scores for the second principal component (y-axis) versus the scores for the first principal component (x-axis) and values for all samples. 12 samples had 5 dots for the 19 metals, middle and bottom levels fig(3.14). The aim was to identify the nutrients with similar chemical characteristics which were initially unknown.

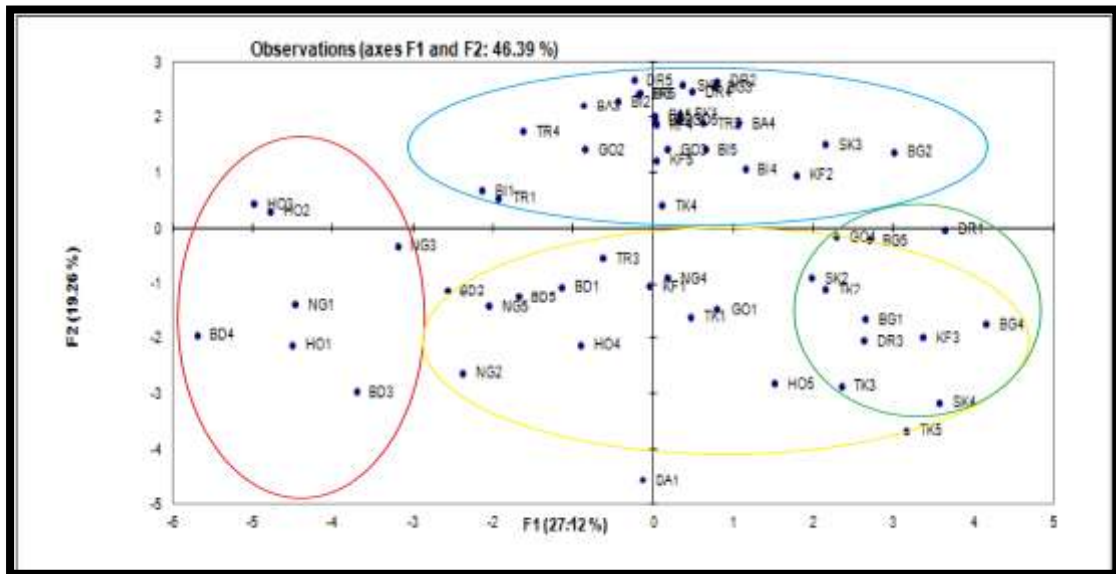


Figure(3.13) : PCA Scree plots of the Eigen value and the principal components of nutrients



Figure(3.14): XLSTAT - Principal Component Analysis (PCA) - PCA type

The samples close or similar to each other were successfully clustered together when they were initially unknown. The choice of final grouping figure(3.15) was made viewing from the above clustering statistics. Three main clusters were identified as represented with red (A), green (B), yellow(C) and blue (D) circles.



Figure(3.15): Cluster pattern for samples. Three main clusters were identified as represented with red (A), green (B), yellow (C) and blue (D) circles.

The clusters attempted to classify the samples into similar chemical characteristics without losing their integrity. Samples C1 and C3 in the red circle were classified as being chemically similar. The blue circle formed close clusters of sample C7 and C8 similar in characteristics. The cluster observation of chemically similar samples was also displayed group C, the green and yellow circles. In this group, samples C4 & C6 were patterned alike as samples C2 and C5 formed the same cluster.

A dendrogram with cluster observations and cluster variables were produced to confirm the similarity groupings of the sample. The dendrogram cluster analysis of the soil samples was analyzed using nutrients variables to characterize the samples into groups of chemical similarity. This high resolution dendrogram graph also identified three similar clusters inherent in the samples as seen in figure(3.16).

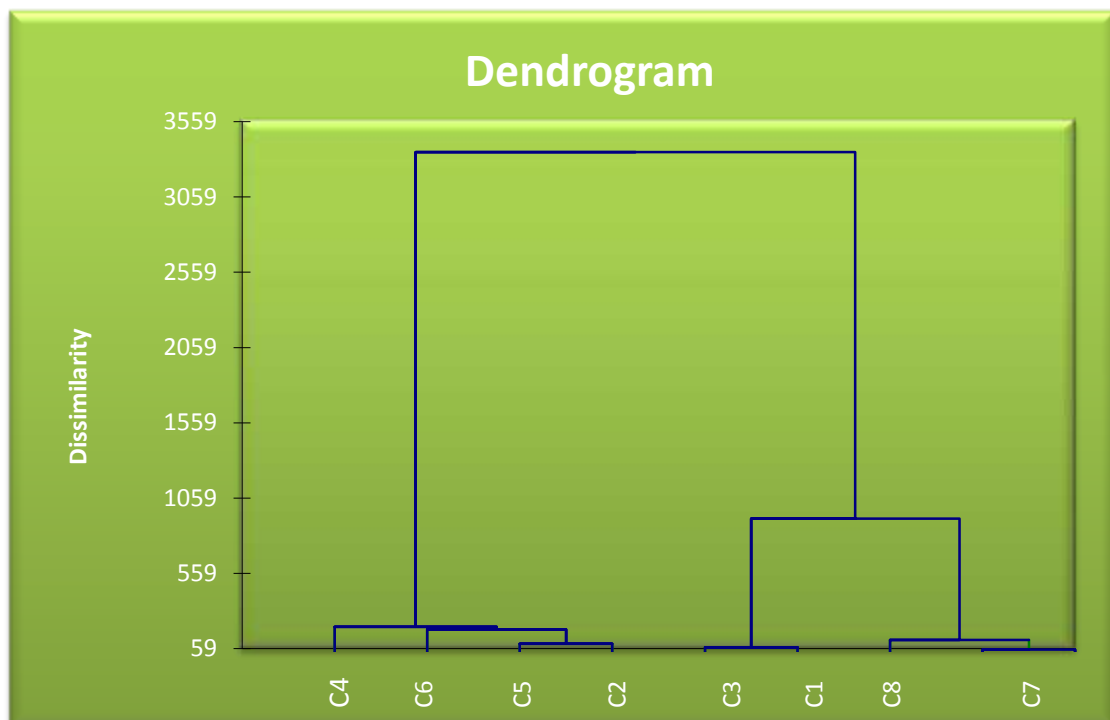
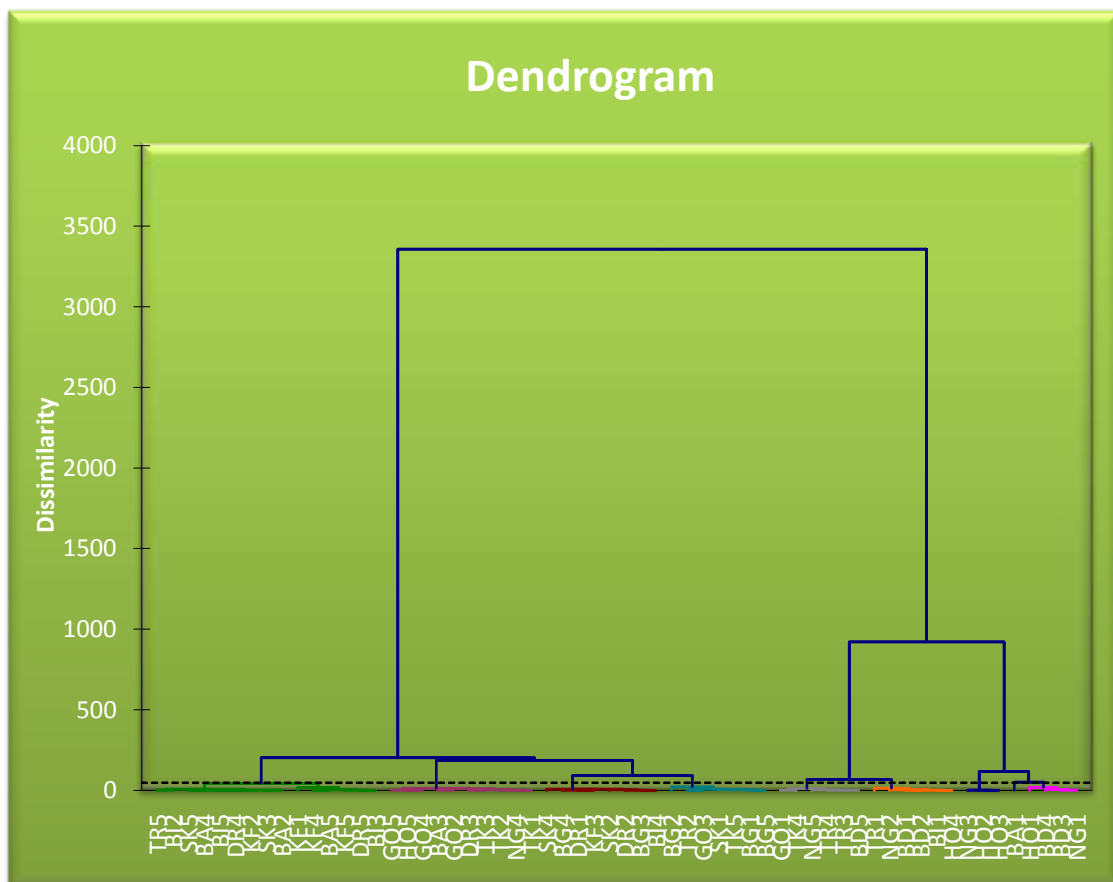


Figure (3.16): Dendrogram analyses of nutrients cluster observations and variables in soil samples

A dendrogram with cluster observations and cluster variables were also produced to show distance observation distribution of the individual samples and plotted using XLSTAT software fig.(3.17). The distribution of samples relative to the distance from the sampling reference point also portrays similar nutrients groupings displayed as a tree diagram below.



Figure(3.17): Distance - dendrogram analyses of nutrients cluster observations in the site confirms the similarity distribution of the samples relatively.

Table (3.8): XLSTAT k-means clustering - Number of classes 11

Results by class:											
Class	1	2	3	4	5	6	7	8	9	10	11
Objects	23	6	11	2	6	4	1	3	2	1	1
Sum of weights	23	6	11	2	6	4	1	3	2	1	1
Within-class variance	0.030	0.028	0.035	0.002	0.076	0.183	0.000	0.330	0.055	0.000	0.000
Minimum	0.057	0.087	0.070	0.031	0.121	0.188	0.000	0.267	0.166	0.000	0.000
Average distance	0.156	0.147	0.166	0.031	0.231	0.347	0.000	0.440	0.166	0.000	0.000
Maximum	0.352	0.213	0.276	0.031	0.422	0.513	0.000	0.658	0.166	0.000	0.000
	TR1	BG1	BG3	BG5	DR5	SK3	SK4	SK5	BA5	TK3	TK4
	TR2	BG2	DR1	BD4	SK1	BA4	1	KF2	BD3	1	1
	TR3	BG4	DR3	2	KF3	GO1		BI5	2		
	TR4	DR4	KF1		KF5	TK5		1			
	TR5	BI1	BI2		BI3	3					
	DR2	NG5	HO1		BA2						
	SK2	6	HO4		6						
	KF4		NG1								
	BI4		NG3								
	BA1		TK1								
	BA3		TK2								
	HO2		9								
	HO3										
	HO5										
	GO2										
	GO3										
	GO4										
	GO5										
	BD1										
	BD2										
	BD5										
	NG2										
	NG4										
	22										

Table (3.9): Agglomeration method, Ward's method Truncation: number of classes 11

Results by class:											
Class	1	2	3	4	5	6	7	8	9	10	11
Objects	25	6	9	4	6	3	1	1	3	1	1
Sum of weights	25	6	9	4	6	3	1	1	3	1	1
Within-class variance	0.035	0.028	0.025	0.088	0.076	0.099	0.000	0.000	0.139	0.000	0.000
Minimum distance	0.058	0.087	0.081	0.198	0.121	0.024	0.000	0.000	0.134	0.000	0.000
Average distance	0.167	0.147	0.141	0.254	0.231	0.217	0.000	0.000	0.284	0.000	0.000
Maximum distance	0.376	0.213	0.225	0.312	0.422	0.321	0.000	0.000	0.385	0.000	0.000
	TR1	BG1	BG3	BG5	DR5	SK3	SK4	SK5	BA5	TK3	TK4
	TR2	BG2	DR1	KF2	SK1	BA4			BD3		
	TR3	BG4	DR3	BI5	KF3	GO1			TK5		
	TR4	DR4	BI2	BD4	KF5						
	TR5	BI1	HO1		BI3						
	DR2	NG5	HO4		BA2						
	SK2		NG3								
	KF1		TK1								
	KF4		TK2								
	BI4										
	BA1										
	BA3										
	HO2										
	HO3										
	HO5										
	GO2										
	GO3										
	GO4										
	GO5										
	BD1										
	BD2										
	BD5										
	NG1										
	NG2										
	NG4										

3.4. Conclusion:

From the data which obtained in this study the technique of energy dispersive X-ray fluorescence combined with multivariate statistic is a rapid method of elemental analysis of soil sample and classification based on their geographical origin, Studies were conducted to know the chemical characteristics of the soils and their classification from Benghazi plain For this purpose, 60 soil samples were analyzed for pH, EC, TDS, pH ranged from 7.2 to 8.1 reflecting between natural and weak alkaline nature of soils. Higher EC in Sedi Khalifa reflecting the salinity of the soil and perhaps this is due to the water used for irrigation, according to the study, conducted for the wells, irrigation water by the water and soil laboratory Benghazi in 1996 and also came in doctoral study, Dr. Abdullah Lama Department of Geography, University of Benghazi in the same year for Benghazi plain. The use of elemental concentration as inputs has shown that each cultivar presents distinctive element content. The classification of sixty soil samples were 100% accurate in total by single value decomposition (SVD), hierarchical cluster analysis (HCA) and principle components analysis (PCA), The present study through the establishment baseline of the relationship between elemental concentration and geographical origin will allow us in the second phase of our project to be able to assess the quality of soil by taking into account both parameters (elemental concentration and geographical sites of Benghazi plain). Through statistical results were obtained on the correlation between the pH, Cd and K where the relationship is that the higher the pH and Cd said the proportion of potassium is known to the important role of

potassium in soil fertility and that as one of the key elements within (P,N and K) for the quality of the soil and in general did not suffer any sit of study areas of deficiency, as that element Al and Si was their relationship proportional meaning it is the greater the concentration of Al increased concentration Si and said the proportion of Ca in the study areas , which suffered some areas such as the Tukra, Sedi Khalifa, Tekah and Boatny of an increase in the proportion of Ca , which has been classified as soils limestone that is, they are valid by large zones of exploitation of pastoral activity and the difficulty of agricultural zones. Areas such as Al- Kwefia and Bograr recorded values of nutrients very good in general , and also did not suffer any of the areas that were under study exceeded in any allowable values of heavy elements such as Cd, Cu and Zn by the values that came in the International Organization for Agriculture (IOA) and the International Center for Agricultural Studies areas of Islamabad, Pakistan(ICARDA).

Recommendation:

1. Vary soils largely around the world, where they are suffering from weak legacy is reflected mainly in the lack of nutrients essential for the growth of crops grown. Even when available those elements enough in the early stages of cultivation of the land, the production capacity is decreasing steadily with the passage of time.
2. Conduct annual periodic analysis of the study site to follow the changes which may occur and compare previous studies.
3. Proposal for a research study for those interested in this field to the same location for two or three consecutive to encourage and increase the interest in this type of research.

3.5. Appendix:

Table (1): Statistical treatment of Aluminum, Al data using ANOVA:

Sites	No. of samples	Mean of Al conc. (μg)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA P-value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	15.3240	2.0448	12.7850	17.8630	0.0000	BI>DR BG>BI DR>BD BA>SK KF>BA HO>GO GO>KF SK>TR BD>TK TK>HO
BG	5	22.6320	1.3062	21.0102	24.2538		
DR	5	20.6980	2.0346	18.1717	23.2243		
SK	5	15.5760	1.6216	13.5625	17.5895		
KF	5	17.9840	1.2075	16.4847	19.4833		
BI	5	20.9780	0.3984	20.4833	21.4727		
BA	5	15.8260	0.9492	14.6474	17.0046		
HO	5	19.5560	2.2504	16.7618	22.3502		
GO	5	18.9680	1.1225	17.5742	20.3618		
NG	5	19.2660	0.8632	18.1943	20.3377		
BD	5	19.7300	2.3587	16.8013	22.6587		
TK	5	19.6580	2.1404	17.0003	22.3157		

Table (2): Statistical treatment of Silicon Si data using ANOVA:

Sites	No. of samples	Mean of Si conc. (μg)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA P – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	4	55.3050	5.6680	46.2859	64.3241	0.0020	BG>GO
BG	5	60.0940	1.8429	57.8057	62.3823		DR>HO
DR	5	64.3880	2.0464	61.8471	66.9289		BA>SK
SK	5	55.7980	4.3988	50.3361	61.2599		NG>KF
KF	5	61.3360	2.0928	58.7375	63.9345		KF>BG
BI	5	63.3760	1.2371	61.8400	64.9120		BG>GO
BA	5	56.7480	4.7459	50.8552	62.6408		HO>BI
HO	5	63.4420	3.7179	58.8256	68.0584		BI>NG
GO	5	60.0600	3.6471	55.5315	64.5885		GO>TK
NG	5	61.3860	1.4977	59.5263	63.2457		BD>DR
BD	5	66.4380	2.3550	63.5139	69.3621		TK>BA
TK	4	59.0675	10.5539	42.2739	75.8611		

Table (3): Statistical treatment of Chlorine, Cl data using ANOVA:

Sites	No. of samples	Mean of Cl conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0440	0.0182	0.0214	0.0666	0.1000	-
BG	4	0.0900	0.0688	-0.0195	0.1995		
DR	4	0.0600	0.0523	-0.0232	0.1432		
SK	4	0.4150	0.5058	-0.3898	1.2198		
KF	4	0.5050	0.4812	-0.2607	1.2707		
BI	5	0.5560	0.6658	-0.2707	1.3827		
BA	4	0.0700	0.0141	0.0475	0.0925		
HO	5	0.0800	0.0524	0.0149	0.1451		
GO	5	0.0600	0.0141	0.0424	0.0776		
NG	5	0.1540	0.2104	-0.1073	0.4153		
BD	3	0.0800	0.0200	0.0303	0.1297		
TK	5	0.2740	0.2902	-0.0864	0.6344		

Table (4): Statistical treatment of, Potassium K data using ANOVA:

Sites	No. of samples	Mean of K conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p<0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	3.0100	0.4477	2.4541	3.5659	0.0010	KF>SK
BG	5	3.2280	0.4940	2.6146	3.8414		SK>NG
DR	5	2.9300	0.3459	2.5005	3.3595		NG>BA
SK	5	3.3500	0.2400	3.0520	3.6480		BA>BG
KF	5	3.6260	0.2692	3.2917	3.9603		BG>BI
BI	5	3.0800	0.5457	2.4024	3.7576		BI>TR
BA	5	3.2340	0.4739	2.6456	3.8224		TR>DR
HO	5	2.8000	0.1313	2.6369	2.9631		DR>GO
GO	5	2.9220	0.2867	2.5661	3.2779		GO>HO
NG	5	3.4240	0.3994	2.9281	3.9199		HO>BD
BD	5	2.7920	0.3832	2.3161	3.2679		BD>TK

Table (5): Statistical treatment of Calcium, Ca data using ANOVA:

Sites	No. of samples	Mean of Ca conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p<0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	17.4160	8.3326	7.0697	27.7623	0.0000	TR>SK
BG	4	3.2150	1.3995	0.9881	5.4419		SK>BA
DR	4	2.4950	2.0668	-0.7938	5.7838		BA>GO
SK	5	16.884	6.3257	9.0296	24.7384		GO>TK
KF	5	6.7980	1.5112	4.9216	8.6744		TK>KF
BI	4	2.5025	1.0311	0.8618	4.1432		KF>NG
BA	5	15.3160	6.8095	6.8609	23.7711		NG>HO
HO	5	4.4960	5.4617	-2.2856	11.2776		HO>BG
GO	5	8.6180	4.2659	3.3212	13.9148		BG>BI
NG	5	6.2800	1.7412	4.1180	8.4420		BI>DR
BD	4	2.3575	1.5085	-0.0428	4.7578		DR>BD
TK	5	8.2180	11.2935	-5.8047	22.2407		

Table (6): Statistical treatment of Titanium, Ti data using ANOVA:

Sites	No. of samples	Mean of Ti conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p<0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.9380	0.1693	0.7278	1.1482	0.0000	BG>BI
BG	5	1.1720	0.0512	1.1084	1.2356		BI>KF
DR	5	1.0900	0.0621	1.0130	1.1670		KF>DR
SK	4	0.9725	0.0772	0.8497	1.0953		DR>NG
KF	5	1.0560	0.0483	0.9961	1.1159		NG>HO
BI	5	1.1140	0.0523	1.0491	1.1789		HO>BD
BA	4	0.8450	0.0874	0.7060	0.9840		BD>GO
HO	5	0.9980	0.0861	0.8910	1.1050		GO>SK
GO	5	0.9960	0.0603	0.9212	1.0708		SK>RK
NG	5	1.0100	0.0765	0.9150	1.1050		TK>TR
BD	5	0.9960	0.0472	0.9374	1.0546		TR>BA
TK	5	0.9580	0.0130	0.9418	0.9742		

Table (7): Statistical treatment of Iron, Fe data using ANOVA:

Sites	No. of samples	Mean of Fe conc. (μg)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	7.1440	1.0517	5.8382	8.4498	0.0000	BG>BI
BG	5	9.8780	0.6318	9.0935	10.6625		BI>DR
DR	5	8.4560	0.8389	7.4143	9.4977		DR>KF
SK	5	7.0120	0.4089	6.5043	7.5197		KF>HO
KF	5	8.3380	0.6457	7.5362	9.1398		HO>AG
BI	5	8.7320	0.3312	8.3208	9.1432		NG>GO
BA	5	7.1880	0.6021	6.4405	7.9355		GO>TK
HO	5	8.0420	0.9631	6.8462	9.2378		TK>BD
GO	5	8.0220	0.4346	7.4824	8.5616		BD>BA
NG	5	8.0360	0.5523	7.3502	8.7218		BA>TR
BD	5	7.7860	1.0025	6.5413	9.0307		TR>SK
TK	5	7.8400	0.3977	7.3461	8.3339		

Table (8): Statistical treatment of Zinc, Zn data using ANOVA:

Sites	No. of samples	Mean of Zn conc. (μg)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0080	0.0084	-0.0024	0.0183	0.1220	-
BG	5	0.0140	0.0055	0.0072	0.0208		
DR	5	0.0140	0.0055	0.0072	0.0208		
SK	5	0.0100	0.0000	0.0100	0.0100		
KF	5	0.0160	0.0055	0.0092	0.0228		
BI	5	0.0120	0.0045	0.0064	0.0175		
BA	5	0.0100	0.0000	0.0100	0.0100		
HO	5	0.0100	0.0000	0.0100	0.0100		
GO	5	0.0060	0.0055	-0.0008	0.0128		
NG	5	0.0120	0.0045	0.0064	0.0175		
BD	5	0.0120	0.0045	0.0064	0.0175		
TK	5	0.0120	0.0045	0.0064	0.0175		

Table (9): Statistical treatment of Gallium, Ga data using ANOVA:

Sites	No. of samples	Mean of Ga conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
BG	5	0.0040	0.0055	-0.0028	0.0108	0.3640	-
DR	5	0.0020	0.0045	-0.0036	0.0076		
SK	3	0.0000	0.0000	0.0000	0.0000		
KF	5	0.0060	0.0055	-0.0008	0.0128		
BI	5	0.0020	0.0045	-0.0036	0.0076		
BA	2	0.0000	0.0000	0.0000	0.0000		
HO	2	0.0000	0.0000	0.0000	0.0000		
GO	3	0.0000	0.0000	0.0000	0.0000		
NG	4	0.0000	0.0000	0.0000	0.0000		
BD	5	0.0020	0.0045	-0.0036	0.0076		
TK	4	0.0025	0.0050	-0.0055	0.0105		

Table (10): Statistical treatment of Rubidium, Rb data using ANOVA:

Sites	No. of samples	Mean of Rb conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0140	0.0055	0.0072	0.0208	0.0000	BG,HO, DR,NG,B D,BI,GO, KF>BA BA>TR TR>SK
BG	5	0.0200	0.0000	0.0200	0.0200		
DR	5	0.0200	0.0000	0.0200	0.0200		
SK	5	0.0120	0.0045	0.0064	0.0176		
KF	5	0.0200	0.0000	0.0200	0.0200		
BI	5	0.0200	0.0000	0.0200	0.0200		
BA	5	0.0160	0.0055	0.0092	0.0228		
HO	5	0.0200	0.0000	0.0200	0.0200		
GO	5	0.0200	0.0000	0.0200	0.0200		
NG	5	0.0200	0.0000	0.0200	0.0200		
BD	5	0.0200	0.0000	0.0200	0.0200		
TK	5	0.0200	0.0000	0.0200	0.0200		

Table (11): Statistical treatment of Strontium, Sr data using ANOVA:

Sites	No. of samples	Mean of Sr conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0700	0.0316	0.0197	0.1203	0.0040	TR>BA BA>NG NG>SK,KF SK,KF>TK TK>GO GO>BG BG>HO HO>BD,BI BD,BI>DR
BG	5	0.0280	0.0084	0.0176	0.0384		
DR	5	0.0200	0.0000	0.0200	0.0200		
SK	5	0.0380	0.0084	0.0276	0.0484		
KF	5	0.0380	0.0084	0.0276	0.0484		
BI	5	0.0240	0.0089	0.0129	0.0351		
BA	5	0.0400	0.0123	0.0248	0.0552		
HO	5	0.0280	0.0179	0.0058	0.0502		
GO	5	0.0340	0.0152	0.0152	0.0528		
NG	5	0.0400	0.0141	0.0224	0.0576		
BD	5	0.0240	0.0089	0.0129	0.0351		
TK	5	0.0380	0.0295	0.0014	0.0746		

Table (12): Statistical treatment of Yttrium, Y data using ANOVA:

Sites	No. of samples	Mean of Y conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0060	0.0055	-0.0008	0.0128	0.0340	BG>HO,TK ,DR,NG,GO >TR,BI TR,BI>KF KF>BD BD>BA BA>SK
BG	5	0.0100	0.0000	0.0100	0.0100		
DR	5	0.0080	0.0045	0.0024	0.0136		
SK	5	0.0000	0.0000	0.0000	0.0000		
KF	5	0.0040	0.0055	-0.0028	0.0108		
BI	5	0.0060	0.0055	-0.0008	0.0128		
BA	5	0.0020	0.0045	-0.0036	0.0076		
HO	5	0.0080	0.0045	0.0024	0.0136		
GO	5	0.0080	0.0045	0.0024	0.0136		
NG	5	0.0080	0.0045	0.0024	0.0136		
BD	5	0.0025	0.0050	-0.0055	0.0105		
TK	5	0.0080	0.0045	0.0024	0.0136		

Table (13): Statistical treatment of Zirconium, Zr data using ANOVA:

Sites	No. of samples	Mean of Zr conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value (p < 0.05)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0940	0.0089	0.0829	0.1051	0.0090	BD>HO HO>TR TR>BI BI>DR DR>TK TK>KF KF>BG BG>BA BA>SK SK>NG NG>GO
BG	5	0.0820	0.0084	0.0716	0.0924		
DR	5	0.0920	0.0084	0.0816	0.1024		
SK	5	0.0780	0.0045	0.0724	0.0836		
KF	4	0.0825	0.0150	0.0586	0.1064		
BI	4	0.0925	0.0050	0.0845	0.1005		
HO	5	0.0940	0.0055	0.0872	0.1008		
BA	5	0.0800	0.0100	0.0676	0.0924		
GO	5	0.0680	0.0335	0.0264	0.1096		
NG	4	0.0750	0.0100	0.0591	0.0909		
BD	4	0.1075	0.0171	0.0803	0.1347		
TK	5	0.0860	0.0089	0.0749	0.0971		

Table (14): Statistical treatment of Niobium, Nb data using ANOVA:

Sites	No. of samples	Mean of Nb conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0040	0.0055	-0.0028	0.0108	0.1930	-
BG	5	0.0020	0.0045	-0.0036	0.0076		
DR	5	0.0060	0.0055	-0.0008	0.0128		
KF	4	0.0000	0.00000	0.0000	0.0000		
SK	4	0.0000	0.0000	0.0000	0.0000		
BI	4	0.0050	0.0055	-0.0042	0.0142		
BA	5	0.0020	0.0045	-0.0036	0.0076		
HO	5	0.0060	0.0055	- 0.0008	0.0128		
GO	5	0.0060	0.0055	-0.0008	0.0128		
NG	4	0.0075	0.0050	-0.0005	0.0155		
BD	4	0.0000	0.0000	0.0000	0.0000		
TK	4	0.0050	0.0055	-0.0042	0.0142		

Table (15): Statistical treatment of Tin, Sn data using ANOVA:

Sites	No. of samples	Mean of Sn conc. (μg)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p - value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0240	0.0055	0.0172	0.0308	0.1390	-
BG	3	0.0200	0.0000	0.0200	0.0200		
DR	4	0.0200	0.0000	0.0200	0.0200		
SK	5	0.0200	0.0000	0.0200	0.0200		
KF	3	0.0200	0.0000	0.0200	0.0200		
BI	4	0.0200	0.0000	0.0200	0.0200		
BA	5	0.0240	0.0055	0.0172	0.0308		
HO	5	0.0200	0.0000	0.0200	0.0200		
GO	4	0.0200	0.0000	0.0200	0.0200		
NG	2	0.0200	0.0000	0.0200	0.0200		
BD	3	0.0200	0.0000	0.0200	0.0200		
TK	3	0.0200	0.0000	0.0200	0.0200		

Table (16): Statistical treatment of Manganese, Mn data using ANOVA:

Sites	No. of samples	Mean of Mn conc. (μg)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	3	0.0200	0.0173	-0.0230	0.0630	0.1130	-
BG	3	0.0633	0.0416	-0.0401	0.1668		
DR	5	0.0700	0.0374	0.0235	0.1165		
SK	3	0.0467	0.0153	0.0087	0.0846		
KF	3	0.0800	0.0100	0.0552	0.1048		
BI	3	0.0667	0.0462	-0.0481	0.1814		
BA	4	0.0275	0.0126	0.0075	0.0475		
HO	4	0.0525	0.0189	0.0224	0.0826		
GO	5	0.0320	0.0130	0.0158	0.0482		
NG	5	0.0760	0.0410	0.0251	0.1269		
BD	3	0.0600	0.0346	-0.0261	0.1461		
TK	5	0.0480	0.0239	0.0184	0.0776		

Table (17): Statistical treatment of Sulfur, S data using ANOVA:

Sites	No. of samples	Mean of S conc. (µg/g)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value (p < 0.05)	L.S.D
				Lower Bound	Upper Bound		
TR	2	0.0350	0.0071	-0.0285	0.0985	0.1920	-
DR	2	0.0650	0.0071	0.0015	0.1285		
KF	3	0.1033	0.0252	0.0408	0.1658		
BI	3	0.0533	0.0305	-0.0226	0.1292		
BA	3	0.0833	0.0208	0.0316	0.1350		
HO	3	0.0433	0.0351	-0.0439	0.1306		
GO	2	0.0600	0.0141	-0.0671	0.1871		
NG	3	0.0800	0.0265	0.0143	0.1457		
TK	4	0.0575	0.0350	0.0018	0.1132		

Table (18): Statistical treatment of Cadmium, Cd data using ANOVA:

Sites	No. of samples	Mean of Cd conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value ($p < 0.05$)	L.S.D
				Lower Bound	Upper Bound		
TR	5	0.0100	0.0000	0.0100	0.0100	0.0700	-
BG	4	0.0050	0.0055	-0.0042	0.0142		
DR	4	0.0075	0.0050	-0.0005	0.0155		
SK	5	0.0100	0.0000	0.0100	0.0100		
KF	3	0.0033	0.0058	-0.0110	0.0177		
BI	4	0.0050	0.0058	-0.0042	0.0142		
BA	5	0.0060	0.0055	-0.0008	0.0128		
HO	5	0.0100	0.0000	0.0100	0.0100		
GO	5	0.0100	0.0000	0.0100	0.0100		
NG	4	0.0100	0.0000	0.0100	0.0100		
BD	4	0.0050	0.0055	-0.0042	0.0142		
TK	3	0.0100	0.0000	0.0100	0.0100		

Table (19): Statistical treatment of Cupper data using ANOVA:

Sites	No. of samples	Mean of Cu conc. ($\mu\text{g/g}$)	Std. Deviation	Confidence %95 Interval for Mean		ANOVA p – value (p < 0.05)	L.S.D
				Lower Bound	Upper Bound		
BG	4	0.0075	0.0050	-0.0005	0.0155	0.8580	-
TR	2	0.0100	0.0000	0.0100	0.0100		
DR	2	0.0100	0.0000	0.0100	0.0100		
BD	3	0.0067	0.0057	-0.0077	0.0210		
BI	3	0.0067	0.0057	-0.0077	0.0210		
KF	4	0.0075	0.0050	-0.0005	0.0155		

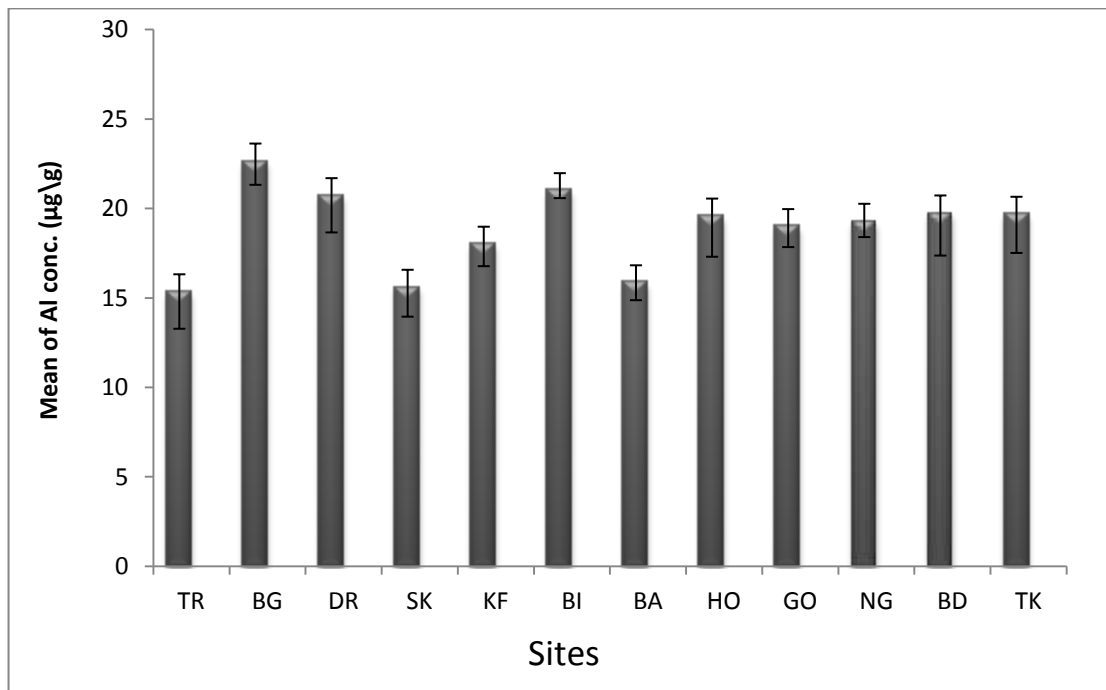


Figure (1): Mean concentration of Aluminum in soil samples.

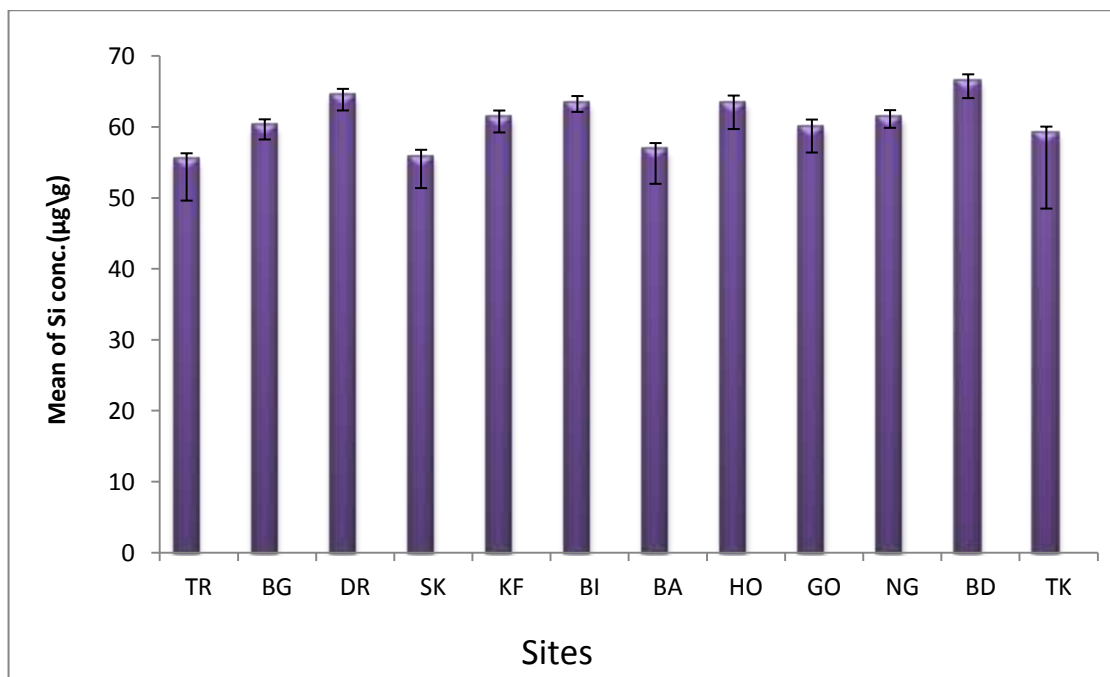


Figure (2): Mean concentration of Silicon in soil samples.

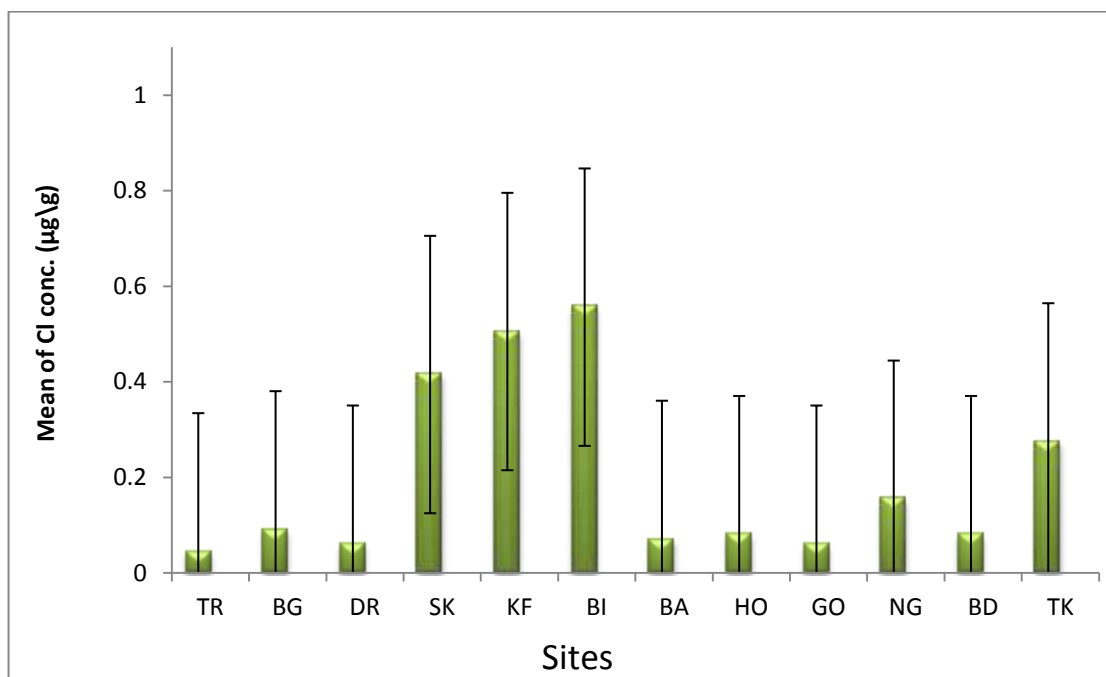


Figure (3): Mean concentration of Chlorine in soil samples.

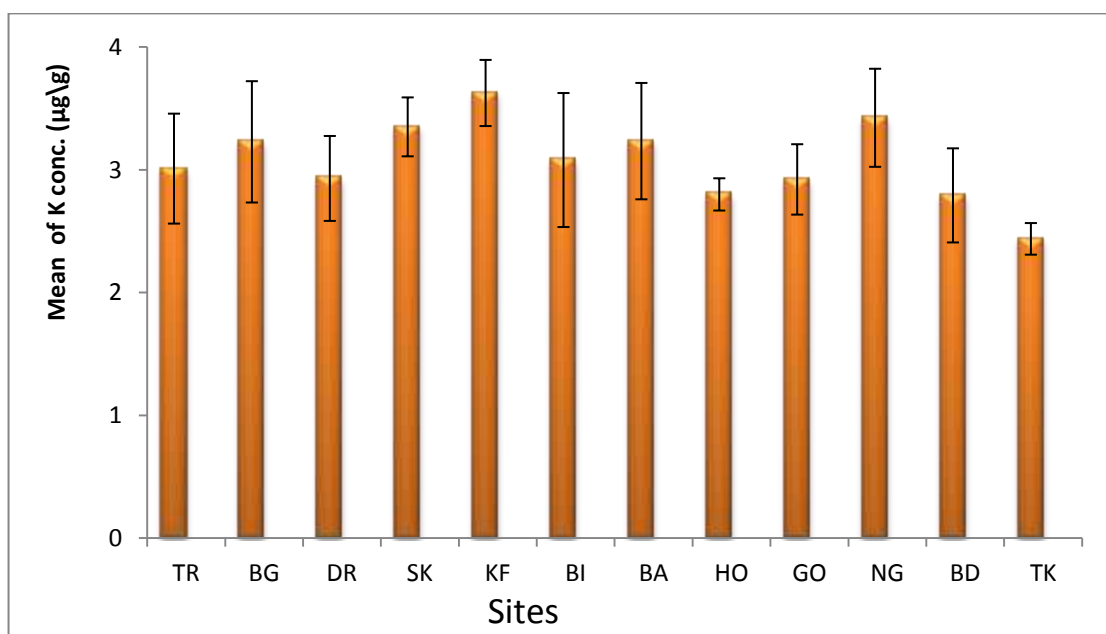


Figure (4): Mean concentration of Potassium in soil samples.

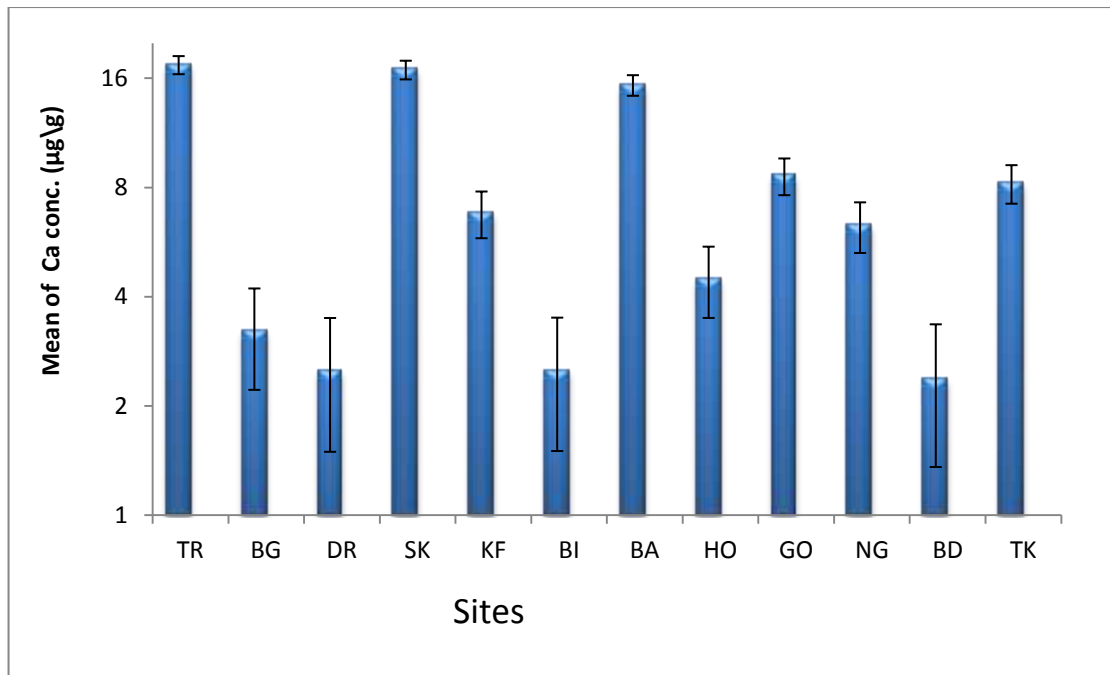


Figure (5): Mean concentration of Calcium in soil samples.

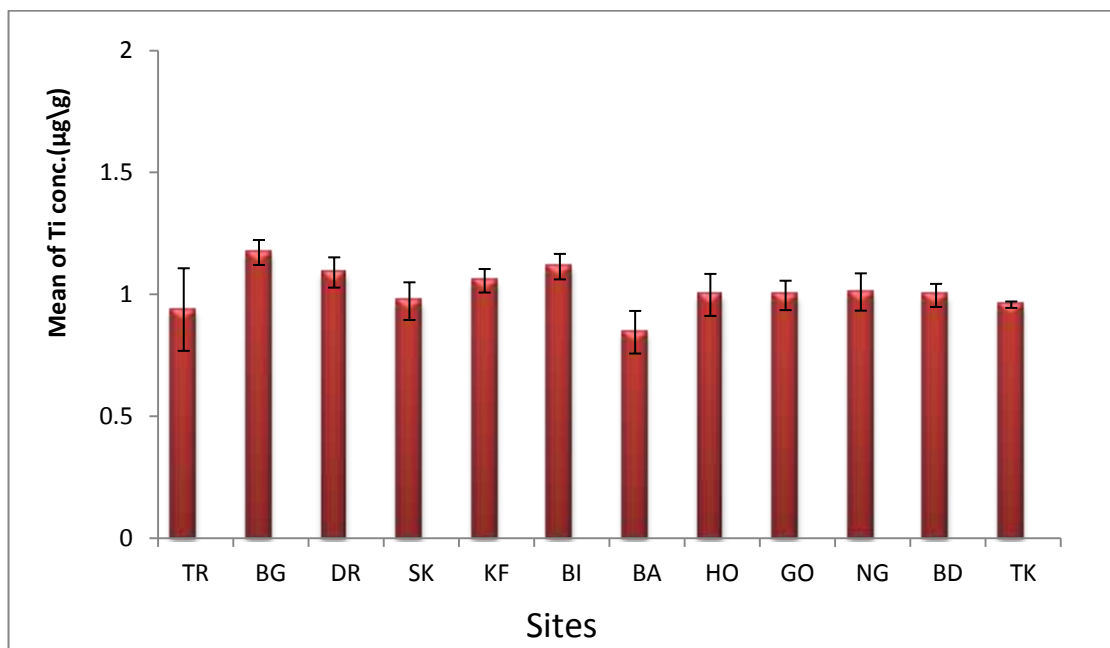


Figure (6): Mean concentration of Titanium in soil samples.

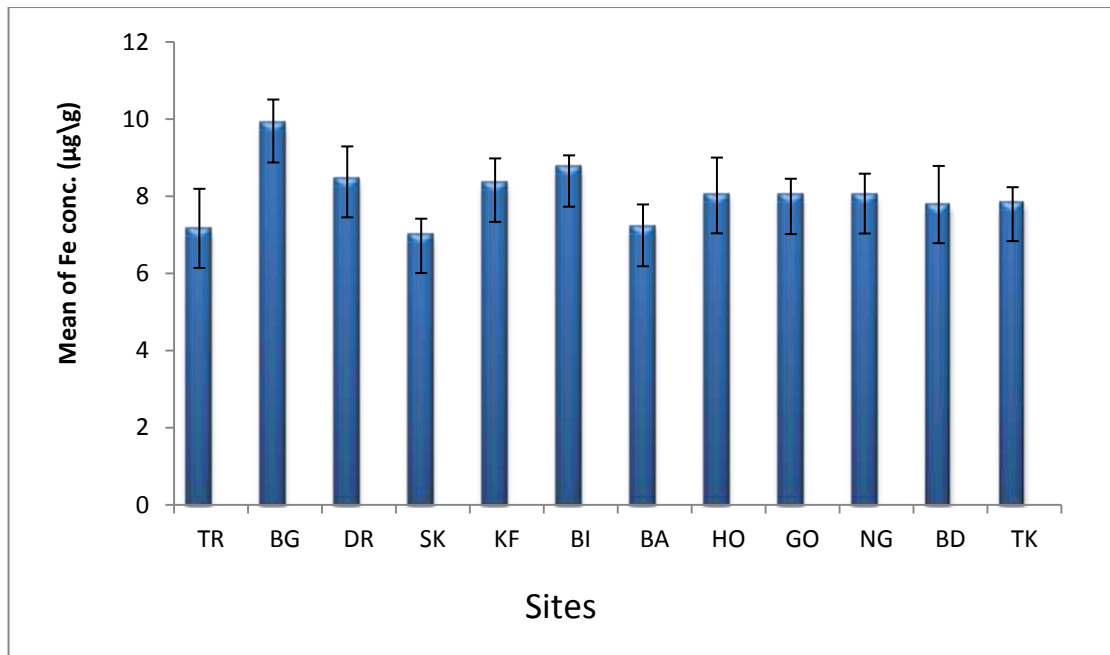


Figure (7): Mean concentration of Iron in soil samples.

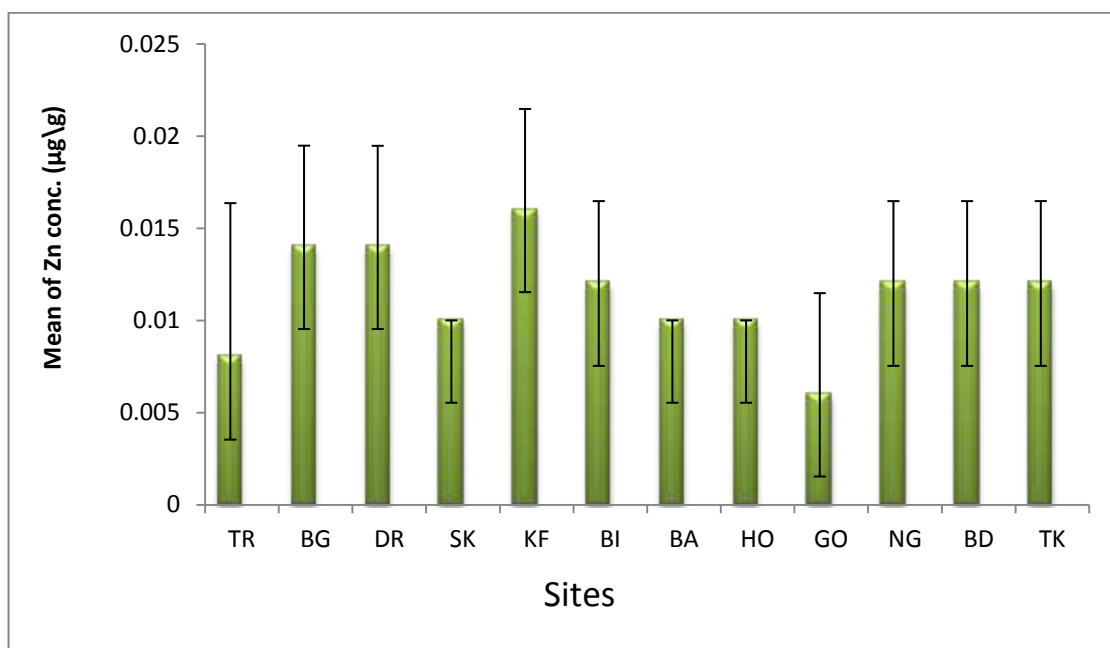


Figure (8): Mean concentration of Zinc in soil samples.

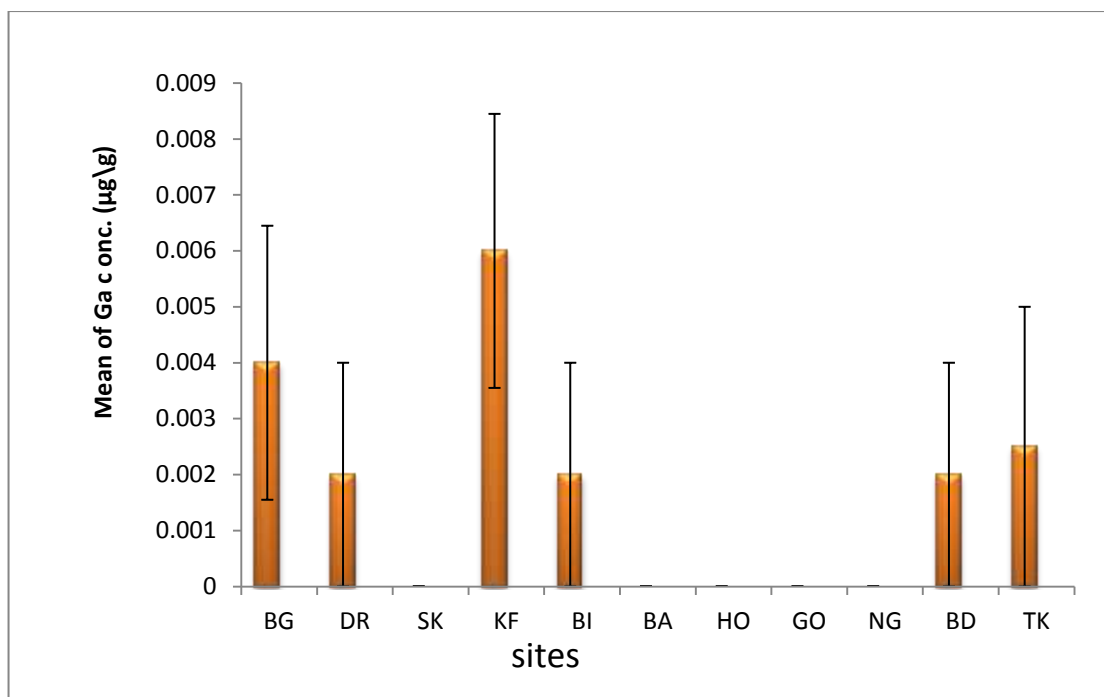


Figure (9): Mean concentration of Gallium in soil samples.

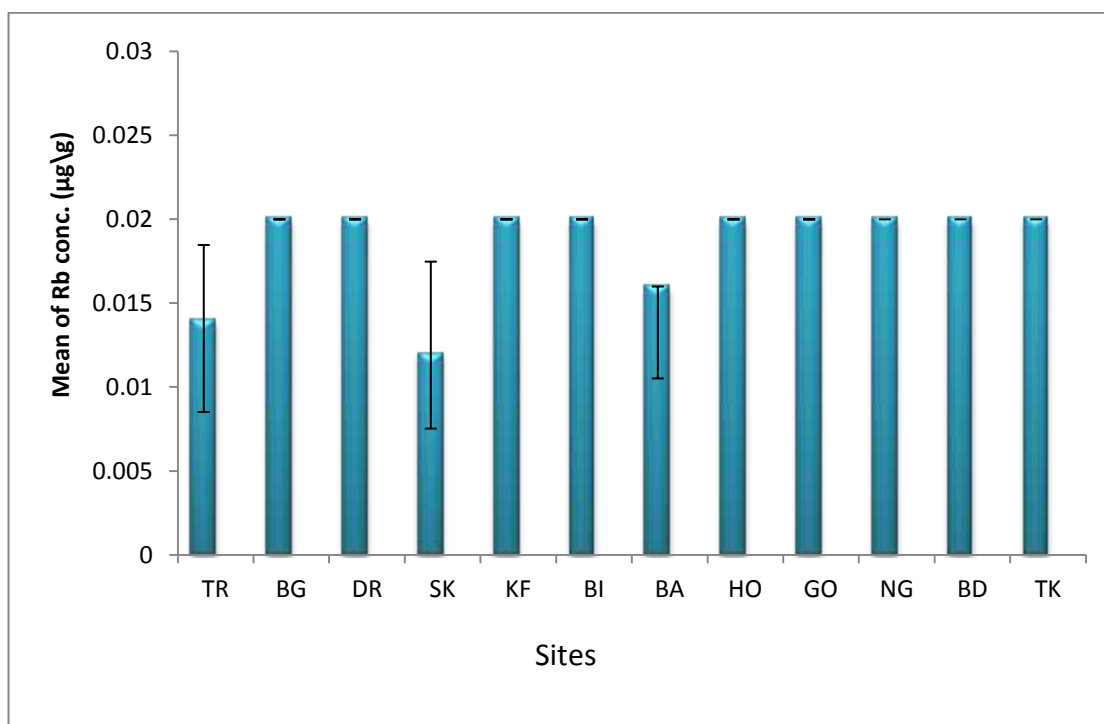


Figure (10): Mean concentration of Rubidium soil samples.

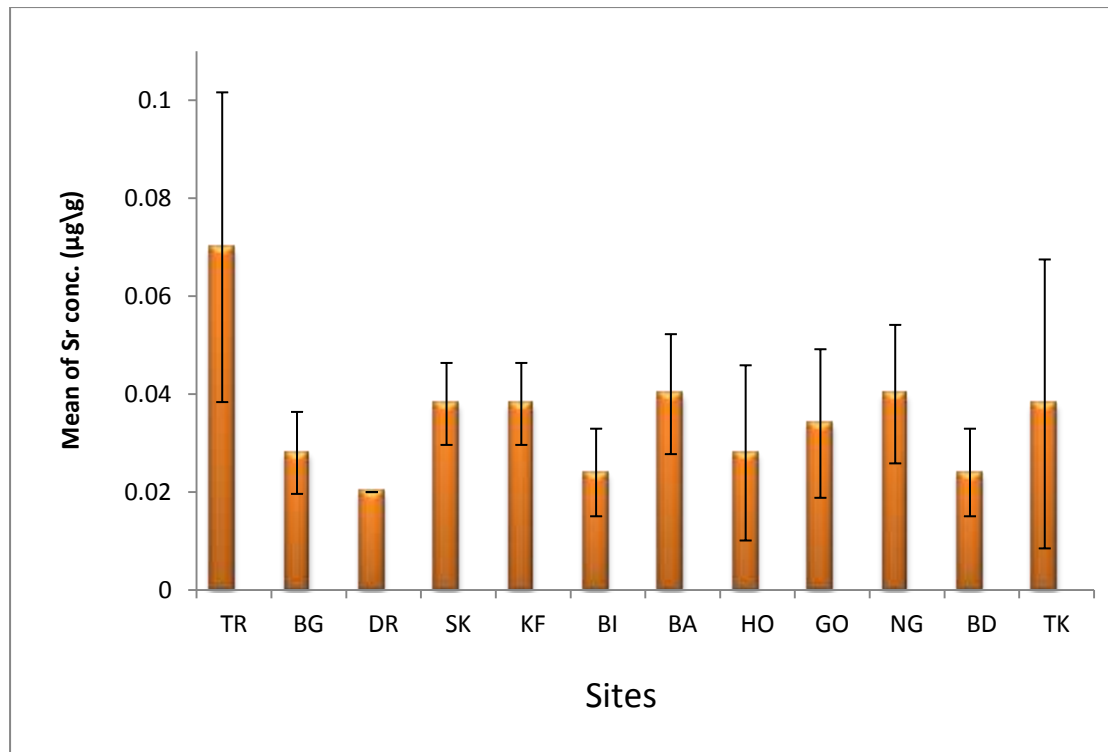


Figure (11): Mean concentration of Strontium soil samples.

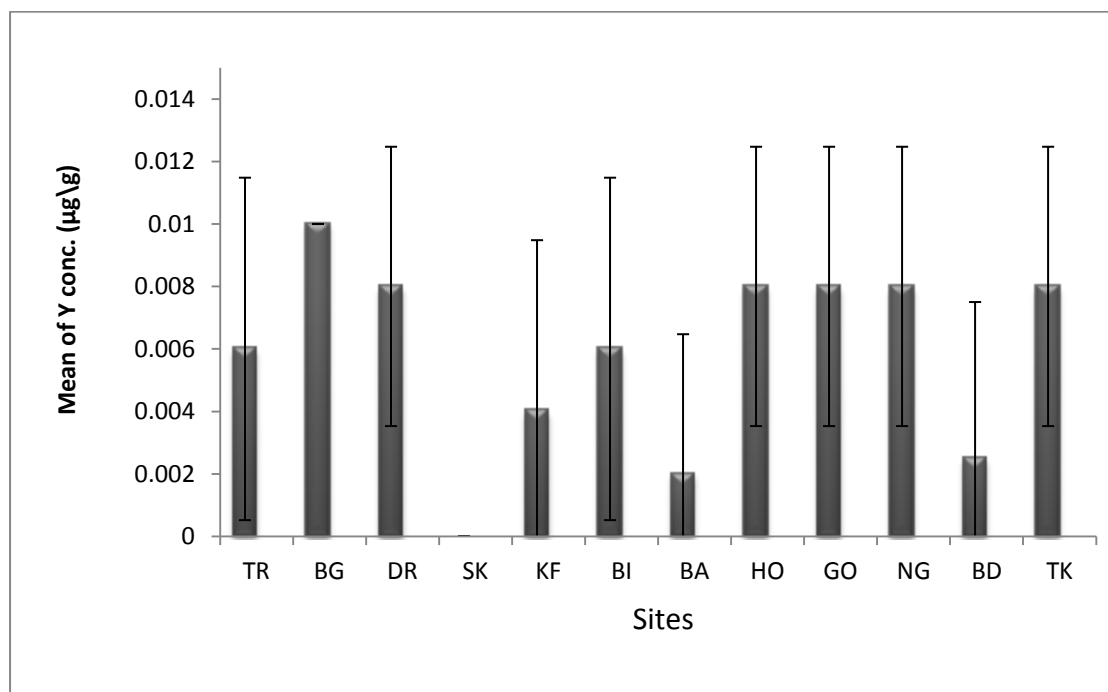


Figure (12): Mean concentration of Yttrium soil samples.

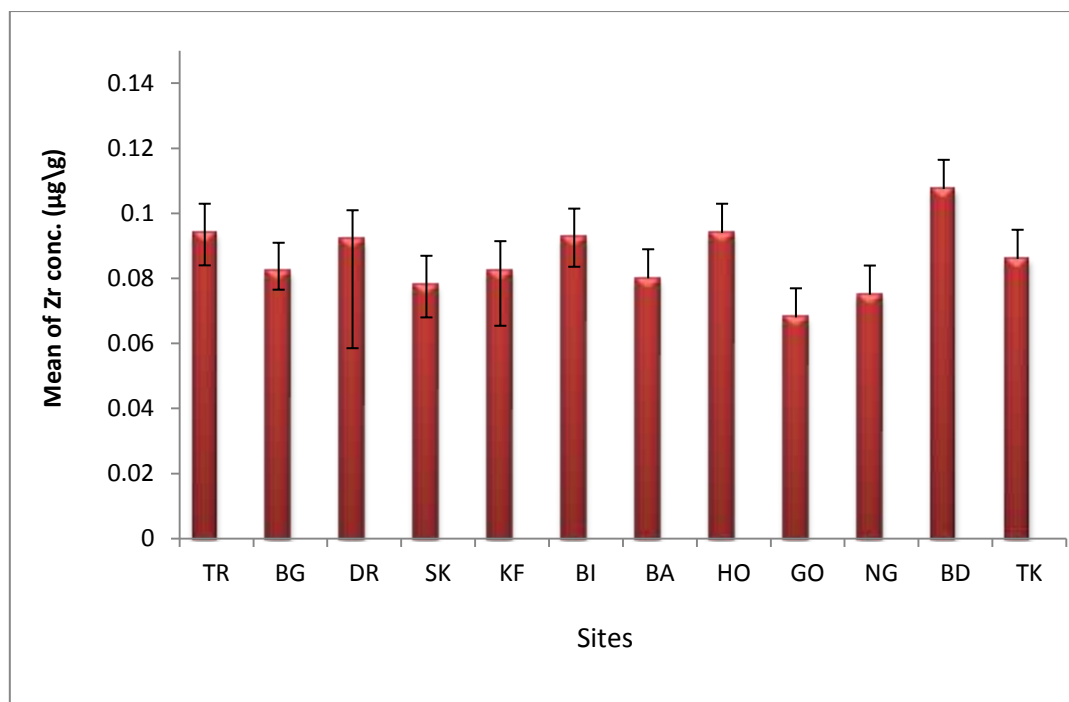


Figure (13): Mean concentration of Zirconium soil samples.

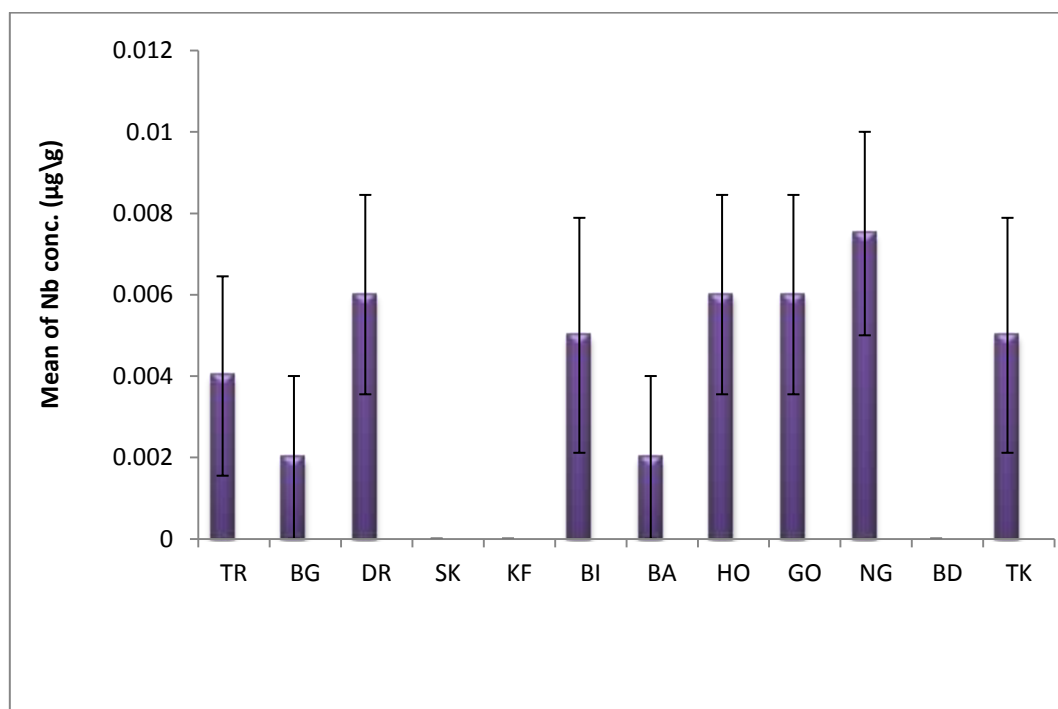


Figure (14): Mean concentration of Niobium soil samples.

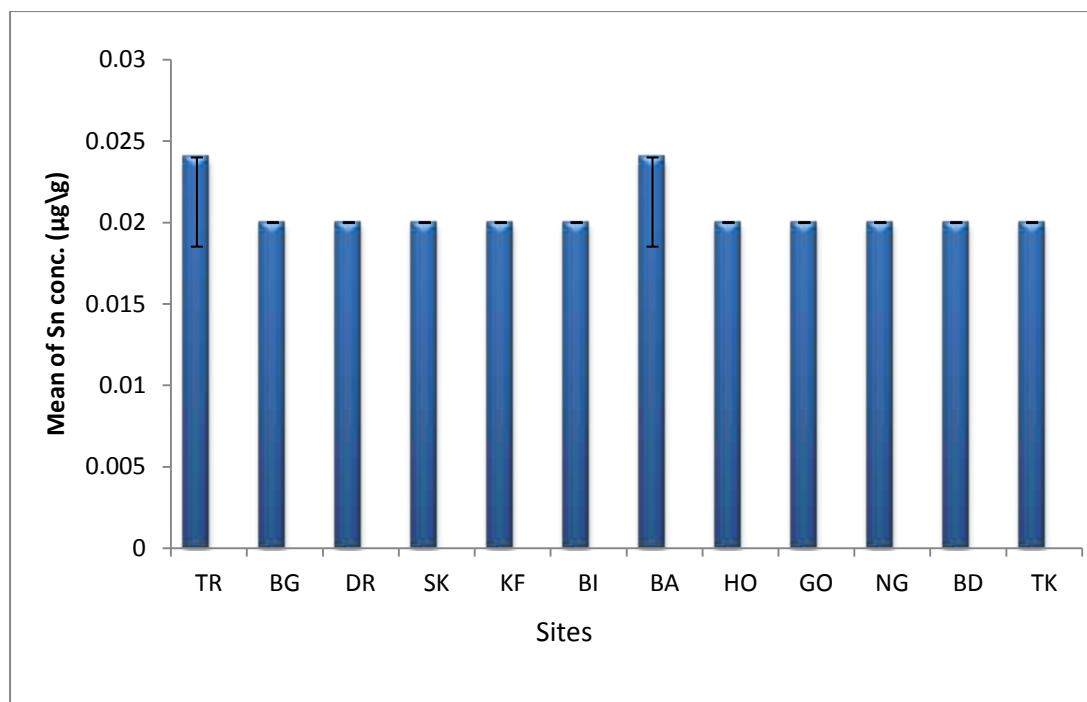


Figure (15): Mean concentration of Tin soil samples.

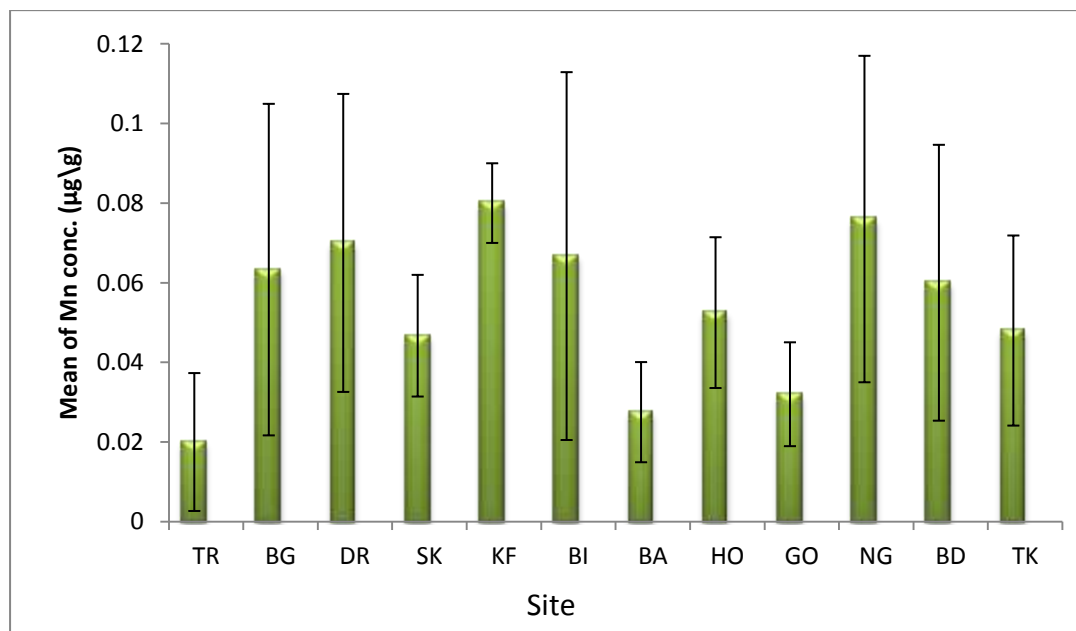


Figure (16): Mean concentration of Manganese soil samples.

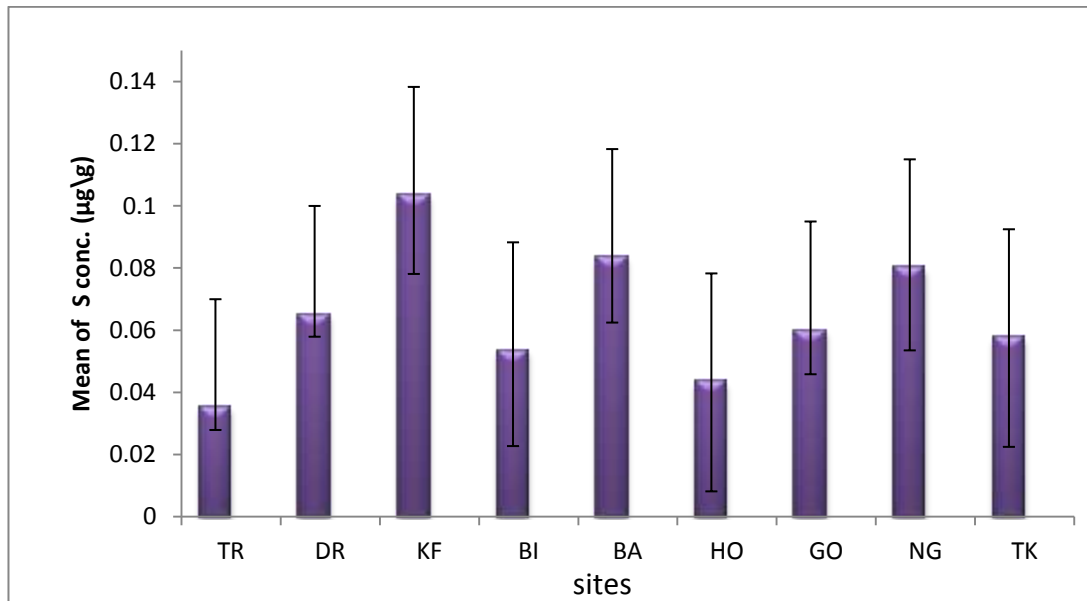


Figure (17): Mean concentration of Sulfur soil samples .

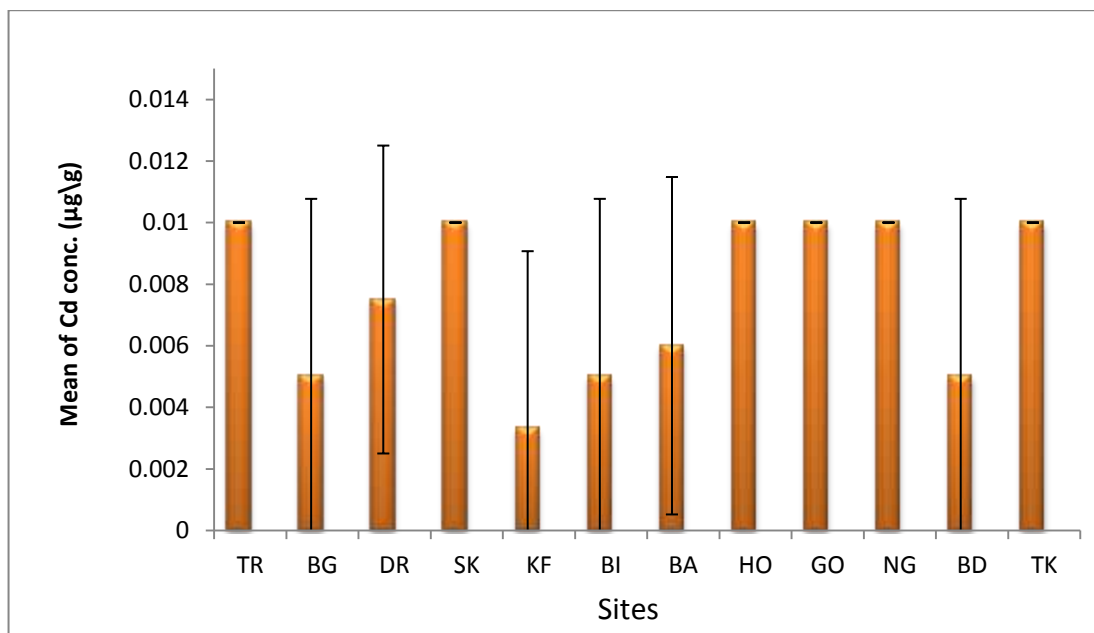


Figure (18): Mean concentration of Cadmium soil samples.

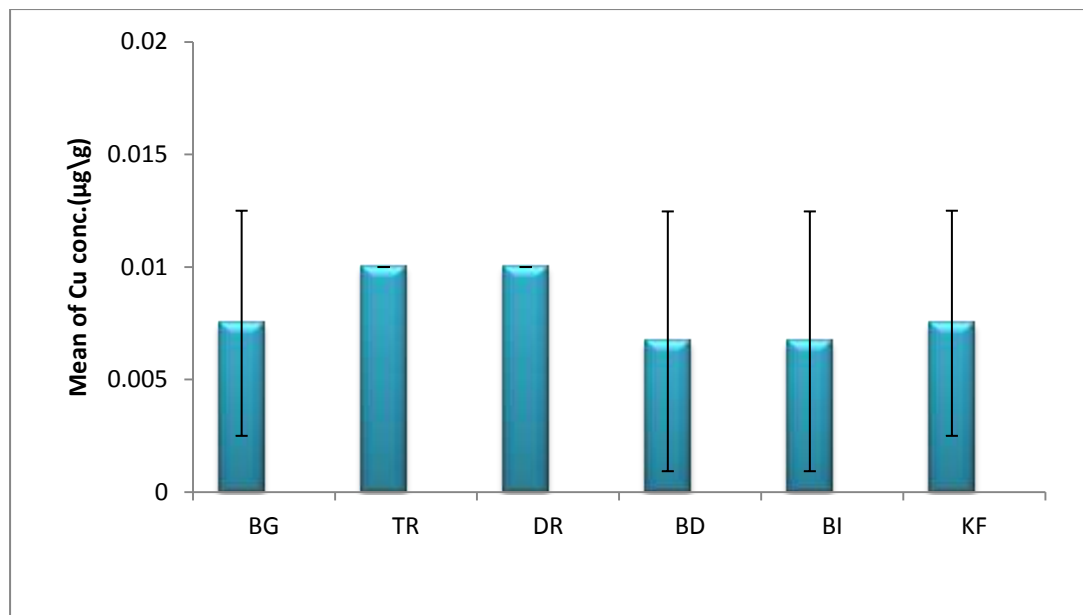


Figure (19): Mean concentration of Copper soil samples.

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جامعة بنغازي

كلية العلوم

قسم الكيمياء



دراسات كيميائية للتربة الزراعية لسهل مدينة بنغازي

لإكمال متطلبات الحصول على الإجازة العليا

(الماجستير)

مقدمة من الطالبة:

مبروكة أحمد محمد عطاء الله

تحت إشراف:

أ.د. عوض عبد الحميد الحصادي

والمشرف المساعد:

د.نبيل رمضان بدر

(2015)

الملخص:

في هذه الدراسة تم استخدام بعض الاستراتيجيات الإحصائية التحليلية و الكيمومترية للمقارنة بين الخصائص الكيميائية ومحتوي العناصر الغذائية لعينات التربة التي تم جمعها من مواقع زراعية مختلفة من سهل بنغازي الممتد من توكرة شرقا الي تيقة غربا .

كما أجريت التحاليل الأولية باستخدام جهاز التحليل الطيفي بالأشعة السينية الوميضية XRF ، بالإضافة لذلك أجريت التحاليل الروتينية لتقدير كلا من : درجة الحموضة والتوصيلية الكهربائية و كمية الأملاح الذائبة الكلية لكل عينات التربة لسهل بنغازي .

تم تصنيف البيانات على حسب المحتوى الغذائي وتركيز العناصر في كل مواقع الدراسة بالجزء من المليون (ppm) والمتحصل عليها من التحليل الكمي والنوعي باستخدام الأشعة السينية لعينات التربة، وقد أشتملت علي 19 عنصر، وكانت كالأتي: (الالومنيوم ، السليكون، الكلور ،التيتانيوم، البوتاسيوم، الكالسيوم ، المنجنيز ،الحديد ، النحاس ، الكبريت، الروبيديوم ، الأسترنشيوم ،الزنك ، الكادميوم ، الجاليوم ، القصدير، الزرنيوم ،النيوبيوم، اليوتريوم) باستخدام برنامج XLStat chemometric، والغرض منه تقييم جودة التربة و رصد التباين والارتباط لمواقع الدراسة واشتملت علي الموقع الجغرافي والعناصر الغذائية للسهل وذلك بتطبيق التقنيات الإحصائية النموذجية مثل : "تحليل المتغيرات (ANOVA) ، والتحليل الهرمي العنقودي (HCA) و التحليل الإحصائي الرئيسي (PCA).

وجد في هذه الدراسة أن تركيز العناصر في عينات التربة المتحصل عليها لم تتجاوز القيم المسموح بها مقارنة مع بيانات المنظمة الدولية للزراعة والمركز الدولي للدراسات الزراعية (إيكاردا) .

