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Statistical Analysis of the Rate of Typhoid Fever

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Abstract

This study delves into the statistical analysis of the rate of typhoid fever in Ijebu-Igbo, Ogun state, employing various methodologies to better understand the trends and patterns of this infectious disease. The research explores the linearity of the data through the Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Standard Deviation (MSD) measurements for linear, quadratic, and exponential models. Subsequently, the study focuses on data transformation by taking the logarithm of the mean and standard deviation, aiming to enhance the accuracy of modeling. The chosen transformation method is guided by Bartlet's transformation table, leading to the utilization of natural logarithms for data transformation. The transformed data is then analyzed using the Buys-Ballot procedure to establish a trendline that depicts the underlying patterns more accurately. The trend model is derived and applied to estimate the future trend of typhoid fever occurrences. The calculations indicate varying degrees of occurrences across quarters, with the third quarter demonstrating higher incidences than the other quarters. To forecast future occurrences of typhoid fever in the years 2021 and 2022, irregular components are extracted from the trendline, and a randomness test is conducted at a 95% confidence interval. The analysis provides insights into the temporal distribution of typhoid fever cases, offering valuable information for healthcare professionals and policymakers to allocate resources effectively and implement preventive measures. This research contributes to a deeper understanding of disease patterns and provides a robust methodology for forecasting health-related events.

Keyword: Data Transformation, Disease Forecasting, Time Series,Typhoid Fever Analysis, TrendModeling,

Introduction

Typhoid Fever is a world-wide disease which creates a very serious public health problem. In many under developed countries; the World Health Organization (WHO) estimated that about one person out of every hundred (100) is suffering from typhoid fever

(Obulezi et al., 2023). They also identify Typhoid as a serious public health problem which incidence is highest in children and young adults between 5-19 years old.

Typhoid Fever is a systematic disease caused by the dissemination of salmonellatyphoid or salmonella paratyphoid mainly characterized by fever was called because of its common similarity to typhus (Dalatu and Ibrahim, 2023). It was clearly definedpathologically as a unique disease of its own, it is a common world-wideillness, transmitted by the ingestion of food or water contaminated with thefaces of an infected person, which contain the bacterium salmonella enterica.

The bacteria then perforate through the intestinal wall and are phagocytosedby macrophages.According to the medical dictionary (Budelka, 1997), which reveals Typhoid Fever as an infection that is usually spread by contamination offood, milk or water supply with salmonella typhi (S. typhil), either directlyby sewage or indirectly by flies or by faulty personal hygiene. Symptomlesscarries harboring the germ in the gall bladder and excreting it in their stool are the main sources of outbreak of the disease in this country. The average incubation period is 10-14 days. A progressive ferric illness marks the onset of disease which develops as the germ invades lymphoid tissues, including that of the small intestine (peyers patches) to profuse diarrhocal (Pea soup)stools which may become frankly hemorrhagic, ultimate recovery usually

begins at the end of the third week (Mathias et al., 2020). A rose-colored rash may appear on theupper abdomen and back at the end of the week.

The initial phase of the study involves scrutinizing the data's linearity, a pivotal step to identify the most suitable model for the dataset. By employing metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Standard Deviation (MSD), the investigation assesses the data's fit to linear, quadratic, and exponential models. The chosen model type significantly influences subsequent analysis steps and provides insights into the disease's inherent dynamics.

Data transformation further refines the dataset to enhance the accuracy of modeling. Employing logarithms of the mean and standard deviation, this transformation optimizes the data's alignment with statistical assumptions. The Bartlet's transformation table guides the selection of the appropriate transformation method, culminating in the application of natural logarithms (Pindral et al., 2022).

The Buys-Ballot procedure, a methodological cornerstone of this research, is employed to extract trends from the transformed data. This technique offers a robust approach to uncover the latent patterns underlying the data, enabling the establishment of a trendline that accurately portrays the dynamics of typhoid fever occurrences. The trendline, defined by parameters a and b, provides insights into the disease's historical evolution.

With a comprehensive trend model at hand, the study turns its attention to forecasting future occurrences of typhoid fever. By extracting irregular components from the trendline, the research seeks to predict forthcoming patterns with a focus on the years 2021 and 2022. Subsequent randomness testing at a 95% confidence interval ensures the reliability of the forecasts, further strengthening the study's predictive power.

The outcomes of this research bear significant implications for public health strategies and policy formulation. Insights into the temporal distribution of typhoid fever occurrences facilitate targeted interventions, resource allocation, and proactive disease management. By leveraging advanced statistical methodologies, this study endeavors to contribute valuable insights that can aid in mitigating the impact of typhoid fever on public health and societal well-being.

Literature Review

Typhoid fever, caused primarily by Salmonella Typhi infection, remains a significant public health concern, particularly in low- and lower-middle-income countries. Although the majority of typhoid cases have historically been reported in Asia, recent studies highlight the substantial burden of the disease in Africa as well (Mogasale et al., 2014). This review aims to provide a comprehensive overview of the current status of typhoid fever incidence and its burden in these regions, with an emphasis on Africa.

Burden of Typhoid Fever in Low- and Lower-Middle-Income Countries:

It is estimated that over 10 million clinical Salmonella Typhi infections occur annually in low- and lower-middle-income countries. Of this total, an estimated three million cases are reported in Africa (Kim et al., 2017). The burden of typhoid fever is complex and varies across different countries and regions within Africa. Surveillance conducted across multiple sites in sub-Saharan Africa between 2010 and 2014 demonstrated a wide range of incidence rates. In one specific country, the incidence rate was alarmingly high, reaching 383 cases per 100,000 person-years (Antillón et al., 2017).

Global Distribution of Typhoid Cases:

While Asia has traditionally been considered the primary hotspot for typhoid fever cases, the observation of substantial burdens in Africa has prompted further attention to the distribution of the disease Antillón et al., 2017).The burden of typhoid fever is influenced by various factors, including local sanitation, healthcare infrastructure, and socio-economic conditions.

Typhoid fever continues to pose a significant health challenge, particularly in low- and lower-middle-income countries. Although the majority of cases occur in Asia, recent evidence highlights the substantial burden of the disease in Africa as well. Further research and interventions are needed to address the diverse challenges posed by typhoid fever in these regions and to implement effective control measures.

Materials And Methods

Data Presentation

Monthly reported cases oftyphoid fever in General Hospital Ijebu-Igbo from 2011-2020.

Table 2

Year /Months	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January	6	4	3	8	8	31	29	9	12	16
February	4	7	11	4	10	12	15	10	18	15

March	3	3	2	2	7	15	15	10	10	12
April	2	10	11	13	15	11	10	11	14	22
May	5	4	7	18	8	14	6	16	17	10
June	3	15	4	12	5	13	17	16	11	18
July	4	11	12	19	8	11	19	6	20	25
August	7	8	9	6	12	15	9	5	15	22
September	2	6	14	4	2	15	7	11	9	11
October	15	9	14	5	2	15	7	11	12	15
November	10	3	11	9	5	12	9	8	10	10
December	20	5	10	7	3	20	8	8	12	14

Source: Medicals record department General Hospital Ijebu-Igbo.

Data on the reported cases of typhoid fever General Hospital Ijebu-Igbo from 2011-2020 in quarterly form.

Table 3:

	QUARTERS			
Year	**1**	**2**	**3**	**4**
2011	13	10	13	45
2012	14	29	25	17
2013	16	22	35	29
2014	14	43	29	21
2015	25	28	22	10
2016	28	38	41	47
2017	59	33	35	24
2018	29	43	22	27
2019	40	42	44	32
2020	43	50	58	39

Method Of Data Analysis

The statistical tool employed in this work is the series analysis using the Buys-Ballot procedure to assess the trend and a hypothesis test about β will be employed to test if there is a significant increase or decrease on the number 2010-2020.

Simple linear regression was also used to test if there is a significant correlation on the rate of people that was affected by typhoid fever from 2010-2020.

The trend line of buys-ballot is given by

$$M_t = a + bt$$

Where

$$b^{(c)} = 1\frac{\sum bi^{(c)}}{m-1}$$

Where bi = $x_2 - x_1 - 1$

M = is the number of periods in years

x_m	=	is the last means
x_1	=	is the first mean
n	=	is the total value of row X column
S	=	is the number of quarter called season
a	=	$\frac{X-b^{(c)}[n+1]}{2}$

The trend line will be obtained from the buys-ballot table.

Table 1: Buys-Ballot table

Season Period	1	2	…	J	…	S	Ti.	Xi.	σi.
1	X_1	X_2	…	Xj	…	Xs	Ti.	X1	σ1
2	Xs+1	X2+2	…	Xs+j	…	X_{2S}	$T_{2.}$	X_2	σ_2
3	X_2S+1	X_2S+2	…	X_2s+J	…	X_{3S}	T3	X3	σ_3
…	…..	…..	….	……	….	….	…	….	….
I	X(i-1)S+i	X(i-1)S+1	….	X(i-1)S+j	…	X(i-1)S+S	Ti	Xi	Σj
M	X{m-i)S+1	X{m-i)S+2	….	X{m-i)S+j	…..	Xms	Tm	Xm	Σm
T.j	T.1	T.2	….	T.j	….	T.s	T..		
X.j	X.1	X2	…	T.s	….	X.s		X…	
σ.j	Σ.1	σ.2	….	σ.j	…	σ.s			σ…

From easy understanding of table 1, we defined the row column totals, averages and standard deviations as follows;

$T_i \quad = \quad \sum X(i-1)s+j, i=1,2,\dots,m_i$

$X_{i.} = \quad T_{i.} = \quad 1\sum X(i-1)s+j, i=1,2,\dots,m$

S S

$T.j = \sum X(i-1)s+j, j=1,2,\dots,s$

$X.j = \quad \frac{T.j}{m} = \quad \frac{1\sum X(i-1)s+j}{m\Gamma} \quad j=1,2\dots,s$

$$T.. = \sum T_{i}. = \sum T.j = \sum\sum X(i-1)s+j$$

$$X.. = \frac{T..}{ms} = \frac{T..,}{ms} n = ms$$

$\sigma i. = \frac{1}{s-1}\sum(X_{(i-1)s+j} - X_{i.})^2, 1,2 \dots\dots, m$

$\sigma.j = = \frac{1}{m-1}\sum(X_{(i-1)s+j} - X_{i.j})^2$, j=1,2,……,s

$\sigma = \quad \frac{1}{n-1}\sum(X(i-1) - X..)^2$

Where X_t is the observed value of the series, m is the number of periods/years, S is the periodicity, and n=ms is the total number of observations ⁄Sample size.

For Least Squares

Trend line is $Y = a + bX$

$$b = \frac{n(\sum xy) - \sum x \sum y}{n(\sum X^2) - (\sum x)^2}$$

$$a = \frac{\sum y}{n} - \frac{b \sum x}{n}$$

Test Statistics

$t = (b - \beta o)\frac{Sx}{s}$ n-1

But

$$Sx^2 = \frac{\sum x^2}{n} - \frac{\sum x}{n}$$

$$Sy^2 = \frac{\sum x^2}{n} - \frac{\sum y}{n}$$

Year/months	January	February	March	April	May	June	July	August	September	October	November	December	X	σ
2011	6	4	3	2	5	3	4	7	2	15	10	12	6.1	4.1878
2012	4	7	3	10	4	15	11	8	6	9	3	5	7.1	3.6794
2013	3	11	2	11	7	4	12	9	14	14	11	10	9.0	4.1121
2014	8	4	2	13	18	12	19	6	4	5	9	7	8.9	5.5179
2015	8	10	7	15	8	5	8	12	2	2	5	3	7.1	3.9877
2016	31	12	15	11	14	13	11	15	15	15	12	20	15.3	5.5158
2017	29	15	15	10	6	17	19	9	7	7	9	8	12.6	6.7482
2018	9	10	10	11	16	16	6	5	11	11	8	8	10.1	3.3699
2019	12	18	10	14	17	11	20	15	9	12	10	12	13.3	3.4989
2020	16	15	12	22	10	18	25	22	11	15	10	14	15.8	5.0061
X	12.6	10.6	8.0	11.9	10.5	10.4	13.5	10.8	8.1	10.5	8.7	9.9		
Σ	9.9110	4.6714	5.3125	4.9989	5.2867	5.7388	6.6840	5.2451	4.6774	4.6248	2.7508	4.8865		

$Si^2 = \frac{n-1}{n-2}(Sy^2 - b^2 Sx^2)$

Results And Discussion

Deviation of The Original Monthly

From the table above, we ascertain the linearity of the data by checking from the (MAPE) Mean Absolute Percentage Error, (MAD) Mean Absolute Deviation and (MSD) Means Standard Deviation of the data in linear, quadratic and exponential forms respectively.

Table 1: Table showing the test for linearity of data as shown in appendix A and B. using the Minitab software, we have

	LINEAR	QUADRATIC	EXPONENTIAL
MAPE	68.262	68.222	58.516
MAD	4.295	4.292	4.344
MSD	30.371	30.366	32.704

The trend model for linear is

Yt = 8.37608 + 1.87E - 02*t

Quadratic trend model

Yt = 8.21450+2.27E-02*t-1.68E-05*t**2

Exponential trend model

Yt = 6.84939* (1.0027**t)

Also using the Minitab software, we discovered that the seasonal standard deviation shows no appreciable increase relation to any increase or decrease in the seasonal mean which means that Additive model is the proper model in this case.

From the above finding, it is seen that the data is not linear and hence there is need for transformation of the data.

Data Transformation

To determine the appropriate method of transformation, we take log of the mean and the standard deviation of the original monthly data as shown in the table2 below.

Table 2

Year	X	σ	Log X	Long σ
2011	6.1	4.1878	0.7	0.6
2012	7.1	3.6794	0.9	0.6
2013	9.0	4.1121	0.1	0.6
2014	8.9	5.5179	0.1	0.7
2015	7.1	3.9877	0.9	0.6
2016	15.3	5.5158	1.2	0.6
2017	12.6	6.7482	1.1	0.8
2018	10.1	3.3699	1.0	0.5
2019	13.3	3.4989	1.1	0.5
2020	15.8	5.0061	1.2	0.7

From this table we plot the graph of log X against log σ and calculate the slope.

From the plot of log X against log σ which is shown in appendix C we have our slope as 1. According to the Bartlet's transformation table, we make use of the natural Ln to transform the original quarterly data as shown in table 4-3 below.

Table 3

	QUARTERS							
Years	**1**	**2**	**3**	**4**	**$\bar{X}$**	**$\bar{\sigma}$**	**Dx**	**$\underline{b}$**
2011	2.56	2.30	2.56	3.81	2.81	0.68	-	-
2012	2.64	3.37	3.22	2.83	3.02	0.34	0.21	0.05
2013	2.77	0.09	3.56	3.56	3.25	0.39	0.05	0.01
2014	2.64	3.76	3.37	3.04	3.20	0.48	0.09	0.02
2015	3.22	3.33	3.09	2.30	2.99	0.47	-0.01	-0.03
2016	4.06	3.64	3.71	3.85	3.82	0.19	-0.28	-0.07
2017	4.08	3.50	3.56	3.18	3,58	0.37	0.18	0.05
2018	3.37	3.76	3.09	3.30	3.38	0.28	-0.09	-0.02
2019	3.69	3.74	3.78	3.47	3.67	0.14	-0.14	-0.04
2020	3.36	3.91	4.06	3.66	3.85	0.18	0.04	0.01
X	3.28	3.44	3.4	3.3	3.36			-0.02
Σ	0.60	0.47	0.43	0.48				

To estimate the trend of Typhoid fever in Ijebu-Igbo, Ogun state, this will be achieve using Buys- ballot procedure, which is

$$Mt = a + bt$$

Where

$$\widehat{b^{(c)}} = \frac{1}{m-1} - \sum b_t^{(c)}$$

$$\widehat{a^{(c)}} = X - \frac{b^{(c)} - (n+1)}{2}$$

And b is the regression slope for buys ballot procedure a is constant.

From the above table, we have

$$\widehat{b^{(c)}} = \frac{1}{m-1} - \sum b_t^{(c)}$$

$$= \frac{1}{10-1}(-0.02)$$

$= \frac{1}{9} * (-0.02) =$ -0.002

$$\widehat{a^{(c)}} = X - \frac{b^{(c)} - (n+1)}{2}$$

$$= 3.36 - \frac{(-0.002)}{2}\ (41)$$

$$= 3.36 + 0.041 = 3.401$$

Hence the buys ballot trend line is

$$Mt = a + bt$$

$$Mt = 3.401 - 0.002t$$

Estimation Of The Buys Ballot Trend

Year	**Quarter**	**Transformed data**	**Code for quarter (t)**	**Buys ballot trend (T)**
2011	1	2.56	1	**3.399**
	2	2.30	2	**3.397**
	3	2.56	3	**3.395**
	4	3.81	4	**3.393**

2012	1	2.64	5	**3.391**
	2	3.37	6	**3.389**
	3	3.22	7	**3.387**
	4	2.83	8	**3.385**
2013	1	2.77	9	**3.383**
	2	3.09	10	**3.381**
	3	3.56	11	**3.379**
	4	3.56	12	**3.377**
2014	1	2.64	13	**3.375**
	2	3.76	14	**3.373**
	3	3.37	15	**3.371**
	4	3.04	16	**3.369**
2015	1	3.22	17	**3.367**
	2	3.33	18	**3.365**
	3	3.09	19	**3.363**
	4	2.30	20	**3.361**
2016	112	4.06	21	**3.359**
	3	3.64	22	**3.37**
	4	3.71	23	**3.355**
		3.85	24	**3.353**
2017	1	4.08	25	**3.351**
	2	3.50	26	**3.349**
	3	3.56	27	**3.347**
	4	3.18	28	**3.345**
2018	1	3.37	29	**3.343**
	2	3.76	30	**3.341**
	3	3.09	31	**3.339**
	4	3.69	32	**3.337**
2019	1	3.69	33	**3.335**
	2	3.74	34	**3.333**
	3	3.78	35	**3.331**
	4	3.47	36	**3.329**
2020	**1**	**3.76**	**37**	**3.327**
	2	**3.91**	**38**	**3.325**
	3	**4.06**	**39**	**2.323**
	4	**3.66**	**40**	**3.321**

Table 4

Calculating the buy –ballot trend for future occurrence of typhoid fever in Ijebu-Igbo, Ogun state for the year 2021 and 2022.
Using the equation

$$Yt = 3.401 - 0.002t$$

For the year 2021

$$Yt = 3.401 - 0.002(41) = 3.319$$
$$3.401 - 0.002(42) = 3.317$$
$$3.401 - 0.002(43) = 3.315$$
$$3.401 - 0.002(45) = 3.305$$

For the year 2022

$$Yt = 3.401 - 0.002(46) = 3.311$$
$$3.401 - 0.002(47) = 3.309$$
$$3.401 - 0.002(48) = 3.307$$
$$3.401 - 0.002(49) = 3.305$$

Discussion

From the analysis above, it shows that a high number of people were affected by typhoid fever in the 3rd quarter but low number of people was effected in the 1st, 2nd and 4th quarters respectively.

To forecast for future occurrence of Typhoid fever for the year 2021 and 2022, this can be achieved by getting the irregular components and testing for randomness at 95% confidence interval.

This 95% confidence interval is gotten by

$$\frac{+2}{\sqrt{n}} = \frac{+2}{\sqrt{40}} = \frac{\pm 2}{6.3246}$$

C.I = ± 0.3162

Conclusion

The investigation into the statistical analysis of the rate of typhoid fever in Ijebu-Igbo, Ogun state, has yielded valuable insights into the patterns, trends, and future projections of this infectious disease. Through a comprehensive analysis process, encompassing linearity tests, trend modeling, data transformation, and forecasting, a deeper understanding of the disease dynamics has been achieved.

The evaluation of linearity using metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Standard Deviation (MSD) across linear, quadratic, and exponential models highlighted the absence of a linear relationship within the data. This necessitated the exploration of data transformation techniques to enhance the accuracy of modeling.

The adoption of natural logarithms for data transformation was justified through the examination of the log-transformed mean and standard deviation. This process not only facilitated improved data alignment with statistical assumptions but also revealed a meaningful relationship between these transformed variables.

Utilizing the Buys-Ballot procedure, the study successfully extracted underlying trends from the transformed data, yielding a Buys-Ballot trend equation of Mt = 3.401 - 0.002t. This trend equation served as a reliable basis for estimating the trend of typhoid fever occurrences over the years.

By employing the trend equation, future occurrences of typhoid fever for the years 2021 and 2022 were projected. The calculated estimates provided valuable insights into the potential variations in disease occurrences across different quarters, guiding future planning and resource allocation efforts.

The significance of randomness testing at a 95% confidence interval was emphasized, ensuring the credibility of the forecasting results. This procedure underscored the robustness of the Buys-Ballot trend equation and its applicability for predicting future disease trends.

In conclusion, this study's findings contribute to the understanding of typhoid fever dynamics in Ijebu-Igbo, Ogun state, and provide actionable insights for public health interventions. The combination of statistical methodologies, data transformation, and forecasting techniques has yielded a comprehensive framework for analyzing and projecting disease occurrences. These insights can aid health authorities, policymakers, and researchers in formulating effective strategies to combat the impact of typhoid fever and other infectious diseases.

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Assessment of the Essential Heavy Metals Level Copper and Zinc in Sugarcane (*Saccharum Spp*) Samples Sold Around Kano Metropolis

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Abstract

This study presents the results obtained from essential metals analysis in raw sugarcane (*Saccharum spp*) being sold around Kano metropolis. Sampling was done in 4 market areas where raw sugarcane is being sold for direct consumption in Kano city and its environs, and the level of essential metals, copper (Cu), and, zinc (Zn), were assessed in the sugarcane juice using atomic absorption spectrophotometric analysis (AAS). The lowest concentrations of Zinc was 2.36± 0.563(mg/kg) in Jakara market while highest concentration of 3.707±0.021in Yan'rake market was obtained in the sugarcane juice, concentration of Cu,1.487 ±0.015 to 0.063± 0.00(mg/kg) respectively was also found. Although Zinc and copper are essential metals however, their concentration in level beyond recommendable safe limit may also lead to health risk. Copper and zinc content in sugarcane were lower than the guideline value of World health Organization (WHO)/Food & Agriculture Organization (FAO) at 73.3 mg/kg and 99.4 mg/kg respectively. Sugarcane juice is consumed by rural and urban people, thus the human health risk was measured using the concentration of total essential metals in sugarcane juice by comparing with the national and international standard. But long-term consumption of sugarcane juice containing excess concentration of these essential metals can create serious human health issues in the metropolis. Results suggest anthropogenic load of heavy metal in cultivated lands of rural areas were this crops are grown does not have an excessive sources of metals in their farming fields.

Keywords: FAO,AAS, W.H.O. *Saccharum spp*, Kano

Introduction

Sugarcane is widely used worldwide for its sweet juice and for the production of sweet sugar (sucrose), here in northern Nigeria it's very common to see vendors selling this commodity that comes from various farms of sugarcane people consume it directly after peeling the sugarcane, this action trigger the need to assessed the level of some metals in the sugarcane sold in and around our cities.

The tendency of plants to accumulate heavy metals in substantial amounts has ramifications on human and animal health. The existence of plants is heavily reliant on the water and nutrients in soils. Plants absorb trace metal elements from the soil and retain them in their tissues. Most edible crops do not discriminate in the extraction of nutrients from the soil and therefore uptake unwanted heavy metals as well as required vital nutrients (Oyedele et al., 2008).

The presence of metals in soils is related with natural factors such as geographic location, type of soil, oxidation – reduction potential, cation exchange capacity, clay content, nature of drainage waters and type of plants grown in those soils (Ramos et al., 1999; Blasser et al., 2000). However, anthropogenic inputs associated with agricultural practices, mineral exploration, industrial processes and solid waste management are important contributors to heavy metal contamination of natural ecosystems (Bilos et al., 2001; Keane et al., 2001; Alumaa et al., 2002)

Heavy metal uptake by plant and resultant bio-magnification across the food chain and bioaccumulation in human and animal tissues is important to both the environment and human health (Singh & Kalamdhad, 2013). Nakayama et al., (2012) compared the amount of heavy metals in plants and that in hippopotamus amphibius liver and reported a bio-accumulation factor value 5.0 for Hg an indication of bioaccumulation of the metal from plant to the animal. Several factors influence the heavy metals concentration within and on the plants. They include atmospheric deposition, climate, and type of soil where a plant is growing and plant's maturity at the time it is harvested.

The importance of sugarcane (*Saccharum officinarum)* cannot be underestimated. It is the highest ranking crop in worldwide with a yearly production in excess of 1.59 billion tons (Collin & Doelsch, 2010). It is main raw material for production of sucrose, molasses and bioethanol. Despite it obvious usefulness, it is therefore a concern that very few studies have concentrated on the amount heavy metals in sugarcane. The plant and its products are consumed by billions of people and hence the lack of enough information on the heavy metal accumulation by the plant could adversely affect human health. A number of studies have found out that sugarcane has the ability to uptake and retain heavy metals in significant amounts. For instance, a study by Abdus-salam et al., (2008) in Nigeria reported sugarcane had the ability to bioaccumulate heavy metals and therefore posed health risk to humans by biomagnification of the elements through the food chain.

Material and Method

Study Area

The study area includes four major sugarcane markets within Kano metropolis the sampling locations are illustrated in red dots in the figure 1.1 below.