Valuation of Nigerian Crude Oil using Heston's Stochastic-Jump Model

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Abstract
Presence of new information in many commodity markets leads to unpredictably changes and jumps in commodity prices. This article investigates the possible existence of jumps in the crude oil prices in Nigeria, an improved version of the Heston's model was developed to take care of these changes and jumps. We present the model and demonstrate its implementation using crude oil price data from 2010 to 2020. Characteristic function approach was adopted to value oil prices. The Non-linear least squares method of calibration was used for the calibration of the model parameters. Simulation studies show that Heston Stochastic-Jump model is suitable for pricing crude oil in Nigeria. The Matlab software was used for both calculations and simulations

Keywords: Heston's Stochastic-Jump Model, Calibration, Volatility, Crude oil

1. Introduction

The oil and gas industries are always challenged with many decisions and uncertainties, therefore accuracy is required in taking decisions in order to reduce risk and determine the cost-effectiveness, success and growth of the industry. Financial models which are vital tools in the financial market are required to handle these uncertainties and estimate reasonable values of several securities. Understanding the underlying stochastic process in natural resources' prices such as crude oil is very important because of its vital role in the Nigerian economy. Many literatures on models for oil and gas prices presume that the market price of crude oil takes a continuous stochastic process. This assumption of continuous stochastic process has led researchers into developing models that enable closed form solutions. However, Cont and Tankov (2004) maintain that continuous stochastic processes are inadequate since they do not reproduce the most significant characteristic experience in the markets which is discontinuous moves in price. This characteristic is of great significance for crude oil markets because they are often confronted with unforeseen information like natural adversities, geopolitical changes, government policies and other unpredicted events. These uncertainties lead to unpredictably changes and jumps in oil prices, which means that the theory of log-return relatives being normally distributed possibly may not be true. In order to capture these unexpected changes, we merge jump components to Heston's volatility model, hence, Heston Stochastic-Jump model (HSJM). This model was developed with contributions from some financial analyst like Heston (1993), Wiggins (1987), Stein and Stein (1991), Hull and White (1987), Tankov and Voltchkova (2017), Nwobi et al. (2019), Onyegbuchulem et al. (2020) and Merton (1976).

This paper however, analyzes the valuation of crude oil prices under the Hesston Stochastic-jump model. We aim at illustrating the usage of the model giving emphasis to its implementation and calibration. The valuation framework of Heston's Stochastic-Jump model and how characteristic function can be used to price the crude oil is presented in Section 2. Section 3 introduces the calibration of the Heston Stochastic-Jump model parameters using Non-Linear Least Square Optimization (NLLS), while section 4 introduces the experiment and result of the models, Section 5 concludes the paper.

2. Valuation Framework of Heston Stochastic-Jump Model

The Heston model was developed to overcome the shortcoming of Black-Sholes model of having constant volatility but the Heston's model sometimes does not produce good fit to market prices at short maturity. In order to have a model that will reduce pricing errors and produces fit that will be better than the Heston's volatility model led to the combination of jumps components with Heston's volatility model which is now referred to as Heston's Stochastic-Jump model (HSJM). The HSJM assumes that the stock price S_t takes the Merton's form of stochastic process given as:

$$dS_t = \left(r - \alpha\mu_{R_t}\right)S_t dt + \sqrt{v_t}S_t dB_1 + R_t S_t dN_t \quad (1)$$

$$dv_t = \kappa\left(\theta - v_t\right)dt + \sigma\sqrt{v_t}dB_2 \quad (2)$$

$$c\text{ov}\left|dB_1, dB_2\right| = \rho dt,$$

$$\Pr\left[dN_t = 1\right] = \alpha dt$$

where

r is the riskless rate, S_t denotes the price of the asset at time t.

v_t is the variance of the asset price at time t.

R_t dictates the jump size of the stock price,

v_0 denotes the initial variance of the asset price for $v_0 > 0$.

θ denotes the long-term variance level for $\theta > 0$.

κ denotes the reversion speed for $(\kappa > 0)$.

σ is the volatility of variance for $(\sigma > 0)$.

ρ is the correlation between the Brownian motions (B_1 and B_2), and for $(-1 \le \rho \le 1)$.

μ_{R_t} is the mean of R_t for $\left(\mu_{R_t} > -1\right)$.

δ^2 is the variance of $\ln(1+R_t)$ for $(\delta \ge 0)$.

the variance δ^2, $(1+R_t)$ has a lognormal distribution:

$$\frac{1}{(1+R_t)\delta\sqrt{2\pi}}\exp\left(\frac{\left[\ln(1+R_t) - \left(\ln\left(1+\mu_{R_t}\right) - \frac{\delta^2}{2}\right)\right]^2}{2\delta^2}\right)$$

α is the intensity of Poisson process N_t for $(\alpha \ge 0)$.

The three new parameters added to the Heston's model are μ_{R_t}, δ^2 and α.

2.1 HSJM's Characteristic Function

The log-stock's price characteristic function in the Heston's Stochastic-Jump model is given as:

$$\phi S_t(u) = \mathrm{E}\left[e^{iuS_t}\right]$$

$$= \exp\left\{C(u,T)\theta + D(u,T)V + P(u)\alpha T + iu\left(\log(S_0) + rT\right)\right\} \tag{3}$$

where

$$P(u) = -\eta J iu + \left[\left(1+\eta J\right)^{iu} e^{\sigma_S^2\left(\frac{iu}{2}\right)(iu-1)} - 1\right] \tag{4}$$

$i = \sqrt{-1}$ is the imaginary unit.

3. Calibration of HSJM to Market Prices

Calibration is the process of fitting models to market data. It entails using optimization procedures aimed at identifying the set of model parameters which decreases the space amid model prices and market prices. The Heston Stochastic-Jump model has eight (8) unknown parameters $\Omega = \left\{\upsilon, \theta, \sigma, \rho, \kappa, \mu_{R_t}, \delta^2, \alpha\right\}$ which need to be calibrated or estimated. In order to find the optimal parameter set, we need to:

(i) state a measure to quantify the distance between model and market prices;

(ii) run optimization procedure to ascertain the parameter values which is capable of reducing such distance. The procedure is to minimize the mean sum of squared differences.

$$P(\Omega) = \sum_{i=1}^{N} \frac{1}{N}\left[C_i^{\Omega}(K_i, T_i) - C_i^{mkt}(K_i, T_i)\right]^2 \tag{5}$$

Ω denotes the set of parameters that will be estimated, N denotes the total number of observations, $C_i^{\Omega}(K_i, \mathrm{T}_i)$ is the model's price and $C_i^{mkt}(K_i, \mathrm{T}_i)$ is the market price. Many calibration methods exist, but in this paper the Non-Linear Least Squares (NLLS) method will be used.

3.1 Non-Linear Least Squares (NLLS) Calibration

Non-Linear Least Squares (NLLS) calibration is performed in the following way:

$$Min_{\Omega} = Min_{\Omega} \sum_{i=1}^{N} \left[P(\Omega) = \sum_{i=1}^{N} \frac{1}{N}\left[C_i^{\Omega}(K_i, T_i) - C_i^{mkt}(K_i, T_i)\right]^2\right] \tag{6}$$

where the term Ω denotes the set of parameters to be estimated, N is the total number of observations, $C_i^{\Omega}(K_i, \mathrm{T}_i)$ is the model price and $C_i^{mkt}(K_i, \mathrm{T}_i)$ is the market price. For this method of calibration, the MATLAB function lsqnonlin $(@fun, x_0, lb, ub)$ will be used. The solution x satisfies the condition: $lb \le x \le ub$, where lb and ub are vectors of lower and upper bounds respectively. The restrictions help during calibration to avoid solutions that are not necessary. The parameters' lower and upper bounds are stated below:

i. θ / υ_0 -Long-term variance and initial variance**:** The volatility of some financial asset does not always get to level beyond 100%.

ii. ρ - Correlation Coefficient: The boundaries for correlation will be set to take values from -1 to 1.

iii. σ - Volatility of variance: This parameter tends to have positive values being a volatility, hence, the lower bound is set to 0 while the upper bound is set to 5 in order to avoid any possible restriction.

iv. κ -Mean-reversion speed: The speed of mean reversion will take positive values since negative values will cause mean aversion. The upper bound is set randomly. The Feller condition, given by $2\kappa\theta - \sigma^2 \geq 0$ has the lower bound set to 0, in order to guarantee that the variance process in HSJM is not negative and will never approach zero.

4. Experiments and Results

Heston's model was calibrated to data obtained from real market as sown in Table 1. The data used comprises the daily closing spot price of crude oil price data from the year 2010 to 2020.

Parameters	v_0	θ	σ	ρ	κ	μ_{R_t}	δ	α
NLLS Method								
Initial Estimate	0.040	0.040	0.10	-0.30	1.30	-0.02	0.20	0.03
Run1	0.027	0.027	0.10	-0.26	1.44	-0.02	0.30	0.03
Run2	0.037	0.037	0.15	-0.33	1.25	-0.02	0.30	0.02
Run3	0.034	0.034	0.14	-0.31	1.24	-0.02	0.30	0.03
Run4	0.01	0.01	0.14	-0.30	1.14	-0.01	0.10	0.01
Run5	0.03	0.03	0.14	-0.30	1.14	-0.01	0.10	0.01

Table 1: Calibration Results Achieved with HSJM using NLLS

Table 1 displays the results achieved with HSJM after running the calibration with the Non-Linear Least Squares method (NLLS).

Using the result of Table 1, the model calculated values were compared with the market prices. As regards the stated acceptance criterion in equation (5), the HSJM's estimated value deviation from the market price is 0.5642, and it is lower than the average distance in the bid-ask spreads wich produces 2.095. Combining jump components with the basic price process enhanced the entire fit of the market prices of crude oil.

5. Conclusion

The result of our investigation shows that Heston Stochastic-Jump model is a good pricing model for crude oil returns because the proposed model's parameters calibrated were able to fit market prices. While investigating the parameter estimates, it was observed that the likelihood of a jump arising is consistent, mainly when there are large data occurrences. Also observed is that when there is new information, the oil prices tend to reduce also. Hence, understanding the stochastic behavior of the crude oil and the use of Heston Stochastic-Jump model will help in crude oil forecasting and policy makers in taking decisions since the price of oil shocks are usually followed by monetary declines.

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Statistical Study on the Impacts of Climatic Factors on the Prevalence of Malaria

(A Case Study of Kaduna State)

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Abstract

Despite immense efforts to rapidly stem the tide of malaria occurrences across the world, climatic factors and weather patterns continue to be major contributors to malaria transmission, especially within vulnerable communities of the world. The purpose of this research is to look into the statistical relationship between climatic variables and malaria presence in Kaduna State, Northwestern Nigeria. For ten years, from 2011 to 2020, data on malaria cases, temperature, and relative humidity were collected monthly in Kaduna state. To assess the relationship, level of association, and model fitness with the dataset, simple and multiple linear regression, correlation coefficients, and coefficient of determination were used. According to the findings, there was a significant correlation between humidity and malaria cases. This implies malaria cases were more prevalent, months humidity were high, as temperatures exhibit a fair negative relationship with malaria cases. As a result, we recommended that greater emphasis be placed on vector control activities and raising public awareness about the proper use of intervention strategies such as interior residual sprays to mitigate the epidemic, particularly during peak periods with favorable weather conditions.

Keywords: climate change, malaria, relative humidity, temperature, health

1. Introduction

Climate change is having an impact on people all over the world, both subtly and dramatically. Weather patterns that are gradually shifting, rising sea levels, and more extreme weather events are all clear and devastating indicators of a rapidly changing climate as a result of anthropogenic activities. Increased frequency and intensity of extreme weather events such as flooding, temperature variation, unpredictable rainfall patterns, and droughts endanger the world's food supply, drive people from their homes, separate families, and jeopardize livelihoods – all of which increase the risk of conflict, disease outbreak, hunger, and poverty.

Climate change is defined by the United Nations Framework Convention on Climate Change (UNFCCC, 1992) as a change in climate that is attributed directly or indirectly to human activity that modifies the components of the atmosphere, as well as natural climate variability, observed over comparable periods, usually one or more decades. It is sufficient to state that the most pivotal points that describe the concept of climate change are the time involved, the level of variability to which the change is subjected, the duration and impact of such variability on humans and the ecosystem (Elisha et al., 2017).

Climate change will undoubtedly have a variety of effects on health, including changes in the distribution and seasonal transmission of vector-borne diseases. The magnitude of these effects, however, remains a source of intense debate, particularly in the case of the projected effect of climate change on the global distribution of malaria, where different approaches have resulted in widely disparate estimates.

Malaria transmission is known to be influenced by several environmental and ecological factors. The three most important are rainfall, temperature, and humidity. Rainfall, especially heavy rain, washes away many of the breeding sites of malaria parasites in mosquito vectors, whereas temperature determines the duration of mosquito larvae development in the environment and parasite development within the vector (Patz et al., 2006).

Malaria is highly contagious, particularly in the tropics in which the environment facilitates disease transmission. Global warming and changes in weather patterns encourage pathogenic parasite breeding, survival, and spread (Short et al., 2017). Furthermore, insecticide resistance in the host vectors and anti-malarial drug resistance in the stubborn species of plasmodium contribute to the epidemic's current prevalence in the developing countries, particularly Sub-Saharan African nations in which the disease trend poses serious health problems (Akinbobola et al., 2013).

Malaria is a major public health issue that has remained a major focus of the Sustainable Development Goals (Sewe et al., 2017). Malaria prevention efforts have yielded some promising results, with reports indicating a 37% decrease in incidence and a 60% decrease in mortality rates globally (World Health Organization, 2015). However, much more needs to be done to reduce malaria prevalence, with over 200 million cases and over 400,000 malaria-related deaths reported in 2017 alone (World Health Organization, 2019). According to reports, 15 countries bear the heaviest malaria burden, accounting for 80 percent of all deaths. Malaria affects 92 percent of the world's population in Sub-Saharan Africa. Nigeria is one of the world's most affected countries, accounting for one-fourth and one-fifth of the total global picture, with an estimated 53.7 million cases and 79,800 deaths (World Health Organization, 2019).

Malaria infection, disease occurrence, and death from catastrophic malaria cases remain high in endemic countries, implying that the disease persists. Despite global control interventions to reduce pandemic transmission and its socioeconomic impact, the Sub-Saharan African region is having difficulty reducing disease intensity, especially in rural areas where there is a lack of good knowledge of disease epidemiology, and inadequate health system, a scarcity of control intervention measures, and a high level of poverty, among other factors (Oguntade et al., 2020). Climate changes and ecological factors continue to be major drivers of malaria transmission dynamics, notwithstanding increasing malaria control and elimination efforts (Oguntade et al. 2020).

Though there had been previous studies extensively conducted on the literature regarding the dynamics of vector-borne disease transmission and malaria incidence, there still exists some level of uncertainties regarding how certain climatic variables particularly exacerbate the trend. This study, therefore, analyzed certain weather variables and their level of relationship with malaria occurrences within the study area.

2. Materials and Methods

2.1 Study Area

Kaduna State, located between latitude and longitude 10.390285° N, 7.7056513° E respectively is the fourth largest and third most populous state in the country, with an estimated landmass of 46,053km^2 and a population of about 10million people across 23 Local Government Area. The state has a tropical dry-and-wet climate, classified by Koppen's as Aw. Wet seasons are known to last April through mid-October, while dry seasons extend from mid-October of one calendar year to April of the next (Abaje et al., 2010).

The highest average air temperature is usually in April (28.90 C) and the lowest is in December (22.90 C) through January (23.10C). During the rainy and dry seasons, the mean atmospheric relative humidity ranges between 70-90 percent and 25-30 percent. During the dry season, the most evaporation occurs. The entire state is covered by heavily weathered and lateralized red-brown to red-yellow ferruginous tropical soils. The tropical grassland vegetation covers the entire state, with the density of trees and other plants decreasing as one moves north (Abaje et al., 2007).

2.2 Data Sources

Relative Humidity data were extracted from the National Aeronautics and Space Administration (NASA) Langley Research Center's (LaRC) Prediction Of Worldwide Energy Resources (POWER) Project site funded through the NASA Earth Science/Applied Science Program (NASA, 2021). The 10years Humidity data were extracted at 2metres from the earth's surface using the study area's exact GPS coordinates. Temperature data were extracted from the World Bank Climate Knowledge Portal repository (World Bank, 2021). Data regarding the occurrence and prevalence of malaria in Kaduna State was extracted from the Kaduna State Integrated Disease Surveillance Routine (IDSR003) template from 2011 to 2020 as obtained from the Kaduna State Primary Healthcare Development Agency (KPHDA – IDSR, 2021). This IDSR data contains information on over 40 diseases collected from the 23 Local Governments in the State.

2.3 Data Presentation

Here, we present a data set used in this study.

Table 1: 10 Years Monthly Average Summary of Temperatures, Relative humidity and Malaria Cases

Mean Monthly Data Summary			
Months	**Malaria Cases**	**Temperatures (°C)**	**Relative Humidity (%)**
January	26,626	25.5	35.64
February	26,032	27.9	31.47
March	26,072	30.3	35.02
April	29,983	30.2	51.57
May	28,498	28.6	72.58
June	34,290	26.4	79.81
July	34,431	25.5	84.39
August	38,115	24.4	86.86
September	37,525	25.2	84.99
October	36,811	26.8	76.82
November	32,965	26.7	56.03
December	28,830	25.1	44.83

2.4 Statistical Analysis

To assess the relationship among monthly malaria cases, relative humidity, and temperatures, as well as the ability to be able to predict malaria prevalence at any time of the year, provided information regarding temperatures and humidity are readily available, Multiple Linear Regression was employed in this regard. The Multiple Linear Regression (MLR) model is a technique that uses more than one explanatory variable to predict the outcome of a response variable. In essence, the MLR is an extension of the OLS because it involves more than one predictor. The regression model can predict the spate of malaria occurrence at a particular time of the year, assuming the same corresponding data about temperatures and humidity are readily provided.
The model is expressed below:

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \mathcal{E}_i \qquad (1)$$

Where Y_i is the response variable, α is the y-axis intercept of the regression line; X_i is the predictors, β_i are the regression coefficients and $\mathcal{E}_i$ is the error term. $\mathcal{E}_i \sim N(0, \delta^2)$. The values of $\hat{\alpha}$ and $\hat{\hat{\beta}}$ can be calculated using the following equations:

$$\hat{\alpha} = \frac{\sum y - b(\sum x)}{n} \qquad (2)$$

$$\hat{\hat{\beta}} = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2} \qquad (3)$$

To understand the level of association between malaria cases and temperatures, as well as malaria cases with relative humidity, and establish which climatic variable exhibits a strong relationship with malaria occurrences, a Correlation coefficient was employed in this regard. Correlation coefficient (r) is a value that indicates the strength of the relationship between two variables.

Mathematically expressed as:

$$r = \frac{n\Sigma xy - \Sigma x \Sigma y}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2]\,[n\Sigma y^2 - (\Sigma y)^2]}} \qquad (4)$$

Where n is the number of samples, Σxy is the summation product of the predictors and response variables, Σx is the summation of all predictors, Σy is the summation of all response variables.

Coefficient of Determination (r^2) was introduced to ascertain the level of variations in monthly malaria occurrences as a result of variations in both mean temperatures and relative humidity. The r^2 value similarly measures how well the regression model fits the data.

The model is expressed thus:

$$r^2 = \frac{\text{SSR}}{\text{SST}} \qquad (5)$$

Where SST = SSR + SSE

SSR = Sum of Squares Regression, SST = Sum of Squares Total, and SSE = Sum of Squares Error.

3. Results and Discussions

3.1 Visualizations of the data sets

Based on analysis obtained from temperature data extracted from the World Bank Climate Knowledge Portal repository (World Bank, 2021), it was observed that monthly average temperatures are found to be much more intense during the 2nd and 4th quarters of the year. These months include February to June and around October to November (fig. 1). Monthly average temperatures stood at 28.7 and 26℃ respectively at these parts of the year, as sunshine and general temperatures within the study area were observed to be lower around July, August, and January with combined average temperatures of 25℃.

Relative humidity was similarly observed to exhibit a positive trend down the year. There was a gradual rise in humidity around April, which was a peak in August and gradually descend towards the end of the year (fig. 2). Average humidity throughout the year was observed to exhibit regular patterns as humidity is always on the high during the middle of the year accounting for about 72.6% of yearly humidity and mostly on the low at the beginning and end of the year.
According to the data extracted from the IDSR (template) form 003 obtained from the Kaduna State Primary Healthcare Development Agency (IDSR - KPHDA, 2021), there was a recorded total of 3,808,555 malaria cases between 2011 to 2020. Of these figures, about 56% of all reported malaria cases occur between June to November with very few malaria cases being reported towards the end and beginning of the year (Table 3).

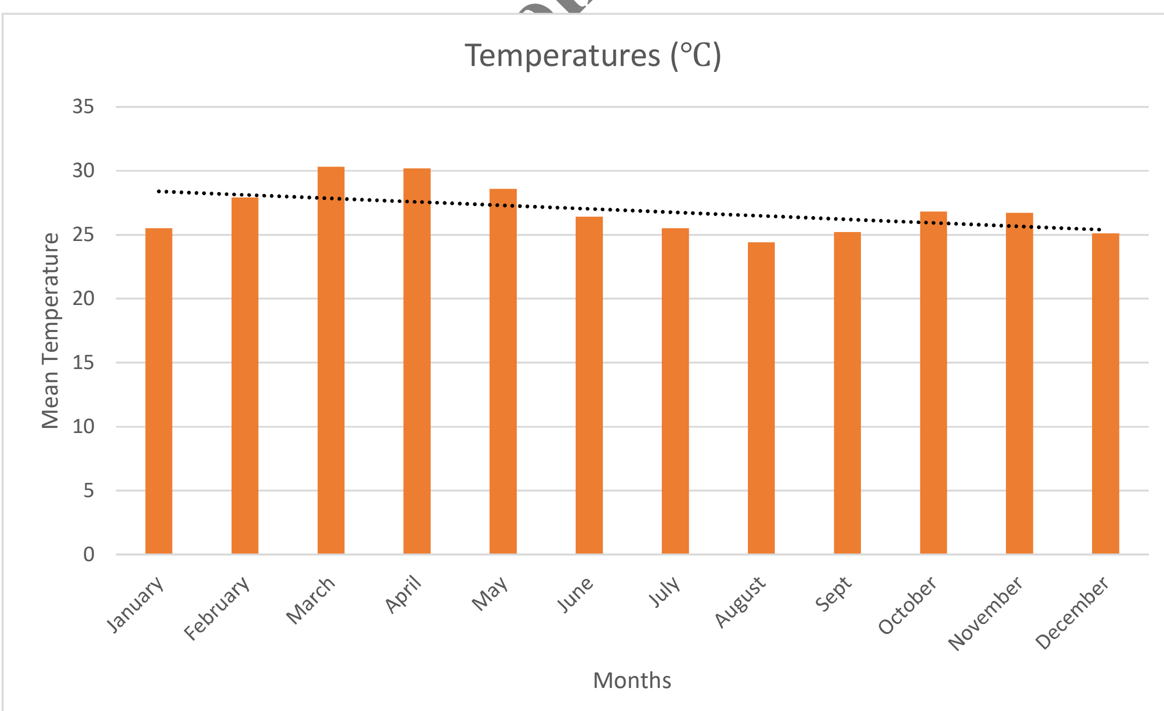

Fig. 1: Visualization of average monthly temperatures measured in degree Celsius

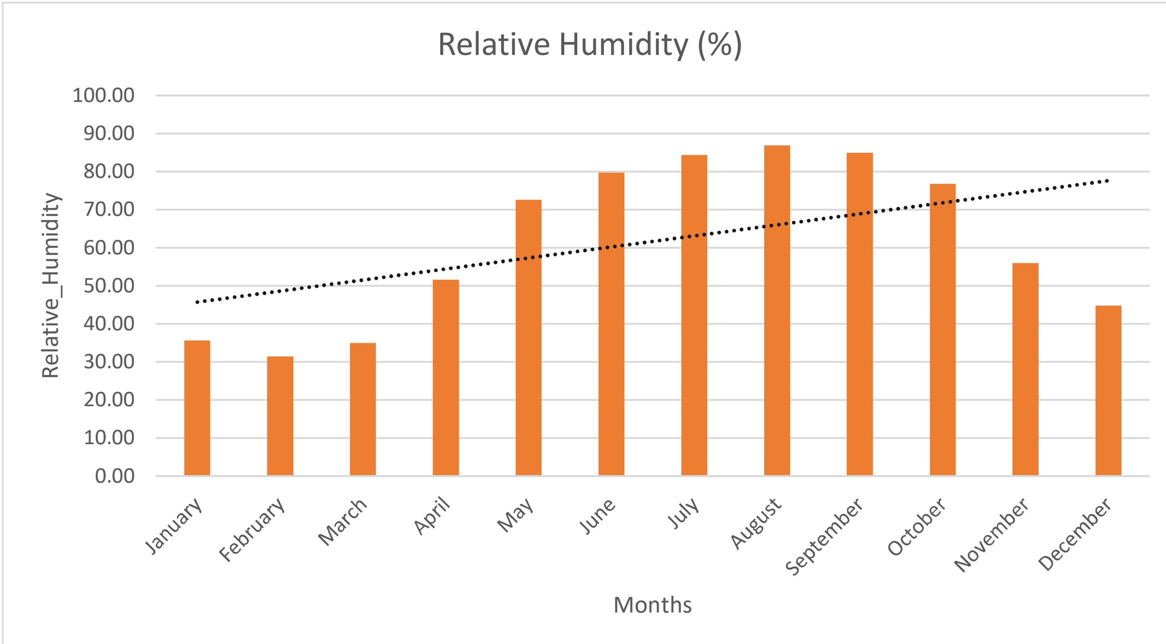

Fig. 2: Visualization of mean monthly relative humidity measured in percentages

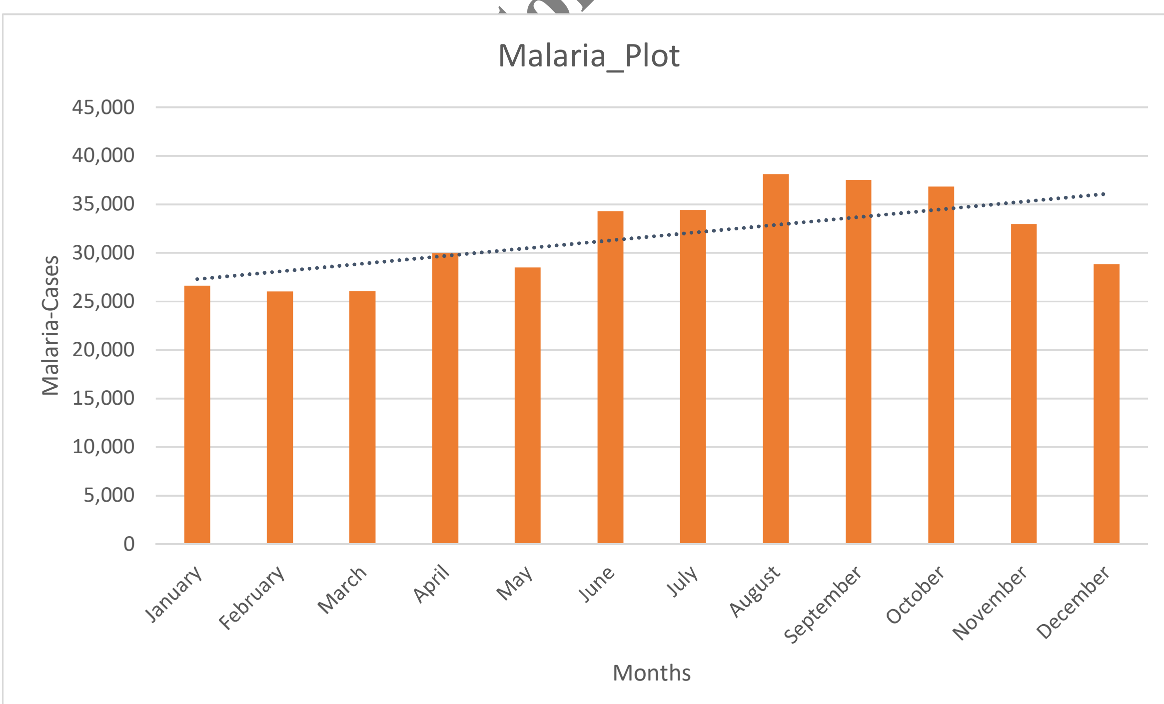

Fig. 3: Visualization of monthly malaria cases

3.2 Correlation and Regression

As indicated in Fig. 2 and 3, relative humidity and malaria occurrence across the months seem to be higher around June to August and lower during the late and early parts of the year. This is as indicated by the strong positive linear trend observed between both variables as obtained in Fig. 4 and the strong positive correlation of 0.8920 obtained from the correlation matrix obtained from table 1. The correlation coefficient indicates that there is a strong relationship between monthly relative humidity and malaria prevalence within the last 10 years from the study area. The positive trend similarly indicates that humidity and malaria occurrences are moving in the same direction – meaning as relative humidity rises in a particular month during the year, malaria cases rise correspondingly.

The level of association between average monthly malaria occurrences and temperatures was observed to exhibit a negative trend with a correlation coefficient of -0.5595 (Fig. 1). This is an indication that both variables are tending towards opposite directions with an inverse relationship. Throughout the year, malaria cases were observed to be on the rise between months when temperatures are seen to be on the decline.

The fitted regression model between malaria cases against temperatures and relative humidity was estimated as:

$$Y_{\text{Malaria Cases}} = 23018.3372 + 182.6665_{\text{Relative Humidity}} - 9.7027_{\text{Temperature}} \quad (6)$$

The Y-intercept α i.e. estimated value of malaria cases in the absence of temperature and relative humidity was predicted to be 23,018. The slope (β_1) i.e. estimated change in reported monthly malaria cases per unit change in monthly relative humidity was estimated to be 182.67 While the second slope (β_2) i.e. estimated change in malaria cases per unit change in relative humidity and temperatures was estimated at 9.7027. The Coefficient of Variation (R^2) i.e. the proportion of variation in malaria cases that can be accounted for by variation in both temperatures and relative humidity is 0.8258. Since R^2 is closer to 1, this indicates that the model is an adequate fit of the dataset. Similarly, The Coefficient of Variation (R^2) i.e. the proportion of variation in malaria cases that can be accounted for by variation in relative humidity alone, is 0.7956. While the R^2 value between malaria cases and temperatures alone is 0.3130.

Table 2: Correlation Matrix for Malaria Cases, Temperatures, and Relative Humidity

	RELATIVE HUMIDITY	TEMPERATURE	MALARIA CASES
RELATIVE HUMIDITY	1.0000	-0.4536	0.8920
TEMPERATURE	-0.4536	1.0000	-0.5595
MALARIA CASES	0.8920	-0.5595	1.0000

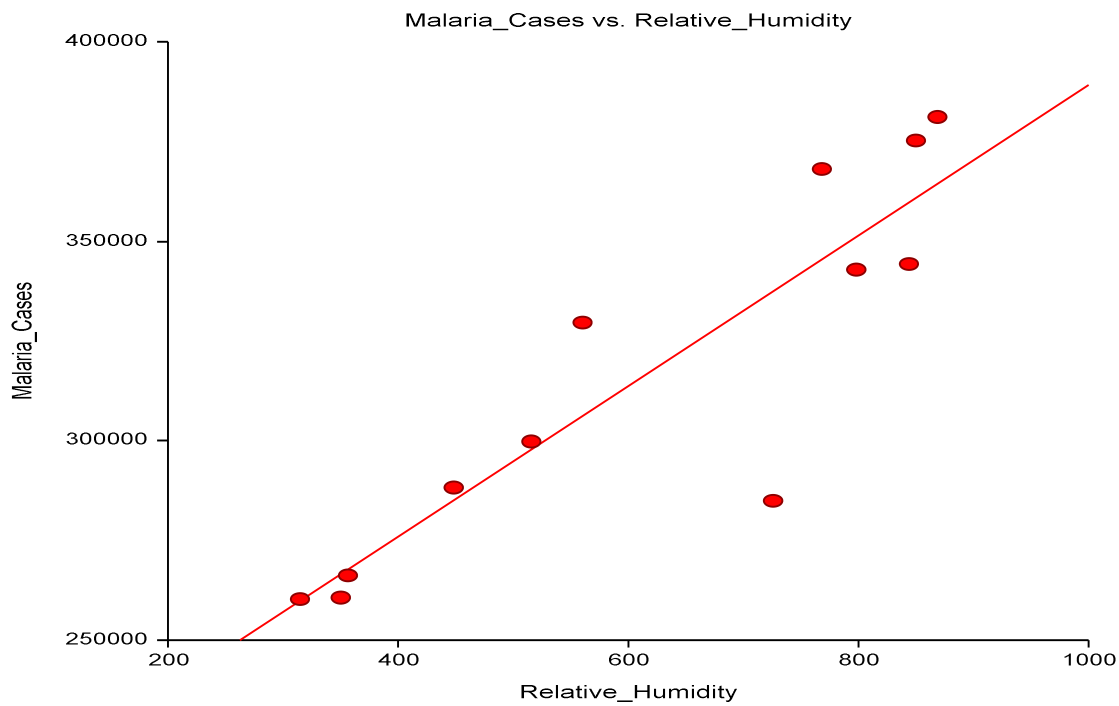

Fig. 4**:** Plot indicating an association between malaria cases and relative humidity

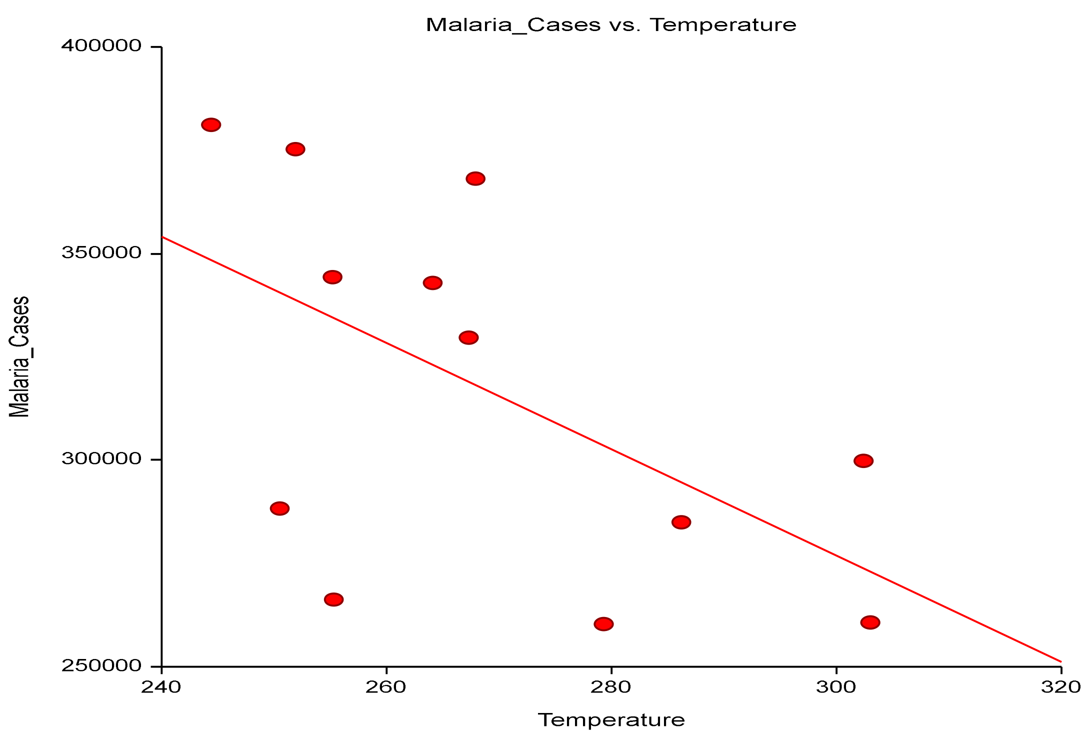

Fig. 5: Plot indicating an association between malaria cases and temperatures

3.3 Normality Test

H_0 = the data is normally distributed
H_1 = the data is not normally distributed
α = 5% (0.05)
Rejection criteria: reject the H_0 if the significance level of the test-statistic (p-value) is less than α

Table 3: Shapiro Wilk's Normality Test Results

Test Name	Test Statistic to Test H0: Normal	Prob. Level
Shapiro Wilk	0.947	0.5992

Conclusion: Since the P-value (0.5992) > α-value (0.05), we fail to reject the H_0 and conclude that the data is normally distributed.

3.4 Software used in the Research

Microsoft excel and Number **Cruncher Statistical System** (NCSS) were both employed for computation, visualization, and analysis of data.

4. Conclusion

In general, these observed climatic conditions (lower temperatures and higher humidity conditions) within months when malaria cases have reportedly risen, are conditions that favor the thriving of (especially) anopheles mosquitos. This observation is inconsistent with a recent study in Abuja (Oguntade et al., 2020). According to data collected in the study area, relative humidity levels between 30% and 80% appear to be ideal for Anopheles mosquitoes to grow and the plasmodium infection to transmit infection. Throughout the year, relative humidity has the largest positive connections with malaria incidence, except in March and October. In this regard, relative humidity, among many other potential malaria predictors, was found to have the greatest impact on the host vector's survival.

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