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An Evaluation on the Incidence of Infant/Child Mortality and Maternal Mortality in the Tamale Metropolis of Ghana

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Abstract

The data consist of child/infant mortality and maternal mortality for a period of 2007-2018 obtained from Tamale Metropolis Health Directorate. These data were investigated statistically by fitting an appropriate model using autoregressive integrated moving average (ARIMA) and the linear trend with seasonal terms (LTST) approach. Data was analysed using R-consol, statistical package for social science (SPSS) and Microsoft Excel. The appropriate model was selected for each of the variables studied based on its coefficient of determination. After a careful evaluation it was evident that linear trend with seasonal terms (LTST) model best fits the under five deaths data whereas the auto regressive integrated moving average (ARIMA) model fitting infant and maternal mortality data in the Tamale Metropolis. It was also evident that there existed a negative significant correlation between the number who died at infant, the number of children dying before their fifth birthday (under five deaths) and the number dying at infant existed a highly positive significantly correlation and finally the time (month) within which live birth occurred in the Metropolis also showed a positive significant correlation with the number of live births in the Metropolis.

Keywords: Mortality, stationary, autocorrelations, regressive

1. Introduction

Under five and infant mortality Child mortality is the mortality of children younger than five. The child death rate, likewise under- five death rate, alludes to the likelihood of dying between birth and precisely five years old per 1,000 live births. It incorporates neonatal mortality and infant mortality. Under- five death rate estimates child survival.

It likewise mirrors the social, financial and natural conditions in which youngsters (and others in the community) live, including their medical services. Infant mortality is the passing of an infant before their first birthday celebration. The newborn child death rate is the number of deaths for each 1,000 live births. Notwithstanding giving us key data about maternal and baby wellbeing, the newborn child death rate is a significant marker of the general soundness of a general public. In 2018, infant mortality rate in the United States was 5.7 deaths per 1,000 live births. As per Ghana Statistical Service the infant mortality rate for Ghana in 2020 is 33.701 deaths for every 1000 live births, a 2.79% decrease from 2019. Again, 34.668 death per 1000 live births for 2019, a 2.71% decrease from 2018. Likewise, 2018 was 35.634 deaths for every 1000 live births, a 4.91% decrease from 2017, and that of 2017 was 37.474 deaths for each 1000 live births, a 4.68% decrease from 2016. This is an obvious sign that Ghana is dealing with its infant mortality rate well.

As per Center for Disease Control and Prevention (CDC) more than 21,000 newborn children died in the United States in 2018. Birth defects, preterm birth and low birth weight, maternal pregnancy complications, sadden baby death syndrome and injuries for example suffocation are the five driving reasons for death. Gideon Kwarteng Acheampong, and Yvette Eyram Avorgbedor (2017) disclosed that under five death rates are a fundamental segment of the United Nations human development index a sensitive indicator of the financial and wellbeing status of a local area. This is on the grounds that more than other age-groups of a population, child survival is subject to the financial states of their current circumstance. Subsequently its significance in the assessment and planning of the general wellbeing techniques. The advancement of good wellbeing and health is a fundamental part of the SDG's. As per the UNs development program, notwithstanding enormous steps taken in lessening avoidable child deaths by the greater part, some figures remain unfortunately high, similar to the way that consistently 6,000,000 children die before their fifth birthday celebration.

Ghana was well-known as encountering quite possibly the most sensational decreases in child mortality in current years, and albeit the pattern of child mortality had been projected to keep on declining. Research demonstrated that the decrease in less than five mortality has slowed down and the impact is more extraordinary at various levels. This has ascribed to some extent to absence progress in social and economic development. The results of MICS (Multiple Indicator Cluster Survey) 2011 on Ghana demonstrate newborn child and under- five death rates are still extremely high, that is 53 deaths for every 1,000 live births and 82 for every 1,000 live births, separately. The data demonstrate that neonatal death rate signifies 60% of the infant death rate while 13% of children under five years old. With actions and progress level regardless, maternal, infant and child mortality levels in Ghana stay high. The necessity to identify reasons that impact under- five mortality to empower the privilege focusing of where, when, and how general wellbeing assets ought to be diverted to solve child health problems, advance wellbeing, and prevent premature deaths can't be belabored. Because of inaccessibility of information on the rate and occurrence of diseases, death rates are generally used to recognize weak and vulnerable populations. Under- five death rate was one of the MDG indicator. The likelihood of a child born into the world in a particular year or period dying prior to attainment of the age of five, is subject to age-specific mortality rate of that time frame.

1.1. Maternal Mortality

Maternal death is described by the WHO as "the death of a woman while pregnant or inside 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accidental or incidental causes. In addition to the description of WHO, the CDC prolongs the time to include 1 year until the finish of a pregnancy with little attention to the result. The effect of a maternal deaths leads to vulnerable families. Babies that survive, are sure to die prior to reaching their second birthday. It also recognized unsafe termination as a significant reason for maternal deaths. As indicated by the WHO in 2009, a woman dies every 8 minutes from complications due to unsafe abortions. Hazardous fetus removal includes drinking poisonous liquids. As of 2007, universally, avoidable deaths from inappropriate procedures performed comprise 13%, and 25% or extra in certain nations. Fetus removals are normal in most developed areas than in developing areas. It is projected that 26% of pregnancies that happen worldwide are ended by incited early terminations. 41% of these happen in developed areas and 23% of them happen in developing areas. Maternal deaths caused by inappropriate techniques are avoidable and amount to 13% of maternal death rate around the world. This f i gure increases to 25% in nations where different reasons for maternal mortality are low. Therefore, making risky abortion procedures the principal reason of maternal death around the world. The WHO additionally added that preclusion and decrease of motherhood deaths is one of the UN's SDGs, explicitly Goal 3. Offering safe types of assistance for expectant women in family planning facilities is relevant to all areas. This is a significant certainty to consider since early termination is legitimate somehow or another in 189 out of 193 nations around the world. Advancing powerful use of contraceptives and circulated information to a more extensive populace, with admittance to top notch care, can essentially lead to ventures towards lessening the risk of abortions. Sexual and regenerative health for women ought to likewise be added in educational program in places of learning. For countries that permit contraceptives, programs ought to be organized to permit the simpler availability of these prescriptions. In any case, this by itself won't dispose of the interest for safe administrations, mindfulness on safe early termination administrations, wellbeing training on pre-birth checks and appropriate usage of diets during pregnancy and lactation likewise add to its counteraction.

2. Methodology

This emphasizes details and complete comprehension of The Box-Jenkins methodology for ARIMA models.

2.1. Profile of Study Area (Tamale metropolis)

The population and housing census report offers basic data about the Metropolis. Utilizing information from the 2010 Census (2010 PHC), the report ponders the population demography of the Metropolis, fertility, mortality, movement, marriage, education and literacy rate, economic status, occupation, employment; The critical results of the study are the following.

Populace size, structure, and composition. The number of inhabitants in Tamale Metropolis is 233,252 as given in the 2010 PHC addressing. Which is 9.4 of the regional population. Of this aggregate, 49.7 are male and 50.3 are females. 80.8 of this populace live in metropolitan zones which is higher than those in rural areas of 19.1. The sex ratio in the city 99.1. The city has an energetic (youthful) populace (with 36.4 of them below the age of 15) this portrays a broad base population pyramid with a little level of old individuals (60+ years) being 5.1.

The total age dependency ratio for the metropolis is 69.4, however, the age dependency ratio for rural communities is (86.5) which is much higher than (65.7) in urban communities. Fertility, mortality, and migration: (2.8) is the Total Fertility Rate for the metropolis, which is fairly lesser, comparing to the fertility rate of 3.5 in the region. The General Fertility Rate is 79.9 births per 1000 women aged 15-49 years. The Crude Birth Rate (CBR) is 21.2 per 1000 population. In the metropolis, the crude death rate is 5.6 deaths per 1000. Accident, violence, homicide, and suicide adds to deaths of about 9.6 while other causes accounts for 90.5. Many migrants (54.9) dwelling in the metropolis are born somewhere else in the region whereas 45.1 born in other regions.

2.2 Data Sources and Types

The study basically tries to model the under-five death, infant mortality, and maternal mortality, with the aim of predicting future patterns using Tamale metropolis as the area of study. This analysis is grounded on secondary data existing at the Tamale metropolis health directorate for the period 2007-2018. The data contain monthly-recorded under 5yrs death, infant mortality and maternal mortality 2014-2018 and annual data from 2007-2018. The variables under study include all the above mentioned.

2.3 Statistical Software to be Employed

The statistical software that would be utilized in analyzing and fitting ARIMA models is the r-console, and the Statistical Package for Social Science (SPSS) for modelling the linear trend with seasonal terms and Microsoft excel for plotting charts and tables. Other arithmetical and statistical methods of parameter approximation would be applied as and when considered appropriate

2.4 Concept of Time Series

Time series is a time dependent sequence which belongs to the set of integers and represents the time steps. If from past knowledge, the future of a time series can be exactly predicted, it is a deterministic series and requires no further investigation. It can be stated as a function known, that is $Y\,t = f(t)$. If it is though expressed as $Y\,t = f(t)$ where X is a random variable then ($Y\,t$) is a stochastic time series.

2.5 Stationary and Non-Stationary Series

A time series is said to be strictly stationary if the joint distribution of $X_{t_1}, X_{t_2}, \ldots X_{tn}$ is the same as the joint distribution of $X_{t_1}+T, X_{t_2}+T, \ldots X_{tn}+T$, for all $t_{1+T} \ldots t_{n+T}$. Thus, shifting the time position by T periods has no effects on the joint distributions, which therefore depends on the interval between $t_1 \ldots t_n$. If a time series is not stationary, then it is said to be non-stationary. A simple non-stationary time series model is given by

$$Y_t = \mu_t + e_t \tag{1}$$

where the mean μ_t is a function of time and e_t is a weakly stationary series. Different from the stationary time series, the mean and variance of the non-stationary method defers with time. If a non-stationary, series is difference one or more times it becomes stationary and that series is then said to be homogeneous.

2.5.1 Lag

Lag is a variance in time between a current observation and an earlier observation. Thus $Y(t - k)$ lags Y_t by k periods.

2.5.2 White Noise

A group of uncorrelated random variables, ω_t, with mean 0 and finite variance $\sigma\omega^2$ this model was first used for noise in engineering applications, white noise was the name given to it. This process is denoted as $\omega_t \sim wn\,(0, \sigma\omega^2)$. The name white comes from the analogy with white light and shows that all possible periodic oscillations are present with equal strength. At sometimes, we will also require the noise to be iid random variables with mean 0 and variance $\sigma\omega^2$. We shall differentiate this case by saying white independent noise, or by writing $\omega_t \sim iid(0, \sigma\omega^2)$. A mainly suitable white noise series is Gaussian white noise, wherein the $\omega_t(s)$ are independent normal random variables, with mean 0 and variance $\sigma\omega^2$; or more succinctly, $\omega_t \sim iidN(0, \sigma\omega^2)$.

2.5.3 Autocorrelation function (acf)

The acf is very important for re-counting the overall procedure employed to come up with a prediction model. It shows the degree of relationship flanked by neighboring observations in a time series. The acf at any lag k is given $COR(Y_t, Y_{t-k})$ and is measured by

$$\rho_k = \frac{COV(Y_t, Y_{t-k})}{\delta_{Y_t}\delta_{Y_{t-k}}} = \frac{E[(Y_t-\mu_Y)(Y_{t-k}-\mu_Y)]}{[E(Y_t-\mu_Y)^2(Y_{t-k}-\mu_Y)^2]} \tag{2}$$

Where Y_t, the observation at time t, Y_{t-k} is observation at time t-k and μ_Y is the observed mean. In theory, acf is mostly not known, it can however be estimated using the sample acf as:

$$\widehat{\rho_k} = \frac{\sum_{t=1}^{n}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t=1}^{n}(Y_t-\bar{Y})^2} \tag{3}$$

Where t is the distance of the time series under study, $\bar{Y}$ is the mean of the Y_t observation and k = 1, 2... k. Usually we calculate the first K to be less than N/4 sample autocorrelations. If the covariance between Y_t and Y_{t-k} is defined as γ_k, then

$$\rho_k = \frac{\gamma_k}{\gamma_0}, \tag{4}$$

Therefore, for a given stochastic process $\rho_0 = 1$. It is also true that $\rho_k = \rho_{-k}$

For a series to be white noise all $\rho_k = 0$, for k > 0. This can be proven using the Box-Pierce test statistic: $Q = n\sum_{k=1}^{k}\widehat{\rho_k}^2$

2.5.4 Partial autocorrelation function

A partial autocorrelation coefficient measures the degree of association between an observation Y_t and Y_{t-k} when the effects of the other time lags are held constant. We consider partial autocorrelation when we are unaware of the appropriate order of the autoregressive process to fit the time series. PACF is denoted by Q_{kk} and is defined as

$$Q_{kk} = \frac{|P_k{}^*|}{|P_k|} \tag{5}$$

Where P_k is a k x k auto correlation matrix and P_k* is P_k with the least column replaced by $[\rho_1\ \rho_2\ ...\ \rho_k]^T$. The partial autocorrelation coefficient of order k is denoted by $\propto_k$ and that can be calculated by regressing Y_t against Y_{t-1} ... Y_{t-k}

$$Y_t = b_0 + b_1Y_{t-1} + b_2Y_{t-2} + \cdots + b_kY_{t-k} \tag{6}$$

Where the variables on the right are previous values of the forecast variable Y_t where the partial autocorrelation $\propto_k$ is the estimated coefficient b_k from the regression equation above.

2.5.5 Auto regressive model AR (p)

Autoregressive models are grounded on the knowledge that the present value of the series X_t, can be expressed as a function of p past values, X_{t-1},X_{t-2}, …X_{t-p}, where p controls the number of steps into the past desired to forecast the current value. An AR model of order p, written as AR (p), is

$$\mathrm{X_t} = \alpha + \emptyset_1\mathrm{X_{t-1}} + \emptyset_2\mathrm{X_{t-2}} + \cdots + \emptyset_\mathrm{p}\mathrm{X_{t-p}} + \omega_\mathrm{t} \tag{7}$$

Where $\mathrm{X_t}$ is stationary, $\emptyset_1, \emptyset_2, \ldots \emptyset_\mathrm{p}$ are constants. Except otherwise specified, we assume that ω_t is a Gaussian white noise series with mean μ zero and variance $\sigma_\omega{}^2$. Nonetheless, if the mean μ of X_t is not zero, replace X_t with $X_t - \mu$ in the AR (p) model.

$$X_t - \mu = \emptyset_1(X_{t-1} - \mu) + \emptyset_2(X_{t-2} - \mu) + \cdots + \emptyset_p(X_{t-p} - \mu) + \omega_t \tag{8}$$

or we write as

$$X_t = \alpha + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t \quad (9)$$

Where $\alpha = \mu(1 - \emptyset_1 - \cdots - \emptyset_p)$

2.5.6 Moving Average Model MA (q)

A moving average model of order q, or MA (q) model, can be well-defined as

$$X_t = \omega_t + \theta_1 \omega_{t-1} + \theta_2 \omega_{t-2} + \cdots + \theta_q \omega_{t-q} \quad (10)$$

Where there are q lags in the moving average and $\theta_1, \theta_2, \ldots, \theta_q$ ($\theta_q \neq 0$) are parameters. The noise ω_t is assumed Gaussian White Noise. The MA (q) process in the equivalent form can be written as

$$X_t = \theta(B)\omega_t \quad (11)$$

Where $\theta(B)$ is a moving average backward shift operator given as

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_p B^p \quad (12)$$

2.5.7 ARMA model

A time series $\{X_t; t = 0, \pm 1, \pm 2, \ldots\}$ is ARMA (p, q) if it is stationary and

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \theta_2 \omega_{t-2} + \cdots + \theta_q \omega_{t-q} \quad (13)$$

$\emptyset_p \neq 0, \theta_q \neq 0$, and $\sigma_\omega{}^2 > 0$. The parameters p and q are the autoregressive and the moving average orders, respectively.

If X_t has a non-zero mean μ, we set $\alpha = \mu(1 - \emptyset_1 - \cdots - \emptyset_p)$ and write the model as

$$X_t = \alpha + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \theta_2 \omega_{t-2} + \cdots + \theta_q \omega_{t-q} \quad (14)$$

Unless otherwise stated, $\{\omega_t; t = 0, \pm 1, \pm 2, \ldots\}$ is a Gaussian white noise sequence.

As indicated earlier, when *q* = 0, the model is an autoregressive model of order *p*, AR (*p*), and when *p* = 0, MA (*q*).

2.5.8 ARIMA Models

ARIMA is an abbreviation with means "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. A non-seasonal ARIMA model is classified as an "ARIMA (p, d, q)" model, where *p* is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lagged forecast errors (moving average) in the prediction equation. A process, X_t is said to be ARIMA (p, d, q) if $\nabla^d X_t = (1 - B)^d X_t$ is ARMA (p, q). the model is written as

$\emptyset(B)(1 - B)^d X_t = \theta(B)\omega_t$. If $E(\nabla^d X_t) = \mu$ the model is written a $\emptyset(B)(1 - B)^d X_t = \propto + \theta(B)\omega_t$,

Where $\alpha = \mu(1 - \emptyset_1 - \cdots - \emptyset_p)$

2.5.9 The Box-Jenkins ARIMA Model

The Box-Jenkins methodology describes the set of methods for detecting, fitting, and examining ARIMA models with time series data. Forecasts take the form of the fitted model. By Box-Jenkins, a p^{th} order autoregressive model: AR (p), generally given as

$$X_t = \alpha + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t \quad (15)$$

Where X_t= Response (dependent) variable at time t, $X_{t-1}, X_{t-2}, \ldots X_{t-p}$= Response variable at time lags t − 1, t − 2, . . . , t − p, respectively.

$\emptyset_1, \emptyset_2, \ldots \emptyset_p$= Coefficients to be estimated, and ω_t = Error term at time t.

Also, a q^{th}- order moving average model: MA (q), has the general form

$$X_t = \mu + \omega_t + \theta_1\omega_{t-1} + \theta_2\omega_{t-2} + \cdots + \theta_q\omega_{t-q} \quad (16)$$

Where X_t= Response (dependent) variable at time t, μ = Constant mean of the process, $\emptyset_1, \emptyset_2, \dots \emptyset_p$= Coefficients to be estimated, ω_t = Error term at time t, and $\omega_{t-1}, \omega_{t-2}, \dots, \omega_{t-p}$ = Errors in previous time periods that are incorporated in the response X_t.

Autoregressive Moving Average Model: ARMA (p, q), which has the general form

$$X_t = \alpha + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t + \theta_1\omega_{t-1} + \theta_2\omega_{t-2} + \cdots + \theta_q\omega_{t-q} \quad (17)$$

To identify a model, we can use a graph of ACF (the sample autocorrelation function) and PACF (the sample partial autocorrelation function), this can be summarized as

Table 2.1: Model Determination Using ACF and PACF

Model	ACF	PACF
AR(p)	Dies down	Cut off after lag q
MA(q)	Cut off after lag p	Dies down
ARMA(p,q)	Dies down	Dies down

Box-Jenkins's forecasting models comprise of a four-step iterative method as;

- Model identification,
- Model Estimation,
- Model checking (Goodness of fit) and
- Model forecasting

The four iterative steps are not straightforward but are entailed in a constant flow chart reliant on the set of data for which you are studying.

2.6.1 Model Identification (Selecting an initial model)

First, we identify if the series is stationary by taking into consideration the graph of ACF. If the graph of ACF of the time series values either cut rapidly or deceases rapidly, then the time series values would be stationary. If the ACF graph deceases too slowly, then the time series values would be non-stationary. If the series is not stationary, it would be transformed to a stationary series by differencing. That is, the original series is substituted by a series of differences. An ARMA model is then stated for the differenced series. We continue differencing till the data shows the series differs about a constant level, and the ACF graph cuts off rapidly. When a stationary series is attained, then detect the form of the model to be used by considering Table 1.

2.6.2 Model Estimation and Evaluation

When a model is known, the subsequent level for Box-Jenkins's method is to evaluate the parameters. For this article, the parameters estimate was completed by the use of the R-Console a statistical software.

2.6.3 Method of Moment's Estimators

For this study, we start with method of moments estimators. The reason for these estimators is that of likening population moments to sample moments and then solving for the parameters in terms of the sample moments. If $E(X_t) = \mu$, the method of moment estimator of μ is the sample average $\bar{x}$. We assume μ = 0. Though the method of moments can bring about good estimators, sometimes they can lead to suboptimal estimators.

2.6.4 Maximum Likelihood Estimators

Let $X_t = \mu + \emptyset_1(X_{t-1} - \mu) + \omega_t$ be a process of time series, where$|\emptyset| < 1$ and $\omega_t \sim iid\ N(0, \sigma_\omega^2)$. For a

given set of data $X_1, X_2, \dots, X_n$, we find the likelihood $\boldsymbol{L}(\mu, \emptyset, \sigma_\omega^2) = f_{\mu,\emptyset,\sigma_\omega^2}(X_1, X_2, \dots, X_n)$In the event of an AR (1), we write the likelihood as $\boldsymbol{L}(\mu, \emptyset, \sigma_\omega^2) = f(X_1)f(X_2 \,/\, X_1) \dots f(X_n \,/\, X_{n-1})$
Where parameters in the densities are dropped, $f(.)$, to ease the notation.
The likelihood is given as $\boldsymbol{L}(\mu, \emptyset, \sigma_\omega^2) = f(X_1)\prod_{t=2}^{n} f_\omega[(X_t - \mu) - \emptyset(X_{t-1} - \mu)]$
To find $f(X_1)$, causal representation can be used $X_t = \mu + \sum_{j=0}^{\propto} \emptyset^j \omega_{1-j}$. To determine X_1 is normal, with mean μ and variance $\frac{\sigma_\omega^2}{(1-\emptyset^2)}$

2.6. 5 AIC, AICc, BIC

The final model can be chosen using a penalty function statistic such as **A**kaike **I**nformation **C**riterion (AIC or AICc) or **B**ayesian **I**nformation **C**riterion (BIC). See Sakamoto et. al. (1986), Akaike (1974) and Schwarz (1978). The AIC, AICc and BIC are a measure of the goodness of fit of an estimated statistical model. In the general case, the AIC, AICc and BIC is estimated as;

$$AIC = 2k - 2\log(L) \quad OR \quad 2k + nlog(\frac{RSS}{n})$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1}$$

$BIC = -2Log(L) + klog(n) \quad OR \; \log(\sigma_e^2) + \frac{k}{n}\log(n)$ where,

k: is the number of parameters in the statistical model
L: is the maximized value of the likelihood function for the estimated model.
RSS: is the residual sum of squares of the estimated model.
n: is the number of observations
σ_e^2: is the error variance
The AICc is a modification of the AIC by Hurvich and Tsai (1989) and it is AIC with a second order correction for small sample sizes. Burnham & Anderson (1998) insist that since AICc converges to AIC as *n* gets large, AICc should be employed regardless of the sample size.

2.6.6 Model checking (Goodness of fit)

At this stage, model should be checked for sufficiency by considering the properties of the residuals whether the residuals from an ARIMA model should have the normal distribution and ought to be random. A general check of model sufficiency is given by the Ljung-Box Q statistic.

The test statistic Q is $Q_m = n(n+2)\sum_{k=1}^{m}\frac{r_k^2(e)}{n-k} \sim \chi_{m-r}^2$

(18)

Where $r_k(e)$= the residual autocorrelation at lag k, n= the number of residuals and m = the number of times lags includes in the test. If the p-value associated with the Q statistic is small (P-value <∝), the model is considered inadequate. We then consider a modified model and continue the analysis until a suitable model has been reached. Additionally, we consider the properties of the residual with the following graph:

(1) Consider the normality by taking into consideration, the normal probability plot, or the p-value from the One-Sample Kolmogorov – Smirnov Test.

(2) Check for randomness of the residuals by taking into consideration the ACF and PACF graph of the residual. The different residual autocorrelation must be small and usually within $\pm 2/\sqrt{n}$ of zero. Residuals must at all cost be white noise. A test to verify if the residuals form a white process is given by a modified version of the Box-Pierce Q statistic in the form:

$Q = (T-d)\sum_{k=1}^{k}\hat{\rho}_k^2$
(19)

Where rho hat is the autocorrelations of the residuals, d is the order of differencing to obtain a stationary series, T is the length of the series, and K is the number of autocorrelations being checked. For this, if Q is greater than the critical value for the chi squared distribution with K-p-q degrees of freedom, the model should be considered insufficient.

2.6.7 Forecasting

When a model is selected and estimated, and residuals are examined and considered to be uncorrelated and parameters measured to be significant and uncorrelated, a forecast can be done. Forecasting with this method is quite direct; the forecast is the expected value, estimated at a specific given time. Confidence limits may simply be arrived at from the standard errors of the residuals.

2.7 Linear Trend with Seasonal Terms

This section is to show how to develop forecasts for a time series that has both trend and seasonal pattern. To the degree that seasonality and trend exists, we need to include it into our forecasting models to ensure precise forecasts. Here we model by setting some dummy variables which will represent the individual months in a given year. The model for the linear trend with seasonal terms is given by,

$$Yt = a + L(t) + SD_1X_1 + \ldots\ldots + SD_iX_j$$

where a= the y intercept, L(t)= the time sequence of the series, SD_i *= seasonal dummy variable, Xi=the month*

2.8 Coefficient of Determination (R^2)

The coefficient of determination in a regression model estimates the proportion of variability in the response variable that is described by the regressor variables. More specifically it gives the percentage variation in the response variable explained by the predictor variables. The coefficient of determination is like the correlation coefficient and R^2 is the square of the correlation coefficient. The coefficient of determination ranges between 0 and 1 or 0 and 100%.

$$R^2 = 1 - \frac{SS_{regression}}{SS_{total}}$$

Where $SS_{regression}$ is sum of squares regression, and SS_{total} is sum of squares total

3.0 Data Analysis

This chapter aims at analyzing live birth data obtained health directorate of the Tamale metropolitan from the period of January 2007 to December 2018. These findings are mainly concerned with preliminary analysis which is basically descriptive and further analysis where we will be looking at finding the best forecasting technique by deriving a model for forecasting the various variables understudy. This will be taken by comparing the coefficient of determination of the auto regressive integrated moving averages (ARIMA) and linear trend with seasonal terms (LTST).

3.1. Preliminary analysis

From the Figure 3.1, plot there exist some form of seasonal fluctuations in the data. It can be deduced that children who die at infant age, most of such cases were recorded in 2017 followed by 2016 and 2015. 2018 experienced a declining rate of infant deaths. From Figure 3. 2, of children dying before their fifth birthday, it is evident that a particular month in 2017 recorded the smallest case with 2016 recording the highest of such case for a particular month. It also displays some seasonal fluctuation, indicating no particular trend in these cases.

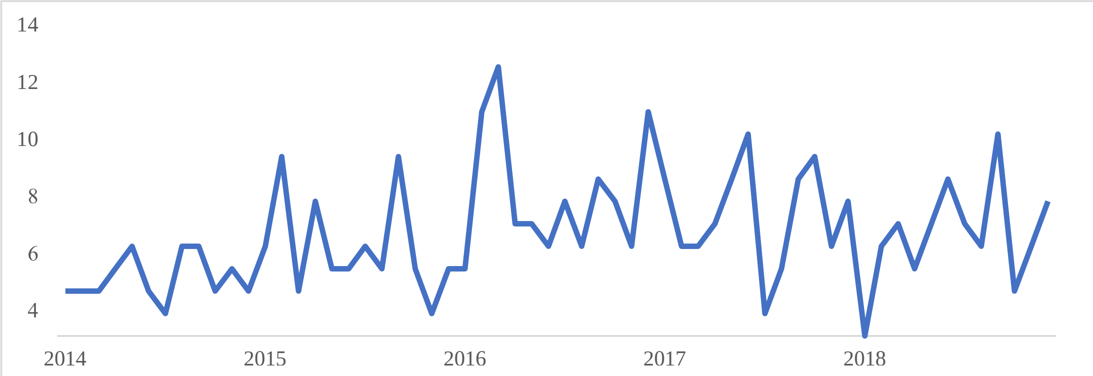

Figure 3.1: Plot of the trend of infant mortality from 2014-2018

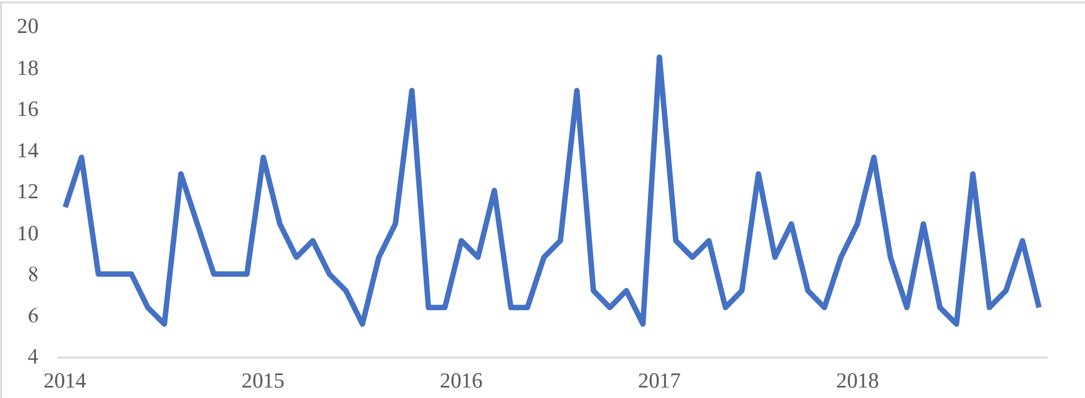

Figure 3.2: Plot of the trend of under 5yrs mortality 2014-2018

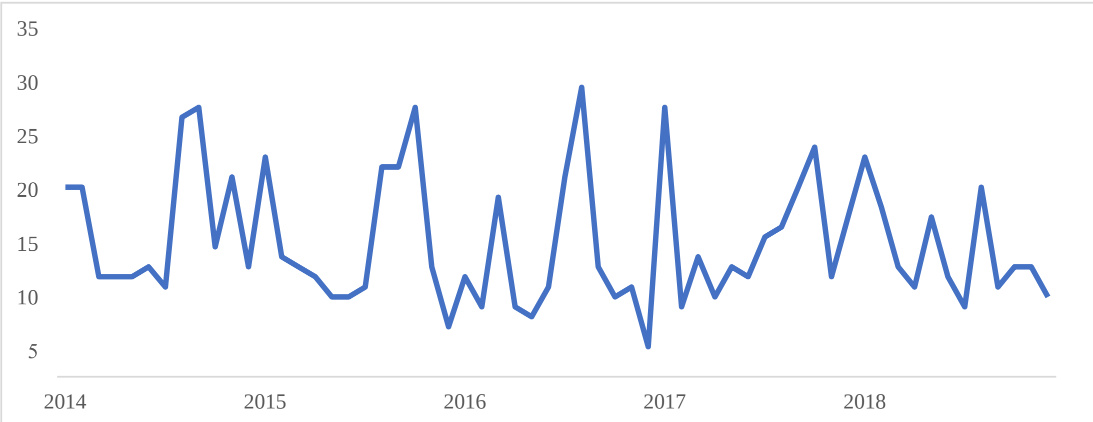

Figure 3.3: trend of maternal mortality 2014-201

From the Figure 3.3, of women who died being pregnant, or within forty-two (42) days of abortion in the Tamale Metropolis, the year 2014 had least of the cases and increased in 2015 followed suit in 2016 but 2017 and 2018 experienced a minimal decline for some months in the Metropolis. From Figure 4, the plot the graph of under five deaths is above the infant deaths, this means that children dying between the age of zero to four in the Tamale Metropolis has

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always been higher for all the years under study than those between the age of four and eight years. Hence Tamale metropolis records more of under- five mortality cases than infant mortality cases. From Figure 5, the plot the Metropolis across the period under study have high cases of child mortality, followed by infant mortality with maternal mortality the least. This is also clear evidence that children in the metropolis who died before their fifth birthday has always been higher than the likes of infant and maternal mortality in the Tamale Metropolis.

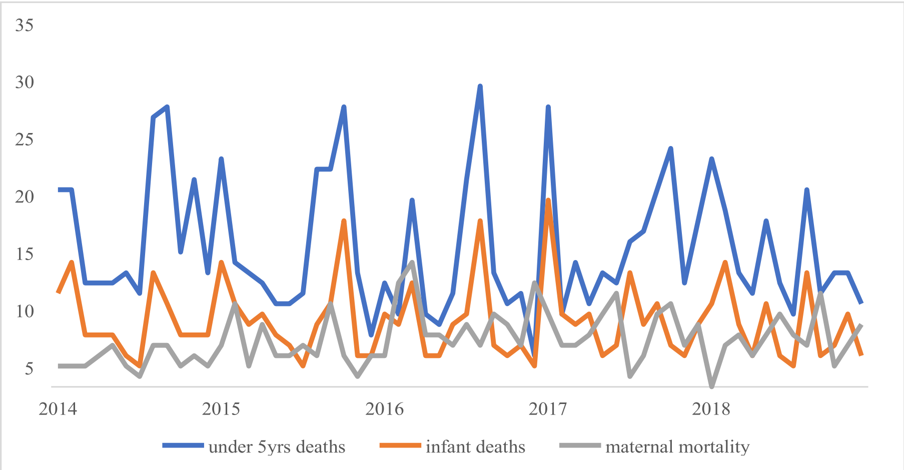

Figure 3.4: Plot of the trend of under-five and infant deaths from 2014-2018

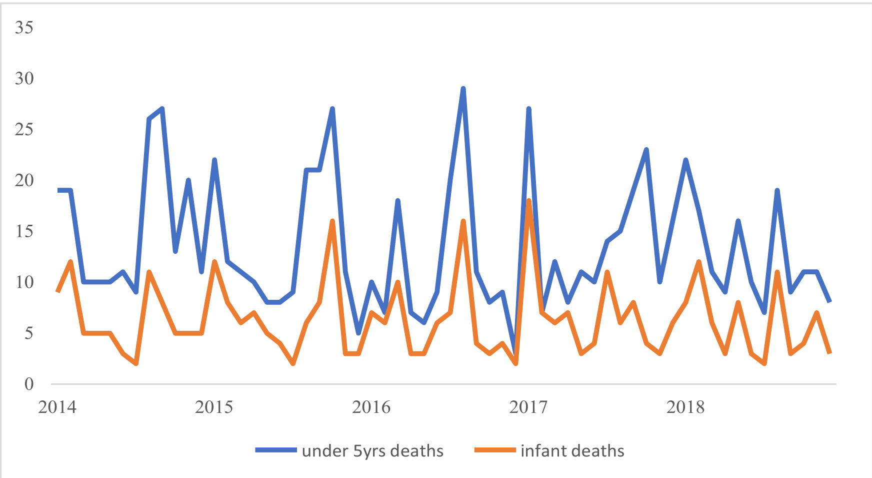

Figure 3.5: Plot of under-five, infant and maternal mortality 2014-2018

From Table 1: it can be pointed out across the years under study that children dying before the age of five in the Metropolis was always high in the third quarter from 2014 to 2016 then the fourth and third quarter took over for 2017 and 2018 respectively. Whereas the least was recorded in second quarter for 2014,2015 and 2017 then the fourth quarter for 2018 and 2016. Of the number of infants who died in the metropolis, the first quarter recorded the most cases across all the years with the exception of 2016 which was in the third quarter. Then the smallest figures of such cases in the third and second quarter for 2014 and 2015 with 2015 equaling in the second and third where the rest of the cases occurred in fourth quarter for 2016, 2017, 2018.

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Regard to maternal mortality, the second and third quarters saw high and high cases in 2015 third quarter, first quarter that of 2016 and second and third quarter for 2017 and 2018 respectively. Also, more live birth in the Tamale metropolis has been in the rise generally in the years under study with more births in the fourth quarter for all the years under study except that of 2014 been in the second quarter.

Table 1: Quarterly Presentation of Under-Five, Infant and Maternal Mortality in the Tamale metropolis

Year	Quarters	Under five deaths	Infant deaths	Maternal mortality
2014	1	48	26	6
	2	31	13	9
	3	62	21	9
	4	44	15	7
2015	1	45	26	14
	2	26	16	12
	3	51	16	15
	4	43	22	7
2016	1	35	23	25
	2	22	12	14
	3	60	27	17
	4	20	9	20
2017	1	46	31	15
	2	29	14	21
	3	48	25	11
	4	49	13	18
2018	1	50	26	9
	2	35	14	15
	3	35	16	18
	4	30	14	12

Further Analysis

The analysis here is to develop a model using the linear trend with seasonal term for it is believed that live birth has a significant correlation with time (months), in the correlation analysis. From table 4.3 above, it is evident that a positive correlation exists between infant mortality and under 5yrs death of 0.768 with a P-value of 0.000 which is also highly significant at 5% level of confidence. This implies that as under 5yrs deaths increases, infant mortality also increases and vice versa. Also there exist a positive correlation between the live birth and the time (months) or period within which both occurred with a coefficient of 0.453 and p-value of 0.000 showing such relationship is very significant. It also means that as the time period increases, the number live birth also increases and vice versa. There exists correlation between the other variables but not as significant as the ones mentioned.

Table 2: Correlation Between the Variables with their P-Values

Variables	Maternal Mortality	Time(Month)	Under 5yrs Death	Infant Mortality
maternal mortality	1	0.297	-0.059	-0.039
P-value	0	0.021	0.654	0.769
time(months)	0	1	-0.123	-0.087
P-value	0	0	0.351	0.506
under 5yrs death	0	0	1	0.768
P-value	0	0	0	0.000
infant mortality	0	0	0	1
P-value	0	0	0	0

3.2.1. Modelling using linear trend with seasonal terms on under 5yrs death

From table 3, it is evident that the model is significant since the P-value (0.001) is less than the significant level of 5%. Hence, is good for forecasting future values of under five deaths

Table 3: Analysis of Variance for the Linear Trend with seasonal Terms

Model	1119.658	12	93.305 3.471 0.001
Residual	1263.325	47	26.879
Total	2382.983	59	

Source SS DF MS F P

It is obvious from table 4 that the constant or intercept, January (X1), August (X8), September (X9) and October (X10) are all significant at 5% level of significance, since their P-values is less than the significance level of 5%. Hence, it presupposes that in predicting a live birth in the metropolis the coefficient of these seasonal dummy variables is significant. Thus, they significantly different from zero

Table 4: Parameter Estimates for under 5yrs death in the Tamale Metropolis

Predictors	Estimate	Standard error	T	P
(Constant)	10.175	2.719	3.742	0.000
Time	-0.044	0.039	-1.109	0.273
X1	10.919	3.308	3.301	0.002
X2	3.362	3.303	1.018	0.314
X3	3.406	3.298	1.033	0.307
X4	-0.15	3.294	-0.046	0.964
X5	1.294	3.291	0.393	0.696
X6	0.737	3.288	0.224	0.823
X7	2.981	3.285	0.908	0.369
X8	13.225	3.283	4.029	0.000
X9	8.669	3.281	2.642	0.011
X10	7.712	3.28	2.351	0.023
X11	3.556	3.279	1.084	0.284

Modelling using auto regressive integrated moving average on infant mortality

From table 5, the test of stationary using the Augmented Dickey Fuller (ADF) test where the null hypothesis (H_o) states that, the series is not stationary and the alternative hypothesis (H_1), the series is stationary resulted in the rejection of the null hypothesis since the P- values (0.000 and 0.000) for both drift and trend are less than the alpha value (0.05), we therefore conclude that the series has passed the stationary test and hence stationary. Also, with Kwiatkowski Philip Schmidt Shin (KPSS) test with null hypothesis (H_o): the series is stationary and the alternative hypothesis (H_1): the series is not stationary; therefore, we have no evidence against the null hypothesis since the critical value (0.146) is greater than the test statistic (0.1219). Hence, we fail to reject the null hypothesis and state that the series is stationary.

Table 5: Stationary Test for the Series (infant mortality)

Test	F-Statistic	P-value
ADF: Drift	23.66	0.000
ADF: Trend	36.02	0.000
Test	Test Statistic	Critical value (5%)
KPSS	0.1219	0.146

Model estimation and evaluation

In selecting these models, the method relays on selecting the model with the least AIC. These are seen in the Table 6 below with matching values of AIC. Amongst these possible models ARIMA (2,0,1) was selected as the suitable model that best fits the data. That model has the least AIC and variance.

Table 6: AICs and Variances of all Suggested Models

ARIMA (p,d,q)	AIC	Variance
ARIMA (1,0,0)	329.99	12.96
ARIMA (1,0,1)	320.81	10.25
ARIMA (2,0,1)	319.41	9.59
ARIMA (2,0,2)	319.80	9.35
ARIMA (1,0,2)	319.53	9.61

From table 7, we are 95% con dent that all the coefficients of the ARIMA (2,0,1) model are significantly different from zero and the estimated values satisfy the stationary condition.

Table 7: ARIMA (2,0,1) Parameter Estimates

Variable	Estimate	Standard Error
Intercept	6.4064	0.0401
AR (1)	0.1488	0.3978
AR (2)	-1.4519	0.4031
MA (1)	-0.5481	0.4001
$\delta^2 = 9.59$		

Modelling using auto regressive integrated moving average on maternal mortality

From table 8, the test of stability of the data (maternal mortality) using the Augmented Dickey Fuller (ADF) test where the null hypothesis (H_o): the series is not stationary and the alternative hypothesis (H_1) : the series is stationary resulted the rejection the null hypothesis since the P-values for both drift and trend are less than the alpha value (0.05), we can therefore conclude that the series is stable by the ADF test. The Kwiatkowski Philip Schmidt Shin (KPSS) test with null hypothesis (H_o): the series is stationary and alternative hypothesis (H_1) : the series is not stationary; therefore, we have no evidence against the null hypothesis since the critical value (0.1323) is greater than the test statistic (0.1219). Hence, we fail to reject the null hypothesis and state that the series is stationary.

Table 8: stationary Test for the Series (maternal mortality)

Test	F-Statistic	P-value
ADF: Drift	20.65	0.000
ADF: Trend	15.64	0.000
Test	Test Statistic	Critical value (5%)
KPSS	0.1323	0.146

Model estimation and evaluation

In selecting these models, the method relays on selecting the model with the least AIC. Among these possible models ARIMA (1,0,0) was selected as the suitable model that the data well. This model has the least AIC even though its variance is slightly higher than the other options.

Table 9: AICs and Variances of all Suggested Models

ARIMA (p,d,q)	AIC	Variance
ARIMA (1,0,0)	283.80	6.00
ARIMA (1,0,1)	284.53	5.85
ARIMA (2,0,1)	286.07	5.80
ARIMA (2,0,2)	286.67	5.65
ARIMA (1,0,2)	286.07	5.80

Table 10: Parameters Estimate for ARIMA (2,0,1)

Variable	Estimate	Standard Error
Intercept	4.5628	0.3795
AR (1)	0.1695	0.1276
$\delta^2 = 6.00$		

It is clear from the table 10, that this is auto regressive of the order one (1), which is significantly different from
zero and follows the stability condition.

Table 11: Models with their respective coefficient of determination

R Square			
Series	LTST	ARIMA	Method
Under 5yrs death	0.470	0.434	LTST
Infant mortality	0.403	0.567	ARIMA
Maternal mortality	0.282	0.465	ARIMA

From table 11 the preferred method to use is based on the coefficient of determination. This the amount of variability in the data explained by the model or the response variable. It is clear that the linear trend with seasonal terms explains 75.5% of the variations in the data (live birth) whereas ARIMA model explains 48.3%. hence it is prudent to use the linear trend with seasonal terms. Also, with the infant mortality ARIMA model explains 56.7% as compared to 40.30% for LTST meaning model will be the preferred choice. Base on this it is clear to ARIMA in modelling maternal mortality and under five mortalities.

4. Discussions

The study has been looking at figures from child /infant mortality and maternal mortality from 2007-2018 in the Tamale metropolis. It was observed from the preliminary analysis that most infant mortality cases recorded across the period was in 2017 followed by 2016 and 2015. The trend was in a fluctuating manner, thus not on the increase nor decrease. Evident from figure 1. Secondly, from figure 1 again it was shown that 2017 recorded the least amount of child mortality with the highest in 2016. There also existed some fluctuations in the data as well. Moreover, from the plot of maternal mortality, there was growth in maternal mortality from 2014 to 2017 indicating that cases of maternal mortality in the Tamale metropolis keeps increasing and declined in 2018. It is also key to note that the month of January in the year 2018 recorded no case of maternal mortality in the metropolis. Whereas there was a clear picture from figure 2 that child mortality in any of the years under study was higher than infant mortality which gives a reason to pay attention to child mortality in metropolis. Same applied figure 2 which still had the graph of child mortality above infant mortality and maternal mortality below. This depicts that maternal mortality is very low in the metropolis compared to child and infant mortality. It can be pointed out across the years under study that child mortality was always at its peak in the third quarter from 2014 to 2016 then the fourth and third quarter took over for 2017 and 2018 respectively. Whereas the least cases happened in the second quarter of 2014,2015 and 2017 then the fourth quarter for 2018 and 2016.

Furthermore, the highest infant mortality cases were recorded in the first quarter for all the years except in 2016 which was in the third quarter. Then the smallest figures of such cases in the second quarter of 2014 and 2015 with 2015 repeating itself in the third quarter where the rest of the figure occurred in fourth quarter for 2016, 2017, 2018. Also, maternal mortality recorded high incidence of cases in the second and third quarters of 2014, third quarter of 2015, first quarter of 2016, second and third quarters of 2017 and 2018 respectively. After the further analysis was carried out using the linear trend with seasonal terms and auto regressive integrated moving average in modelling, the coefficient of determination was the basis for selecting the best model. It was clear that the linear trend with seasonal terms explains was the best model to be used in forecasting for under five years death and live birth with r-square 47% and 75.5% respectively and the auto regressive was also fitting for infant and maternal mortality with 56.70% and 46.50% as the r-square. Thus, the models explain such amount of variation in the response variable. In the modelling of using the linear trend with seasonal terms on child mortality, the analysis of variance table in table 3 had a p-value (0.001) showing a 95% confidence in the model derived to be significant. Also, the constant or intercept and the coefficient of determination for the seasonal dummy variables such as January ($X1$), August

($X8$), September ($X9$) and October($X10$) are all significant at 5% level of significance, hence they play a vital role in the prediction of future values. Also modelling the live birth in the metropolis showed that the model derived is also significant with p-value (0.000). And the coefficient of the seasonal dummy variables representing these months April, May, September, October and November where all significant. Modelling using the auto regressive integrated moving average on both infant and maternal mortality passed the stationary test using the ADF and the KPSS and the best model based on the AIC was ARIMA (2,0,1) and AR (1) respectively.

5. Conclusions

We can therefore come to a conclusion that, evident from the analysis carried out, child mortality in the Tamale metropolis is on the rise compared to infant and maternal mortality. Also, it is understandable from the correlation analysis performed that there was a mild correlation between all the mortality cases and live birth in the metropolis. But there exists a strong positive correlation between infant mortality and maternal mortality. It was also derived that child mortality can best be predicted using the linear trend with seasonal terms whereas infant and maternal mortality can be best predicted by the auto regressive integrated moving average in the metropolis. Which confirms with Smart (2013) and David et al, (2018) in modelling maternal mortality.

6. Declaration

We declare that the research work has not been published in any Journal but is just situated in the student data base of Kwame Nkrumah University of Science and Technology, where the candidate had his master of philosophy degree. And part of the research work has been presented for publication.

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