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Projection of HIV/AIDS Mortality in Adamawa State through the Lee-Carter Model: Strides toward SDG-3

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Abstract

Globally, HIV/AIDS remains a significant health concern, with profound impacts in developing nations, including Nigeria. This study aims to project mortality among HIV patients in Adamawa State using the Lee-Carter model to assess progress towards the third Sustainable Development Goal (SDG-3) - terminating AIDS by 2030. Mortality data for 2011-2020 on HIV patients aged 15-59 years receiving antiretroviral therapy (ART) was obtained from Adamawa State AIDS control database. The Lee-Carter model, using the Singular Value decomposition (SVD) for parameter estimation was fitted to estimate age-specific parameters. The time series component was forecast using ARIMA(0,1,0). Mortality data from 2011 to 2020 revealed a substantial 296% reduction in mortality, a testament to government and NGO interventions. The study delineates varied age group responses to improvements in mortality rates, pinpointing ages 55-59 as the most affected, while ages 15-19 exhibit the lowest mortality rates. Furthermore, individuals aged 20-24 show heightened responsiveness to general mortality improvements compared to other age cohorts. This work substantiates that Adamawa State has achieved substantial progress, exceeding the SDG-3 target of a 90% decline in HIV/AIDS patient mortality rate, setting a promising trajectory towards an AIDS-free society by 2030. However targeted strategies are still needed for older patients.

Keywords: Mortality, HIV/AIDS, Lee-Carter Model, Projection, Nigeria

Introduction

HIV/AIDS has been a major health concern for the past decades, as it has not only affected the economic growth of sub-Saharan Africa, but has also permeate the sustainable development (Odugbesan and Rjoub, 2019, 2020). On a global level, Nigeria has a ranking as one of the top three countries with People Living with HIV(PLHIV) (Ukaegbu *et al.*, 2022).

Though significant progress has been made to curtail the prevalence of HIV (Jones *et al.*, 2019), propelled by SDG-3-("Ensure healthy lives and promote well-being for all at all ages") which has a commitment to obliterate the prevalence of the epidemics of tuberculosis, AIDS, malaria and all other health threats by the year 2030 (Project 2030). This goal can only come to fruition within the stipulated deadline if the number of new infections and deaths attributed to HIV/AIDS declines by at least 90% between 2010 and 2030 (Assefa and Gilks, 2020). This is year 2023 the question is; has Nigeria meet up to these expectations? More specifically, has Adamawa State as a part of the northeast meet up to these expectations? Can we find out how close we are to these goals?

The main challenges actuaries face is the modeling of future mortality evolution. To that effect, the Lee-Carter (LC) model serves as a major breakthrough and a benchmark mortality forecasting model (Chen and Khaliq, 2022; Liu *et al.*, 2019). The LC model and its variants has been given special consideration by actuaries as a tool to forecast the constantly evolving mortality rates as the demand for future mortality data is on the rise to determine the amount of premium which ought to be paid by a company (Safitri *et al.*, 2018; Safitri *et al.*, 2019).

The LC model and its variant has been used to forecast trends in the general mortality of population, cause specific mortality and mortality by sex or as many categories as possible and also to predict the future trends of mortality. Also, the model, because of its parsimonious quality have gain an edge over the other mortality forecasting models in actuarial science. However, little or no attempt have been made to study the trends and make forecasts of the likely future of HIV AIDS patients mortality using LC approach. This study aims to bridge the gap by projecting the mortality of HIV AIDS patients using the LC model. Their likely future and how well the antiretroviral therapy (ART) care intervention is efficient.

Literature Review

Fajar and Fajariyanto (2022) in their study fitted the LC model to mortality data of Indonesia by age group from a period of 1950-2015 using the Bayesian approach. Their results shows that average infant mortality rate is high however at the age of toddlers the average mortality rate decreased. Moreso, average mortality rate in children and adolescents, young and older age people shoot up again. Zili *et al.* (2018) Likewise in their study of the Indonesian mortality rate estimated the LC model parameters using the Singular Value Decomposition (SVD) technique. They observe that the data fits the LC model well, however a better result could be obtained if more data were processed than the one used in their study. Ibrahim *et al.* (2021) made a critical observation about the best fitting period of LC model. In their study, they fitted the Lee-Carter model to Malaysian central mortality rate from year 1970-2018. They determined two different fitting period due to changes in the general pattern of mortality. The first set consist of 24years period from the year 1970-1993 and a second fitting period of 31 years from 1970-2000. They evaluated the performance of the LC model for each fitting period using the Akaike Information Criterion (AIC). Their results indicated that first set better fits the LC model than the second set.

Since the first formulation of the LC model in 1992, various extension to the original model has been formulated in an effort to better fit and forecast the evolving mortality rates of population under study. Nigri *et al.* (2019) in their paper, posited an alternative model to forecast the Kt parameters using the Recurrent Neural Network with a Long Short-Term Memory and integrate the LC model to enhance the predictive capacity as opposed to the traditional ARIMA approach. According to their study, their proposed alternative provides a better performance in forecast and hence an improvement in the overall performance of the model.

One of the assumptions of the LC model is the assumption of constant age-specific response to the general time index. Bergeron-Boucher and Kjærgaard (2022) in their study, investigated and provided a better evaluation of this bias by age. They focused on ages 65 and above, as death rate is higher at older ages. Their study came to the conclusion that the LC model at its basic form is not biased but rather the aforementioned assumption often leads to a constant rate in mortality improvement which is not the case in most populations at older ages.

Peres (2022) made a comparative study of the LC model in extrapolating the general level in the number of hospital admissions in state of São Paulo, Brazil. They used the traditional time series ARIMA model and compared it with the Long Short-Term Memory (LSTM) neural network. They fitted the model to a data of hospital admissions from 2008-2019. The results revealed that the LSTM model and the time series ARIMA have similarities in root mean square error (RMSE) and also the mean absolute error (MAE) performance.

Debón *et al.* (2021) asserted that the model developed in 1992 by Lee and Carter for modeling of mortality rates in USA was a major breakthrough in forecast of life expectancy. Since then, the classical LC model and various extensions to it with different hypothesis and constraints to the parameters have been employed to better fit the historic mortality data and hence to improve forecast. Their work was aimed to analyze the difference between models using different mortality indicators. To achieve this, nine setoff indicators were compared each with samples of size fifty. Their result suggests model's forecast should be checked in the aspect of the mortality indicators and their probabilities.

Research Method

The choice of the LC model is almost a no brainier as scholars have used the model in the study of most mortality related data for the pass decades. we chose an easy and appropriate method to estimate the parameters of the LC model. At the first stage, Singular Value Decomposition (SVD) was applied to the matrix of $\log(m_{x,t}) - \alpha_x$ to obtain estimate of β_x and then k_t. To forecast the kappa parameter, the time series ARIMA model is fitted to the estimates of kappa obtained.

Source of data for the study

The data set used in this paper comprised of HIV/AIDS records of patients on ART for the period of ten years (2011-2020), the sample of interest is the number of deaths within each

age group 15 - 59 for each year, obtained from Adamawa State Agency for the Control of AIDS database. All statistical data analyses and computations was carried out using R Software Version 4.1.0.

Model Specification

The LC model is the model adopted for the purpose of this study and is explained as follows:

The LC model is a simple model comprises of two independent linear variables x which represent (age) and t which represent (time) or period, defined as

$$\ln m_{x,t} = \alpha_x + \beta_x k_t + \varepsilon_{x,t} \quad (1)$$

Where, $m_{x,t} = \frac{d_{x,t}}{e_{x,t}}$, represent the matrix of mortality rate on a specific age group at age, x, ($x = x_{1,\ldots,}x_n$)=x_1,...,x_n) over a period (t) $(t = t_{1,}t_1 + 1, +T - 1)$, traditionally it is defined as the ratio of total death at age x in year t to the number of persons at risk at age x in year t.

α_x; captures the average (overtime) of the logarithm the rate describing the general mean of the age profile.

β_x; captures the sensitivity rate to the changes in general level of mortality at age x I.e (it represents the rate at which an individual at age x will respond to changes attributed to general mortality fluctuations).

k_t; represent the time index of the general level of mortality of the cohort under study.

$\varepsilon_{x,t}$; denotes the residual or a set of random error (white noise) from factors not captured by the model.

$$\boldsymbol{\varepsilon_{x,t} \sim N(0, \sigma^2),\ \ E(\varepsilon_{x,t}) = 0,\ \ var(\varepsilon_{x,t}) = \sigma^2} \quad (2)$$

The above parameters can be interpreted using sets of constraint as follows

$$\boldsymbol{\alpha_x = \frac{1}{T}\sum_t \ln m_{x,t}} \quad (3)$$

$$\boldsymbol{k_t = \sum_t (lnm_{X,t} - \alpha_x)} \quad (4)$$

The equation $\widehat{\alpha_x} = \frac{1}{T}\sum_{t=t1}^{tn} \ln(m_{x,t})$ represents the mortality evolution over time.

ARIMA Model:

To forecast the mortality index, the ARIMA model come in handy. After the estimation of the model parameters of the LC model, the kappa estimates are then fitted to the univariate model of ARIMA (0, 1, 0). After trying various techniques to forecast the time series component of the model, it turns out that the random walk with drift is the best model to forecast the kappa parameters. The model is given by

$$\boldsymbol{k_t = k_{t-1} + \theta + \varepsilon_t} \quad (5)$$

Where;

θ::is the drift parameter.

ε_t: is the error term with mean zero and a variance $\varepsilon_t \sim N(0, \sigma^2)$. The drift parameter $\widehat{\theta} = \frac{\hat{k}_T - \hat{k}_1}{T-1}$.

It is obvious that the drift parameter $\hat{\theta}$ depends only on the first and last of k_t estimates of the model. To forecast like two periods ahead, one need just to substitute for the definition of $\hat{k}_{t-1}$ which is denoted by $m_{x,t+1,} e^{\widehat{\alpha_x} + \widehat{\beta_x}\widehat{k_t}}$ moved back in time one period that is;

$$\widehat{k_t} = \widehat{k_{t-1}} + \hat{\theta} + \varepsilon_t$$

$$= \left(\widehat{k_{t-2}} + \hat{\theta} + \varepsilon_{t-1}\right) + \hat{\theta} + \varepsilon_t$$

$$= \widehat{\boldsymbol{k_{t-2}}} + \boldsymbol{2\hat{\theta}} + (\boldsymbol{\varepsilon_{t-1}} + \boldsymbol{\varepsilon_t}) \quad \textbf{(6)}$$

Now to forecast kappa $\widehat{k_t}$ at any time period say T+ (Δt) using the data available for a period say T, we iterate the procedure for (Δt) times and obtain as follows:

$$\widehat{\boldsymbol{k}}_{\boldsymbol{T+(\Delta t)}} = \widehat{\boldsymbol{k_T}} + (\boldsymbol{\Delta t})\hat{\boldsymbol{\theta}} + \sum_{\boldsymbol{n}}^{(\boldsymbol{\Delta t})} \boldsymbol{\varepsilon_{T+n-1}} \quad \textbf{(7)}$$

$$= \widehat{\boldsymbol{k_T}} + (\boldsymbol{\Delta t})\hat{\boldsymbol{\theta}} + \sqrt{(\boldsymbol{\Delta t})\boldsymbol{\varepsilon}_{\boldsymbol{t}}} \quad \textbf{(8)}$$

t=1, 2, ---, T

Result and Discussion

Mortality Patterns and Age-Specific Trends

The estimation of the αx and βx parameters of the LC model shows that mortality patterns vary significantly across different age groups (Table 1). Since αx is the first parameter in the LC model, it is obtained as the mean of the age-specific death rate across the years (time). And Figure 1 shows a line graph of α_x parameter of the Lee-Carter model.

Table 1: The result of the estimated αx and βx parameter of the LC model

Age group	Alpha (α_x)	Beta estimate (β_x)
15-19	-3.61103	0.137785
20-24	-2.44994	0.150946
25-29	-2.60628	0.133639
30-34	-2.40348	0.125468
35-39	-2.84586	0.131830
40-44	-2.95407	0.142838
45-49	-2.83516	0.138213
50-54	-1.02519	0.026645
55-59	-0.72909	0.012636

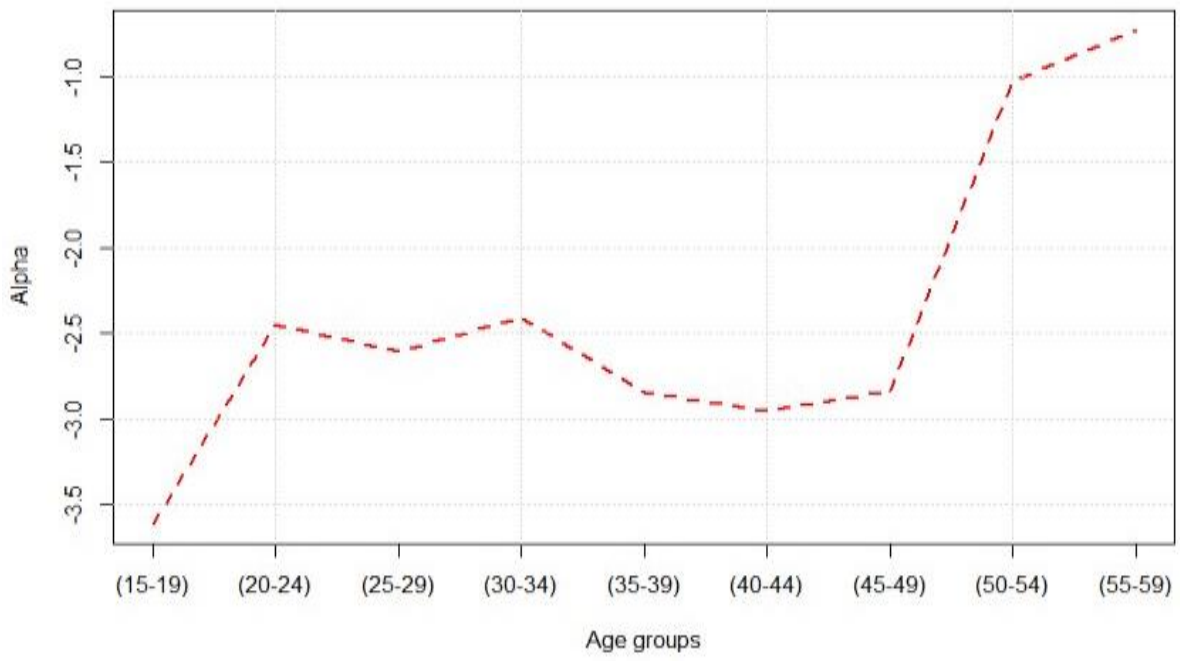

Figure 1: Graph of Estimated Alpha α_x

The αx parameter, which represents the general level of mortality, is lower for younger age groups (15-19) and increases as individuals get older, particularly for those aged 50-59. This suggests that younger populations, particularly those in the age group of 15-19, experience the lowest mortality rates, potentially due to fewer HIV/AIDS-related deaths at this stage of life. This finding aligns with the general trend observed in HIV/AIDS research, where younger populations tend to have lower HIV-related mortality rates, as highlighted in previous studies (Mills *et al.*, 2011). Conversely, the older age groups (50-59) exhibit higher mortality rates, indicating a more severe impact of HIV/AIDS in older populations. This observation is consistent with existing literature, which suggests that older HIV-positive individuals often experience more complications and higher mortality due to comorbidities and a slower immune response to treatment (Smit *et al.*, 2015). These findings are critical, as they emphasize the need for targeted healthcare interventions for older populations to reduce mortality rates and improve quality of life.

Responsiveness to Mortality Fluctuations

The estimation of the βx parameter represents the rate at which individual at the age will respond to the changes attributed to general mortality fluctuations (Table 1). It shows that individuals aged 20-24 are most sensitive to changes in the overall mortality rate (Figure 2). This finding indicates that individuals in this age group are more likely to experience improvements in survival as general mortality rates decrease. Previous research has shown similar trends, where younger adults (20-24) tend to benefit more from antiretroviral therapies (ART) and other medical interventions compared to older age groups, due to better adherence and immune recovery (Rodger *et al.*, 2013).

However, the βx parameter also suggests that older individuals (50-59) are less responsive to changes in mortality, indicating that improvements in general mortality rates have

a limited impact on this age group. This underscores the challenge of reducing mortality in older HIV-positive populations, as they often face multiple health challenges beyond HIV infection itself, such as cardiovascular diseases and diabetes (Guaraldi *et al.*, 2011).

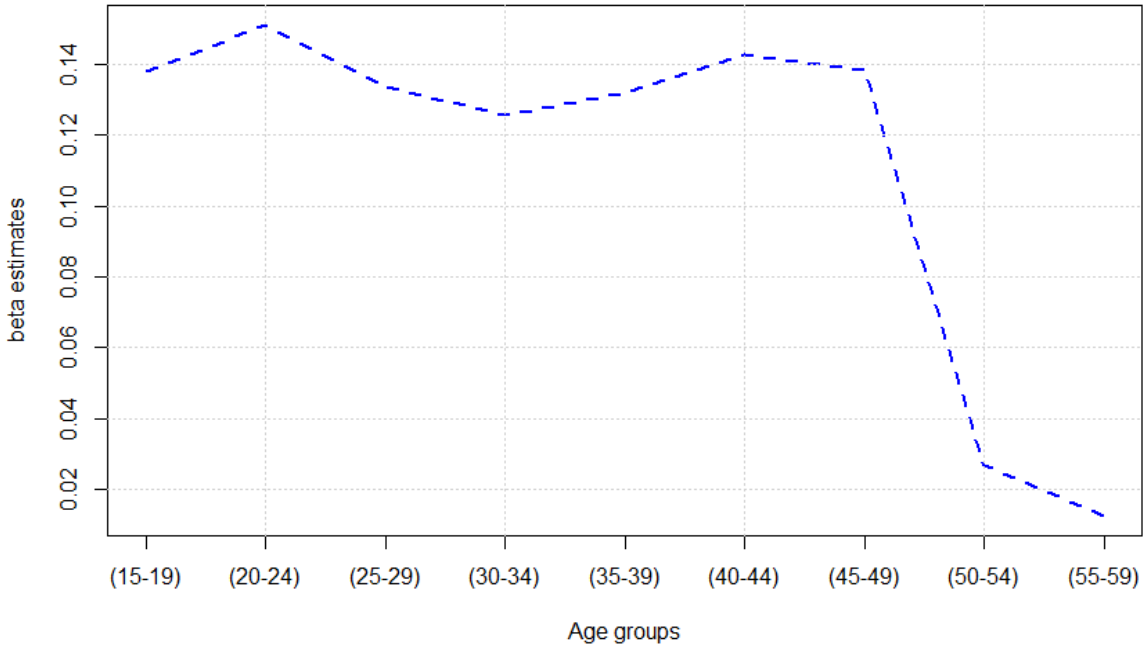

Figure 2: Graph of estimated Beta β_x

Estimation of the κ_t Parameter of LC Model

Table 2 shows the estimate of the time series component of the LC model. Figure 3 gives line graph for the estimated k_t parameter.

Table 2: Result of the estimated (κ_t) parameter of the Lee-Carter Model

YEAR	KAPPA_ESTIMATE
2011	3.99378
2012	3.54397
2013	2.65515
2014	1.88735
2015	1.22478
2016	0.91715
2017	0.88900
2018	0.88900
2019	-7.97910
2020	-7.81300

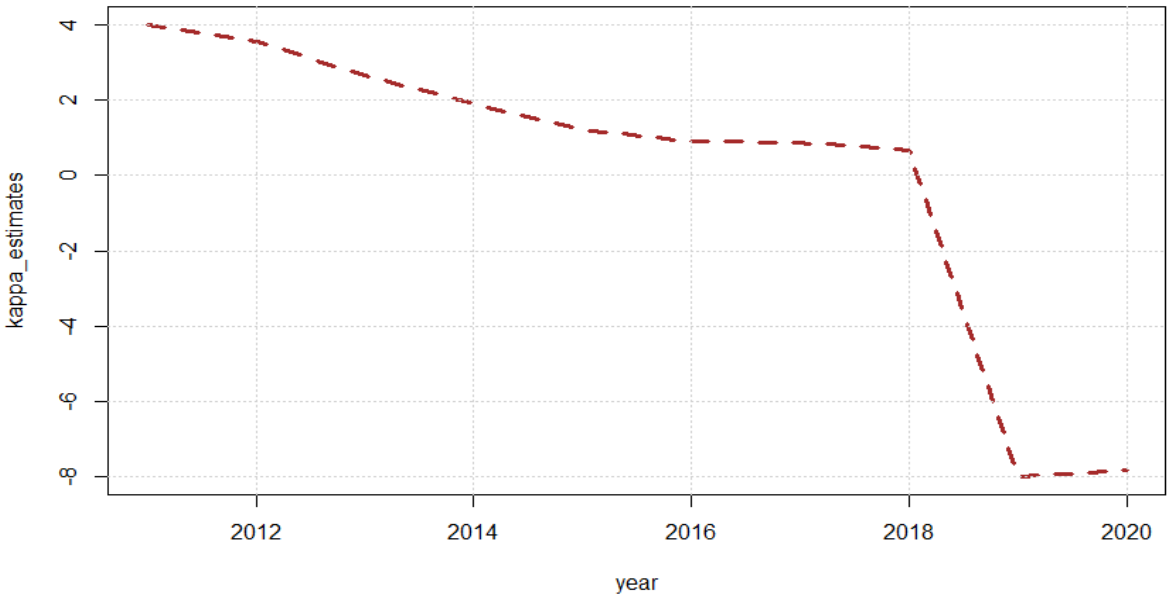

Figure 3: Graph of estimated kappa parameter κ_t

The parameter k_t represents the general level of mortality of the population under study at that index year. It is also known as the mortality index tracking the main time pattern on the logarithm scale of mortality for all the ages. k_t is obtained from the vector value ($k_t = D_1 V_{t1}$), findings show a downward trend in mortality pattern from 2011 to 2020, reflecting a substantial decline in mortality rates during this period. This is consistent with global trends in HIV/AIDS mortality, where advancements in ART and improvements in healthcare access have led to significant reductions in mortality rates (UNAIDS, 2020). The data indicate a reduction of approximately 296% in mortality rates between 2011 and 2020, suggesting that Adamawa State has made notable progress in controlling HIV/AIDS-related deaths.

Forecasting the Kappa (κ_t) Component of the Lee-Carter Model

The application of the ARIMA model for forecasting mortality rates reveals that the ARIMA (0,1,0) model provides the best fit for predicting future mortality trends, with no significant fluctuations expected in the k_t component beyond 2020 (Table 3). The minimum AIC was 47.29, hence it is the best predictive model based on the model selection creteria of AIC for forecasting the κ_t parameter. This forecast aligns with studies that project stable or declining HIV/AIDS mortality rates in regions with effective ART programs (Mahy *et al.*, 2021). The predicted stability of mortality rates suggests that, if current healthcare practices are maintained or improved, the state is on track to meet the 2030 Sustainable Development Goal (SDG-3) of significantly reducing HIV/AIDS-related deaths.

The plot of the autocorrelation function (Figure 4), shows a significant spike at lag zero that is considered as insignificant in determining the order of the Moving Average (MA) term of the ARIMA model. Hence an MA term of zero and consequently, the drift parameter θ is also zero since it is accounted for by the order of the MA term. The plot of the partial autocorrelation function shows no significant spike at any lag in the lifetime of the series. This implies an AR term of order zero in the ARIMA model**.** Hence, the best fit for the kappa values

can also be determined by examining the partial autocorrelation factor (PACF) and the autocorrelation factor (ACF) plots alone.

Table 3: Summary of the best ARIMA models

Model	Sigma squared	AIC
ARIMA(2, 1, 1)	7.953	52.95
ARMA(2, 1, 0)	8.953	51.28
ARIMA(1, 1, 1)	8.976	51.29
ARIMA(0, 1, 1)	8.976	49.29
ARIMA(0, 1, 0)	8.976	47.29
ARIMA(1, 1, 0)	8.976	49.29

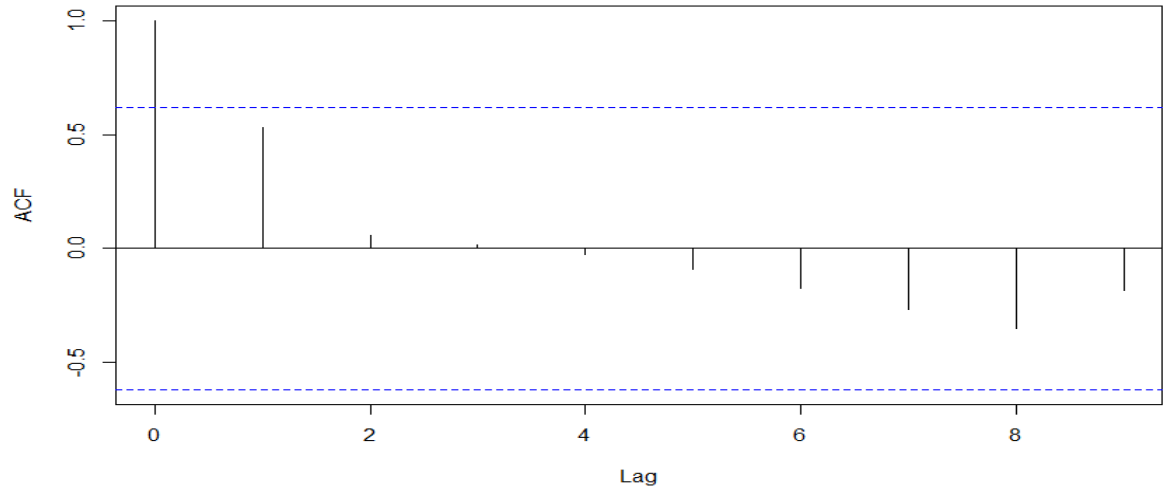

Figure 4: Autocorrelation function: series k_t estimates

In forecasting the future mortality rates of the Lee-Carter model the equation (5) is employed and only the k_t parameter is forecasted. The forecast of the parameter estimates is presented in Table 4 which shows the forecasted values of the time component of the LC model base on the ARIMA(0,1,0).

$$\boldsymbol{k_t = k_{t-1} + \theta + \varepsilon_t} \qquad \textbf{(9)}$$

Table 4: Forecast of the kappa value

Year	Point Forecast	Lo80	Hi80	Lo95	Hi95
2021	-7.813	-11.653	-3.9734	-13.685	1.94080
2022	-7.813	-13.243	-2.3829	-16.117	0.49154
2023	-7.813	-14.463	-1.1626	-17.984	2.35793
2024	-7.813	-15.492	-0.1338	-19.557	3.93137
2025	-7.813	-16.399	0.77265	-20.944	5.31761
2026	-7.813	-17.218	1.59211	-22.197	6.57085
2027	-7.813	-17.972	2.34568	-23.349	7.72334
2028	-7.813	-18.673	3.04708	-24.422	8.79604
2029	-7.813	-19.332	3.70585	-25.429	9.80354
2030	-7.813	-19.955	4.32893	-26.382	10.7565

Figure 5 shows the plot of the forecasted kappa values base on the ARIMA(0,1,0) which is the model with the minimum AIC and hence the best fit for the kappa values.

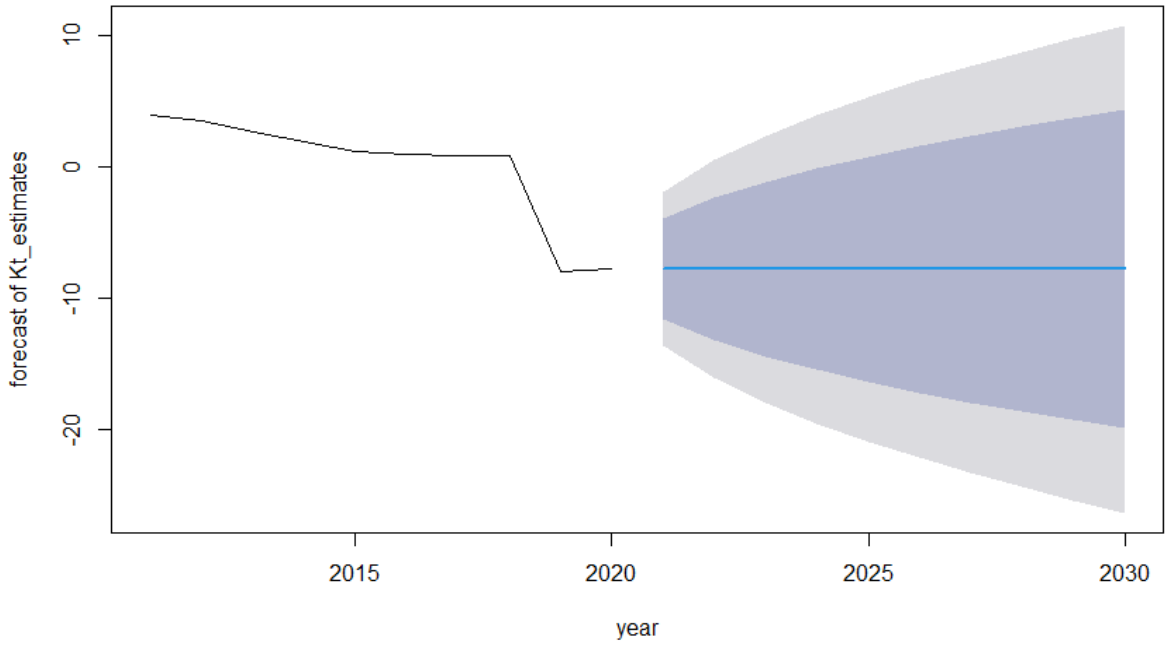

Figure 5: The plot of forecast value from ARIMA(0,1,0)

Death Rates Forecast

The forecast of death rate is obtained from the equation of the Lee-Carter model;

$$\ln m_{x,t} = \alpha_x + \beta_x k_t \quad \textbf{(10)}$$

From Table 5, the point forecast of the general level of mortality κ_t is constant throughout the years. This is because the drift parameter θ is zero because of the MA term of zero in the ARIMA (0,1,0), hence constant κ_t. However, all the other age component parameters are varying depending on a group as can be seen in Table 1.

Table 5 present the age-specific death rate forecast of HIV/AIDS mortality from 2021 to 2030. The forecast indicates a declining mortality rate across all age groups.

Table 5: Death rate forecast $[exp(\alpha_x + \beta_x k_t)]$

Year	Age Groups								
	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59
2021	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2022	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2023	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2024	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2025	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2026	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2027	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2028	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2029	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007
2030	0.008455	0.045355	0.049325	0.051398	0.021117	0.026022	0.024745	0.028015	0.075007

This study investigated the possibility of bringing to end the epidemic attributed to HIV/AIDS in Adamawa State within the stipulated deadline, by examining the death rates of PLHIV. The findings of this study are consistent with other research on HIV/AIDS mortality, particularly in sub-Saharan Africa. Studies have shown that the introduction of ART has had a profound impact on reducing mortality rates, particularly in regions with high HIV prevalence (Mills *et al.*, 2011; Smit *et al.*, 2015). The decline in mortality rates observed in Adamawa State mirrors similar patterns seen in countries like South Africa and Uganda, where widespread ART distribution has significantly reduced AIDS-related deaths (Mahy *et al.*, 2021).

However, despite these positive trends, the higher mortality rates among older populations observed in this study remain a challenge. Studies suggest that older HIV-positive individuals require more comprehensive care, including management of comorbidities and age-related health issues (Guaraldi *et al.*, 2011). These findings highlight the need for targeted interventions for older PLHIV, as well as continued efforts to reduce stigma and improve healthcare access for all age groups.

Conclusion

The study provides important insights into the mortality patterns of HIV/AIDS patients in Adamawa State, highlighting the differential impact of the epidemic across age groups. The results show a significant reduction in overall mortality rates, particularly among younger populations, and project a continued decline in deaths by up to 296% if current healthcare interventions are maintained. However, the study also underscores the need for targeted healthcare strategies for older HIV-positive individuals, who remain at higher risk of mortality. These findings contribute to the broader understanding of HIV/AIDS mortality trends and provide a basis for future public health interventions aimed at achieving the SDG-3 target of ending the AIDS epidemic by 2030.

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