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Temporal and Spatial Analysis of Lymphatic Filariasis in Nigeria: Evaluating the Impact of Mass Drug Administration Interventions

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A B S T R A C T

Lymphatic filariasis (LF) remains one of Nigeria's most persistent neglected tropical diseases, despite over two decades of targeted intervention. This study applied advanced statistical methods to analyze the temporal and spatial patterns of LF in Nigeria from 2013 to 2023, with particular focus on evaluating the effectiveness of the Mass Drug Administration (MDA) program. Annual LF incidence and coverage data obtained from the World Health Organization were analyzed using time series models, interrupted time series regression, and exploratory spatial analysis. The findings revealed that although national LF incidence has declined over time, substantial regional disparities persist, with several northern states maintaining high burden levels. The interrupted time series results indicated that MDA interventions produced statistically significant, though regionally uneven, reductions in disease incidence. Spatial visualization and clustering analyses highlight persistent hotspots, reinforcing the importance of region-specific strategies. The study concluded that sustained MDA coverage, strengthened surveillance, and socio-economic improvements are essential for achieving LF elimination targets by 2030.

1. Introduction

Lymphatic filariasis (LF), commonly known as elephantiasis, remains one of the most disabling neglected tropical diseases (NTDs) in tropical and subtropical regions. It is caused primarily by *Wuchereria bancrofti* and transmitted by mosquito vectors namely *Anopheles* and *Culex* species (WHO, 2020; Simpnsen *et al*., 2014). The infection leads to chronic lymphedema, hydrocele, and other severe deformities that cause lifelong disability, social stigma, and economic hardship (Molyneux *et al*., 2000). Although the disease is preventable and targeted for global elimination through the World Health Organization's Global Programme to Eliminate Lymphatic Filariasis (GPELF) introduced in 2000 (Shirley *et al*., 2024), it continues to pose a serious public health challenge in many developing countries. At the turn of the millennium, the World Health Organization (WHO) estimated that over 120 million people were infected across 73 countries, with more than one billion at risk (WHO, 2000). Globally, significant progress has been made, particularly in Asia, where sustained Mass Drug Administration (MDA) campaigns have drastically reduced

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transmission (Ottesen *et al*., 2008; Ramaiah & Ottesen, 2014), inclusive are Bangladesh and Lao People Democratic Republic which entered elimination list in 2023 (Shirley *et al*., 2024). As at 2024, 37 countries no longer requires mass drug administration (MDA) and the target to make 80% endemic countries attain elimination as a public health problem by 2030 is ongoing (WHO, 2025). However, progress in Africa has been less consistent (Gyapong & Boatin 2016). Nigeria, in particular, remains one of the most affected countries, carrying nearly 40% of the LF burden in sub-Saharan Africa (Okorie *et al*., 2021; WHO, 2022). An estimated 80–120 million Nigerians remain at risk with a prevalence of 11.18%. The breakdown is as follows: North West (1.59%); North Central and North East (4.52%); South West (1.26%) while South South with South East (3.81%) (Waje *et al*., 2024; Adewale *et al*., 2019).

Since 2000, Nigeria's elimination programme has relied primarily on annual Mass Drug Administration (MDA) campaigns using Ivermectin and Albendazole. The WHO recommends at least 65% population coverage to interrupt transmission, yet Nigeria has struggled to sustain this target uniformly across states. Studies such as Eigege *et al.*, (2013, 2017) have documented significant progress in certain areas like Plateau and Nasarawa states following consistent MDA implementation. However, other regions particularly in the northern and riverine zones continue to experience persistent transmission (Okorie & Ademowo, 2019). Environmental, socio-economic, and infrastructural disparities further compound these challenges, creating distinct regional differences in LF distribution.

Existing literature on LF in Nigeria has focused largely on prevalence mapping, clinical epidemiology, community surveys, and programmatic assessments (Waje *et al.,* 2024; Okonofua, 2023). While these studies have provided useful descriptive insights, most lack the application of advanced statistical techniques that can rigorously evaluate disease trends and intervention outcomes over time. Few have systematically assessed how MDA interventions have altered incidence trends or whether coverage improvements correspond to measurable declines in LF burden. Likewise, although several studies have used geospatial visualization to describe regional variation, few have examined how these spatial patterns evolve alongside programmatic interventions (Bernal *et al.,* 2017; Anselin, 1995; Getis & Ord, 1992).

This study addresses these methodological gaps by applying temporal and spatial analytical approaches to LF data from 2013 to 2023. Time series and interrupted time series (ITS) regression models are used to evaluate changes in LF incidence trends and the impact of MDA interventions, while exploratory spatial mapping techniques are employed to visualize regional disparities in coverage and burden across Nigerian states. Nigeria's size and diversity further complicate the situation. With over 200 million people spread across 36 states and the Federal Capital Territory, the country faces unique challenges in disease elimination compared to smaller nations like Togo and Malawi which were first to successfully eliminated LF in Sub-Saharan Africa in 2017 and 2020 respectively (Shirley *et al*., 2024; Barrett *et al*, 2024). Vast differences in ecology, culture, and healthcare infrastructure make it difficult to implement one-size-fits-all solutions. Without strong, evidence-based strategies supported by statistical analysis, designing effective interventions for such a complex setting is nearly impossible. This integrated approach provides a more comprehensive understanding of LF dynamics, combining statistical rigor with spatial insight to inform targeted elimination strategies. By bridging descriptive epidemiology and quantitative modeling, this study contributes to the evidence base for

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Nigeria's LF elimination efforts. The findings provide policymakers with a clearer view of both temporal progress and regional inequalities, offering data-driven guidance to optimize intervention strategies and accelerate progress toward the WHO's 2030 elimination targets (WHO, 2021).

2. Methodology

Data were obtained from the World Health Organization (WHO) Global Health Observatory and the Global Programme to Eliminate Lymphatic Filariasis (GPELF) (WHO, retrieved 2024). These datasets provide standardized, country-level information on LF incidence, population at risk, and Mass Drug Administration (MDA) coverage, which ensures consistency and reliability for statistical analysis. The data covered the period 2013 to 2023.

The study area, Nigeria, consists of 36 states and the Federal Capital Territory (FCT). As the most populous country in Africa, Nigeria exhibits significant ecological and socio-economic diversity, which influences vector distribution and LF transmission dynamics. The unit of analysis is the individual state, which enabled comparisons across regions and the identification of high-burden areas. Nigeria's national LF elimination programme, launched in 2000, relies on annual MDA using ivermectin and albendazole, though coverage has varied widely across states. This uneven progress underscores the importance of applying spatio-temporal statistical models to better understand disease patterns and evaluate intervention effectiveness.

2.1 Variables considered include:

1. **LF incidence rate** (cases per 100,000 population).

   Incidence $Rate_{it} = \frac{New\ LF\ Cases_{it}}{Population_{it}}\ X\ 100{,}000$

   where *i* denotes the state, and *t* the year.

2. **MDA coverage (%)** – proportion of population treated during each annual round.
3. **Population at risk** – WHO-estimated number of individuals in each state exposed to LF transmission.
4. **Intervention periods** – year(s) of full MDA program implementation in each state, serving as breakpoints in ITS models.
5. **Derived variables** – such as average coverage (2013–2023) and year-to-year incidence changes.

2.2 Methods of Data Analysis

The methodology combines three major strands of statistical analysis:

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2.2.1 *Time Series Analysis*

To investigate temporal trends in LF incidence, time series analysis was applied (Chatfield, 2000).

Step 1: Decomposition

Each series was decomposed into:

$$Y_t = T_t + S_t + E_t$$

where:

- Y_t = observed LF incidence.
- T_t = underlying trend.
- S_t = seasonal or cyclical variation.
- E_t = error term.

Step 2: ARIMA Modeling

The Auto-Regressive Integrated Moving Average (ARIMA) model captures both persistence and shocks in incidence trends:

$$Y_t = c + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + .. + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t$$

where:

- Y_t= LF incidence at time t.
- $\emptyset$= differencing operator for stationarity.
- θ = moving average parameters.
- $\in_t$ = Error term

2.2.2 *Model Identification and Selection*

To determine the most appropriate ARIMA model, multiple specifications were fitted, and their goodness-of-fit compared using the Akaike Information Criterion (AIC). The AIC penalizes model complexity while rewarding fit, ensuring that the most parsimonious model is selected.

AIC = -2ln$(L) + 2K$

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where:

- L = maximum likelihood of the fitted model
- k = number of estimated parameters

The model with the lowest AIC was selected as the optimal ARIMA specification for each state's LF incidence series.

2.2.3 *Interrupted Time Series (ITS) Regression*

To evaluate the causal effect of MDA, ITS regression was employed.
The general ITS model is:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \epsilon_t$$

where:

- Y_t = LF incidence at time t
- T_t = time since start of observation period
- X_t = intervention indicator (0 = pre-MDA, 1 = post-MDA)
- $X_t T_t$ = interaction term (to capture change in slope post-intervention)
- β_0 = baseline level
- β_1= pre-intervention slope
- β_2 = immediate level change after MDA introduction
- β_3 = change in slope following MDA

2.2.4 *Model Diagnostics and Validation*

After fitting ARIMA and ITS models, residual diagnostics were conducted to ensure adequacy.

1. **Stationarity Tests:** Augmented Dickey–Fuller (ADF) test was used to confirm stationarity after differencing.
2. **Residual Independence:** The Ljung–Box Q-test was applied to test whether residuals were uncorrelated (white noise).

$$Q = n(n+2)\sum_{k=1}^{m}\frac{p_k^2}{n-k}$$

where:

- n = sample size

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- m = number of lags
- p_k = autocorrelation at lag k

3. **Model Fit Assessment:** Residual plots and autocorrelation function (ACF/PACF) of residuals were visually inspected.

3. Data Analysis and Interpretation

3.1 Temporal Trend Analysis of Lymphatic Filariasis (LF) Incidence in Nigeria (2013–2023)

3.1.1 *Method*

In order to determine the change in the burden of lymphatic filariasis (LF) overtime in Nigeria, the number of persons treated (popTreat) per year between 2013 and 2023 was examined. The proxy indicator of LF incidence was provided by this metric on a premise that the level of treatment is a proxy measure of the burden and the control of a disease. The data was aggregated into a univariate time series first at the national scale by year. Figure 1 shows the Seasonal-Trend decomposition with Loess (STL). Through the STL decomposition, it was observed how the LF patterns of treatment occurred with time, how seasons impacted, and how there were irregular fluctuations.

A trend component of the series was developed using the ARIMA (1,1,1) that was fitted to the series after decomposing it. The concern of possible non-stationarity of the original data was dealt with by using first-order differencing (d=1). The parameters of the model gave an idea about persistence and structure of the trend over the time which allows a more rigorous assessment of the dynamics of LF burden in Nigeria through the study period.

3.1.2 *Result of Temporal Trend Analysis of LF*

Figure 1 shows the STL decomposition of the annual number of individuals who sought treatment of lymphatic filariasis (popTreat) between 2013 and 2023. In this approach, the time series is broken up into its component parts: trend, seasonal, and residual, which gives a better insight into the nature of time-dependent developments.

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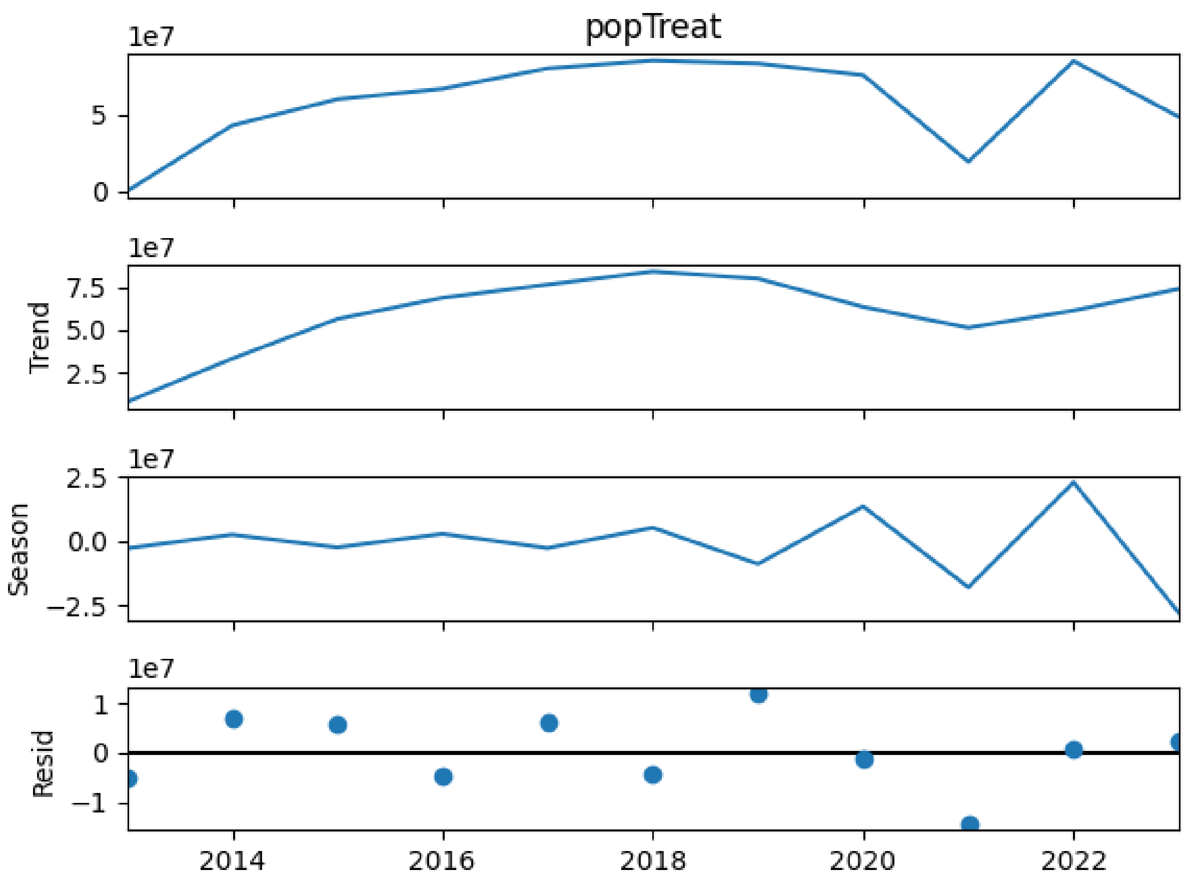

Figure 1a,b,c,d: Decomposition of Lymphatic Filariasis

Figure 1a panel presents the original time series and this indicates the annual tallies of individuals treated. A unique pattern of the trend can be observed in the Figure 1b, the upward trend in the number of treatments flowed during 2014-2018 which is related to either the growth of intervention rates or the heavier burden of the disease in this timeframe. Since 2019, however, the pattern indicates the positive slope inclination decrease moderately, which may be ascribed to the decline in the prevalence of the disease, the alteration of program execution, or the reporting and collection of data issues. Figure 1c captures a very small seasonal factor as it is supposed to be with the annual data. This attests to the fact that the number of treatments is not observed based on a regular intra-annual pattern and is in line with the characteristic of LF interventions that are normally seen at particular programmatic cadences but not seasons. Figure 1d that contains residual element observes short run. It is important to note that there is a large decline in 2021 which is presumably due to interference during the COVID-19 pandemic during the provision of health services, mass drug administration (MDA) activities, or information reporting.

3.1.3: *STL Decomposition of LF Treatment in Nigeria (2013–2023)*

The ARIMA (1,1,1) model produced the following results as shown in Table 1.

Table 1: Results Produced by ARIMA (1,1,1)

Parameter	Estimate	Std. Error	p-value
AR(1)	–0.7720	2.423	0.75
MA(1)	0.3298	2.42	0.892
σ^2	7.88 x10^14	–	<0.001

Other diagnostic indicators include AIC (378.62), Ljung-Box test ($p = 0.91$), JB test ($p = 0.41$).

According to the ARIMA model, the series became stationary after it was differenced using the first order. Although the AR and MA terms were not significant, the model shows a structural basics that there was general upward trend and a subsequent slowdown. These findings are indications that the countries national LF control interventions, particularly Mass Drug Administration (MDA) was productive in increasing treatments in the early years. Therefore, the tendency of upward trend in recent years can be caused by either the decrease of treatment necessity because of lower endemicity or decrease of the intensity of MDA.

3.2 Impact of Mass Drug Administration (MDA) Using Interrupted Time Series (ITS)

3.2.1 *Method*

An Interrupted Time Series (ITS)-based examination of the difference in outcomes related to the escalated Mass Drug Administration (MDA) at the country level using yearly treatment data between 2013 and 2023 was used to determine the impact of lymphatic filariasis (LF) control. It was chosen as the intervention point in 2017, which can be regarded as the time at which the coverage of MDA became considerably larger in Nigeria. Three variables were built in order to model the effects of this intervention:

Time: a continuous variable on the scale 1 to 11 for years 2013-2023;

Intervention: a binary indicator variable, coded 0 during the pre-intervention part (2013-2016) and 1 during the post-intervention part (2017-2023);

Post-time: the counter of years following the intervention, with the value coded 0 at all years prior to 2017 and increasing per unit time.

3.2.2 *Result*

The regression output is summarized below in Table 2.

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Table 2: Results of Regression Analysis on Mass Drug Administration

Variable	Coefficient	Std. Error	p-value	Interpretation
Intercept	-11,930,000	26,100,000	0.662	Starting point (not significant)
Time	21,680,000	9,540,000	0.057	*Upward trend before intervention (marginally significant)*
Intervention	-11,550,000	29,900,000	0.711	*No significant jump in level after 2017*
Post-Time	-27,350,000	10,400,000	**0.033**	*Significant downward slope after 2017*

Table 3: Results of Model Diagnostics

Statistic	Value
R-squared	0.607
F-statistic	3.602 (p = 0.074)
Durbin-Watson	2.94
Jarque-Bera	p = 0.230

Model diagnostics as shown in Table 3: R-squared (0.607) shows that about 61% of variability in population treated was explained by the model. F-statistic (3.602, p = 0.074) suggests that the model is moderately significant. Durbin-Watson (2.94) shows no strong autocorrelation in residuals. While, Residuals passed normality tests (Jarque-Bera p = 0.230) and shows no major issues with skewness or heteroscedasticity.

The ITS findings indicate that prior to 2017, the trend was positive and near statistical significance (p=0.057), which means growing coverage of treatment. The intervention year (2017) did not report a strong increase in the level of intervention (p=0.711) which means that there was no increase in the intervention after introduction of MDA scaling up. And the slope of post intervention became highly negative (p = 0.033) which suggests that there was a gradual reduction in the coverage of the treatment since the peak years.

3.3 Regional Differences in LF Burden

3.3.1 *Method*

Descriptive statistics and visualization were applied to study the patterns of spatial distribution of LF treatment. The variable person treated (popTreat) was the one on which the analysis was done and it takes the total number of those who have been treated. This variable was summed up on a state level, including all states in Nigeria (36) and Federal

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Capital Territory (FCT) in the years 2013-2023.

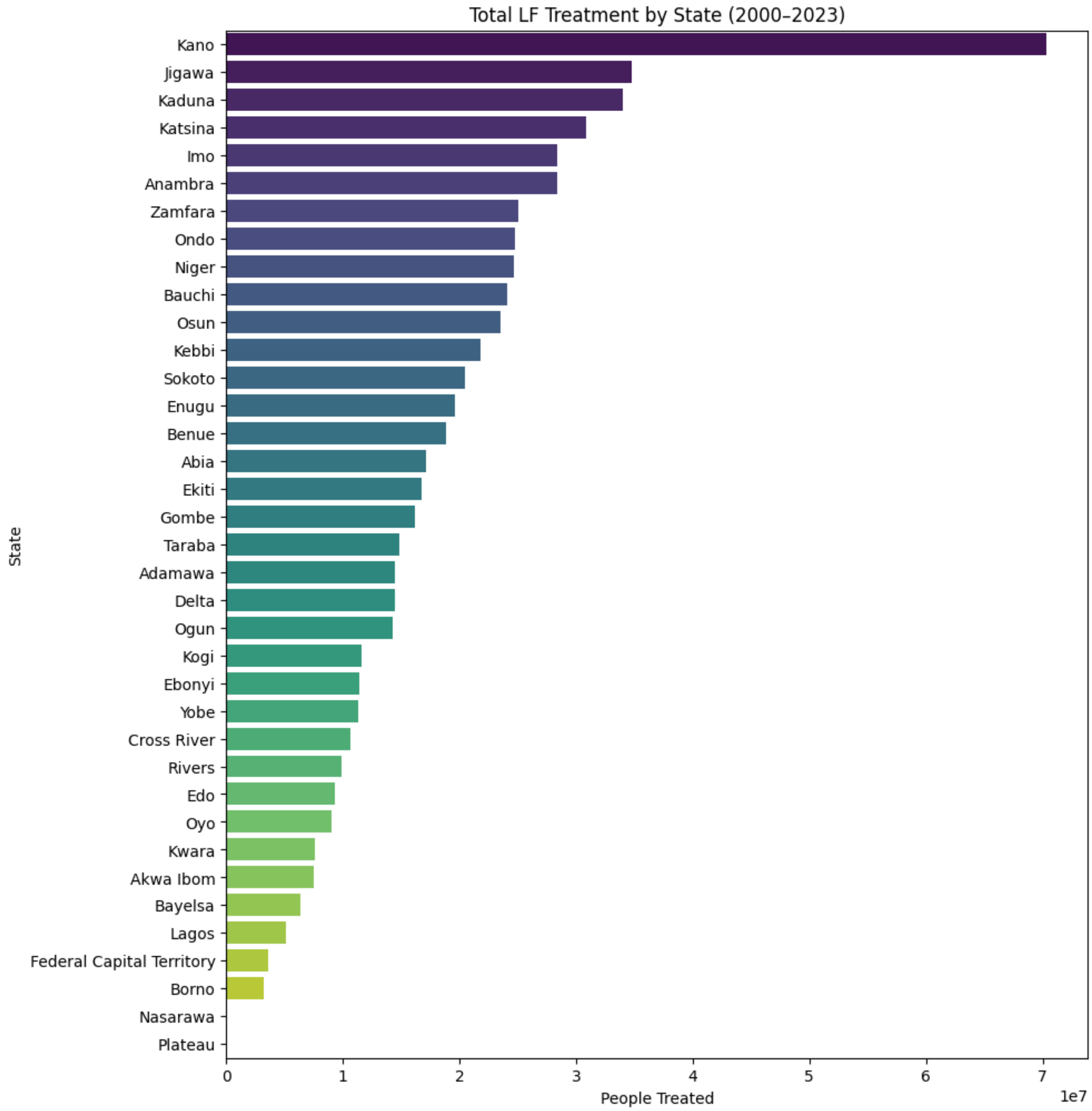

Figure 2: Total LF treated in thousands by State in Nigeria (2013–2023)

The geographical burden of LF as well as the geographical coverage of MDA programs is represented by the treatment tally by region in Figure 2. The results reveal significant regional disparities in LF treatment across Nigeria. The top five states with the highest cumulative number of individuals treated were Kano, Jigawa, Kaduna, Katsina and Imo respectively. While states with the lowest total treatment coverage are Plateau, Nasarawa, Borno, FCT, Lagos and

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Bayelsa respectively.

3.4 Spatial Analysis of Lymphatic Filariasis Treatment Coverage

To explore the geographical distribution of lymphatic filariasis (LF) treatment coverage across Nigeria, spatial visualization was carried out using choropleth maps from 2013 to 2023. These maps provide a clear visual impression of regional disparities in Mass Drug Administration (MDA) performance.

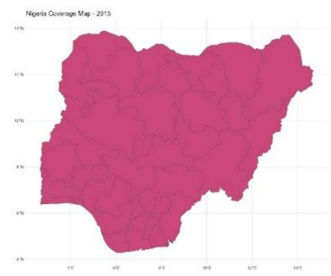

Figure 3: Coverage map 2013

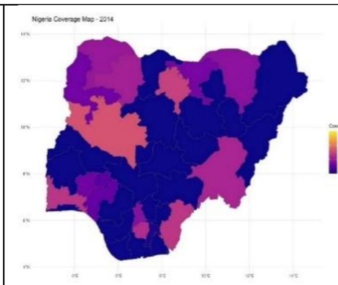

Figure 4: Coverage map 2014

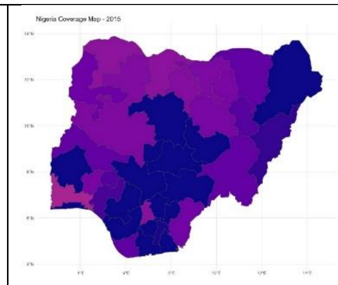

Figure 5: Coverage map 2015

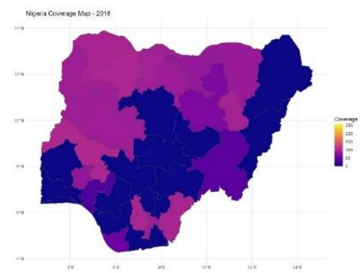

Figure 6: Coverage map 2016

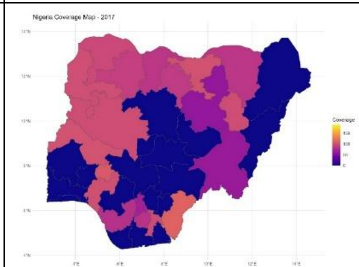

Figure 7: Coverage map 2017

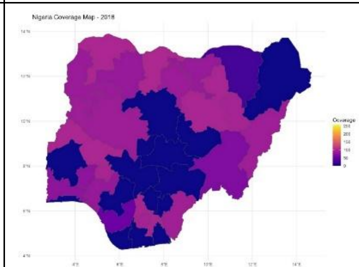

Figure 8: Coverage map 2018

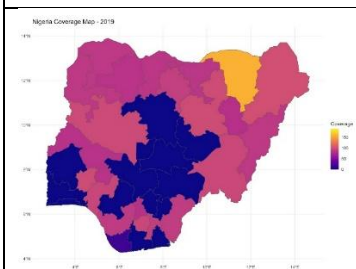

Figure 9: Coverage map 2019

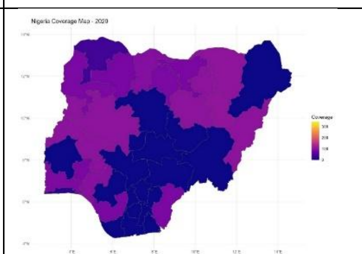

Figure 10: Coverage map 2020

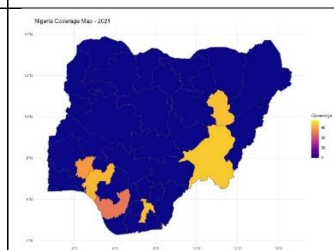

Figure 11: Coverage map 2021

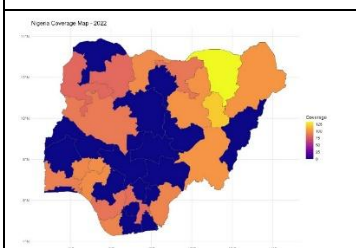

Figure 12: Coverage map 2022

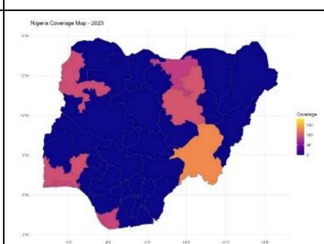

Figure 13: Coverage map 2023

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Figure 3 (2013 Coverage Map) shows that in the early years of intervention, many states particularly in the northern and some central regions were marked by low treatment coverage. Only a handful of states in the south recorded relatively higher values, indicating early unevenness in programme uptake.

Figure 6 (2016 Coverage Map) suggests gradual improvements in coverage across parts of the south and middle belt. However, several northern states continued to remain in the lowest coverage classes, reinforcing the pattern of regional disparity visible in the baseline year.

Figure 9 (2019 Coverage Map) highlights modest progress, with more states shifting into higher coverage categories. Nevertheless, pockets of low coverage persisted in the far north, indicating that despite years of implementation, uniform progress was not achieved nationally.

Figure 13 (2023 Coverage Map) presents the most recent picture, where a number of states achieved higher coverage rates compared to previous years. Yet, the clustering of low-coverage states in the northern region remains striking, while southern states overall show stronger treatment reach.

Taken together, the maps reveal a consistent spatial pattern. Coverage has generally improved over the decade, but disparities remain geographically entrenched, this is also evident in the study carried out in Ghana (Koray, 2024). Low clusters appear repeatedly in northern zones, while higher coverage clusters are more common in southern states. This visual evidence indicates that LF intervention performance is not randomly distributed but spatially structured, pointing to the need for region-specific strategies to close the treatment coverage gap.

4. Conclusion

This study examined the temporal and spatial dynamics of lymphatic filariasis (LF) in Nigeria between 2013 and 2023, using statistical approaches to evaluate the effectiveness of Mass Drug Administration (MDA) interventions. The findings highlight that while Nigeria has made measurable progress in reducing LF transmission in several regions, elimination remains incomplete unlike Zambia which is waiting for certification for no further need for MDA rounds (Shirley *et al*., 2024). Temporal analysis showed gradual but inconsistent declines in incidence, suggesting that while MDA has had a positive impact, its effects have not been uniformly distributed across the country. The persistence of transmission in certain states indicates operational and contextual challenges, including irregular MDA coverage, weak surveillance systems, and underlying socio-economic disparities that continue to drive disease risk, this is relevant to studies on health belief model (Karl *et al.,* 2021; Rosenstock, 1974). Spatial analysis revealed distinct geographic clustering, with high-burden areas concentrated in northern and riverine states. These spatial patterns emphasize that LF transmission is not random but shaped by shared ecological and social factors, as evident in literature (Akogun, *et al*., 2025; Johnson *et al.,* 2021). The continued presence of “hotspot” regions suggests the need for sustained and region-specific strategies rather than a uniform national approach. By integrating time series and spatial methods, this research demonstrates the critical role of statistical modeling in providing evidence-based insights for disease control.

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Overall, the study underscores that the elimination of LF in Nigeria requires not only continued pharmaceutical interventions but also data-driven evaluation and resource prioritization. Robust statistical analysis serves as a foundation for adaptive public health policy, enabling Nigeria to align its efforts with the World Health Organization's 2030 elimination targets.

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