COMPARISON OF CHANGE-POINTS DETECTION OF COVID-19 INFECTIONS AND DEATHS WITHIN THE PANDEMIC PERIOD IN FIVE SELECTED AFRICAN COUNTRIES

Ojo, Adedayo Emmanuel.[1] Afolabi, Rotimi Felix.[1]

[1]Department of Epidemiology and Medical Statistics, Faculty of Public Health, College of Medicine, University of Ibadan, Nigeria.

Ojemmanuel185990@gmail.com

Abstract

Coronavirus disease (COVID-19) has significantly affected global health, leading to increased morbidity, mortality, and strain on healthcare systems. Although numerous studies have examined COVID-19 globally, shifts in infection and death patterns during the pandemic remain underexplored in Africa. This study identifies multiple change-points in COVID-19 infections and deaths across five African countries. Kenya, Egypt, South Africa, Nigeria, and the Democratic Republic of Congo, to better understand the region's pandemic dynamics.

This secondary data analysis utilized publicly available COVID-19 data from the World Health Organization, covering the period from March 11, 2020, to May 5, 2023. The five countries were selected to represent the major subregions of Africa based on their reported case magnitude. Daily data on infections and deaths were aggregated to weekly counts. Descriptive statistics, including medians, interquartile ranges, and time-series plots, summarized the trends. Multiple change-point detection was performed using the E-divisive method implemented in R (version 4.1.1) via the ecp package, while the Mann Kendall and Sen's slope tests were applied to assess trends at a 5% significance level.

Results revealed distinct temporal patterns across the countries. Four major change-points were detected in each, except Nigeria, which had one for deaths. Peaks in infection occurred around February–March 2022, with South Africa consistently recording the highest infection and death rates.

These findings provide valuable insights into the temporal progression of COVID-19 in Africa, identifying critical phases that correspond with public health interventions. The study emphasizes the usefulness of change-point analysis in evaluating disease trends and guiding evidence-based responses to future outbreaks.

Keywords: COVID-19, change-point analysis, Africa, infections, deaths, R software, time-series analysis.

Introduction:

Change-points in a time series is referred to as moments when discontinuity or a significant shift in the data occur, example includes changes in the mean, variance, or distribution. Detecting the change-points was essential in order to understand data dynamics, as this assist in identifying the underlying trends and structural changes (Chen & Gupta, 2001). While a

ISSN NUMBER: 1116-249X

single change-point indicated one distinct shift, using multiple change-points provided a more comprehensive understanding of data behavior, especially when several transitions occurred over time (Killick et al., 2012). Multiple change-points were particularly useful in fields such as epidemiology and public health, where they revealed shifts in disease trends and offered insights into evolving health patterns.

In public health, change-point analysis had been widely applied to monitor disease outbreaks and chronic conditions, facilitating timely interventions and resource allocation. Previous studies employed multiple change-point analysis to examine COVID-19 infections and deaths, identifying significant shifts in the spread of the virus. For instance, Dehning et al. (2020) detected change-points in the effective growth rate of COVID-19 in Germany, which corresponded with the introduction of public health measures. Similarly, Pavan et al. (2022) and Jiang et al. (2023) demonstrated that multiple change-point methods effectively captured transitions in epidemic trajectories and policy impacts across different regions.

The COVID-19 pandemic, which began in Wuhan, China, in late 2019, spread rapidly across the world, infecting millions and straining health systems. In Africa, the pandemic had a significant impact, with countries such as South Africa, Egypt, Nigeria, Kenya, and the Democratic Republic of Congo (DRC) recording high numbers of infections and deaths. Despite limited testing capacity and infrastructure, these countries experienced sustained community transmission. However, research that explored multiple change-points in COVID-19 data from African countries remained limited, leaving gaps in understanding the temporal dynamics of the pandemic on the continent.

Several studies globally had utilized multiple change-point methods to analyze time-series data. For example, Dion-Bian et al. (2023) addressed challenges in detecting change-points in Poisson process data using a minimum contrast estimator and cross-validation, while Pedersen and Meneghini (2021) identified policy-related shifts in Italy's COVID-19 trajectory. Mandal and Mandal (2020) examined India's lockdown phases and observed declines in transmission after implementing specific containment measures. Despite these advancements, few studies had applied such methods within African settings.

Therefore, this study aimed to fill this gap by applying multiple change-point analysis to COVID-19 infection and death data across five selected African countries, Nigeria, South Africa, Egypt, Kenya, and the DRC. The findings provided a clearer understanding of how the

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pandemic evolved across the continent and contributed to evidence-based approaches for improving public health responses to future outbreaks.

Literature Review

Several studies had explored the use of change-point analysis to understand the dynamics of the COVID-19 pandemic, focusing on the development, application, and relevance of multiple change-point detection methods. The COVID-19 pandemic, caused by the SARS-CoV-2 virus, spread rapidly across the globe, leading to high morbidity, mortality, and an overwhelming burden on healthcare systems (World Health Organization, 2020). The virus, belonging to the Coronaviridae family, was closely related to SARS-CoV and MERS-CoV but exhibited a higher transmission rate and lower fatality (Gebru et al., 2021).

Originating in Wuhan, China, in late December 2019, the virus, COVID-19 spread globally through means such as community transmission and international travel (Lai et al., 2020). Several efforts were made by several researchers to understand the epidemiological patterns, transmission dynamics, and the effects of intervention measures of COVID-19. Roujian et al. (2020) analyzed the prevalence and incidence of COVID-19, while Dehning et al. (2020) identified statistical change-points in Germany’s infection trajectory that corresponded with lockdown policies, illustrating how time-series and change-point methods could be applied to evaluate pandemic trends and intervention effectiveness.

Change-point detection is regarded as the identification of moments when the statistical properties of a time series, such as mean, variance, or trend underwent significant changes (Hinkley, Reid, & Richardson, 1977). In the epidemiological surveillance, detecting such points was vital for identifying abrupt shifts in disease incidence and understanding the impact of public health interventions. A single change-point model captured one significant alteration but often oversimplified complex epidemic behavior, which evolved through multiple waves or phases (Sharma et al., 2016). Multiple change-point detection, on the other hand, allowed for the identification of several shifts over time, offering a more comprehensive understanding of the temporal evolution of diseases. This approach had proven particularly effective in epidemiology, economics, and environmental research, where it provided insight into how systems changed in response to internal and external factors.

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There have been various researchers that had applied multiple change-point analysis in the context of COVID-19. For example, Dion-Blanc et al. (2023) used a nonparametric approach to detect multiple change-points in Poisson processes, incorporating cross-validation to determine optimal segmentation. Correspondingly, Jiang et al. (2023) modeled global COVID-19 trajectories using a piecewise linear trend model with multiple change-points, and this revealed clear phase transitions in epidemic growth across different 30 countries. Shang and Xu (2022) also conducted a study in Belgium to examine excess deaths, the study identified distinct pre- and post-pandemic mortality phases, while study by Pedersen and Meneghini (2021) revealed two major change-points in the epidemic curve in Italy and it was linked to the mandates of using mask and the lockdowns. Furthermore, Pavan et al. (2021) applied the E-divisive method to COVID-19 data across WHO regions, it demonstrated multiple upward shifts which correspond to dissimilar waves infection. Going by the findings of these studies, they collectively reveled that multiple change-point analysis effectively captured shifts in epidemic behaviour and provided insight into effectiveness of policy and disease progression.

Various of algorithms had been developed for change-point detection, including Binary Segmentation, PELT (Killick et al., 2012), Bayesian models, and the E-divisive method (Matteson & James, 2014). Each of this algorithm offered different advantages depending on data type and objective. While Binary Segmentation was simple and computationally efficient, it has the tendency of missing subtle shifts. The PELT algorithm performed well for long time series, and Bayesian methods provided probabilistic interpretations at the cost of computational intensity. The E-divisive method, distribution-free and nonparametric was particularly advantageous for epidemiological data characterized by irregularity and non-normality, making it the preferred choice for this study.

Despite a wide global research applying change-point analysis to COVID-19 data, there have been a dearth of studies focusing on Africa. Most existing literatures concentrated on developed regions with comprehensive data systems, while countries in African were often limited to single-country analyses. Additionally, few studies simultaneously examined both infection and death change-points across several African countries. This existing gap highlighted the novelty and relevance of the present research, which applied the E-divisive multiple change-point detection method to COVID-19 infection and death data from countries like Nigeria, South Africa, Egypt, Kenya, and the Democratic Republic of Congo. By doing so, the study provided a clearer understanding of the temporal evolution of the pandemic in Africa and contributed

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evidence-based insights for future epidemic preparedness and public health interventions across the continent.

Methods:

This study was a secondary data, with the dataset obtained from the World Health Organization database, spanning from March 2020 to May 2023, and analyzing COVID-19 daily infection and death. The data were aggregated into weekly totals to reduce daily variability and enhance temporal stability. Descriptive statistics such as medians, interquartile ranges, and time-series plots, were used to summarize the data. The E-divisive method was adopted because it is a nonparametric, data-driven approach that detects multiple change-points without assuming a specific data distribution (Matteson & James, 2014). Unlike methods such as Binary Segmentation or PELT, which require predefined models, the E-divisive algorithm can identify both mean and distributional changes, making it suitable for epidemiological data that are often irregular and non-Gaussian. Additionally, its robustness to outliers and ability to capture complex temporal patterns made it ideal for the present study's COVID-19 datasets. Trend analyses within each identified phase were assessed using the Mann Kendall and Sen's slope tests to determine the direction and magnitude of temporal trends. All analyses were conducted using R software (version 4.1.1), with the ecp, Kendall, trend, and ggplot2 packages. Equations and symbols were defined to describe the change-point estimation process, ensuring clarity and reproducibility of the analysis.

The daily reported cases of COVID-19 infections and deaths were aggregated to weekly data to facilitate analysis. The trends and patterns of the outcome variables were visualized using time series plots. To assess the distribution of the data, a Shapiro-Wilk test for normality was performed. Since the data did not follow a normal distribution, the outcomes were summarized using descriptive statistics such as the median, interquartile range, minimum, and maximum values. To investigate changes in the infection and death trends, change-point analysis was performed on the weekly data. In order to visualize the temporal trends of COVID-19 infections and deaths over the pandemic period, Time series plots were used. These plots assisted in identifying patterns, fluctuations, and somewhat significant shifts that occur in the data over time. A Shapiro-Wilk test was used to assess the normality of the COVID-19 infection and death data and findings from the results showed that the data were not distributed normally, and this led to the use of non-parametric statistics for further analysis. For

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summarization of the data, descriptive statistics such as the median, minimum, maximum and interquartile range were computed to sum.

The equation for E-divisive method for detecting multiple change-points:

$$\hat{Q}(\tau) = \frac{\tau(n-\tau)}{n}\left[\frac{2}{\tau(n-\tau)}\sum_{i=1}^{\tau}\sum_{j=r+1}^{n}\left\|X_i - X_j\right\|^{\eta} - \binom{\tau}{2}^{-1}\sum_{i=1}^{\tau-1}\sum_{k=i+1}^{r}\left\|X_i - X_k\right\|^{\eta} - \binom{n-\tau}{2}^{-1}\sum_{j=r+1}^{n-1}\sum_{k=j+1}^{n}\left\|X_j - X_k\right\|^{\eta}\right]$$

(1)

Where $\eta \in (0,2)$.

For simplicity $\eta = 1$, then the equation (1) above becomes:

$$\hat{Q}(\tau) = \frac{\tau(n-\tau)}{n}\left[\frac{2}{\tau(n-\tau)}\sum_{i=1}^{\tau}\sum_{j=r+1}^{n}\left\|X_i - X_j\right\| - \binom{\tau}{2}\sum_{i=1}^{\tau-1}\sum_{k=i+1}^{r}\left\|X_i - X_k\right\| - \binom{n-\tau}{2}\sum_{j=r+1}^{n-1}\sum_{k=j+1}^{n}\left\|X_j - X_k\right\|\right]$$

(2)

Where $\|.\|$ denotes the Euclidean distance, n denotes the size of time series.

$$\frac{2}{\tau(n-\tau)}\sum_{i=1}^{\tau}\sum_{j=r+1}^{n}\left\|X_i - X_j\right\|$$

(3)

Expression (3) denotes the average Euclidean distance of time points belonging to different phases.

$$\binom{\tau}{2}\sum_{i=1}^{\tau-1}\sum_{k=i+1}^{r}\left\|X_i - X_k\right\|$$

(4)

Expression (4) denotes the average within phase distance for Phase 1.

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$$\binom{n-\tau}{2} \sum_{j=r+1}^{n-1} \sum_{k=j+1}^{n} \left\| X_j - X_k \right\|$$

(5)

Expression (5) denotes the average within phase distance for Phase 2.

The optimum change-point was estimated by considering, which τ value maximize $\hat{Q}$. The second step focused on estimating if the change-point was significant through the permutation test. After the change-point was estimated, the significance was tested at pre-specified significant level $\alpha > 0.002$ level, a point which maximizes the value of $\hat{Q}$. The method carried out by generating R permuted time series obtained by randomly changing the time order of the sequence.

At the third step, after the change-point obtained in the first step found significant, the series was further divided into one more phase to find any additional change-point. Those points were structured in hierarchically order. This process continues till the optimal (non-significance of the change-point) change-points obtained for the data series, and no further bisection of data into phases was showing significance. According to Matteson & James (2014), the e-divisive method was consistent with the estimation of change-points.

Mann-Kendall test which is a non-parametric test which is commonly employed to detect monotonic trends in time series data. For the null hypothesis, there was no trend in the reported cases of COVID-19 infection or death within pandemic period while for the alternative hypothesis, there was trend in the reported cases of COVID-19 infection or death within pandemic period.

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn\left(X_j - X_k\right)$$

(6)

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$$sgn(x) = \begin{cases} 1 & if \quad x > 0 \\ 0 & if \quad x = 0 \\ -1 & if \quad x < 0 \end{cases}$$

(7)

Where X_j and X_k are sequential data values.

The variance of S is given as

$$\sigma^2 = \frac{1}{18}\left\{n(n-1)(2n+5) - \sum_{j=1}^{p} t_j(t_j-1)(2t_j+5)\right\}$$

(8)

Where 'j' varies over set of tied rank and t_j is the frequency that rank t appears. The test statistic will be

$$Z = \begin{cases} \frac{S-1}{\sigma} & if \quad S > 0 \\ 0 & if \quad S = 0 \\ \frac{S+1}{\sigma} & if \quad S < 0 \end{cases}$$

(9)

Where $\sigma =$ Standard deviation. If there is no monotonic trend, the Significance of the trend is tested at $5\%(\alpha = 0.05)$ level.

The magnitude of the trend is estimated by Sen's slope. The magnitude of the trend estimated using Sen's slope Q (Sen, 1986) is based on the median values of variable (X_{ij}). The test statistics is given by

$$Q = \begin{cases} \beta_{\frac{(N+1)}{2}} & where\ N\ is\ odd \\ \frac{1}{2}\left(\beta_{\frac{N}{2}} + \beta_{\frac{N+2}{2}}\right) & where\ N\ is\ even \end{cases}$$

(10)

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Where N represents total number of reported cases of COVID-19 infection or death within the pandemic period and β-slope estimator. A positive Q value indicates an upward trend and a negative value represent a downward trend. The magnitude of the trend is tested at 5% ($\alpha = 0.05$) significance level is considered.

Results:

The figure1 showed the plot of reported COVID-19 infections, it was observed from the plot of reported COVID-19 infections that all the selected Africa countries appear to show a trend in the reported infections, especially with a rise in the month of April 2021 and March 2022 in all the selected countries and gone drastically reduced after March 2022. South-Africa has highest number of reported cases of infections and DR Congo has lowest. Nigeria, South-Africa and Kenya have similar pattern in the reported infections, while Egypt and DR Congo have different pattern of the reported infections.

The figure 2 showed the plot of reported COVID-19 deaths, South-Africa has the highest number of reported cases of death and Nigeria with the lowest, there was an increase in the death reported cases from the month September 2020 in Nigeria, South-Africa and Egypt, before the trend was declined, out of all the selected countries, DR Congo only has reached her highest peak at the early stage of the pandemic with a peak, but others had more than a peak.

From the Table 1, it was revealed that there was a total of 4 change-points estimated for all the five Africa Countries. In the case of Nigeria, South-Africa and Kenya, the first significant change-point, with respect to change in mean (μ) was estimated on the October 2020, 7months after the WHO has declared it a pandemic, why for Egypt and DR Congo were February 2021 and January 2021 respectively. The significant change-points were estimated every 6months for Egypt between 2nd, 3rd and 4th change-point compare to other countries. DR Congo also maintain consistence in the reported cases between the 1st to 4th change-point.

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Weekly resported COVID-19 infections in the five Africa selected countries.

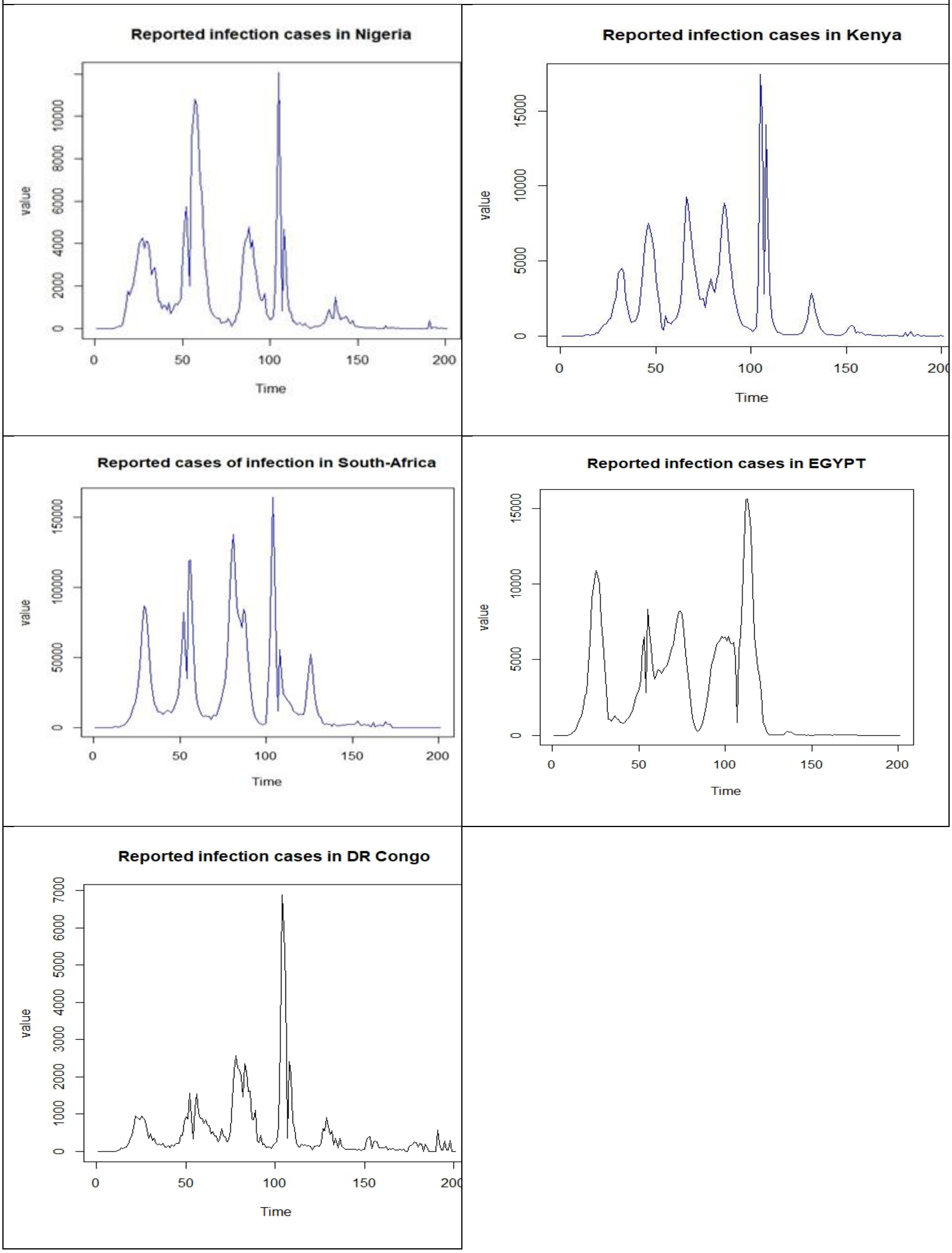

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Figure 1: Time plot for weekly reported COVID-19 infections across five African countries (March 2020–May 2023).

Weekly resported COVID-19 deaths in the five Africa selected countries.

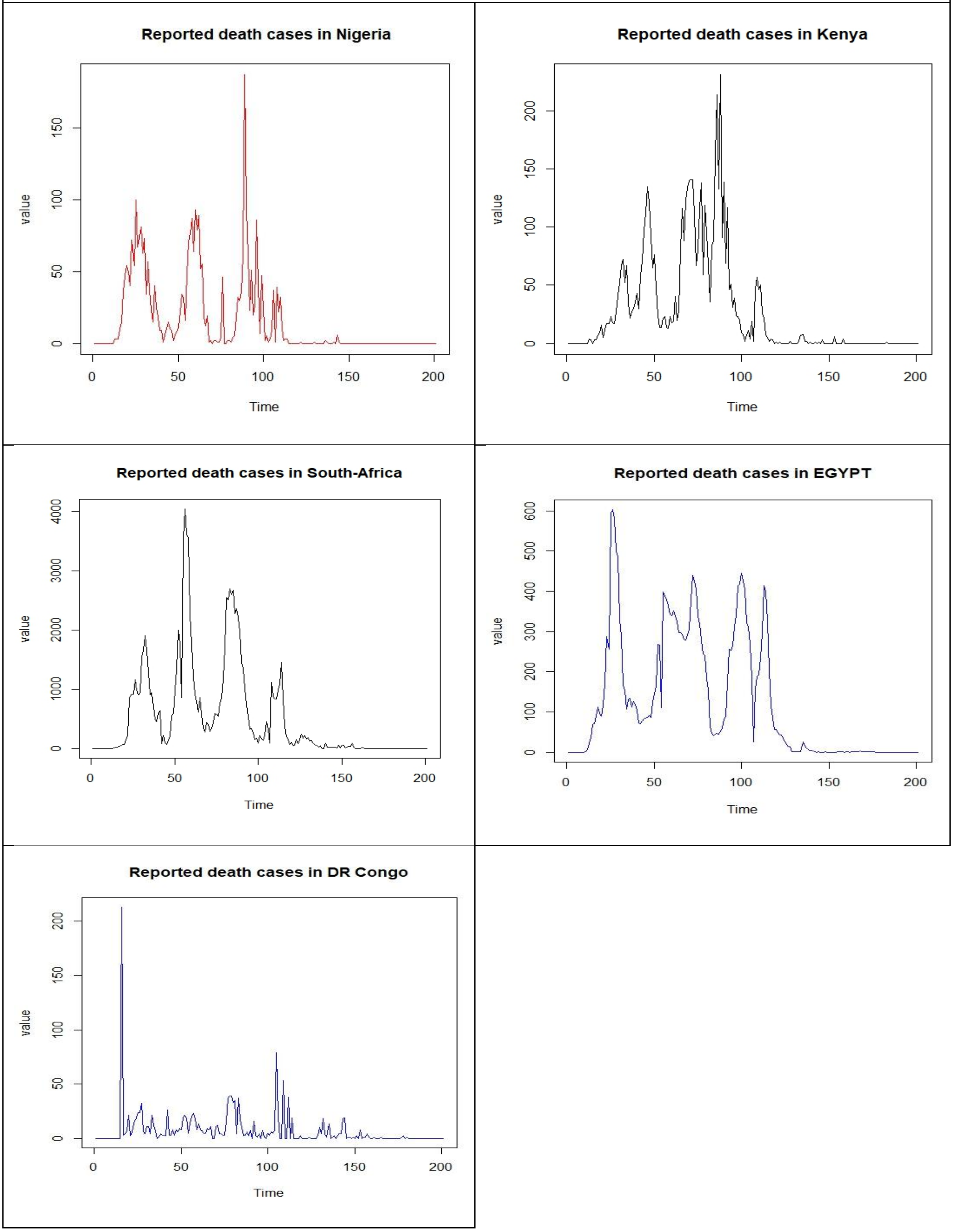

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Figure 2: Time series plot for weekly reported COVID-19 deaths across five African countries (March 2020–May 2023).

Table 1: Estimated change-points for reported cases of COVID-19 infections in Nigeria, South Africa, Egypt, Kenya, and DRC.

		1st	2nd	3rd	4th
Nigeria	CP	31	65	112	148
	P-value	0.002	0.008	0.008	0.002
	Day	7/10/20	2/6/21	4/5/22	11/1/23
South-Africa	CP	31	77	131	172
	P-value	0.002	0.002	0.006	0.002
	Day	7/10/20	1/9/21	14/9/22	28/6/23
Egypt	CP	51	92	122	152
	P-value	0.002	0.002	0.004	0.002
	Day	3/3/21	15/12/21	13/7/22	8/2/23
Kenya	CP	31	63	112	160
	P-value	0.002	0.002	0.002	0.002
	Day	7/10/20	26/5/21	4/5/22	5/4/23
DR Congo	CP	49	79	112	142
	P-value	0.002	0.016	0.006	0.008
	Day	17/2/21	15/9/21	4/5/22	30/11/22

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Table 2: Estimated change-points for reported cases of COVID-19 deaths in Nigeria, South Africa, Egypt, Kenya, and DRC.

		1st	2nd	3rd	4th
Nigeria	CP	112			
	P-value	0.002			
	Day	4/5/22			
South-Africa	CP	50	87	117	157
	P-value	0.002	0.002	0.014	0.002
	Day	24/2/21	10/11/21	8/7/22	15/3/23
Egypt	CP	51	81	119	149
	P-value	0.002	0.002	0.004	0.002
	Day	3/3/21	29/9/21	22/6/22	18/1/23
Kenya	CP	31	65	114	147
	P-value	0.002	0.002	0.002	0.002
	Day	14/10/20	9/6/21	18/5/22	4/1/23
DR Congo	CP	49	85	115	159
	P-value	0.002	0.016	0.006	0.008
	Day	17/2/21	27/10/21	25/5/22	29/3/23

Table 3 presented the estimated trends within the detected multiple change-points for reported COVID-19 infections across the five selected African countries. The positive Kendall's Tau values, which were close to 1, indicated strong monotonic increasing trends in infection patterns within the identified change-point intervals. Although some Tau values approached 1.0, reflecting nearly perfect positive associations, this was verified through re-analysis and confirmed to result from consistent upward movements in cumulative case counts during the pandemic phases, rather than from computational or data-entry errors. The p-values for all five countries were below the predetermined significance level (α=0.05), leading to the rejection of the null hypothesis of no trend. These findings confirmed the presence of statistically significant upward trends in infection counts within the detected multiple change-points.

Similarly, Table 4 showed the estimated trends within the detected multiple change-points for reported COVID-19 deaths across the same countries. The positive Tau values also indicated

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strong monotonic increasing mortality trends across all regions. As in the infection series, the p-values for all countries were less than 0.05, confirming the statistical significance of these upward trends. The verification of calculations confirmed that identical Tau values across countries were due to parallel cumulative death trajectories during major outbreak phases rather than computational duplication.

Importantly, the detected change-points corresponded closely with key public health interventions during the pandemic period. The first change-points (around October 2020) aligned with the easing of lockdown restrictions in most African countries, which was followed by renewed surges in infection and death rates. The second and third change-points (around February–July 2021) coincided with the introduction of national vaccination programmes and partial reopening of schools and businesses. The final change-points, observed around early 2022, reflected the decline in cases and deaths associated with expanded vaccine coverage and improved treatment protocols. These temporal correspondences supported the robustness of the multiple change-point detection approach in capturing the effects of interventions on COVID-19 dynamics.

Table 3 Trend within the detected multiple change-points for COVID-19 infections in Nigeria, South Africa, Egypt, Kenya, and DRC.

Country	Tau-value	p-value
Nigeria	1	2.22×10^{-16}
South-Africa	1	3.26×10^{-16}
Egypt	1	8.14×10^{-14}
Kenya	1	5.56×10^{-12}
DR Congo	1	5.56×10^{-6}

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Table 4 Trend within the detected multiple change-points for reported death cases of COVID-19 within the pandemic period in Nigeria, South Africa, Egypt, Kenya, and DRC.

Country	Tau-value	p-value
Nigeria	1	$8.447 \text{ x } 10^{-7}$
South-Africa	1	$2.22 \text{ x } 10^{-16}$
Egypt	1	$2.22 \text{ x } 10^{-16}$
Kenya	1	$8.447 \text{ x } 10^{-7}$
DR Congo	1	$8.447 \text{ x } 10^{-7}$

Discussion

This study investigated multiple change-points in reported COVID-19 infections and deaths across five African countries, Nigeria, South Africa, Egypt, Kenya, and the Democratic Republic of Congo (DR Congo), during the pandemic period. Across these countries, approximately four significant change-points were detected for both infections and deaths, except in Nigeria, where only one change-point was observed for deaths. The detection of multiple change-points provided insights into distinct phases of the pandemic and helped identify periods of increased or reduced transmission.

For infections, the first change-points in Nigeria, South Africa, and Kenya occurred approximately 31 weeks after their first reported cases, while Egypt and DR Congo recorded theirs later, at around 50 and 48 weeks, respectively. The timing of these change-points closely corresponded with the relaxation of initial lockdown measures and the emergence of new variants across the continent. A general downward trend was observed between the second and third change-points in Nigeria, South Africa, and Kenya, likely associated with the implementation of public health measures such as mask mandates, travel restrictions, and vaccination campaigns. In Egypt, infection rates declined between the first and second change-points (March–December 2021), aligning with the early vaccination rollout. DR Congo, however, exhibited relatively stable infection trends across its four change-points, possibly reflecting lower testing capacity and slower intervention implementation.

In terms of deaths, Nigeria recorded only one significant change-point, approximately 112 weeks after the pandemic was declared, coinciding with the mass vaccination phase in early

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2022. Other countries experienced up to four change-points, with South Africa and DR Congo showing consistent 30-week intervals between the second and third points before a steady decline. Egypt and Kenya displayed a decline in deaths between their second and third change-points, followed by a mild resurgence, reflecting fluctuations in case management capacity and possible differences in variant impact. Overall, Nigeria experienced comparatively lower COVID-19 mortality, which may be attributed to under-reporting, a younger population structure, and early adoption of public health interventions.

The observed variations in change-points across countries underscored the influence of timing and effectiveness of interventions, health system capacity, and data accuracy in shaping the pandemic's trajectory in Africa. The findings demonstrated that change-point analysis is a valuable epidemiological tool for identifying critical transitions in epidemic behavior and for evaluating the effects of interventions over time. The results also highlighted the need for improved real-time surveillance and data integration to guide timely policy responses during future outbreaks.

Limitations

This study depended on secondary data from the World Health Organization, and it is subject to under-reporting, data incompleteness, and inconsistent testing rates across countries. The analysis also assumed uniform data quality, which might not hold due to differences in health infrastructure and reporting systems. Additionally, the use of aggregated national data may obscure regional variations in infection and death patterns within countries.

Conclusion and Recommendations

This study identified multiple statistically significant change-points in COVID-19 infections and deaths across five major African countries, reflecting key transitions in the pandemic's progression and response. The timing of these change-points corresponded to major intervention phases, such as lockdowns, vaccination rollouts, and subsequent relaxations, underscoring the value of change-point analysis in evaluating public health strategies.

From a policy perspective, the findings emphasized the need for:

1. Strengthened disease surveillance systems that can detect early shifts in outbreak dynamics.
2. Improved data reporting mechanisms, ensuring accuracy and timeliness across all health sectors.

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3. Adaptive public health interventions, where change-point detection can inform the timing of measures such as mobility restrictions, vaccine campaigns, and resource allocation.
4. Regional collaboration in data sharing and response coordination, given the interconnected nature of epidemic spread in Africa.

This study revealed that the application of multiple change-point analysis provided critical insights into the temporal dynamics of COVID-19 in Africa. By identifying significant shifts in infection and death trends, this approach can guide proactive public health decision-making and enhance preparedness for future pandemics.

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