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Temporal Analysis and Forecasting of Malaria Cases in Children Under 5 in Senegal's Tambacounda, Kolda, and Kédougou Regions: Using STL and Arima Models

Journal of Electrical Systems

Abstract: **-** This study analyzes temporal trends and forecasts malaria cases in children under five years old in three regions of Senegal (Tambacounda, Kolda, and Kédougou), which are heavily affected by the disease. Using advanced statistical models, namely Seasonal and Trend decomposition using Loess (STL) and the Auto-Regressive Integrated Moving Average (ARIMA) model, the study aims to break down malaria time series into long-term trends, recurring seasonal patterns, and anomalies. The comparative performance of the STL and ARIMA models in predicting future cases is also assessed, offering insights to improve malaria control strategies.The results reveal a marked seasonal variation with a significant peak around 2018, followed by a stabilization of malaria cases, although regional differences were observed, with Kolda showing more pronounced fluctuations. The study highlights the importance of region-specific monitoring and control strategies and suggests that integrating additional data, such as climatic factors, could enhance future forecasts. This research provides a detailed understanding of malaria dynamics in these key regions, aiming to support more targeted and effective public health interventions.

Keywords: Malaria in young children, STL decomposition, ARIMA model, case forecasting, malaria control, epidemiological surveillance.

I. Introduction

Malaria remains a major public health threat in Senegal, particularly in the regions of Kolda, Tambacounda, and Kédougou, located in the southern and southeastern parts of the country. These areas are severely affected, with the disease taking a heavy toll, especially on children under five years old, who are the most vulnerable population. This study stands out for its in-depth analysis of malaria's temporal trends in these three regions, utilizing advanced statistical tools such as Seasonal and Trend Decomposition using Loess (STL) and AutoRegressive Integrated Moving Average (ARIMA) models. The goal is to uncover long-term trends, recurring seasonal patterns, and anomalies while assessing the effectiveness of these models in forecasting future malaria cases. By focusing on these key regions, the study provides critical insights for improving the planning and effectiveness of health interventions. It offers strategic recommendations to better target malaria control efforts, thereby significantly reducing the disease's impact on vulnerable children in these areas.

II. Literature Review

The STL model (Seasonal and Trend Decomposition using Loess), developed by Robert Cleveland and his colleagues in 1990, was designed to overcome the limitations of traditional methods such as moving averages and simple multiplicative or additive models. STL allows for the decomposition of time series into three components: trend, seasonality, and residuals, offering great flexibility for analyzing complex data.

STL is widely used in public health to study disease trends and the impact of environmental conditions. For example, Nunes and Patricio (2012) employed it to analyze respiratory diseases and influenza, while Zhang et al. (2017) used it to examine the effects of weather conditions on health.

In the context of malaria, STL has been applied to understand seasonality and long-term trends. Abeku et al. (2004) in East Africa and Noor et al. (2015) in Zambia demonstrated that malaria is closely tied to climatic variations, which helped adjust intervention strategies. Similarly, Adusei et al. (2019) in Ghana used STL to identify critical intervention periods.

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Finally, Thompson et al. (2013) studied the impact of climate change on malaria in Tanzania, providing essential insights for adapting public health strategies. STL has thus become a key tool for understanding malaria dynamics and optimizing health interventions.

Positioning of Our Study

This study represents the first in-depth analysis of malaria dynamics in the regions of Kolda, Tambacounda, and Kédougou in Senegal, using both STL and ARIMA methods. These regions have not previously benefited from a detailed analysis combining these two approaches to better understand and forecast the spread of the disease. The innovation lies in comparing the performance of STL and ARIMA models for predicting malaria cases. The findings will provide key insights for health authorities to target interventions based on local and temporal dynamics. By identifying high-risk periods and forecasting future fluctuations, this study directly contributes to improving malaria prevention strategies. It marks a significant advancement in the epidemiological management of the disease, opening new avenues for better management in these priority regions of Senegal.

III. METHODOLOGY

The study analyzes malaria case dynamics in children under five in three regions of Senegal. Epidemiological data from the National Malaria Control Program (PNLP) were cleaned and aggregated by month and year using R software, revealing overall and seasonal trends. The STL method decomposed the data into three components: trend, seasonality, and residuals. An ARIMA model was then applied to forecast future cases, taking into account temporal dependencies and uncertainty. The results provided recommendations for improving surveillance and public health interventions.

3.1 WHY CHOOSE THE REGIONS of TAMBA, KOLDA, and KEDOUGOU?

The following graph presents a heatmap showing the distribution of malaria cases in children under five by month and by region in Senegal from 2016 to 2019. The varying color intensities indicate the number of cases, with shades ranging from white (low or no cases) to dark red (very high number of cases).

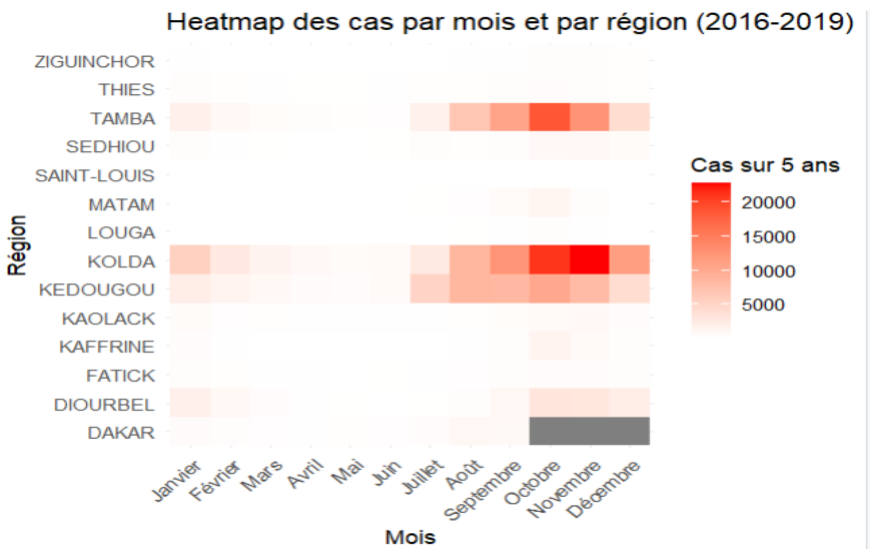

Fig.1 Heatmap of Monthly Malaria Cases by Region in Children Under 5

The heatmap reveals a concerning concentration of malaria cases in the regions of Kolda, Tambacounda, and Kédougou, particularly at the end of the rainy season. These regions should be the primary targets for malaria control interventions in Senegal.

3.2 STL DECOMPOSITION of MALARIA CASES in CHILDREN UNDER 5 in THE REGIONS of TAMBA, KOLDA, and KÉDOUGOU

The STL decomposition applied to the regions of Tamba, Kolda, and Kédougou divides the time series for each area into three main components: trend, seasonality, and residuals. These graphs allow for the analysis of long-term variations (trend), regular seasonal cycles (seasonality), and unpredictable fluctuations (residuals) specific to each region. This approach provides a clear and detailed view of the temporal dynamics of malaria in each region, facilitating a better understanding of the disease's transmission patterns and enabling the adaptation of public health strategies to local specificities.

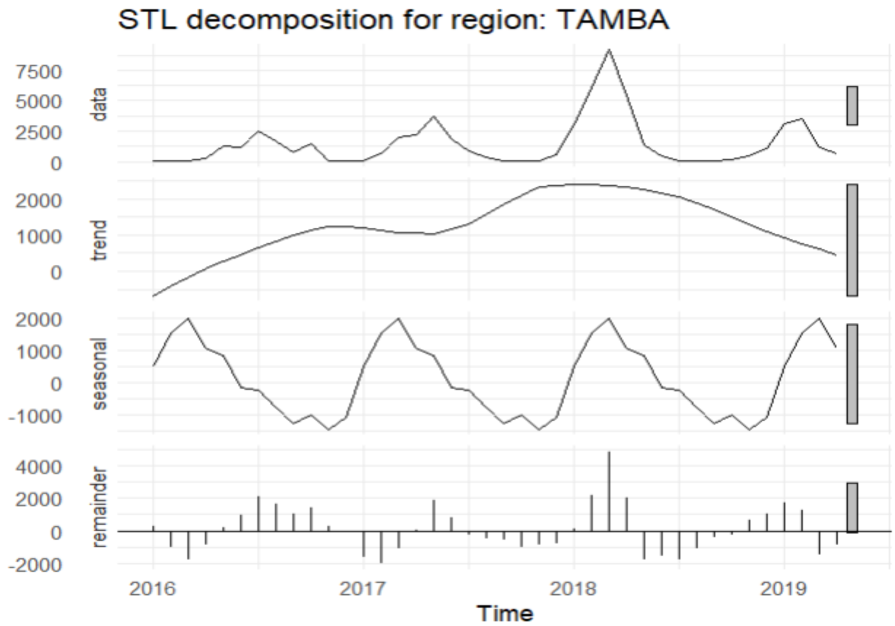

Fig.2: STL decomposition for Tamba

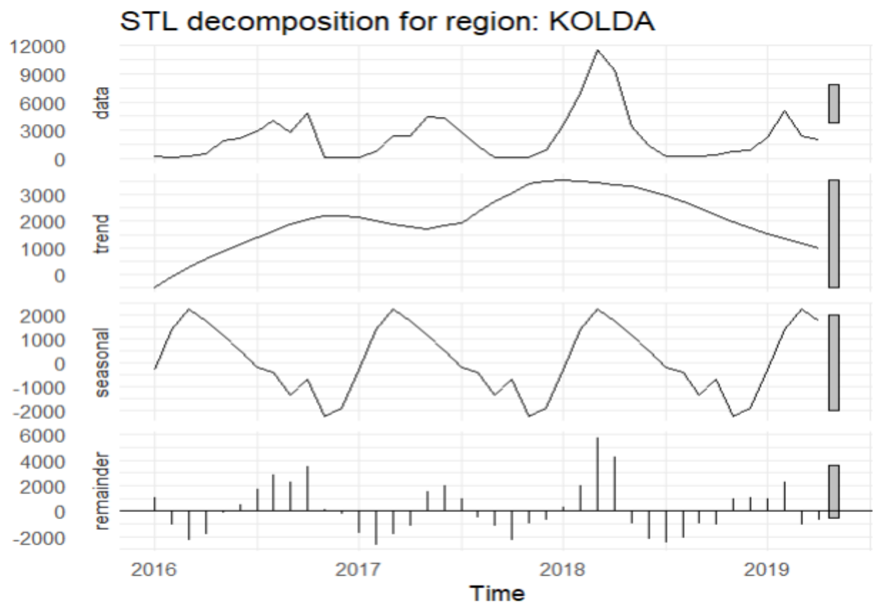

Fig.3: STL decomposition for Kolda

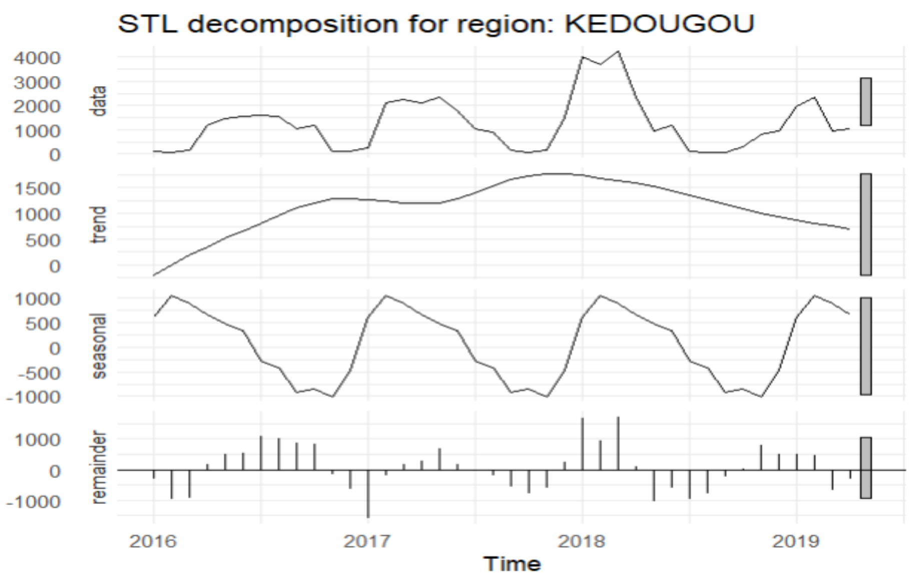

Fig.4: STL decomposition for Kedougou

The trend for these three regions reveals the long-term fluctuations in malaria cases, helping to identify periods of prolonged increase or decrease. For instance, in each region, a significant peak is observed around 2018, followed by a gradual decline in cases.

The seasonal component shows the regular and recurring patterns of malaria cases according to climatic or environmental cycles. In all three regions, seasonality is pronounced, with peaks generally coinciding with the rainy season, confirming the impact of climate on disease transmission. This information is crucial for planning prevention campaigns, such as the distribution of insecticide-treated bed nets or indoor residual spraying.The residuals, on the other hand, represent variations that are not explained by either trend or seasonality. They can indicate specific events or anomalies, such as local outbreaks or targeted interventions. For example, noticeable residuals around 2018 in some regions may reflect exceptional conditions that influenced malaria cases.

In summary, the STL analysis for Tamba, Kolda, and Kédougou provides a detailed view of the temporal dynamics of malaria. By combining the analysis of trends, seasonality, and residuals, this approach enables a more precise targeting of malaria control strategies based on the specific characteristics of each region.

3.3 OVERALL EVALUATION HIGHLIGHTING SIMILARITIES and DIFFERENCES:

Based on the analysis of the adjusted STL components for these three regions, here is an overall evaluation that highlights the similarities and differences:

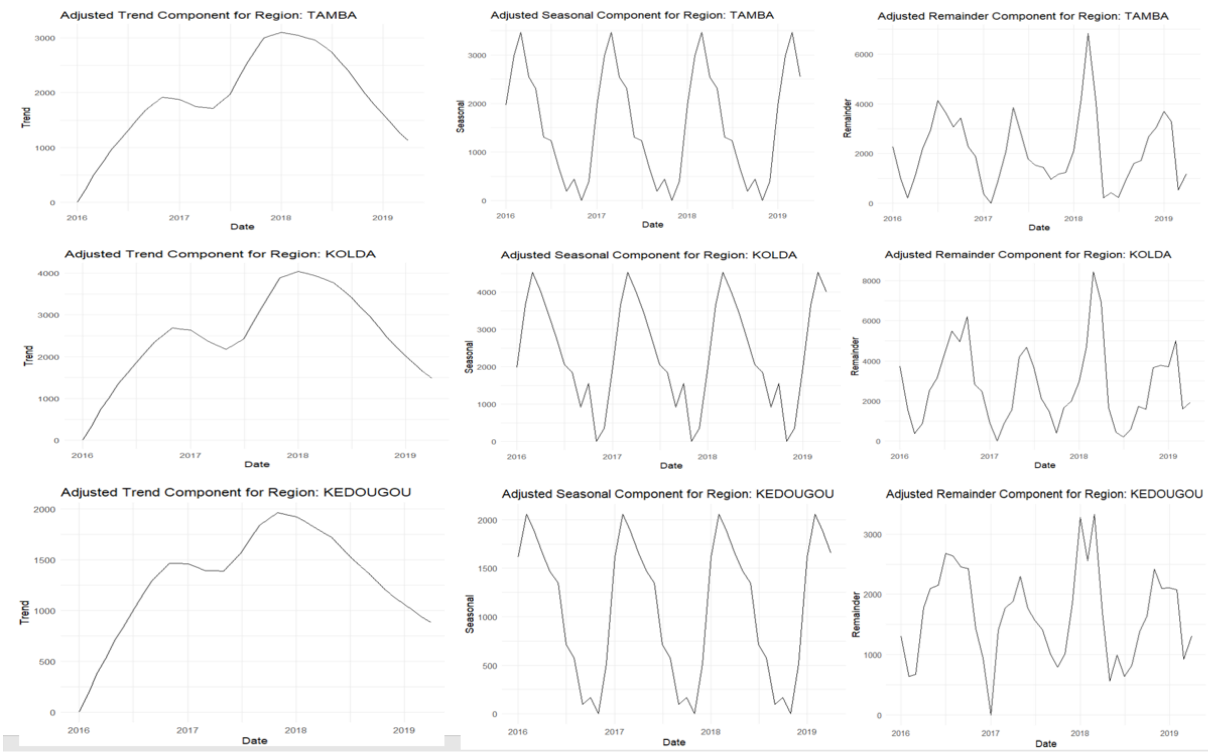

Fig. 5: Cumulative diagram of the three regions

The analysis of malaria trends in the regions of Kolda, Tambacounda, and Kédougou reveals several similarities and differences. In all three regions, the overall trend shows a gradual increase in cases until 2018, followed by a decline, forming a bell-shaped curve. This suggests a critical period before 2018, likely due to climatic conditions or insufficient interventions, followed by an improvement. The seasonal patterns are regular and similar, with recurring peaks during the same periods each year. However, differences emerge in the amplitude of the components. Kolda exhibits the greatest variation in trends and more pronounced seasonality, while Tambacounda shows less pronounced seasonal fluctuations. The residuals, representing unexplained variations, are more volatile in Kolda, especially after 2018, indicating specific events not captured by the model. Kédougou, on the other hand, shows more stable residuals.

While common strategies can be considered for these three regions, the specific characteristics of each area—such as the amplitude of variations and anomalies—require tailored interventions, particularly in Kolda, where the volatility of the residuals demands enhanced surveillance.

3.4 PREDICTION of MALARIA CASES in THESE THREE REGIONS:

The following graphs display the ARIMA model forecasts for the three regions.

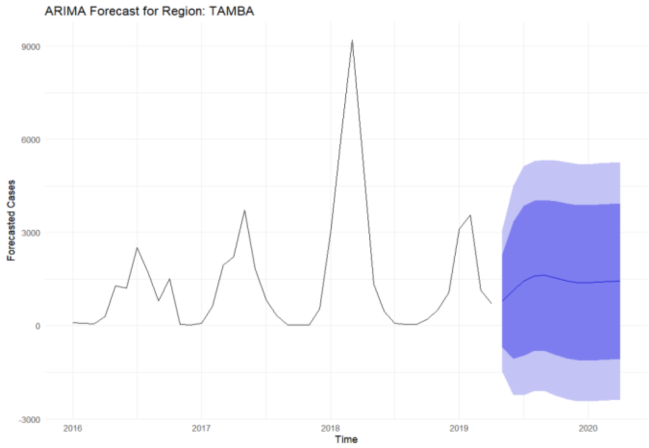

Fig. 6: Forecast of Malaria Cases for the Tamba Region

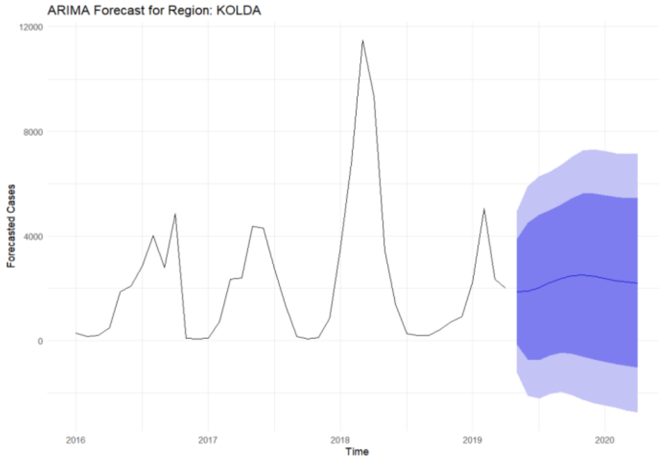

Fig. 7: Forecast of Malaria Cases for the Kolda Region

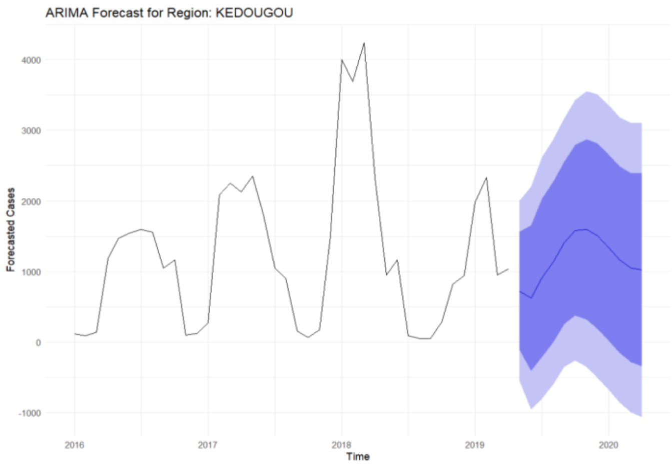

Fig. 8: Forecast of Malaria Cases for the Kedougou Region

The forecasts for 2020 and beyond, based on the ARIMA model, indicate a stabilization of malaria cases in these three regions, although uncertainties remain. In Tambacounda, a slight increase is expected before stabilization, but the confidence intervals reveal volatility, necessitating ongoing monitoring. For Kolda, the model predicts stabilization at a low level with no major outbreaks, though uncertainty remains high due to past fluctuations. Kédougou shows similar trends, with a slight downward tendency, but increasing uncertainties call for vigilance. In conclusion, while the models forecast stabilization in all three regions, historical volatility and wide uncertainty margins demand constant adjustments to public health strategies and active surveillance to prevent any unforeseen resurgence. Health authorities must remain alert, adapting interventions to local developments to sustain the progress made in malaria control.

3.5 RESIDUAL ANALYSIS of the ARIMA MODEL for the THREE REGIONS

The following graphs display the residuals of the ARIMA model for the three regions. Each graph includes three sub-graphs: a histogram of the residuals with a fitted normal curve, the residuals plotted over time, and the autocorrelation function (ACF) of the residuals.

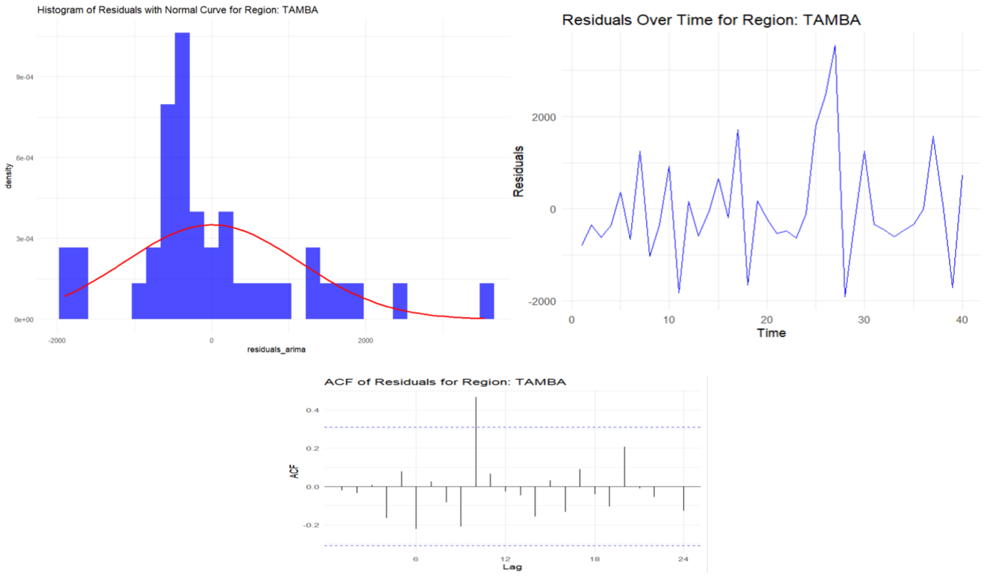

Fig. 9: Residual Analysis of the ARIMA Model for the Tamba Region.

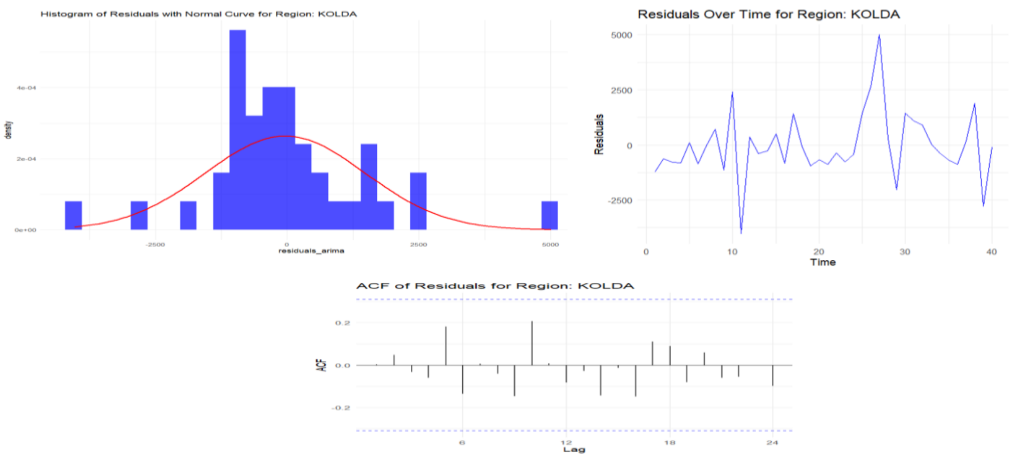

Fig. 10: Residual analysis of the ARIMA model for the Kolda region.

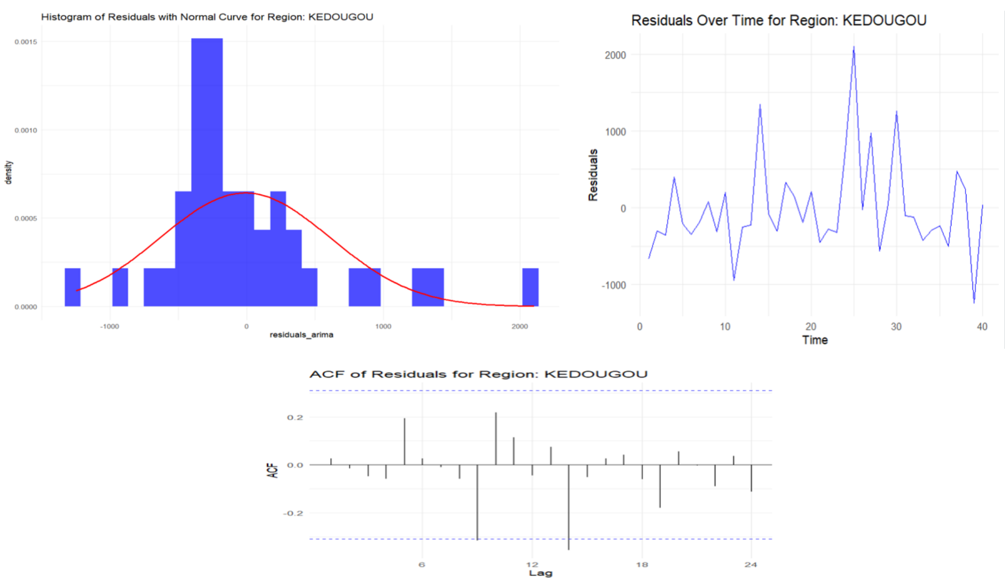

Fig. 11: Residual analysis of the ARIMA model for the Kedougou region

The residual analysis for the regions of Tambacounda, Kolda, and Kédougou reveals varied dynamics. In Tambacounda, a significant autocorrelation at Lag 10 suggests an unmodeled structure, while the other lags are non-significant, indicating a generally well-fitted model. In Kolda, no lag exceeds the confidence interval, confirming that the model appropriately captures the data. For Kédougou, Lag 14 shows a significant negative autocorrelation, pointing to a possible cyclical pattern not captured by the model. Model adjustments should focus on these significant lags to improve overall performance.

IV. Discussion

The STL decomposition (Seasonal and Trend Decomposition using Loess) revealed three key components: trend, seasonality, and residuals. It highlighted significant peaks, particularly around 2018, followed by a gradual decline in cases. This overall trend, marked by an increase until 2018 and then a decrease, could reflect the effects of seasonal fluctuations, public health interventions, and other environmental and climatic factors. The well-defined seasonal cycles suggest an annual predictability of malaria cases, reinforcing the link between the disease and climatic variations.

However, the residuals showed fluctuations not captured by the main components, emphasizing the importance of monitoring anomalies and specific events. The results revealed that Kolda exhibited the most pronounced variations, followed by Tambacounda, and then Kédougou.

The use of ARIMA models for forecasting indicated a general trend towards stabilization, but with notable uncertainty, especially in Kolda, where forecast errors were more pronounced. The residual analysis uncovered anomalies and temporal dependencies not captured by the models, with more extreme residuals and significant autocorrelations, particularly in Kolda. This underscores the need to adjust the models to better capture these region-specific dynamics and improve forecast accuracy.

Recommendations

- Strengthening surveillance capacities, particularly in Kolda, is crucial for quickly detecting any resurgence of cases.
- Targeted regional approaches are necessary, with interventions specifically tailored to local dynamics.
- Prevention strategies should be intensified during periods of seasonal peaks.
- Improving forecasting models, particularly by exploring more complex models such as SARIMA or machine learning models, would enhance accuracy. Including variables such as climatic conditions and population movements would further strengthen the analysis.
- Finally, strengthening public health interventions remains essential, including the distribution of bed nets and insecticide spraying before critical periods.
- Prioritizing access to healthcare for children under 5 is also recommended to reduce malaria-related morbidity and mortality.

V. Conclusion

This study analyzed the temporal dynamics of malaria in children under 5 in three Senegalese regions: Tambacounda, Kolda, and Kédougou. Using STL decomposition and ARIMA models, long-term trends, seasonal patterns, and anomalies were identified. The results reveal marked seasonality across all three regions, with peaks around 2018 and a trend toward stabilization. However, Kolda stands out due to greater case volatility, with more extreme residuals. It is recommended to strengthen epidemiological surveillance, particularly in regions with unpredictable fluctuations like Kolda, and to adjust prevention strategies based on seasonality and local specificities. The study also emphasizes the importance of a flexible and continuous approach to monitoring the disease's progression and suggests integrating climatic data and more sophisticated models to refine future forecasts.

Perspectives

- Integrating climatological data could enhance the accuracy of predictive models by accounting for environmental conditions that influence malaria transmission.
- Developing multi-regional models would allow for a more comprehensive analysis of interdependencies between regions.
- The use of machine learning techniques, such as neural networks, could offer more precise forecasts by identifying complex patterns not captured by traditional methods.

ACKNOWLEDGMENTS

- ✓ Global Development Hub of Imperial College London
- ✓ MRC Centre for Global Infectious Disease Analysis (Imperial College London)
- ✓ National Malaria Control Program (NMCP) Senegal
- ✓ The AMMnet (Applied Malaria Modeling Network) network
- ✓ Cheikh Anta Diop University

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