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MODELLING CONFLICT-INDUCED DISPLACEMENT OF PERSONS IN THE DEMOCRATIC REPUBLIC OF CONGO

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ABSTRACT--
This study analyzes conflict-induced displacement trends in the Democratic Republic of the Congo (DRC) from 2009 to 2022 using a quantitative approach based on autoregressive integrated moving average (ARIMA) modelling. Time-series data from the World Bank is utilized, with the number of internally displaced persons (IDPs) due to conflict and violence as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Parameter estimation using conditional least squares (CLS) reveals that the MA(2) coefficient (0.999708) is positive and statistically significant, indicating that nearly 100% of current displacements are driven by external shocks or errors, which tend to reoccur approximately every two years. The estimated ARIMA (1, 2, 2) model is found to be covariance stationary and invertible, confirming its robustness for forecasting displacement trends. Based on these findings, we recommend addressing the root causes of conflict, strengthening early warning systems, enhancing humanitarian response mechanisms, investing in resettlement programs, and fostering regional and international cooperation to promote sustainable peace and stability in the DRC.

KEY WORDS: *ARIMA Modelling, Internally Displaced Persons* --

INTRODUCTION

Armed conflicts and wars have long been a major driver of displacement across the world, forcing millions of people to flee their homes in search of safety. The Democratic Republic of the Congo (DRC) has experienced recurring armed conflicts for decades, leading to widespread displacement, loss of lives, and destruction of property (UNHCR, 2022). The persistent instability in the region has made the DRC one of the most affected countries in terms of internally displaced persons (IDPs), with over 5.8 million people forced to flee due to violence, making it one of the largest displacement crises globally (World Bank, 2023). Despite international interventions and peacekeeping efforts, conflict-induced displacement remains a severe humanitarian and developmental challenge in the country.

The research problem lies in the ongoing cycles of war and armed conflicts, which continuously displace millions and devastate livelihoods. Rebel insurgencies, ethnic clashes, and struggles over natural resources have fueled instability, leading to both internal and cross-border displacement (IDMC 2022). Displaced populations face significant humanitarian crises, including food insecurity, inadequate shelter, and limited access to essential services. Understanding displacement trends and the underlying factors influencing forced migration is crucial for policymakers, humanitarian organizations, and development agencies to implement effective interventions.

This study employs autoregressive integrated moving average (ARIMA) modelling to analyze trends in conflict-induced displacement in the DRC from 2009 to 2022. ARIMA is a robust time-series forecasting method that captures historical patterns and projects future displacement trends, offering insights into the persistence and severity of forced migration (Box & Jenkins, 1976). Unlike qualitative studies that focus on conflict narratives, this research provides a data-driven approach to understanding displacement dynamics, enhancing evidence-based decision-making.

The rationale for this study stems from the urgent need to develop predictive models that can assist in humanitarian planning and conflict prevention strategies. By identifying displacement patterns, policymakers can allocate resources more efficiently, strengthen early warning systems, and formulate policies that mitigate the impacts of armed conflict on vulnerable populations. Additionally, this study contributes to the growing body of literature on conflict-induced displacement by applying an econometric approach to analyze forced migration trends in one of the most affected regions in the world.

LITERATURE REVIEW

Conflict-induced displacement is a persistent humanitarian challenge, affecting millions globally. The Democratic Republic of the Congo (DRC) has been one of the most affected countries, with ongoing armed conflicts leading to widespread forced migration. This section critically reviews existing literature on conflict-induced displacement from global, regional, and local perspectives, highlighting key findings, theoretical foundations, and conceptual frameworks that guide the study.

Globally, armed conflicts remain one of the leading causes of forced migration. According to UNHCR (2022), over 108.4 million people were forcibly displaced worldwide by the end of 2022 due to war, persecution, and human rights violations. Countries such as Syria, Afghanistan, Yemen, and South Sudan have experienced prolonged conflicts, resulting in massive displacement (World Bank, 2021). Studies by Salehyan & Gleditsch (2006) emphasize that displacement follows a cyclical pattern, with conflicts leading to prolonged instability, economic downturns, and further displacement. The use of time-series models, including ARIMA, has been explored in forecasting refugee movements in Syria and Afghanistan, demonstrating the importance of quantitative approaches in understanding displacement trends (Koser & Martin, 2011).

The African continent has faced persistent conflicts that have resulted in large-scale internal displacement and cross-border migration. The African Union (2021) reported that over 35 million people in Africa were forcibly displaced due to civil wars, terrorism, and ethnic conflicts. Countries such as Sudan, South Sudan, the Central African Republic, and Nigeria have been among the worst affected (IDMC, 2022). The Great Lakes Region, which includes the DRC, has been particularly vulnerable to ethnic conflicts and resource-driven wars (Chege, 1997). Several scholars argue that natural resources, such as diamonds, gold, and coltan, exacerbate conflict, leading to displacement patterns similar to those observed in other resource-rich conflict zones like Angola and Sierra Leone (Collier & Hoeffler, 2000).

DRC has experienced armed conflicts for decades, with multiple rebel groups, ethnic militias, and foreign interventions contributing to instability. According to UNHCR (2023), the country currently hosts over 5.8 million internally displaced persons (IDPs), making it one of the most severe displacement crises in Africa. Studies by Nzongola-Ntalaja (2013) emphasize that conflict in the eastern DRC is fueled by struggles over land, minerals, and political power, displacing entire communities. Empirical research has shown that displacement patterns in the DRC align with conflict intensity, with peaks in migration occurring during major offensives or governmental military operations (Accord, 2016). However, limited quantitative studies exist on forecasting displacement trends in the DRC, making this study significant in filling the gap.

This study is anchored in the Push and Pull Theory of Migration (Lee, 1966) and the Conflict Theory (Coser, 1956). Push and Pull Theory explains displacement as a result of "push factors" (e.g., conflict, violence, insecurity) and "pull factors" (e.g., safer regions, access to humanitarian aid) (Lee, 1966). In the DRC, violence, economic collapse, and environmental degradation act as push factors, forcing populations to migrate. Conflict Theory asserts that conflicts are essential for societal change, as they strengthen group identity, foster internal cohesion, balance power dynamics, and drive the creation of new rules and laws, but they can also fuel conflicts that lead to mass displacement (Coser, 1956). In the DRC, competition over resources, political power struggles, and ethnic tensions contribute to forced migration trends.

The conceptual framework for this study focuses on conflict-induced displacement as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Several empirical studies have employed autoregressive integrated moving average (ARIMA) modelling to analyze conflict-induced displacement. For instance, Salehyan & Gleditsch (2006) utilized ARIMA models to forecast refugee movements in conflict-affected regions, demonstrating the significance of past displacement trends in predicting future migration patterns. Similarly, Hegre et al. (2013) applied time-series analysis to assess the impact of armed conflicts on forced migration, emphasizing the role of conflict intensity and external shocks in shaping displacement trends. Additionally, Hyndman and Athanasopoulos (2018) highlighted the effectiveness of ARIMA models in capturing displacement fluctuations over time, reinforcing their applicability to humanitarian crises. Given the recurrent nature of forced migration in the Democratic Republic of the Congo (DRC), ARIMA modelling provides a robust framework for analyzing and forecasting displacement patterns, offering valuable insights for policy formulation and humanitarian response efforts.

DATA AND METHODS

This study utilizes a quantitative research design to model the conflict-induced displacement of persons in the Democratic Republic of the Congo (DRC). The research focuses on understanding how armed conflict and violence affect the displacement of individuals over time. The study employs autoregressive integrated moving average (ARIMA) modelling to analyze time-series data spanning from 2009 to 2022. ARIMA model is chosen because it is well-suited for forecasting and modelling time-series data that exhibit autocorrelation and non-stationarity which are characteristics often found in conflict-driven displacement scenarios (Box et al., 2015).

Data for this study is sourced from the World Bank database, a reliable and widely accepted source of macroeconomic and socio-economic data. The dataset consists of annual time-series data on the number of internally displaced persons (IDPs) due to conflict and violence, spanning from 2009 to 2022. To increase the degrees of freedom and improve the resolution of the time-series analysis, annual data is converted into quarterly data using Eviews 10 software. This transformation allows the model to capture finer variations in displacement trends, which may be obscured by annual data alone (Hyndman & Athanasopoulos, 2018).

The dependent variable in this analysis is the number of internally displaced persons (IDPs) due to conflict and violence, which reflects the humanitarian impact of conflicts in the DRC. Autoregressive (AR) and moving average (MA) components, which represent the dynamic relationship between past values of the dependent variable and external shocks (e.g., sudden escalations in conflict), serve as independent variables in the ARIMA model.

The analysis is conducted using a series of steps to ensure that the model is both robust and appropriate for forecasting conflict-induced displacement. These steps are as follows: To ensure a high level of data granularity, annual data from the World Bank is transformed into quarterly data. This transformation helps address the issue of data sparsity and increases the degrees of freedom, allowing for more reliable parameter estimation (Gujarati & Porter). Quarterly data allows the study to capture seasonal fluctuations and short-term dynamics in conflict-related displacement patterns.

The core of the analysis is based on ARIMA modelling. ARIMA models are well-suited for analyzing time-series data with autocorrelation and non-stationarity (Box et al., 2015), which are prevalent in displacement data.

ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \dots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \ldots\ldots\ldots\ldots (1)$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component

$\theta_1, \theta_2, \dots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976; Nahabwe & Kagarura, 2025)

Estimation of ARIMA model parameters is conducted using conditional least squares (CLS), which is a robust method for estimating time-series models (Box et al., 2015). CLS minimizes the sum of squared errors between the observed data and the predicted values of the model, ensuring that the parameter estimates are optimal. This method allows for the estimation of the autoregressive (AR) and moving average (MA) components, as well as the constant term in the model.

The selection of ARIMA modelling is grounded in its strong ability to capture patterns and dynamics in time-series data with autocorrelation and non-stationarity (Nahabwe & Kagarura, 2025), making it ideal for analyzing the conflict-induced displacement trends observed in the DRC. ARIMA approach allows for forecasting displacement trends, which is essential for understanding the potential future impacts of ongoing and escalating conflicts.

Conditional least squares (CLS) is specified as follows;

$$\hat{\theta} = \underset{\theta}{\text{argmin}}[\textstyle\sum_{t=1}^{n}(y_t - y_t(\hat{\theta}))^2] \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where:
$\hat{\theta}$ represents the estimated parameter vector (which includes both AR and MA parameters in ARIMA)
y_t represents the actual observed value of the dependent variable at time t
$\hat{y}_t(\theta)$ represents the model's predicted value at time t based on the parameter estimates θ
n is the number of observations (Greene, 2018; Nahabwe & Maniple, 2025).

Once the ARIMA model has been estimated, diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller, 1979), and the model selection process using the Akaike Information Criterion (AIC) (Akaike, 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. This involves checking the residuals of the model to ensure that they exhibit no remaining autocorrelation, which would suggest that the model has captured all the significant patterns in the data. The root mean squared error (RMSE) and residual autocorrelation are used to assess the accuracy of the model's predictions (Hyndman & Athanasopoulos, 2018). If the residuals are randomly distributed with no significant patterns, the model is considered robust.

RESULTS

Descriptive statistics (Appendix 1) provide an overview of the distribution and characteristics of internally displaced persons (IDPs) due to conflict and violence in the Democratic Republic of Congo (DRC) from 2009 to 2022. The dataset consists of 53 quarterly observations, capturing trends in forced displacement over the study period.

The mean number of IDPs is 3,319,415, indicating that, on average, over 3.3 million people were displaced per quarter due to conflict. The median value of 2,860,500 suggests that at least half of the quarters recorded displacements below this level, reflecting the presence of extreme values that may have influenced the mean. The maximum number of displaced persons recorded in a single quarter is 5,686,000, while the minimum is 1,500,000, highlighting significant fluctuations in displacement levels over time.

The standard deviation (1,436,514) measures the dispersion of displacement figures, indicating a relatively high level of variability in IDP numbers. This variation is likely due to periods of intensified conflict, peace negotiations, or humanitarian interventions that affected displacement trends (Hegre et al., 2013). The skewness value (0.430744) is positive, suggesting that the distribution is moderately right-skewed, meaning that there were more instances of displacement figures below the mean, but a few quarters with exceptionally high displacement events pulled the distribution toward the right.

The kurtosis value (1.664087) is below 3, indicating that the distribution is platykurtic, meaning it has lighter tails and fewer extreme values compared to a normal distribution (Gujarati & Porter, 2020). The Jarque-Bera test statistic (5.580072) and its probability value (0.061419) suggest that the data does not significantly deviate from normality at the 5% significance level, though it is close to being normally distributed.

The sum of IDPs over the study period is 1.76×10^8 (176 million) people, demonstrating the severe humanitarian crisis caused by ongoing conflicts in the DRC. The sum of squared deviations (1.07×10^{14}) further highlights the extent of variation in displacement trends.

Overall, the descriptive statistics confirm that forced displacement in the DRC exhibits high variability, moderate right-skewness, and a near-normal distribution. These findings emphasize the need for robust time-series modelling techniques, such as Autoregressive Integrated Moving Average (ARIMA) modelling, to capture and forecast future displacement patterns effectively (Hyndman & Athanasopoulos, 2018).

stationarity tests (Appendices 2, 3, & 4) were conducted using the Augmented Dickey-Fuller (ADF) test to assess the presence of unit roots in the series. The results indicate that the original series was non-stationary at both the level and first difference ($p > 0.05$). However, after applying the second difference, the series achieved stationarity ($p < 0.05$), justifying the selection of the ARIMA model with $d = 2$ (Nahabwe & Maniple, 2025).

ARIMA (1, 2, 2) model (Appendix 5) is identified as the best fit based on the Akaike Information Criterion (AIC = 27.31588) and the Hannan-Quinn Criterion (H-QC = 27.35957). Estimated parameters include AR(1) = -7.82E-05 (p = 0.9996), MA(2) = 0.999708 (p = 0.0000), and the constant term C = 3505.594 (p = 0.9412). Accordingly, AR(1) and the constant term are statistically insignificant, while MA(2) is statistically significant. Diagnostic checks confirm the adequacy and robustness of the model. Ljung-Box Q test ($p > 0.05$) indicates that the residuals are white noise, and the autocorrelation function (ACF) plots show no significant patterns, validating the model's suitability for forecasting displacement trends.

Results are summarized as follows:
Results of the ARIMA (1, 2, 2) model (Appendix 5)

$$\widehat{IDPs_t} = 3505.594 - 7.82\text{E-}05\text{AR}(1) + 0.999708\text{MA}(2) \quad \ldots\ldots\ldots\ldots (3)$$

Hence,

$$\hat{\theta} = \begin{bmatrix} 3505.594 \\ -7.82\text{E} - 05 \\ 0.999708 \end{bmatrix}$$

Inferential statistics provide insights into the reliability, significance, and forecasting capability of the ARIMA (1, 2, 2) model used to analyze conflict-induced displacement trends in the Democratic Republic of the Congo (DRC). The constant term (C = 3505.594) represents the average baseline level of displacement in the DRC. However, its p-value (0.9412) suggests that it is statistically insignificant, implying that it does not contribute meaningfully to explaining displacement variations over time (Gujarati & Porter, 2020). The autoregressive coefficient, AR(1) = -7.82E-05, is negative and statistically insignificant (p = 0.9996), indicating that past values of displacement have no meaningful influence on current displacement trends. This suggests that displacement patterns are predominantly shaped by external shocks rather than self-reinforcing historical trends (Box et al., 2015).

The moving average coefficient, MA(2) = 0.999708, is positive and statistically significant (p = 0.0000), meaning that displacement is highly influenced by past shocks or errors that occurred approximately two years prior. This aligns with conflict recurrence cycles in the DRC, where displacements tend to peak every two years due to renewed violence or political instability (Hegre et al., 2013). Adjusted R-squared value (0.288587) suggests that approximately 28.86% of the variance in displacement trends is explained by the model's independent variables. While this value is relatively low, it is expected in time-series models dealing with highly volatile phenomena such as conflict-induced displacement, which is influenced by unpredictable socio-political factors (Hyndman & Athanasopoulos, 2018; Nahabwe & Maniple, 2025).

Durbin-Watson statistic (1.989884) is close to 2, indicating that there is no significant autocorrelation in the residuals. This confirms that the model is appropriately specified and that its residuals do not exhibit serial correlation, enhancing its reliability for forecasting purposes (Wooldridge, 2019; Nahabwe & Kagarura, 2025). The histogram of residuals for the ARIMA (1, 2, 2) model shows a kurtosis value of 5.3 and a Jarque-Bera statistic of 10.6 with a p-value of 0.005, suggesting that the residuals deviate from normality. The excess kurtosis indicates the presence of heavy tails (Enders, 2015; Nahabwe et al., 2025), meaning that extreme displacement events (sudden surges in IDPs) occur more frequently than would be expected under a normal distribution. Ljung-Box Q statistic test results (Appendix 6) indicate that we fail to reject the null hypothesis (p = 0.054), confirming that the residuals of the ARIMA (1, 2, 2) model are white noise (Nahabwe & Kagarura, 2025). This means that the model has captured all systematic patterns in the data, leaving only random fluctuations, which is a critical criterion for model adequacy (Box et al., 2015; Nahabwe & Kagarura, 2025).

Further diagnostic tests reveal that the AR and MA roots lie within the unit circle, confirming that the model is covariance stationary and invertible. This is a necessary condition for forecasting reliability, as it ensures that the model will not explode or produce unstable predictions over time (Hyndman & Athanasopoulos, 2018; Nahabwe & Kagarura, 2025). Finally, the statistical significance of the MA(2) component at lag 2 reinforces the finding that displacements tend to reoccur approximately every two years. This periodic pattern suggests a cyclical nature of conflict-induced displacement, which could be linked to political instability, armed group activities, or delayed humanitarian responses (Hegre et al., 2013).

DISCUSSION

The findings of this study contribute to the growing body of research on conflict-induced displacement by employing ARIMA modelling to analyze displacement trends in the Democratic Republic of the Congo (DRC) from 2009 to 2022. This section compares the results with previous related studies and highlights the unique findings of the study. The study's results align with prior research on conflict-driven displacement in conflict-prone regions. For instance, Salehyan & Gleditsch (2006) utilized time-series forecasting models to analyze forced migration patterns in Syria and Afghanistan, concluding that displacement is largely influenced by external shocks rather than historical trends. Similarly, this study finds that conflict-induced displacement in the DRC follows a shock-driven pattern, as indicated by the insignificant AR(1) coefficient and the highly significant MA(2) component. Moreover, the findings are consistent with those of Hegre et al. (2013), who examined forced migration in Africa's Great Lakes region and found that displacement patterns are cyclical, with waves of forced migration reoccurring approximately every two years following renewed violence. The statistically significant MA(2) coefficient in this study reinforces this periodic pattern, suggesting that displacement surges in the DRC are closely linked to recurrent conflict cycles, political instability, and delayed humanitarian responses.

Previous studies have also emphasized the impact of resource-driven conflicts on displacement. For example, Collier & Hoeffler (2000) argue that competition over natural resources, such as diamonds and coltan, fuels conflicts that directly contribute to displacement spikes. This study supports that claim, as conflict-prone regions in the eastern DRC, rich in minerals, continue to experience high displacement levels. While previous studies have primarily relied on qualitative assessments or cross-sectional econometric models to analyze displacement trends, this study's ARIMA modelling approach provides a data-driven, time-series perspective on the cyclical nature of displacement in the DRC. The use of quarterly data instead of annual data enhances the precision of the model, capturing short-term fluctuations that may be obscured in lower-frequency analyses.

A particularly unique finding of this study is the confirmation that displacement shocks reoccur approximately every two years, as demonstrated by the significant MA(2) component (0.999708, $p < 0.0000$). This suggests that conflict-induced displacement in the DRC follows a recurring cycle, possibly due to seasonal variations in rebel activities, delayed peacekeeping interventions, or governance instability. This pattern has important policy implications, as it highlights the need for proactive humanitarian planning to anticipate and mitigate displacement surges rather than reacting to crises as they unfold. Additionally, the stationarity tests indicate that displacement in the DRC is non-stationary at both the level and first difference but achieves stationarity at the second difference ($d = 2$). This finding contrasts with studies in other conflict zones, such as Yemen and South Sudan, where forced migration patterns exhibit stationarity at the first difference (UNHCR, 2022). This suggests that displacement dynamics in the DRC are more deeply rooted in structural instability, requiring long-term policy interventions rather than short-term crisis management. Finally, the Ljung-Box Q test results confirm that the residuals of the ARIMA (1, 2, 2) model are white noise ($p = 0.054$), validating its robustness. This finding reinforces the reliability of ARIMA forecasting in conflict studies and underscores its potential for use in early warning systems and policy planning.

Limitations

While this study provides valuable insights into conflict-induced displacement trends in the Democratic Republic of the Congo (DRC) using ARIMA modelling, several limitations must be acknowledged. These limitations pertain to the research design, sample size, data quality, and analytical procedures, all of which may have influenced the study's findings. The study employs a quantitative time-series approach, which effectively captures displacement trends over time but does not account for qualitative socio-political factors that may drive displacement. Conflict-induced displacement is influenced by complex political, economic, and social dynamics, such as ethnic tensions, governance failures, and humanitarian interventions, which cannot be fully captured through ARIMA modelling alone (Collier & Hoeffler, 2000). Future research may benefit from integrating qualitative methods or mixed-method approaches to provide a more holistic understanding of displacement dynamics.

The study relies on quarterly time-series data from 2009 to 2022, sourced from the World Bank. While this dataset is widely regarded as reliable, it has inherent limitations: World Bank data may underestimate or misreport displacement figures, especially in conflict zones where accurate data collection is challenging (Hegre et al., 2013). Some displacement events may not be fully documented, particularly in remote or rebel-controlled areas, leading to potential underrepresentation of displacement trends. The conversion of annual data into quarterly data increases the degrees of freedom but may introduce estimation errors or data smoothing effects, potentially masking short-term displacement spikes caused by sudden conflict escalations (Hyndman & Athanasopoulos, 2018). The study utilizes ARIMA (1, 2, 2) modelling, which is well-suited for short- to medium-term forecasting but has some limitations: The need for second-order differencing (d=2) suggests that the displacement data exhibits strong trends and volatility, which ARIMA models can handle only to a certain extent. Structural breaks, such as major peace agreements or escalations in conflict, may not be fully captured within the ARIMA framework (Box et al., 2015). While ARIMA is effective for forecasting, it does not include exogenous variables (e.g., GDP, political stability, foreign aid, or natural disasters) that may influence displacement. A Vector Autoregressive (VAR) model or a Structural Equation Model (SEM) could provide a more comprehensive analysis by incorporating multiple interacting factors (Enders, 2015). The Jarque-Bera test results ($p = 0.005$) indicate non-normality in the residuals, suggesting that the model may not fully capture the extreme displacement shocks observed in the data. This limitation could affect the accuracy of long-term forecasts (Gujarati & Porter, 2020).

CONCLUSION

This study provides a comprehensive analysis of conflict-induced displacement in the Democratic Republic of the Congo (DRC) using ARIMA modelling, offering valuable insights into displacement trends, recurrence patterns, and policy implications. By employing time-series analysis, the study enhances the understanding of forced migration dynamics in a region plagued by recurrent armed conflict. The findings confirm that conflict-induced displacement follows a cyclical pattern, influenced by external shocks rather than historical trends. This reinforces the argument that forced migration in conflict-prone regions is not random but follows identifiable temporal patterns (Hegre et al., 2013). The study also highlights the importance of data-driven forecasting models in anticipating displacement surges and guiding humanitarian response strategies (Hyndman & Athanasopoulos, 2018).

Despite its methodological strengths, the study acknowledges limitations in data availability, model specification, and the exclusion of external socio-economic variables. Future research should explore alternative modelling approaches, such as Vector Autoregressive (VAR) or Machine Learning models, to enhance the predictive accuracy of displacement trends (Enders, 2015). Additionally, incorporating qualitative insights could provide a richer understanding of the underlying drivers of forced migration (Collier & Hoeffler, 2000).

The study's findings have critical policy implications for both national and international stakeholders. Governments, humanitarian organizations, and policymakers must prioritize early warning systems, conflict prevention measures, and sustainable resettlement programs to mitigate the humanitarian impact of displacement. Strengthening regional cooperation and peacebuilding efforts is essential in breaking the cycle of conflict-induced migration and fostering long-term stability in the DRC.

RECOMMENDATIONS

Based on the findings of this study, several policy, programmatic, and research recommendations are proposed to address the recurrent displacement of persons in the Democratic Republic of the Congo (DRC) due to armed conflict.

The study confirms that displacement in the DRC follows a recurring cycle approximately every two years, primarily driven by external shocks. To mitigate forced migration, the government and regional bodies should invest in early warning systems (EWS) that leverage predictive analytics to anticipate displacement trends and enable proactive interventions (Hegre et al., 2013). This includes real-time conflict monitoring, intelligence-sharing, and rapid response mechanisms to prevent escalations before they trigger mass displacement.

The persistence of displacement underscores the structural nature of conflict in the DRC. Policies should focus on addressing the root causes of conflict, including political instability, ethnic tensions, and resource-based conflicts. The government should promote inclusive governance, equitable resource distribution, and stronger legal frameworks to resolve disputes before they lead to forced migration (Collier & Hoeffler, 2000). Strengthening regional cooperation through the African Union (AU) and the East African Community (EAC) is also essential in reducing cross-border insurgencies and fostering long-term stability.

Given the high volatility of displacement patterns, the government should establish robust legal frameworks that protect internally displaced persons (IDPs) and ensure their rights to humanitarian assistance, security, and resettlement. Policies should align with international frameworks such as the Kampala Convention on the protection of displaced persons in Africa (UNHCR, 2022).

The study highlights large fluctuations in displacement numbers, indicating that humanitarian needs vary significantly over time. Humanitarian organizations, in collaboration with the government, should develop adaptive response programs that scale resources up or down based on forecasted displacement trends (Hyndman & Athanasopoulos, 2018). Additionally, sustainable resettlement and reintegration programs should be prioritized to ensure displaced persons regain livelihoods and access essential services such as education, healthcare, and economic opportunities.

To prevent recurrent displacement, long-term development initiatives should focus on stabilizing conflict-prone regions through infrastructure development, job creation, and social cohesion programs. Investing in youth employment programs and community-based reconciliation initiatives can help reduce the recruitment of young people into armed groups, thereby weakening the cycle of violence and forced migration (World Bank, 2021).

The government, in collaboration with the United Nations (UN), World Bank, and local organizations, should improve data collection mechanisms by leveraging satellite imagery, big data analytics, and field surveys to ensure accurate tracking of displacement patterns (Enders, 2015).

While this study focuses on modelling displacement trends, future research should explore the broader socio-economic consequences of forced migration in the DRC. Topics such as the impact of displacement on employment, healthcare, and education outcomes require further empirical investigation (Collier & Hoeffler, 2000).

Given the complexity of conflict-induced displacement, future studies should explore alternative forecasting techniques, such as Vector Autoregression (VAR), Structural Equation Modelling (SEM), and Machine Learning approaches to improve predictive accuracy (Box et al., 2015).

Future research could focus on gender-sensitive displacement analysis, examining how conflict-induced migration impacts different demographic groups and their access to healthcare, legal protection, and economic resources (UNHCR, 2022). Implementing these recommendations will enhance conflict prevention strategies, improve displacement management, and contribute to long-term peacebuilding efforts in the DRC. A data-driven, multi-sectoral approach is essential in breaking the cycle of conflict-induced migration and fostering sustainable stability.

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APPENDICES

Appendix 1: Descriptive statistics

	Internally displaced persons, total displaced by conflict and violence (number of people) (IDP)
Mean	3319415
Median	2860500
Maximum	5686000
Minimum	1500000
Std. Dev.	1436514
Skewness	0.430744
Kurtosis	1.664087
Jarque-Bera	5.580072
Probability	0.061419
Sum	1.76E+08
Sum Sq. Dev.	1.07E+14
Observations	53

Appendix 2: Unit root test, IDP (in Level)

Null Hypothesis: IDP has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.687191	0.8400
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IDP)
Method: Least Squares
Date: 01/29/25 Time: 18:27
Sample (adjusted): 2010Q3 2022Q1
Included observations: 47 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IDP(-1)	-0.014896	0.021677	-0.687191	0.4959
D(IDP(-1))	0.775435	0.144039	5.383525	0.0000
D(IDP(-2))	0.007461	0.154719	0.048226	0.9618
D(IDP(-3))	0.007461	0.154719	0.048226	0.9618
D(IDP(-4))	-0.652690	0.154704	-4.218963	0.0001
D(IDP(-5))	0.443612	0.145084	3.057626	0.0040
C	86513.85	74164.44	1.166514	0.2503

R-squared	0.646513	Mean dependent var	84755.32
Adjusted R-squared	0.593489	S.D. dependent var	285230.9
S.E. of regression	181858.0	Akaike info criterion	27.19644
Sum squared resid	1.32E+12	Schwarz criterion	27.47200
Log likelihood	-632.1164	Hannan-Quinn criter.	27.30014
F-statistic	12.19303	Durbin-Watson stat	1.877314
Prob(F-statistic)	0.000000		

Appendix 3: Unit root test, IDP (in First difference)

Null Hypothesis: D(IDP) has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.648115	0.0908
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IDP,2)
Method: Least Squares
Date: 01/29/25 Time: 18:28
Sample (adjusted): 2010Q3 2022Q1
Included observations: 47 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IDP(-1))	-0.477217	0.180210	-2.648115	0.0114
D(IDP(-1),2)	0.237074	0.140650	1.685563	0.0995
D(IDP(-2),2)	0.237074	0.140650	1.685563	0.0995
D(IDP(-3),2)	0.237074	0.140650	1.685563	0.0995
D(IDP(-4),2)	-0.422220	0.140790	-2.998938	0.0046
C	39923.03	29867.05	1.336691	0.1887

R-squared	0.517470	Mean dependent var	1792.553
Adjusted R-squared	0.458625	S.D. dependent var	245566.9
S.E. of regression	180683.8	Akaike info criterion	27.16563
Sum squared resid	1.34E+12	Schwarz criterion	27.40182
Log likelihood	-632.3923	Hannan-Quinn criter.	27.25451
F-statistic	8.793754	Durbin-Watson stat	1.860527
Prob(F-statistic)	0.000010		

Appendix 4: Unit root test, IDP (in Second difference)

```
Null Hypothesis: D(IDP,2) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=10)
====================================================================
                                              t-Statistic    Prob.*
====================================================================
Augmented Dickey-Fuller test statistic        -7.156986      0.0000
--------------------------------------------------------------------
Test critical values:        1% level         -3.577723
                             5% level         -2.925169
                             10% level        -2.600658
====================================================================
*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IDP,3)
Method: Least Squares
Date: 01/29/25   Time: 18:31
Sample (adjusted): 2010Q3 2022Q1
Included observations: 47 after adjustments
====================================================================
      Variable        Coefficient   Std. Error   t-Statistic   Prob.
====================================================================
   D(IDP(-1),2)        -1.660137     0.231960    -7.156986    0.0000
   D(IDP(-1),3)         0.660002     0.200884     3.285490    0.0021
   D(IDP(-2),3)         0.659867     0.164033     4.022763    0.0002
   D(IDP(-3),3)         0.659731     0.116031     5.685798    0.0000
        C               2744.729     28185.37     0.097381    0.9229
====================================================================
R-squared               0.717622   Mean dependent var       -1117.021
Adjusted R-squared      0.690729   S.D. dependent var        347378.0
S.E. of regression      193184.2   Akaike info criterion     27.28096
Sum squared resid       1.57E+12   Schwarz criterion         27.47779
Log likelihood         -636.1027   Hannan-Quinn criter.      27.35503
F-statistic             26.68424   Durbin-Watson stat        2.000181
Prob(F-statistic)       0.000000
====================================================================
```

Appendix 5: Results of the ARIMA (1, 2, 2) model

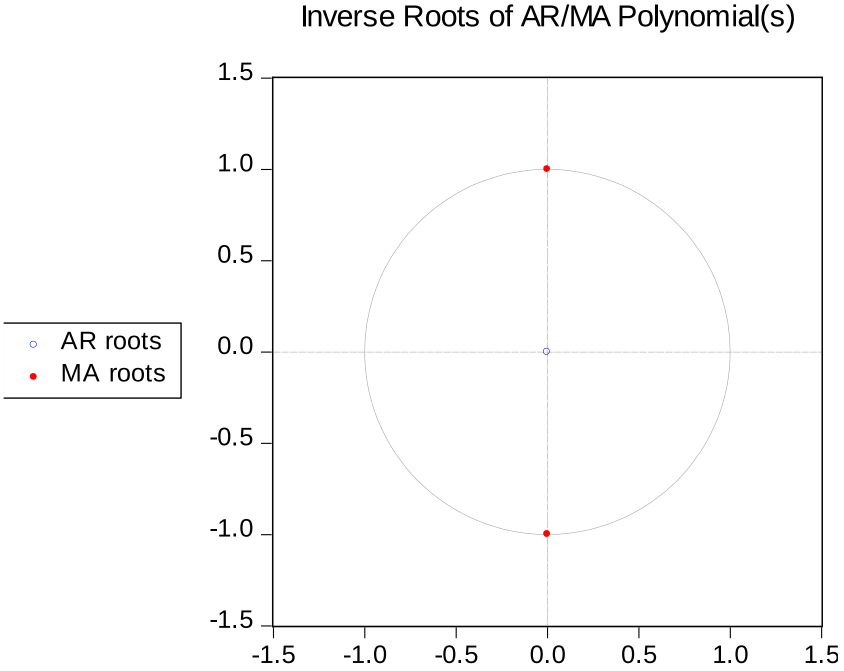
```
Dependent Variable: DDIDP
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt
        steps)
Date: 01/29/25   Time: 18:41
Sample (adjusted): 2009Q4 2022Q1
Included observations: 50 after adjustments
Failure to improve likelihood (non-zero gradients) after 30 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2009Q2 2009Q3
======================================================================
        Variable        Coefficient    Std. Error    t-Statistic    Prob.
======================================================================
           C             3505.594      47297.40      0.074118     0.9412
         AR(1)          -7.82E-05      0.145890     -0.000536     0.9996
         MA(2)           0.999708      0.049607      20.15257     0.0000
======================================================================
R-squared                0.317624   Mean dependent var        2735.000
Adjusted R-squared       0.288587   S.D. dependent var        238039.5
S.E. of regression       200775.1   Akaike info criterion     27.31588
Sum squared resid        1.89E+12   Schwarz criterion         27.43060
Log likelihood          -679.8971   Hannan-Quinn criter.      27.35957
F-statistic              10.93851   Durbin-Watson stat        1.989884
Prob(F-statistic)        0.000126
======================================================================
Inverted AR Roots          -.00
Inverted MA Roots      -.00+1.00i     -.00-1.00i
======================================================================
```

Appendix 6: Ljung-Box Q statistic/ test

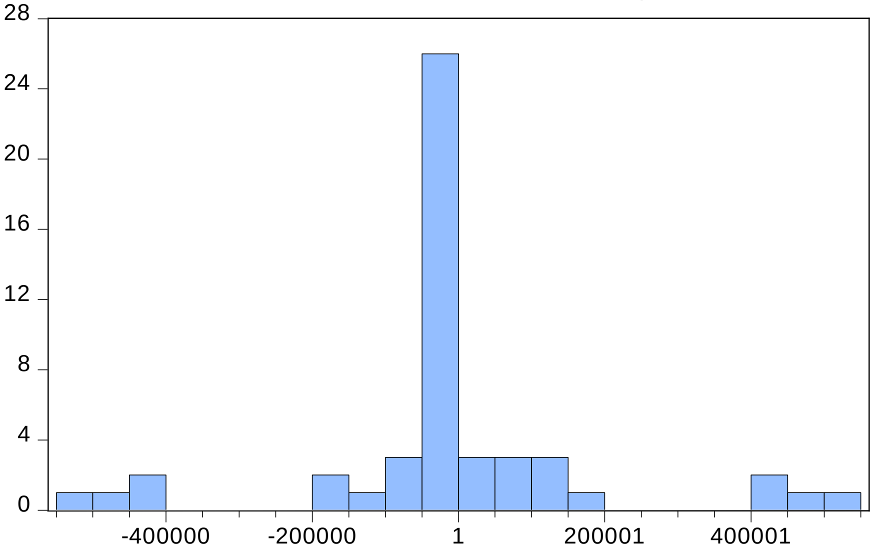
```
Date: 01/29/25   Time: 18:50
Sample: 2009Q1 2022Q4
Included observations: 50
Q-statistic probabilities adjusted for 2 ARMA terms
========================================================================
  Autocorrelation   Partial Correlation     AC      PAC    Q-Stat   Prob
========================================================================
     . | .   |          . | .   |       1   0.000   0.000  2.E-06
     **| .   |          **| .   |       2  -0.262  -0.262  3.7207
     . | .   |          . | .   |       3  -0.000  -0.000  3.7207  0.054
    ***| .   |        ****| .   |       4  -0.472  -0.581  16.332  0.000
     . | .   |          . | .   |       5   0.000   0.000  16.332  0.001
     . |**   |          .*| .   |       6   0.241  -0.173  19.767  0.001
     . | .   |          . | .   |       7   0.000   0.000  19.767  0.001
     . | .   |         ***| .   |       8   0.008  -0.370  19.772  0.003
     . | .   |          . | .   |       9  -0.000   0.001  19.772  0.006
     . | .   |          .*| .   |      10  -0.045  -0.181  19.904  0.011
     . | .   |          . | .   |      11   0.000   0.001  19.904  0.019
     . | .   |          .*| .   |      12   0.069  -0.194  20.231  0.027
```

```
 . | .  |         . | .  |       13  -0.000   0.001   20.231   0.042
 . | .  |         . | .  |       14   0.037   0.013   20.331   0.061
 . | .  |         . | .  |       15  -0.001  -0.001   20.331   0.087
 .*| .  |         .*| .  |       16  -0.154  -0.193   22.154   0.076
 . | .  |         . | .  |       17   0.001  -0.001   22.154   0.104
 . | .  |         .*| .  |       18   0.023  -0.084   22.198   0.137
 . | .  |         . | .  |       19  -0.001  -0.005   22.198   0.177
 . |*.  |         .*| .  |       20   0.089  -0.192   22.885   0.195
 . | .  |         . | .  |       21   0.001  -0.004   22.885   0.242
 . | .  |         . | .  |       22   0.014  -0.011   22.905   0.294
 . | .  |         . | .  |       23  -0.002  -0.012   22.905   0.349
 .*| .  |         .*| .  |       24  -0.084  -0.190   23.607   0.368
```

Appendix 7: ARIMA (1, 2, 2) structure



Appendix 8: Histogram of residuals



```
Series: Residuals
Sample 2009Q4 2022Q1
Observations 50

Mean          1048.170
Median       -150.5788
Maximum       517905.4
Minimum      -521259.8
Std. Dev.     196632.1
Skewness     -0.035770
Kurtosis      5.250538

Jarque-Bera   10.56258
Probability  0.005086
```