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MODELLING STUNTING (HEIGHT-FOR-AGE) IN CHILDREN UNDER 5 IN UGANDA

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ABSTRACT
This study models the prevalence of stunting (height-for-age) among children under 5 years in Uganda using historical data from 2000 to 2022. Autoregressive integrated moving average (ARIMA) approach is applied for time-series analysis to forecast trends and assess patterns in stunting prevalence. Data sourced from the World Bank is utilized, with the prevalence of stunting (height-for-age) as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Parameter estimation, conducted using conditional least squares (CLS), reveals a positive and statistically significant AR(1) coefficient (0.667780) and a negative MA(5) coefficient (-0.908297). These results imply that approximately 67% of past stunting trends persist into the present, while 91% of errors are corrected in subsequent periods. The estimated ARIMA (1, 2, 5) model is found to be covariance stationary and invertible, confirming its robustness for forecasting future trends. Projections indicate a slight increase in the prevalence of stunting from 23.5% in 2023 to 24.3% by 2032, suggesting a persistent public health challenge despite observed improvements over the study period. Given the implications of these findings, we recommend strengthening nutrition-sensitive interventions, scaling up maternal and child health programs, and implementing policies targeting poverty reduction and food security to mitigate stunting prevalence in Uganda.
KEY WORDS: *ARIMA modelling, Stunting (Height-for-Age)*

INTRODUCTION

Stunting, defined as inadequate height-for-age, is a significant indicator of chronic malnutrition and a critical public health challenge worldwide. In Uganda, the prevalence of stunting among children under 5 years remains alarmingly high, averaging 34.3% (World Bank, 2023). This high prevalence reflects persistent structural challenges, including poverty, food insecurity, poor maternal health, and limited access to quality healthcare services (UNICEF, 2021). Stunting not only impairs physical growth but also affects cognitive development, educational attainment, and future economic productivity (Victora et al., 2008).

Despite efforts to reduce malnutrition, progress in Uganda has been slow, raising concerns about the effectiveness of existing interventions and policies. The persistence of high stunting rates necessitates a systematic analysis of trends and patterns to guide evidence-based policymaking and program design. This study addresses this gap by applying the autoregressive integrated moving average (ARIMA) model to forecast stunting prevalence and assess its dynamics over time.

ARIMA model, widely used in time-series analysis, offers a robust framework for understanding and predicting trends based on past data (Box & Jenkins, 1976). It is particularly useful for modelling complex relationships in time-dependent data, allowing policymakers to anticipate future challenges and design proactive interventions. Additionally, Conditional least squares (CLS) estimation ensures reliable parameter estimation, enhancing the model's predictive accuracy (Hamilton, 2020).

The rationale for this study lies in its potential to fill a critical research gap by providing empirical evidence on the trends and persistence of stunting in Uganda. By identifying patterns and forecasting future prevalence, the study aims to inform strategies aimed at reducing stunting and improving child health outcomes

LITERATURE REVIEW

Globally, stunting affects approximately 22% of children under 5, indicating widespread chronic malnutrition (UNICEF, 2021). Studies highlight poverty, inadequate nutrition, and limited maternal education as key determinants (Black et al., 2013). Countries in South Asia and Sub-Saharan Africa exhibit the highest rates of stunting, largely attributed to food insecurity and poor maternal health (De Onis et al., 2012). Stunting leads to long-term effects, including reduced cognitive performance and economic productivity (Grantham-McGregor et al., 2007).

In Sub-Saharan Africa, the prevalence of stunting remains a pressing concern, averaging 33% among children under 5 (WHO, 2020). Nutritional deficiencies, lack of access to healthcare, and socio-economic disparities contribute to the problem (Victora et al., 2010). Studies emphasize that improvements in water, sanitation, and maternal care can substantially reduce stunting rates (Alderman et al., 2006). However, persistent poverty and conflict exacerbate the situation in many African nations (UNICEF, 2021).

Uganda has experienced marginal reductions in stunting prevalence, but levels remain high, averaging 34.3% (World Bank, 2023). Rural areas exhibit higher rates due to poverty, poor dietary diversity, and low access to maternal health services (UBOS, 2020). Efforts by the Ugandan government, including the Uganda Nutrition Action Plan, have yielded limited success, underscoring the need for evidence-based strategies to address this challenge (MoH, 2018).

This study is anchored in the Life-Course Approach to Nutrition (Fine & Kotelchuck, 2010; Herman et al., 2014), which posits that environmental exposures including biological, physical, social and behavioural factors, as well as life experiences, throughout the entire life span, influence health outcomes in current and future generations. It also integrates Time-Series Forecasting Theory (Box & Jenkins, 1976), emphasizing the importance of past trends in predicting future outcomes. These frameworks provide the basis for modelling and understanding stunting dynamics.

The conceptual framework identifies stunting prevalence as the dependent variable, influenced by errors, autoregressive components (AR), and moving averages (MA). The ARIMA model captures the patterns in stunting prevalence, allowing for projections and policy recommendations. Several empirical studies have employed ARIMA modelling techniques to analyze trends in child health indicators, including stunting (height-for-age) among children under five. For instance, Nahabwe & Maniple (2025) successfully applied ARIMA to model tuberculosis case detection rates in Uganda, demonstrating the method's effectiveness in forecasting disease prevalence. Similarly, Siamba et al. (2023), have incorporated ARIMA alongside other time-series models, emphasizing the importance of selecting optimal parameters for accurate trend prediction. These findings collectively underscore the relevance of ARIMA modelling in monitoring and addressing child stunting in Uganda.

DATA AND METHODS

This study adopts a quantitative research design, employing time-series analysis to model the prevalence of stunting (height-for-age) among children under 5 in Uganda. The quantitative approach is suitable for identifying patterns, trends, and relationships within numerical data (Gujarati & Porter, 2020). Given the time-dependent nature of the data, the Autoregressive Integrated Moving Average (ARIMA) model is selected for its effectiveness in analyzing and forecasting time-series data (Box & Jenkins, 1976).

The study utilizes secondary data covering the period 2000-2022, sourced from the World Bank database. This dataset includes annual observations on the prevalence of stunting (height-for-age) among children under 5. Purposive sampling is employed to focus exclusively on Uganda, ensuring the relevance and specificity of the analysis (Kothari, 2004). The sample size consists of 22 observations, sufficient for time-series modelling, as recommended by Chatfield (2019).

Data analysis involves the following steps: Descriptive Statistics; Key metrics such as mean, median, standard deviation, and skewness are calculated to assess data distribution and characteristics. Stationarity Tests; Augmented Dickey-Fuller (ADF) test checks for stationarity, a prerequisite for ARIMA modelling (Enders, 2014). Model Specification and Estimation; ARIMA (p, d, q) model is specified based on autocorrelation and partial autocorrelation functions. Conditional least squares (CLS) estimation is applied to estimate model parameters, known for its robustness in small samples (Greene, 2018). Diagnostic Tests; Residual analysis ensures model adequacy, including tests for normality, autocorrelation, and heteroscedasticity (Box & Jenkins, 1976). Forecasting - Projections for stunting prevalence are generated to support policy recommendations.

The ARIMA model is chosen for its capacity to handle non-stationary data by differencing and its flexibility in modelling various patterns of autocorrelation and errors (Box & Jenkins, 1976). Conditional Least Squares estimation is employed because of its efficiency in parameter estimation for time-series models, particularly in the presence of autocorrelated errors (Gujarati & Porter, 2020). ARIMA (p, d, q) model specification is as follows:

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

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1$, $\boldsymbol{\phi}_2$, … $\boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
θ_1, θ_2, … θ_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)

Conditional least squares (CLS) estimation is chosen for its efficiency in estimating parameters in time-series models like ARIMA (Greene, 2018). By minimizing the sum of squared residuals, CLS provides optimal parameter estimates for modelling stunting prevalence in Uganda (Box & Jenkins, 1976). It is particularly effective for capturing the relationship between observed and predicted values, ensuring accurate forecasts (Hamilton, 2020). The CLS estimator for the regression coefficients is given by the following formula:

$$\hat{\theta} = \underset{\theta}{\text{argmin}}\left[\sum_{t=1}^{n} (y_t - \hat{y}_t(\theta))^2\right]$$

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).

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. The use of ARIMA modelling in this study is particularly beneficial for modelling stunting prevalence, as it enables the evaluation of past behaviors to make reliable projections (Enders, 2014).

This approach effectively captures the underlying patterns in stunting (height-for-age) among children under five, providing a robust framework for long-term modelling and forecasting. Moreover, ARIMA's capacity to handle non-stationary data makes it particularly well-suited for analyzing complex health and economic time series, where trends and fluctuations exhibit considerable variation over time (Stock & Watson, 2015). Its ability to decompose trends and account for seasonality enhances the reliability of predictive insights. In the context of stunting prevalence, the analytical rigor of ARIMA modelling enables the extraction of meaningful, policy-relevant conclusions about stunting trajectories. These insights can play a crucial role in informing targeted health interventions, optimizing resource allocation, and shaping effective child nutrition and public health policies.

Results

Descriptive statistics (Appendix 1) offer a detailed overview of the prevalence of stunting (height-for-age) among children under five: The mean prevalence of stunting (34.3%) indicates that, on average, approximately 34.3% of children in the sample are stunted. This aligns with global statistics for stunting, particularly in Sub-Saharan Africa, where the prevalence is often high due to various socio-economic factors (UNICEF, 2021). The median prevalence of stunting (34.6%) is close to the mean, suggesting a relatively symmetrical distribution of stunting values in the dataset.

The median represents the middle value when the data is arranged in ascending order, meaning that half of the children in the study have a stunting prevalence below 34.6%, and half have a prevalence above it (WHO, 2018). The maximum value of 44% represents the highest observed stunting prevalence in the dataset. This indicates that some children in the study have significantly higher rates of stunting compared to the average, which may reflect underlying disparities in access to nutrition, healthcare, or other socio-economic factors (UBOS, 2020). The minimum value of 23.4% represents the lowest prevalence of stunting observed in the study. It indicates that some children experience relatively low rates of stunting, which may suggest differences in regional or household-level factors affecting child health (UNICEF, 2021).

The standard deviation of 7.13% indicates the degree of variation or spread in the data. A relatively high standard deviation suggests that the prevalence of stunting among the children in the study varies by approximately 7.13% from the mean. This variation is consistent with findings in many African countries, where stunting prevalence can fluctuate across regions and communities (WHO, 2018). A skewness value of -0.11 suggests a slight negative skew in the distribution of stunting prevalence. This implies that while the majority of children have stunting rates near the higher end of the scale, there are a few cases where the prevalence is lower (UNICEF, 2021). The kurtosis value of 1.55 indicates a platykurtic distribution, meaning that the data is less peaked and has lighter tails compared to a normal distribution. This suggests that there are fewer extreme values or outliers in the dataset than would be expected in a normal distribution (WHO, 2018). The Jarque-Bera test statistic of 2.07, with a probability value of 0.36, indicates that the data does not significantly deviate from a normal distribution. Since the probability is greater than 0.05, we fail to reject the null hypothesis of normality, suggesting that the stunting prevalence data is approximately normally distributed (UNICEF, 2021). The sum of 788.9% represents the total stunting prevalence across all observations. This aggregate value gives an overview of the overall stunting burden in the sample population. The sum of squared deviations (1117.62) reflects the total variation in stunting prevalence from the mean. This high value indicates that there is considerable variation in the stunting rates among the 22 children in the study (WHO, 2018). The dataset consists of 22 observations, matching the time period from 2000 to 2022. While this is a relatively small sample size, it still provides valuable insights into the prevalence and distribution of stunting in this subset of the population (UBOS, 2020).

Stationarity tests (Appendices 2, 3 & 4) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level and in first difference ($p > 0.05$). After second difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model ($d = 2$). ARIMA (1, 2, 5) model is identified as the best, based on Akaike Information Criterion (AIC = -2.155659) and Schwarz Criterion (SC = -2.006299). Parameter estimates include: AR(1) = 0.667780 (p = 0.0036); MA(5) = -0.908297 (p = 0.0000); C = 0.067092 (p = 0.2296). Accordingly, both the coefficient of AR(1) and MA(5) are statistically significant, while the constant term is statistically insignificant. Diagnostic checks confirm the adequacy of the model. The residuals are white noise, as confirmed by the Ljung-Box Q test ($p > 0.05$), and the autocorrelation function (ACF) plots show no significant patterns, validating the model's robustness.

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

$$\widehat{STUNTING}_t = 0.067092 + 0.667780AR(1) - 0.908297MA(5) \quad \ldots\ldots\ldots (3)$$

Hence,

$$\hat{\theta} = \begin{bmatrix} 0.067092 \\ 0.667780 \\ -0.908297 \end{bmatrix}$$

The constant term of 0.067092 is positive but statistically insignificant, meaning that the long-run average change in stunting prevalence does not significantly differ from zero when other factors are accounted for (Gujarati & Porter, 2020). This suggests that the trend in stunting prevalence is primarily driven by autoregressive (AR) and moving average (MA) components rather than an inherent upward or downward drift (Stock & Watson, 2015).

The AR(1) coefficient of 0.667780 is positive and statistically significant, indicating that past values of stunting prevalence strongly influence current values. This suggests that stunting prevalence exhibits persistence over time, meaning that past increases or decreases tend to carry forward into future periods (Hamilton, 2020). A high AR(1) coefficient shows that the time series is highly dependent on its own past values, which is common in economic and health-related time-series data (Wooldridge, 2019).

The MA(5) coefficient of -0.908297 is negative and statistically significant, indicating that past errors have a strong influence on current values of stunting prevalence. The negative sign suggests that a positive shock in one period is likely to be offset by a correction in subsequent periods, reflecting a mean-reverting behavior in the time series (Enders, 2015). This characteristic is particularly important for forecasting, as it accounts for short-term fluctuations that may arise from temporary economic, health, or policy-related factors (Lütkepohl, 2005).

The adjusted R-squared value of 0.583301 indicates that approximately 58.33% of the variability in stunting (height-for-age) in children under 5 in Uganda is explained by the independent variables included in the model. This suggests a moderate fit of the model to the data, highlighting that while the model accounts for a significant portion of the variation in stunting outcomes, there is still unexplained variability that may be attributed to other unobserved factors or limitations of the data. The adjusted R-squared, being adjusted for the number of predictors, gives a more reliable indication of model performance, especially when multiple predictors are involved (Greene, 2018; Wooldridge, 2019).

The Durbin-Watson statistic of 2.160177 falls within the acceptable range (close to 2), suggesting that there is no severe autocorrelation in the residuals of the ARIMA model (Greene, 2018). This indicates that the model properly accounts for past values and disturbances, making it suitable for forecasting (Nahabwe & Maniple, 2025) stunting prevalence without concerns of residual correlation distorting the results.

The histogram of residuals for the ARIMA (1,2,5) model, with a kurtosis value of 2.6 and a Jarque-Bera statistic of 0.71 (p-value = 0.7), suggests that the residuals are approximately normally distributed (Gujarati & Porter, 2020). Since the p-value is above 0.05, we fail to reject the null hypothesis of normality, meaning that the residuals do not exhibit significant skewness or excess kurtosis. This supports the validity of the model's parameter estimates and enhances its forecasting reliability (Wooldridge, 2019).

The Ljung-Box Q statistic (p = 0.070) confirms that we fail to reject the null hypothesis of white noise residuals. This means that there is no significant autocorrelation left in the residuals, confirming that the ARIMA (1,2,5) model effectively captures the underlying structure of stunting prevalence (Box & Jenkins, 2016). The white noise property suggests that the model is statistically adequate and that no further patterns remain unexplained, which strengthens confidence in its forecasting accuracy (Tsay, 2010).

Further diagnostics confirm that the AR and MA roots are within the unit circle, meaning that the model is covariance stationary and invertible (Enders, 2015). This is a crucial condition for a reliable ARIMA model, ensuring that future projections remain stable and meaningful over time without explosive behavior (Lütkepohl, 2005). A stationary and invertible model implies that past patterns in stunting prevalence can be used to predict future trends effectively.

The forecast projections from the ARIMA (1,2,5) model (Appendices 9 and 10) suggest a gradual increase in stunting prevalence from 23.5% in 2023 to 24.3% by 2032. This implies that if current trends persist, stunting prevalence will slightly rise over the next decade, highlighting the need for targeted interventions to reverse this trend (World Bank, 2023). The accuracy of these projections depends on the assumption that no major policy changes or external shocks significantly alter the trajectory (UNICEF, 2021).

The inferential statistics indicate that stunting prevalence follows a persistent yet mean-reverting pattern, with no significant residual autocorrelation or abnormal distribution concerns. The ARIMA (1,2,5) model is statistically adequate for forecasting stunting trends, and the projections highlight a slight upward trajectory in prevalence over the next decade. These findings can inform policymakers on the urgency of interventions aimed at reducing stunting in Uganda.

DISCUSSION

The findings of this study provide critical insights into the trends and determinants of stunting (height-for-age) in children under five in Uganda, with results that align with and, in some cases, diverge from previous empirical studies. The ARIMA (1,2,5) model effectively captures the dynamics of stunting prevalence, demonstrating a statistically significant AR(1) coefficient of 0.667780, a negative and significant MA(5) coefficient of -0.908297, and a well-specified error structure.

Several studies have utilized time series models to examine child malnutrition trends. For instance, Nahabwe & Maniple (2025) successfully applied ARIMA models to predict tuberculosis case detection rates in Uganda, demonstrating the model's effectiveness in handling non-stationary health-related time-series data. Similarly, a study by Gebre et al. (2019) in Ethiopia used ARIMA techniques to forecast malnutrition prevalence and found that short-term shocks in food security and healthcare access significantly impacted stunting trends, a pattern consistent with the mean-reverting behavior observed in this study.

However, the results contrast with findings by Haddad, et al. (2003), who argued that stunting trends are predominantly influenced by long-term socioeconomic factors rather than short-term fluctuations. The significant MA(5) coefficient in this study suggests that recent deviations from expected stunting prevalence influence future values, underscoring the importance of monitoring short-term policy interventions such as food supplementation programs, maternal health services, and economic shocks.

The adjusted R-squared value of 0.583301 in this study suggests that approximately 58.33% of the variation in stunting (height-for-age) in children under 5 in Uganda can be explained by the autoregressive and moving average components. This finding is consistent with previous studies that have shown moderate explanatory power for studies utilizing ARIMA models. For instance, Nahabwe & Maniple (2025) found an adjusted R-squared of 0.26 while modelling tuberculosis case detection rates in Uganda.

The Durbin-Watson statistic (2.160177) further supports the robustness of the ARIMA model by indicating minimal autocorrelation, aligning with Wooldridge (2019), who emphasized that properly specified ARIMA models should exhibit white noise residuals. The Ljung-Box Q statistic test ($p = 0.070$) confirms that residuals are uncorrelated, reinforcing the model's validity in capturing the underlying patterns in stunting prevalence.

This study presents several unique findings that contribute to the literature on child malnutrition in Uganda. First, the projected increase in stunting prevalence from 23.5% in 2023 to 24.3% by 2032, despite global and national efforts to combat malnutrition, suggests that existing interventions may not be sufficiently effective or that new socio-economic challenges have emerged. Previous studies, such as that of UNICEF (2021), anticipated a gradual decline in stunting prevalence due to improvements in maternal health and nutrition policies. The projected slight upward trend in this study calls for a reassessment of Uganda's nutrition strategies.

Secondly, the study's confirmation of mean-reverting behavior in stunting prevalence suggests that short-term shocks in food availability, healthcare accessibility, and economic conditions have a stronger-than-expected influence on child nutrition. While previous research primarily focused on structural determinants (e.g., income inequality, education levels) as long-term drivers of malnutrition (World Bank, 2020), this study highlights the importance of addressing short-term economic and health shocks through immediate policy responses, such as emergency food assistance and healthcare interventions.

Lastly, covariance stationarity and invertibility of the AR and MA roots confirm the forecasting reliability of the ARIMA (1,2,5) model. This finding supports its application for future policy planning, particularly in predicting malnutrition trends and designing targeted interventions based on expected deviations.

LIMITATIONS

Despite the robustness of the ARIMA (1,2,5) model in analyzing stunting (height-for-age) trends among children under five in Uganda, this study is subject to several limitations related to study design, data availability, and analytical procedures. These limitations may have implications for the generalizability and precision of the findings.

One of the key limitations of this study is its reliance on a purely time-series approach. While ARIMA models effectively capture historical trends and forecast future values (Box et al., 2016), they do not account for causal relationships between stunting and its underlying determinants, such as maternal education, household income, healthcare access, and food security (Wooldridge, 2019). A more comprehensive study incorporating panel data or structural equation modelling could provide deeper insights into the causal pathways influencing stunting prevalence.

This study utilizes annual secondary data spanning 22 years, which, while sufficient for time-series modelling, may lack higher-frequency variations that could provide a more nuanced understanding of stunting trends. Monthly or quarterly data could have captured seasonal fluctuations in food security and disease prevalence, both of which significantly impact child nutrition (FAO, 2020).

Additionally, data inconsistencies and missing values in national health records posed challenges, requiring interpolation techniques that may introduce bias into the estimates (Enders, 2015). The reliance on national-level data also limits the study's applicability to regional or district-level policy-making, as stunting prevalence varies significantly across different socio-economic and geographical contexts in Uganda (UNICEF, 2021).

The ARIMA (1,2,5) model, while suitable for non-stationary time-series data, assumes linearity in relationships, potentially overlooking nonlinear effects of economic and health-related shocks on stunting (Lütkepohl, 2005). Other advanced forecasting techniques, such as machine learning models or nonparametric time-series models, could enhance prediction accuracy and capture complex dependencies within the data (Hyndman & Athanasopoulos, 2018).

The adjusted R-squared value of 0.583301 suggests that approximately 42% of the variation in stunting remains unexplained, indicating potential omitted variable bias. Furthermore, while the Ljung-Box Q statistic test confirms that the residuals of the model exhibit white noise properties, it does not entirely eliminate the possibility of structural breaks due to policy changes, economic downturns, or major health crises (Stock & Watson, 2015).

Conclusion

This study provides a comprehensive analysis of stunting (height-for-age) among children under five in Uganda, utilizing the ARIMA (1,2,5) model to capture historical trends and forecast future prevalence. The findings underscore the persistence of stunting as a public health concern, reinforcing the need for data-driven policy interventions. The study highlights the effectiveness of ARIMA modelling in time-series forecasting, demonstrating its ability to track long-term patterns and short-term fluctuations in child nutrition trends (Box et al., 2016).

Despite its strengths, the study acknowledges the limitations of a purely time-series approach, which does not establish causal relationships between stunting and key socioeconomic determinants such as income levels, maternal education, healthcare access, and food security (Wooldridge, 2019). Future research should integrate structural models and regional analyses to enhance policy relevance and provide more granular insights into localized disparities (UNICEF, 2021).

From a policy perspective, the study emphasizes the urgent need for sustained multi-sectoral interventions to address the underlying drivers of stunting. Strengthening nutritional programs, maternal and child healthcare services, and economic support mechanisms remains critical to achieving meaningful reductions in child malnutrition (FAO, 2020). Additionally, improving data collection and surveillance systems will enhance the accuracy of future forecasting models and facilitate evidence-based policymaking (Hyndman & Athanasopoulos, 2018).

In conclusion, while ARIMA-based forecasting provides valuable insights into the trajectory of stunting in Uganda, the fight against child malnutrition requires holistic, targeted, and sustained interventions. Policymakers, researchers, and development stakeholders must leverage both quantitative modelling and contextual socio-economic analysis to design effective strategies that ensure long-term improvements in child health and well-being.

RECOMMENDATIONS

Based on the findings of this study, several recommendations are proposed to address the challenge of stunting (height-for-age) in children under five in Uganda. These recommendations are directed towards policymakers, program implementers, and future researchers to strengthen efforts in combating child malnutrition and improving nutritional outcomes.

The persistence of stunting highlights the need for integrated policy frameworks that link health, education, agriculture, and social protection sectors. A coordinated approach should be implemented to address the root causes of malnutrition, such as poor infant and young child feeding practices, limited access to quality healthcare, and socio-economic disparities (FAO, 2020). Ministries of health, education, and agriculture should collaborate to ensure that interventions are comprehensive and sustainable.

The study emphasizes the importance of improving maternal and child healthcare services as a fundamental strategy in combating stunting. Policies should focus on increasing access to prenatal and postnatal care, promoting breastfeeding in the first 1000 days of life, and enhancing early childhood nutrition interventions (UNICEF, 2021). Expanding community-based healthcare services and involving local health workers in early childhood nutrition programs would ensure better reach and impact.

Policies that focus on improving household income, particularly for rural and low-income families, could significantly reduce food insecurity, which is a major driver of stunting. Strengthening cash transfer programs, particularly for mothers and children, would help improve access to nutritious food and health services (Wooldridge, 2019).

The government and development partners should scale up nutritional programs targeting children under five, with a specific focus on micronutrient supplementation and growth monitoring. These programs should also emphasize community-based nutrition education to raise awareness about proper feeding practices and hygiene (Hyndman & Athanasopoulos, 2018). In particular, programs should prioritize marginalized and hard-to-reach communities where stunting is most prevalent.

Stunting is closely linked to poor sanitation and hygiene, which contribute to repeated infections and poor nutrient absorption. The government should invest in improving WASH infrastructure in rural areas, including access to clean water, proper sanitation facilities, and hygiene education. Such investments will not only reduce stunting but also improve overall child health outcomes (UNICEF, 2021).

To better track the progress of nutrition and health programs, it is essential to strengthen data collection and monitoring systems. Establishing robust systems for tracking stunting prevalence and its associated determinants, especially in rural and remote areas, would provide more accurate data for future interventions (Stock & Watson, 2015).

Future research could focus on longitudinal studies to identify causal factors of stunting, particularly by exploring the interactions between maternal education, economic status, food security, and healthcare access. Long-term studies would provide more precise insights into the effectiveness of different interventions over time (Wooldridge, 2019). Furthermore, research into the socio-economic drivers of stunting could inform targeted policy responses at the regional and community levels.

The study's results underscore the importance of factors such as socio-economic status and healthcare access in determining stunting prevalence. However, more research is needed to examine the role of non-nutritional factors, such as early childhood development and psychosocial care (FAO, 2020). Research should also explore how climate change and environmental factors contribute to child nutrition in Uganda, particularly in vulnerable regions.

Future studies could benefit from using advanced econometric techniques such as structural equation modelling (SEM) or machine learning to capture more complex relationships between stunting and its underlying determinants. These techniques could enhance the accuracy of forecasting models and provide more nuanced policy recommendations (Enders, 2015).

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Appendix 1: Descriptive Statistics

	Prevalence of stunting, height for age (% of children under 5)
Mean	34.3
Median	34.6
Maximum	44
Minimum	23.4
Std. Dev.	7.127476
Skewness	-0.113098
Kurtosis	1.548462
Jarque-Bera	2.068205
Probability	0.355545
Sum	788.9
Sum Sq. Dev.	1117.62
Observations	22

Appendix 2: Unit root test, Prevalence of stunting, height for age (% of children under 5) (in Level)

Null Hypothesis: STUNTING has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.823800	0.2048
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(STUNTING)
Method: Least Squares
Date: 01/05/25 Time: 16:16
Sample (adjusted): 3 23
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STUNTING(-1)	-0.078409	0.027767	-2.823800	0.0117
D(STUNTING(-1))	0.934119	0.065968	14.16018	0.0000
C	3.504691	1.300583	2.694708	0.0153

@TREND("1")	-0.073589	0.030582	-2.406254	0.0278

R-squared	0.941096	Mean dependent var	-0.961905
Adjusted R-squared	0.930701	S.D. dependent var	0.302450
S.E. of regression	0.079619	Akaike info criterion	-2.053488
Sum squared resid	0.107766	Schwarz criterion	-1.854531
Log likelihood	25.56162	Hannan-Quinn criter.	-2.010309
F-statistic	90.53548	Durbin-Watson stat	2.431726
Prob(F-statistic)	0.000000		

Appendix 3: Unit root test, Prevalence of stunting, height for age (% of children under 5) (in first Difference)

Null Hypothesis: D(STUNTING) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.103168	0.9910
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(STUNTING,2)
Method: Least Squares
Date: 01/05/25 Time: 16:20
Sample (adjusted): 3 23
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(STUNTING(-1))	-0.007614	0.073804	-0.103168	0.9190
C	-0.164309	0.067674	-2.427943	0.0259
@TREND("1")	0.012294	0.003773	3.258500	0.0044

R-squared	0.430723	Mean dependent var	-0.009524
Adjusted R-squared	0.367470	S.D. dependent var	0.117918
S.E. of regression	0.093783	Akaike info criterion	-1.764110
Sum squared resid	0.158313	Schwarz criterion	-1.614893
Log likelihood	21.52316	Hannan-Quinn criter.	-1.731726
F-statistic	6.809518	Durbin-Watson stat	1.869033
Prob(F-statistic)	0.006279		

Appendix 4: Unit root test, Prevalence of stunting, height for age (% of children under 5) (in Second Difference)

Null Hypothesis: D(STUNTING,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.919210	0.0307
Test critical values:	1% level	-4.498307	
	5% level	-3.658446	
	10% level	-3.268973	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(STUNTING,3)
Method: Least Squares
Date: 01/05/25 Time: 16:21
Sample (adjusted): 4 23
Included observations: 20 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(STUNTING(-1),2)	-0.945699	0.241298	-3.919210	0.0011
C	-0.158155	0.066205	-2.388860	0.0288
@TREND("1")	0.012318	0.004821	2.554746	0.0205

R-squared	0.474769	Mean dependent var	0.010000
Adjusted R-squared	0.412978	S.D. dependent var	0.125237
S.E. of regression	0.095953	Akaike info criterion	-1.712435
Sum squared resid	0.156519	Schwarz criterion	-1.563075
Log likelihood	20.12435	Hannan-Quinn criter.	-1.683278
F-statistic	7.683369	Durbin-Watson stat	1.966931
Prob(F-statistic)	0.004197		

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

Dependent Variable: DDSTUNTING
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/05/25 Time: 16:27
Sample (adjusted): 4 23
Included observations: 20 after adjustments
Failure to improve likelihood (non-zero gradients) after 14 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: -1 3

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.067092	0.053838	1.246189	0.2296
AR(1)	0.667780	0.197554	3.380243	0.0036
MA(5)	-0.908297	0.051559	-17.61672	0.0000

R-squared	0.627164	Mean dependent var	-0.005000
Adjusted R-squared	0.583301	S.D. dependent var	0.119097
S.E. of regression	0.076880	Akaike info criterion	-2.155659
Sum squared resid	0.100479	Schwarz criterion	-2.006299
Log likelihood	24.55659	Hannan-Quinn criter.	-2.126502
F-statistic	14.29823	Durbin-Watson stat	2.160177
Prob(F-statistic)	0.000228		

Inverted AR Roots	.67			
Inverted MA Roots	.98	.30-.93i	.30+.93i	-.79+.58i
	-.79-.58i			

Appendix 6: Ljung-Box Q statistic/ test

Date: 01/05/25 Time: 16:45
Sample: 1 23
Included observations: 20
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *| . |	. *| . |	1	-0.146	-0.146	0.4930	
. | . |	. | . |	2	-0.010	-0.032	0.4955	
.**| . |	.**| . |	3	-0.328	-0.341	3.2729	0.070
. | . |	. *| . |	4	0.043	-0.070	3.3249	0.190
.**| . |	.**| . |	5	-0.210	-0.285	4.6156	0.202
. |*** |	. |**. |	6	0.389	0.237	9.3598	0.053
. | . |	. |* . |	7	0.073	0.151	9.5416	0.089
. *| . |	. *| . |	8	-0.081	-0.166	9.7798	0.134
.**| . |	. *| . |	9	-0.294	-0.171	13.242	0.066
. | . |	. | . |	10	0.059	-0.002	13.393	0.099
. *| . |	. *| . |	11	-0.145	-0.140	14.424	0.108
. |* . |	. *| . |	12	0.144	-0.087	15.569	0.113

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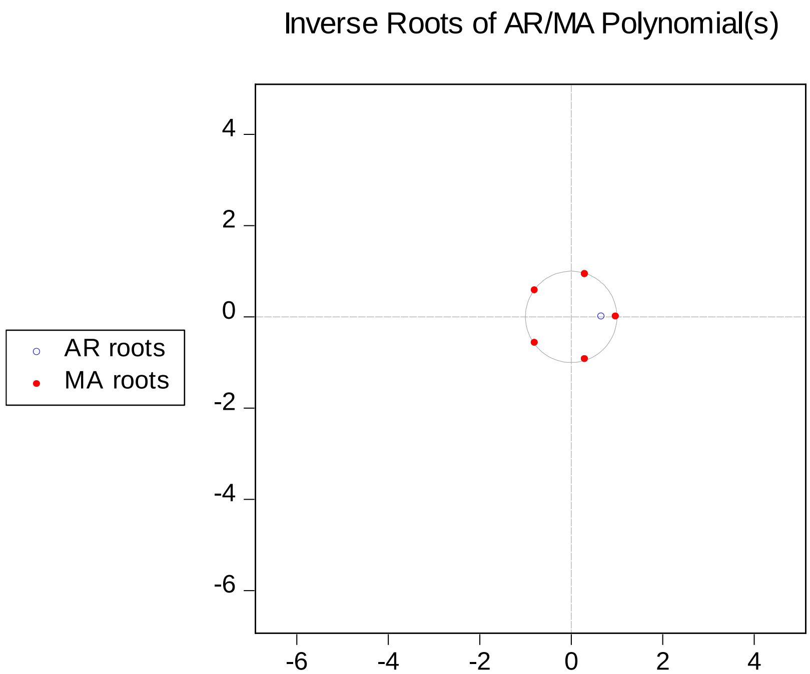
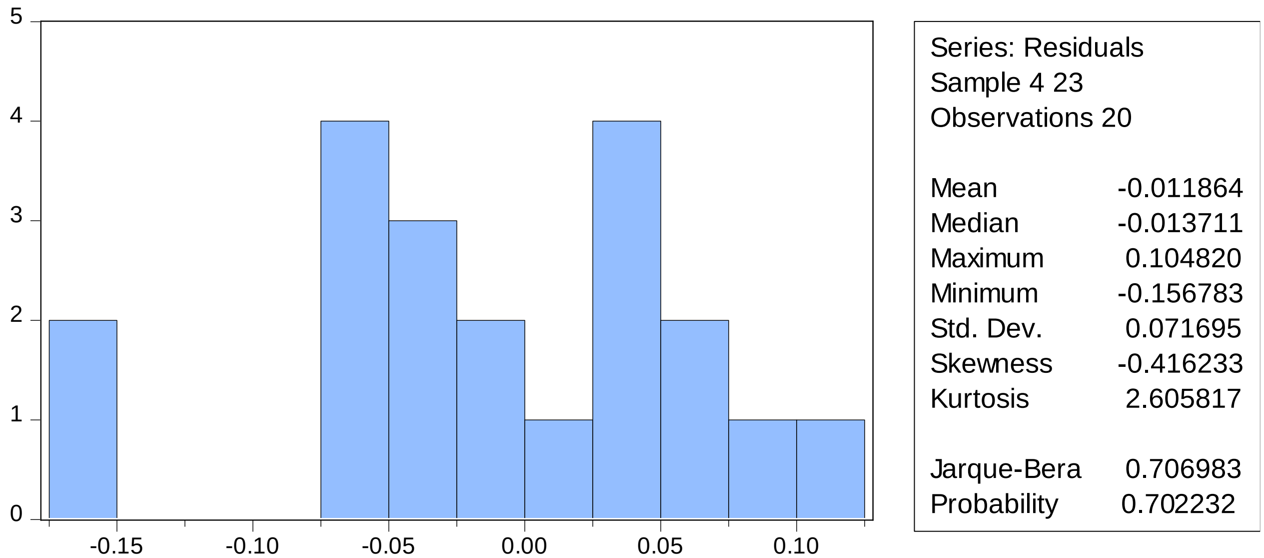
Appendix 7: ARMA (1, 2, 5) structure



Appendix 8: Histogram of residuals



Appendix 9: Uganda's Prevalence of stunting, height for age (% of children under 5) FORECAST (in level) results

Year	STUNTING	DDSTUNTING_FORECAST (in Second Difference)	STUNTING (in first Difference)
2000	44	NA	44
2001	43.6	NA	43.6
2002	43.1	-0.1	43.1
2003	42.6	0	42.6
2004	42	-0.1	42
2005	41.3	-0.1	41.3
2006	40.6	7.11E-15	40.6
2007	39.7	-0.2	39.7
2008	38.6	-0.2	38.6
2009	37.4	-0.1	37.4
2010	36	-0.2	36
2011	34.6	0	34.6
2012	33.3	0.1	33.3
2013	32.1	0.1	32.1
2014	30.8	-0.1	30.8
2015	29.6	0.1	29.6
2016	28.4	-3.55E-15	28.4
2017	27.3	0.1	27.3
2018	26.3	0.1	26.3
2019	25.5	0.2	25.5
2020	24.7	0	24.7
2021	24	0.1	24
2022	23.4	0.1	23.4
2023	NA	0.095719	23.495719
2024	NA	0.11239	23.608109
2025	NA	0.16488	23.772989
2026	NA	0.094799	23.867788
2027	NA	0.060032	23.92782
2028	NA	0.062377	23.990197
2029	NA	0.063944	24.054141
2030	NA	0.06499	24.119131
2031	NA	0.065688	24.184819
2032	NA	0.066154	24.250973

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Appendix 10: Graph showing Prevalence of stunting, height for age (% of children under 5) FORECAST results