
ARIMA FORECASTING OF THE PREVALENCE OF ANEMIA IN CHILDREN IN ETHIOPIA

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ABSTRACT

Childhood anemia is a preventable condition. High prevalence rates of childhood anemia in Ethiopia can be prevented and or controlled. Using annual time series data on the prevalence of anemia in children under 5 years of age in Ethiopia from 1990 – 2016, the study makes predictions for the period 2017 – 2025. The paper applies the Box-Jenkins ARIMA methodology. The diagnostic ADF tests show that, AE, the series under consideration is an I (0) variable. Based on the AIC, the paper presents the ARIMA (5, 0, 0) model as the parsimonious model. The diagnostic tests further reveals that the presented model is stable and its residuals are not serially correlated. The results of the study indicate that the prevalence of anemia in Ethiopian children is expected to increase over the out-of-sample period.

INTRODUCTION

Anemia is a major health problem worldwide (Assefa et al., 2014). Generally speaking, anemia is a common conundrum of nutritional deficiency worldwide, and its prevalence is higher in developing countries than developed countries (Djokic et al., 2010; Hioui et al., 2010), because of health and socioeconomic problems (Assefa et al., 2014). Anemia can also be caused by heavy blood loss, parasitic infections and congenital hemolytic diseases (WHO, 2001). Research has shown that the causes of anemia are basically multi-factorial, although iron deficiency is the most common cause, explaining about half of the cases (WHO, 2015). The worldwide prevalence of anemia in children under 5 years of age is estimated to be 42.6% (ibid). Not surprisingly, it is in fact, more often found in low and middle-income countries, with South East Asia and Africa being the most affected (Melse-Boonstra & Mwangi, 2016). The consequences of childhood anemia range from increased susceptibility to infectious diseases, fatigue, decreased physical capacity and if persistent, lower cognitive function and economic productivity in adulthood (Haas & Brownlie, 2001; Brownlie et al., 2002; Atukorala et al., 2003; Walker et al., 2007). When a large part of the population is affected, this can have large scale consequences for economic productivity (Horton & Ross, 2003).

With a prevalence of 64.6% among pre-school children (Kuziga et al., 2017), anemia is a major cause of morbidity and mortality for children in Africa (Atkinson et al., 2006; Kuziga et al., 2017) and Ethiopia is not an exception (Assefa et al., 2014; Malako et al., 2018). Over the past few years there has been a resurgence in the prevalence of anemia in children aged below 5 years in Ethiopia, as shown by an increase from 40% to about 72.3% in 2016 (CSA, 2016). Regardless of efforts done so far, anemia remains a serious health threat in this category (Woldie et al., 2015; Roba et al., 2018). So, modeling and forecasting the prevalence of anemia in the group is needed to develop more effective interventions. Therefore, main goal of this study is to forecast the prevalence of anemia in children under the age of 5 in Ethiopia over the period 2017 – 2025. The findings of this study will be fundamental in the implementation of anemia control measures in the country.

LITERATURE REVIEW

Assefa et al. (2014) conducted a study whose main purpose was to determine the magnitude of anemia among school children Jimma Town, Southwest Ethiopia. A cross-sectional household survey was conducted in January 2011 on 423 children, aged 6-14 years, selected through systematic random sampling method. Sociodemographic and anthropometric data were collected using a pre-tested questionnaire. The association between predictors and the outcome variables were measured by a step-wise regression model. The results of the study indicated that anemia was a moderate public health problem in the study area. The study also found out that family income, educational status of parents and inadequate plant and animal food intake are the main predictors of anemia. Consistently, Malako et al. (2018) investigated the prevalence of anemia in children aged 6-23 months, in Damot Sore District, Wolaita Zone, South Ethiopia. A community-based cross-sectional study was carried out among 485 children of Damot Sore, South Ethiopia from March to April 2017. Data on socio-demographic, dietary, blood samples for hemoglobin level, and malaria infection were collected. A multivariate logistic regression model was applied to analyze factors associated with anemia in children. The study established that the prevalence of anemia was a severe public health problem in the study area. However, both studies did not forecast the prevalence of anemia in their respective study areas. This study will add value to literature by forecasting the prevalence of anemia in children aged below 5, for the whole country.

METHODOLOGY

3.1 The Box – Jenkins (1970) Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to

highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018c). This approach will be used to analyze, AE, the series under consideration.

3.2 The Applied Box – Jenkins ARIMA Model Specification

If the sequence $\Delta^d AE_t$ satisfies an ARMA (p, q) process; then the sequence of AE_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d AE_t = \sum_{i=1}^p \beta_i \Delta^d L^i AE_t + \sum_{i=1}^q \alpha_i L^i \mu_t + \mu_t \dots \dots \dots [1]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

3.3 Data Collection

This study is based on annual observations (that is, from 1990 – 2016) on the prevalence of anemia in children under the age of 5 in Ethiopia [denoted as AE]. Prevalence of anemia in children under 5 years of age in Ethiopia, refers, to the percentage of children under the age of 5 whose hemoglobin level is less than 110 grams per liter at sea level. Out-of-sample forecasts will cover the period 2016 – 2025. All the data was gathered from the World Bank online database.

3.4 Diagnostic Tests & Model Evaluation

3.4.1 The ADF Test in Levels

Table 1: with intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
AE	-4.930761	0.0006	-3.737853	@1%	Stationary
			-2.991878	@5%	Stationary
			-2.635542	@10%	Stationary

Table 1 shows that AE is stationary in levels. Hence, it is said to be integrated of order one, that is I (0).

3.4.2 Evaluation of ARIMA models (without a constant)

Table 2: Evaluation of ARIMA Models (without a constant)

Model	AIC	U	ME	RMSE	MAPE
ARIMA (1, 0, 0)	97.06401	0.99204	1.8615	15.016	5.3434
ARIMA (2, 0, 0)	-4.314483	0.16492	2.8661	14.974	3.9443
ARIMA (3, 0, 0)	-5.056375	0.15623	2.8574	14.974	3.927
ARIMA (0, 0, 1)	271.2578	27.982	33.903	35.553	53.865
ARIMA (4, 0, 0)	-6.400175	0.14703	2.8511	14.974	3.9095
ARIMA (5, 0, 0)	-13.13538	0.13571	2.8446	14.974	3.8808
ARIMA (6, 0, 0)	-12.43323	0.13467	2.8429	14.974	3.8773
ARIMA (7, 0, 0)	-10.4405	0.13469	2.8428	14.974	3.87

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018b) Similarly, the U statistic can be used to find a better model in the sense that it must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018a). In this research paper, only the AIC is used to select the optimal model. Therefore, the ARIMA (5, 0, 0) model is finally chosen. It is essential to remember that this model is in fact an AR (5) model. However, for the purposes of consistency, throughout the paper, we maintain the former rather the later.

3.5 Residual Tests

3.5.1 Correlogram of the Residuals of the ARIMA (5, 0, 0) Model

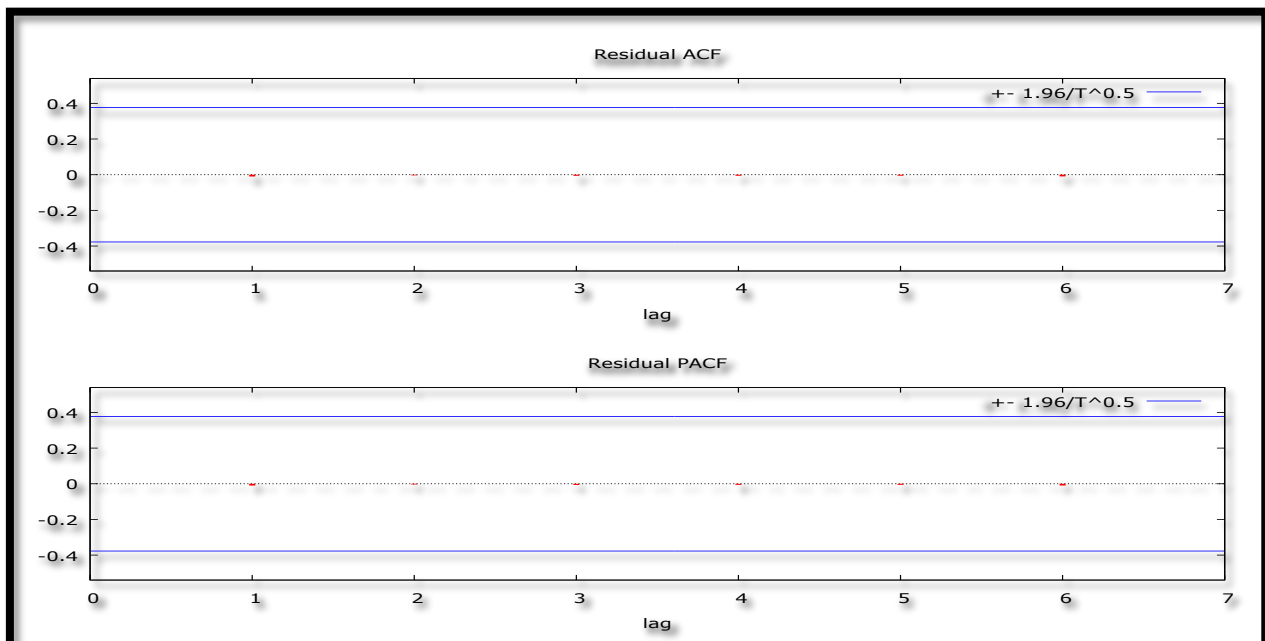


Figure 1: Correlogram of the Residuals

Figure 1 indicates that the estimated ARIMA (5, 0, 0) model is adequate since ACF and PACF lags are quite short and within the bands.

4.0 FINDINGS OF THE STUDY

4.1 Results Presentation

Table 3: Main Results

ARIMA (5, 0, 0) Model:				
The chosen optimal model, the ARIMA (5, 0, 0) model can be expressed as follows:				
$AE_t = 1.9833AE_{t-1} - 0.719304AE_{t-2} - 0.00746731AE_{t-3} - 0.794006AE_{t-4} + 0.537433AE_{t-5} \dots \dots \dots [2]$				
Variable	Coefficient	Standard Error	z	p-value
β_1	1.9833	0.162006	12.24	0.0000***
β_2	-0.719304	0.392643	-1.832	0.067*
β_3	-0.00746731	0.422243	-0.01768	0.9859
β_4	-0.794006	0.396942	-2	0.0455**
β_5	0.537433	0.167808	3.203	0.0014***

Table 3 shows the main results of the ARIMA (5, 0, 0) model.

Forecast Graph

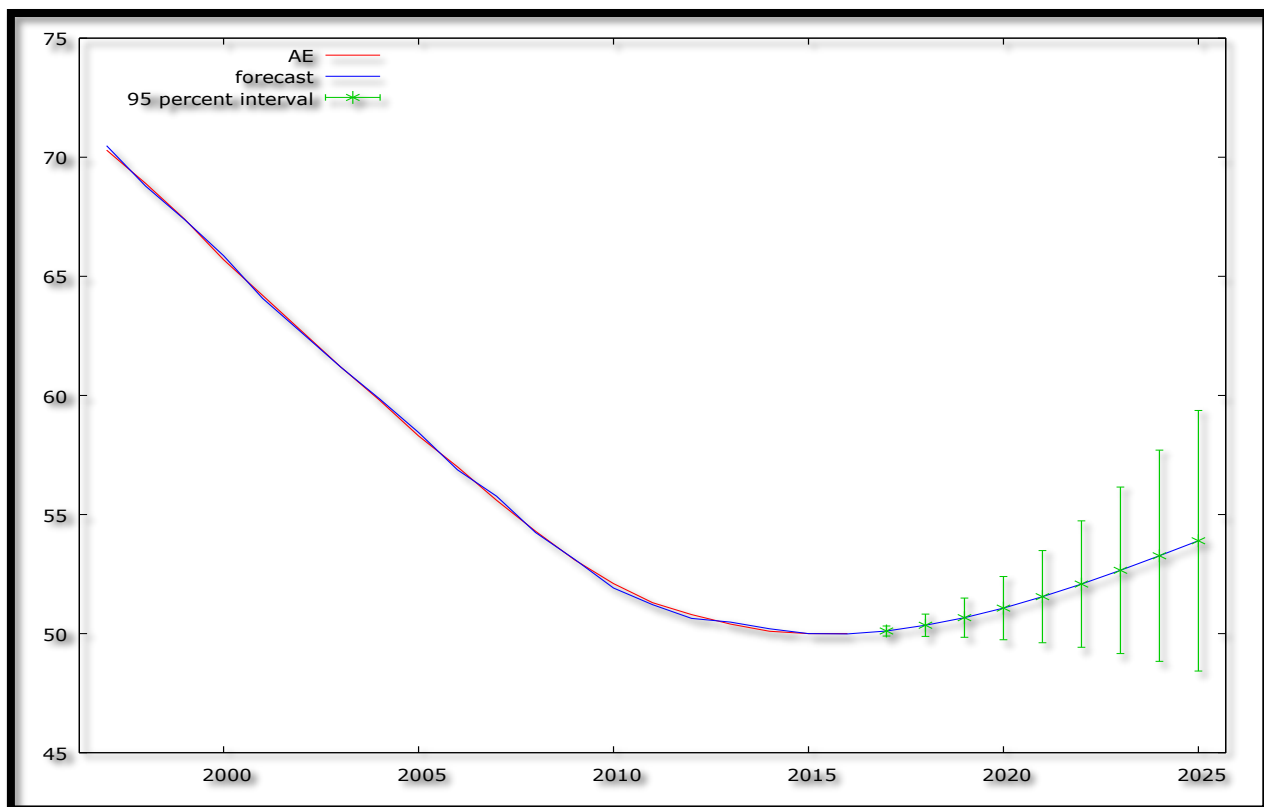


Figure 2: Forecast Graph – In & Out-of-Sample Forecasts

Figure 2 shows the in-and-out-of-sample forecasts of the AE series. The out-of-sample forecasts cover the period 2017 – 2025.

Predicted AE– Out-of-Sample Forecasts Only

Table 4: Predicted AE

Year	Predicted AE	Standard Error	95% Confidence Interval
2017	50.1096	0.107521	(49.8988, 50.3203)
2018	50.3509	0.238819	(49.8828, 50.8189)
2019	50.6688	0.420082	(49.8454, 51.4921)
2020	51.0712	0.677249	(49.7438, 52.3986)
2021	51.5518	0.987029	(49.6172, 53.4863)
2022	52.0804	1.35466	(49.4253, 54.7355)
2023	52.6574	1.78342	(49.1620, 56.1528)
2024	53.2693	2.26217	(48.8355, 57.7031)
2025	53.8985	2.79074	(48.4288, 59.3683)

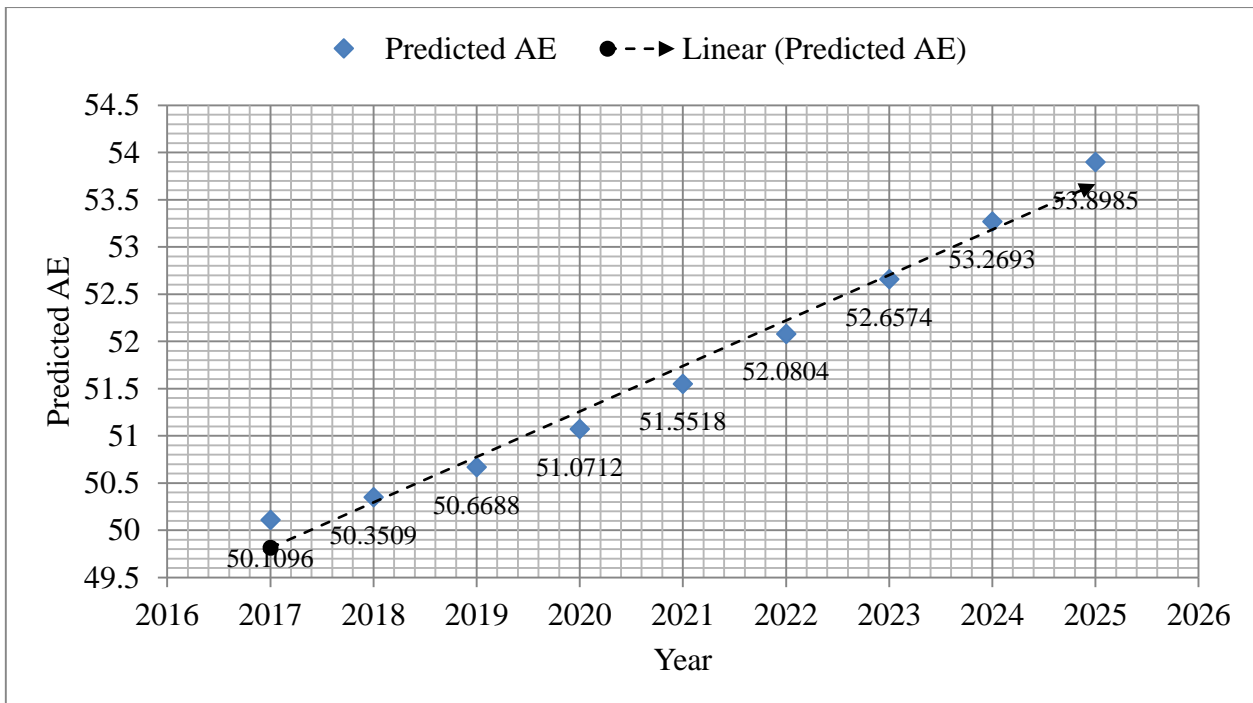


Figure 3: Graphical Analysis of Out-of-Sample Forecasts

Table 4 and figure 3 show the out-of-sample forecasts only. The prevalence of anemia in Ethiopian children is projected to increase from the estimated 50.1% in 2017 to approximately 53.9% by 2025.

CONCLUSION

The study shows that the ARIMA (5, 0, 0) model is stable and suitable for forecasting the prevalence of anemia in children in Ethiopia over the study period. The model predicts a possible resurgence in the prevalence of anemia in children in Ethiopia. The model predicts an increase in the prevalence of anemia in the country, from 50.1% in 2017 to about 53.9% by 2025. The study recommends that the government of Ethiopia should expand its

nutritional supplementation and food fortification programmes, especially in rural areas where significant groups of households have a poor economic status. In this regard, the Ethiopian government should introduce poverty alleviation self-help projects, for example, community vegetable gardens as well as goat projects. The government of Ethiopia should timeously provide resources for prompt diagnosis and treatment of pediatric HIV/TB in order to reduce the prevalence of anemia secondary to TB/HIV. Furthermore, in as much as refresher trainings for healthcare workers on Integrated Management of Childhood Illnesses (IMCI) are critical and ought to be prioritized, the need for women socio-economic empowerment, as well as health education cannot be overlooked in the fight against anemia in Ethiopia.

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