ANALYZING STUNTING AND UNDERWEIGHT IN CHITUNGWIZA URBAN DISTRICT IN ZIMBABWE

Dr. Smartson. P. NYONI[1], Thabani NYONI[2]

[1] *Medical Doctor, ZICHIRe Project, University of Zimbabwe, Harare, Zimbabwe*
[2] *MSc Economics Scholar, Department of Economics, University of Zimbabwe, Harare, Zimbabwe*

ABSTRACT

In this paper, ANN models were applied in forecasting malnutrition trends (stunting and underweight) for children aged below 15 and living in Chitungwiza urban district. The employed data covers the period January 2013 to December 2019 and the out-of-sample period ranges over the period January 2020 to December 2021. The residuals and forecast evaluation criteria of the applied models reveal that the models are adequate in predicting malnutrition dynamics in Chitungwiza urban district over the out-of-sample period. The results of the study basically indicate that chronic malnutrition will sharply rise over the out-of-sample period. However, underweight cases have been projected to slightly decrease over the out-of-sample period. Therefore, it is clear that malnutrition still remains a major problem in children under the age of 5 in Chitungwiza urban district. Hence, the study offers a 8-fold policy recommendation for consideration by relevant authorities in Chitungwiza urban district.

Keyword: - *ANN, Forecasting, Malnutrition, Stunting, Underweight*

1.0 INTRODUCTION

Nutrition is a fundamental pillar of human life, health and development across the entire life-cycle. Proper and well balanced nutrition through out the life-cycle is very important in maintaining a healthy status (Mushonga *et al.*, 2014; Kuona *et al.*, 2014). Unfortunately, food insecurity and chronic malnutrition remain particularly severe in developing countries where improvements in economic conditions have tended to benefit the advantaged groups and resulted in widespread inequalities in health (Hong, 2007). Chronic malnutrition is more severe in African regions (UN, 2004). In Zimbabwe, malnutrition is a major problem exacerbated by the declining economy and the HIV/AIDS pandemic (Lahariya, 2008). One in every three children in Zimbabwe suffers from chronic malnutrition (UNWFP, 2012; CAI, 2013). In this study, malnutrition of children under 5 years of age, will be assessed using data on stunting (moderate-severe) [i.e chronic malnutrition] and underweight (moderate-severe) children in Chitungwiza urban district.

Stunting can be defined as low height for age (less than -2 SD from median height from age of reference population) (FASEB, 1995). Weight-for-age z-score below -2 indicates underweight (Onis *et al*., 2007). Hence underweight is weight considered too low for good health and is usually due to poor infant feeding. Stunting, just like underweight, is a marker for both chronic malnutrition and consequently poor child development outcomes (USAID, 2016). It often begins in utero due to poor maternal nutrition and continues during the first 2 years of life due in part to inadequate hygiene and infant and young child feeding practices, and reflects a failure to reach one's genetic potential for height (Frongillo, 1999; Golden, 2009).

Globally, approximately 160 million children under 15 years of age are either stunted or underweight. In fact, 45% of mortality for children under 5 is attributable to various forms of malnutrition, of which stunting is a significant contributor. Zimbabwe's overall stunting rate is approximately 27% (USAID, 2020). Underweight rate for children under 5 in Zimbabwe is approximately 10% (Zimstats, 2012). Poor infant and young child feeding practices contribute to child malnutrition in Zimbabwe (USAID, 2018). Children who are stunted are at an increased risk for repeated infections and are more likely to die from diarrhoea, pneumonia and measles, and may be at an increased risk in adulthood for chronic diseases such as cardiovascular disease (Black *et al*., 2013). Childhood stunting is associated with development delays that can significantly and adversely impact a person's ability to learn. A stunted child may have altered socio-emotional behaviours and reduced activity (Gardner *et al*., 1999). Figure 1 and 2 are different illustrations of the trends of malnutrition in Chitungwiza urban district:

Figure 1: Malnutrition (stunting [Y] and underweight [X]) cases in Chitungwiza urban district – separate graphs

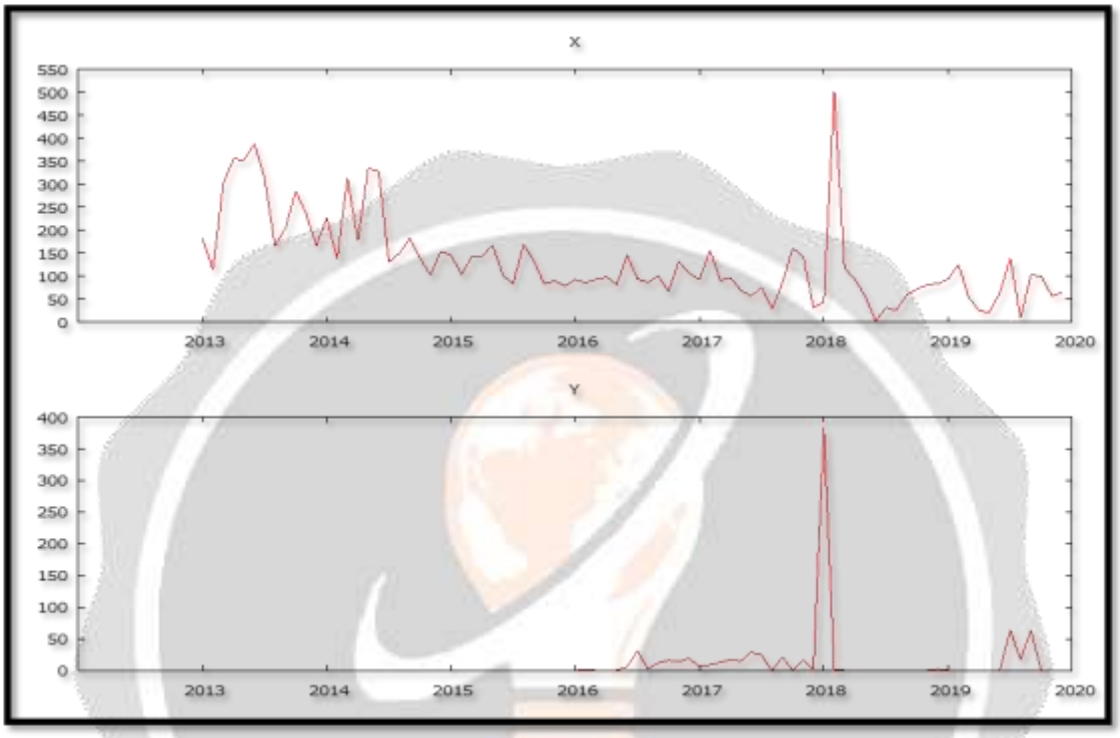
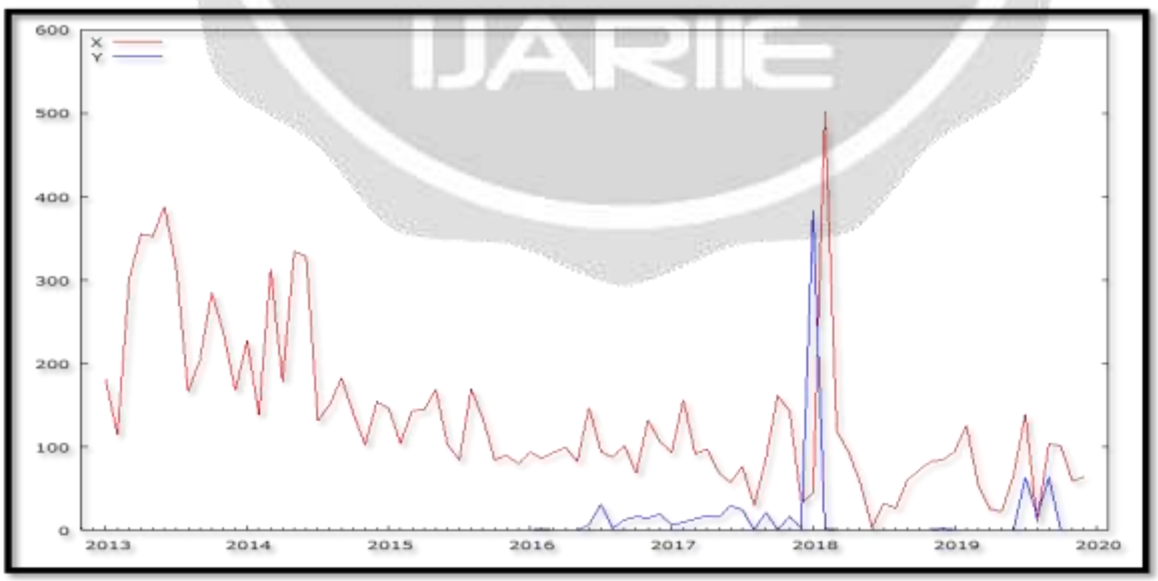


Figure 2: Chronic malnutrition cases in Chitungwiza urban district – single graph



In figure 1, the number of underweight children is declining over the period under study and this is a desirable health outcome. In figure 2, it is clear that underweight children are usually more than children with stunting. The most desirable health outcome is to observe a declining trend of both series. This study seeks to analyze the trend of the two series in order to advise relevant authorities in Chitungwiza urban district on the way forward in terms of reducing the burden of malnutrition in Chitungwiza.

1.1 OBJECTIVES

i. To analyze chronic malnutrition cases in Chitungwiza urban district over the period January 2013 to December 2019.
ii. To forecast chronic malnutrition cases in Chitungwiza urban district over the period January 2020 to December 2021.
iii. To determine whether malnutrition cases (i.e X and Y) in Chitungwiza urban district are increasing or decreasing over the period January 2020 to December 2021.

2.0 RELATED STUDIES

Mbuya *et al.* (2010) analyzed biological, social, and environmental determinants of low birth weight and stunting among infants and young children in Zimbabwe and basically found out that, of multiple-birth children, 60% have low birth weight and at the time of the survey 58% were stunted. Rusinga & Moyo (2012) examined the determinants of child malnutrition in Chingazi Ward in Chimanimani district in Zimbabwe and found out that insufficient food at the household level was the most important underlying factor of child malnutrition. Dandajena (2012) examined factors associated with chronic malnutrition in Mazowe district in the Mashonaland central province of Zimbabwe using a 1:1 unmatched case control study. A total of 78 cases and 78 controls were enrolled into the study. The study concluded that chronic malnutrition was associated with diarrhoea, failure to breastfeed and fever in Mazowe district.

Makoka (2013) investigated the impact of maternal education on child nutrition in Malawi, Tanzania and Zimbabwe and found out that in all three countries the three measures of child nutritional status significantly decrease with increased levels of mother's education. The results of the study also indicate that, after controlling for other factors, maternal education reduces the odds of the three measures of child nutrition in all three countries. Mushonga *et al*. (2014) carried out a retrospective study of the nutritional status of primary school children in Harare. The results of the study demonstrate a decreasing prevalence in stunting in primary school children but there is an increase in prevalence of wasting in primary school children. Khan *et al*. (2019) forecasted malnutrition disease using various machine learning algorithms in order to help doctors in diagnosing malnutrition patients. The results of the study indicate that processing efficiency and prediction accuracy of linear regression is better than that of, k-nearest neighbor, decision tree and multilayer perceptron regression algorithms.

From the reviewed studies, not even a single study attempted to forecast the number of children with stunting and underweight in Zimbabwe. Most studies have analyzed the prevalence of malnutrition as well as its associated factors in the country. This paper will be the first of its kind but will only zero-in on Chitungwiza urban district.

3.0 METHODOLOGY

This study will apply Artificial Neural Networks (ANNs) in analyzing malnutrition dynamics in Chitungwiza urban district in Zimbabwe. This study uses the multilayer perceptron ANN because it has proven to be an effective alternative to quantitative techniques (Gardner & Dorling, 1998).

3.1 Data Issues

The chronic malnutrition data has been captured in this study as moderate-severe underweight (X) and moderate-severe stunting (Y) and covers the period January 2013 to December 2019 and was recorded for children living in Chitungwiza urban district, aged below 5. All the data was collected from the DHIS2 system for Chitungwiza urban district.

4.0 FINDINGS OF THE STUDY

4.1 DESCRIPTIVE STATISTICS

Table 1: Descriptive statistics

Variable	Mean	Median	Minimum	Maximum
X	133.30	102.00	3.0000	502.00
Y	9.3214	0.0000	0.0000	383.00
Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
X	94.177	0.70652	1.5734	2.5469
Y	42.865	4.5985	8.0738	67.487
Variable	5% Perc.	95% Perc.	IQ range	Missing obs.
X	25.250	347.50	80.000	0
Y	0.0000	30.500	2.0000	0

Table 1 shows the descriptive statistics of the series under study. On average, approximately 133 children suffer from underweight on a monthly basis in Chitungwiza urban district; while an average of nearly 9 children are seen with chronic malnutrition (stunting) on a monthly basis. Minimum X and Y are 3 and 0 respectively while maximum X and Y are 502 and 383 respectively. It is clear, as already observed in figures 1 and 2 that underweight children are always more than chronic malnutrition children.

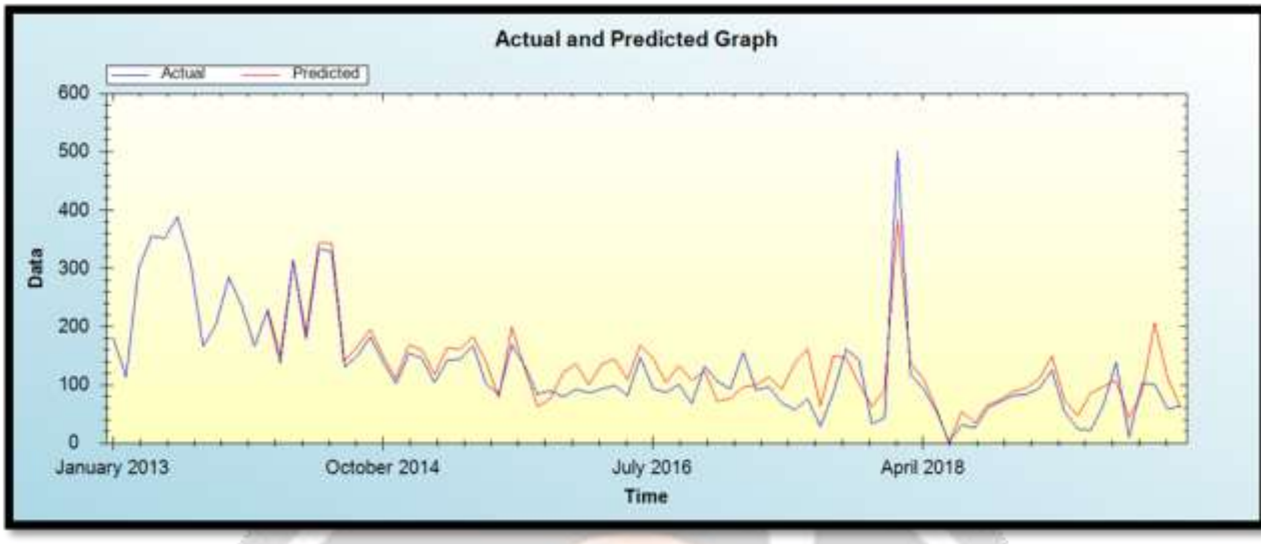
4.2 ANN MODEL SUMMARY-X

Table 2: ANN model summary – X

Variable	X
Observations	72 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	12
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.126829
MSE	1236.220550
MAE	26.374795

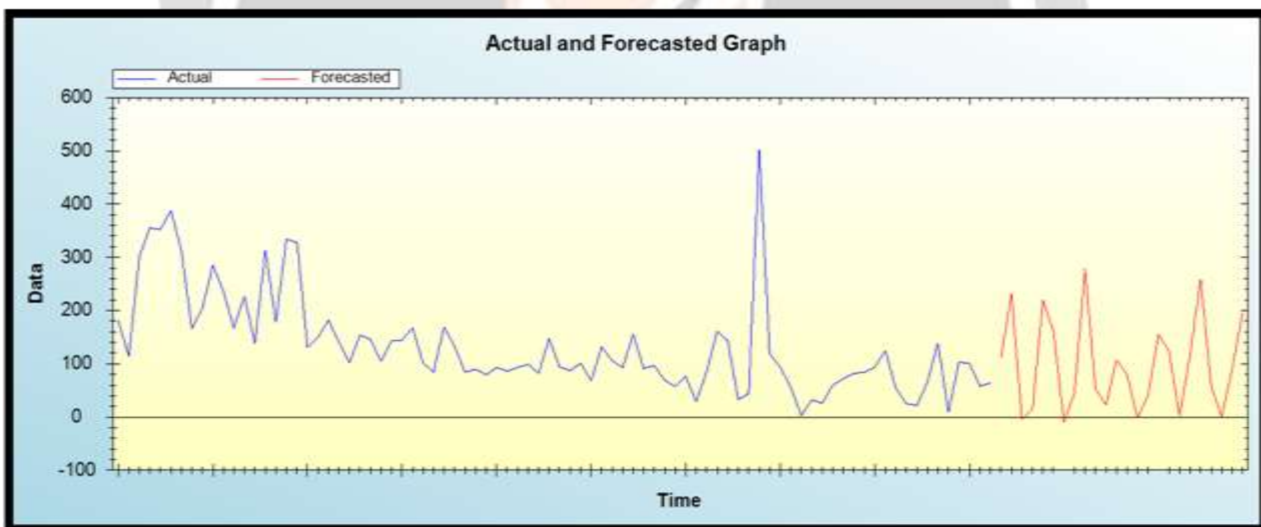
In-sample Forecast – GUD in X

Figure 3: In-sample forecast – X



Out-of-Sample Forecast – X: Actual and Forecasted Graph

Figure 4: Out-of-sample forecast – X: actual and forecasted graph



Out-of-Sample Forecast – X: Forecasts only

Table 3: Out-of-sample forecast – X: forecasts only

Month/Year	Predicted X
January 2020	111.2642
February 2020	231.9515
March 2020	-3.9075
April 2020	14.5542
May 2020	220.0675
June 2020	160.1093
July 2020	-10.4984
August 2020	46.0937

September 2020	278.6575
October 2020	52.8635
November 2020	22.7367
December 2020	107.7605
January 2021	80.2197
February 2021	-1.4943
March 2021	41.1619
April 2021	155.4321
May 2021	123.0962
June 2021	2.1734
July 2021	117.5451
August 2021	259.4102
September 2021	59.2538
October 2021	0.3814
November 2021	89.5765
December 2021	195.6035

Figure 5: Graphical presentation – X: out-of-sample forecasts only

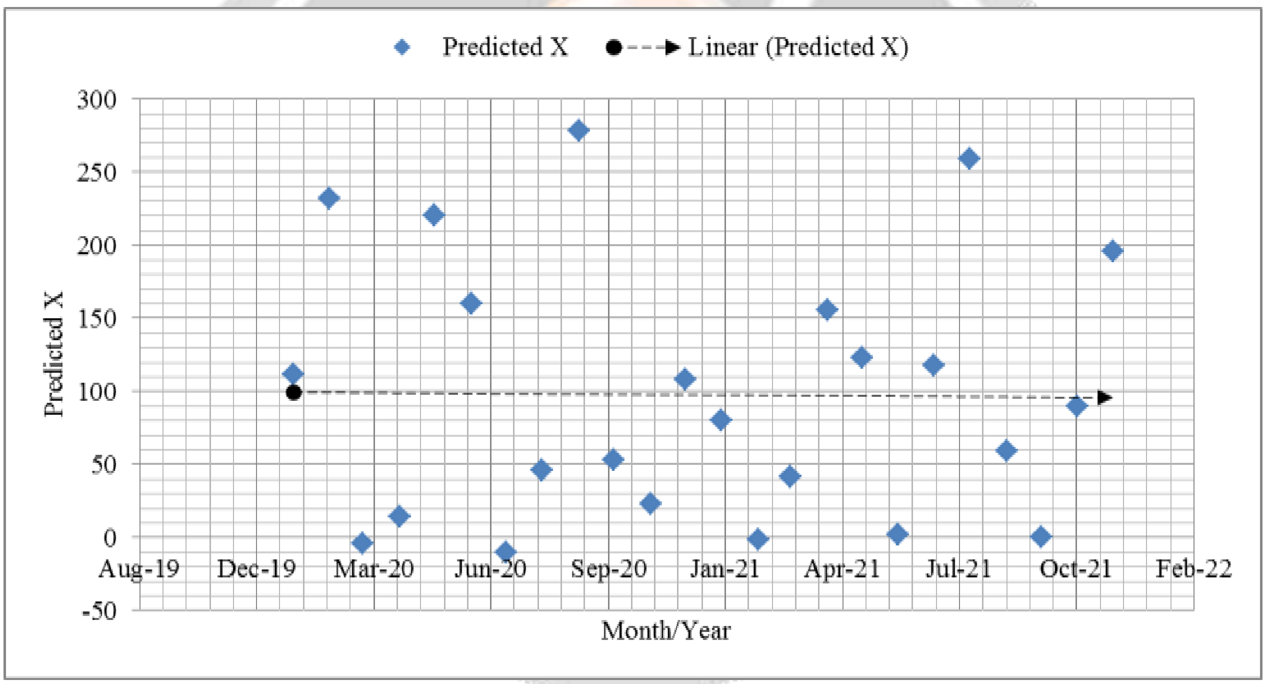


Table 2 is the model summary for the series X. Figure 3 shows the in-sample forecast while figure 4 shows the out-of-sample forecast just like table 3. Figure 5 is the graphical representation of the predicted X series. Basically, the number of underweight children in Chitungwiza urban district is expected to slightly go down over the out-of-sample period.

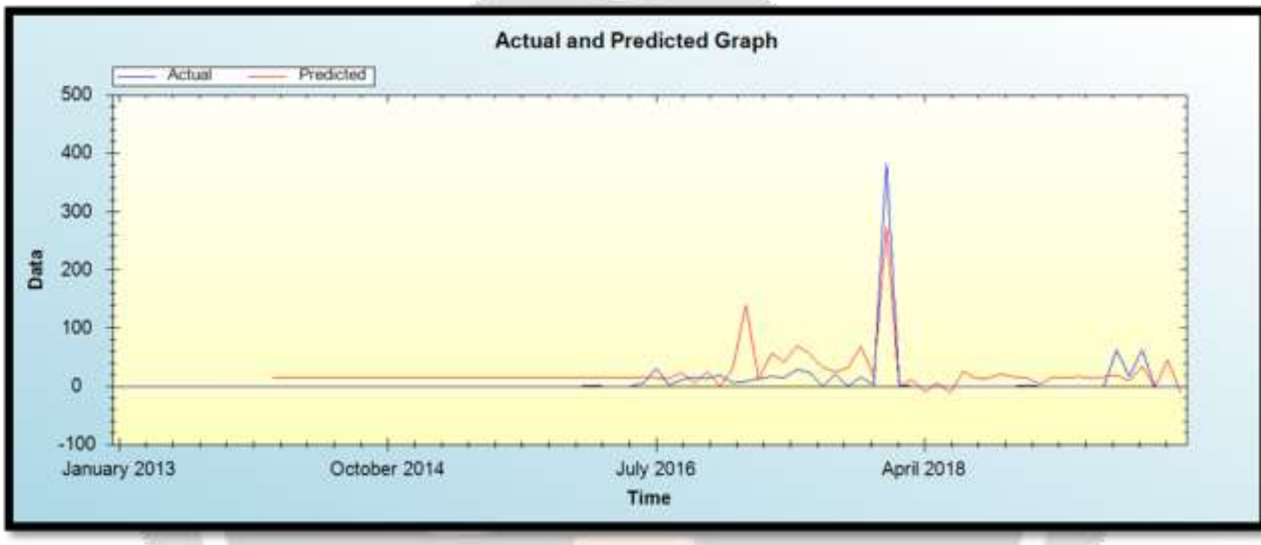
Table 4: ANN model summary – Y

Variable	Y
Observations	72 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	12
Hidden Layer Neurons	12

Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.132572
MSE	795.707809
MAE	20.278564

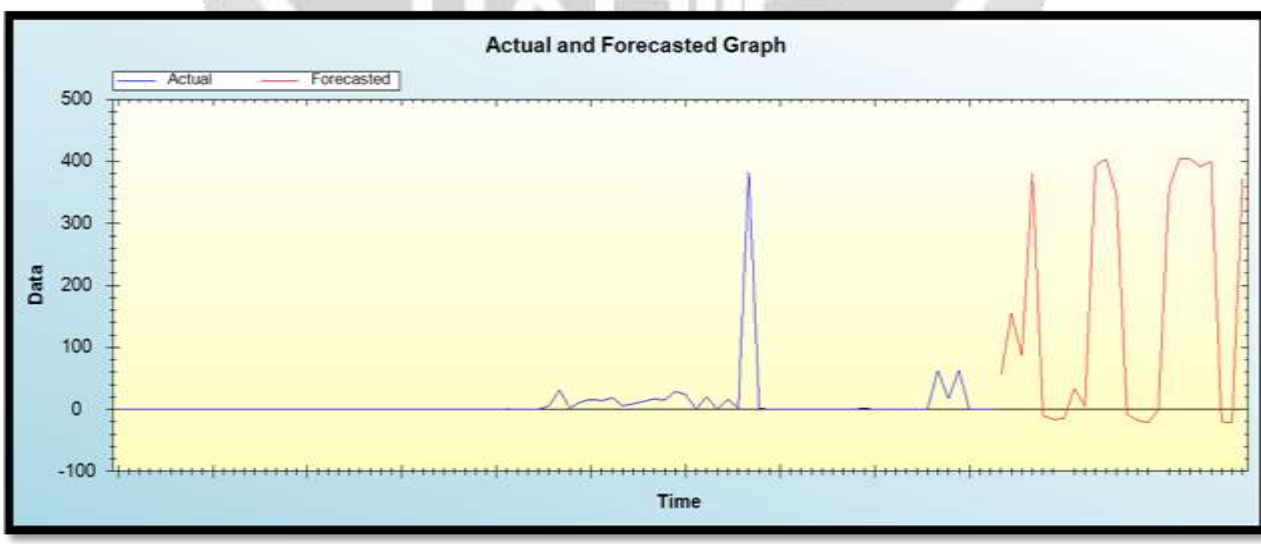
In-sample Forecast – Y

Figure 6: In-sample forecast – Y



Out-of-Sample Forecast – Y: Actual and Forecasted Graph

Figure 7: Out-of-sample forecast – Y: actual and forecasted graph



Out-of-Sample Forecast – Y: Forecasts only

Table 5: Out-of-sample forecast – Y: forecasts only

Month/Year	Predicted Y
January 2020	54.7078
February 2020	155.0056
March 2020	86.7225
April 2020	381.2333
May 2020	-9.7523
June 2020	-16.5079
July 2020	-14.6793
August 2020	33.8152
September 2020	5.0377
October 2020	393.6276
November 2020	404.1702
December 2020	346.2230
January 2021	-7.4474
February 2021	-17.9776
March 2021	-21.2756
April 2021	-0.4574
May 2021	357.1382
June 2021	404.2769
July 2021	404.2506
August 2021	391.3060
September 2021	399.8571
October 2021	-19.9555
November 2021	-21.2687
December 2021	372.5188

Figure 8: Graphical presentation – Y: out-of-sample forecasts only

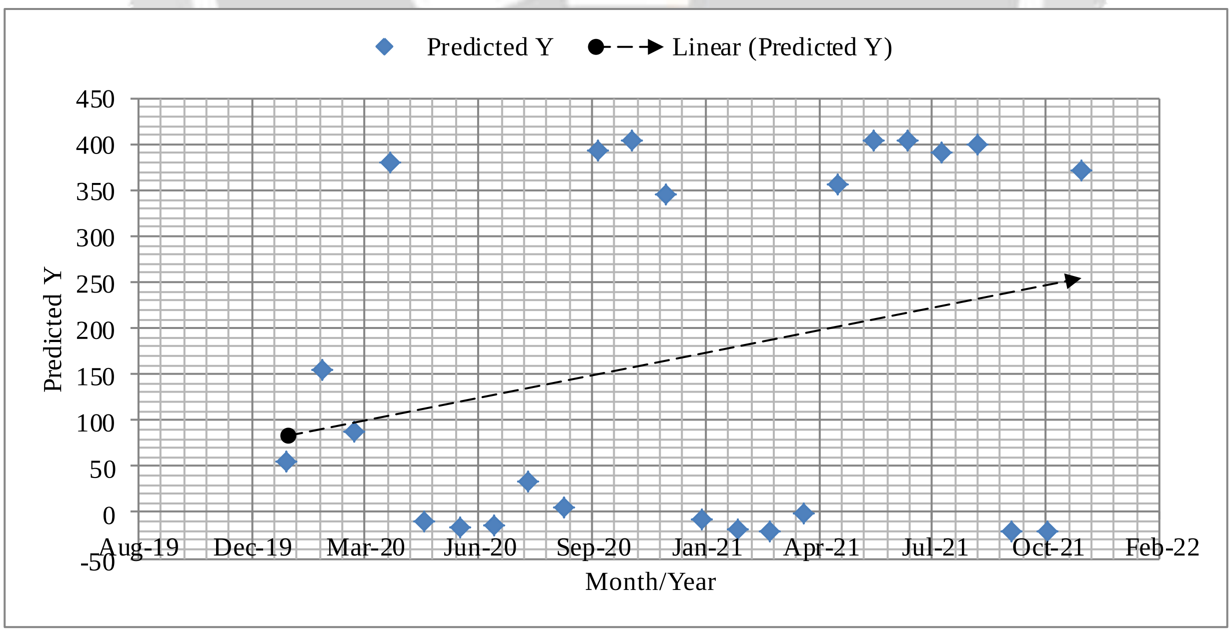


Table 4 shows the model summary for the series Y. Figure 6 displays the in-sample forecast while figure 7 shows the out-of-sample forecast just like table 5. Figure 8 is the graphical representation of the predicted Y series. Clearly, the number of children with chronic malnutrition in Chitungwiza urban district is expected to sharply increase over the out-of-sample period. This is possible, as argued by Lahariya (2008), especially when considering

Zimbabwe's declining economy and the HIV/AIDS pandemic, now exacerbated by the current global outbreak of the Covid-19 pandemic (Sohrabi, 2020; Legido-Quigley, 2020).

Predicted X and Y on a Single Graph

Figure 9: Predicted X and Y on a single graph

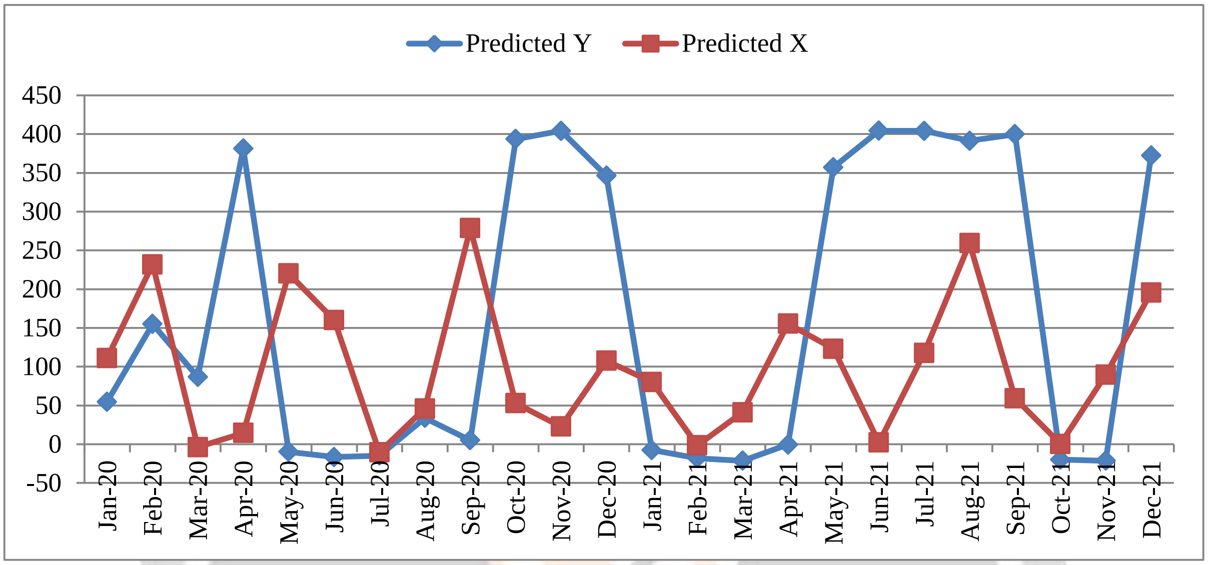
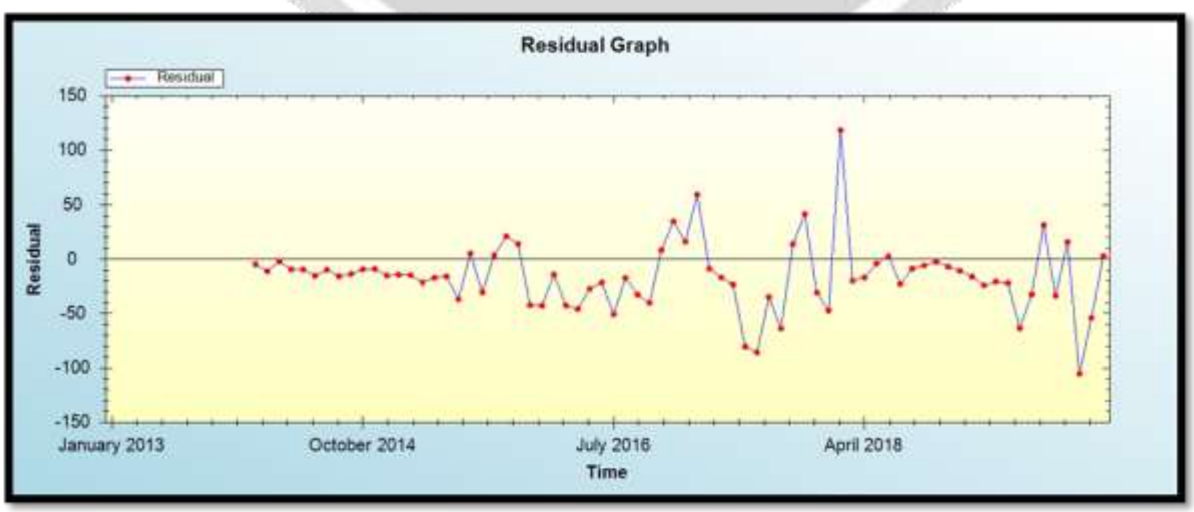


Figure shows the predictions of X and Y plotted on the same graph. Ideally, both cases should be declining sharply especially if malnutrition programmes are achieving the desired health outcomes in Chitungwiza urban district. However, figure 8 indicates that Y is largely above X in most instances. This is not consistent with the in-sample trends shown in figure 1 and 2. Hence this is a warning signal to public health policy makers for Chitungwiza urban district; they have to plan ahead for them to be able to properly handle the predicted increase in chronic malnutrition cases over the period January 2020 – December 2021.

Residual Analysis and Forecast Evaluation for the ANNs

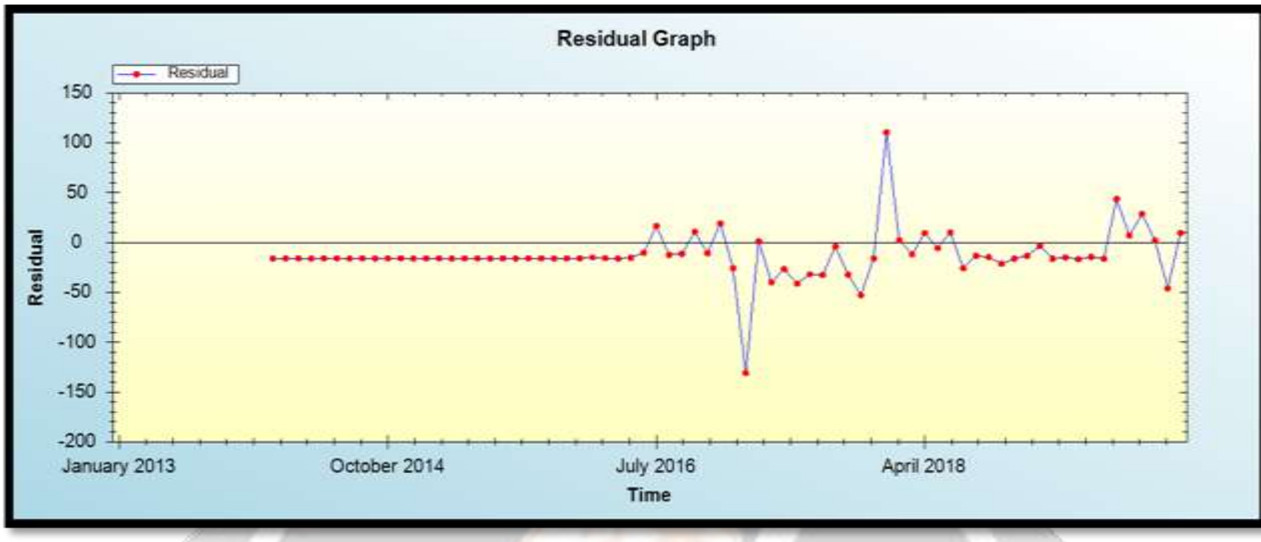
Residual Analysis for X

Figure 9: Residual analysis for X



Residual Analysis for Y

Figure 10: Residual analysis for Y



Forecast Evaluation Statistics for Both X and Y ANNs

Table 6: Forecast evaluation statistics

Evaluation Statistic	X ANN	Y ANN
Error	0.126829	0.132572
MSE	1236.220550	795.707809
MAE	26.374795	20.278564

Figure 9 and 10 indicate that the residual of the models applied in this paper. In both instances, the residuals are as close to zero as possible; therefore the models are quite acceptable for predicting X and Y in Chitungwiza urban district. Table 6 shows the model evaluation criteria. These evaluation statistics should typically be as small as possible. As shown in table 6, the evaluation statistics are quite very minimum and thus the models are relatively accurate.

4.3 RECOMMENDATIONS

i. Early identification of malnutrition cases in the community by City Health Promoters (CHPs). In this regard, relevant authorities ought to strengthen the screening of under 5 children in order to identify malnourished children and manage them according to IMCI (Integrated Management of Childhood Illnesses).
ii. Furthermore, there is need to strengthen linkages between management of malnutrition and TB/HIV programs in Chitungwiza urban district.
iii. The government of Zimbabwe should also fund "self-help" projects in Chitungwiza urban district in order to boost household income thereby improving the nutritional status of under 5 children.
iv. Iron and folate supplement for women pre-conception and during pregnancy in Chitungwiza urban district.
v. Vitamin A supplementation (6 – 59 months) in Chitungwiza urban district.
vi. Early initiation of breastfeeding in Chitungwiza urban district.
vii. Relevant health authorities in Chitungwiza urban district should promote behavior change and engage in public awareness campaigns in order to demystify malnutrition.
viii. There is need for proper hygiene and sanitation in Chitungwiza urban district. The government has a role to play in terms of providing access to safe water to residents.

5.0 CONCLUSION

Poor nutritional status of children has long-run health consequences, and the ramifications extend to inter-generational low productivity and perpetuation of poverty (Sheeran, 2008; Horton, 2008; Victora *et al*., 2008). Being the first study to forecast malnutrition dynamics in Zimbabwe, the study concentrated on Chitungwiza urban district. The study employed ANN models in order to analyze the trend of malnutrition in Chitungwiza urban district. The study is envisioned to go a long way in helping the country reduce the incidence of both chronic malnutrition and underweight in children.

REFERENCES

[1] CAI (2013). Food Insecurity and Malnutrition in Africa, *CAI*, Nairobi.
[2] Dandajena, G. (2013). Factors Associated With Chronic Malnutrition in Mazowe District, Mashonaland Central Province, 2012, Masters Thesis, *University of Zimbabwe*, Harare.
[3] FASEB (1995). Nutrition Monitoring in the United States, *FASEB*, Washington DC.
[4] Gardner, J. M., *et al*. (1999). Behaviour and Development of Stunted and Nonstunted Jamaican Children, *Journal of Child Psychology and Psychiatry*, 40 (5): 819 – 827.
[5] Gardner, M., & Dorling, S. (1998). Artificial Neural Network, *Atmospheric Environment*, 58 (2): 1 – 6.
[6] Hong, R. (2007). Effect of Economic Inequality on Chronic Childhood Undernutrition in Ghana, *Public Health Nutrition*, 10 (4): 371 – 378.
[7] Horton, R. (2008). Maternal and Child Undernutrition: An Urgent Opportunity, *Lancet*, 371 (9608): 169 – 179.
[8] Khan, R., *et al*. (2019). Predicting Malnutrition Disease Using Various Machine Learning Algorithms, *International Journal of Scientific & Technology Research*, 8 (11): 3690 – 3695.
[9] Kuona, P., *et al*. (2014). Serum Selenium Levels and Nutritional Status of School Children From an HIV Prevention Programme in Zimbabwe, *Journal of Tropical Diseases*, 2 (3): 1 – 7.
[10] Lahariya, C. (2008). State of the World's Children, *Indian Pediatrics*, 45: 222 – 223.
[11] Legido-Quigley, H. N. A. (2020). Are High-performing Health Systems Resilient Against the Covid-19 Epidemic? *Lancet*, pp: 848 – 850.
[12] Makoka, D. (2013). The Impact of Maternal Education on Child Nutrition: Evidence From Malawi, Tanzania and Zimbabwe, *USAID*, Harare.
[13] Mbuya, M. N. N., *et al*. (2010). Biological, Social, and Environmental Determinants of Low Birth Weight and Stunting Among Infants and Young Children in Zimbabwe, Zimbabwe Working Papers, *Government of Zimbabwe*, Harare.
[14] Mushonga, N. G. T., *et al*. (2014). A Retrospective Study of The Nutritional Status of Primary School Children in Harare, *African Journal of Food, Agriculture, Nutrition and Development*, 14 (3): 8837 – 8847.
[15] Onis *et al*. (2007). Growth Reference for School-aged Children and Adolescents, *Bulletin of WHO*, 85: 660 – 667.
[16] Rusinga, O., & Moyo, S. (2012). Determinants of Child Malnutrition of Chingazi Ward in Chimanimani District, Zimbabwe, *Journal of Emerging Trends in Educational Research and Policy Studies*, 3 (3): 187 – 192.
[17] Sheeran, J. (2008). The Challenge of Hunger, *Lancet*, 371 (9608): 180 – 181.
[18] Sohrabi, C. (2020). World Health Organization Declares Global Emergency, *International Journal of Surgery*, pp: 71 – 76.
[19] UN (2004). Nutrition for Improved Development Outcomes, *UN*, New York.
[20] UNWFP (2012). Fighting Hunger Worldwide, *UNWFP*, New York.
[21] USAID (2018). Zimbabwe: Nutrition Profile, *USAID*, Harare.
[22] USAID (2020). Poverty and Malnutrition in Zimbabwe: Findings From Matebeleland North Province, *USAID*, New York.
[23] Victora, C. G., et al. (2008). Maternal and Child Undernutrition: Consequences for Adult Health and Human Capital, *Lancet*, 371 (9609): 12 – 24.
[24] Zimstats (2012). Zimbabwe Demographic Health Survey, *Zimstats*, Harare.