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DOES THE BOX-JENKINS "CATCH ALL" MODEL EXPLAIN MALARIA EPIDEMIOLOGY IN CHITUNGWIZA URBAN DISTRICT?

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ABSTRACT

This paper employs monthly time series data on confirmed Malaria cases in Chitungwiza urban district from January 2012 to December 2018; to forecast Malaria cases over the period January 2019 to December 2020. Unit root tests indicate that the Malaria cases series is basically an I (1) series. The study applies the Box-Jenkins "catch all" model in order to explain Malaria epidemiology in Chitungwiza urban district. The residual correlogram of the applied model further reveals that the model is stable and indeed suitable for predicting Malaria cases in Chitungwiza urban district. This model shows that Malaria cases will generally decline over the period January 2019 to December 2020. The main policy prescription emanating from this paper is two-fold and is envisioned to enhance Malaria prevention and control in Chitungwiza urban district.

1. INTRODUCTION

Malaria has been around since ancient times and is one of the oldest prominent and ancient diseases which has been profiled and studied in tropical regions (Appiah *et al*, 2015). The early Egyptians wrote about it on papyrus, and the famous Greek medical doctor Hippocrates described it in detail. It devastated the invaders of the Roman empire. In ancient Rome, as in other temperate climates, Malaria lurked in marshes. Hence, the name is derived from the Italian, "mal aria", or bad air (NIAID, 2007). Malaria is a disease caused by the Plasmodium genus that is transmitted between humans by female Anopheles mosquitoes (the vector) which require blood to nurture her eggs (Anokye *et al*, 2018) as discovered in 1880 by the French scientist Alphonse Laveran. The plasmodium parasite has four species, namely; plasmodium falciparum, plasmodium vivax, plasmodium ovale and plasmodium malariae (Dan *et al*, 2014). There are two important vector species responsible for transmission of Malaria in Zimbabwe and these are Anopheles gambiae and Anopheles fenustus. The most common infection Zimbabwe is with the parasite species Plasmodium falciparum (Guidelines for Management of Malaria in Zimbabwe, 2015).

When Malaria parasites enter the blood stream of a person, they infect and destroy the red blood cells and this leads to fever and flu-like symptoms such as chills, headache, muscle aches, tiredness, nausea, vomiting and diarrhea. When Malaria is not treated; it can lead to coma and hence death (Dan *et al*, 2014) but it is a very preventable and treatable disease (Hassan & Bin, 2018; Awaab *et al*, 2019). The most effective prevention for Malaria is through prevention of mosquito bites, that is; vector control and personal protection/prevention strategies (Guidelines for Management of Malaria in Zimbabwe, 2015). Historically, the United States of America (USA) is no stranger to the tragedy of Malaria. This disease, then commonly known as "fever and ague", took a toll on early setters. Malaria has been a significant factor in virtually all of the military campaigns involving the USA. In World War II and the Vietnam War, more personnel lost their lives due to malaria than to bullets (NIAID, 2007).

Zimbabwe has seasonal and geographic variation in Malaria transmission that corresponds closely with the country's rainfall pattern. In general, the major Malaria transmission season occurs during the rainy season between November and April, the average

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temperature ranging between 18 and 30 degrees Celsius. Peak transmission is February through April. The annual rainfall varies from less than 700mm in Matabeleland South Province to more than 1500mm in Manicaland province. Malaria transmission is lower in the low rainfall areas and higher in the high rainfall provinces (US President's Malaria Initiative, 2018). The primary Malaria zones in Zimbabwe are in the northern and eastern areas bordering Mozambique and Zambia. However, of the 62 districts in Zimbabwe, 45 are considered malarious (USAID, 2015).

In Zimbabwe, the majority of people seek care for fever and suspected Malaria from public sector facilities (US President's Malaria Initiative, 2018). Early prediction of malaria cases is very important for its control and intervention (Getnet & Ayalew, 2017). In Chitungwiza urban district, suspected Malaria cases are seen in the outpatient departments in various health facilities and rapid diagnostic tests for Malaria are done. The positive cases are confirmed Malaria cases. For negative cases, blood samples are sent for microscopy to look for the parasite in the blood. Those patients who test negative by rapid diagnostic and microscopy are then screened for other febrile illnesses like TB, meningitis and typhoid. Uncomplicated Malaria cases are treated with oral coartem and the complicated cases are referred to Chitungwiza Central Hospital for admission where they receive intravenous (IV) Artesunate. If Artesunate is not available, Quinine IV is given. Complicated Malaria is a medical emergency and needs prompt action. Besides giving Intravenous Artesunate, other things need to be done such as:

i. Giving oxygen per face mask.
ii. Correcting fluid and electrolyte imbalance.
iii. Correcting hypoglycemia.
iv. Treatment of seizures.
v. Blood transfusion.

This study will go a long way in facilitating proper planning and evaluation in the implementation of programs to prevent, monitor and control malaria in Chitungwiza urban district.

OBJECTIVES OF THE STUDY

i. To identify the months during which Malaria cases mostly occur in Chitungwiza urban district.
ii. To determine whether the Box-Jenkins "Catch All" model can optimally predict Malaria cases in Chitungwiza urban district.
iii. To analyze the influence of past Malaria cases in Chitungwiza urban district to the present time.

STATEMENT OF THE PROBLEM

Malaria remains a major health challenge to mankind all over the world (WHO, 2013) and in Zimbabwe too, it continues to be a major public health problem (Guidelines for Management of Malaria in Zimbabwe, 2009; 2015) with about 50% of the population living in Malaria transmission areas (Guidelines for Management of Malaria in Zimbabwe, 2015). Malaria accounts for an estimated 2 to 3 million deaths annually and is also responsible for untold morbidity in nearly 300 to 500 million people annually. Vulnerable groups are children and adults who have host or never acquired immunity (Smith *et al*, 2002). The overwhelming majority that is 90% of Malaria cases occur in Africa (Medical Research Council, 2001). In fact, Malaria is said to kill at least one African (whether a child or an adult) every 15 seconds (Salako, 2002) and most of the deaths occur in children (WHO, 2014). Malaria is responsible for over 10% of the overall African disease burden, of which children under 5 years of age (22% of the population) and pregnant women (20% of the population) are the most susceptible to Malaria (Guillet *et al*, 2001). Malaria victims are usually in the poorest and sometimes most remote parts of the world, increasing the difficulty in finding support to cope with the disease (Davies & Eaton, 2018). Malaria is the third leading cause of illness and mortality in Zimbabwe (USAID, 2015). Annually, in Zimbabwe; close to 1.5 million malaria episodes are reported whilst an average of 1000 people die from this disease. Malaria accounts for 30% of outpatients at clinics and 40% of hospital admissions in Zimbabwe (Guidelines for Management of Malaria in Zimbabwe, 2009). Despite local and international efforts towards prevention of the disease, the rate at which people in Chitungwiza urban district become sick (and sometimes die) as a result of Malaria is alarming.

SIGNIFICANCE OF THE STUDY

This paper is apparently in line with the revised National Malaria Strategic Plan (NMSP) for 2016 – 2020 and being the first study of its kind not only for "Chi-town" but also for Zimbabwe at large; its significance is precisely four-fold:

i. The study is a starting point for researchers who want to conduct further studies in application of Box-Jenkins type models in analyzing Malaria cases.
ii. The study will provide information and policy advice on Malaria control in Chitungwiza urban district.
iii. People living in Chitungwiza urban district are envisioned to benefit from this study in terms

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of gaining more evidence-based information about Malaria.

iv. This study will enable relevant authorities in Chitungwiza urban district to foresee and allocate optimal resources to maintain a steady decrease of the spread of Malaria.

2. LITERATURE REVIEW

Table 1: Literature Summary on Forecasting Malaria Cases

Author/Year	Country	Period	Methodology	Main Findings
Briet *et al* (2008)	Sri Lanka	January 1972 – December 2005	SARIMA, EWMA, ARIMA	Heterogeneity patterns of Malaria in Sri Lanka requires regionally specific prediction models
Dan *et al* (2014)	Nigeria	January 1996 – December 2013	SARIMA	The SARIMA $(1,1,1)(0,0,1)_{12}$ was found to be the best model
Appiah *et al* (2015)	Ghana	January 2009 – December 2013	ARIMA	The best model was found to be the ARIMA (1,0,0) model
Jere & Moyo (2016)	Zambia	January 2009 – December 2013	ARIMA	The appropriate model is the ARIMA (1,0,0) model
Anwar *et al* (2016)	Afghanistan	January 2005 – September 2015	ARIMA	ARIMA models can be applied to forecast malaria patterns in Afghanistan
Bosson-Amedenu (2017)	Ghana	January 2008 – December 2013	ARIMA	The ARIMA (1,1,2) model is the best model
Hussien *et al* (2017)	Sudan	January 2009 – December 2013	ARIMA, ETS, TM, MA	The TM method performed significantly better than other methods
Getnet & Ayalew (2017)	Ethiopia	January 2007 – June 2016	ARIMA, SARIMA, GARCH	The SARIMA $(1,1,1)(2,1,1)_{12}$ and GARCH (1, 1) models were found to be the best models
Alhassan *et al* (2017)	Ghana	January 2010 – December 2015	ARIMA	The ARIMA (1,0,1) model fits the data well
Hassan & Bin (2018)	Sudan	January 2005 – December 2008	SARIMA	The ARIMA model is an appropriate model for malaria warning
Ebhuoma *et al* (2018)	South Africa	January 2005 – December 2014	SARIMA	The SARIMA $(0,1,1)(0,1,1)_{12}$ is the best fit model
Anokye *et al* (2018)	Ghana	January 2010 – December 2016	ARIMA, QM	The ARIMA (1,1,2) model is the optimal model
Twumasi-Ankrah *et al* (2019)	Ghana	January 2008 – December 2017	SARIMA, ANN, ETS	The SARIMA technique is the appropriate statistical technique
Awaab *et al* (2019)	Ghana	January 2009 – December 2016	ARIMA, LTM, QTM	The best models are the quadratic trend and ARIMA (0,1,0) models

From table 1 above, it is almost unnecessary to note that in the case of Zimbabwe, no similar study has been done so far. This is the first study to model and forecast Malaria cases in Chitungwiza urban district in Zimbabwe. From table 1 above, we can also see that all the previous studies reviewed used either the ARIMA or the SARIMA or both models. Other studies such as Briet *et al* (2008), Hussien *et al* (2017) and Getnet & Ayalew (2017) also employed additional forecasting approaches such as EWMA; ETS, TM, MA; and GARCH, respectively. Due to their simplicity and superiority, the ARIMA and SARIMA models have been shown to grab the lion's share in terms of empirical applicability. This study follows the intuition of previous studies that employed the SARIMA model in forecasting Malaria cases, particularly, Ebhuoma *et al* (2018) who basically concluded that the Box-Jenkins "catch all" model was the optimal model for predicting monthly Malaria cases in KwaZulu Natal, South Africa. All the studies reviewed acknowledge the superiority and adequacy of the ARIMA technique in forecasting Malaria cases, except Hussien *et al* (2017) who concluded that the trend model (TM) method performs significantly better than other methods.

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3. METHODOLOGY

A number of models have been used to analyze malaria patterns, for example, linear regression (Craig *et al*, 2004), poisson regression (Teklehaimanot *et al*, 2004), spearman's correlation (Bi *et al*, 2003) as well as non-linear methods (Zhou *et al*, 2004). However, this study chooses to apply the Box-Jenkins ARIMA model, precisely because it is relatively simple and stable in predicting malaria cases (Pascual *et al*, 2008). The model looks for temporal dependence between successive observations (Helfenstein, 1991). Due to the transmissibility and seasonality of Malaria, models with an ARIMA structure have more predictive power compared to other models (Nobre *et al*, 2001); such models have been used to forecast numerous infectious diseases with similar periodic patterns over the past decades (Earnest *et al*, 2005; Ture *et al*, 2006; Gomez-Elipe *et al*, 2007; Luz *et al*, 2008; Wu *et al*, 2008; Wangdi *et al*, 2010; Aboagye-Sarfo *et al*, 2010; Liu *et al*, 2011; Siriwan *et al*, 2012; Nsoesie *et al*, 2014; Zheng *et al*, 2015; Imai & Hashizume, 2015; Xie, 2018; Coelho *et al*, 2019)

The SARIMA Model

The Box – Jenkins technique belongs to Box & Jenkins (1970) and in this paper; it will be used for analyzing monthly confirmed Malaria cases for Chitungwiza urban district in Zimbabwe. A generalized Box-Jenkins SARIMA model is as shown in equation [1] here:

$$\phi_p(B)\emptyset_p(B^s)M_t = \theta_q(B)\Theta_q(B^s)\varepsilon_t \dots\dots\dots\dots\dots\dots\dots [1]$$

Where B is the backshift operator, $\phi_p, \emptyset_p, \theta_q \; and \; \Theta_q$ are polynomials of order p, P, q and Q respectively. ε_t is a white noise process and $M_t = \nabla_d \Delta_s^D Y_t$ is the differenced M series.

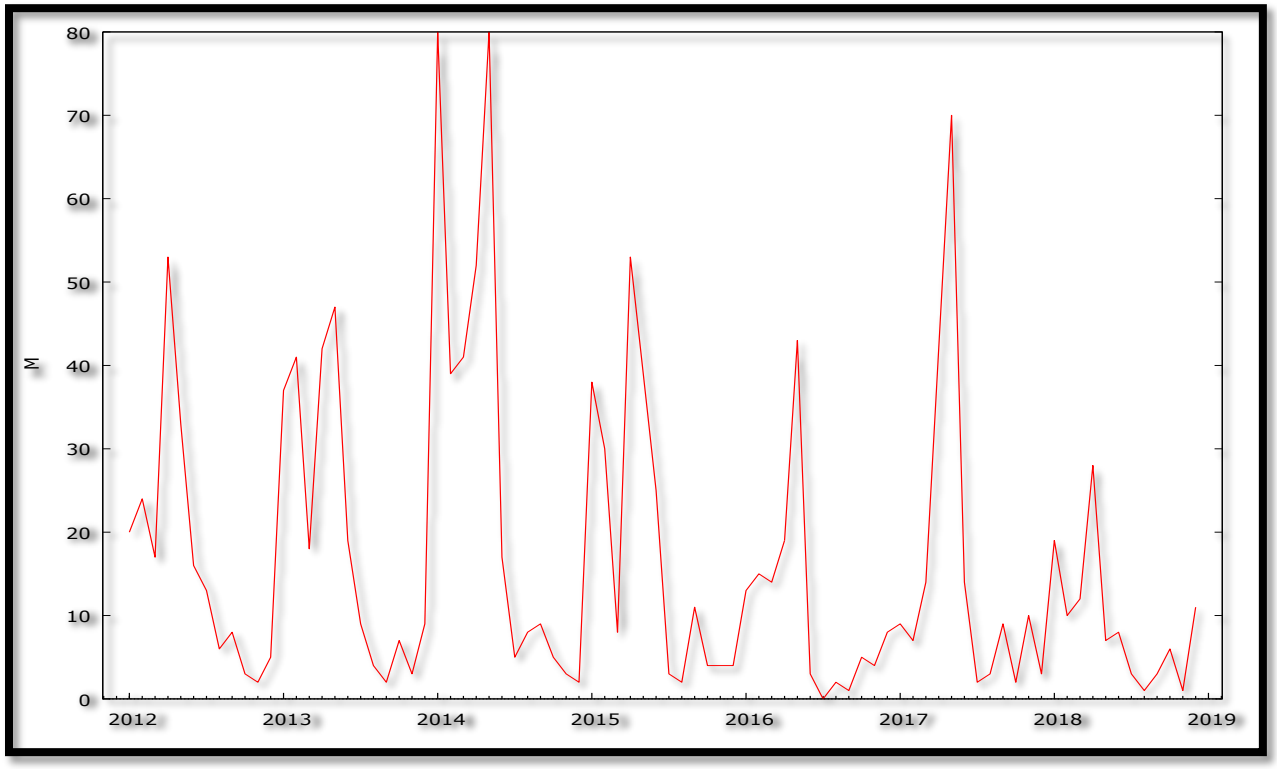
Data

This study is based on monthly confirmed cases of Malaria [M] (adults and children-all age groups) in Chitungwiza urban district, from January 2012 to December 2018. The out-of-sample forecast ranges over the period January 2019 to December 2020. All the data employed in this research was gathered from the DHIS2 health information system for Chitungwiza city.

Diagnostic Tests and Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1: Graphical Analysis



In figure 1 above, M is plotted against time to detect and correct for non-stationarity. The series displayed in figure 1 above are suspiciously noisy and there is need to carry out a formal test stationary in

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order to confirm the stationarity of the series. This is done in tables 1 – 7 below. Apparently, we can also see that the monthly peaks for Malaria cases in Chitungwiza urban district over the period under study are as follows: 53 cases in April 2012, 47 cases in May 2013, 80 cases in both January and May 2014, 53 cases in April 2015, 43 cases in May 2016, 70 cases in May 2017 and 28 cases in April 2018. Highest peaks were experienced in the months of January and May 2014 with an alarming 80 confirmed Malaria cases each. From figure 1 above, malaria transmission season largely covers the period January to June for Chitungwiza urban district and this is quite different from what is traditionally know that malaria transmission season occurs between November and April with peaks usually observed in February through April. For Chitungwiza urban district, malaria transmission peaks have largely been experienced over the months of April and May. This deviation from the general traditional trends could be attributed to climate change and climate variability. The months of July – December have relatively less confirmed Malaria cases, with the lowest being 1 case which occurred for the months of September and August 2016 and 2017 respectively.

The ADF Test

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M_t	-5.466163	0.0000	-3.511262	@1%	Stationary
			-2.896779	@5%	Stationary
			-2.585626	@10%	Stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M_t	-5.734663	0.0000	-4.072415	@1%	Stationary
			-3.464865	@5%	Stationary
			-3.158974	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
M_t	-0.671644	0.4227	-2.597476	@1%	Not stationary
			-1.945389	@5%	Not stationary
			-1.613838	@10%	Not stationary

Table 5: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(M_t)$	-7.800639	0.0000	-3.524233	@1%	Stationary
			-2.902358	@5%	Stationary
			-2.588587	@10%	Stationary

Table 6: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(M_t)$	-7.889242	0.0000	-4.090602	@1%	Stationary
			-3.473447	@5%	Stationary
			-3.163967	@10%	Stationary

Table 7: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(M_t)$	-7.837588	0.0000	-2.597476	@1%	Stationary
			-1.945389	@5%	Stationary
			-1.613838	@10%	Stationary

Tables 2 – 7 basically indicate that M is an I (1) variable.

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Analysis of the Residuals of the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ Model

Residual Correlogram of the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ Model

Figure 2: Residual Correlogram

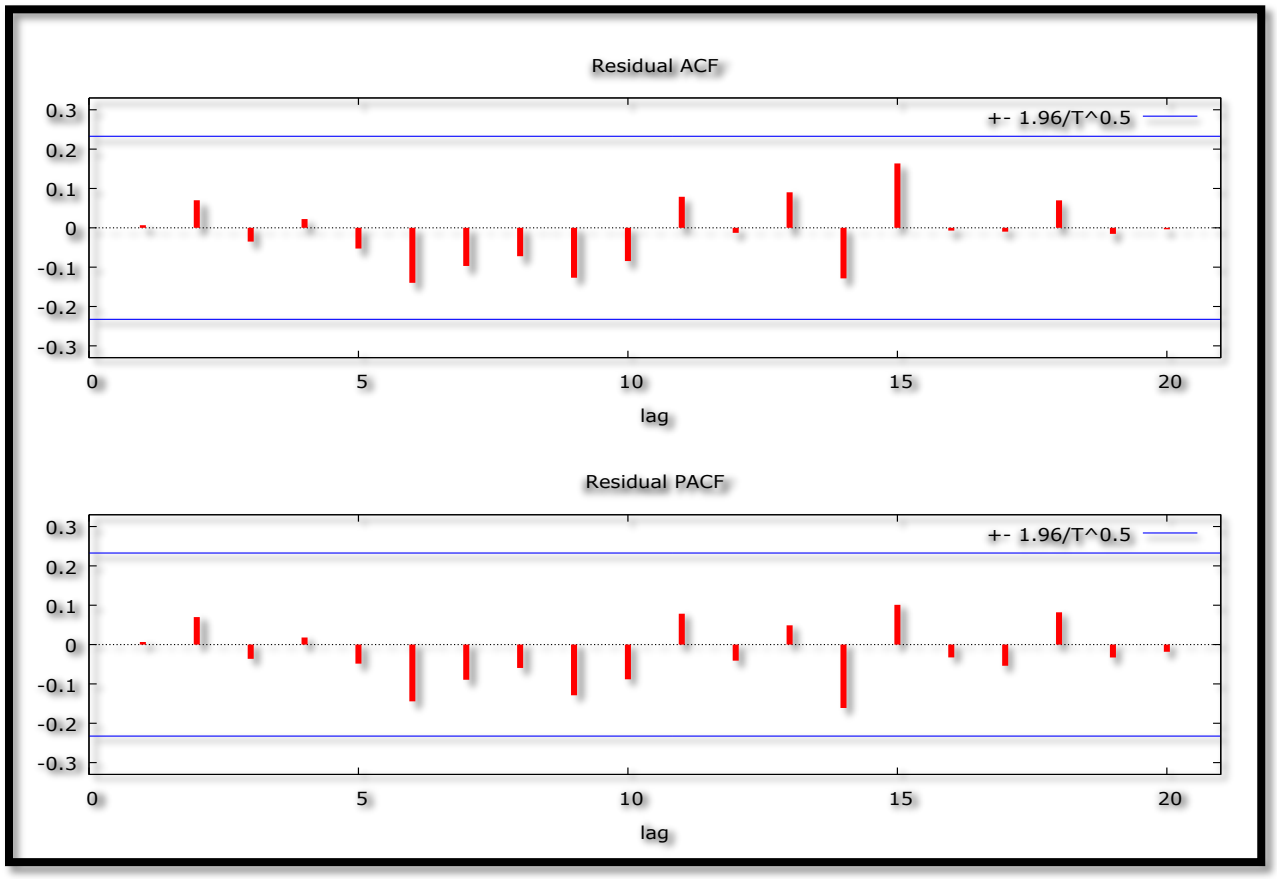

Figure 2 indicates that the residuals of the Box-Jenkins "catch all" model are stable and this proves beyond any reasonable doubt that our predictive model is adequate.

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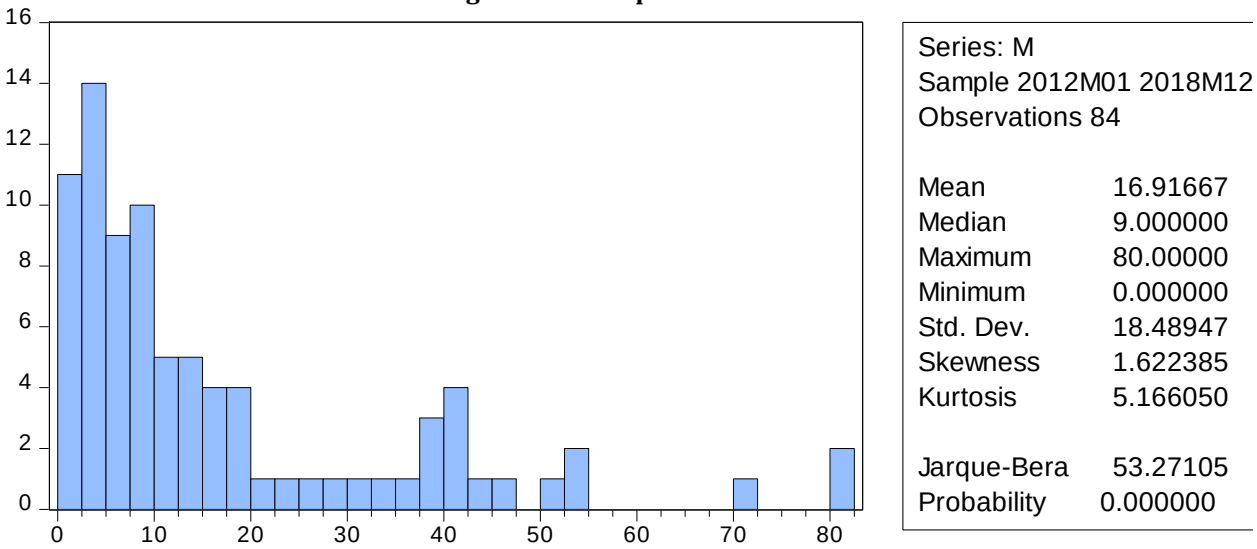
4. RESULTS OF THE STUDY

Descriptive Statistics

Figure 3: Descriptive Statistics



The striking feature of figure 3 above is the maximum which is 80 Malaria cases. This maximum number of confirmed Malaria cases was experienced in the months of January and May 2014 in Chitungwiza urban district. This could be attributed to heavy rains and relatively higher temperatures that were experienced in the period November 2013 – April 2014. Notably also, is a minimum of zero confirmed Malaria cases, that occurred in July 2016. The average Malaria transmission in terms of cases per month is 17 cases per month over the period under study as shown in figure 3 above. Although this is not really too much, it is not acceptable given the fact that Malaria is a preventable scourge and also that Chitungwiza urban district has the capacity to sustainably maintain a Malaria-free "Chi-town".

Results Presentation[1]

Table 8: Main Results of the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ Model

The SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model can be presented as follows:

$$(1 - B)(1 - B^{12})N_t = (1 - 0.733426B)(1 - 0.890687B^{12})\varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [2]$$

Variable	Coefficient	Standard Error	z	p-value
θ_q	-0.733426	0.0782124	-9.377	0.0000****
Θ_q	-0.890687	0.440018	-2.024	0.0429**

[1] ****, ** and * means significant at 1%, 5% and 10% level of significance, respectively.*

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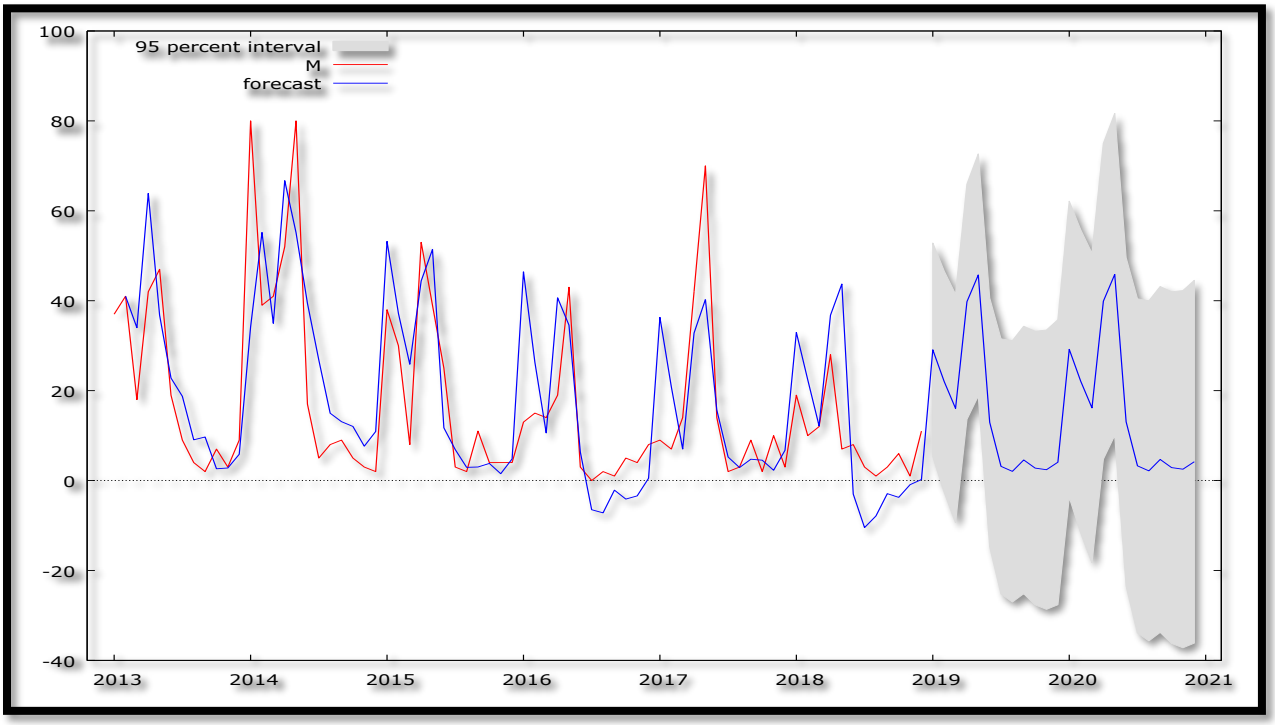
Forecast Graph

Figure 4: Forecast Graph



Out of Sample Forecasts

Table 9: Out-of-sample forecasts

Year: Month	Prediction	Standard Error	95% Confidence Interval
2019:01	29.0824	12.1203	(5.32696, 52.8378)
2019:02	22.0256	12.5436	(-2.55942, 46.6106)
2019:03	16.0483	12.9530	(-9.33920, 41.4358)
2019:04	39.7801	13.3499	(13.6148, 65.9455)
2019:05	45.7432	13.7353	(18.8224, 72.6640)
2019:06	12.9543	14.1102	(-14.7013, 40.6098)
2019:07	3.15895	14.4754	(-25.2123, 31.5302)
2019:08	2.04304	14.8316	(-27.0264, 31.1125)
2019:09	4.57938	15.1795	(-25.1718, 34.3306)
2019:10	2.76740	15.5195	(-27.6503, 33.1851)
2019:11	2.41211	15.8523	(-28.6578, 33.4820)
2019:12	4.07356	16.1782	(-27.6351, 35.7822)
2020:01	29.1943	16.8074	(-3.74764, 62.1362)
2020:02	22.1375	17.1853	(-11.5451, 55.8201)
2020:03	16.1602	17.5551	(-18.2472, 50.5676)
2020:04	39.8920	17.9173	(4.77486, 75.0092)
2020:05	45.8551	18.2722	(10.0422, 81.6680)
2020:06	13.0662	18.6204	(-23.4292, 49.5615)

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2020:07	3.27085	18.9622	(-33.8945, 40.4362)
2020:08	2.15493	19.2980	(-35.6684, 39.9783)
2020:09	4.69128	19.6280	(-33.7789, 43.1615)
2020:10	2.87930	19.9526	(-36.2270, 41.9856)
2020:11	2.52401	20.2719	(-37.2082, 42.2563)
2020:12	4.18546	20.5863	(-36.1630, 44.5339)

Graphical Presentation of the Predicted Monthly Malaria Cases in Chitungwiza Urban District (Out-of-Sample)

Figure 5: Graphical presentation of out-of-sample forecasts

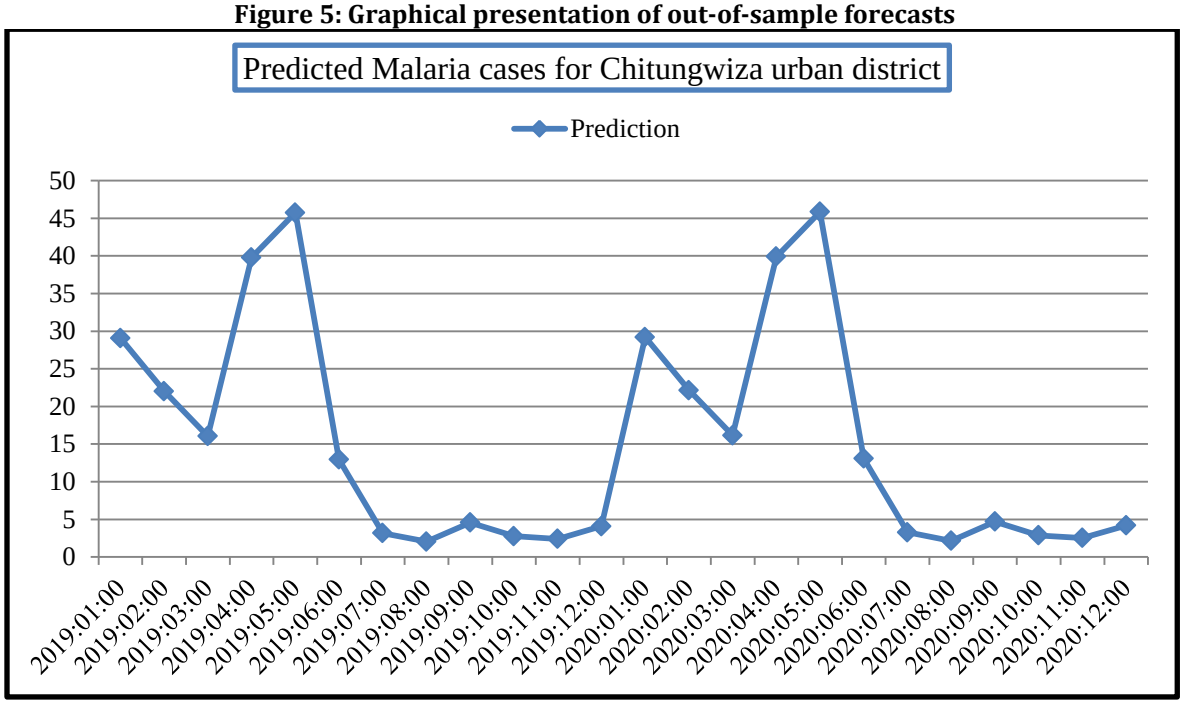

Table 8 shows the main results of the Box-Jenkins "catch all" model for Malaria cases in Chitungwiza urban district. Equation [2] is just a mathematical representation of the estimated predictive model. Figure 4 and 5 as well as table 9 show the forecasted Malaria cases over the period January 2019 to December 2020. The results of this study basically indicate that Malaria cases will decline over the out-of-sample period. The observed and forecasted relative decline in Malaria cases in Chitungwiza urban district is largely attributed to effective vector control measures and appropriate case management through deployment of rapid diagnostic tests (RDTs) as well as efficacious medicines that impact transmission.

These results are in line with the observation made by the USAID (2015) that Malaria incidence in Zimbabwe appears to be decreasing nationally and Chitungwiza urban district is one of the districts which is contributing to such a decrease, although other districts as highlighted by USAID (2015) remain a major challenge. The results of this study are also consistent with the observation made by the government of Zimbabwe (Guidelines for Management of Malaria in Zimbabwe, 2015) that Malaria incidence in Zimbabwe has progressively declined over the years, from 155 cases/1000 population in 2003 to 29 cases/1000 population in 2013. Our results also tally with Sande *et al* (2017) who argue that an intensive effort to control Malaria in Zimbabwe has produced dramatic reductions in the burden of the disease, especially over the past decade.

5. RECOMMENDATIONS

i. The government of Zimbabwe, with the help of its supporting partners should intensify malaria surveillance programs not only in Chitungwiza urban district but also for the whole country at large. In this regard, the following Malaria control measures ought to be considered:
   - ✓ Eliminating vector breeding places.
   - ✓ Creating public awareness.

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- ✓ Provide insecticide treated nets (ITNs)
- ✓ Engage in indoor residual spraying.
- ✓ Engage in Malaria in Pregnancy (MIP) initiatives.
- ✓ Improve pharmaceutical management (provision of Malaria commodities, especially critical malaria medicines, along with artemisinin-based combination therapy [ACTs] as well as rapid diagnostic tests [RDTs]).

ii. Decision makers, not only in Chitungwiza urban district but also in the whole country, should engage in continuous projection of future Malaria cases and consequently act proactively.

6. CONCLUSION

There is no doubt; Malaria continues to be major threat to public health in Zimbabwe. However, this scourge is preventable and can also be treated successfully. In order to reduce morbidity and mortality caused by Malaria, this study offers a two-fold policy recommendation. This paper is strictly restricted to the Box-Jenkins "catch all" model and therefore further studies are encouraged to construct various SARIMA models and choose the parsimonious model from a set of estimated models. This can potentially lead to better model fit. Further studies can also look into developing different SARIMA models for various age-groups; that can actually generate more detailed information on the epidemiology of Malaria in Chitungwiza urban district.

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