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Modelling COVID-19 infection with seasonality in Zimbabwe

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ABSTRACT

This paper presents evidence and the existence of seasonality in current existing COVID-19 datasets for three different countries namely Zimbabwe, South Africa, and Botswana. Therefore, we modified the SVIR model through factoring in the seasonality effect by incorporating moving averages and signal processing techniques to the disease transmission rate. The simulation results strongly established the existence of seasonality in COVID-19 dynamics with a correlation of 0.746 between models with seasonality effect at 0.001 significance level. Finally, the model was used to predict the magnitude and occurrence of the fourth wave.

1. Introduction

In Zimbabwe since the onset of COVID-19, millions of people have felt the socio-economic burden of the disease while it has also claimed more than 4082 lives and infected more 125 555 people in a population estimated to be around 15 092 171 people (Anon, 2021a,b,c,d,e). The pandemic has continued to cause havoc despite many intervention strategies that have been implemented which include series of lockdowns, quarantines, banning of alcohol and smoking, social distancing measures, banning of super spreader events, masking up and sanitisation (Lone and Ahmad, 2020). However, most of the health systems, cemeteries and funeral parlours around the country have been overwhelmed by the effects of this pandemic. Again, this virus continues to evolve in its host and in ecology resulting in emergent of numerous new variants (Ciotti et al., 2020). Regardless of this chaos, scientist around the world have developed the first generation of vaccines to help us fight this pandemic and Zimbabwe started its vaccination programme on 18 February 2021. Up until now the country has so far seen an increased uptake of vaccines with more 1 718 351 people fully vaccinated and about twice as much receiving their first jab. The vaccination rate currently stands at an average of 41 964 people per day (Anon, 2021d; Musuka et al., 2021; McAbee et al., 2021; Murewanhema et al., 2021).

Several studies have explored the linkages of COVID-19 and environmental factors that contributes to its seasonality (Liu et al., 2020; Aabed and Lashin, 2021; Hu et al., 2020). For example, in a cold day people tend to pack inside their rooms in their homes hence it becomes difficult to adhere to social distancing measures. Therefore, during cold weather usually houses are poorly ventilated as people would be avoiding cold and this is the case for developing countries where most of the building cooling infrastructure has not yet been adopted by general populace. However, some studies (Damette et al., 2021; Altamimi and Ahmed, 2020; Chin et al., 2020) have made some advances to establish the correlation of temperature, humidity, solar radiation and rainfall patterns with COVID-19 cases though to some extent the relationship has not been fully understood. Furthermore, there are positives in this direction of research because of increasing COVID-19 datasets and availability which if fully utilised can bring about quality and clarity on the subject of seasonality of COVID-19. Various source COVID-19 data-sets can be accessible online with no charge (Anon, 2021a,b,c,d,e,f).

There are many factors that can be used to generate seasonality which include environmental factors such as temperature and rainfall (Guangbo et al., 2020; Bherwani et al., 2020). However, seasonality can be as a result of cultural, socio-economic human behaviour think of this in terms of vacation, holidays (Christmas) which are congruent to periodic events and exhibit repetitive, generally systematic and predictive patterns (Byun et al., 2021). In the case of time-series data seasonality can be viewed as any predictable fluctuation or pattern that recurs or repeats over a time interval. In addition, with time-series data-sets the following values to measure seasonality can be computed seasonal factor, seasonal index or seasonal relativity. Again, these measures will explain seasonality stating how much surplus and deficit about the expected value (mean/average) for a particular period (Anon, 2021g; van den and Watmough, 2002). Finally, this paper seeks to fit a mathematical model using the data-set for Zimbabwe from the period of 20-Feb 2020 to 20-Aug 2021.

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2. Model formulation

2.1. Model description

In this part of the paper we discuss the formulation of COVID-19 basic model applicable to the Zimbabwe framework which presents the insights of the spread of this virus. Thus, the human population at any given time (t) is given by the susceptible individuals (S) generated by Eq. (1), vaccinated individuals (V) generated by Eq. (2), infected asymptomatic individuals (I_a) generated by Eq. (3) and infected symptomatic individuals (I_s) generated by Eq. (4) and the recovered individuals (R) generated by Eq. (5). There is also an inclusion of the environmental contamination where the environment acts as the reservoir for the disease represented by (E_v) as shown in Eq. (6). The basic model is developed from the traditional SIRV model by modifying the model to account for environmental contamination of surface and surrounding air. The susceptible individuals can either be vaccinated at a rate γ or be infected with two infection possibilities firstly at rate of β_a which implies infected but then progress to be asymptomatic and secondly at rate β_s which implies infected but then progress to the symptomatic class. The susceptible class has a recruitment rate Λ and natural death rate of μ. Also, an individual from the vaccinated class can progress to infectious class through the rate α_a and α_s for asymptomatic and symptomatic infectious classes respectively. Therefore, the probability of being infected and progress to symptomatic class is κ and the probability of progressing to symptomatic class is κ. Individuals from infectious classes can succumb to the disease with rate σ_a and σ_s for asymptomatic and symptomatic classes, again individuals from these two classes will recover at a rate π_a and π_s respectively. It is of great importance to note that the infectious classes can transmit the virus onto the environment at the following rates ω_a and ω_s for asymptomatic and symptomatic classes. The virus can only survive for a certain limited period of time in the environment hence we assume that the virus can die-out at a rate ρ. Finally, since we will be simulating for short time period we assumed that the recoveries do not progress to be susceptible.

Based on the above descriptions we obtain the following system of ordinary differential equations to represent the transmission dynamics of the disease.

$$\frac{dS}{dt} = \Lambda - \gamma S - \mu S - \beta_s S I_s - \beta_a S I_a - \kappa E_v S - (1-\kappa) E_v S \tag{1}$$

$$\frac{dV}{dt} = \gamma S - \mu V - \alpha_s V I_s - \alpha_a V I_a \tag{2}$$

$$\frac{dI_s}{dt} = \beta_s S I_s + \alpha_s V I_s - (\sigma_s + \pi_s) I_s + \kappa E_v S \tag{3}$$

$$\frac{dI_a}{dt} = \beta_a S I_a + \alpha_a V I_a - (\sigma_a + \pi_a) I_a + (1-\kappa) E_v S \tag{4}$$

$$\frac{dR}{dt} = \pi_a I_a + \pi_s I_s - \mu R \tag{5}$$

$$\frac{dE_v}{dt} = \omega_a I_a + \omega_s I_s - \rho E_v \tag{6}$$

where, the total population $N = S + V + I_a + I_s + R$ and E_v is the viral load on the environment.

2.2. Limitations of the study

In this section, we discuss the limitations of the study. The main limitation of the model was that it only captures seasonal effect interaction with the environmental factors. However, there are many environmental factors influencing the seasonality of the disease from climate to geospatial factors. Thus, the model parameters considers these different environmental factors as a collection set of all factors affecting the viral load directly and indirectly. Again, another limitation was the testing capacity of different countries and the availability of procurement of test kits during the onset of the disease. To some extent, this has an influence on the datasets as the number of confirmed positive cases strongly depends on the testing capacity of a country. Furthermore, the baseline data used in this study only spanned less than two years. Hence, we recommend that future studies should focus on different levels of environmental factors and consider larger datasets to gain more insight into the seasonality of the disease.

3. Qualitative analysis

The model was analysed qualitatively to obtain key information about the parameters under study. Firstly, the fixed point theorem can be applied to establish the feasibility of solution and the reproduction number R_0 was computed together with both equilibrium points and stability analysis.

3.1. Equilibrium points

The equilibrium states were obtained by setting the right hand side of the formulated model system of differential equations to zero.

- The disease free equilibrium point (DFE) $E_0^*[\frac{\Lambda}{\gamma+\mu}, \frac{\gamma\Lambda}{\mu(\gamma+\mu)}, 0, 0, 0, 0]$ which implies that at this level the disease cannot invade the population.
- The disease equilibrium point $E_1^*[S^*, V^*, I_s^*, I_a^*, R^*, E_v^*]$, which implies that under these conditions the disease can invade the population.

3.2. Reproduction number

Before we discuss about the reproduction number there is need to state the following:

Lemma 3.2.1. *The disease free equilibrium point is locally asymptotically stable when $R_0 < 1$ and this means the disease cannot spread. When $R_0 > 1$ then, the disease equilibrium point is said to be unstable and the disease can invade the population.*

The effective reproduction R_e number was calculated using the next generation matrix method presented by Tang et al. (2020) and we obtained the following results.

$$R_e = max\{R_1, R_2\}$$

where

$$R_1 = \frac{\gamma \Lambda \alpha_s + \Lambda \mu \beta_s}{\mu(\gamma + \mu)(\pi_s + \sigma_s)} \tag{7}$$

and

$$R_2 = \frac{\gamma \Lambda \alpha_a + \Lambda \mu \beta_a}{\mu(\gamma + \mu)(\pi_a + \sigma_a)} \tag{8}$$

The linear stability of the disease-free equilibrium point is determined by the effective reproductive number. The above reproduction numbers have common parameters like γ, Λ, and μ which are difficult to control. However, taking a closer look at R_1 the drivers of infection are parameters for the symptomatic population and the same can observation is noted in R_2 that the drivers of infection are parameters from the asymptomatic population. Thus, we can note that there are two reproduction numbers driving the diseases of two different classes of the population implying that the larger of the two reproduction numbers becomes the more effective reproduction number.

3.3. Local stability

The local stability of the disease-free equilibrium point, E_0 is described by examining the linearised form of the system at the steady state. This is done by computing the Jacobian matrix of the system. The Jacobian matrix is computed by differentiating each equation in the system with respect to the state variables S, V, I_s, I_a, R, E_v. The Jacobian matrix at equilibrium point was obtained to be:

$$\mathbf{J} = \begin{pmatrix} -\gamma-\mu & 0 & \frac{-\beta_s \Lambda}{\gamma+\mu} & \frac{-\beta_a \Lambda}{\gamma+\mu} & 0 & \frac{\Lambda}{\gamma+\mu} \\ \gamma & -\mu & \frac{-\alpha_s \gamma \Lambda}{\mu(\gamma+\mu)} & \frac{-\alpha_a \gamma \Lambda}{\mu(\gamma+\mu)} & 0 & 0 \\ 0 & 0 & \frac{\beta_s \Lambda}{\gamma+\mu} + \frac{\alpha_s \gamma \Lambda}{\mu(\gamma+\mu)} - d_s & 0 & 0 & \frac{\kappa \Lambda}{\gamma+\mu} \\ 0 & 0 & 0 & \frac{\beta_a \Lambda}{\gamma+\mu} + \frac{\alpha_a \gamma \Lambda}{\mu(\gamma+\mu)} - d_a & 0 & \frac{(1-\kappa)\Lambda}{\gamma+\mu} \\ 0 & 0 & \pi_s & \pi_a & -\mu & 0 \\ 0 & 0 & \omega_s & \omega_a & 0 & -\rho \end{pmatrix} \quad (9)$$

The local stability of E_0^* is determined based on the signs of the eigenvalues of the Jacobian matrix $\mathbf{J}(E_0^*)$. The disease-free equilibrium point, E_0^*, is said to be locally asymptotically stable if the real parts of the eigenvalues are all negative, otherwise it is said to be unstable. Consider the above Jacobian matrix and let Φ be the eigenvalues. Then we have $\mid J - \Phi I \mid = 0$, where J is the matrix $\mathbf{J}(E_0^*)$ in Eq. (9) and I is a 6×6 identity matrix. The eigenvalues are given as:

$\Phi_1 = -\mu$, $\Phi_2 = -\mu$, $\Phi_3 = -\gamma - \mu$, $\Phi_{4,5} = \frac{\mp\sqrt{D}}{\mu(\gamma+\mu)}$, and $\Phi_6 = -\rho$. where D is the discriminant. It follows from Lemma 3.2.1, that the disease-free equilibrium is locally asymptotically stable when $R_e < 1$. In contrast, if the interventions are not strong enough such that $R_{\{1,2\}} > 1$, then the disease-free equilibrium becomes unstable and a disease outbreak occurs. Thus they are five eigenvalues with negative real parts and when$R_{\{1,2\}} > 1$, the eigenvalues with positive real parts maybe obtained for $\Phi_{4,5}$ with its governing condition. Then $R_e = max\{R_1, R_2\} < 1$ when is in the close neighbourhood of zero by manifold analysis. Hence, the disease-free equilibrium is locally asymptotically stable when $R_e < 1$.

4. Data and methods

4.1. Data source and country

The internet is rich with free accessible COVID-19 datasets from different countries including Zimbabwe, most of these websites and databases capture almost similar variables and data values which come from similar sources although some differences can exist in a few cases. Mainly in Anon (2021a,b,c,d,e), the datasets capture cumulative cases, cumulative deaths, cumulative recoveries, new cases, new deaths, new recoveries and recently includes vaccinated population with the number of doses administered per time interval (day/week) (Anon, 2021c,d,f). In Anon (2021d), Damette et al. (2021) an interesting variable is included which is the mobility of the population, however, COVID-19 dashboards from websites have enabled researchers to trace the trends of the pandemic and also to be able to predict future trends and impact of the diseases on different regions continents and countries. For comparison purposes, we only focused on the datasets for three interlinked countries which were Botswana, South Africa along with Zimbabwe.

Following from Fig. 1, the COVID-19 cases for Botswana exhibits seasonal and fluctuating patterns, this is evident by very low amplitude waves with small wavelength at the onset of the disease. However, these two attributes increase with respect to time. This is highlighted by the last wave with greater amplitude, greater wavelength, and more pronounced as compared to the first series of waves. Overall, even though our data set was small it exhibited some seasonality features hence our motivation to include the seasonality effect on our COVID-19 model.

Fig. 2, in the case of South Africa the COVID-19 trend graph indicated a very clear seasonal pattern with all the three waves having almost the same wave amplitude and wavelength. While the only noticeable difference was in the ranges of the waves. The third wave seems to have lasted longer than the first two waves. In addition, the clarity on the South African COVID-19 daily cases pictorial view can be attributed to rapid testing as compared to the other two neighbouring countries.

Fig. 3 shows Zimbabwe COVID-19 daily cases for a period of seventeen-month since the onset of the virus in the country. The graph exhibits seasonality patterns with three distinct waves of increasing amplitude from left to right. Although, we only used data for about seventeen months the evidence is pointing to the fact that like other countries in Zimbabwe COVID-19 cases are seasonal in nature and hence any COVID-19 mathematical model at the population level should incorporate seasonality effect on the dynamics of the disease. Therefore, the presentation of seasonality by datasets from these countries has motivated us to modify the basic model and include the seasonal effect component. It will be interesting also to note that the application of seasonality index computation and machine learning tools can be used to prove that seasonality exists in all three countries' datasets (Mushayi et al., 2021).

4.2. Seasonality in data

In brief as observed from Fig. 1, Fig. 2, and Fig. 3 that COVID-19 daily cases trends revealed the existence of seasonality in different datasets. Therefore, there are many factors contributing to the seasonality patterns of COVID-19. These may include, within-host factors like diet, viral dynamics evolution, and immunology. Again the between-host interactions can affect seasonality for example humans interact at different levels like cultural level, socio-economic level, and lifestyle level. Environmental factors like climate, temperature, terrain, rainfall, radiation, and humidity have been established to affect seasonality (Kronfeld-Schor et al., 2021). Other factors that can affect seasonality are policies that have an impact on human behaviour. Policies such as lockdown were implemented when cases are skyrocketing based on advice by the health professionals, hence this might have contributed to seasonality in the datasets (Anon, 2021h,i; Magocha, 2021).

In some cases, data collection strategies deployed by different countries might have led to the scaling down of the seasonal magnitude in the datasets. Since daily testing statistics revealed that the number of individuals who tested positive for the virus was increasing with respect to a time period where the amplitude was relatively high. On the other hand, the issue of migration of people from one point to the other leads to a high number of cases. Usually, migration is a seasonal component which explains the high amplitude between November and February of the following year as human mobility between regions was influenced by the festive holiday and this was common in all the 3 countries (Zimbabwe, South Africa, and Botswana). The first low amplitudes (especially in the case of Botswana Fig. 1) could be due to quick action but policy enforcers in enforcing the lockdown, testing, quarantine, and closing borders but it is clear from the graphs Fig. 1 that the cases were rising at the time period between May and August as well as November and February. During May–September, according to Fig. 2 and Fig. 3 significant amplitude wave could be noticed may be due to the correlation of the disease with the cold winter weather (noting that there may be other confounding factors that caused the high amplitude) together with the November–February wave likely caused by migration of people though it will be summer. The focus of the study was to establish the existence of seasonality patterns in COVID-19 data from the three countries and hence develop a mathematical model that captures the seasonal component.

5. Modified model

5.1. Seasonal effect

The seasonal effect was introduced to this modelling by considering the theoretical approach of making use of trigonometry function in this case we make use of sine. In turn, this will induce a forced seasonality

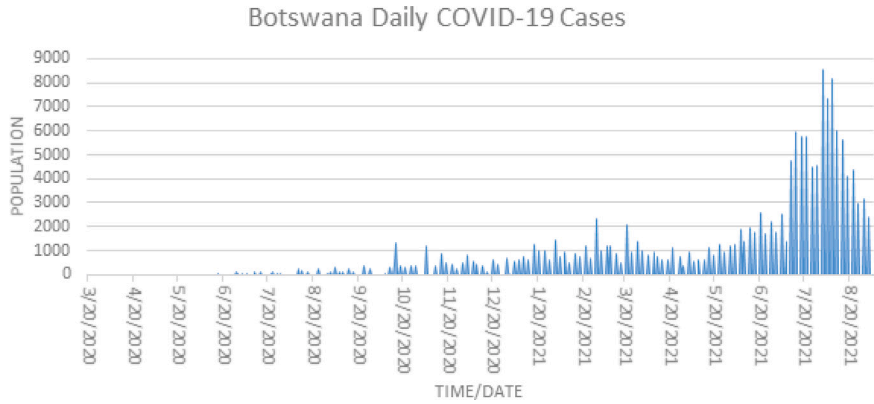

Fig. 1. Botswana COVID-19 daily cases trends from February 2020 to August 2021.

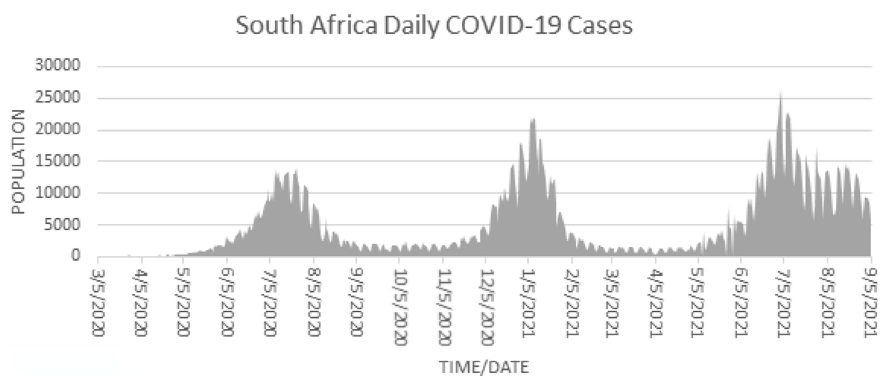

Fig. 2. South Africa COVID-19 daily cases trends from February 2020 to August 2021.

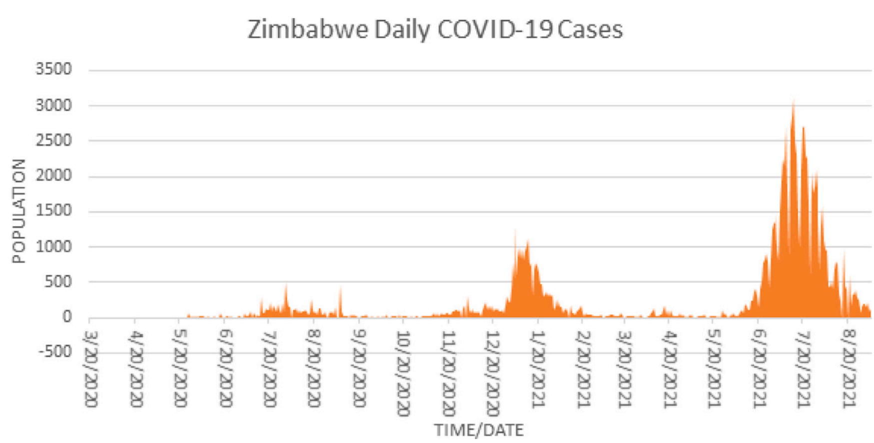

Fig. 3. Zimbabwe COVID-19 daily cases trends from February 2020 to August 2021.

effect in the mathematical model structure. Therefore, this will ensure that the model exhibits rise and fall that are not of a fixed period. Such seasonal fluctuations are assumed to be due to seasonality factors discussed and are often related to the COVID-19 cycle; their period usually extends beyond a single year, and the fluctuations are usually of at least two years (Anon, 2021b; Guangbo et al., 2020; Anon, 2021g).

5.2. Seasonal scaling effect of transmission rate

Many forecasting techniques have been widely used to fit model into dataset or for parameter estimating which presents an opportunity and novelty for this study to apply digital process signalling techniques in scaling of the transmission rate. Since we identified profiles of seasonality in Zimbabwe COVID-19 datasets we modified the transmission rate to account for seasonality. Thus by making use of the following simple difference equation:

$$y(n) = \frac{1}{3}(x[n-1] + x[n] + x[n+1]) \tag{10}$$

And this equation is known as the moving average filter. Hence, in MatLab we transformed this equation to

$$y(z) = \frac{1}{3}(z)\left[z^{-1} + 1 + z^{1}\right] = \frac{1}{3}(z)\left[\frac{1}{z} + 1 + z\right] = \frac{z}{3}\left[\frac{1+z+z^2}{z}\right] \tag{11}$$

Then this gives us the numerator coefficients, num (1 1 1) times $\frac{1}{3}$ and the denominator coefficient given as, den (1). Because the transmission rate is different from one interval to the other for example if we compared transmission rate between a lockdown and a period without a lockdown we established fluctuations of the transmission rates. Hence,

Table 1
Table with model parameters values.

Parameter	Value	Source
Λ	0.0342	Mushayabasa et al. (2020)
γ	0.00985	Anon (2021f)
μ	0.0342	Mushayabasa et al. (2020)
β_a	[0.183–0.524]	Fitted
β_s	[0.183–0.524]	Fitted
κ	0.5363	Estimated
α_a, α_s	0.0002	Anon (2021a)
$\sigma_a, \sigma s$	[0.0384–0.0611] 0.03565	Kronfeld-Schor et al. (2021)
π_a, π_s	0.07071	Estimated
ω_a, ω_s	[0.4–0.5]	Estimated
ρ	0.5	Estimated

to modify further we apply the process signalling technique by letting the new transmission rate β to be periodic and also dependent on time (t) then $\beta = \beta_i * \sin(t)$ for $i = \{a, b\}$. Due to uncertainty on the magnitude of the disease we introduce randomness by applying the Gaussian distribution n. Therefore, we obtain the filtered transmission rate to be

$$\beta_n = \texttt{filter}(num, den, \beta) \tag{12}$$

therefore, this equation (eqn 12) was used to factor seasonality into the model system.

6. Simulation results

In this section of the paper, we present the numerical values used in the running of simulation together with simulation graphs in order to sense the behaviour of disease after certain parameters in the formulated model were modified to incorporate the seasonal effect. In the end, we present the results from comparing numerical values from the non-seasonal model, a seasonal model with the actual constructed baseline data (monthly averages Zimbabwe COVID-19 dataset).

6.1. Model parameters

A model parameter is a configuration variable that is internal to the model and whose value can be estimated from data. The following Table 1 shows values of parameters together with the source.

Most of these values were obtained from other researchers, and other values were assumed. The estimated parameters were varied in order to obtain different models simulations. It is critical to vary parametric values so as to clearly understand the behaviour of the model under different scenarios.

6.2. Zimbabwe COVID-19 dynamics without seasonality effect

The following Fig. 4 shows the simulations from a model without any modifications.

The susceptible population decreases rapidly to a minimum tuning point within the first five months and then levels off to a limit for the remaining number of months. Again, the infected populations characterise almost the same time series patterns that is a rapid increase of the infected populations to a maximum within the first two months and then followed by a decrease for the next three months after which we observed a steady behaviour for the remainder of the months. However, the vaccinated shows some fixed growth to limit then it remains at a constant for the remaining months.

This type of graph as the one shown in Fig. 4 represents simulations from classical epidemiological models. Surely from this graph Fig. 4, one can observe that the patterns are far from suggesting or accounting for any seasonality behaviour of the disease. Even though mathematical models are powerful tools in unlocking our understanding of the progression dynamics of pandemic much needs to be done in terms of their correct use to better represent different factors of the disease. Finally, the advent of a dashboard and free datasets should also enable researchers to integrate and validate their models with baseline data.

6.3. Zimbabwe COVID-19 dynamics with seasonality effect

The following Fig. 5 shows the simulations from a model with seasonal effect modifications.

In running the simulation, we assumed slightly higher initial conditions for the infected populations and this was because of the fact that during the onset of the disease in the country, the world was still perfecting its testing tools which were very limited in most developing countries hence we assume that the actually observed datasets might have been lower than the actual number of cases in the population. However, the infected population decreases within the first month then the figures were maintained at lower levels. On the other hand, the first clear wave had the peak on month ten and the next peak was observed at month fifteen these two months conceded with December 2020 and May 2021 respectively. Again, the next peak after the first two peaks was observed on month twenty-two which concedes with December 2021, these results suggest that the 4th wave is highly likely to occur and have a peak during the month of December 2021. Furthermore, this seasonal nature of the disease is likely to continue to occur for the coming years up-until new disease management strategies are designed or new vaccines with high efficacy rates are developed.

6.4. A comparison of Zimbabwe COVID-19 dynamics with and without seasonality effect

The following graph in Fig. 6, shows the simulations from both seasonal model and non-seasonal model together with the actual Zimbabwe COVID-19 cases.

For comparison, we extracted total infected population data points from the seasonal and non-seasonal models for the first seventeen months and complied them together with the Zimbabwe COVID-19 daily cases data categorised with monthly means to create seventeen data points for comparison. Hence, to better understand the relationship between these datasets we computed the correlation between actual data and extracted data from the models. Fig. 6 indicates the existence of a correlation between the seasonal model graph and the actual Zimbabwe COVID-19 cases datasets. Therefore, we computed the correlation for these datasets and established a correlation of $.746^{**}$ between the model with seasonal effect and the baseline dataset with correlation significant at $.001$ level. On the other hand, there was no significant correlation between the model with non-seasonality and the baseline dataset. Though much work needs to be done to calibrate the model to improve its predictive scale, however one important thing has been highlighted by the results i.e. the seasonal model is better in modelling COVID-19 as compared to a model without the seasonality effect since we established that this pandemic is seasonal by nature.

7. Conclusion

Zimbabwe has experienced three COVID-19 waves and the pandemic has spread widely or rapidly enough to show seasonality amongst the general population. SARS-CoV-2 in Zimbabwe has infected over 120 thousand people at the time of writing these lines, hence it is essential to understand and project the transmission pattern of COVID-19. Coupling available data and numerical simulation of mathematical models can enable us to observe possibilities of seasonality and how seasonality patterns can impact Zimbabwe's social and economic progression. Again these tools can provide us with a highlight of the outbreaks of each wave occurrences and sometimes predict the burden of the diseases on in wave. This study qualitatively and quantitatively analysed the effect of seasonality in the progression dynamics of COVID-19 in Zimbabwe. We established that COVID-19 in South Africa

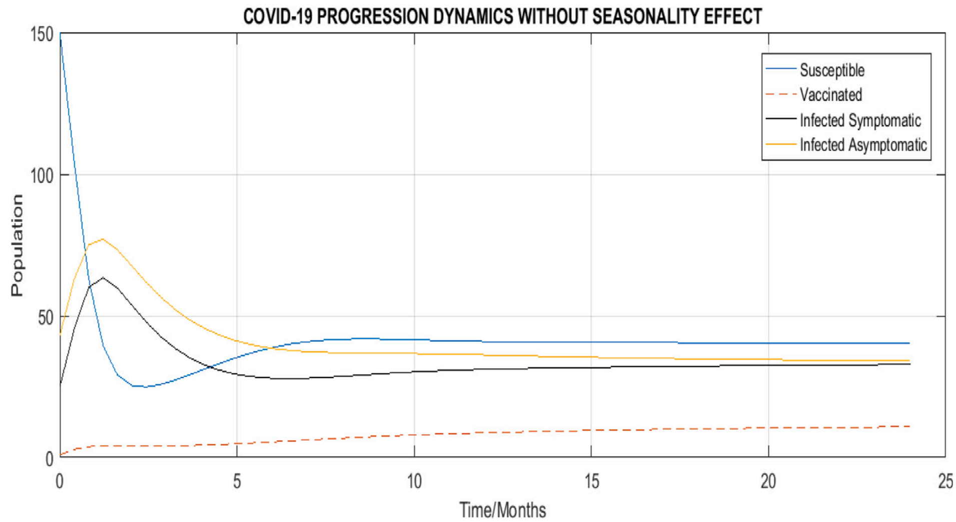

Fig. 4. Infected, susceptible and vaccinated classes from a non-seasonal model.

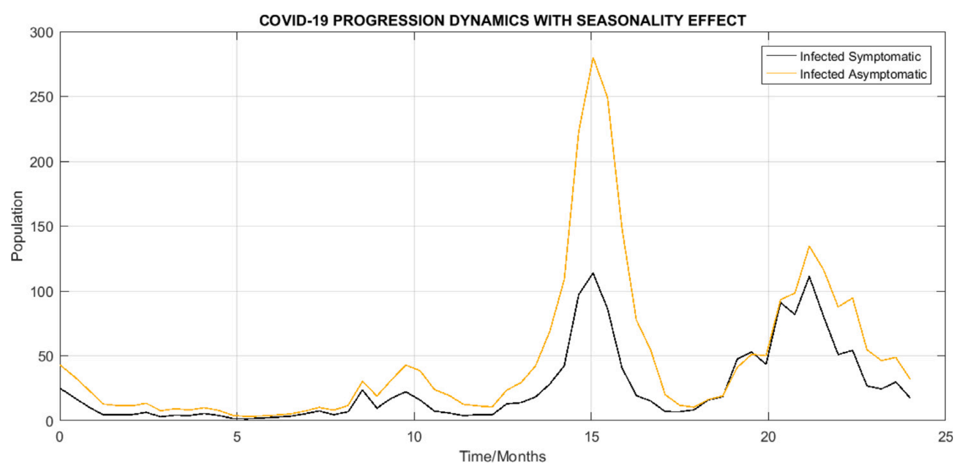

Fig. 5. Infected classes from a seasonal model.

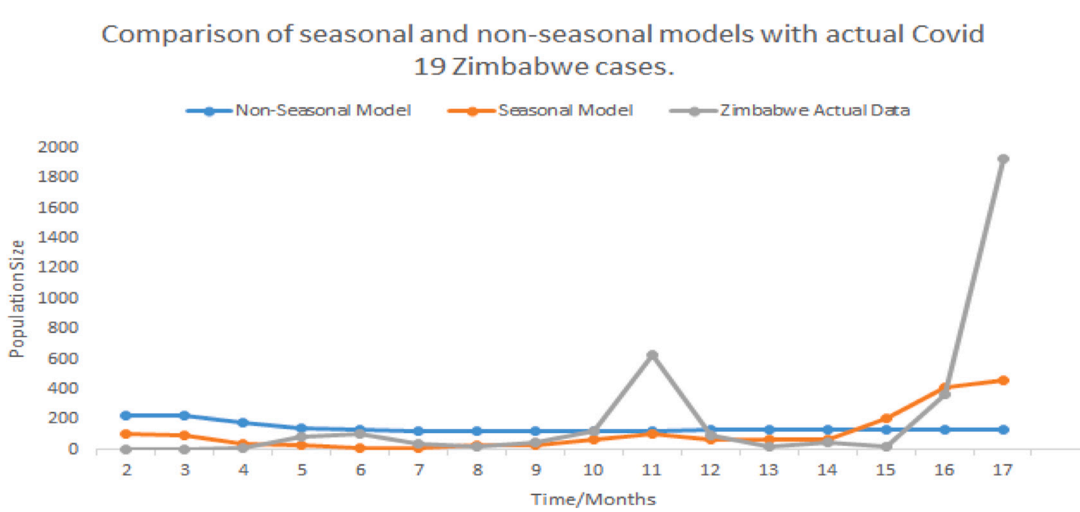

Fig. 6. A graph of seasonal model, non-seasonal model and actual Zimbabwe COVID-19 monthly reported cases.

Zimbabwe and Botswana exhibited COVID-19 seasonality infectivity which was more pronounced in the first two countries. On the other hand, the numerical simulation indicates that there is no relationship between patterns of non-seasonal model and actual data but they exist a significant correlation of .746 at $\alpha = .001$ level between a seasonal model and actual data. Of great significance, we found out that in the presence of a lower vaccination rate it is impossible to eradicate the disease hence more vaccines with high efficacy rates might provide a solution to this global challenge. Therefore, we recommend that the seasonality of the disease should be taken to account in the future planning of programmes and calendar year. For example, schools and universities should restructure their academic year calendar to cater for COVID-19 seasonality and reduce time lost due to lockdowns. These findings have important implications on strategic planning especially for control and prevention of COVID-19 by the Zimbabwe COVID-19 task force team. Again this knowledge might be helpful in the design of indigenous health systems and technology which consider the seasonality effect in our context. Finally, the findings predicted that a fourth wave is likely to occur however it should be less pronounced as compared to the third wave.

Although, our results are construed in the framework of several study limitations. The seasonality incorporated in the modified SVIR model is an empirical formula, is the major innovation of this study to apply moving averages, stochastic, and signal processing techniques to transform an epidemiological model to produce seasonality patterns. Here we provide a general framework on how to introduce seasonality into epidemiological models. Thus, the impact of incorporating this seasonality effect into the model greatly improved the reliability of model. Furthermore, the modified SVIR model in this paper is limited to the accuracy of forecasting techniques and moving averages formulas used. This seasonality effect introduced can be subdivided into environmental and non-environmental seasonal effects and factored into the model to assess the new trends of the disease. To conclude we suggest an effective multi-discipline collaboration among mathematicians, statisticians, epidemiologists, environmental scientists, meteorologists, sociologists, etc. is essential to fully establish all the COVID-19 seasonality mechanisms.

CRediT authorship contribution statement

Meshach Ndlovu: Designed the model, Compartmental model, Performed the simulations, Wrote the manuscript with input from all other authors. **Rodwell Moyo:** Performed the quantitative analysis. **Mqhelewenkosi Mpofu:** Performed a qualitative analysis of the model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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