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Operationalisation of Model for Dynamics of COVID-19 in Kenya: Trajectory of Omicron Wave in Kenya

Shem Otoi O. Sam, Khama Rogo

LREB Secretariat, COVID-19 Advisory Committee, Lake Region Economic Bloc, Kisumu, Kenya
Email: shem.sam@gmail.com, rogokhama@gmail.com

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Abstract

Kenya has experienced five COVID-19 surges driven by Alpha, Beta, Delta (2x), and Omicron. These waves are accurately predicted by the OTOI-NARIMA model. Consequently, in Kenyan Lake Region Economic Bloc (LREB), private sector and NGO partnerships have been forged to strengthen regional health systems and prepare effectively for epidemic resurgence. The co-development and implementation of the so-called "LREB COVID-Dx" digital platform enable efficient epidemic monitoring in semi-real time, referral of patients, optimal use of limited resources, and community of practice among regional health practitioners. In this paper, we describe the practical implementation of the OTOI-NARIMA model and COVID-Dx digitized platform in Kenyan COVID-19 reality, with emphasis on the latest Omicron wave. In estimating the trajectory of Omicron wave, 612 data points of daily case infections are used. The order of moving average is calculated and corresponds to reproduction number, R_0. The series are normalized, superimposed, and used to derive OTOI-NARIMA model. The model is estimated and interpreted. Test statistics including Ljung-Box test, ACF, and PACF are conducted. The COVID-Dx data digitization is used to inform epidemic preparedness. The OTOI-NARIMA model in general successfully established the periodicity and seasonality of COVID-19 resurgences in Kenya. The model is used to inform preparedness, including vaccines rollout. During alert stages of the wave, on December 4, 2021, the model was reused to *nowcast* the trajectory of the wave. Omicron wave was projected to peak in Kenya between November 23, 2021, and January 4, 2022. The wave showed strong likelihood of declining after January 29, 2022. In reality, Omicron wave was experienced from November 27, 2021, to January 29, 2022. The model predicted that Omicron variant will have run its full course by June 22, 2022, and possibly replaced by another variant, recombinant or sub-variant. According to OTOI-NARIMA model, dominant variants are replaced after every six months, which gives insights into suitable periods for administration of vaccine boosters. The total number of Kenyan patients (symptomatic or asymptomatic) during Omicron resurgence was estimated to be ~4.5 million. The total number of patients hospitalized during the wave is estimated to be ~2000. Effective, efficient, and economical response to Omicron resurgence in LREB benefitted from meticulous infusion of mathematical modelling and digitization of relevant data for epidemic preparedness and rapid decision making. The study has two limitations: Incomplete merging of stochastic processes and deterministic methods; calculating with accuracy the period it takes to fully replace a dominant COVID-19 variant. These two limitations may be considered for further research.

Keywords

Omicron Trajectory, OTOI-NARIMA, COVID-Dx

1. Introduction

Kenya reported the first COVID-19 case on March 13, 2020 [1]. Since then, Kenya experienced five successive waves, driven by Beta, Alpha, Delta (2x), and Omicron variants [2]. With the latest Omicron wave, unlike previous waves, the government did not implement strict restrictive measures like banning international flights, suspending public events, closing learning institutions, randomly screening people, disinfecting markets, and instituting nationwide curfews, and cessation of movement across the country.

The Lake Region Economic Bloc comprises fourteen counties in western Kenya: Bomet, Bungoma, Busia, Homa Bay, Kakamega, Kericho, Kisii, Kisumu, Migori, Nandi, Nyamira, Siaya, Trans Nzoia, and Vihiga. It is one of the regional economic blocs in Kenya formed under the Intergovernmental Relations Act (IRA 2012)[1]. To implement and coordinate its operations LREB Governors Summit established the secretariat in Kisumu City. The governors also constituted the LREB COVID-19 Advisory and Socioeconomic Recovery Committee whose membership is drawn from diverse professional backgrounds representing each of the member counties.

For Kenya, especially Lake Region Economic Bloc (LREB) where OTOI-NARIMA model [3] is being used to establish seasonality and periodicity of COVID-19 surges, the 5th Wave was predicted two months before it actually occurred. These predictions and attendant advisories were widely reported to policy makers and in mainstream media to inform preparedness.

The first run of the modelling predicted occurrence of Omicron wave. The LREB COVID-Dx implementing team begun training medical laboratory technologists (MLTs), and hospital records and information officers (HRIOs) in 84

[1] http://www.parliament.go.ke/sites/default/files/2017-05/IntergovernmentalRelationActNo2of2012.pdf.

public and private health facilities to submit data to the Commcare supported platform. In the COVID-Dx digital platform, clinical case investigation form (CCIF) is configured in Commcare software accessible on internet enabled android phones and tablets. When the form is filled by the trained data providers, it is submitted and visualized in testing and results dashboard. On the other hand, hospital capacity dashboard features both baseline and daily status tool. Hospital capacity indicators like isolation beds, ICU beds, oxygen capacity, among others, are captured in the daily tool and submitted each day before 10:00 a.m. Monitored over time, the COVID-Dx platform has visualized emerging trends in COVID-19 infections. In addition, data on genomic sequencing results is equally submitted and visualized in the dashboard.

When Omicron wave struck as predicted by mathematical model, practitioners had clear information on regional capacity to manage COVID-19 patients. Response team knew where what capacity of services was available in semi-real time. Patients' referral across LREB was supported through the digitized COVID-Dx platform. All the 84 LREB facilities were linked and an effective community of practice was established.

Conceptually, OTOI-NARIMA model is a unique infusion of stochastic and deterministic functions adapted under autoregressive integrated moving averages framework such that normalization of series replaces logarithmic transformation [3]. Through mathematical manipulation of moving averages, the model is robust enough to give longer forecasts. For instance, in 2021, it was used to accurately forecast the 2nd, 3rd, and 4th COVID-19 waves in one run, as evidenced in the 7th Advisory[2].

With forewarning forecasts, Kenyan authorities increased vaccination efforts to reach a target of 10 million fully vaccinated Kenyans before the predicted 5th wave by December 2021. The LREB region features added advantage of comprehensive resurgence preparedness resulting from implementation of digitized platform known as COVID-Dx Dashboard [4]. Conceptually, COVID-Dx platform was initiated to coordinate resurgence response, support optimal use of limited resources, and establish effective patients' referral mechanism in the region. Without the use of COVID-Dx platform, some response challenges would have been insurmountable.

In this paper, we describe the course of Omicron infections in Kenya, whose similarity may or may not be considered global [5]. Although studies [6] have shown than Omicron variant infections are milder compared to original variant, Alpha, Beta, and Delta [7], hospitalizations in LREB paint a slightly different picture regarding all variants except Delta. It is postulated that the hospitalization in LREB was exacerbated by insignificant vaccination rate compounded by considerable number of immunocompromised residents with underlying conditions. However, these hospitalizations resulted in fewer deaths as COVID-Dx

[2]https://COVID19advisory.lreb.or.ke/wp-content/uploads/2022/01/LREB-COVID19-7th-advisory-KR-1.pdf.

project strengthened the regional health systems.

After two and half years of COVID-19 infections around the globe, it is observed that successive waves [8] are driven by emerging variants [9]. In the evolution of COVID-19 infections, the period it takes to replace dominant variants with emerging ones varies, [10]. The periodicity and seasonality established by OTOI-NARIMA model estimate that variants are replaced by emerging ones, recombinant, and/or sub-variants within a period of approximately six months. The data from which variant replacement is extracted is however inconclusive. As such, according to seasonality of COVID-19 waves, OTOI-NARIMA model estimates the period during which the Omicron variant is considered to have run its full course and the possibility of being replaced by a new and/or emerging sub-variant—the estimate is June 22, 2022.

2. Method

The OTOI-NARIMA model works under the framework of ARIMA [11]. It has the autoregressive part AR(p), integration (d), and moving average MA (q) parts known as (P, D, Q) [12]. In OTOI-NARIMA normalization replaces logarithmic transformation. In addition, stationarity, and Johansen Cointegration tests among others are performed to limit drifting apart of series and avoid spurious regression. Once orders of (P, D, Q) are arrived at mathematically, residuals are tested for autocorrelation using ACF and PACF. In addition, further validity test is done using Ljung-Box test. The model uses daily case infections. By manipulating the moving average part (which also constitute reproduction number, (R_0), restricting or expanding intervals, it is possible to estimate likely hospitalizations and total number of cases during the wave: asymptomatic and symptomatic. Unlike daily cases, case fatality when used give misleading forecasts. There exists multiplicity of determinants of COVID-19 fatalities, which can be modelled with other techniques but not forecasting. For instance, clinically, longevity of patients before succumbing to COVID-19 depends on comorbidities, underlying conditions, vaccination, and age [13]. Availability of medical oxygen, antivirals, specialist doctors, and other services also determine the effectiveness of critical care in facilities where COVID-19 patients are hospitalized. In this paper, we use 612 data points to model the trajectory of Omicron in Kenya. We have normalized and superimposed original series as shown in the calculations below. R software is used to run the estimated model.

2.1. Sample Size

Whereas a sample of 30 data points increases confidence level such that one may draw general conclusion about a population, the study considered 612 data points whose variance is $s^2 = 1.07$ and mean = −0.05. As such, according to central limit theory, a large sample of this nature tend to have variance and mean which are approximately equal to that of the population from which the sample is drawn, and has standard normal distribution parameters. The variance 1.07 - 1 and mean 0 - −0.05.

Furthermore, normality test below indicates that the data is sufficient.

Normality of data used

Continuation of [3], Equation (9)

Forecast (F)

$$F = \frac{1}{2}\left[\left(\frac{1-\pi\beta_2}{1-\lambda\beta_1}\right)e_{0t} + \left(\frac{1-\Omega\beta_4}{1-\omega\beta_3}\right)e_{1t}\right]$$

Let $\frac{1-\pi\beta_2}{1-\lambda\beta_1}$ be Γ,

And $\frac{1-\Omega\beta_4}{1-\omega\beta_3}$ be Ψ

$$F = \frac{1}{2}\left[\Gamma e_{0t} + \Psi e_{1t}\right] \quad (1)$$

2.2. Assumptions

1) COVID-19 infection waves travel in moving averages. The transmissibility of COVID-19 variants vary when measured by daily number of infections and translated to moving averages.

2) Smoothening restricts drifting apart and maintains the intervals at the closest minimum necessary for longer forecasts. Like logarithm transformation, normalization reduces time series data irregularity, that is, outlying data points and variations are reduced. This increases boundary consistency over range of time.

3) Reproduction number (R_0) is intrinsic in the moving averages of daily infections. For instance, the average number of people hypothetically capable of being infected by one individual with Delta variant is significantly lower than a case of Omicron variant.

4) Cyclic nature of seasonality corresponds to socio-environmental attributes. The interplay of seasons in terms of humidity, temperature, and human behaviour have causative influence on etiology of viral infections.

3. Results

The LREB COVID-19 Advisory Committee used the model on September 19, 2022, to predict the Omicron wave two months before being experienced in Kenya, from November 23, 2021 to January 29, 2022. We used the model to describe the trajectory of Omicron until it runs a full course and possibly replaced by an emerging variant or sub-variant. On December 4, 2021, the model, as shown in **Figure 1** described the trajectory of Omicron variant. From the result, Omicron is likely to run its full course by June 22, 2022, before being replaced. In addition, the Omicron wave was predicted to peak between 24th December 2021 and January 4, 2022. The total number of hospitalization was estimated to be 2000 during the wave, **Figure 2**. In addition, the total number of asymptomatic patients in Kenya was estimated to be approximately 4,500,000 as shown in **Figure 3**. Both ACF and PACF tests in **Figure 4** and **Figure 5** show no auto

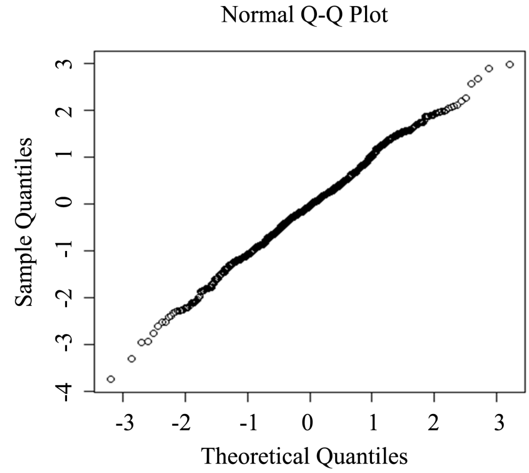

Figure 1. Normality test of data used.

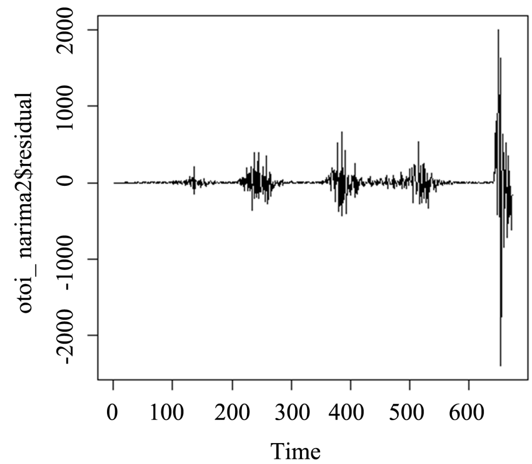

Figure 2. Total hospitalization projected (using OTOI_NARIMA residuals) during Omicron wave in Kenya.

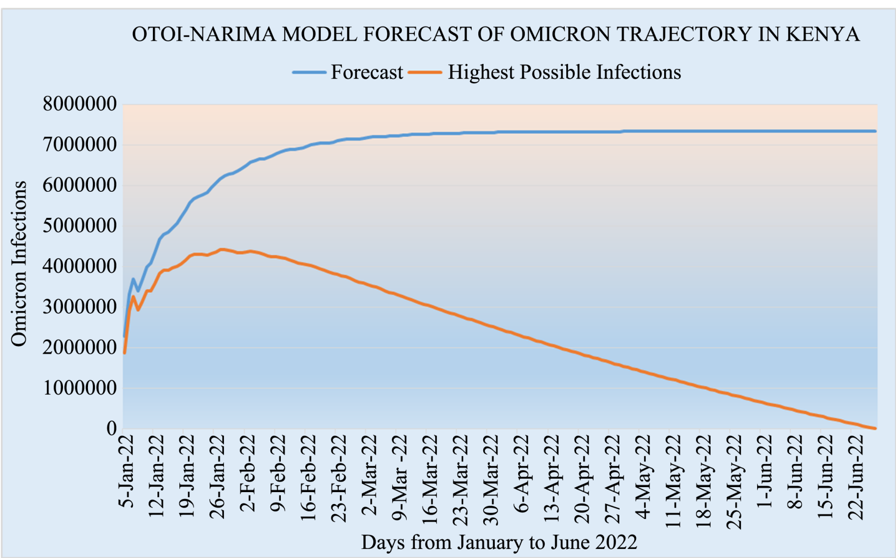

Figure 3. Omicron trajectory.

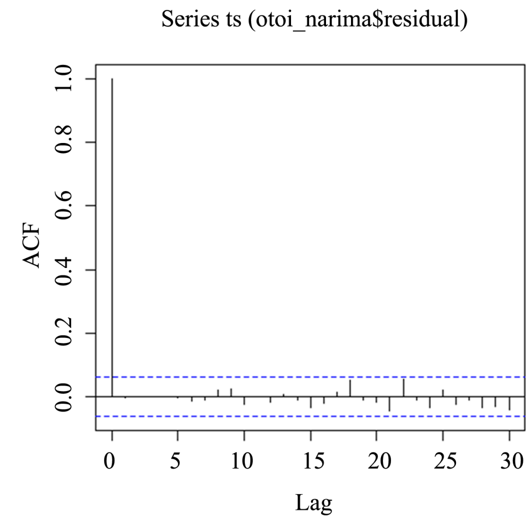

Figure 4. Autocorrelation function test.

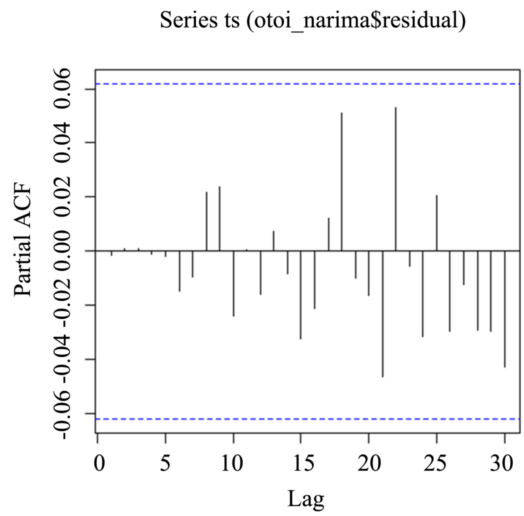

Figure 5. Partial autocorrelation function test.

correlation in the residuals of the model indicating validity in model estimated. Lastly, Ljung-Box test confirms the validity of the model.

3.1. Omicron Trajectory Forecasts

Omicron Trajectory Summary Results

1) Omicron wave peaked in Kenya between December 23, 2021, and January 4, 2022 and exhibited strong likelihood of declining after January 29, 2022 as predicted.

2) There is strong evidence that Omicron variant will have run its full course by June 22, 2022 and will be likely replaced by another variant or sub-variant. Most dominant variants seem to be replaced by new and emerging once after every six months (inconclusive data).

3) There is a likelihood that Kenya may experience the sixth wave peak after May 17, 2022.

4) The total number of patients (symptomatic or asymptomatic) during the Omicron resurgence in Kenya was estimated to be approximately 4.5 million.

5) The total number of patients who shall have been hospitalized during the wave is estimated to be approximately 2000.

3.2. The Diagnostic Tool Which Reduced Regional Disease Burden: COVID-Dx

See Figure 2 and Figures 6-9.

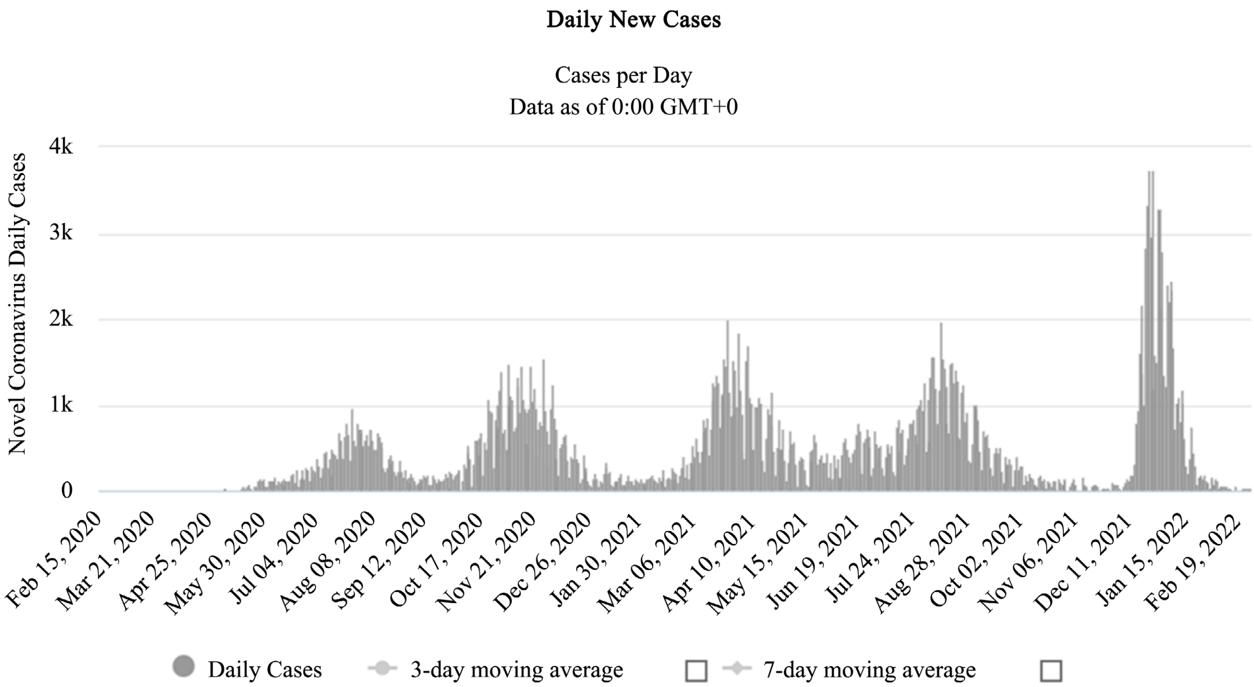

Figure 6. Actual Kenyan waves as captured in John Hopkins University website[3].

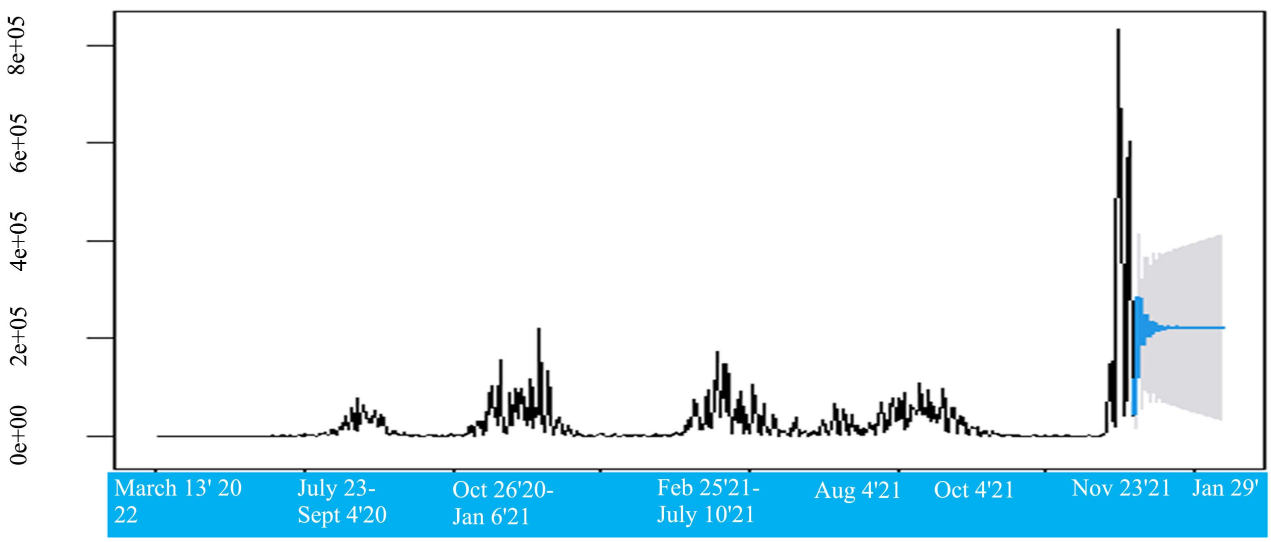

Figure 7. Five Kenyan waves as predicted by OTOI_NARIMA model.

[3]https://www.worldometers.info/coronavirus/country/kenya/.

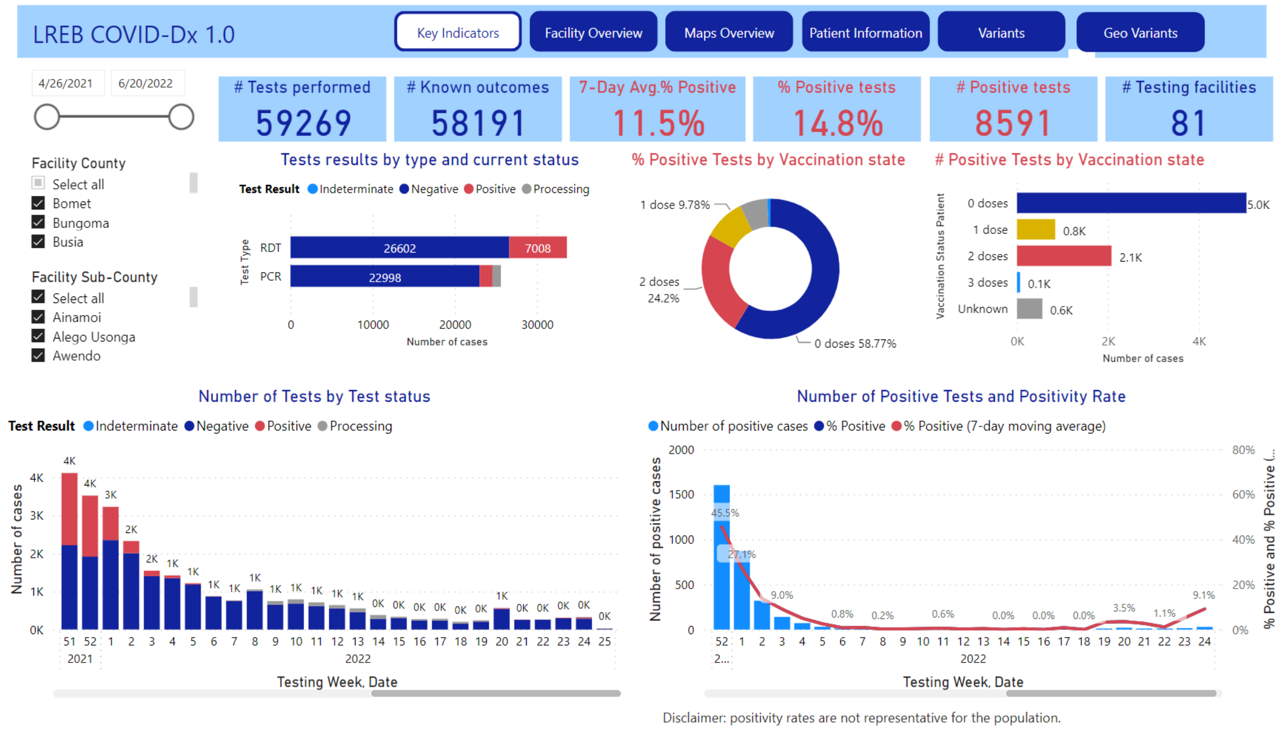

Figure 8. Testing and results dashboard.

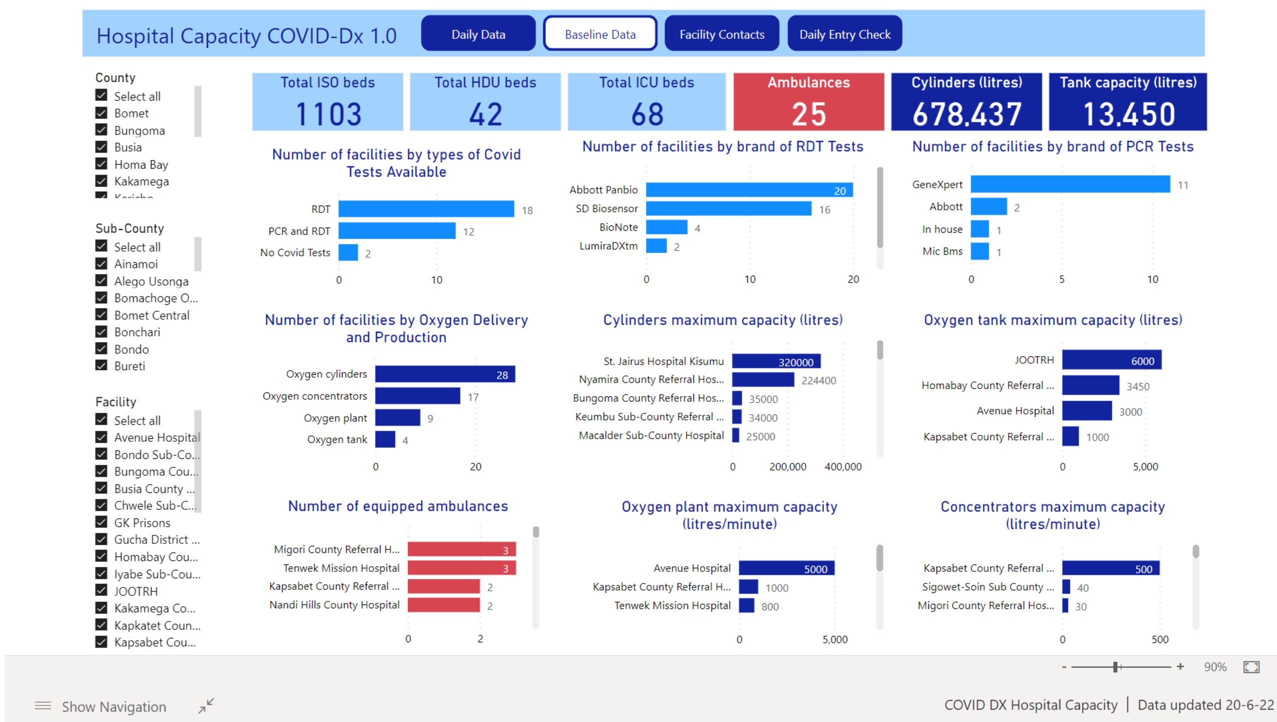

Figure 9. COVID-Dx hospital capacity dashboard.

3.3. Tests

Autocorrelation tests indicating stationarity over time such that the model estimated remains valid.

ACF

PACF

Validity Test

Box-Ljung test

H_o = The model does not show lack of fit.

H_A = The model shows lack of fit.

LJUNG-Box Test	
p-value	0.667
DF	3
X-squared	1.5638

In Ljung-Box test, a significant p-value implies that the model lacks fit [3]. In this case we reject the null hypothesis.

4. Discussion

The trajectory of all Kenya's five waves were accurately predicted by OTOI-NARIMA model. For instance, the 1st wave occurred from 23rd July to 4th September 2020 after the Government relaxed containment measures on July 7, 2020. The period coincided with fourteen (14) days average communicable period for COVID-19. People's livelihoods were interrupted [14] such that families moved to areas for economic easy, mostly to rural areas. Likewise, the 2nd wave occurred from 26th October 2020 to 6th January 2021 following partial reopening of learning institutions on October 12, 2020 for candidates -among other socio-environmental factors. Intriguing of all waves was the 3rd which began on February 25, 2021, with a short lull between 23rd April to 15th May 2021 before peaking on June 26 and declining on July 10, 2021-as described in Advisory 7[4] before it occurred. The 3rd wave, which ran into the 4th wave, was partly driven by Delta. The 4th Wave, largely driven by Delta, was experienced from August 3 to October 4, 2021. Presently, Kenya just emerged from the 5th wave driven by Omicron variant which started on November 23, 2021 and declined on January 29, 2022, as predicted.

A very important characteristic of the model is the ability to establish both seasonality and periodicity with accuracy [3] before they occur, as shown in **Figure 7**. The replacements of variants [10] by their sub-variants and/or recombinant variants has conjectured by analysis of OTOI-NARIMA model during Omicron wave has been confirmed by[5] KEMRI in sequencing Omicron sub lineages driving the 6th Kenya's wave. We had postulated that Omicron would have been replaced by its sub lineages on June 22, 2022. Whereas other tradi-

[4]https://COVID19advisory.lreb.or.ke/wp-content/uploads/2021/08/LREB-COVID-PREPAREDNESS-ASSESSMENT-REPORT.23.7.2021_2.pdf.

[5]KEMI policy brie no.51: Omicron sub lineages BA.4 and BA.5 are increasingly being detected in the 6th COVID-19 wave in Kenya.

tional models used in Kenya have given inaccurate[6,7] forecasts[8] as they relied solely on reproduction number (R_0) and serosurvey, OTOI-NARIMA captures socio-environmental factors which are intrinsic in seasonality. In addition, (R_0) is captured in the moving average part of the model. Another distinctive feature of the model is its ability to make longer forests as observed in Advisory 7. The accuracy of OTOI-NARIMA model has been widely reported by both local[9] Kenya media[10] and international media including Europe[11], Eastern US[12], and international conferences[13]. Because of its accuracy, the National Emergency Response Committee, National Vaccine[14] Committee, and National Oxygen Committee have used the model's predictions to mobilize citizens to accept and be vaccinated. The observation that predictions correspond with reality (**Figure 6** and **Figure 7**) of waves as experienced in Kenya has made LREB region, where the model was officially adopted, to exercise leadership in advisory roles as demonstrated by LREB COVID-19 Advisory Committee. In that way, the LREB COVID-19 Advisory Committee[15] has issued and disseminated 19 advisories and 3 policy briefs.

In as much Omicron variant infection is considered mild [6], in LREB, the implementation of COVID-Dx [4] project kept residents safe. Through digitization of COVID-19 data in Test and Results dashboard (**Figure 8**) as well as Hospital Capacity tool (**Figure 9**), there was (and still is) significant level of preparedness to manage epidemic resurgences. The project trained 179 MLTs and HRIOs in 84 LREB health facilities who submitted data to the COVID-Dx platform. That data was (is) used to coordinate response, establish efficient regional patients' referral, have in place community of practice among practitioners, optimal use of limited regional resources, and preservation of institutional memory. It now evidenced that earlier study [15] on regional COVID-19 infection was both accurate and futuristic.

5. Conclusion

The study has two limitations. First, the authors have attempted to merge stochastic processes with deterministic methods and there are gaps to be filled. Much as the authors have graphically estimated the period it takes for a dominant COVID-19 variant to be fully replaced, calculating that duration with precision remains a challenge. These two limitations may be considered for further

[6]https://twitter.com/citizentvkenya/status/1410662307408011272.
[7]https://allafrica.com/stories/202107210074.html.
[8]https://www.kemri.go.ke/wp-content/uploads/2021/07/POLICY-BRIEF-Explaining-the-Three-Waves-of-the-COVID-19-Transmission-in-Kenya-using-a-Mathematical-Model-compressed.pdf.
[9]https://www.youtube.com/watch?v=QqTRfF49Mts&t=36s.
[10]https://nation.africa/kenya/news/the-face-behind-COVID-19-modelling-that-predicts-infection-waves-3540542.
[11]https://www.dw.com/en/kenya-ramps-up-fight-against-COVID/a-59902393.
[12]https://adf-magazine.com/2021/09/kenyan-mathematician-forecasts-COVID-19-waves/.
[13]https://www.linkedin.com/in/shem-otoi-sam-phd-13baa427/recent-activity/.
[14]https://nation.africa/kenya/news/COVID-vaccines-key-as-fifth-wave-looms-experts-say-3583636.
[15]https://COVID19advisory.lreb.or.ke/.

research.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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