RESEARCH ARTICLE

COVID-19 Pandemic Situation in Kenya: A Data Driven SEIR Model

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Abstract

Background: COVID-19 disease has persisted since it was declared a global pandemic by the World health organization (WHO) in February 2020. Kenya had notified a total of 203,213 cases, reported 3,931 deaths by July 26, 2021. Currently, Kenya is experiencing the fourth wave of the pandemic that is driven by the delta variant which has become dominant in the country. Non-pharmaceutical and vaccination interventions have been ongoing in the country. With the emergence of new variants, it's challenging to know the future of the pandemic and its effects on the healthcare systems, vaccination plans, public readiness, and social behavior. To attain realistic predictions, data-driven modeling approaches are paramount. The goal of this study was to model COVID-19 cases in Kenya using the already available data to estimate parameters

Methods: An SEIR compartmental model was developed to predict the daily new cases, severe, critically ill, and death cases of COVID-19. The model had 8 compartments containing sub-populations of: Susceptible, Exposed, Symptomatic Infectious, Asymptomatic Infectious, Hospitalized, Intensive Care Unit, Deaths and Recovered. The model equations were then solved to obtain the number of cases that would be infected on a daily basis beginning March 14th to July 2021.

Results: The results demonstrated evidence of three peaks, first in mid July 2020, second in mid-October 2020 and third in early March of 2021. The number of daily cases in wave 1 was 1128 then increased to 1344 in the second wave and finally a decline was observed in wave 3 with 1057 number of daily of infections. The number of severely, critical and deaths followed a similar pattern. This therefore means that with the absence of herd immunity in the general human population, relaxation of the mitigation measures will eventually result to progression of COVID-19 cases.

Conclusion: Increased vigilance on the COVID-19 curve is indispensable. Continued interventions such as testing, social distancing measures, vaccination, and health facilities preparedness are imperative to ensure that new infections are isolated in real-time. Use of real time data to estimate the pandemic trends is a more realistic way of informing new and appropriate interventions amidst the ongoing pandemic.

Introduction

The novel coronavirus 2019 is a constituent of a group of corona viruses revealed in 1968 by an eight-member group of virologists. The emergent coronavirus in 2019 was first called '2019-novel coronavirus' (2019-nCov) by the Word Health Organization (World Health Organization, 2020) on 22th January 2020. Later, WHO christened the disease caused by the virus as 'COVID-19'. The spread of the virus is said to have originated from an animal to human ([1]). Later, through human-to-human transmission, the disease was spread to most of the countries globally with 194,080,019 confirmed cases and 4,162,304 deaths as at 26th July 2021.

The clinical symptoms include; fever, cough, gastro-intestinal infections and difficulty in breathing ([2],[3]). This led to development of global standard precautionary elements for acute respiratory diseases (ARDs) namely; hand hygiene; use of personal protective equipment (PPE) to avoid contact with the patient's body fluids and non-intact skin; respiratory hygiene and cough etiquette; waste management; and cleaning and disinfection of the environment and equipment among other [3].

Since the first case in Kenya was reported on 13th March 2020, various public health interventions which include social distancing measures, wearing of protective masks, curfews, closure of schools, isolation, quarantine and cessation of movement were instituted. A total of 197,959 cases have since been notified and 3872 deaths by 26th July 2021. One of the major challenges that Countries are facing in controlling the disease is the mutation of the corona-virus that has led to multiple waves of the pandemic in most of the affected Countries. According to WHO, the variant of concern at the moment is the Delta variant which is more transmissible.

A study done in China by [4] found out that there was a great effect of the interventions implemented in reversing the transmission of new infections. Kenya Continues to implement the non-pharmaceutical measures and in addition rolling out the vaccination to its citizens. Despite all the efforts being made, the number of cases continue to increase and so far, 3 waves of the pandemic have already been observed. The most transmissible variant; delta was first detected in Kisumu County in the Western Kenya. This variant has since spread to various counties in the country that include, Nairobi, Mombasa, Nakuru, Siaya, Homabay, Kiambu, Machakos among others.

Given the dynamics of this pandemic, countries have to keep monitoring and tracking the disease status to ensure control interventions are put in place up front. Disease modeling has been cited as one of the strategic tools in understanding the disease patterns and evaluating the impact of various control measures ([5], [6]).

Further to the use of mathematical models to predicting the future of COVID-19 transmission, a study by Thompson referred them to be of utmost importance in determining the undefined impact of "re-opening economies" decisions ([6], [12]), Kiarie et.al (Preprint,2021)]. A number of mathematical modeling studies have been done so far in different Countries. Most of them have used global parameters to model the disease progression ([7], [8]).

The objective of this study was to model the progression of COVID-19 cases in Kenya. An SEIR deterministic model was developed by first using the available data to estimate the model parameters, and secondly modeling the pandemic using the local parameters. This will be useful in informing planning of resources, prepared-ness of health facilities and creating awareness on the future curves, daily infections and peak times.

Methods

To describe the transmission and spread of COVID-19, eight (8) disease states compartmental model is used. The total population N(t) at any time t is sub divided into compartments (S) containing the susceptible individuals, (E) the exposed who are presumed to be in the incubation stage of the disease, after exposure some of the individuals will develop the disease without symptoms (A), others will develop the disease and show symptoms (M). The infected will then be hospitalized (H) and it's assumed that some will move to critical illness (C). Some of the critically ill will die due to severity of the disease (D). The individuals that recover from either asymptomatic disease, symptomatic disease, hospitalization or critical illness will be denoted by (R). Where,

$$N(t) = S(t) + E(t) + A(t) + M(t) + H(t) + C(t) + D(t) + R(t) \qquad (1)$$

The transmission model is illustrated in the flow diagram labeled Figure 1.

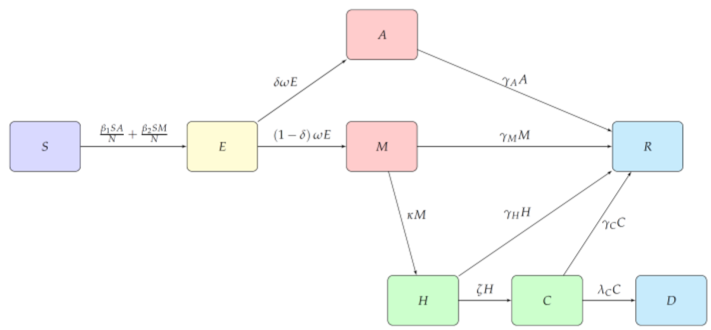

Figure 1 SEIR model of COVID-19 transmission

The COVID-19 transmission model parameters are defined in the table 1.

Parameter description	**Symbol**	**Value**
Proportion of symptomatic infectious people	δ	0.803
Progression rate from E to either I_A or I_M	ω	0.15
Recovery rate of the asymptomatic infected individuals	γ_A	0.9495
Recovery rate of the symptomatic infected individuals	γ_M	0.4996
Recovery rate of the hospitalized individuals	γ_H	0.5003
Recovery rate of the critically ill individuals	γ_C	0.55
Rate of movement from hospitalization to critical illness condition	ζ	0.4994
Hospitalization rate of the symptomatic infected individuals	k	0.02598
Death rate of the critically ill due to the virus	λ_c	0.4999

The parameters listed in the table above were estimated from the data reported up to 26th July 2021.

The ordinary differential equations of the transmission model are therefore formulated as follows.

$$\begin{cases} \frac{dS}{dt} = -\left(\frac{\beta_1(t)SA}{N} + \frac{\beta_2(t)SM}{N}\right) \\ \frac{dE}{dt} = \left(\frac{\beta_1(t)A}{N} + \frac{\beta_2(t)M}{N}\right)S - \omega E \\ \frac{dA}{dt} = \delta\omega E - \gamma_A A \\ \frac{dM}{dt} = (1-\delta)\,\omega E - (\gamma_M + k)\,M \\ \frac{dH}{dt} = kM - (\zeta + \gamma_H)\,H \\ \frac{dC}{dt} = \zeta H - (\gamma_C + \lambda_C)\,C \\ \frac{dD}{dt} = \lambda_C C \\ \frac{dR}{dt} = \gamma_A A + \gamma_M M + \gamma_H H + \gamma_C C \end{cases} \tag{2}$$

Where,

$$\beta_1(t) = \gamma_A R_e(t)\frac{Y_t}{\sum_t Y_t}$$

and

$$\beta_2(t) = \gamma_M R_e(t)\frac{Y_t}{\sum_t Y_t}.$$

$R_e(t)$ is the effective reproductive number estimated from the data, Yt is the number of cases observed daily. The initial conditions are;

$$S(0)\geq 0,\ E(0)\geq 0,\ A(0)\geq 0,\ M(0)\geq 0,\ H(0)\geq 0 \qquad (3)$$

The susceptible transition to latent phase of the disease at a rate $\frac{\beta 1(t)SA}{N}$ and $\frac{\beta 2(t)SM}{N}$.

Movement from latency to either asymptomatic or symptomatic infected happen at a rate of ω. The infected then progress to hospitalization at a rate k and either move to the critically ill compartment at a rate ζ or to recovery at a rate γ. The critically ill cases could either recover or die at a rate of γ and λ respectively. The recovery rate of the asymptomatic cases is defined by γ. The main aim of social distancing interventions is to minimize the rate at which the infectious individuals come into contact with the susceptible population.

In this work, the parameters were estimated using the least squares method. Where $y = y_1, y_2, ..., y_N$ and σ2 is the estimated measurement error which is calculated as the mean square error ($MSE = \frac{RSS}{N - p}$). RSS is the residual sum of squares; N represents the number of measurements and p the number of parameters in the model.

Results

Based on the available data, the number of new cases was forecasted to be 1128, 1344, and 1057 at the peak of waves 1, 2, and 3 respectively. The days when the highest number of cases (peak) were detected was projected to be day 122 (Mid July 2020), 221 (Mid October 2020) and 358 (Early March 2021) for the 3 waves respectively. The severe cases were also predicted to be 87, 106, and 75 on the 129th (Mid July 2020, 232 (End of October 2020), and 365th days (Mid-March 2021) of the three waves. These are the highest cases within the 3 waves that would require to be hospitalized for treatment. The critically ill cases that would require ICU admissions were also estimated as 33, 41, and 29 at 135th (End July 2020), 236th (Early November 2020), and 371st (Mid-March 2021) day of the 1st, 2nd and 3rd wave respectively. The number of deaths expected was also estimated to be 33, 41, and 28 on the 135th (End July 2020), 236th (Early November 2020), and 371st (Mid-March 2021) days of the three waves. These results are summarized in table 1 and the individual charts of the observed data versus fitted models in Figures 2 to 5.

Discussion

The model shows that the pandemic has persisted with 3 waves already experienced as at 26th July 2021. According to the peak days observed in the three waves, it takes about 120 days on average to get to the peak of each of the three waves of infections with over 1000 new cases reported daily. Withdrawal of social restriction measures and reopening of Countries' economies is a major risk to resurgence of new infections and at a higher rate of transmission. This could be associated to social behavior changes, more contact time at places of work, schools, in travels among other avenues. This study results are in agreement with those of ([9] [10]) whose findings were that the aggregate number of cases had an exponential growth with time when mitigative measures were stopped. Other studies like that done by [11] also indicated that re-opening economies and withdrawing interventions could result in a devastating state of the disease. Further,[12] found out that ignoring infection prevention control measures; social distancing, wearing masks, hand washing and travel controls would result to ravaging effects on the susceptible individuals.

Other authors like ([14]-[19]) used local data to determine the local parameters in their modeling; their findings were that data driven models are able to account for variations in dynamics (e.g., new outbreaks, interventions). Therefore, they provide more realistic estimates of the epidemic size than other epidemiological models.

Conclusion

With such effects of lifting mitigation measures, it is important to conduct continuous testing for COVID-19, put an emphasis on vaccination and use data to come up with real time parameters to predict future trends of the pandemic. This will ensure that new infections are isolated in real-time, well-informed policies are created, health systems are prepared as well as herd immunity against disease is attained.

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Author's contributions

J.K. wrote the main manuscript text and prepared all the figures and the tables. S.M. and R.M. provided mentorship, reviewed the manuscript and proof read the final text.

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Availability of data and materials

The data used to estimate parameters is available in the website and can be shared upon request.

Ethics approval and consent to participate

Not Applicable.

Consent for publish

Not Applicable.

Competing interests

The authors declare that they have no competing interests

References

1. Heymann DL, Shindo N. COVID-19: what is next for public health?. *The Lancet*. Feb 22 2020;395(10224):542-545.
2. Guo YR, Cao QD, Hong ZS, et.al. The origin, transmission and clinical therapies on coronavirus disease 2019 (COVID-19) outbreak–an update on the status. *Military Medical Research*. Dec 2020;7(1):1-10.
3. World Health Organization. Epidemic-Prone and Pandemic-Prone Acute Respiratory Diseases: Infection Prevention and Control in Health-Care Facilities. *WHO. Indonesia Partner in Development*. 2008;53(2):8-25.
4. Leung K, Wu JT, Liu D, Leung GM. First-wave COVID-19 transmissibility and severity in China outside Hubei after control measures, and second-wave scenario planning: a modelling impact assessment. *The Lancet.* Apr 25 2020;395(10233):1382-1393.
5. Jewell NP, Lewnard JA, Jewell BL. Predictive mathematical models of the COVID-19 pandemic: underlying principles and value of projections. *JAMA : the journal of the American Medical Association*. May 19 2020;323(19):1893-1894.
6. Thompson RN. Epidemiological models are important tools for guiding COVID-19 interventions. *BMC medicine*. Dec 2020; 18:1-4.
7. Zareie B, Roshani A, Mansournia MA, et.al. A model for COVID-19 prediction in Iran based on China parameters. *MedRxiv*. Jan 1 2020.
8. Santosh KC. COVID-19 prediction models and unexploited data. *Journal of medical systems*. Sep 2020;44(9):1-4.
9. Saez M, Tobias A, Varga D, et.al. Effectiveness of the measures to flatten the epidemic curve of COVID-19. The case of Spain. *Science of the Total Environment*. Jul 20 2020; 727:138761.
10. Courtemanche CJ, Garuccio J, Le A, et.al. Did Social-Distancing Measures in Kentucky Help to Flatten the COVID-19 Curve?
11. Feng Z, Damon-Feng H, Zhao H. Sustaining social distancing policies to prevent a dangerous second peak of covid-19 outbreak. *medRxiv*. 1 Jan 2020.
12. Mwalili S, Kimathi M, Ojiambo V, et.al. SEIR model for COVID-19 dynamics incorporating the environment and social distancing. *BMC Research Notes*. Dec 2020;13(1):1-5.
13. Kiarie J, Mwalili S, Mbogo R. COVID-19 Flattening Curve," A Recipe for Second Wave of Infections in Kenya".
14. Ranjan R. Temporal dynamics of COVID-19 outbreak and future projections: a data-driven approach. *Transactions of the Indian National Academy of Engineering*. Jun 2020;5:109-15.
15. Kuhl E. Data-driven modeling of COVID-19—Lessons learned. *Extreme Mechanics Letters*. Aug 2020 14:100921.
16. Ghamizi S, Rwemalika R, Cordy M, et.al. Data-driven simulation and optimization for covid-19 exit strategies. *InProceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. Aug 23 2020 (pp. 3434-3442).
17. Pereira IG, Guerin JM, Silva Júnior AG, Garcia GS, Piscitelli P, Miani A, Distante C, Gonçalves LM. Forecasting Covid-19 dynamics in Brazil: a data driven approach. *International Journal of Environmental Research and Public Health*. Jan 2020;17(14):5115.
18. Liu X, Zheng X, Balachandran B. COVID-19: data-driven dynamics, statistical and distributed delay models, and observations. *Nonlinear Dynamics*. Aug 2020;101(3):1527-1543.
19. Chintalapudi N, Battineni G, Amenta F. COVID-19 virus outbreak forecasting of

registered and recovered cases after sixty day lockdown in Italy: A data driven model approach. *Journal of Microbiology, Immunology and Infection*. Jun 1 2020;53(3):396-403.

Tables

Pandemic Peak days and number of cases by Wave in Kenya				
Wave		**First Wave**	**Second Wave**	**Third Wave**
New Cases	Day	122	221	358
	No of Cases	1128	1344	1057
Severe Cases	Day	129	232	365
	No of Cases	87	106	75
Critical Cases	Day	135	236	374
	No of Cases	33	41	29
Deaths	Day	135	236	371
	No of Cases	33	41	28

Table 2. Summary of Peak days and number of Cases

Figures

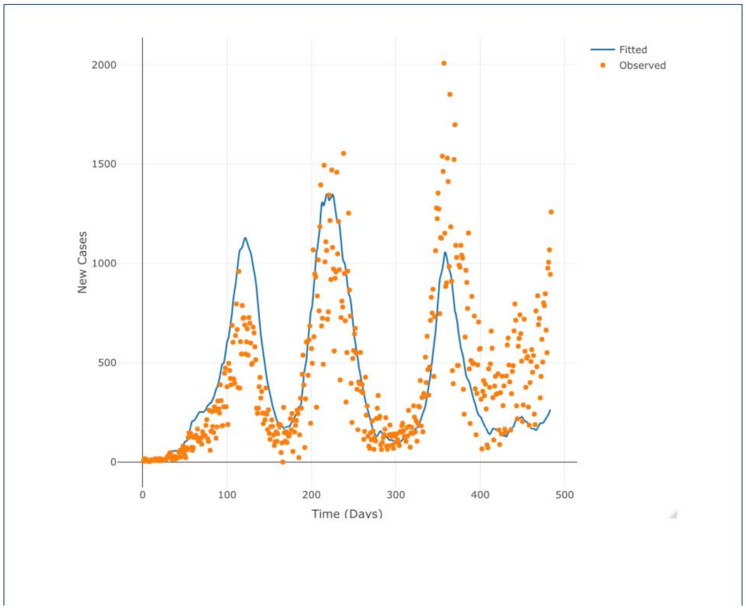

Figure 2. New cases of Covid-19

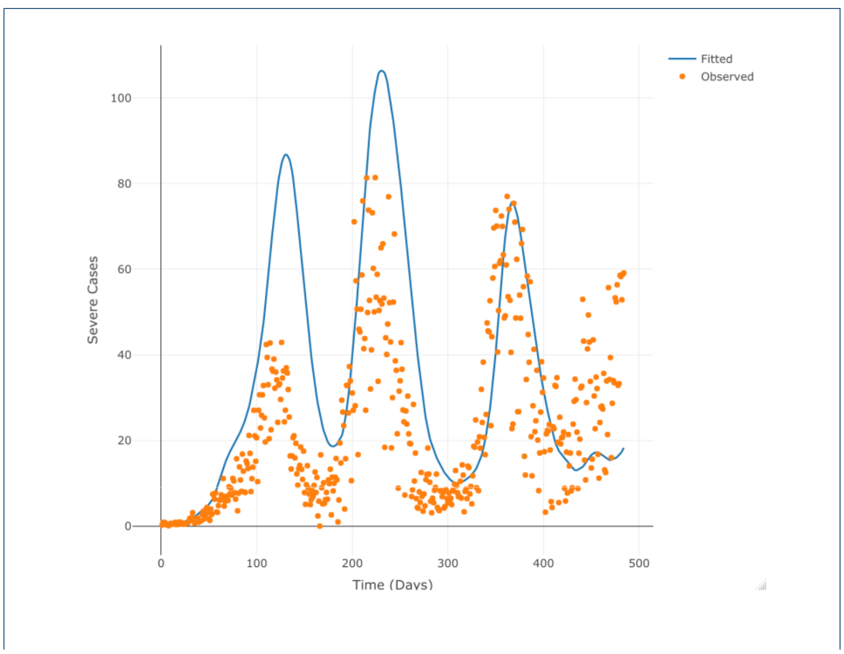

Figure 3. Severe cases of Covid-19

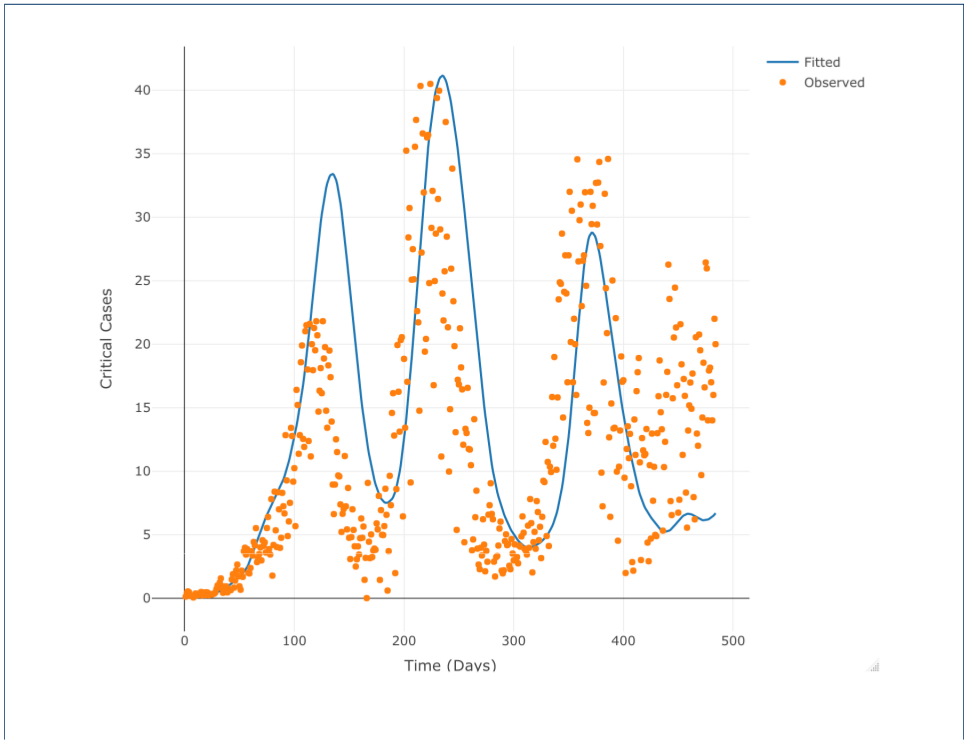

Figure 4. Critical cases of Covid-19

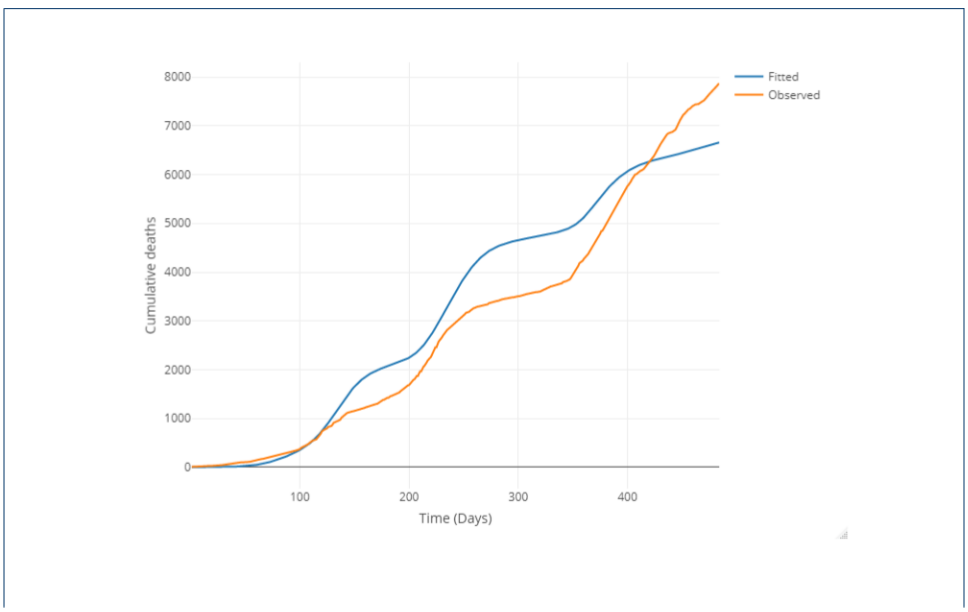

Figure 5. Cumulative death cases of COVID-19

