MATHEMATICAL MODELLING FINAL REPORT

TEAM MEMBERS:

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Selected countries: **Brazil, Japan, and Nigeria.** Data downloaded from
https://covid19.who.int/info/ https://www.worldometers.info/coronavirus/

INTRODUCTION

What is a mathematical model?

1. A mathematical model is a process of using a model in mathematics to visualise and solve a problem.
2. Mathematical model allows students to analytical skills to solve a problem and visualise the results to understand better.
3. Mathematical model requires conceptual understanding and mathematical precision.
4. Modelling presents problem-solving as a creative, iterative process as they support many possible justifiable answers.

How does covid-19 spread?

SARS-CoV-2, the virus that causes COVID-19, can spread from person to person through droplets produced during coughing or breathing during close contact with an infected individual. Infection can also occur indirect contact when these droplets land on objects and surfaces around the infected individual and the other person touches these objects or surfaces, then touches their eyes, nose or mouth. This is why it is important to stay at least 1-2 meters (3-6 feet) away from a person who is sick. Given that some individuals have no symptoms while still infected with the virus, physical distancing of 1-2 meters should be observed regardless of whether the other person seems sick.

Using mathematical modelling we will analyse the impact of covid-19. By analysing the initial impact and how the spread effected the population. This will help us better understand and to predict the future events. The goal is to predict the number of infected persons in the future. This study will not only help us to understand the behaviour pattern for each country on how well they manage themselves during such events but also we can use similar experience to predict any future event big or small/large population size or small population size.

OBJECTIVE

Key objectives for Mathematical Model are:

- Understanding the change from the beginning of the epidemic to the final stages of covid-19.
- Analysing the change in behaviour for each country on how they will approach towards this issue.
- By understanding the measures each country takes we will study the magnitude of change in covid-19 cases. This study will guide us towards on how and why certain change can be seen.
- After understanding the important factors affecting the change in infected population we will make predictions for future waves.
- Individual response towards covid-19 (SIR model)
- Human exhausted rate in which countries was higher?
- Understanding why there is a change in infected population for each county? Which country was effected more? Reason for a rapid increase in a certain country? Does population of county will affect the number of infected persons?
- Detailed study of epidemic, how thing works? Human reaction after second wave, importance of social distancing, lockdown, wearing masks, etc.

COUNTRIES SELECTION and REASON:

The countries that we have selected are: Brazil, Japan and Nigeria.

If we talk about the country's population then according to https://www.worldometers.info/

1. The population of Brazil is **216016535**
2. The population of Japan is **125591188**
3. The population of Nigeria is **217933707**

The main reason behind choosing these countries was to compare the results on the basics of technological advancement of each country. This is challenging task and according to our choices we expected to see variation in our study but the results were somewhat different. We saw similarities in Nigeria and Brazil infected population. Japan showed us different results because of its population and also good tracking of covid-19 cases by Japanese government. This also showed us how prepared the countries were and what measures they take after the first wave of covid-19. Such as in case of Nigeria there was poor record keeping of infected persons and the number of people vaccinated this is why later in the project you will see that Nigeria shows explosion of covid-19 cases but a saturation state throughout the time period. There could be another possibility that after the first wave people in Nigeria develop good immunity to fight second wave. In case of Brazil we saw a good percentage of population being infected and further in second wave was weaker and infected less people, again this shows two things people having the immunity to face second wave and also the effect of imposing various restrictions by the government to stop the spread.

HUERISTICS: STRAIGHT LINE FRAGMENTS ON LOGARITHMIC GRAPH

The heuristic we have used for our mathematical modelling is Straight line fragments on a logarithm graph.

The covid-19 is one of the greatest challenges that mankind has ever faced. But if you do studies on covid-19 cases directly by straight taking the number of cases infected over the total population is very challenging because the rate of infection is not even linear manner. The rate of growth rapidly grows up almost like a vertical line when we go on. So, for avoiding this we are taking a logarithmic approach as a heuristic.

On a logarithmic scale, numbers on the Y-axis don't move up in equal increments but instead each interval increases by a set factor – it's often 10 but could be a factor of 3 or 350 or 3,500, anything at all. It all depends on what is deemed to be the most effective way of interpreting the data. The logarithmic scale is ideal for measuring rates of change, particularly rates of growth. While taking this, we can easily study the rate of growth. Because the logarithmic measure is ideal for that. It flattens out the rate of growth, so it becomes easier to see. On a logarithmic graph of COVID-19 infections, even though the overall numbers are still increasing, you can see the point at which the rate of growth starts to level off when that exponential growth has stopped. So, we can depict the nature of the growth as taking the number of waves.

The heuristic we have used for our mathematical modelling is Straight line fragments on logarithm graph. As we know for any exponential growth the equation can be written as Y= kxn Using logarithms, we can express y=kxn in the form of the equation of a straight line which can be written as y=mx+k. (Where k can be interception on the y axis after plotting the the graph of the equation in form y=mx+k)

In statistics, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) can be described as the average of the squares of the errors—in other words it can be explained as the average squared difference between the estimated values and the actual value.

$$MSE = \frac{1}{n}\sum_{i=k}^{k+n-1}\left(P_i - P_i^m\right)^2.$$

Where is observed value and is model prediction values. Why have we chosen MSE or sum squared error?

We have not used sum squared error as MSE is more preferable to use for this model as sum squared error as the sum squared error will give a really huge number whereas a MSE would come out in comparatively small number and its magnitude would make more sense given the range of our predictions.

NUMBER OF WAVES IN EACH COUNTRY:

1. **Brazil**

   In Brazil we saw 2 waves in which the first wave was more severe as compare to the second wave. After second wave there were very few cases reported as compare to the prime time when covid-19 started. Hence in case of Brazil we see 2 waves.
2. **Japan**

   In Japan we saw 4 short waves out of which the first wave made more impact on the number of infected persons. Further in case of Japan we saw sudden increase in cases just after the first wave. Almost after 120th day from beginning of covid-19 after this government put strict lockdown to control the spread. Hence after that few short waves can be seen and less number case been reported.

3. **Nigeria**

   In Nigeria we see 2 waves, the first wave made its impact till 120 days from the beginning of covid-19. After the first wave we saw less cases been reported.

   Hence the number of waves for all the countries are same expect in the case of japan we considered only 3 waves.

COUNTRIES MEASURES TO RESTRICT COVID-19 SPREAD:

BRAZIL:

As of December 31, 2020, Brazil had the second-highest burden of COVID-19 worldwide. Given the absence of federal government coordination, it was up to the local governments to maintain healthcare provision for non-COVID health issues.

Immediately after the impact of covid-19 brazil increased the number of health workers and health and welfare infrastructure. On March 24, 2020, a partial lockdown was decreed in Brazil, as a measure to hinder the spread of COVID-19, which consisted in prohibiting crowding and advising people to stay home, except for urgent or extremely necessary matters. The local government introduces the importance of social distancing and mandate use of masks in public places.

JAPAN:

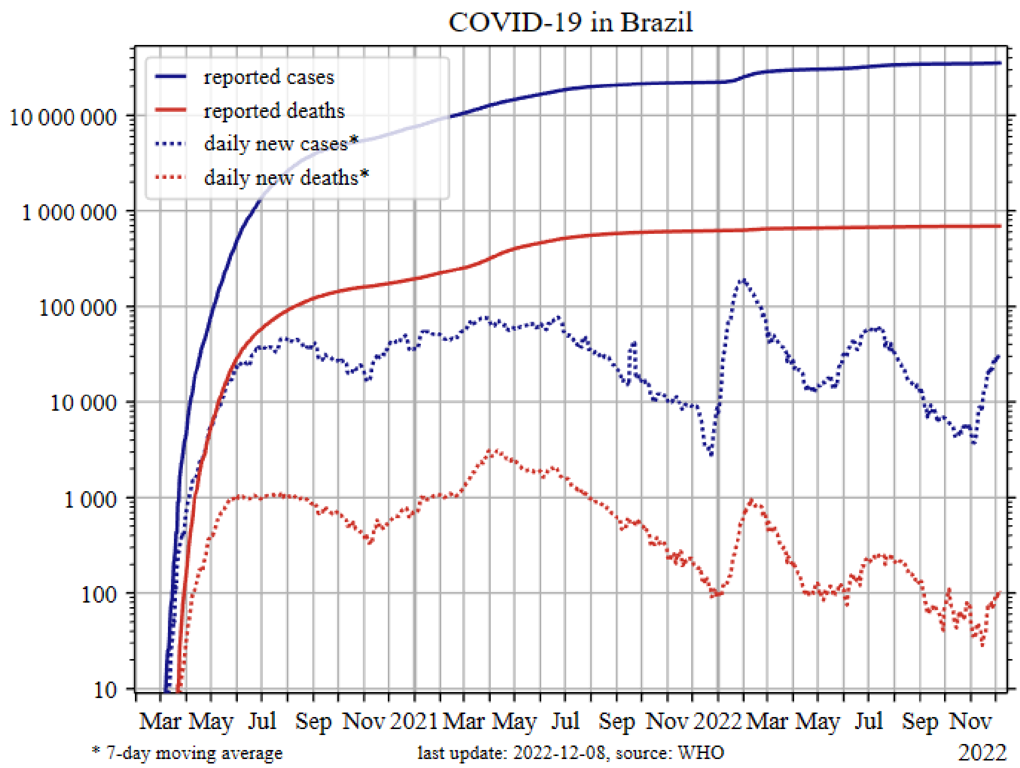
A very innovative approach introduced by Japanese government. Basic infection control measures include avoidance of the "Three Cs" ((1) Closed spaces (with poor ventilation), (2) Crowded places (with many people), and (3) Close-contact settings (with conversation or speech at arm's reach)), maintaining distance from others, wearing masks, hand washing and other hand hygiene, and ventilation. It is also important to enact effective measures to reduce the flow of people and opportunities for contact with people, taking into consideration the outbreak situation. Basic instructions to aware the local people about social distancing and wearing masks in public.

NIGERIA:

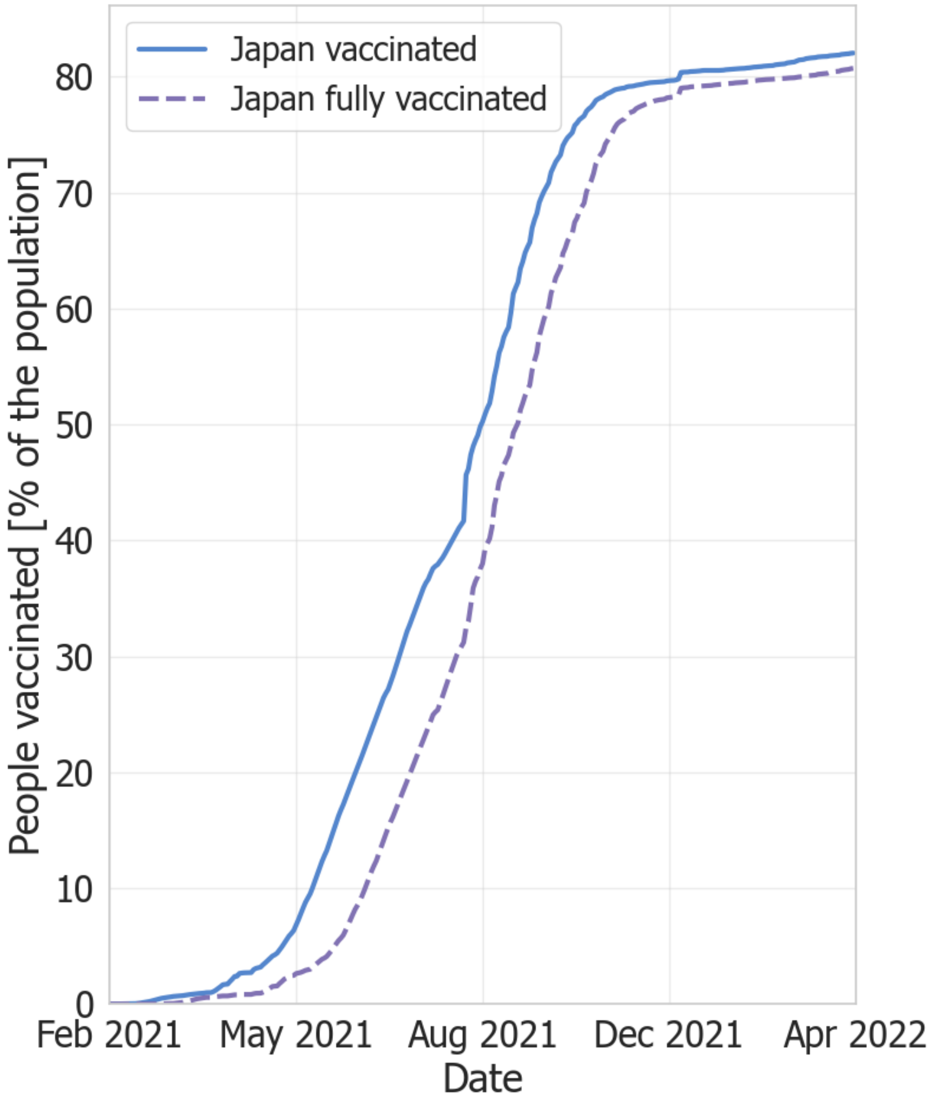
Several measures have been instituted by the Federal Government of Nigeria through the PTF-COVID-19 together with the Federal Ministry of Health to curtail the spread of the disease and protect the health of Nigerians. This includes an initial lockdown of non-essential activities; closure of schools; a ban on international flights etc. Nigeria is one of many countries that have commenced the gradual easing of lockdown measures initially instituted at the beginning of the COVID-19 pandemic. This is to ensure a balance between preserving lives and livelihoods while addressing the socio-economic disruptions caused by the outbreak. Maintaining the restrictions on mass gatherings outside the workplace to no more than 50 persons. Mandatory use of non-medical facemasks in public spaces. '**No mask, no entry. No mask, no service.**

STATS OF COUNTRIES BEFORE AND AFTER COVID

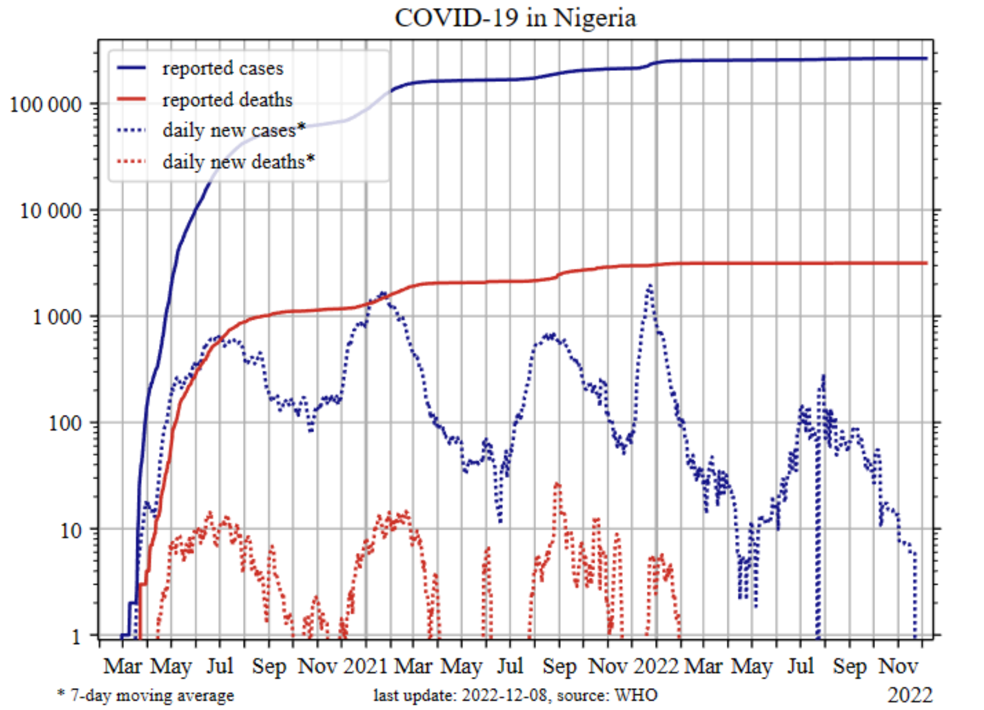
1. Brazil



2. Japan


Japan vaccinated
Japan fully vaccinated
People vaccinated [% of the population]
0
10
20
30
40
50
60
70
80
Feb 2021
May 2021
Aug 2021
Dec 2021
Apr 2022
Date

3. Nigeria



This data is taken from https://en.wikipedia.org/

CHAPTER :1

Introduction:

The aim is to analyse the number of covid-19 cases overtime for each country. This is will help us understand which dates each country hit its first wave. This visualisation study will help us to divide the first wave into two fragments of explosion and saturation. This means the immediate impact of covid-19 first wave and the effects after that. Here we will not only work on the first wave but will understand when we hit second wave for each country. Using visualisation skills we can compare all three countries we have selected and compare the impact of covid-19 on each country. The aim is to study the wave pattern of number infected persons throughout the epidemic and making considerable prediction for future cause.

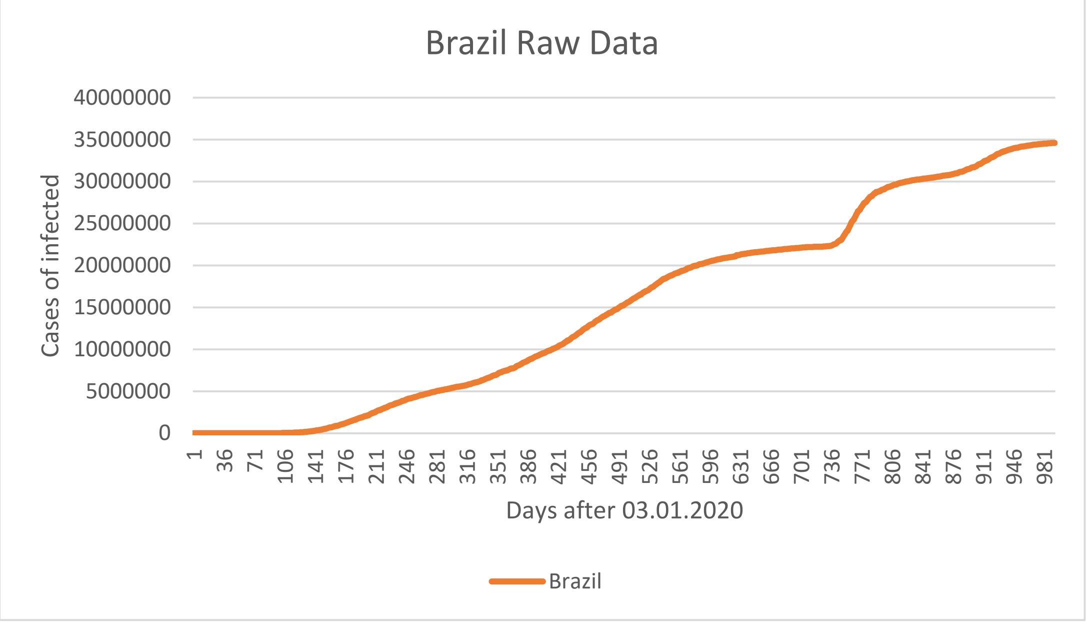
Objective:

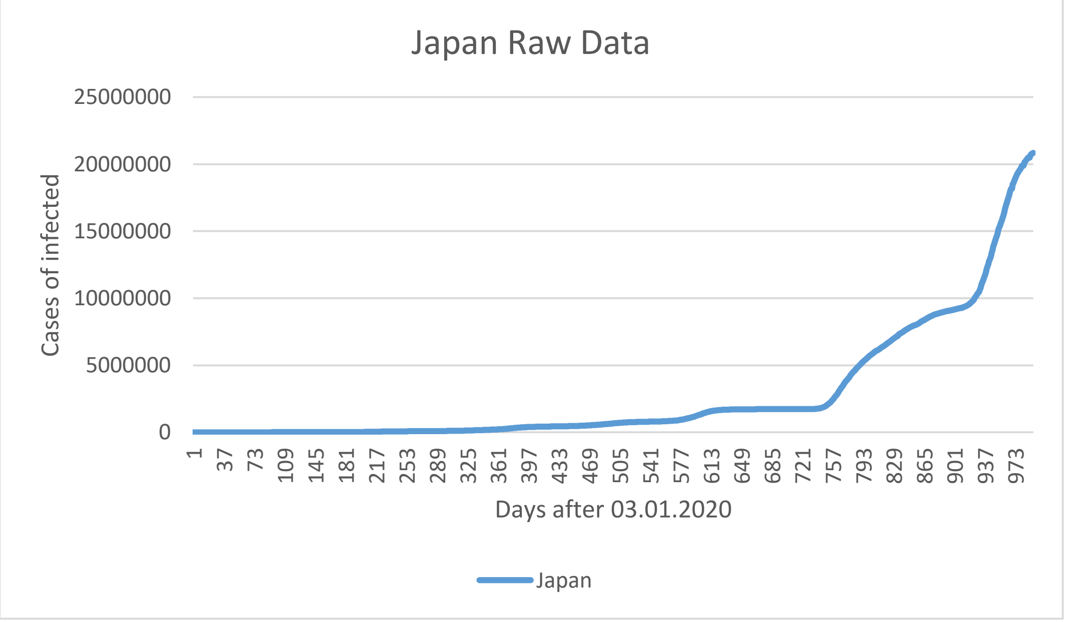
The main objective of this graphical analysis to build a model that will allow us to make prediction on the basis of our study and application of heuristic. Further in the project we improve our prediction by changing the K value to make it more precise. We will Normalise the cumulative data and consider after 100 cumulative cases to make the graphs more precise and help us understand better.

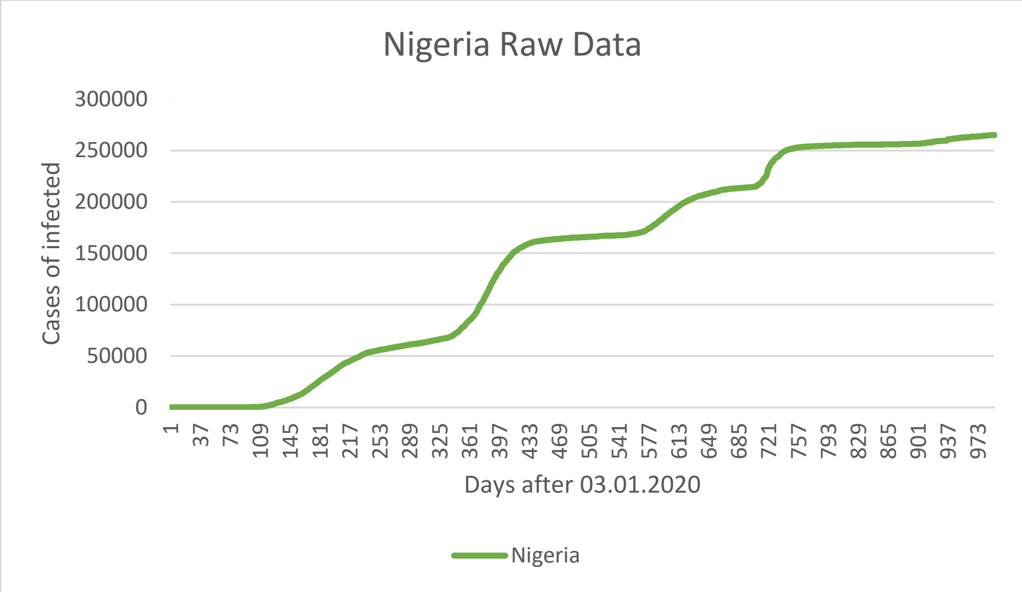
Graphical Analysis:

Task 1-3:

Graphs of cumulative cases are presented in figure 1. There is a distinction in each graph because of different scale of population of the countries. In this graph we are demonstrating covid-19 cases affected in these countries from the beginning of the epidemic (03.01.2020).







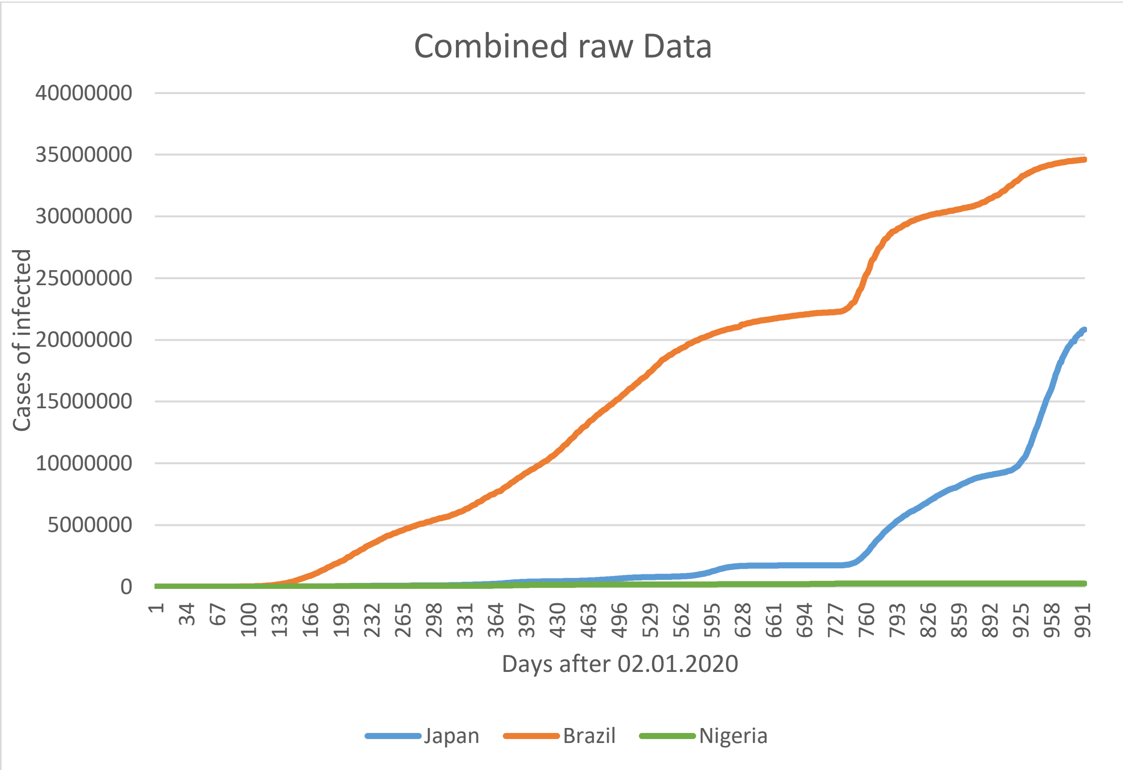


Figure 2. Combined graph of cumulative cases infected in the countries from beginning of the covid-19.

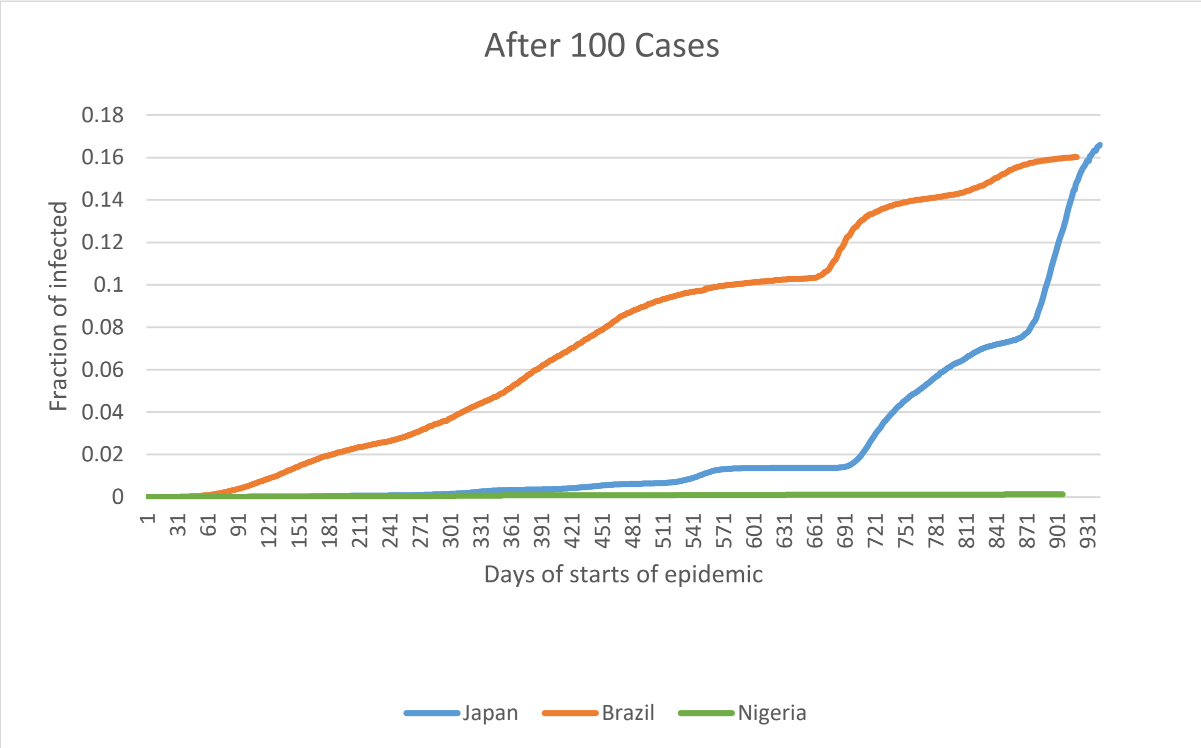
From figure 2. we can observe that there is a big difference in the infected persons between each country. Also, nature of waves in each country are entirely different. The main factors for these differences are their population differences, geographical differences, population density etc.

Task 4-5:

I decided to use value 100 of cumulative cases as beginning of epidemic. This value is almost negligible compared to population of selected countries but seems far enough from zero to be sure that it is not zero.

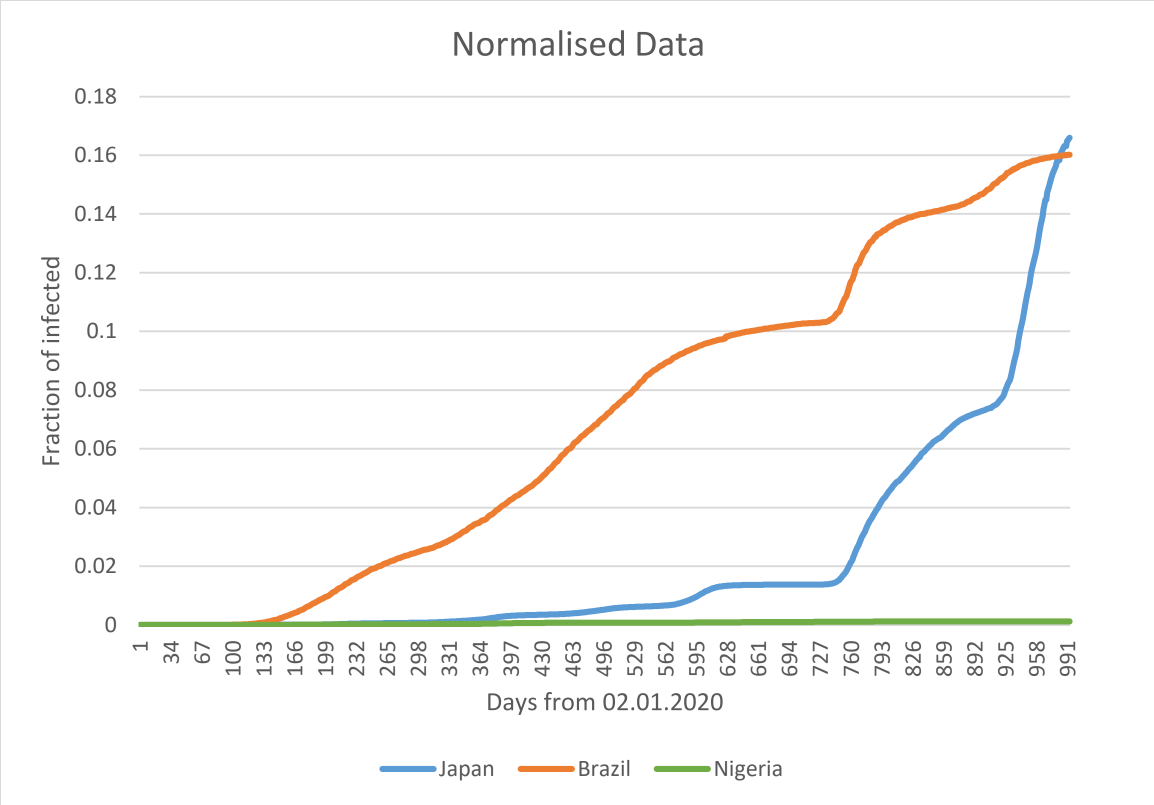
We can see that Brazil, Japan and Nigeria reported 100 cumulative covid-19 cases on 16.03.2020, 22.02.2020 and 30.03.2020 respectively. Also, we can't make the comparison between countries by observing the figure 2. (Combined). So, we plot the different individual graphs for each country (figure 1.). So, we can clearly see the "waves".

In below we can see the combined graph of after 100 reported covid-19 cases as beginning of epidemic.



Task 6:

Now we are using normalised value (Cumulative fraction) for comparing each country. Reason for taking cumulative fraction is because of their difference in their population. Also, it will give fair results in comparison. Now we are depicting the new graph (Figure 4) with normalised value.



Now we can fairly compare each country. In Figure 4. We can see that fraction of infected in Brazil is high compared to other countries in early days of epidemic. Then, Japan is gaining very high after days goes on and overtaking the Brazil in some point of the covid-19 days. We cannot see this comparison in Figure 2. Because it is compared to the total population of the countries. But in the case of Nigeria the graph (Figure 4.) is not showing much difference because their infected rate is very low compared to Brazil and Japan. There are factors behind this trend, some of them are Government pre-caution action, geographical location, population distribution, ecology of human habitation, social contacts, covid-19 testing, immunity, genetics, broader socio-cultural dynamics etc.

Task 7:

In this task we are splitting the graph into separate waves. For this we are using a heuristic called **Logarithmic heuristic approach**. Also, we are only taking after 100 cumulative cases. Then, we are plotting log graphs for each country.

1. For Brazil

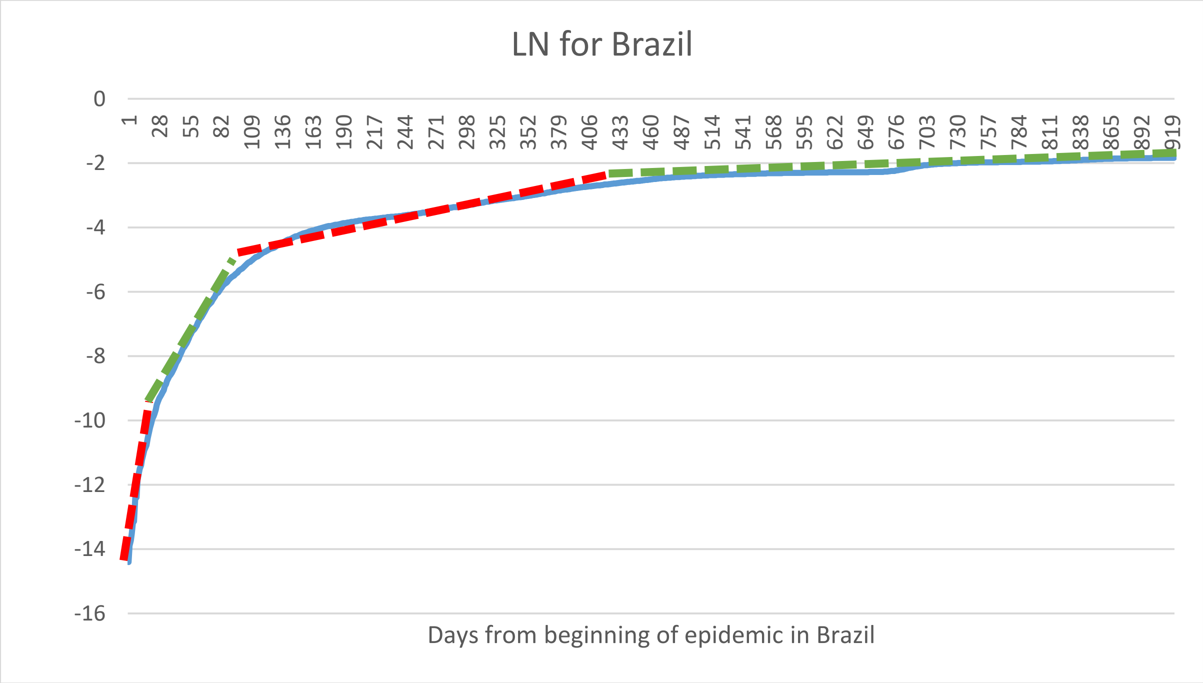


Figure 5. (Straight line fragments of log graph of Brazil data)

In figure 5. Shows that 4 fragments with straight line approximation of logarithmic data. In this we are observing 2 waves (start of red dashed lines), first wave starts from day 1 of epidemic and ends in 89th day of covid-19 outbreak. From 26th day (start of green dashed line) of wave 1, we can see that it is gradually getting saturated till 101th day of covid-19 outbreak. The second wave starts from 102th day of covid-19 outbreak, this trend getting saturated from the 426th day to the end.

2. For Japan

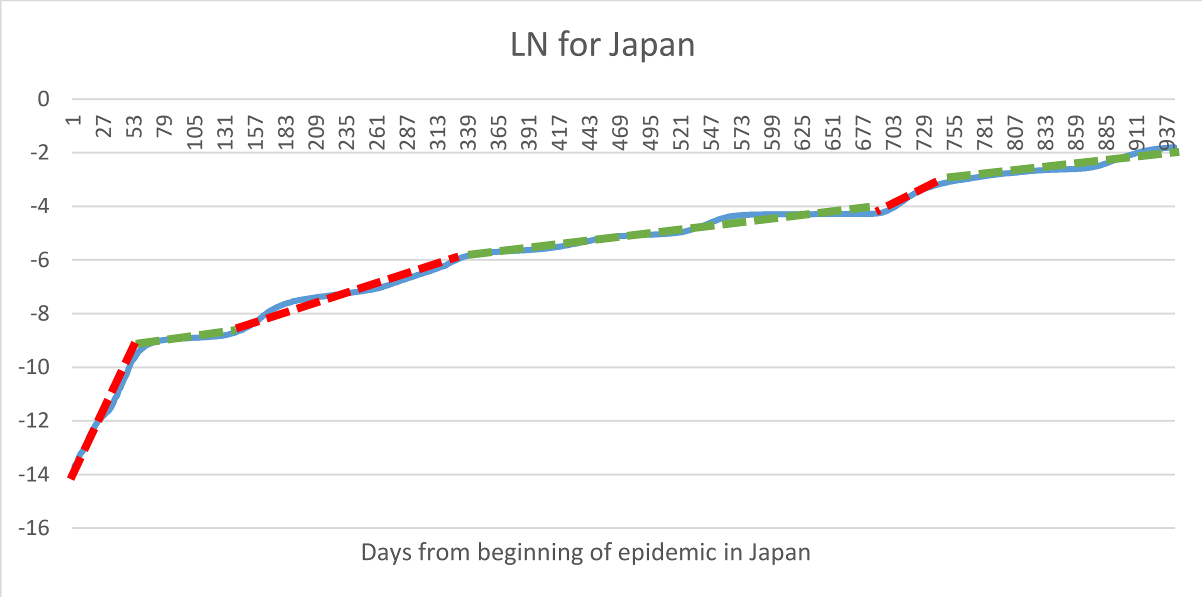


Figure 6. (Straight line fragments of log graph of Japan data)

In figure 6. Shows that 6 fragments with straight line approximation of logarithmic data. In this logarithmic graph of Japan, we can see 3 waves.

1. <u>First wave</u>: Beginning to 125th day. From the beginning rate of infection very high, then it starts to getting saturates from 27th day to the end of the first wave.
2. <u>Second wave</u>: 126th day to 677th day. This wave is the longest wave in Japan compared to first and third wave. From 335th day the rate of infection starts saturates.
3. <u>Third wave</u>: 678th day to the end. From the beginning of third wave the rate of infection suddenly gets exploded and gets saturates on 750th day of the covid-19 outbreak.

3.For Nigeria

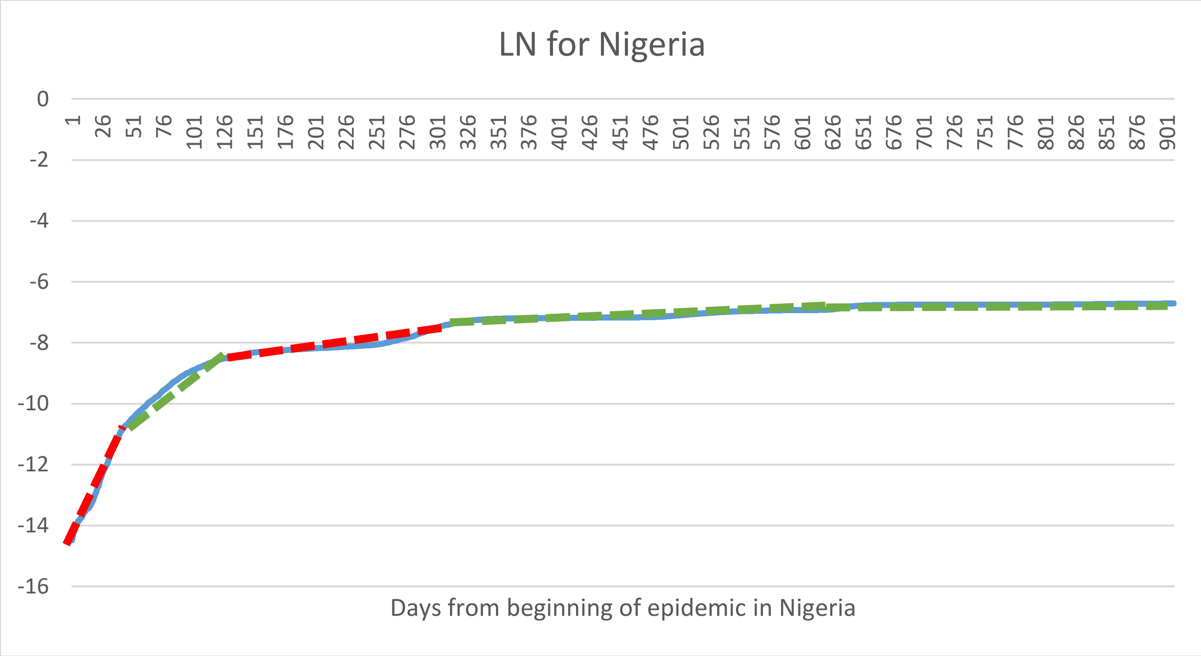


Figure 7. (Straight line fragments of log graph of Nigeria data)

In figure 7. Shows that 4 fragments with straight line approximation of logarithmic data. We can see 2 waves in Nigeria in the given data. First wave from the beginning of the covid-19 to the 120th day of the epidemic. Firstly, we can see the sudden explosion in the rate of infection in Nigeria till 30th day and it get starts to saturates. The same trend shows till 120th day of the epidemic. From 121st day the second wave started. It remains till the end. Also, it started saturation on 300th day of outbreak.

<u>Task 8</u>:

- **Japan**

<u>Wave 1</u>:

The first wave for Japan defined by the logarithmic heuristic is interval from 1 to 125. Graphs of normalised fractions and logarithm of this value are presented in Figure 8. As we can see the first horizontal interval is from 1 to 50. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$.

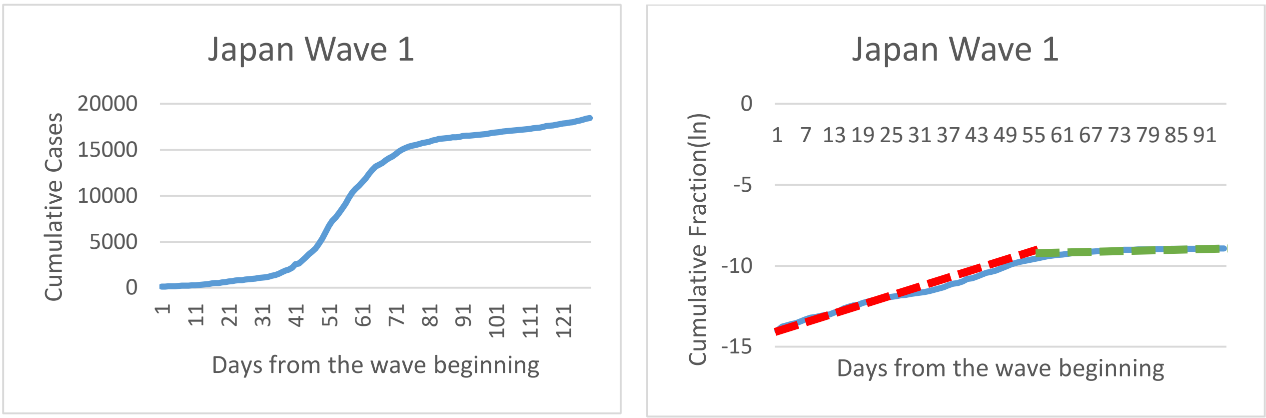
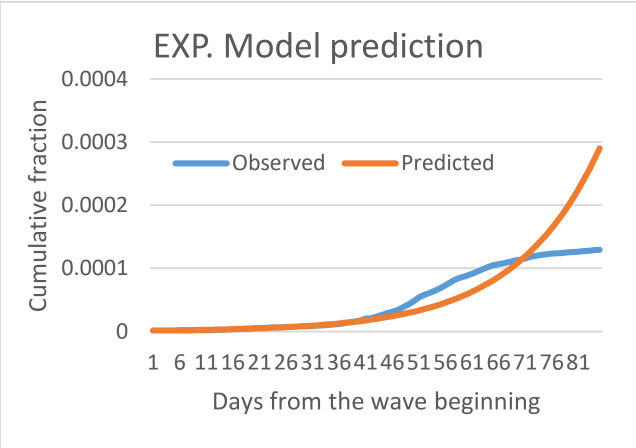


Figure 8. Cumulative fraction of infected population and logarithm of it for the first wave of Japan.

As we can see from figure 8, exponential model with parameters $a =$ -13.88620699 and $r = 0.07632707$ work only for the first 50 days. Let us try to estimate Carrying capacity from calculated parameters. As we can see in figure 10, K has big values at the beginning of wave and become more or less constant at the end of interval. Moreover, for days from 9 to 17 and day 24 value of $K > 1$ which is meaningless. Let us take value $k = 0.063$as initial estimation. Let us now estimate parameters of logistic grows for logistic model.



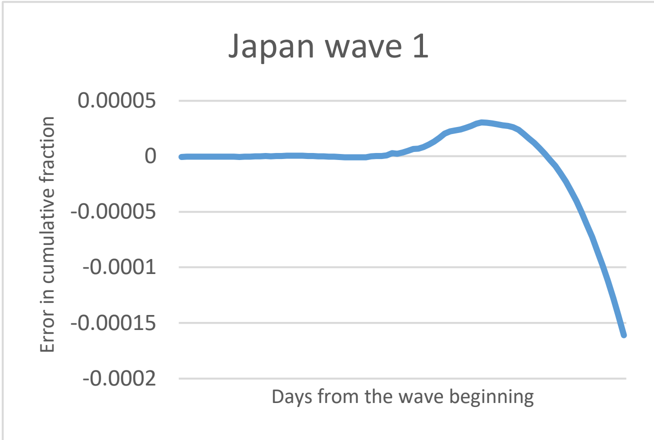


Figure 9. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

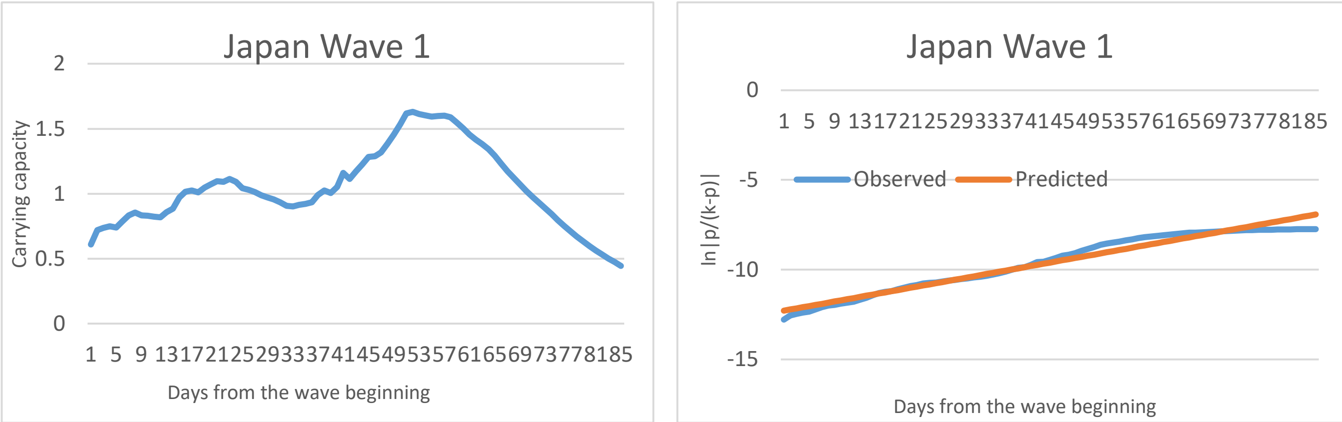


Figure 10. (Carrying capacity as function of time (left) and estimation of logistic model parameters).

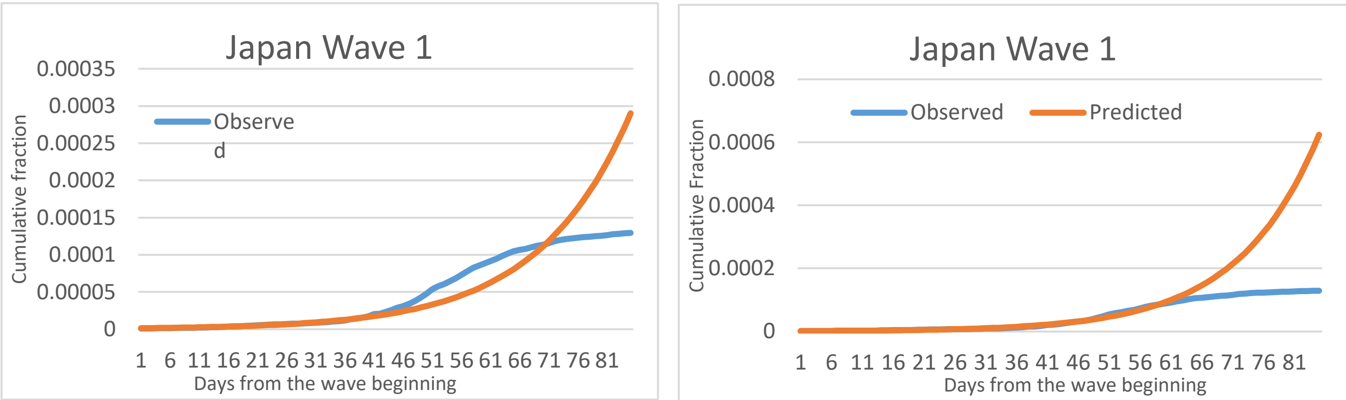


Figure 11. (Logistic model prediction for initial value of K (left) and for optimal value of K)

Table 1. Values of parameters for different models of the first wave of Japan

Model	a	r	K	SSE
Exponential	-13.5654	0.0637	NA	9.37×10^{-8}
Logistic (initial K)	-12.756	0.063775	0.44541	1.29×10^{-7}
Logistic (optimal K)	-12.78	0.06377	0.29690	1.19×10^{-7}

The curve for Japan's first wave is not looking good as there were increasing cases immediate saturation or control in population can be seen which is why it challenging to predict a good inclination of observed and predicted value.

Wave2: The second wave for Japan defined by the logarithmic heuristic is interval from 126 to 337. Graphs of normalised fractions and logarithm of this value are presented in Figure 12. As we can see the first horizontal interval is from 1 to 140. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$

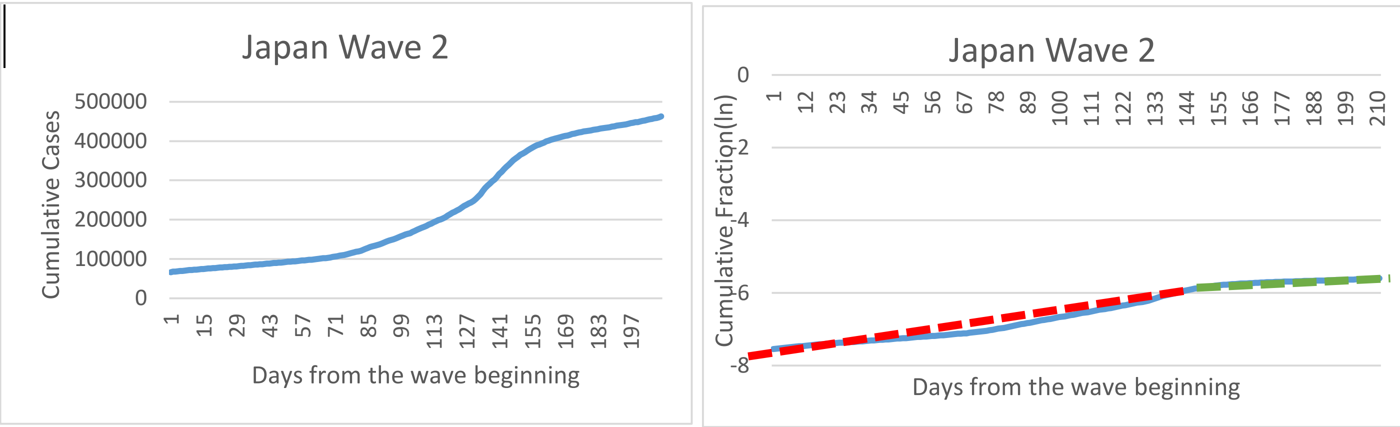


Figure 12. (Cumulative fraction of infected population and logarithm of it for the second wave of Japan)

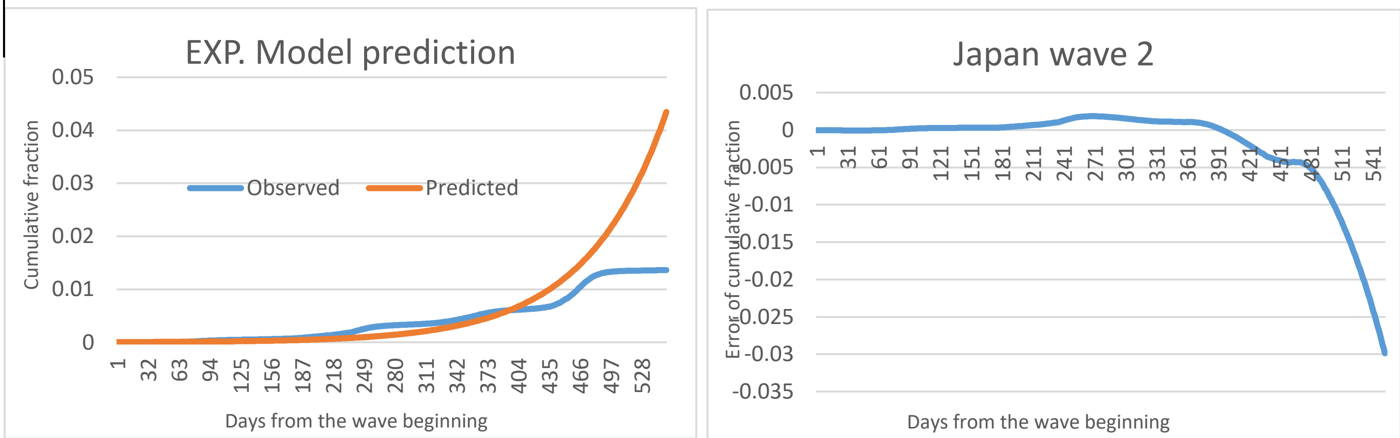


Figure 13. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

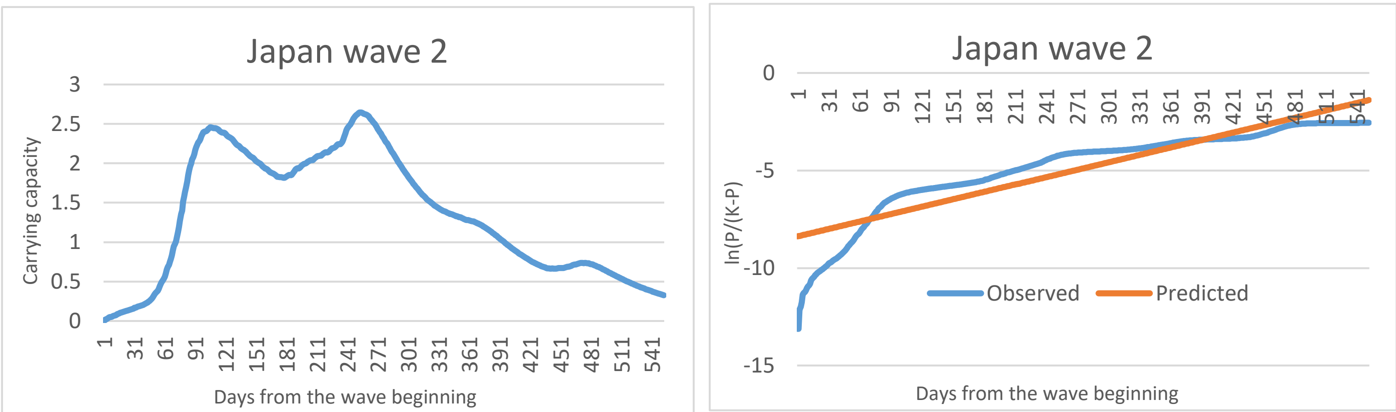


Figure 14. (Carrying capacity as function of time (left) and estimation of logistic model parameters)

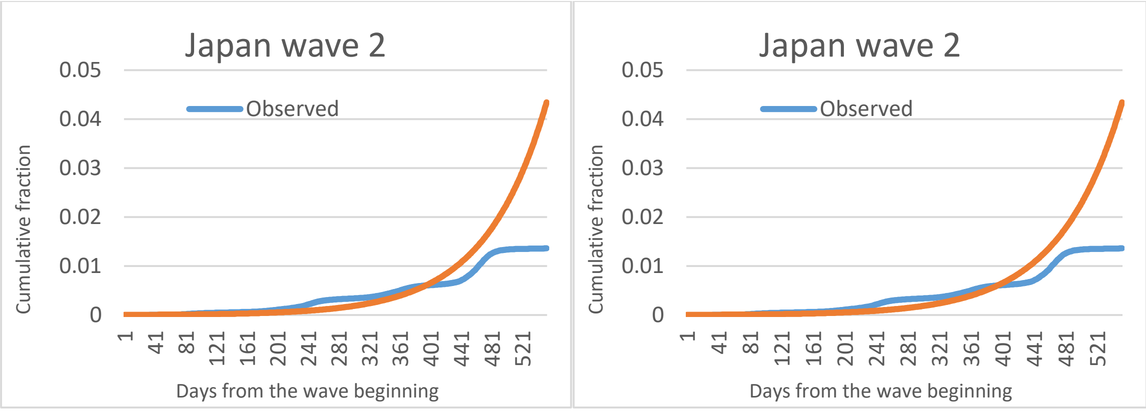


Figure 15. (Logistic model prediction for initial value of K (left) and for optimal value of K(right))

Table2. Values of parameters for different models of the second wave of Japan

Model	a	r	K	SSE
Exponential	-10.0315	0.01249	NA	0.020467
Logistic (initial K)	-8.9045	0.01262	0.32675	0.0186531
Logistic (optimal K)	-8.38845	0.012681	0.188731	0.0158194

Wave 3: The third wave for Japan defined by the logarithmic heuristic is interval from 337 to so on. Graphs of normalised fractions and logarithm of this value are presented in Figure 16. As we can see the first fragment is from 30 to 70th days of wave 3. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$

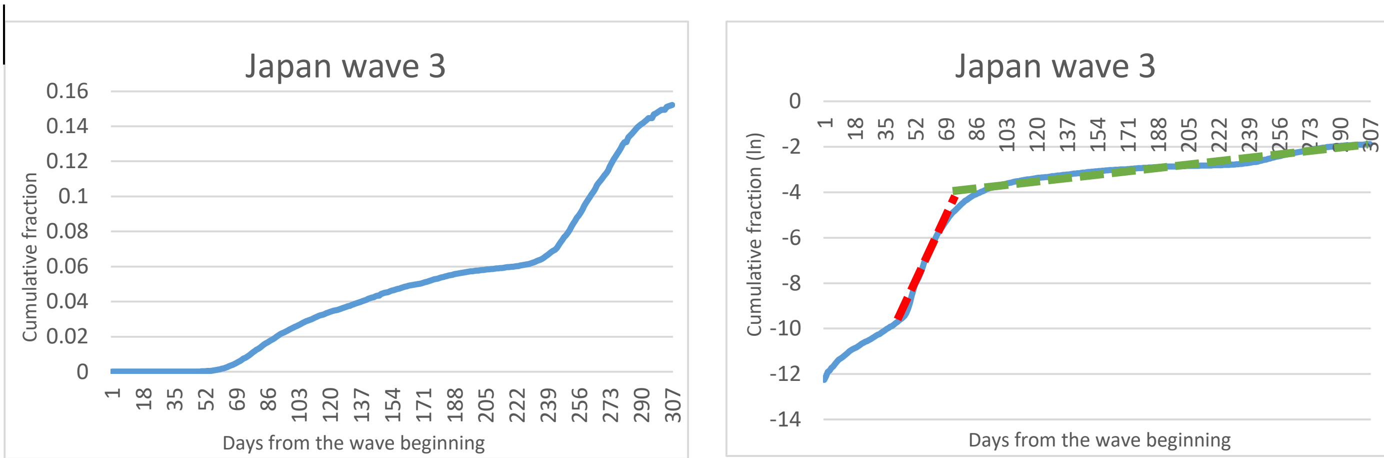


Figure 16. (Cumulative fraction of infected population and logarithm of it for the Third wave of Japan)

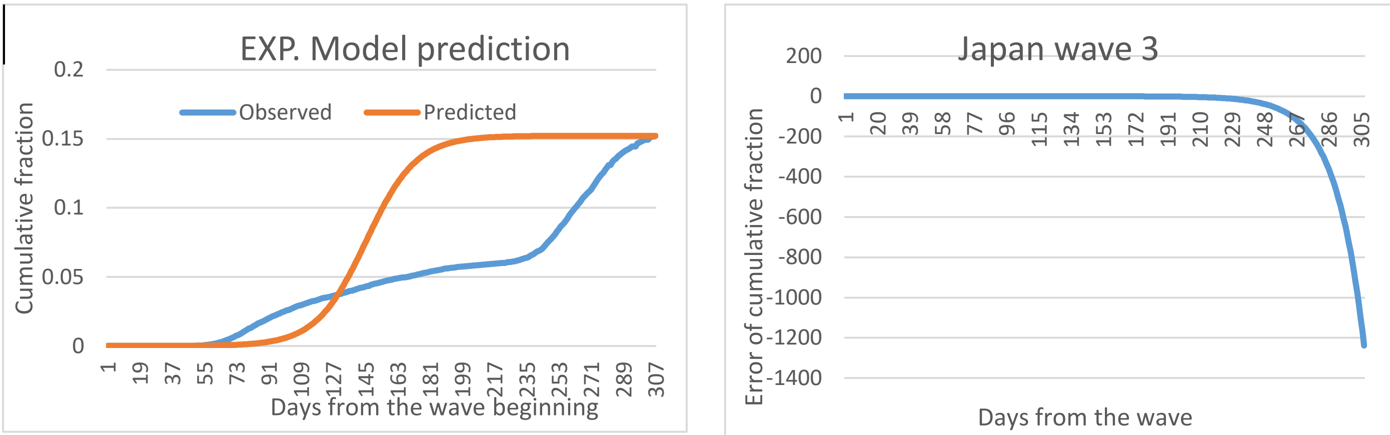


Figure 17. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

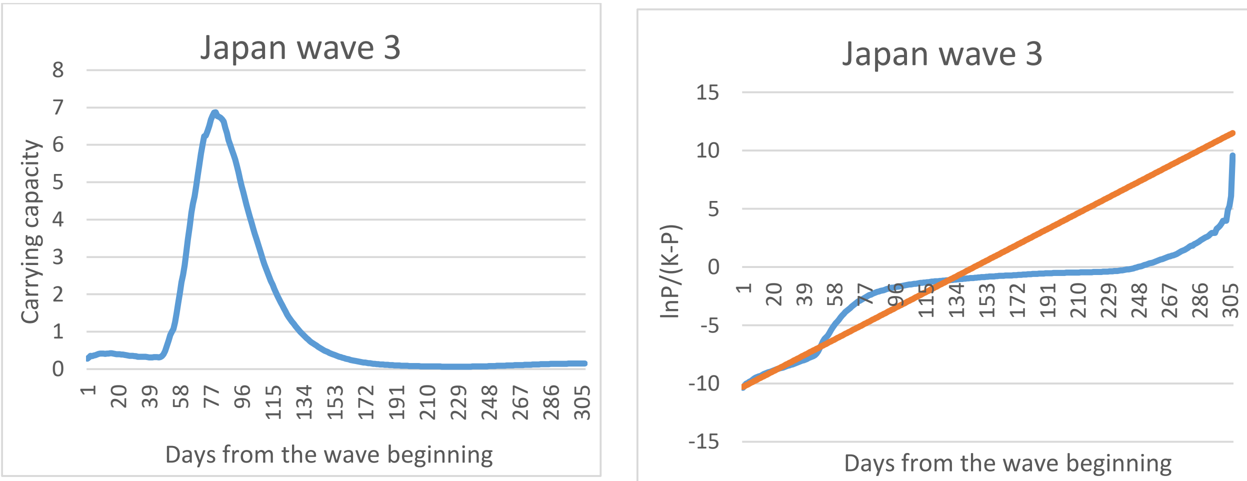


Figure 18. (Carrying capacity as function of time (left) and estimation of logistic model parameters)

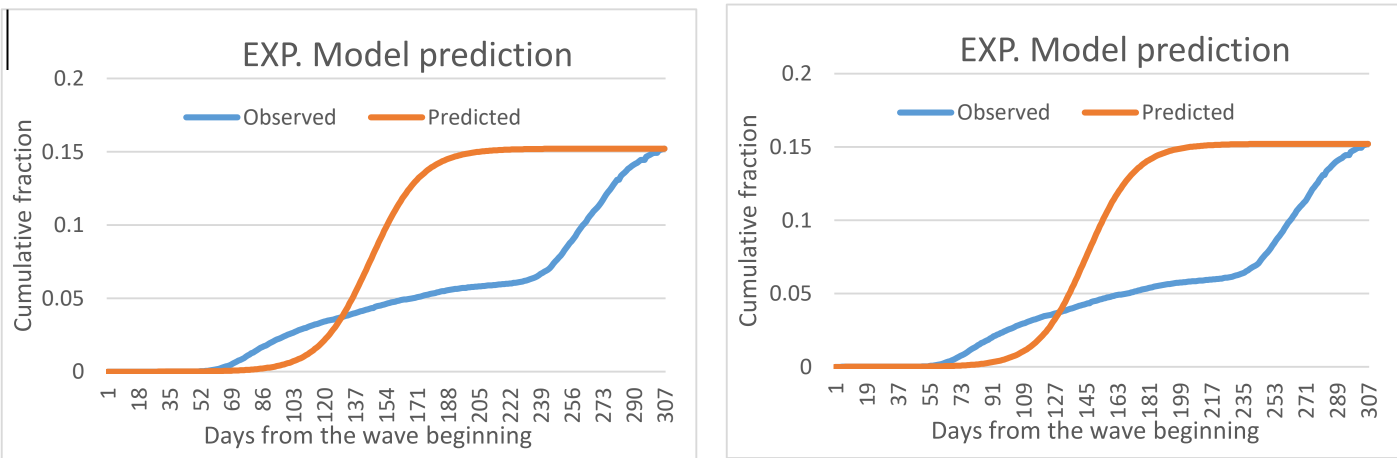


Figure 19. (Logistic model prediction for initial value of K (left) and for optimal value of K(right))

Table 3. Values of parameters for different models of the Third wave of Japan

Model	a	r	K	SSE
Exponential	-11.0358	0.059144	NA	12202110.6
Logistic (initial K)	-11.2494	0.071232	0.36772	10.555692
Logistic (optimal K)	-10.3677	0.071258	0.15221	0.8078718

For all three waves in Japan, we see multiple curves. Whenever we see increase in cases immediate implementation can be seen to control the spread of COVID19. Japan took slight change or increase in cases seriously and imposed complete lockdown, even though Japan's population is very less as compared to Brazil and Nigeria, but excellent track of record keeping is there.

- **Brazil**

Wave 1: The first wave for Brazil defined by the logarithmic heuristic is interval from 1 to 154. Graphs of normalised fractions and logarithm of this value are presented in Figure 20. As we can see the first fragment is from 5 to 50th days of wave 1. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$

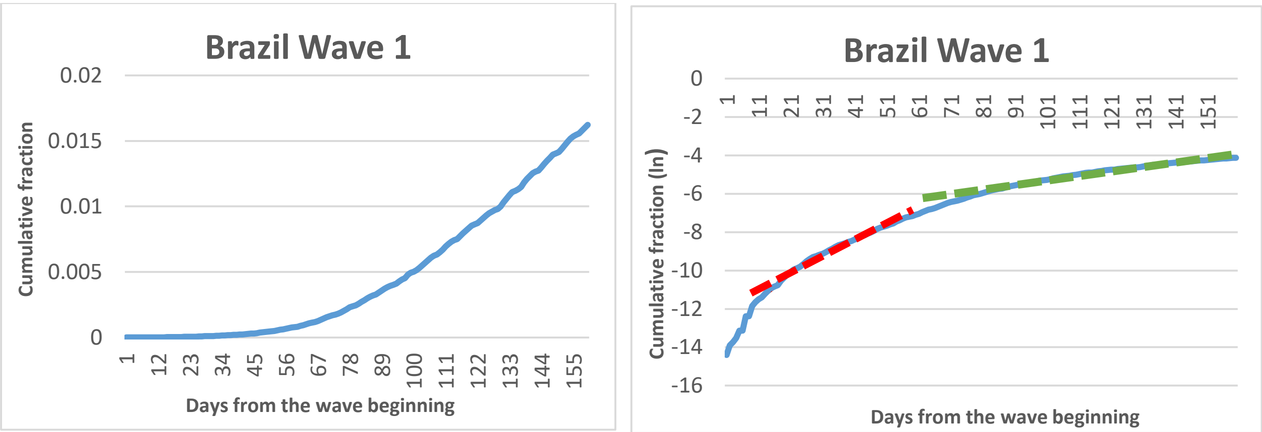
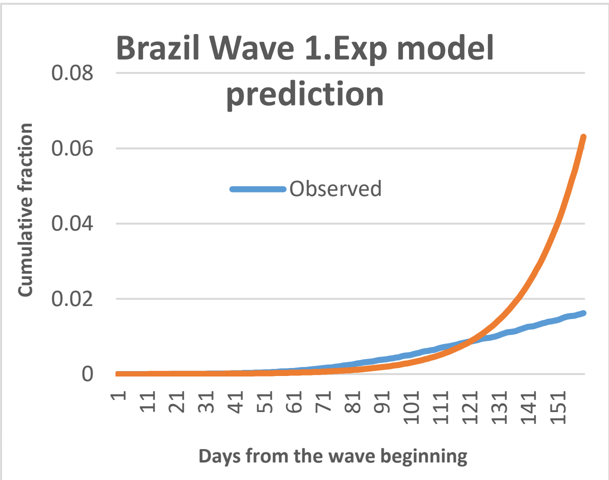


Figure 20. (Cumulative fraction of infected population and logarithm of it for the first wave of Brazil)



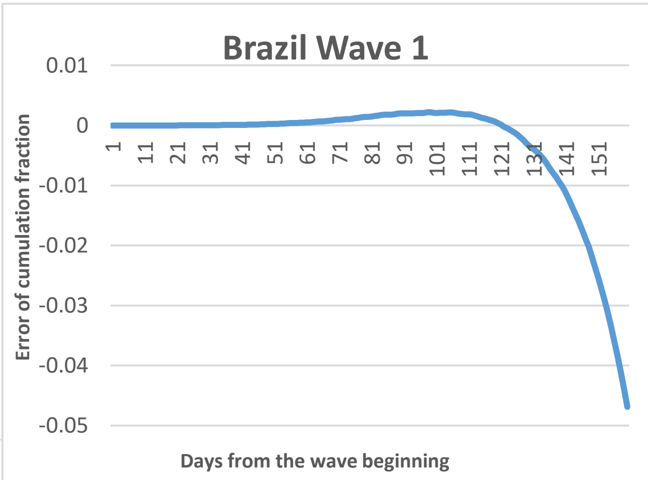


Figure 21. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

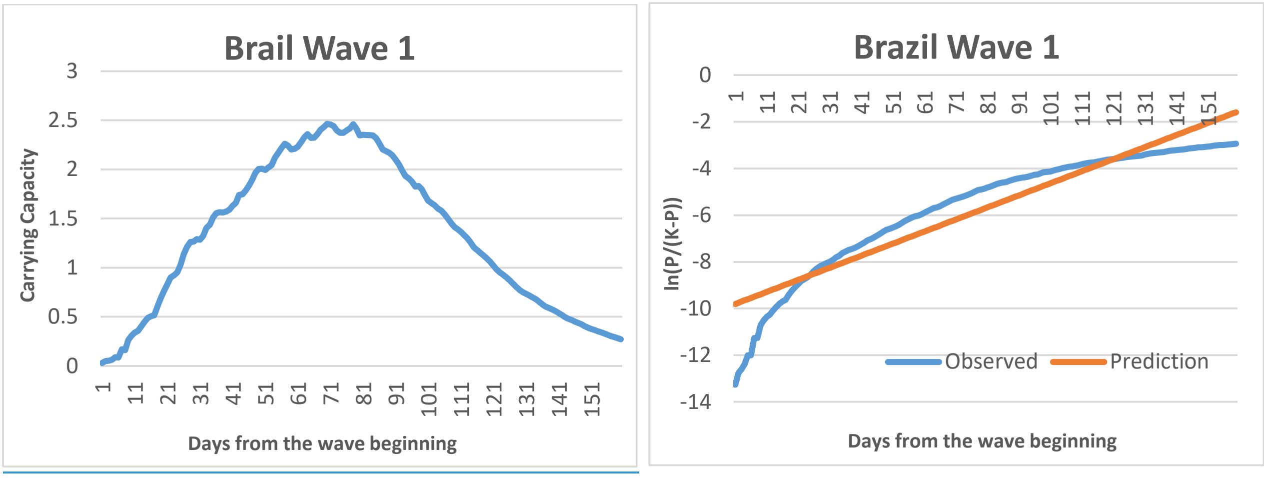


Figure 22. (Carrying capacity as function of time (left) and estimation of logistic model parameters)

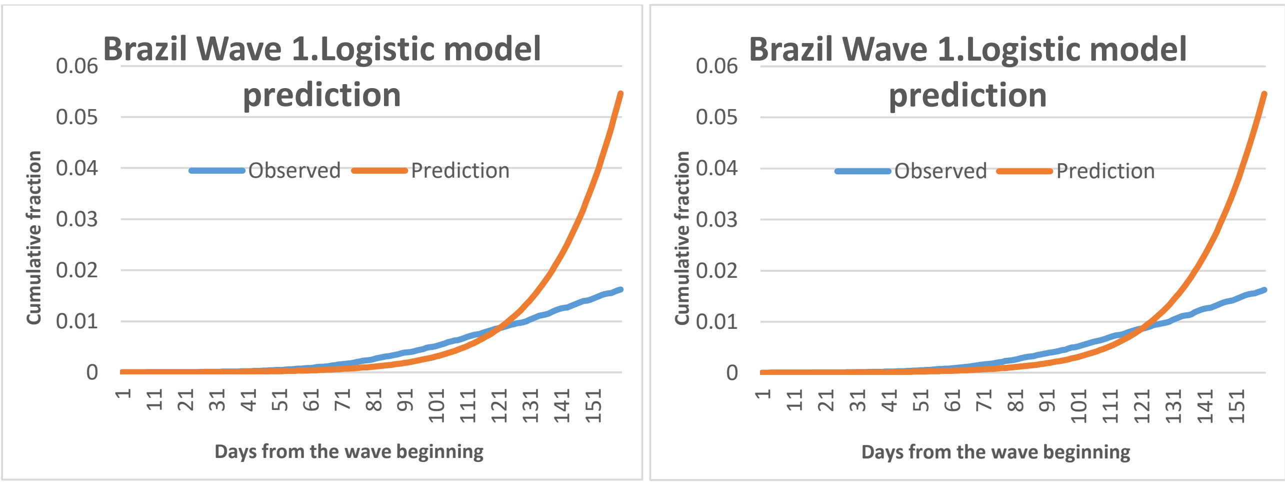


Figure 23. ((Logistic model prediction for initial value of K (left) and for optimal value of K(right))

Table 4. Values of parameters for different models of the first wave of Brazil

Model	a	r	K	SSE
Exponential	-10.3410	0.05123	NA	0.0166
Logistic (initial K)	-9.68475	0.051710	0.271534	0.011536
Logistic (optimal K)	-9.85658	0.051464	0.32312	0.012207

Wave 2: The second wave for Brazil defined by the logarithmic heuristic is interval from 155 to so on. Graphs of normalised fractions and logarithm of this value are presented in Figure 24. As we can see the first fragment is from 1 to 15th days of wave 2. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$

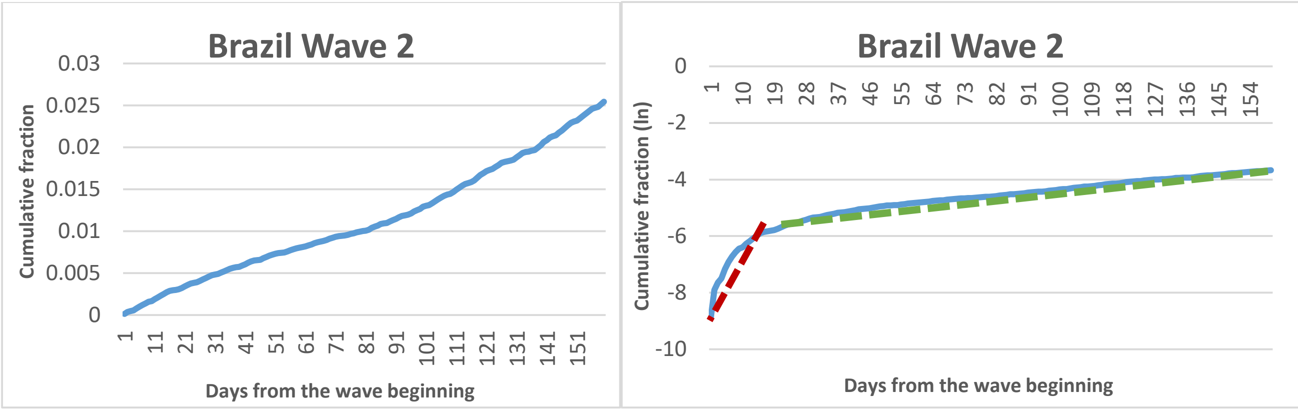


Figure 24. (Cumulative fraction of infected population and logarithm of it for the second wave of Brazil)

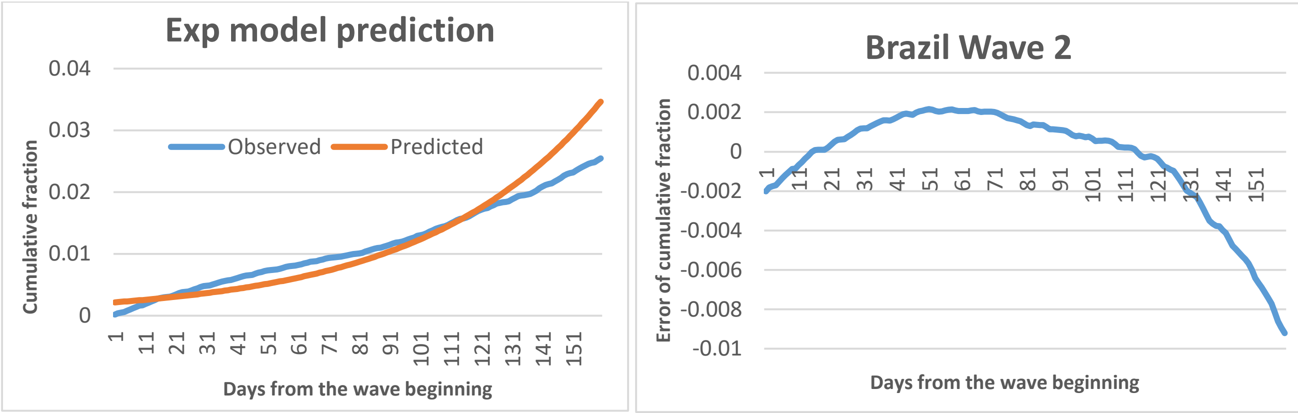


Figure 25. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

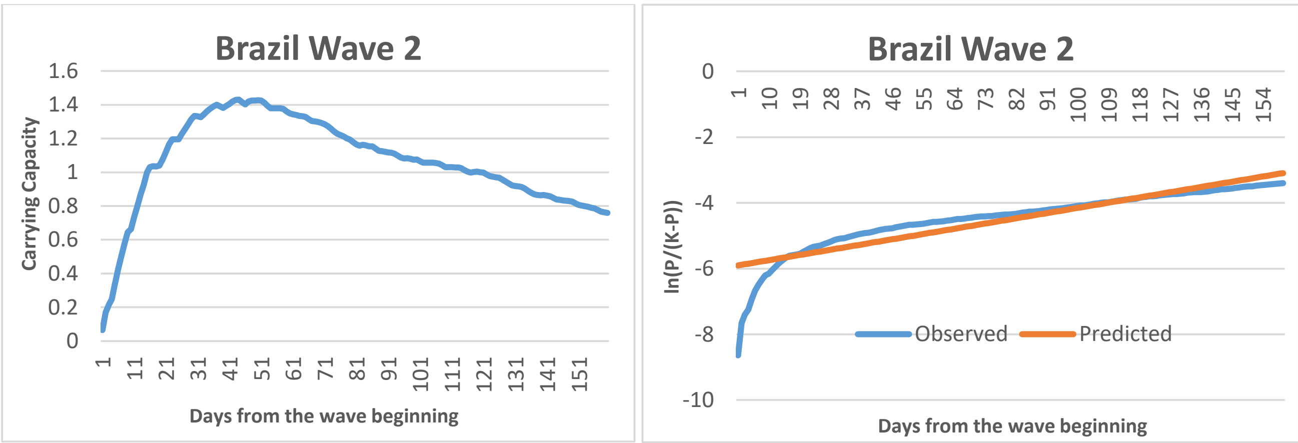


Figure 26. (Carrying capacity as function of time (left) and estimation of logistic model parameters)

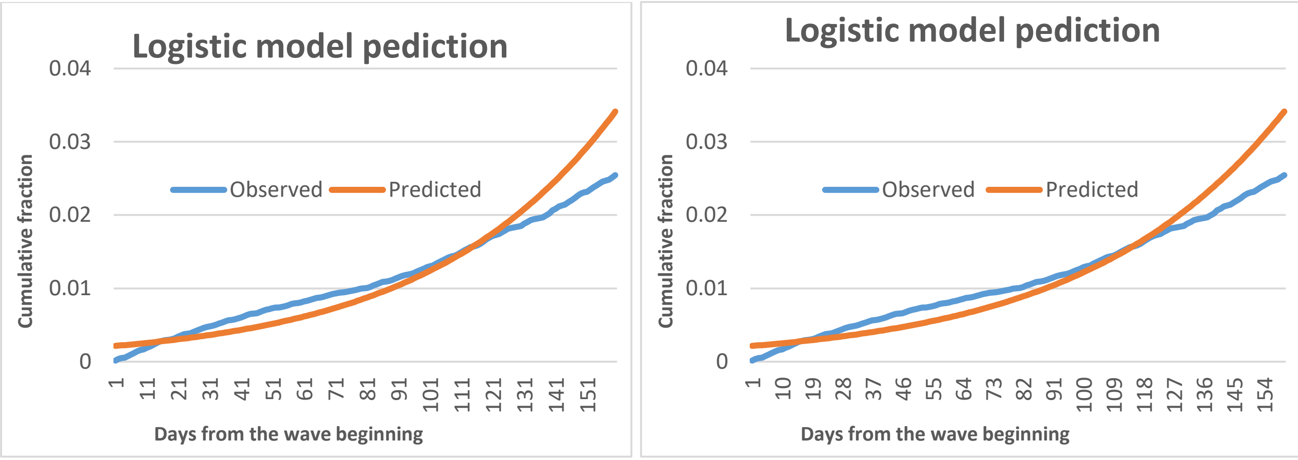


Figure 26. ((Logistic model prediction for initial value of K (left) and for optimal value of K(right))

Table 5. Values of parameters for different models of the second wave of Brazil

Model	a	r	K	SSE
Exponential	-6.15831	0.017474	NA	0.001193
Logistic (initial K)	-5.88383	0.01769	0.759511	0.0010980
Logistic (optimal K)	-5.92058	0.01766	0.78796	0.001101

For Brazil wave 1 and 2, it is evident that, what we have predicted model is almost like the observed data. We have observed that SSE (sum squared error) is almost minimal. So that we got the observed data almost similar to that of a predictive model.

- **Nigeria**

Wave 1: The first wave for Nigeria defined by the logarithmic heuristic is interval from 1 to 240. Graphs of normalised fractions and logarithm of this value are presented in Figure 27. As we can see the first fragment is from 1 to 60th days of wave 1. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$

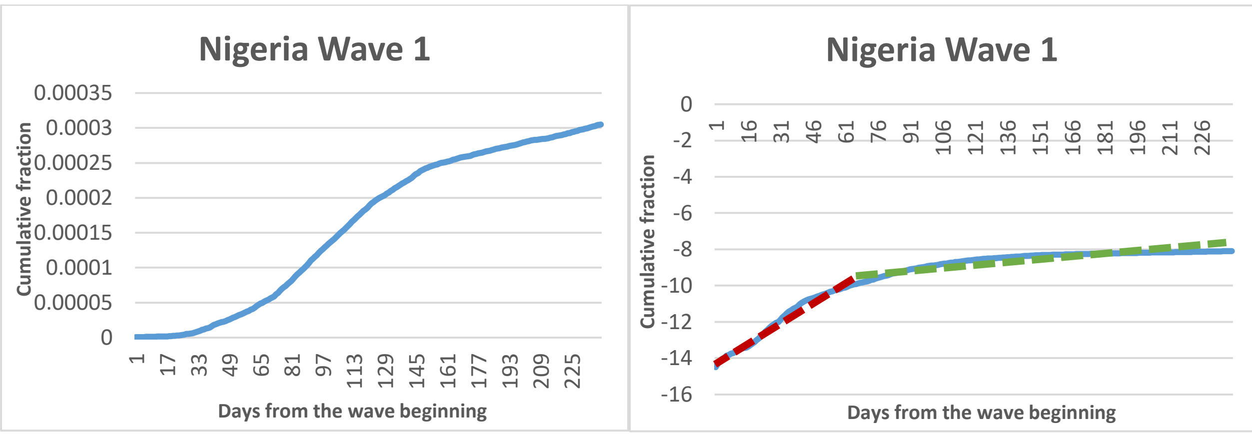


Figure 27. (Cumulative fraction of infected population and logarithm of it for the first wave of Nigeria)

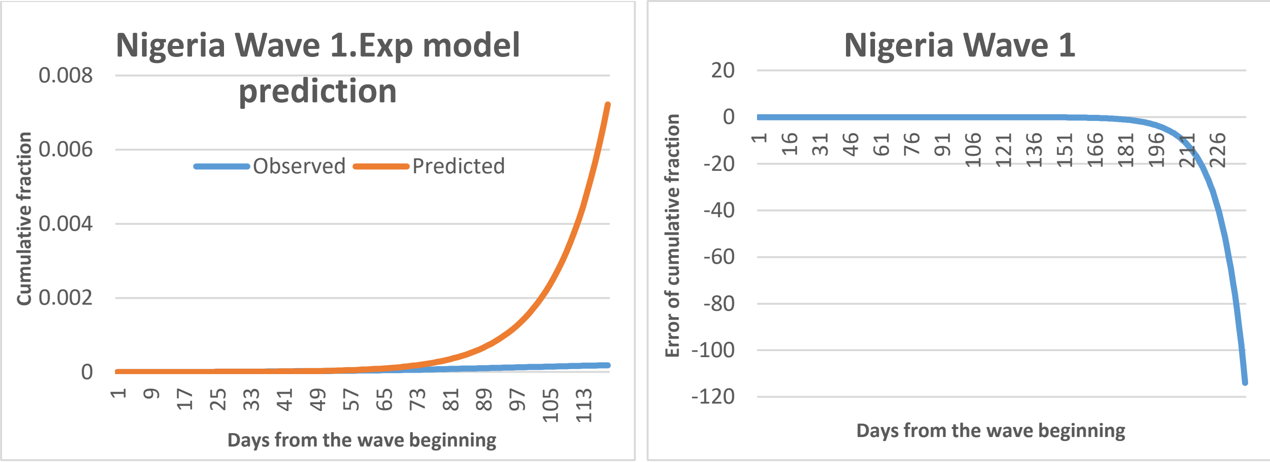


Figure 28. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

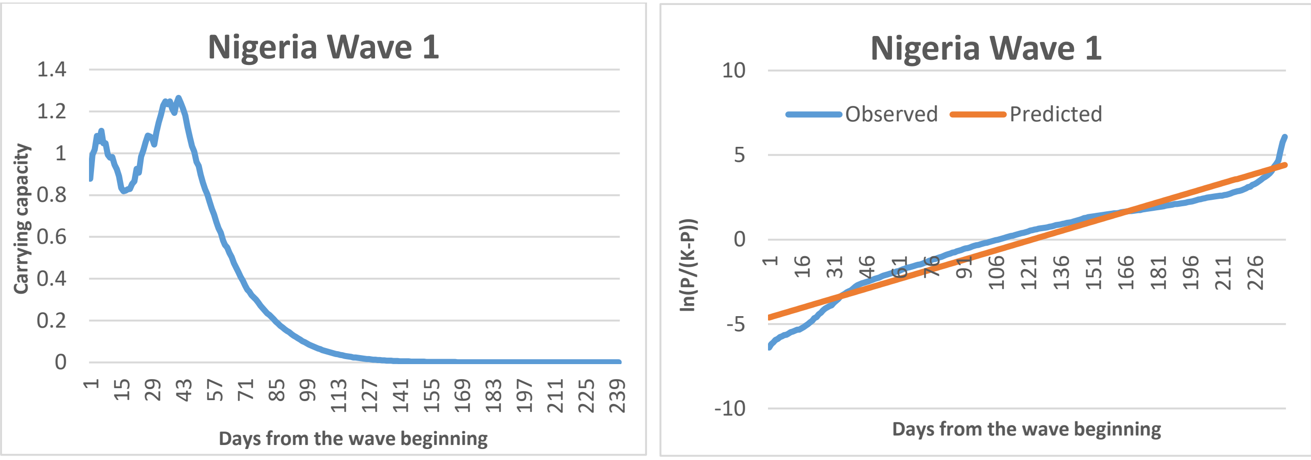


Figure 29. (Carrying capacity as function of time (left) and estimation of logistic model parameters)

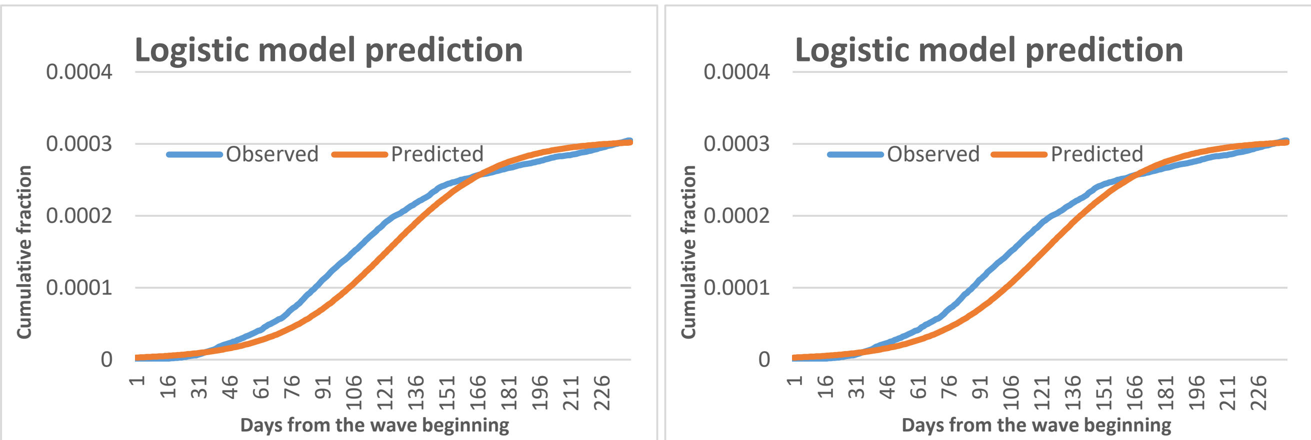


Figure 30. ((Logistic model prediction for initial value of K (left) and for optimal value of K(right))

Table 6. Values of parameters for different models of the first wave of Nigeria

Model	a	r	K	SSE
Exponential	-14.4394	0.07990	NA	88097.9
Logistic (initial K)	-4.58961	0.036812	0.00030753	1.26×10^{-7}
Logistic(optimal-K)	-4.64699	0.037768	0.00030	1.12×10^{-7}

Wave 2: The second wave for Nigeria defined by the logarithmic heuristic is interval from 240 to so on. Graphs of normalised fractions and logarithm of this value are presented in Figure 31. As we can see the first fragment is from 1 to 65th days of wave 1. We will use it to estimate parameters of model: $\ln \hat{P}(t) = a + rt$

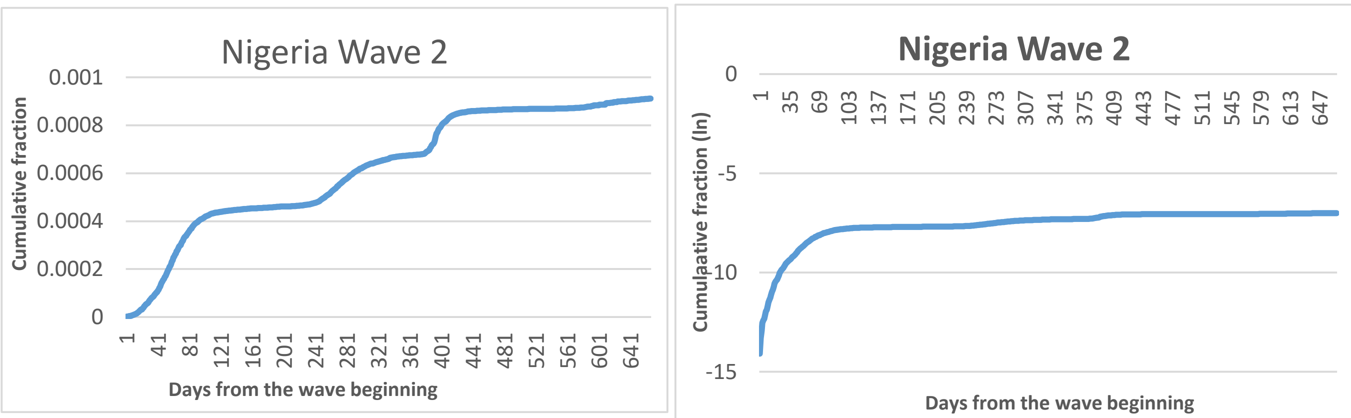


Figure 31. (Cumulative fraction of infected population and logarithm of it for the second wave of Nigeria)

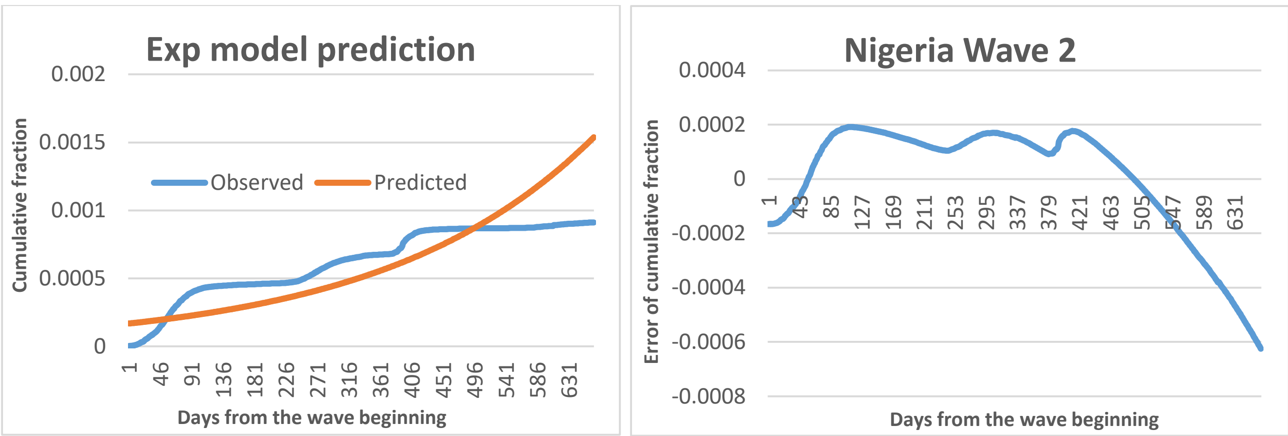


Figure 32. (Cumulative fraction of infected population prediction (left) and error of prediction (right))

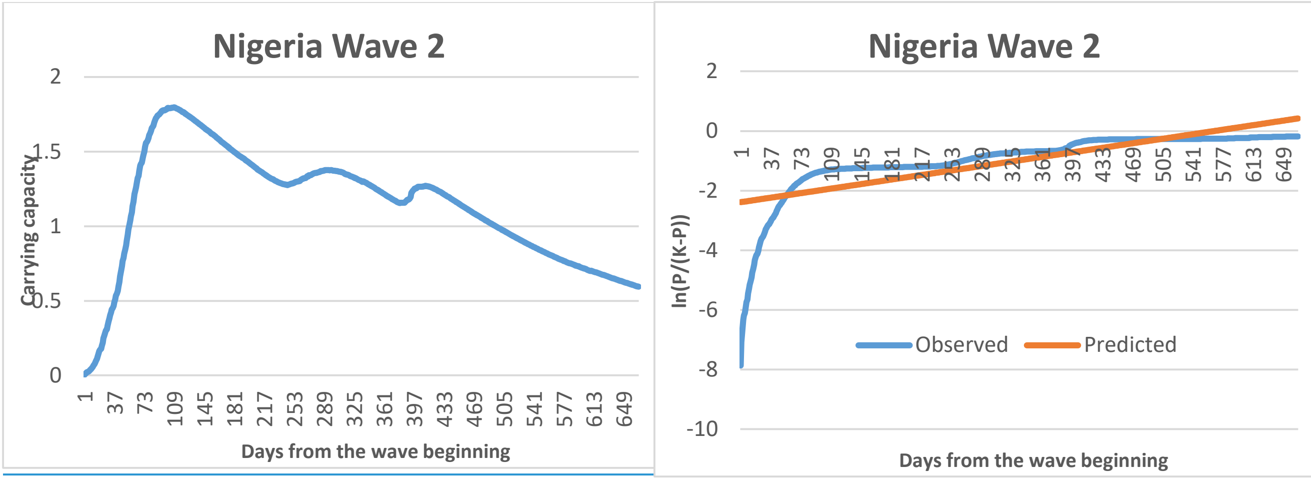


Figure 33. (Carrying capacity as function of time (left) and estimation of logistic model parameters)

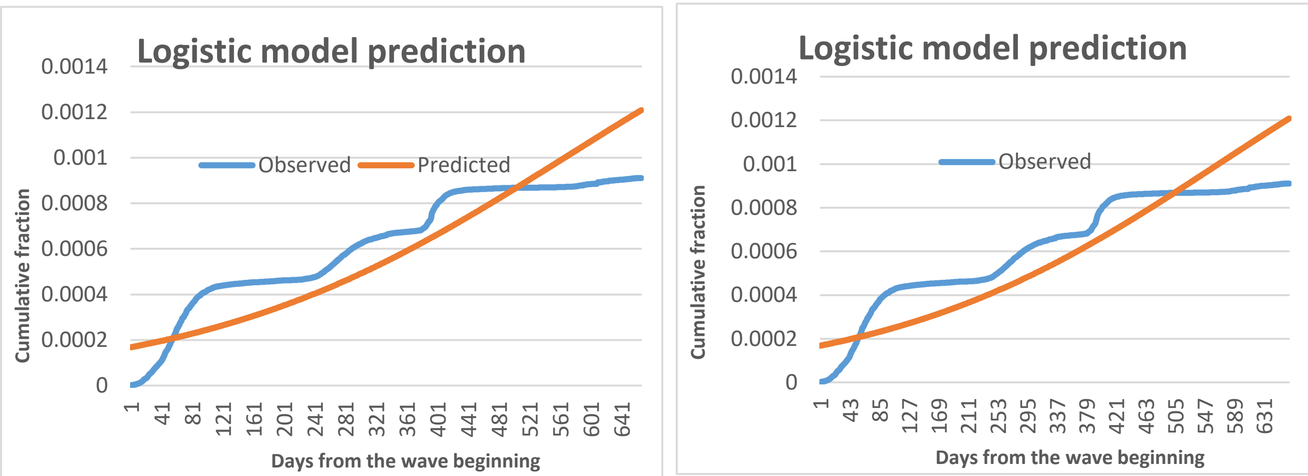


Figure 34. (((Logistic model prediction for initial value of K (left) and for optimal value of K(right))

Table 7. Values of parameters for different models of the second wave of Nigeria

Model	a	r	K	SSE
Exponential	-8.69809	0.0033284	NA	2.95×10^{-5}
Logistic (initial K)	-8.17647	0.003363	0.593766	1.30×10^{-5}
Logistic (optimal K)	-2.3923	0.004217	0.00200	1.21×10^{-5}

For Nigeria wave 1, it is evident that, what we have predicted model is almost like the observed data. We have observed that SSE (sum squared error) is almost minimal. So that we got the observed data almost like that of a predictive model. For wave 2 we are getting almost like that of predictive model, but we are facing minimal deviation with respect to the predictive model.

CONCLUSION:

- Japan
  There is total of 3 waves in Japan. While comparing Japan's first and second waves we are getting synchronous graphs for both the waves. We can conclude from this that, both the explosion and saturation of both the waves are almost identical.
- Brazil
  While comparing the wave 1 and wave 2 of Brazil, we can see similar trend for the prediction.
- Nigeria
  In Nigeria for the wave 1, we are getting similar graph that of prediction while in the case of wave 2, we are getting a deviated observe model that of predictive. So, we can conclude that wave 1 and wave 2 are asynchronous.

TEAM OVERVIEW:

In Japan we have 3 waves, but in Nigeria and Brazil we have only 2. While compare these countries, Japan shows more covid-19 cases as compared to Brazil and Nigeria. Main reason for this is that Japan is a developed, also testing rate Japan very higher compared to others. Also, Japan is near to China (origin of covid19) but Nigeria and Brazil are distant from China. Furthermore, other factors behind this trend, are Government pre-caution action, geographical location, population distribution, ecology of human habitation, social contacts, covid-19 testing, immunity, genetics, broader socio-cultural dynamics etc.

CHAPTER :2

INTRODUCTION:

The population is divided into 3 categories: Susceptible, Infected and Recovered.

Susceptible a person who can be infected.

Infected a person who is infected with covid-19.

Recovered a person who has been recovered from the virus.

What is a SIR model?

The SIR model is a classical model of disease transmission within a population. It can be modified to account for several important population dynamics, such as death rate, immigration or birth rate, recovery, and immunity - but even the most basic model has powerful public health applications. Here we examine the most basic model, a good starting point for further study. We assume disease spread depends on population size; infection is instantaneous; no one is resistant to the disease at the start; immunity, once gained, is permanent; and that the disease is not fatal.

The SIR model works by placing all individuals in the population into one of three classes at any given time: individuals susceptible to disease, infected individuals, and "removed" individuals. The removed class counts those individuals that are not infected and not susceptible; in other words, immune, quarantined, or dead individuals. The class is significant; in other SIR model variants, it can account for both permanent or temporary immunity acquired from vaccination or from having the disease. Again, however, we choose to use the simplified model where immunity (or lack of susceptibility) is permanent, and describe the recovery rate as the parameter σ. Our assumption is a reasonable one for diseases like flu, for which vaccines have been developed only recently and which generally do not afflict an individual more than once in the course of an epidemic. Individuals may move from one class to another; for example, an individual may move from the infected class to the removed class upon recovery. Thus the model accounts for the interdependency of the different classes within the population.

THE SIR MODEL VARIATION

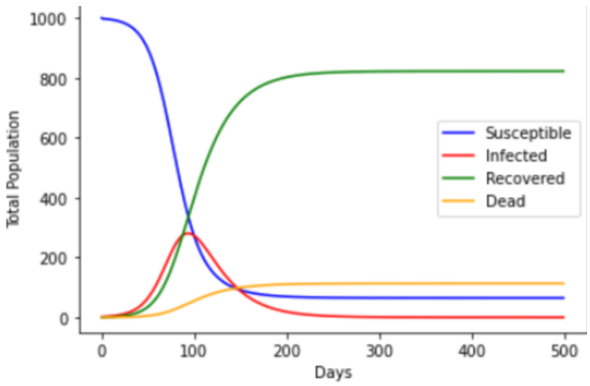
1. The SIS Model

The SIS model is the simplest compartment model with only two populations, the susceptible and infectious groups S and I. This model is characterized due to some infectious diseases, for example common cold or influenza, which reduces the immunity of the individual after recovery from the disease leading them back to becoming susceptible rather than recovered.

Because we are able to analytically solve the dynamics of its two populations, S(t) and I(t), at any point t in time, the SIS model is frequently utilized as an illustration of the fundamental characteristics of compartment models.

2. <u>The SIRD Model</u>

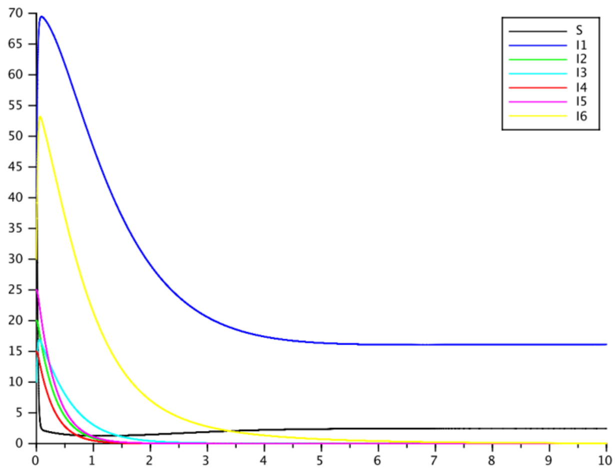
The SIRD model is one of the derivatives of the SIR model with an addition of two assumptions which are recovery with immunity and Death. So the model consists of four parameters the susceptible, infected, recovered and removed or decreased.



The mortality rate (mu) constant, which represents the rate at which infected individuals die, is taken into account by the SIRD model when modeling the death rate. The mortality rate is calculated by dividing the number of infected people by the mortality rate. You will concur with me that the number of infected individuals who died must be subtracted from the number of infected individuals. If we reduce the number of people who have passed away, our rate of infection change over time will slow down to compensate for the loss caused by death.

3. The MSIR Model

In this model, newborn babies are not born into susceptible compartment, due to protection from maternal antibodies, some diseases may give newborns temporary passive immunity. As a result, we must include an additional class M that includes infants with passive immunity. The infant moves up to the susceptible class S if the body no longer contains the maternal antibodies.



OBJECTIVE:

Mathematical models such as the Susceptible, Infectious, and/or Recovered (SIR) model are used to predict different scenarios related to epidemiologic factors and possible outcomes to assess epidemic spread. The reproduction number ($R0$) is used to estimate the capacity of viral transmission from one person to another.

Task 1:

Firstly, we are taking after 250 cumulative cases for each country from the epidemic start because there is no significant increase in the cases before 250 cases. Then Normalised the data by dividing the cumulative cases by the country's total population.

We are only taking the first two waves of each country for further analysis.

Task 2:

The logarithmic graphs of the first two waves of each country are illustrated below;

BRAZIL

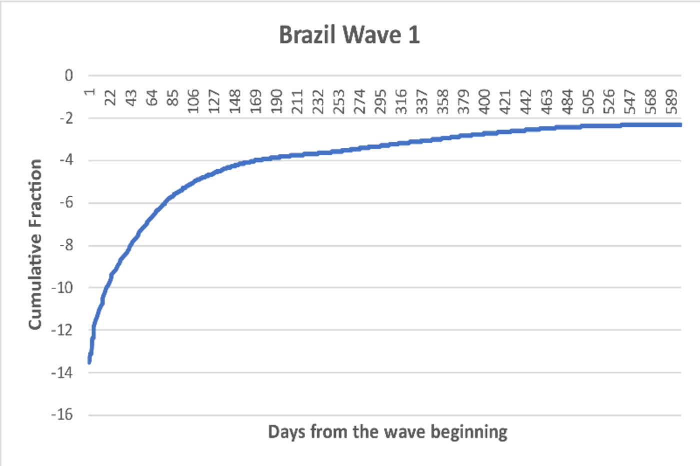


Figure 1

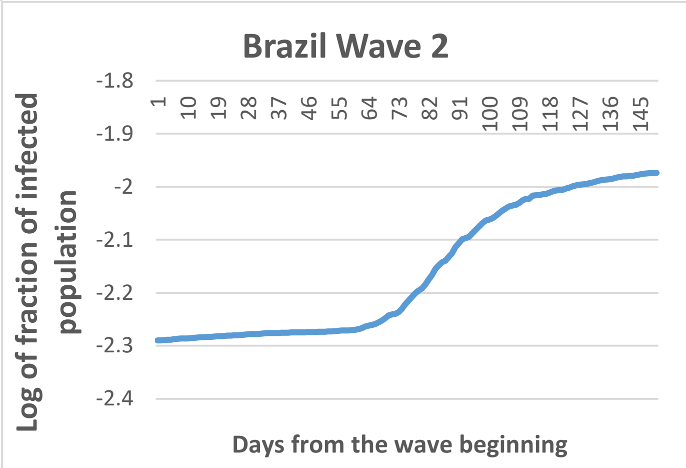


Figure 2

JAPAN

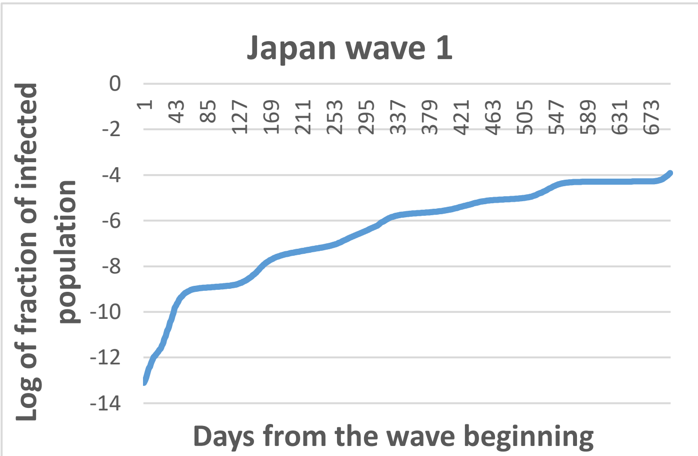


Figure 3

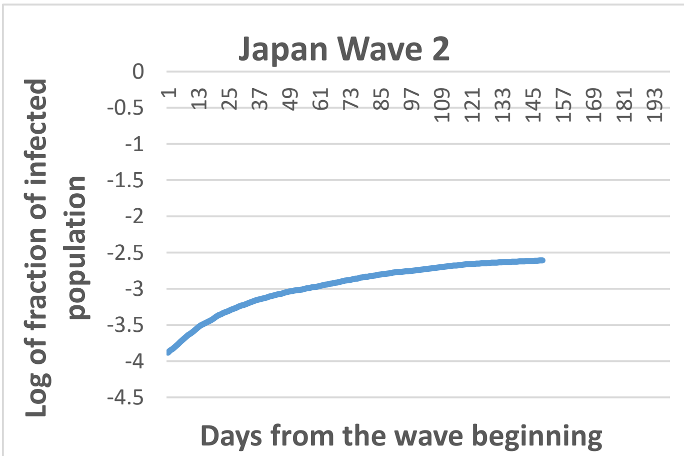


Figure 4

NIGERIA

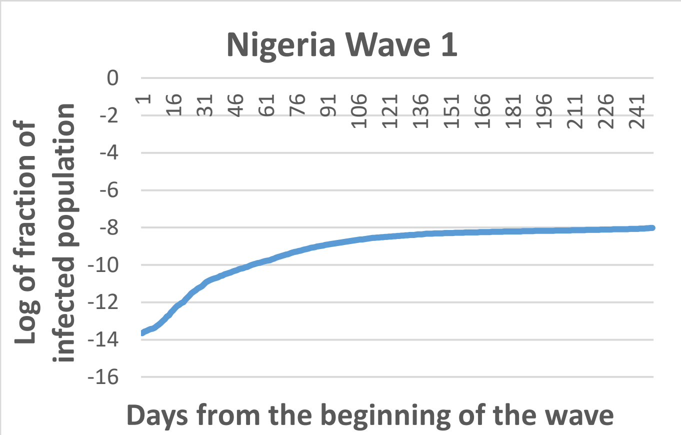


Figure 5

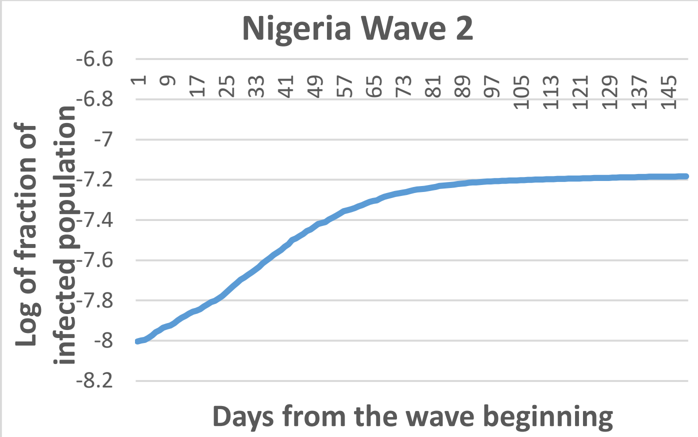


Figure 6

Using these logarithmic graphs, we can find the intervals of exponential growth in each wave. The intervals are;

- Brazil wave 1: 1st day of wave 1 to 85th day of wave 1.
- Brazil wave 2: 67th day of wave 2 to 103rd day of wave 2.
- Japan wave 1: 1st day of wave 1 to 52nd day of wave 1.
- Japan wave 2: 1st day of wave 2 to 58th day of wave 2.
- Nigeria wave 1: 1st day of wave 1 to 60th day of wave 1.
- Nigeria wave 2: 1st day of wave 2 to 66th day of wave 2.

For finding S at the beginning and end of the exponential growth period, we need to explain the SIR model.

SIR MODEL

It is one of the models to explain the spread of the epidemic. In this model, the total population is divided into three categories. That's are;

Susceptible (S) – can be infected.

Infector (I) – the person who is infected and spreads infection.

Removed (R) - recovered or dead.

In this model, we assumed that the total population is constant. Also, the rate of increase in infective is proportional to the contact between S and I.

$$S \rightarrow I \rightarrow R$$

Reactions.

Become infected:

$$S + I \to 2I$$

Removing

$$I \to R$$

Stoichiometric vectors

$$\alpha_{11} = 1; \alpha_{12} = 1; \alpha_{13} = 0; \beta_{11} = 0; \beta_{12} = 2; \beta_{13} = 0$$

$$\alpha_{21} = 0; \alpha_{22} = 1; \alpha_{23} = 0; \beta_{21} = 0; \beta_{22} = 0; \beta_{23} = 1$$

$$\gamma = \beta - \alpha$$

$$\gamma_1 = (-1, 1, 0)^T;\ \gamma_2 = (0, -1, 1)^T$$

Reaction rates

$$r_1 = aS^{\alpha_{11}} I^{\alpha_{12}} R^{\alpha_{13}} = aSI$$

$$r_2 = bS^{\alpha_{21}} I^{\alpha_{22}} R^{\alpha_{23}} = bI$$

$$\frac{dc}{dt} = \sum_{\rho=1}^{2} \gamma_\rho r_\rho = \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} r_1 + \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix} r_2 = \begin{pmatrix} -aSI \\ aSI \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ -bI \\ bI \end{pmatrix}$$

Finally, we have

$$\frac{dS}{dt} = -aSI$$

$$\frac{dI}{dt} = aSI - bI$$

$$\frac{dR}{dt} = bI$$

Stoichiometric conservation law

For each reaction we should have $\sum_i b_i \gamma_{\rho i} = 0$

$$-b_S + b_I = 0 \to b_S = b_I$$

$$-b_I + b_R = 0 \to b_I = b_R$$

$$b_S = b_I = b_R = 1$$

Conservation law is

$$b_S S + b_I I + b_R R = S + I + R = const.$$

$$S + I + R = 1$$

How to use this conservation law?

We have

$$\frac{dS}{dt} = -aSI$$

$$\frac{dI}{dt} = aSI - bI$$

$$\frac{dR}{dt} = bI$$

$$S + I + R = 1$$

Let us remove R:

$$R = 1 - S - I$$

$$\frac{dS}{dt} = -aSI$$

$$\frac{dI}{dt} = aSI - bI$$

For Finding S (Task 2);

We have $P(t) = I(t) + R(t)$

We need to find $S(t) = 1 - P(t)$

- For Brazil wave 1:

$$\ln P \in [-13.5, -9.5]$$

$$P \in [0.999998629, 0.99992515]$$

- For Brazil wave 2:

$$\ln P \in [-2.25, -2.03]$$
$$P \in [0.894600775, 0.86866448]$$

- For Japan wave 1

$$\ln P \in [-13.11, -9.36]$$
$$P \in [0.999997975, 0.86866448]$$

- For Japan wave 2

$$\ln P \in [-3.88, -3.03]$$
$$P \in [0.979349175, 0.95168436]$$

- For Nigeria wave 1

$$\ln P \in [-13.42, -9.78]$$
$$P \in [0.999998515, 0.99994343]$$

- For Nigeria wave 2

$$\ln P \in [-7.99, -7.30]$$
$$P \in [0.999661166, 0.99932446]$$

➔ The value of exponent r by linear regression for the normalised cumulative data (logP ≈ c+rt) is same as what we did in last time.

Task 3:

The parameters of SIR model are defined above.

a) When S is close to 1, the When exponent is r ≈ a−b, according to the SIR model.

We estimated f, r from $\ln\left(P(t)\right) = f + rt$

For small time we have $S(t) \approx 1; I(t) \approx 0; R(t) \approx 0$

$$P(t) = I(t) + R(t) \approx I(t)$$

$$\frac{dP(t)}{dt} \approx \frac{dI}{dt} = aSI - bI \approx aI - bI = (a-b)I$$

$$\frac{dI}{dt} = (a-b)I$$

$$\frac{1}{I}dI = (a-b)dt$$

$$\ln I = (a-b)t$$

Finally:

$$f + rt = \ln P(t) \approx \ln I(t) = (a-b)t$$

This means

$$f + rt = (a-b)t$$

This means that at the beginning we can use $r = a - b$

Hence it is proved

b and c)

Now we are taking b = 0.1 (time is measured in days; b = 1/τ, where τ is, approximately, the time of virus spreading by an infected person; we take here τ ≈ 10 days).

Thus, we know b = 0.1 and a = r +b.

Country		a	b	r
Brazil	Wave 1	0.1516474	0.1	0.0516474
	Wave 2	0.11766281	0.1	0.01766281
Japan	Wave 1	0.163772	0.1	0.063772
	Wave 2	0.124587	0.1	0.024587
Nigeria	Wave 1	0.13776849	0.1	0.03776849
	Wave 2	0.104216979	0.1	0.004216979

Task 4:

We can calculate the initial values ($S(0), I(0), R(0)$) using these equations.

$$I(0) + R(0) = P(0)$$

$$S(0) = 1 - P(0)$$

From assumption of belonging to infector for 10 days we can conclude that

$$R(0) = P(-10).$$

$$I(0) = P(0) - P(-10)$$

Country		$S(0)$	$I(0)$	$R(0)$
Brazil	Wave 1	0.99999894	1.08×10^{-6}	6.02×10^{-8}
	Wave 2	0.998872	0.025435	0.024307
Japan	Wave 1	0.9999973	2.02×10^{-6}	7.40×10^{-7}
	Wave 2	0.99355	0.00330	0.00315
Nigeria	Wave 1	0.99999856	1.16×10^{-6}	4.45×10^{-7}
	Wave 2	0.99947	0.00027	0.00026

We have taken $I(0)$ on 254th cumulative case. Then for getting $R(0)$, we have assuming normalised data of cumulative cases before 10 days.

Now we are taking different values for $I(0)$. And according finding the values of $S(0)$ and $R(0)$.

Country		$S(0)$	$I(0)$	$R(0)$
Brazil	Day 120	0.98377981	0.0089198	0.00730039
	Day 400	0.87275011	0.06500926	0.06224063
	Day 900	0.68165646	0.15950698	0.15883656
Japan	Day 120	0.99971164	0.00014711	0.00014125
	Day 400	0.99245039	0.00386432	0.00368529
	Day 935	0.67356167	0.16594146	0.16049687
Nigeria	Day 120	0.99961268	0.00020388	0.00018344
	Day 400	0.99848272	0.00075947	0.00075781
	Day 898	0.99757056	0.001216	0.00121344

As it is evident from the table that, the rate of infectors increases with decrease in the rate of susceptible while the days move on.

While comparing the data, in initial days Brazil shows high infection rate but in final days Japan rate of infection exponentially increased. Whereas we can see in Nigeria that the total number of susceptibilities is almost constant. There are so many factors behind this trend, that are Government pre-caution action, geographical location, population distribution, ecology of human habitation, social contacts, covid-19 testing, immunity, genetics, broader socio-cultural dynamics.

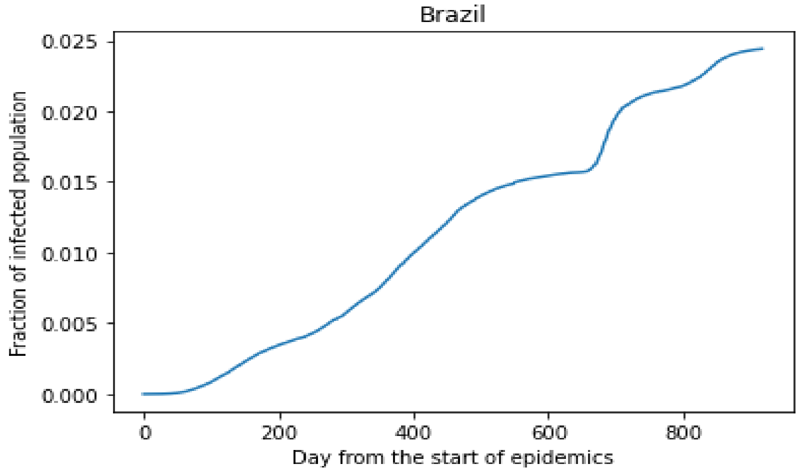
<u>Task 5</u>:

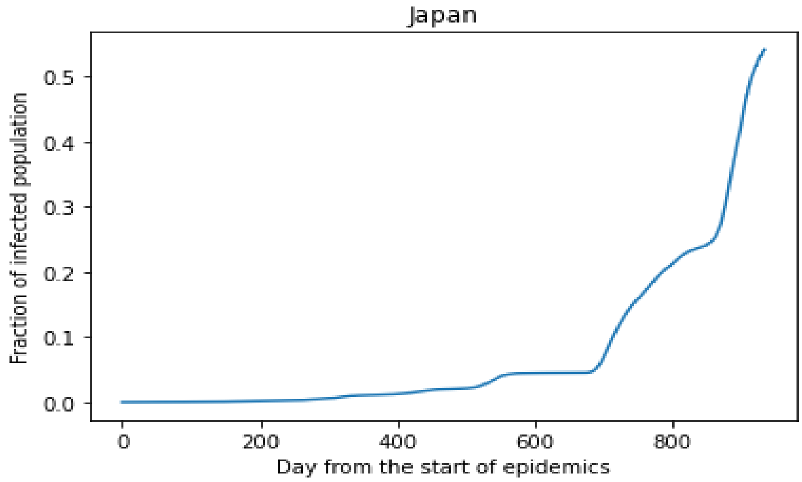
In here we are taking one random day in initial days, in mid days and in final days for each country for getting the SIR values.

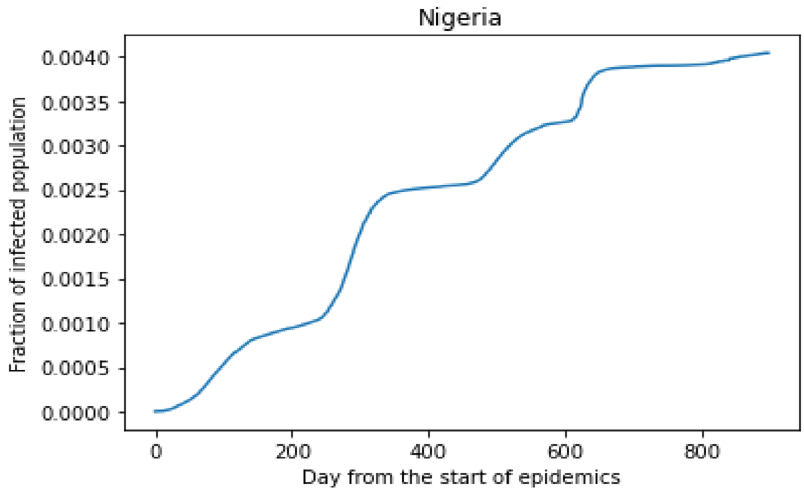
Country		S	I	R
Brazil	Initial Days	0.98377981	0.0089198	0.00730039
	Mid Days	0.87275011	0.06500926	0.06224063
	Final Days	0.68165646	0.15950698	0.15883656
Japan	Initial Days	0.99971164	0.00014711	0.00014125
	Mid Days	0.99245039	0.00386432	0.00368529
	Final Days	0.67356167	0.16594146	0.16049687
Nigeria	Initial Days	0.99961268	0.00020388	0.00018344
	Mid Days	0.99848272	0.00075947	0.00075781
	Final Days	0.99757056	0.001216	0.00121344

From the given table, we can see that the fraction of susceptible for Japan and Nigeria for initial and mid days are constant (no change) that is, the rate of infector is less compared to Brazil. There saw a drastic increase in the number of covid-19 cases in Brazil during themed and final days. Whereas, we can see Japan Skyrocketed in the final days, stating that a huge outbreak has taken place. While the number of susceptible remained unchanged in Nigeria for the all period with a smaller number of infective due to Government pre-caution action, geographical location, population distribution, ecology of human habitation, social contacts, covid-19 testing, immunity, genetics, broader socio-cultural dynamics. In conclusion, we can state that Japan reported the highest amount of covid-19 cases in the final days followed by Brazil and Nigeria respectively.

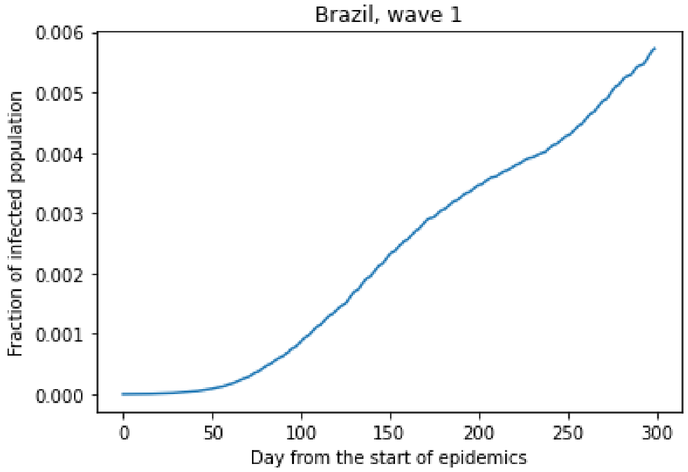
NORMALISED DATA: BRAZIL, NIGERIA AND JAPAN



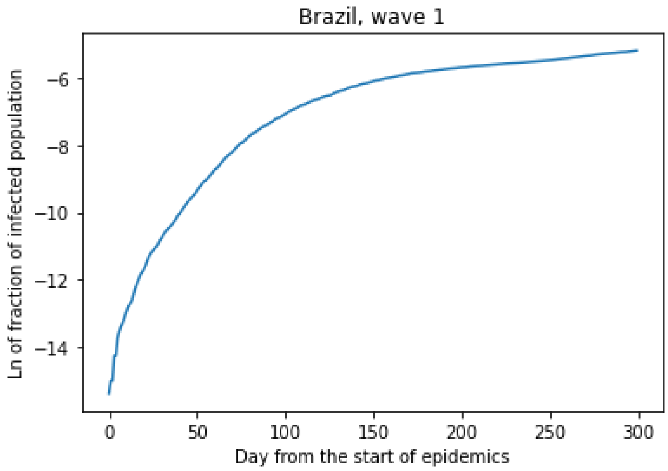




BRAZIL

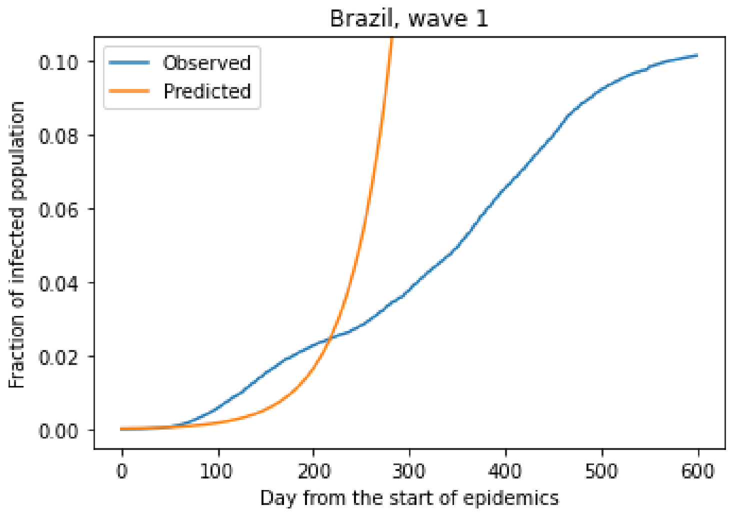


Wave 1 Normalised Data



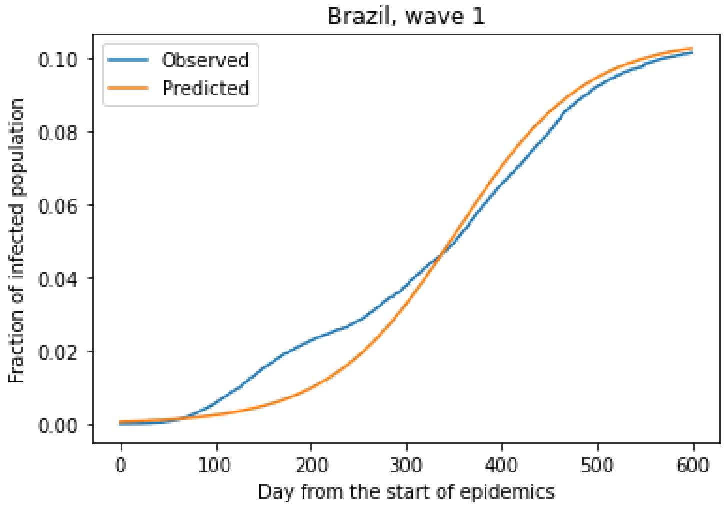
Ln Wave 1

The logarithmic graph shows better explosion of cases for Brazil population for the first 100 days. The impact of first wave we can see till first 180 days.



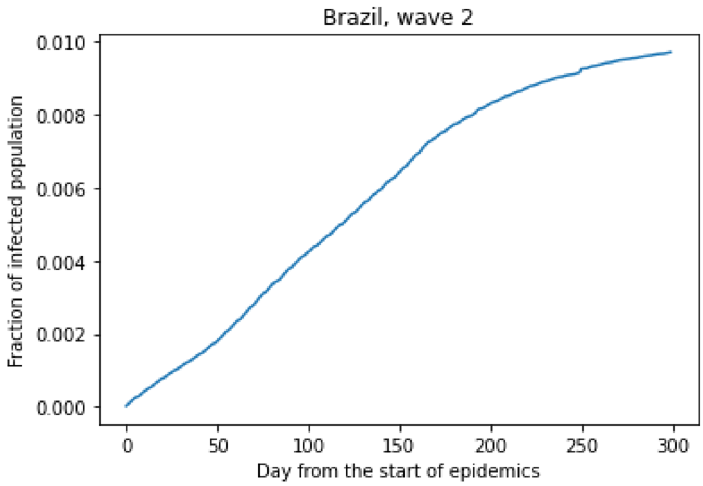
Exponential Model Wave1

As we can see the predicted wave is not inclined with the observation, we got for the first wave of Brazil.

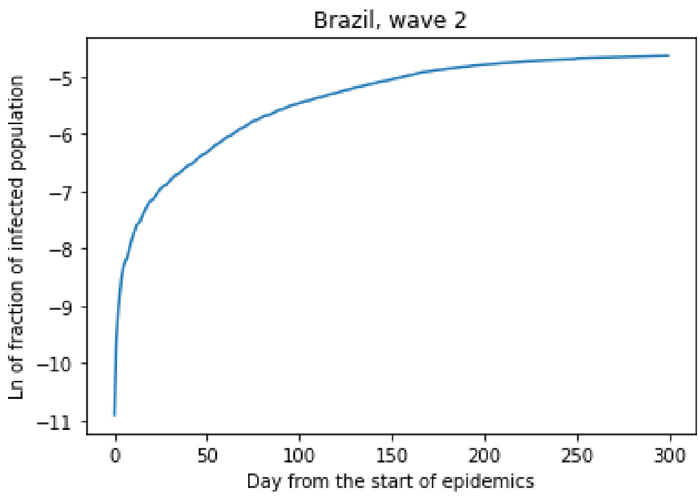


Logistic Model Wave 1

Here we can see the model is much better and prediction is much better. For the first 500 days of Brazil almost 10 % is affected which is why we can see explosion of cases for the first 100 days. As more and more people were getting vaccinated, we can see people getting the immunity to face second wave.

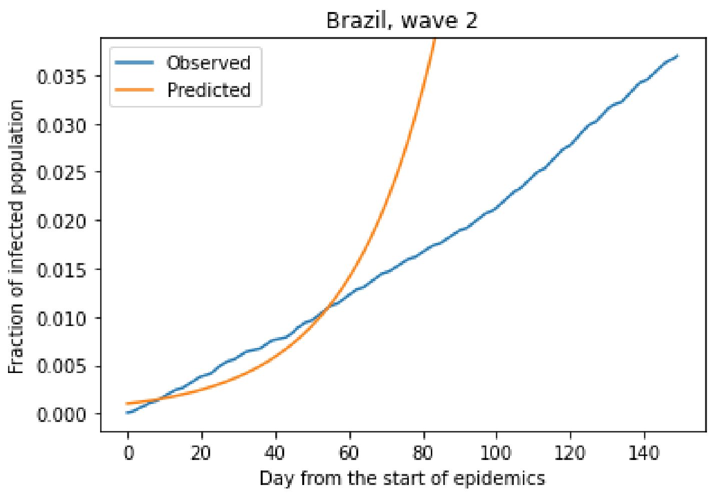


Normalised Data Wave 2



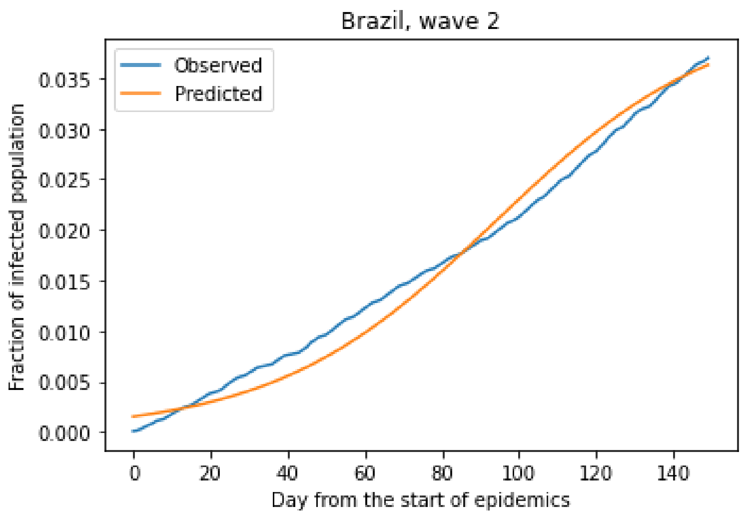
Ln wave 2

Brazil wave2 impact can be seen from 250th day till 450th day from the beginning of the pandemic.



Exponential Model wave 2

The prediction made are not looking good, inclination can be seen for first 60 days from the beginning of the second wave but after that model is not understandable.

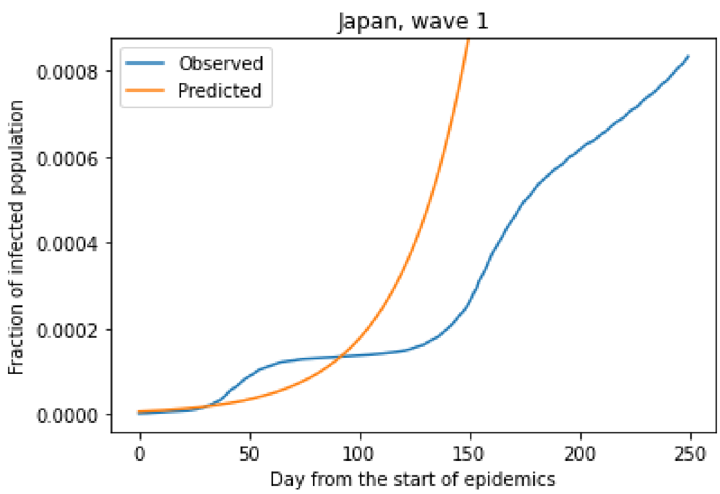


Logistic Model Wave 2

Brazil second wave model is much more informative as prediction made is inclined with what we observed. Although Brazil second wave did not bring much cases as majority of population was affected in the first wave and after vaccination there were less infected/deaths in second wave.

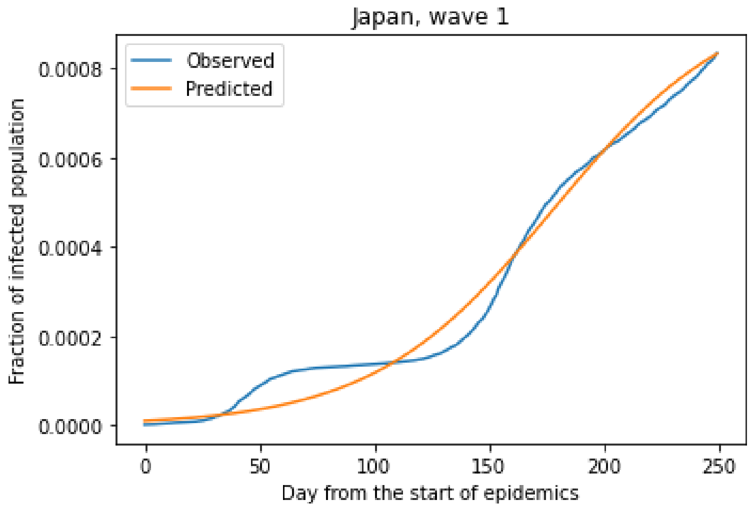
<u>Japan</u>

Ln wave1



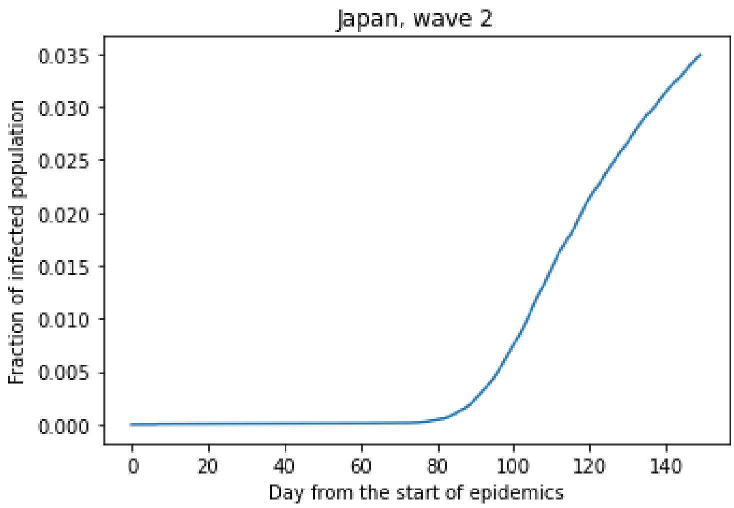
Exponential Model wave 1

Predicted made for the first wave of japan is not looking good also because of immediate action made by Japan's government results in good control of infected/deaths. Which provide some challenges to predict both the waves for Japan as mentioned in previous chapter.

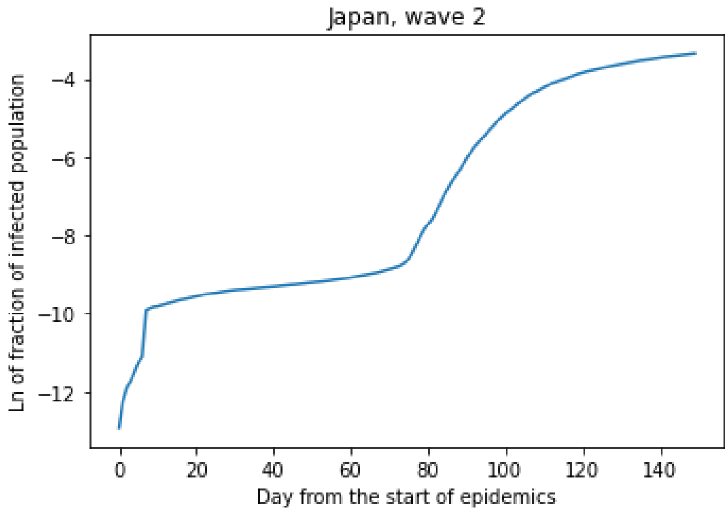


Logistic Model wave 1

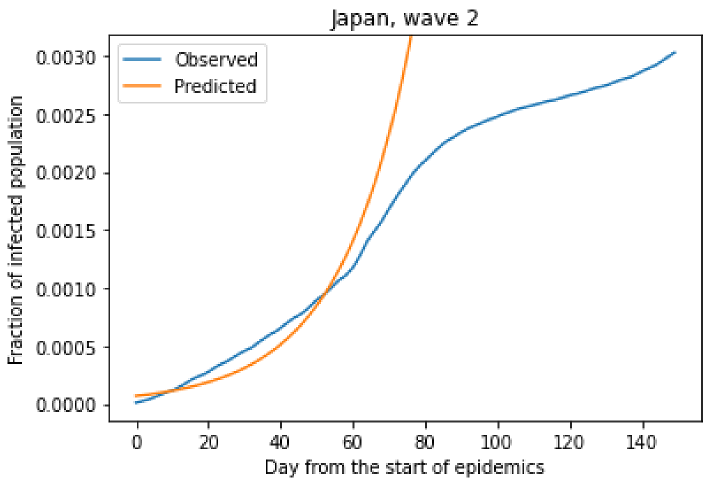
The predicted wave is less inclined for the initial 60 days from the beginning of the pandemic because a fluctuation is cases can be seen during this period using Ln graph. Which divides this into two fragments 0-60(Logistic Growth) and 60-120(Saturation zone). Because impact was observed between April to May.



Normalised wave 2

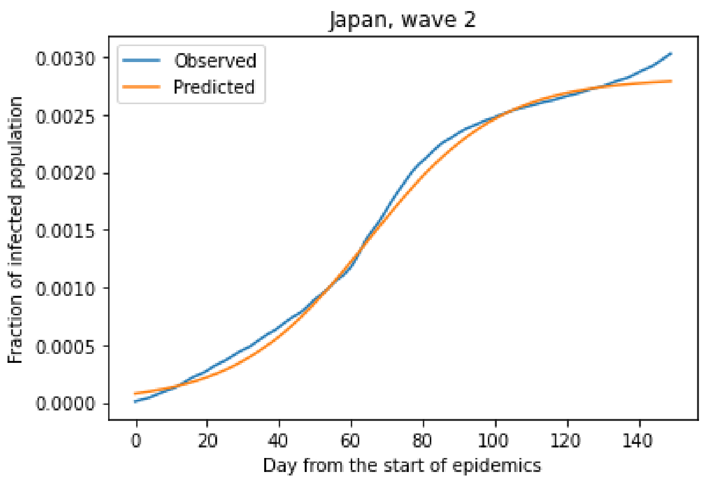


Ln wave 2



Exponential Model wave 2

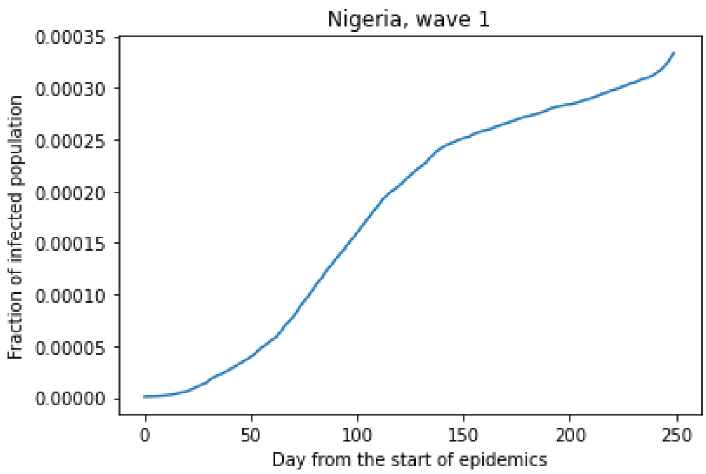
The predict model is less understandable as predicted wave does not match with what we actually observed. After first 120 days from the beginning of the second wave impact can be observed for 80 days (120-200) for Japan population.



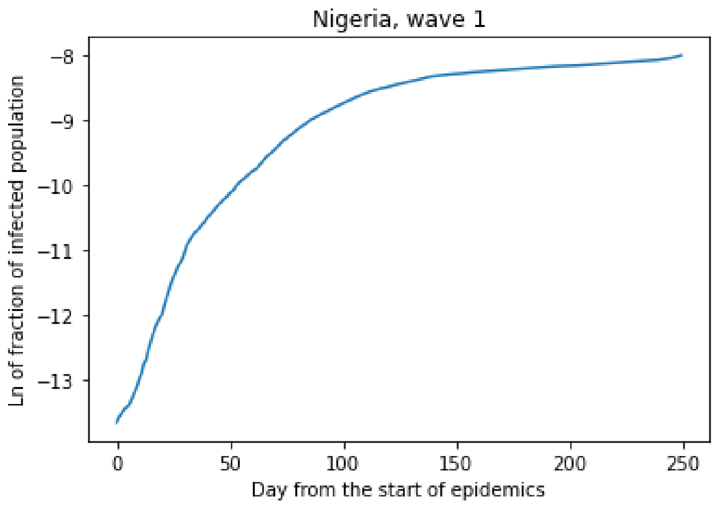
Logistic Model Wave 2

The predicted model for Japan second wave from the beginning of the pandemic is more informative and predicted results look more readable. As per Logarithmic graph for Japan we can see multiple hikes in cases and immediate control of infected/deaths. As mentioned before this because less fraction of Japan population was affected in the first wave which is why when second wave impacted increase of infected/deaths can be seen not only for initial waves of Japan but throughout. As less people get infected less people recovered with immunity to face covid-19.

NIGERIA

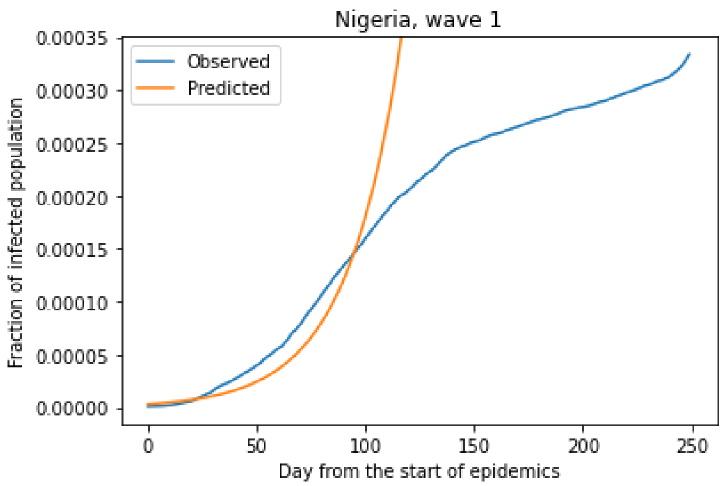


Normalised wave 1

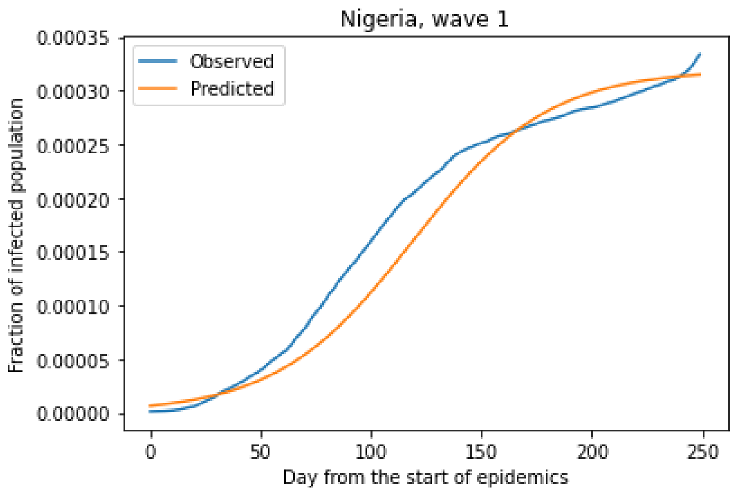


Ln wave 1

Logarithmic graph for Nigeria first wave 0-120 days from the beginning of the pandemic. We can see for the first wave explosion of cases from 0-40 days from the beginning of the pandemic. And from 40-120 days a slow growth can be seen because of imposed lockdown. This result in more people getting recovered and received vaccination as vaccination started from 5th of March in Nigeria.

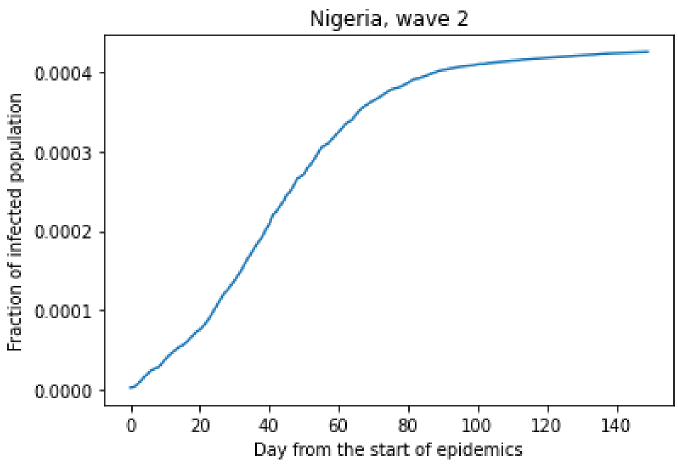


Exponential Model wave 1

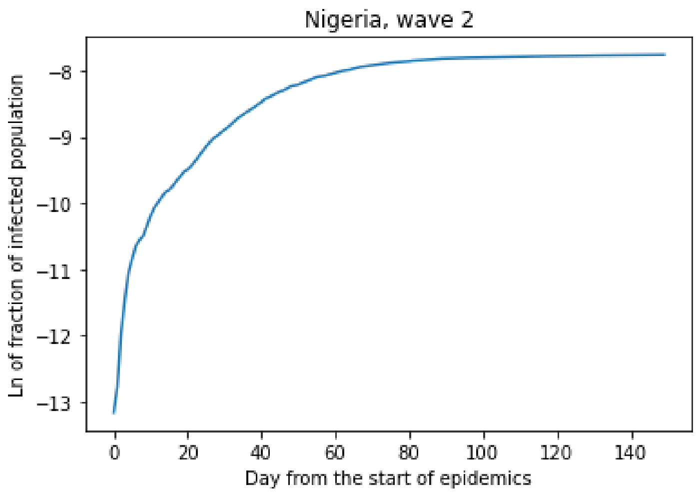


Logistic Model wave 1

Predicted model for the first wave of Nigeria from the beginning of the pandemic intercepts the observed wave in the end. Similarity can be seen when comparing the logarithmic graph for Nigeria and Brazil for both the countries immediate hike in cases can be seen for the first 120 days from the beginning of the pandemic.

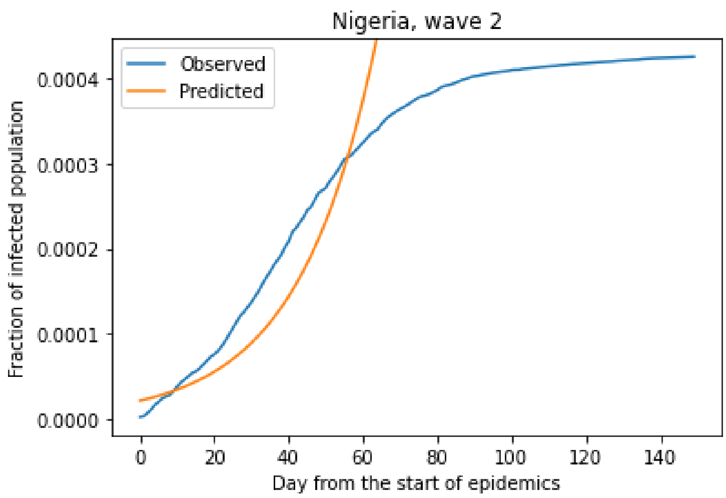


Normalised wave 2

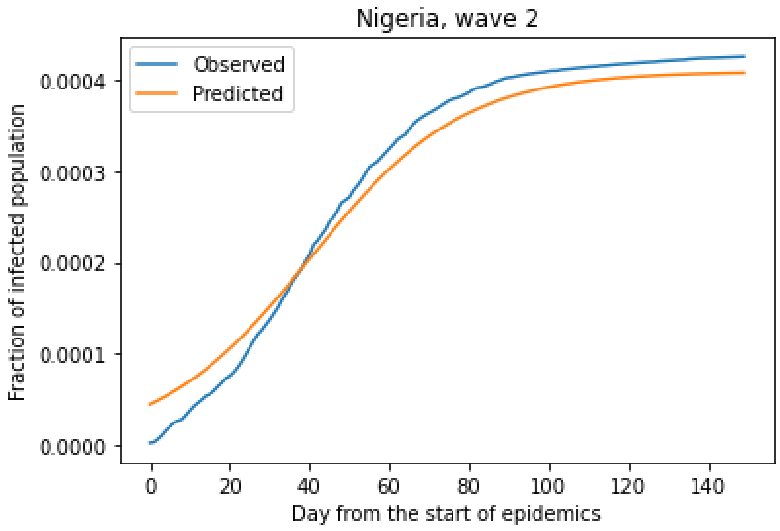


Ln wave 2

The second wave for Nigeria from the beginning of the pandemic started on 250th day from the start and the impact can be seen till 50 days 300th day from the start. Less population was infected as per given data also poor record keeping cause lack of specific numbers of infected/deaths.



Exponential Model wave 2



Logistic Model wave 2

After second wave (300 days from the beginning of the pandemic) till the final stages in Nigeria less impact can be seen as more and more people get vaccinated but also recovered from covid-19.

Task 6

SIR MODEL TABLE

Country		$S(0)$	$I(0)$	$R(0)$
Brazil	Day 120	0.98377981	0.0089198	0.00730039
	Day 400	0.87275011	0.06500926	0.06224063
	Day 900	0.68165646	0.15950698	0.15883656
Japan	Day 120	0.99971164	0.00014711	0.00014125
	Day 400	0.99245039	0.00386432	0.00368529
	Day 935	0.67356167	0.16594146	0.16049687
Nigeria	Day 120	0.99961268	0.00020388	0.00018344
	Day 400	0.99848272	0.00075947	0.00075781
	Day 898	0.99757056	0.001216	0.00121344

While comparing the data with the SIR model, it is depicted that the states Susceptible, Infector and Recovered are co related.

$$S \rightarrow I \rightarrow R$$

Also,

$$\frac{dS}{dt} = -aSI$$

$$\frac{dI}{dt} = aSI - bI$$

Advantage of SIR Model

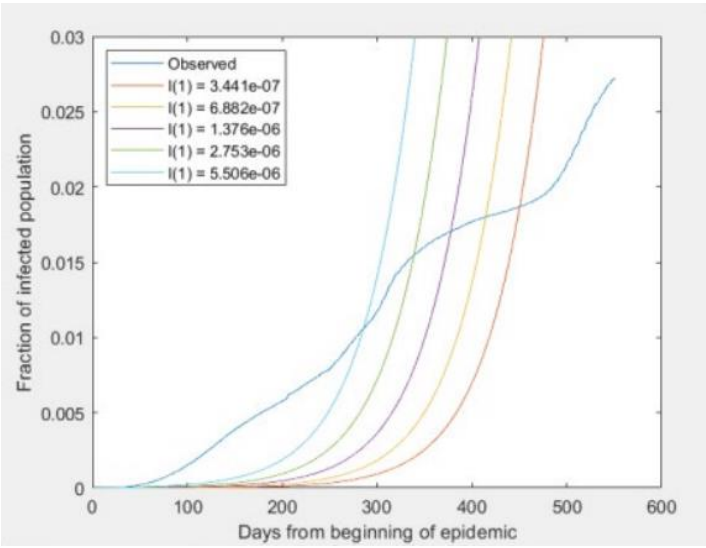
- From the table it is evident that, we can find the rate of susceptible using the function.

$$S(0) = 1 - I(0) - R(0)$$

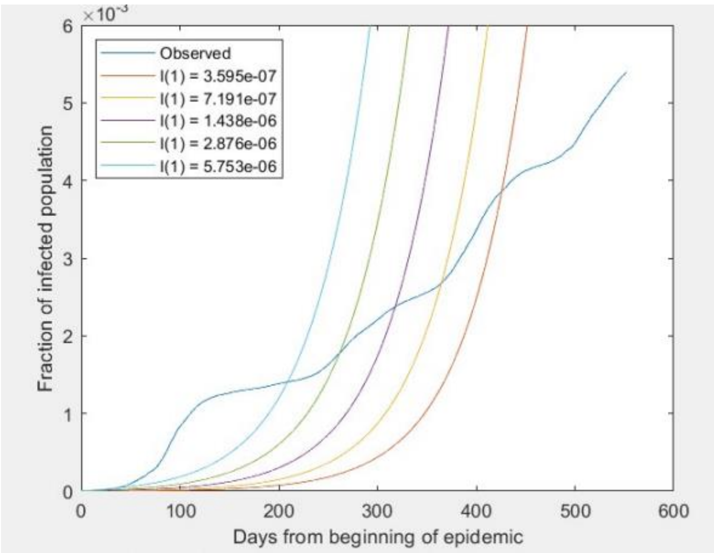
- Similarly, it is used to find the rate of change of parameters S, I, R
- The model is easy to use and plot the data.
- We can find the optimal value of coefficients; with which we are able to predict the growth rate of the pandemic

Disadvantage of SIR Model

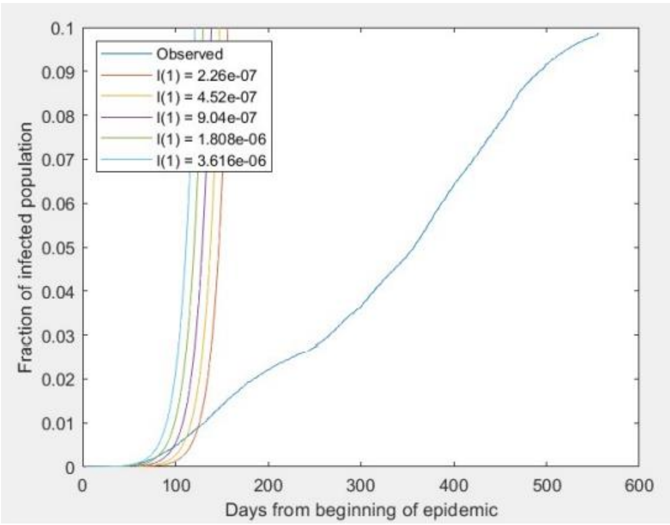
- The assumptions that we are take cannot be accurate as the data keeps changing with respect to time.
- We need to add some more parameters in order to improve the efficiency of the model.
- We are unable to find the exact optimal value of the coefficients because there are some other factors which governs the model that is missing in the data leading to slight irregularities with the predictive model graphs.



Japan



Nigeria



Brazil

<u>Task 7</u>:

For getting Improved SIR model (ISIR model), we are dividing total population into seven compartments: susceptible individuals in the free environment (S), undiagnosed and non-isolated infectious individuals (I), recovered individuals (R), death individuals (D), free Exposed (E), Confirmed and isolated infectious individuals (Q), and Patients with suspected (P). The transfer relationships between compartments are shown.

CHAPTER:3

The dynamics of epidemics depend on how people's behaviour changes during an outbreak. At the beginning of the epidemic, people do not know about the virus, then, after the outbreak of epidemics and alarm, they begin to comply with the restrictions and the spreading of epidemics may decline. Over time, some people get tired/frustrated by the restrictions and stop following them (exhaustion), especially if the number of new cases drops down. After resting for a while, they can follow the restrictions again. But during this pause, the second wave can come and become even stronger than the first one. Studies based on SIR models do not predict the observed quick exit from the first wave of epidemics.

The States here are:

1. S - Susceptible
2. I - Infected/infector
3. R - Removed (recovered or dead)

System of transitions:

- We have seen globally this pattern: $S \rightarrow I \rightarrow R$
- Constant Population Size: $S+ I +R = N =$ const.
- Dimensionless Variables: $\{S, I, R\} = \{S N, I N, R N\}$
- $S+I +R = 1$

In the epidemic, a person will be infected when if he/she comes in contact with an infected person ($S \rightarrow I$). S and I. Also, the intensity of transition is $S \rightarrow I$ is aI (Infected) and the flux $S \rightarrow I$ is aSI, $a =$ const.

Assuming as per the instructions that the intensity of recovering (or death) is constant (b) and, therefore, the flux $I \rightarrow R$ is bI.

General adaptation syndrome (GAS) describes the process your body goes through when you are exposed to any kind of stress, positive or negative. It has three stages: alarm, resistance, and exhaustion.

GAS consists of three phases:

1. *Alarm*

2. *Resistance*

3. *Exhaustion* phase

To simulate the population dynamics within the conditions of aggressive COVID-19 spreading, the susceptible group of persons can be divided into three subgroups of individuals according to their behaviour modes. The models of behaviour in which people are seen as behaving in different ways at different times and in different contexts are widely used in the game theory and analysis of economic and social behaviour. According to the concept of GAS and stress, we consider three modes:

(i) ignorant mode (persons living without any restrictions as it was before the pandemic)
(ii) resistance mode (conscious persons practising the social distancing rules to avoid the appeared danger)
(iii) exhaustion mode (the depletion of the person's resources leading to the reduction of following social distancing rules)

Let’s imagine that there are four types of human behaviour and four subpopulations in S, and they are

1. Sign – “Ignorant people that do not know anything worrying about the epidemic

2. Sal – people in the “Alarm phase”

3. Sres – people in a “Resistance” state, with very rational and safe behaviour

4. Sexh –people in an “Exhaustion” state. They are Cred of the epidemic, behave unsafely and do not react to alarm stimuli.

And here S = Sign +Sal +Sres +Sexh

Initially, S (0) = Sign (0) and all other components have zero population Sal (0) = Sres (0) = Sexh (0) = 0 In order to reduce the complexity of the previous equation. Removing the alarm phase and fixing it in others. So, the new equation is

S = Sign +Sres +Sexh

Stress level with respect to time:

The observation we made during the initial stages of COVID -19 in the behaviour of people was mostly ignorant and the people were not expecting this level of change in their daily life. The majority of the crowd took no precautions which show indiscipline.

As per observation during the second wave, people were more attentive towards the effect of COVID-19. This time people were maintaining social distancing wearing proper masks and using sanitisers to keep them safe. This change in behaviour cause a big change in the COVID cases which can be seen in our study.

During the third wave, people can be seen again ignorantly dealing with and not being cautious toward themselves. This is due to the majority of people being vaccinated and having built an immunity to fight COVID-19. People are now doing social gatherings and celebrating events and stopped wearing masks.

Transitions Sign → Sres → Sexh → Sign

Sign +I → 2I; I → R

Sign +I → Sres +I; Sres → Sexh; Sexh → Sign

Reactions	Reaction rate	Stoichiometric vector
$S_{ign} + I \rightarrow 2I$	$r1 = aSignI$	$(-1, 0, 0, 1, 0)^T$
$Sign + I \rightarrow Sres + I$	$r2 = k2SignI$	$(-1, 1, 0, 0, 0)^T$
$Sres \rightarrow Sexh$	$r3 = k3Sres$	$(0, -1, 1, 0, 0)^T$
$S_{exh} + I \rightarrow 2I$	$r4 = aSexhI$	$(0, 0, -1, 1, 0)^T$
$I \rightarrow R$	$r_5 = bI$	$(0, 0, 0, -1, 1)^T$
$Sexh \rightarrow Sign$	$r6 = k6Sexh$	$(1, 0, -1, 0, 0)^T$
$Sign + 2I \rightarrow Sres + 2I$	$r2' = qSignI2$	$(-1, 1, 0, 0, 0)^T$

• When the Reaction rate constant for Sres → Sexh is 1/50 (a8er 50 days in "Resistance" state people become *red)

Then value of

$$\frac{dS_{ign}}{dt}, \frac{dS_{res}}{dt}, \frac{dS_{exh}}{dt}$$

values will be changed. And now it depends on this value 1/50 which is equal to 0.02

• When the Reaction rate constant for Sexh → Sign is 1/100 (After 100 days in "Exhaustion" state people again behaving like "Ignorant" and become sensitive to the alarming signals)

Then this change will eventually affect our ignorant rate because it will become higher and higher in this scenario.

It also effects the dI/dt, because now the exhaustion rate is changing.

• When the Reaction rate constant for Sign + I → Sres + I is 1

• Therefore We have taken in consideration the following assumptions. k2=0.02 k3=1 k6=0.01

(The transition rate is the product kSignl; we assume that if the proportion of I is close to 1 then ignorant people modify their behaviour to resistant with characteristic time 1 day)

Here we can clearly judge that Sign → Sres previously but now when the behaviour of people changes this value also changes. Ideally, I=1 in this scenario.

• We have used the parameter of a and b which were obtained in task 2 for convenience

As guided, we have used cumulative cases in the last 2 coursework and in this course as well to demonstrate and analyse the effects of COVID-19. And it's not just COVID-19 cumulative cases we have taken into account also we have studied the behaviour of that region. How the rate of infected people is affected because of susceptibility issues and not following proper guidelines for COVID-19 such as wearing masks in public, avoiding social gatherings, etc.

After integrating equations numerically from the initial data in chapter 2nd we got different patterns of results. We have built the comparison in Fraction of Infected people v/s Days from the beginning of the epidemic. Further predicted model between fractional cases and first 200 days.

If we investigate experimental data, we can see a lack of accuracy which means more precision is required in the model. The factors we are taking are ideal factors, but a few other things also played an important role in minimising the COVID-19 rate it's vaccination drives, social distancing, human immune system.

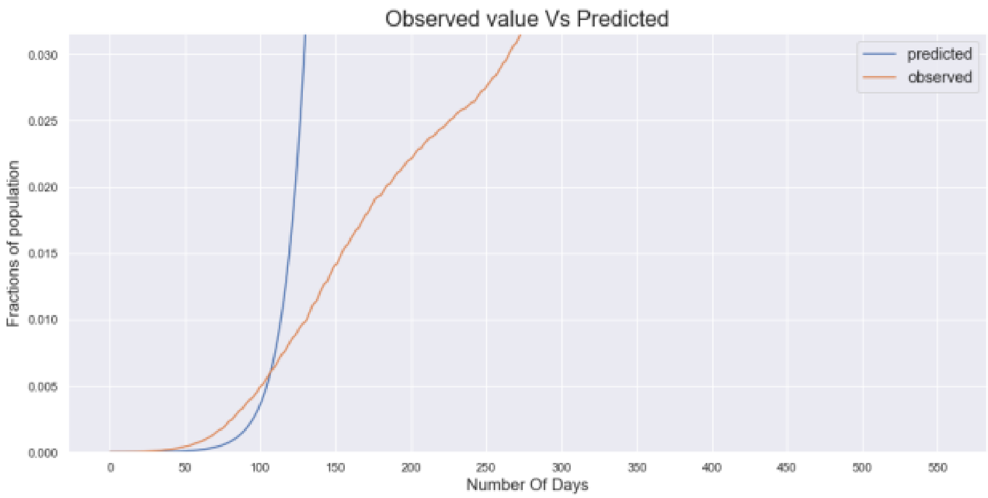
In the future event that we are required to create a Mathematical Model, we have to consider all these factors for more precision in our model and better accuracy in our predictions.

Brazil

k2=0.02 k3=1 k6=0.01

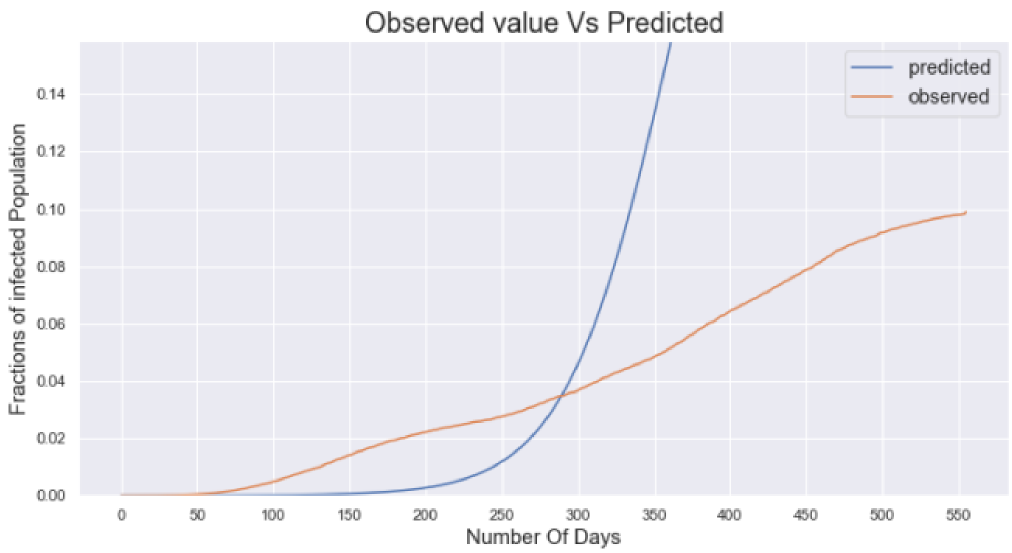
The following graphs are for the 2 different intervals for Brazil. The graphs below are for intervals 1-105. We can see that graph is matching up to 100 days.

Observed vs Predicted



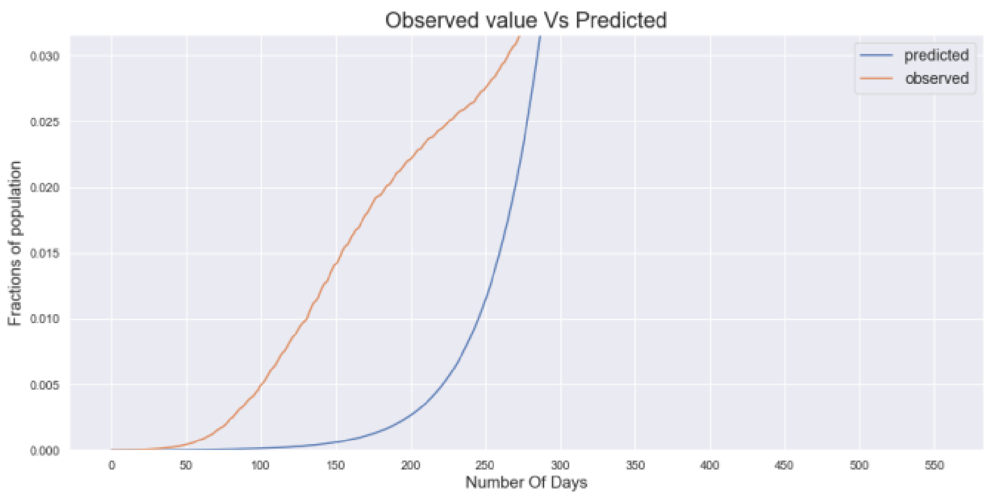
We also tried plotting the predicted vs observed graph using the optimized initial condition and with the above-mentioned reaction rates. Our prediction is increasing exponentially after 200 days, and we can see that observed increases gradually. Our model doesn't fit accurately with these assumptions.

Observed vs Predicted

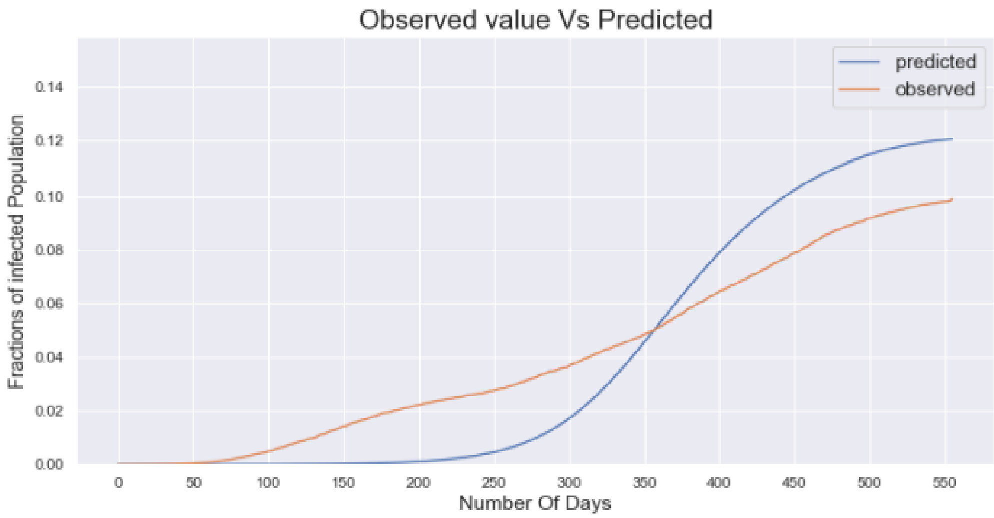


Now we have changed our reaction rates to k2, k3 and k6 as to get the best output. We increased the days after which people get tired of the resistance state to 200 days and we also changed k6 A8er 60 days in the “Exhaustion” state people return to the initial” Ignorant” state and become sensitive to the alarm signals.

Observed vs Predicted



We can observe our wave is better predicted after taking these changes into consideration, Brazil has been suffering very badly in covid and it is safe to say people were more careful after the first wave. And hence we’ve observed better predictor

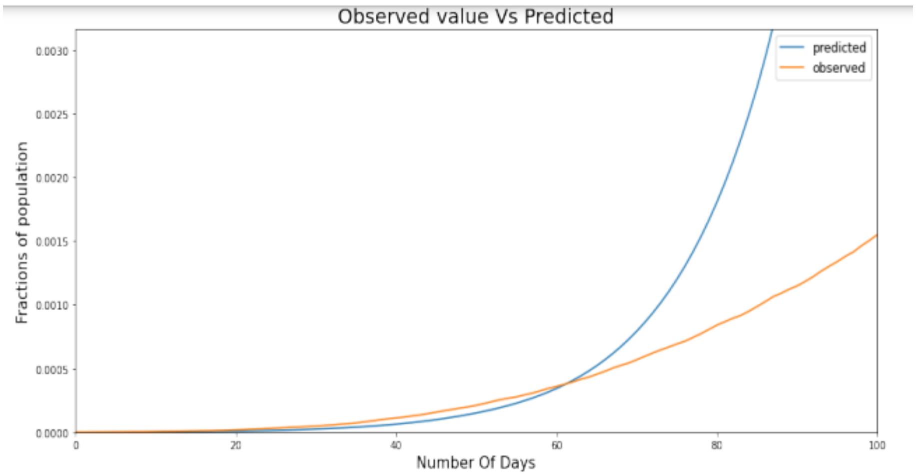


Japan

k2=0.02 k3=1 k6=0.01

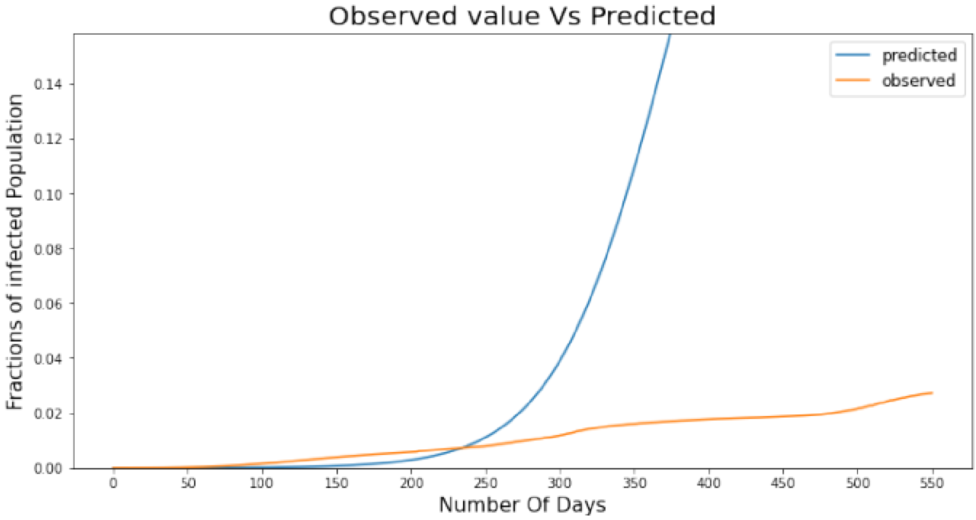
The following graphs are for the 2 different intervals The graphs below are for the interval 1-120. Our prediction is going in line with the observed value.

Observed vs Predicted



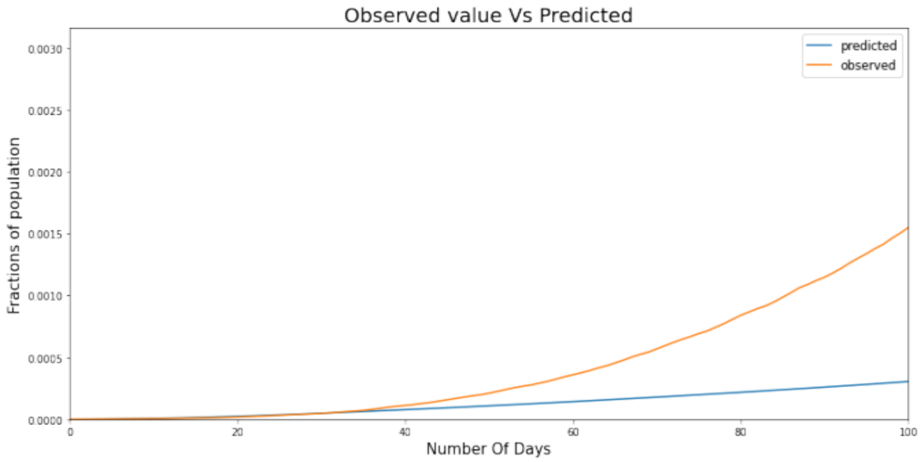
Now we have used the optimised value from task 2 and achieved the below graph but we can see that our predicted line is going off after 100 days from the beginning of the epidemic and we can assume this as we should consider different reaction rates for wave 2

Observed vs Predicted



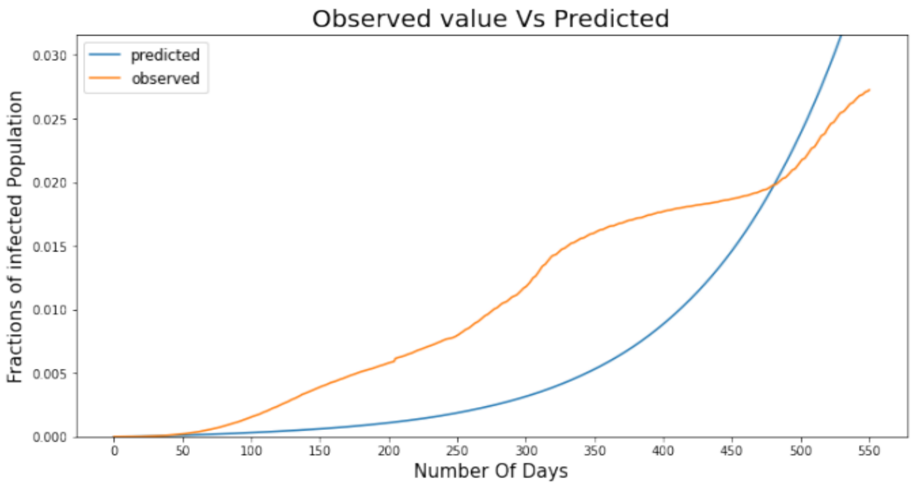
We tried changing the reaction coefficient and observed the below graphs. We have observed Our wave is increasing gradually and slowly compared to the observed wave. We have changed our k2 here.

Observed vs Predicted



After plotting the complete graph, we've observed our prediction crosses the observed wave at 200 days from the beginning of the second wave. I would like to consider other factors like vaccination rate and different variant as we've observed some variant is very infectious than other. At the beginning of covid, a person would take usually 14 days to show symptoms but later it would take 2-3 days to show symptoms as we saw during the second wave of COVID-19 new variant of the virus can be seen which is more damaging or effective So, we need to consider the changes and variations in viruses to achieve perfect predictions.

Observed vs Predicted

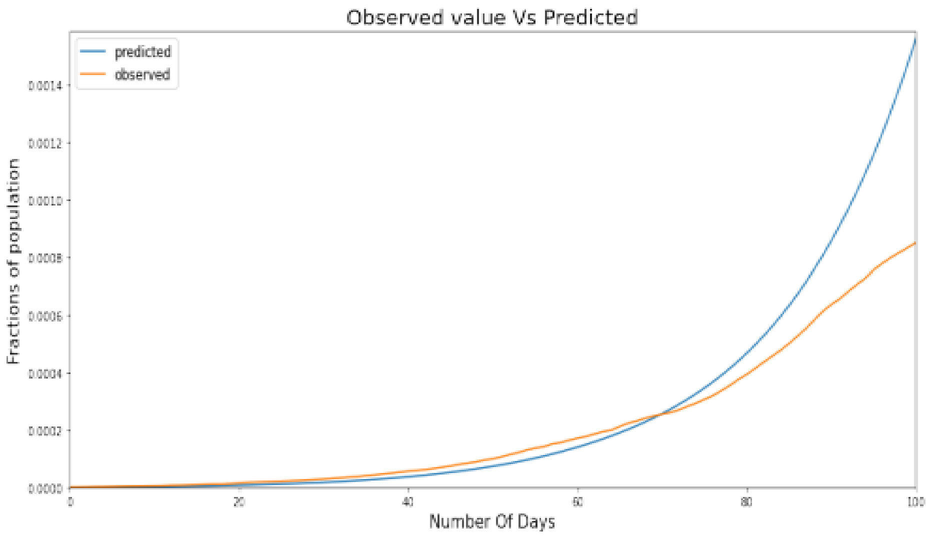


Nigeria

k2=0.02 k3=1 k6=0.01

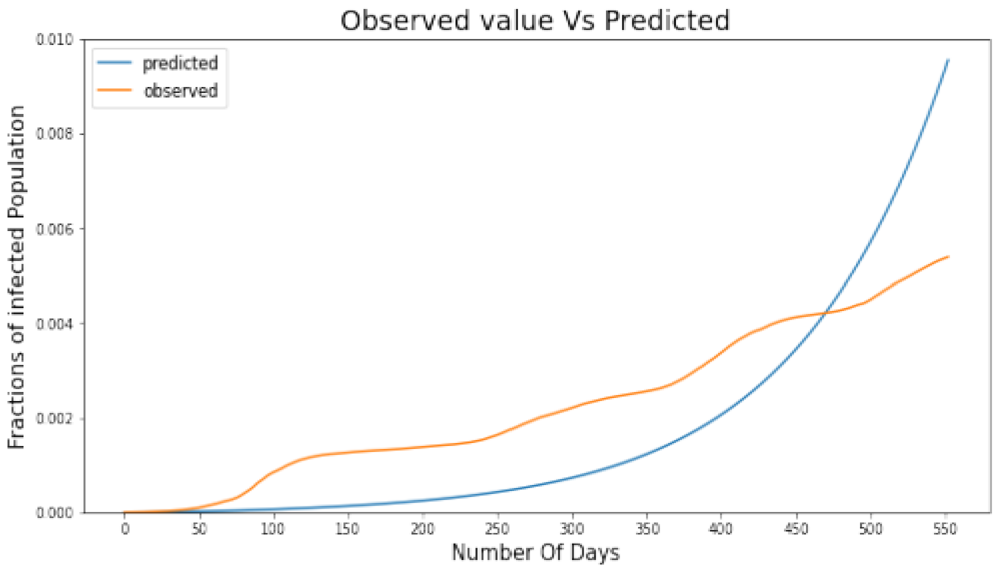
The following graphs are for the 2 different intervals The graphs below are for the interval 1-140. The prediction wave is increasing more than the observed wave after 100 days.

Observed vs Predicted



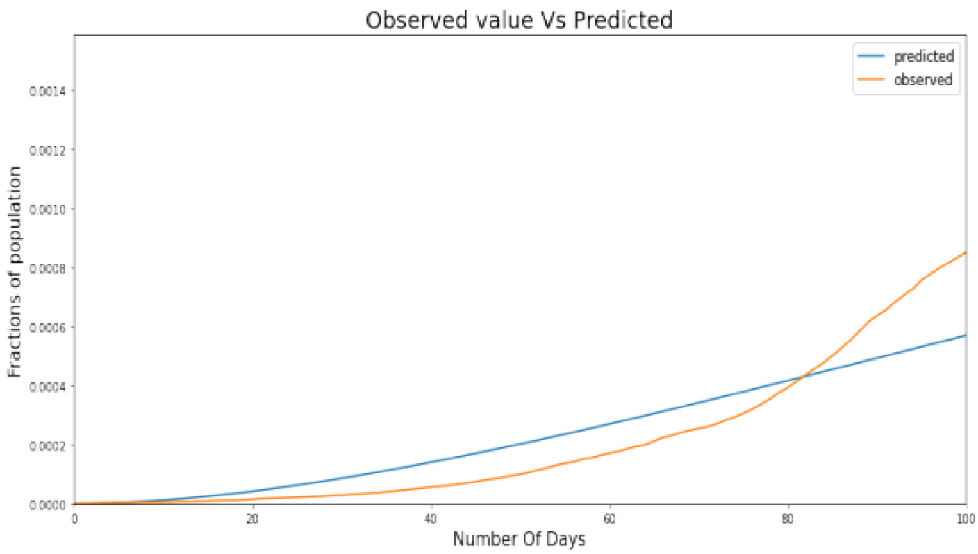
The following graphs are for the complete interval, and we've observed our prediction is not very good when we've considered the above assumption.

Observed vs Predicted



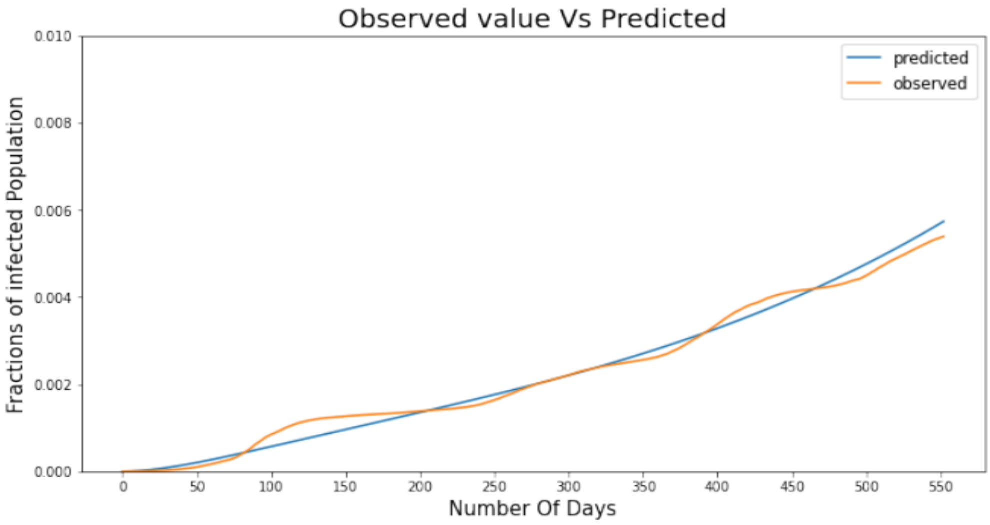
Now when we changed our k2, and k3 we've achieved the following graphs. For the same interval mentioned above.

Observed vs Predicted



After changing the hypothesis, we can say our prediction has been better, and also we can conclude in a country like Nigeria the reaction coefficient has been constant through and hence we've achieved a very good prediction. This is our conclusion from this graph.

Observed vs Predicted



<u>Crowd Effect:</u>

If we are assuming that the alarm is increasing super linearly then yes, the reaction form also changes and now it would be

Sign + 2I → Sres + 2I

And hence now the reaction rate becomes qSignI 2 (it's the combination of q, S ignorant I2)

Here q is the "new constant". If we want the calculate the value of q, then we pick a small proportion on of infected I. Another important thing here is that the reaction rate is as same as linear reaction.

Let's say here I = Ip = 0.02 (2% of population)

qSignI 2 p = kSignIq.

Then q = k/Ip

What is q ? For I=I_{panic} we have r_2 =r'$_2$.

$$I_P = 2\%$$

$$k_2 S_{ign} I_p = q S_{ign} I_p^2$$

$$k_2 = q I_p$$

Here Ip means visibility of epidemic and mainly depends on mass media.

If we modify all of this scenario with crowd effect, then we need to analyse it in more detail

Then we can see crowd effect changes the pattern of this equation from this equation

$$Sign + 2I \rightarrow Sres + 2I$$

To this equation

$$Sign + 3I \rightarrow Sres + 2I + Sexh$$

Then eventually the reaction rate becomes qSignI

And if we can imagine that I = Ip = 0.01 (1% of population)

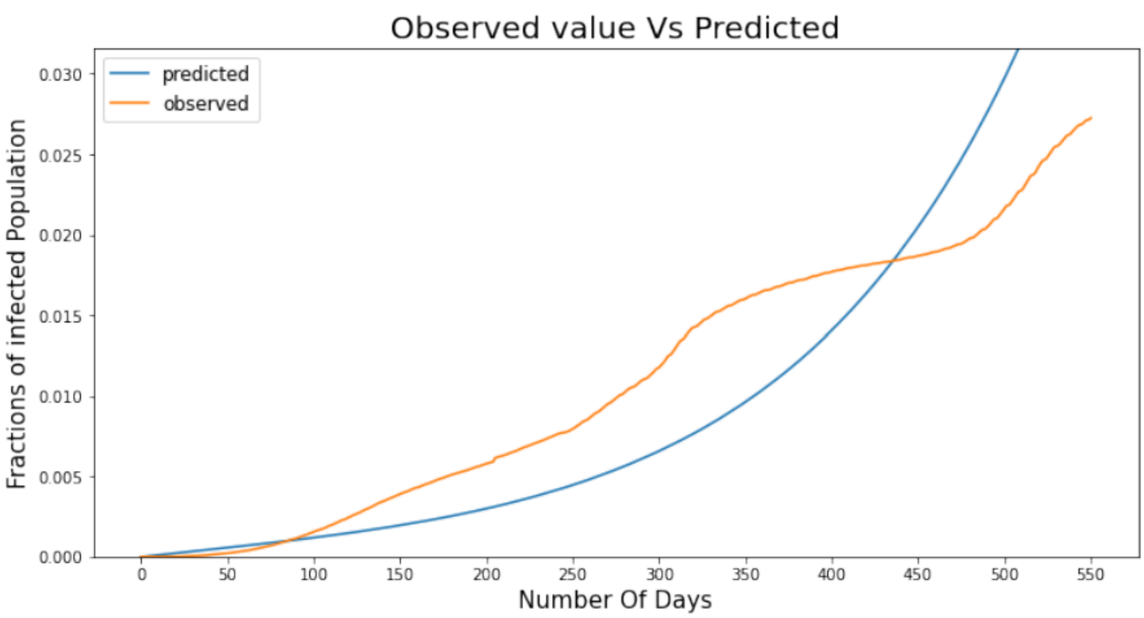
$$qSignI\ 2\ p = kSignI\ 3\ q.$$

Then q = 3k/2Ip

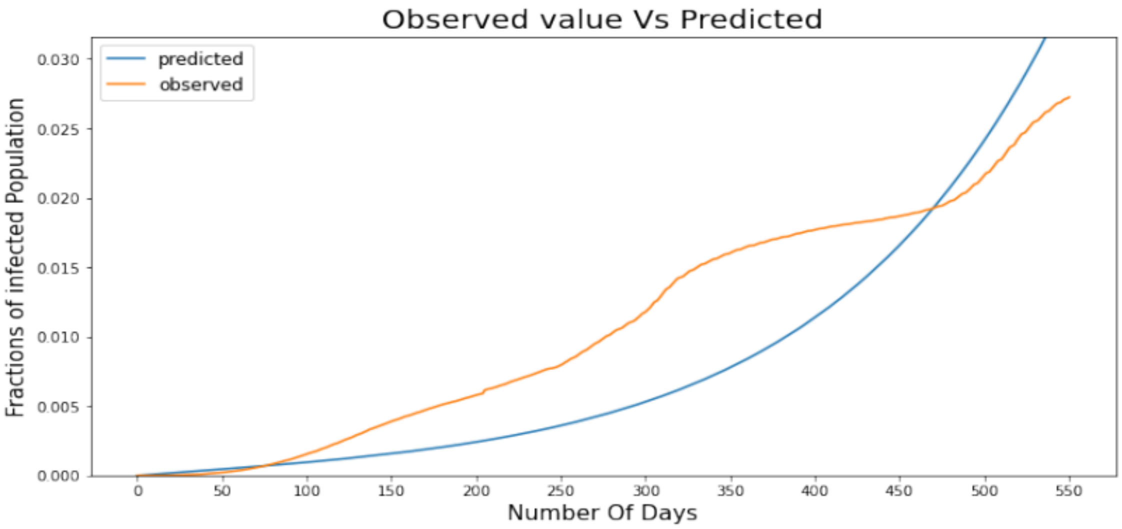
Here the q value predicted would give us better result according to crowd effect modelling.

Brazil

1) Graph of Brazil after applying the crowd effect method has improved our predictions.

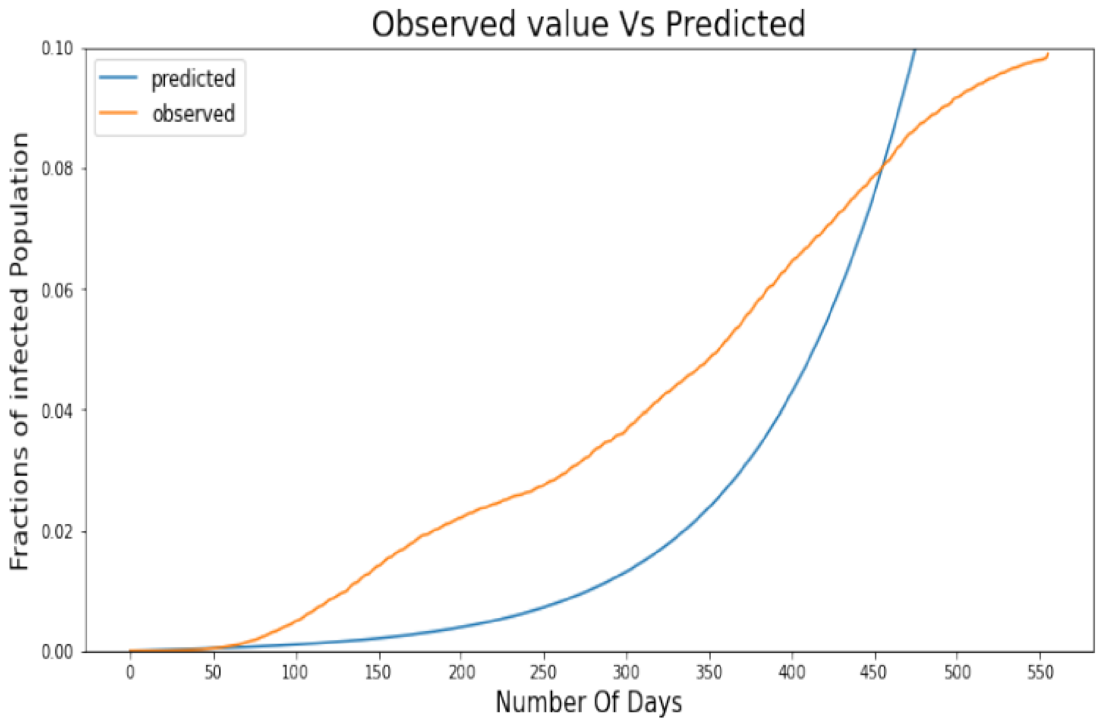


2) We used modified changes in reaction rates and obtained optimized graphs.

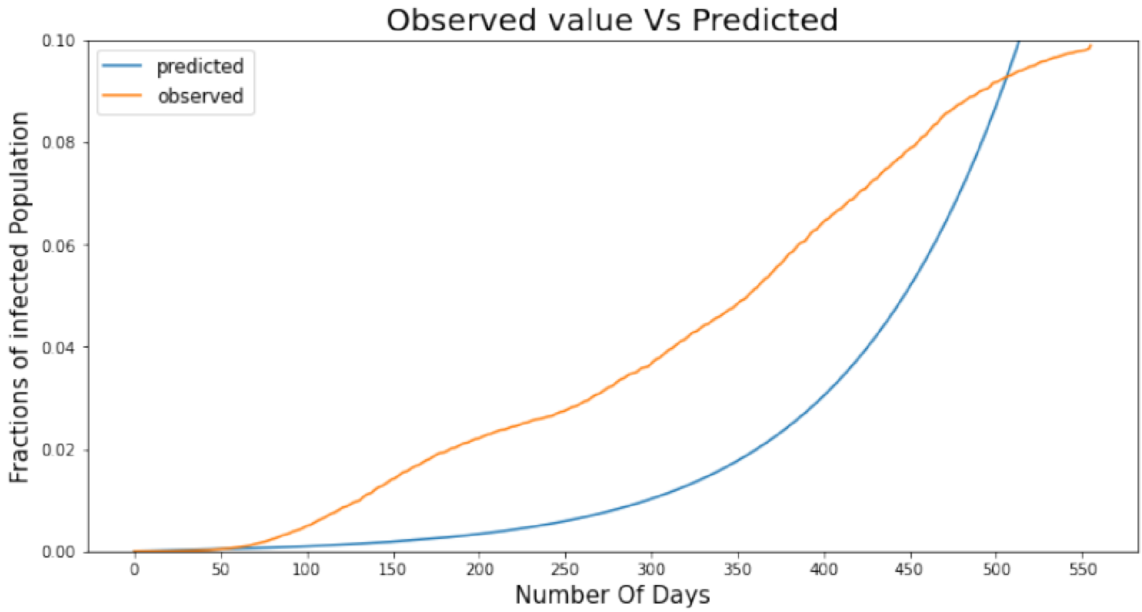


Japan:

1) After changing the k2 to q we've achieved a little improved predicted waves.

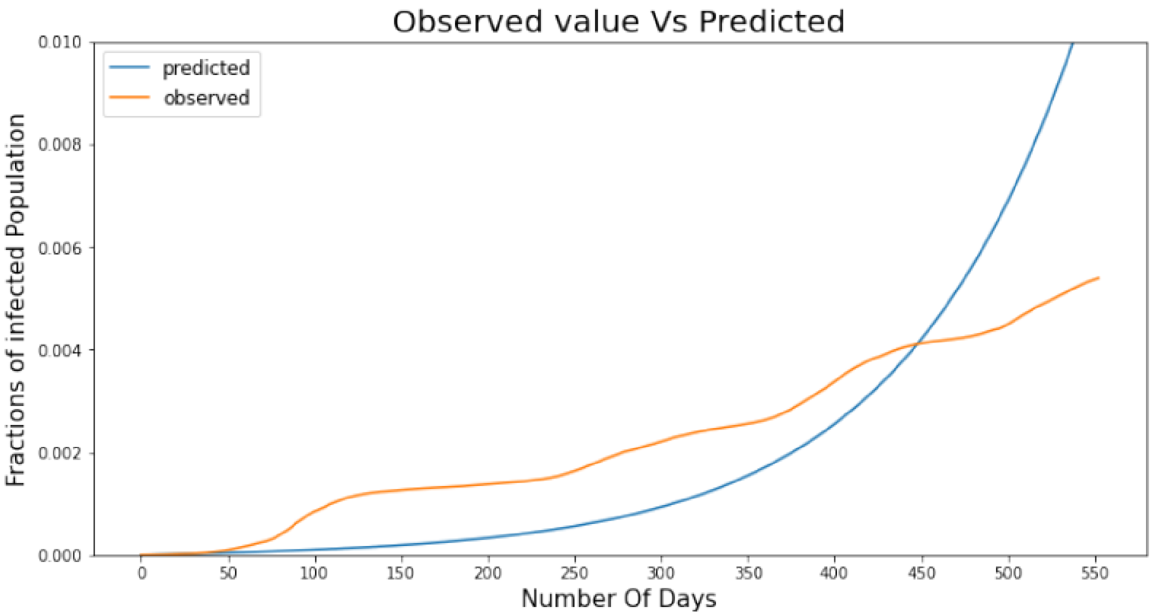


Now we've tried improving the graph by changing our optimised reactions rates.

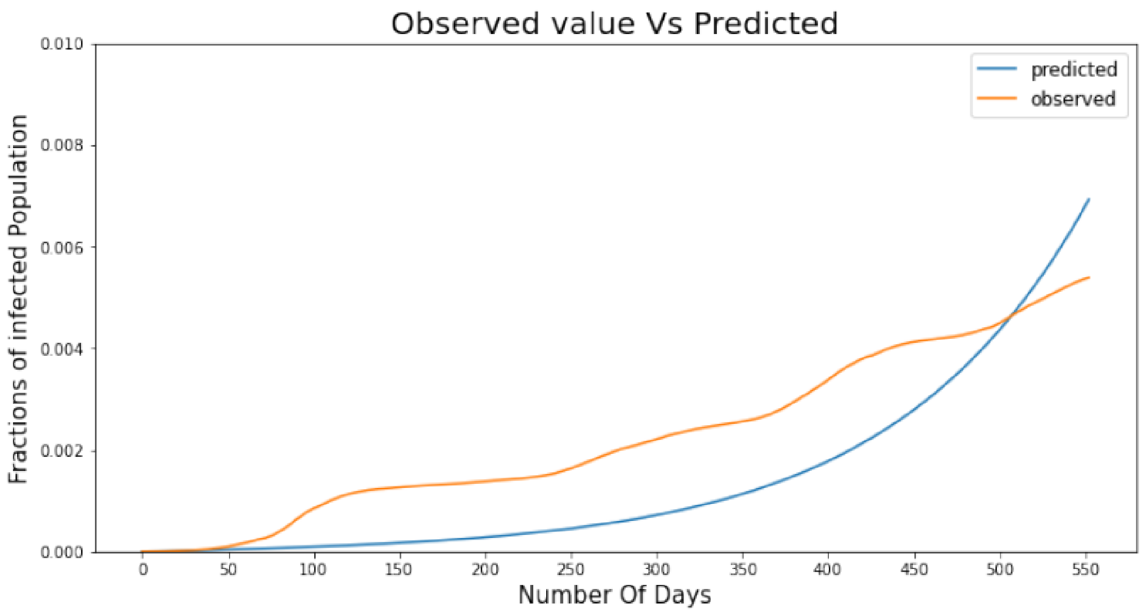


Nigeria

1)Using crowd effect



2)Using optimised reaction rate



Task 5:

While performing task 2 with crowd effect. We have tried to use the value of the Ip that we got in section 4 and then implemented it in our coding to get the result.

After getting the results from previous tasks. We changed different parameters multiple times to get more specific results and see the behaviour of these waves.

So, after changing Ip we have observed that in Brazil and Nigeria the change was a bit less but in the case of Japan, the change was a bit higher and also effecting the second wave pattern.

So hence we can conclude here that the value of Ip has the power to completely modify the behaviour patterns of our waves.

CONCLUSION:

Modelling COVID in this course was a completely different experience. Starting with COVID-19 we have seen different behaviour patterns as an individual in our home countries. But after doing complete research about the patterns and behaviours we can predict better things about the pandemic and the global behaviour of all humans under stress. Furthermore, how some countries managed this stress in a much better way than other countries. The stress and exhaustion rate were really high in the USA, Colombia Iran etc. as far as our group's point of view is concerned if we want to implement this system on more real on-ground analysis then we must consider some other things as well while building this system. We know that this thing might make our model more complex, but it is necessary to think about these factors as well like the regional factor, age, religious belief, ethnicity, and immune system strength system. If we also include these things in addition to the vaccination process, then we can build a much stronger model. Otherwise, if we talk about this S-I-R model. This is a very interesting topic for our team to learn and implement it helped us to better understand different groups and identify groups among them.

Modification Suggestions:

The modification needed in the real world needs to be implemented in the future world as well. Whenever we make assumptions in the current world, we must make changes to our model accordingly. With time new implementations will be there hence with time our models must be improved to meet the needs this will result in better prediction, more accuracy, and precise decision-making.

So, we did this step by modifying the values of our variables to get better results and obtain better graphs. These results may look similar to the real world but not exactly similar to the observed and predicted value. After doing multiple attempts to predict exactly similarly we understand is not likely to obtain results exactly similar to the observed value. Hence in real-world scenarios, it's difficult to predict 100% results.

To propose something further, then yes, the entire model can be modified in which we can work on small chunks of data according to the timeline and focus on obtaining better results on a smaller level. After, if we provide better results we can cluster our results to predict on a larger scale. This can be challenging and will require time and work.

This means the reactions coefficients changes for one country, and another also changes from one wave to another as some countries are vaccinated more than 75% after wave 1 such as Japan and Brazil whereas else there are other countries that didn't even cross 50% after 2 waves in case of Nigeria, also poor record keeping of COVID cases so these are the factors we should consider.

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