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Effectiveness of Government COVID-19 Interventions in Rwanda

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Introduction

A lot of interventions are being put in place by various governments to mitigate the spread of the Corona virus (COVID-19) within the community. Rwanda as a country was quick in her response to the pandemic with government interventions being put in place when the number of cases were significantly low. Though these interventions were designed to decrease the spreading rate, their effectiveness are not actually known.

This analysis which is based on the COVID-19 pandemic focuses on determining the effectiveness of these interventions by quantifying the spreading and growth rate and how they change at each change point when the cases are dominated by community transmission only. The following interventions put in place by the Rwandan government were considered: 20 April 2020, mandatory wearing of masks; 30 April 2020, loosed lockdown and instituting an 8pm to 5am curfew, while allowing free movement within each province during the day and hotels, restaurants opened till 7pm; 4 May 2020 (contact ban) a gradual easing of lockdown measures was introduced with selected businesses allowed to resume operations while adhering to health guidelines. Domestic movement restrictions were partially relaxed but strict physical distancing measures mandated in public buses. Bars remain closed, and schools will only re-open in September

The distribution of the cases in regions within Rwanda vary. The actual number of infected patients may differ from the number of reported cases due to weaker surveillance systems, poor contact tracing, slow testing and clinical diagnosis. All these factor play a major role in data collected and may cause delay, as the change in spreading rate due to each change point may not be visible immediately.

Overview

This analysis was carried out by estimating epidemiological parameters using the Bayesian Inference technique. These parameters were established using the SIR model and applying the Bayesian model comparison to select models that best fit the observed data; Rwanda COVID-19 reported cases.

The SIR model is an established class of compartmental model for epidemic outbreaks. It is compartmental because it divides the population into susceptible, infectious and recovery compartments and also recognizes how each compartment changes. The SIR model has been used to model epidemic spreads as it played a dominant role in the analyses of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic (1), which makes it best suited as a model for the COVID-19 pandemic. The model is formulated in form of ordinary differential equations which state the central epidemiological parameters. The central parameters are the spreading rate λ, the recovery rate μ, the reporting delay D, and the number of initially infected people I_0.

However, the SIR model can take an exponential form at the onset phase of an epidemic since only a very small fraction of the population is infected (I) or recovered (R), and thus it is assumed that the susceptible people are approximately equal to the total population (S = N >> 1, such that S/N = 1). The differential equation for the infected reduces to a simple linear equation, exhibiting an exponential growth.

$$\frac{dI}{dt} = \lambda \frac{SI}{N} = \mu I \quad \text{..... 1}$$

$$\frac{dI}{dt} = (\lambda - \mu) I \quad \text{....... 2}$$

Integrating (2) the equation becomes exponential

$$I(t) = I(0)\ell^{(\lambda-\mu)t}$$

Bayesian inference was used in combination with the SIR model to estimate the epidemiological parameters using the Markov chain Monte Carlo sampling. However, the time-discrete version of the SIR model was used which includes a time dependent spreading rate. The time dependence was implemented as change points in the spreading rate, which we assume to be driven by governmental interventions and the associated change of individual behavior (1). The interventions considered were: first was 20 April 2020, when it became mandatory to wear masks; second was 30 April 2020, when the lockdown was loosed; third was 4 May 2020, where a contact ban was stated. Indicating that at each change point, the estimated epidemiological parameter shows the effectiveness of each intervention.

Change Point Analysis

The effectiveness COVID-19 non-pharmaceutical intervention policies were evaluated by observing the change points in the spreading rate. To detect the change points, an initial spreading rate was assumed and up to three potential change points motivated by Rwandan governmental interventions: In the modeling, the first change point was expected around 20 April 2020 (t1) as a result of the mandatory mask wearing. The second change point was expected around 30 April 2020 (t2), when the lock down was loosed. A third change point was expected around 4 May 2020 (t3), when a contact ban was enacted.

The figure below gives a visualization of the effect of each change. The infection growth rate is defined as $\lambda^*(t) = \lambda(t) - \mu$ can be determined from the visualization in fig 1 below. First, the spreading rate λ decreased form an initial value of 0.20 to 0.13. The date of the change point was inferred to be 19 April 2020 which basically matches the timing of the first governmental intervention considered, which included mandatory mask wearing. After this first intervention, the (effective) growth rate $\lambda^*(t) = \lambda(t) - \mu$ decreased, from median $\lambda_0 - \mu = 0.08$ to median $\lambda_1 - \mu = 0.01$, given that the recovery rate was inferred as $\mu = 0.12$. At the second change point, $\lambda(t)$ increased from $\lambda_1 = 0.13$ to $\lambda_2 = 0.14$. This change point corresponds to 30 April 2020 and this inferred date matches the timing of the second Rwandan governmental intervention. After this second intervention, the median growth rate became $\lambda^*(t) = \lambda_2 - \mu = 0.02 \approx 0$ and is thus in the vicinity of the critical point yet still slightly positive. A third change point, when $\lambda(t)$ increased from $\lambda_2 = 0.14$ to $\lambda_3 = 0.15$, was inferred on 4 May 2020 and this inferred date matches the timing of the third governmental intervention including contact ban. After this third intervention did the median (effective) growth rate, $\lambda^*(t) = \lambda_3 - \mu = 0.03$ increase by a factor of 0.01. These interventions thereby mitigated the spread of COVID-19 in Rwanda by drastically reducing the growth rate, but did most likely not lead to a sustained decline of new infections. In summary, we have related the change points to the non-pharmaceutical interventions to quantify their effect.

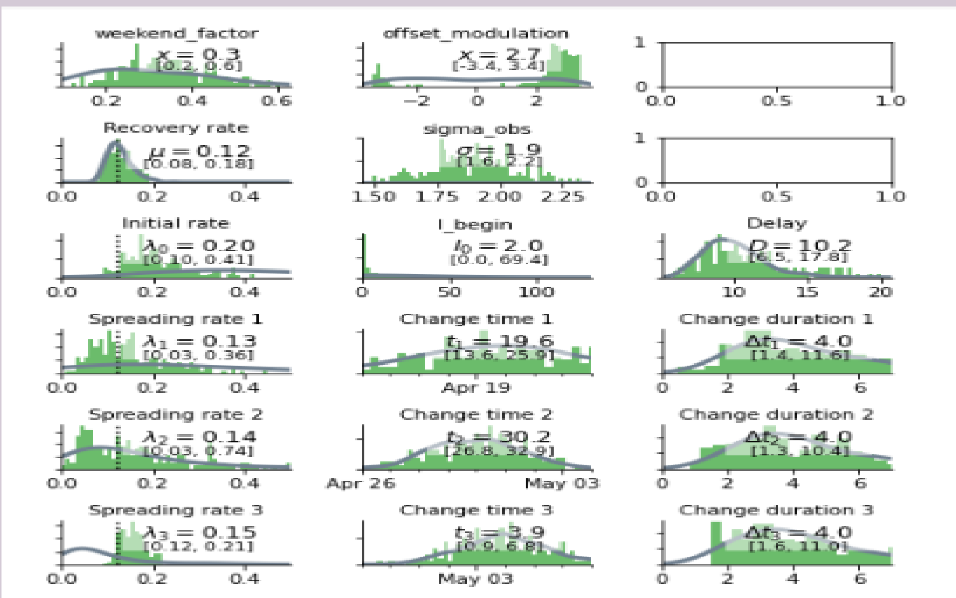

Fig 1: Change point visualization

The visualization below shows the trend of the growth rate, daily new cases and cumulative daily cases. From the growth rate trend, a slight decline was observed corresponding to the period when interventions were set by the government of Rwanda. This also reflected as a slight decrease in the daily and cumulative case during this period. Though there was a drastic decrease in the growth rate, it showed that it didn't lead to a sustained decline in the growth infection rate. Even though the rate was approximately zero, it still had a positive value and only a negative value would have ensured a sustained decline in the number of cases.

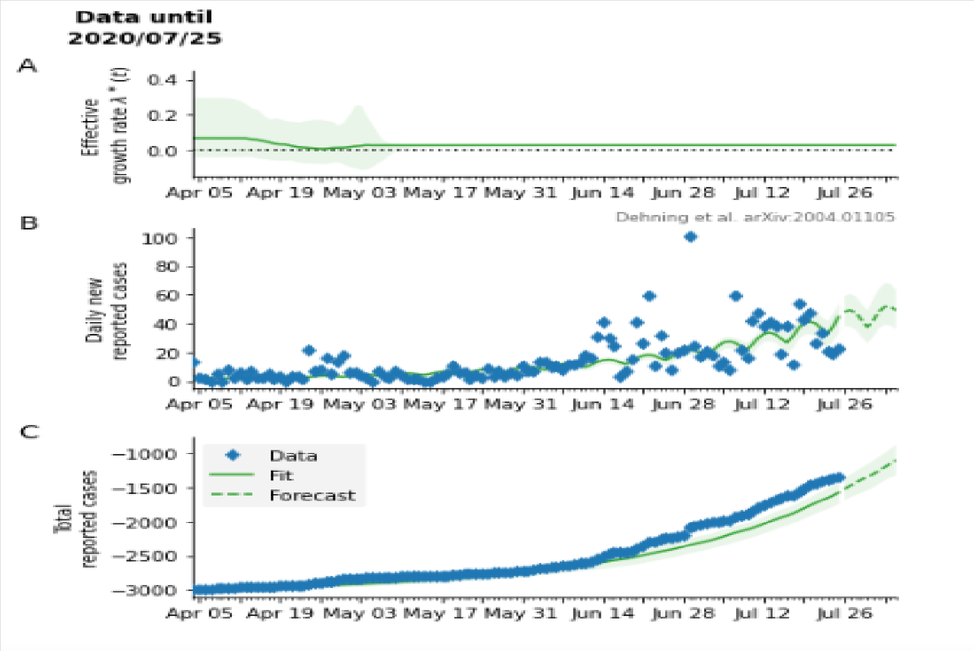

Fig 2: Visualization Trend

Limitations

During the course of the analysis, the following limitations were encountered

- Rwanda was very quick to respond to the COVID-19 pandemic. A major government intervention was implemented before the cases were dominated by community transmissions only. On the 20 March 2020 the nationwide lockdown was put in place, which could have served as a major intervention to include in the analysis.
- The model assumed that every person infects the same amount of people but in reality it is not so.
- People don't take interventions seriously making it difficult to determine exact spreading rate after each intervention was put in place.

Conclusion

From the above analysis the effectiveness of each considered interventions were determined. There was an increase in growth rate though substantial when the third intervention was put in place, it therefore recommended that the government should act cautiously while re-opening the country in order to avoid escalating the infection rate.

Task 1.2

This analysis can also be used in other scenarios that may not necessarily be an epidemic. For instance, to determine the number of daily tweets containing the word corruption from a given country for a year. Based on the analysis being related to the first task, get the tweets (data) from twitter using twitter API. A sentiment analysis is carried out on the tweets to check the number of corruption related word are used in the tweets. We can determine the interest of people in corruption issues by actively analyzing their tweet data at each change point. Here, the change points could be these stated triggers: the first change point will be expected at the beginning of February, when reports emerge about a politician taking bribes. The second the 15th August when the politician was convicted. The third being the slow rising during this year of every-day bribery (police, clerks, etc.)