Tittle:

Change point analysis to quantify the impact of African government policy interventions to slow the spread of COVID-19, case study Rwanda.

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INTRODUCTION

Since the outbreak of the novel coronavirus(nCov19) various rapid response measures have been put in place by different agencies to mitigate the spread of the virus. These measures include both pharmaceutical and non-pharmaceutical. The effect of these mitigations, more so non-Pharmaceutical that is social distancing, cancellation of public gathering, closing of schools and events may not be known at first. In this research we try to assess the impact of the non-pharmaceutical policies using Bayesian Inference on the SIR model.

BACKGROUND

The African Union is looking for evidence-based insight from the continent on which public health and social measures are most effective at reducing the spread of Covid19.

OBJECTIVES

The main business objective of this challenge is to quantify the statistical significance of a public health policy introduced by African governments to slow down the spread of COVID-19.

METHODOLOGY

DATA

The data was retrieved from the John Hopkins University database. The data includes cases of the confirmed, recovered and infected with Covid19 for individuals in Rwanda.

MODELLING

We split the data into training data and validation data. The training data was as from when the country reached 100 cases until 25th of July 2020 which was used to fit the model. The test set was from 26th of July to 7th of August which was compared with the forecasted values to validate the model. In Rwanda major mitigations were made prior the 100 cases, in this model we captured 3 mitigations which were implemented after the country reached 100 cases as the change points. These change points are:
20th of April 2020: Mandatory wearing of masks
30th of April 2020: loosening of lockdowns
4th of May 2020: Gradual easing of past mitigations

SIR MODEL

The susceptible-infected-recovered (SIR) model specifies population compartments and the rates at which they change (susceptible people becoming infectious and infectious people recovering). It is suitable for this data given that Covid19 dataset is in different compartments. The model in this case is useful for planning purposes and decision making informing the government on how to slow the spread of COVID-19 by determining how fast people move from being susceptible to exposed, from exposed to infected, and from infected to recovered. These rates help measure, which interventions made have the most effect on slowing the spread in the country, and help support public health preparedness in terms of policies to reduce the spread and response planning by improving surveillance, giving an indication of how feasible it would be to contain the virus.

BAYESIAN INFERENCE

Bayesian Inference, which is based on Markov Chain Monte Carlo is applied to estimate the parameters of the SIR model. The aim of Bayesian Inference is to learn about the probability of posterior distribution by fitting a prior distribution to a set of data. It is based on Bayes' theorem.

$$Pr(\,parameters|data) \;=\; \frac{Pr(\,data|parameters)\,Pr(\,parameters)}{Pr(\,data)}$$

Estimation of the model parameters using Bayesian inference with MCMC relies on the Python package PyMC3 with NUTS (No U-Turn Sampling) using multiple, independent Markov chains. We consider a time-discrete version of the standard SIR model. In short, we assume that the disease spreads at rate λ from the infected population compartment (I) to the susceptible compartment (S), and that the infected population compartment recovers (R) at rate. This well-established model for disease spreading can be described by the following set of (deterministic) ordinary differential equations;

Within a population of size N,

$$\frac{dS}{dt} = -\lambda\frac{SI}{N}$$

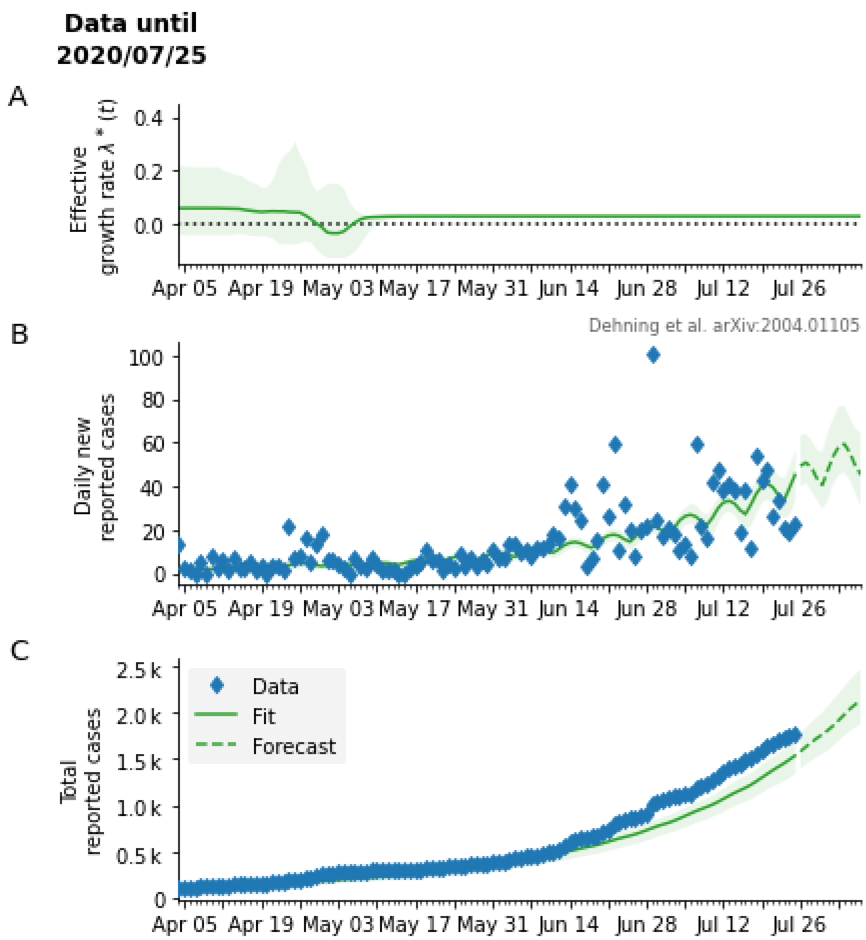
$$\frac{dI}{dt} = \lambda\frac{SI}{N} - \mu I$$

$$\frac{dR}{dt} = \mu I$$

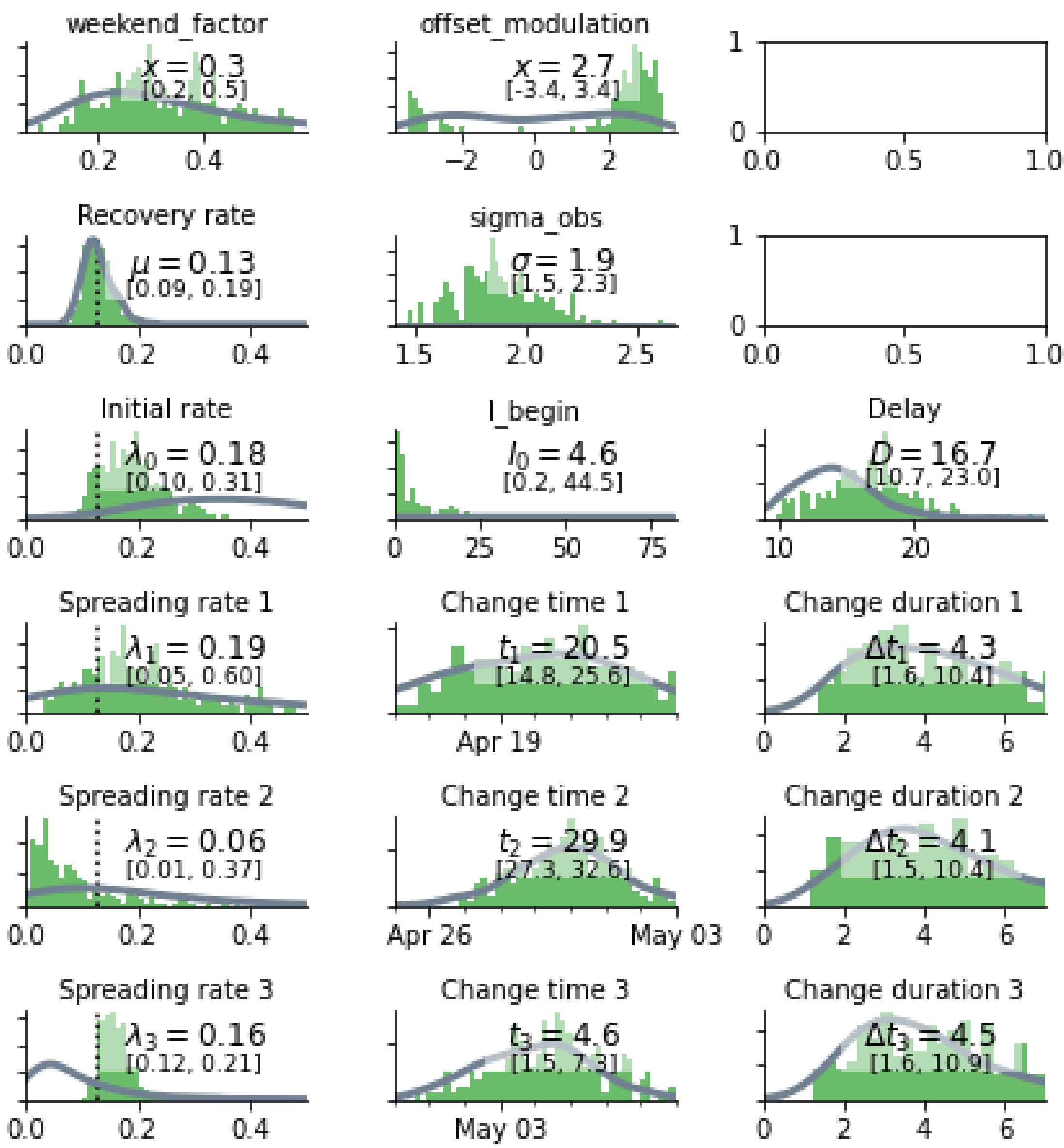
RESULTS AND FINDINGS

The following plots shows the trends of Covid19 cases in Rwanda until 25th of July 2020 together with a 12 days forecast, used in validating the model.

Subplot A shows a time-dependent model estimate of the effective spreading rate l*(t). Subplot B shows a comparison of daily news reported cases and the model with green solid line for median fit with 95% confidence Interval, dashed line for median forecast with a 95% confidence Interval. Subplot C shows a comparison of total reported cases and the model.



Change point detection to quantify the effect of non-pharmaceutical interventions.



Ideally, detected changes can be related to specific mitigation measures so that one gains insights into the effectiveness of different measures .Our model comparison had three change points with the following posteriors of the parameters:

I. λ (t) increased from λ_0 = 0.18 (CI [0.10,0.31]) to λ_1 = 0.19 (CI [0.05,0.60]). The date of the change point was inferred to be 20th of April 2020 and this inferred date matches the timing of the first governmental intervention, which included a directive by the government of a mandatory wearing of the masks. After this first intervention, the (effective) growth rate $\lambda^*(t)$ = λ (t) – μ, increased from a median of λ_0 - μ = 0.05 to a median of λ_1 - μ = 0.06, given that the recovery rate was inferred as μ = 0.13 (CI [0.10, 0.31]).

II. λ (t) decreased from $\lambda_1 = 0.19$ to $\lambda_2 = 0.06$ (CI [0.01,0.37]). The date of this change point was inferred to be 30th April 2020 and this inferred date matches the timing of the second governmental intervention where there was a loosening of the lockdown mandating the wearing of masks outside and instituting an 8pm to 5am curfew, while allowing free movement within each province during the day. Hotels and restaurants were allowed to operate until 7pm. After this second intervention, the median growth rate, $\lambda^*(t)$ became $\lambda_2 - \mu = -0.07$ which is a negative, enabling a sustained decrease in the number of new infections. This second intervention in Rwanda mitigated the spread of COVID-19 drastically reducing the growth rate, but did most likely not lead to a sustained decline of new infections.

III. λ (t) increased from $\lambda_2 = 0.07$ to $\lambda_3 = 0.16$ (CI [0.12,0.21]), was inferred on 4th May 2020 and this inferred date matches the timing of the third governmental intervention including a gradual easing of lockdown measures was introduced with selected businesses allowed to resume operations while adhering to health guidelines.. After this third intervention, the median growth rate increased, $\lambda^*(t) = \lambda_3 - \mu = 0.03$ which is greater compared to the median growth rate of the second intervention.

We have related the change points to the non-pharmaceutical interventions to quantify their effect. It is evident that some of the mitigations were effective while other proved futile.

LIMITATIONS

I. We assume that the spreading rate for the disease from one person to another is constant. In the real world scenario, this is not the case.

II. The aim of our modeling is to forecast different scenarios on the spread of COVID-19 in Rwanda. Apart from picking a suitable model, the main challenge is to estimate model parameters.

III. The available real-world data is not informative enough to fit all free parameters, or to empirically find the underlying distributions.

IV. In the SIR model used, population is viewed as continuous entities, and individuals are not considered. The SIR model also imposes further simplifications with respect to contact patterns, as it is not designed to capture details of individual.

RECOMMENDATIONS

I. We noticed that there were some increased in growth rate even after some mitigations were put in place. This can be attribute by the negligence of the public. For effective mitigations, the government should ensure that the public adheres to the policies put in place. This can be done by creating awareness at the community levels of the impact of the nCov19.

II. There was also an increase in growth rate after easing mitigations. The government should act cautiously while reopening the country to avoid further escalating the infections.