Bayesian Inference of COVID-19 spreading rates in South Africa - A summary

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Outline

Problem Description

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Bayesian inference for the rescue!

Model

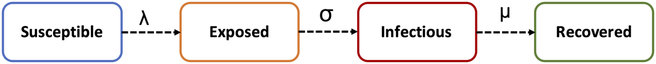
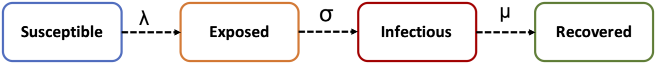


Figure: SEIR model [MM20]



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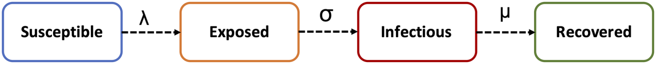
$$\frac{dI}{dt} = \sigma E - \mu I$$
$$\frac{dR}{dt} = \mu I$$

S(E)IR



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- Basic reproductive number $R_0 = \frac{\lambda}{\mu}$
- Delay D in becoming infected (I^{new}) and being reported
- λ time-varying with change points corresponding to NIPs

Bayesian model

Parameter	Prior Distribution
Spreading rate λ_0	LogNormal(log(0.4),0.5)
Spreading rate λ_1	LogNormal(log(0.4),0.7)
Spreading rate λ_2	LogNormal(log(0.4),0.7)
Incubation to infectious rate σ	LogNormal(log(1/5),0.5)
Recovery rate μ	LogNormal(log(1/8),0.2)
Reporting Delay D	LogNormal(log(8),0.2)
Initial Infectious I_0	Half-Cauchy(20)
Initial Exposed E_0	Half-Cauchy(20)
Change Point t_1	Normal(2020/03/18,1)
Change Point t_2	Normal(2020/03/28,1)

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- Likelihood function Student-T distribution
- Initial $R_0 = 3.278$ (CI[2.715, 3.73])
- Hamiltonian Monte Carlo (HMC) method to sample from posterior distribution
  - No-U-Turn Sampling (NUTS)
  - 5000 samples with 1000 burn-in

Results I

Model	Change Points	LOO	Effective Parameters
SIR	2	448.00	10.27
SEIR	1	457.77	11.60
SEIR	2	459.94	12.00
SIR	1	463.03	8.51
SEIR	0	464.69	16.14
SIR	0	517.72	4.72

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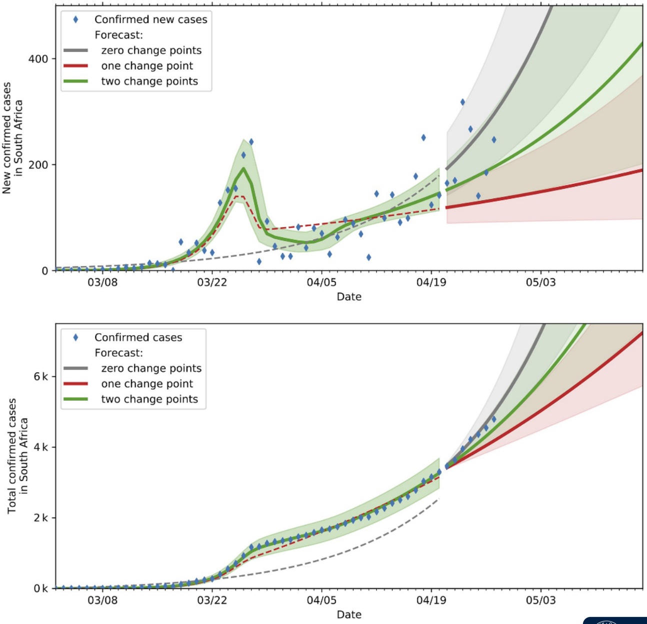
- SIR model with two change points yields lowest LOO cross entropy loss



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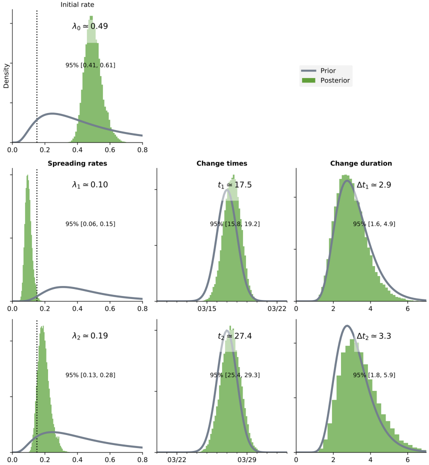
Results II



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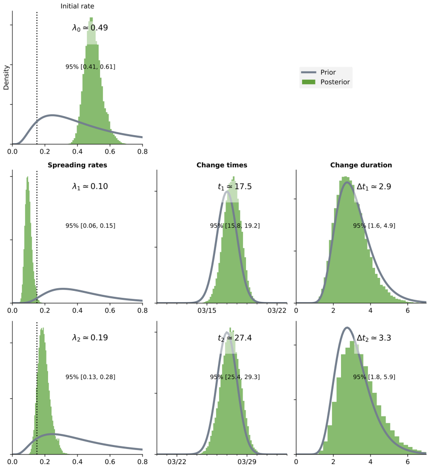

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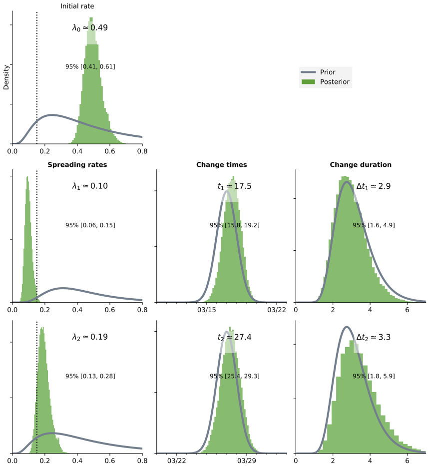

- Change points peak on 18/03 (travel ban, social distancing) and 28/03 (mass testing)
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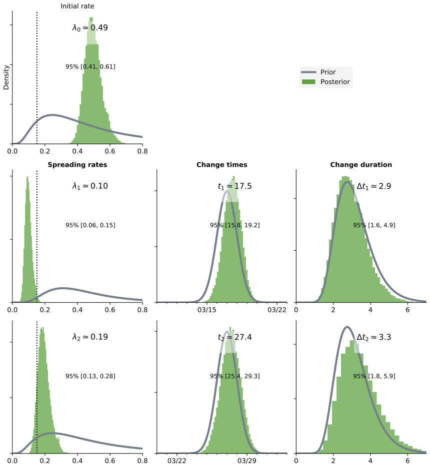

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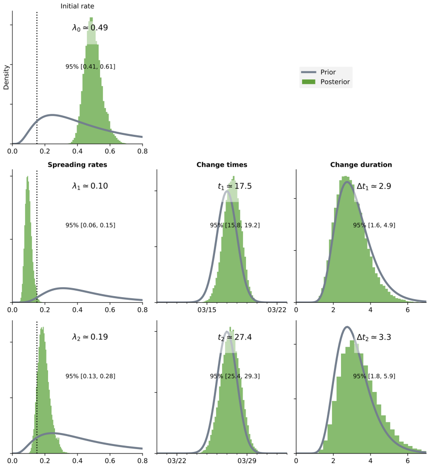

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- Delay $D \approx 6.848$ including incubation period of 4.537 days, laboratory delay of 2.311 days
- Recovery rate $\mu \approx 0.151$ implies mean infectious period of 6.62 days

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- Parameter estimates help quantify the dynamic of the pandemic and account for uncertainty
- Assumptions on prior distributions?
- Take into account local, provincial developments

Rendani Mbuvha and Tshilidzi Marwala.
Bayesian inference of covid-19 spreading rates in south africa.
04 2020.