**2. Method**

Intro to the chapter…

**2.1. CALIBRATION METHODS COMPARED**

We compare the following calibration methods; Rejection Approximate Bayesian Computation (Rejection ABC), Sequential Approximate Bayesian Computation (Sequential ABC) and Bayesian Maximum Likelihood estimation (BMLE). In the next sections, we will shortly explain each of these.

**2.1.1. Rejection ABC**

Rejection ABC is the most basic form of ABC. This method operates by sampling parameter values () from the prior distributionand given these sampled parameter values, data (*y*) is simulated under a model. A summary statistic () of the simulated data () must satisfy a proximity criterion with the target statistic () of the observed data (*x*) such that, where *d* expresses the distance between the target and summary statistics *t* and *s*, and *ϵ* represents a tolerance level. The algorithm retains sampled parameter values for which the model produces simulated summaries (*s*) that are closer to the target statistic (t) than the tolerance (ϵ) (Sunnaker). *Figure 1* illustrates how the rejection ABC algorithm functions. The simulator (M) is run each time with a newly sampled parameter value (θ) from the prior distribution obtaining a simulated summary statistic. When the distance between a summary statistic and the target statistic () is smaller than (ϵ); the parameter value is retained (red dot). Otherwise, it is discarded.

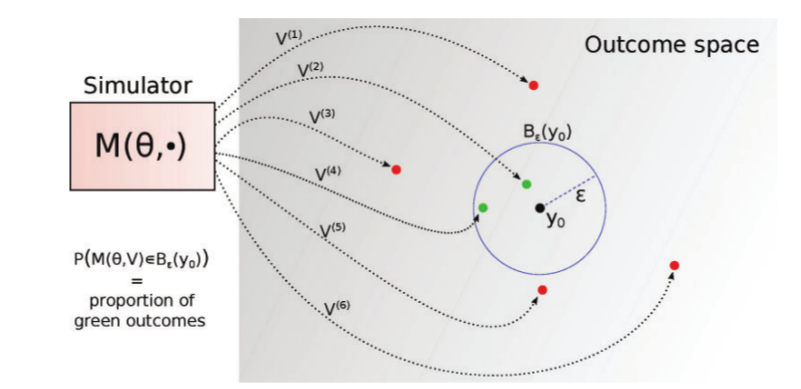


Figure 1 : Rejection ABC(Lintusaari)

The distribution of these retained parameter values is expected to assume posterior density without the explicit calculation of the likelihood. From Bayesian statistics, estimation of the posterior distribution depends on the prior distribution and the likelihood. The posterior is defined as

|  |  |  |
| --- | --- | --- |
|  |  | 1 |

Where is a vector of parameters, *x* is the observed data, is the posterior distribution, is the likelihood and is the prior distribution. ABC techniques use this same knowledge in the approximation of the posterior. They use summary statistics of the observed data instead of the entire observed data. Thus, equation … is modified to approximate the posterior as follows

These summaries are compared to the summaries of the simulated data in order to approximate the posterior without performing explicit calculations of the likelihood since the likelihood is intractable.

**2.1.2. Sequential ABC**

Sequential ABC is a class of ABC methods that approximates the posterior progressively by drawing samples from the prior sequentially (Lenormand). The prior for a particular sampling step depends on the previous retained sample except for the first sampling step which draws from the prior parameter space provided. Thus, the tolerance of the initial sampling step is less restrictive compared to the subsequent ones (Trevelyan). The sample at the current sampling step () is derived from the previous sample () using a decreasing sequence of tolerance levels. These methods determine by themselves the tolerance level used at each sampling step and provide a stopping criterion. This choice of tolerance for the current sampling step is determined as a function of the distances simulated in the previous sampling step (McKinley). Figure 2 gives an illustration of how the sequential ABC algorithm works. The simulator (M) is run for the first time with newly sampled parameter values () selected from the prior distribution with tolerance obtaining a simulated sample. Having obtained the first retained sample of parameter values at a much bigger tolerance level, the simulator starts a second step of simulation with the first retained sample as the prior parameter space and a decreased tolerance. A second sample of parameter values is obtained at tolerance and this process if repeated until a stopping criterion is reached. At each sampling step, a decision is made whether to retain a particular parameter value or discard it. If a simulated summary statistic at that step is further from the target statistic () than the tolerance level () of that step, that particular parameter value is discarded, otherwise it is retained. The final sample approximates the posterior distribution.

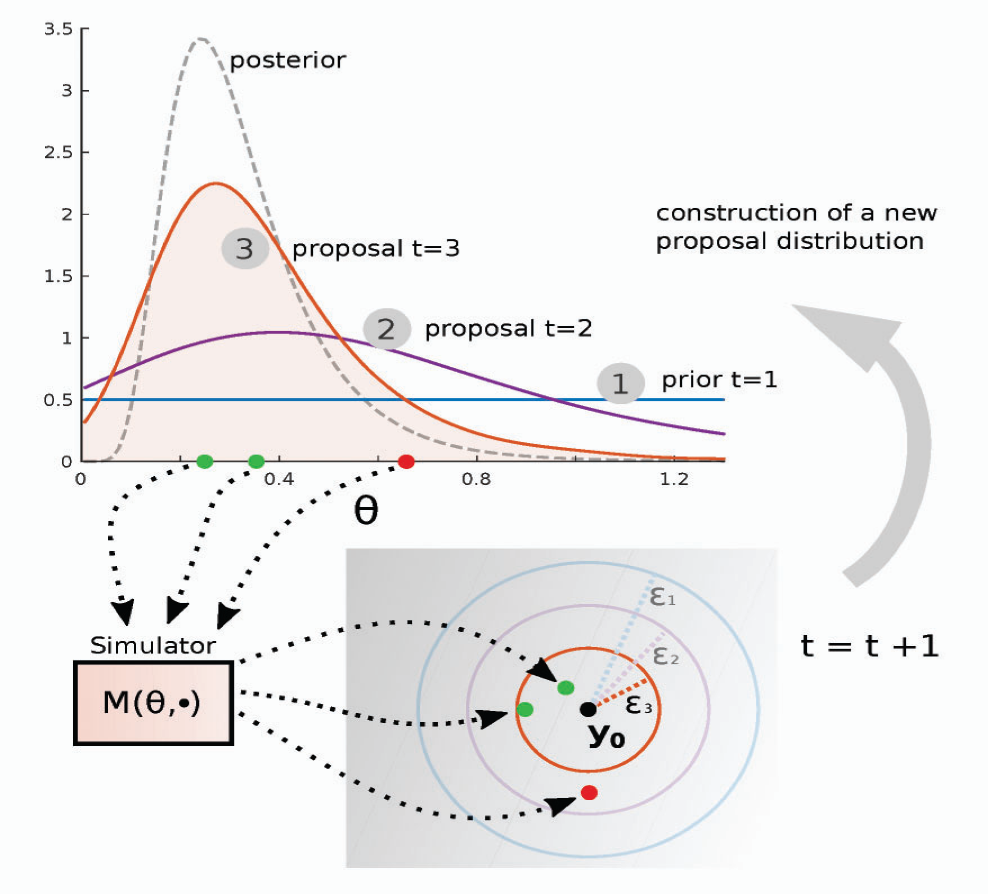


Figure 2 : Sequential ABC(Lintusaari)

**2.1.3. Bayesian Maximum Likelihood Estimation (BMLE)**

Data simulation with Bayesian Maximum Likelihood Estimation (BMLE)

Parameter combinations with high values of the likelihood are more consistent with the target supplied. This property allows the assessment of how the data supports one parameter combination compared with another.

**Steps from Menzies paper (to be developed…)**

1. Draw a large number of parameter sets from the prior distribution
2. For each parameter set, run the model and estimate model outcomes
3. Using these model outcomes, estimate the likelihood for the parameter set and retain this value (log likelihood)
4. Resample from the original parameter sample with replacement, using the likelihood values as sampling weights.

**THE SIMULATION MODEL**

**The SIR model**

The algorithms of the abovementioned methods require an input model under which simulation is performed. In this study, the methods performed simulations firstly under a simple stochastic SIR (Susceptible - Infectious - Recovered) model which was used to generate both observed data and model outputs. The SIR model is an epidemiological and compartmental model that computes the number of infectious individuals with an infectious disease in a closed population over time. A closed population implies that the population size remains constant over time. The population is characterised by three health states – susceptible, Infectious and recovered with rates that signify how individuals transit from one health state to the other.

**Susceptible**

**Recovered**

**Infectious**

**β**  **γ**

Figure 3: Structure of the SIR compartmental model

This model involves a system of three non-linear ordinary differential equations (ODEs) that relates the number of susceptible, number of infectious, and number of recovered individuals (Weiss). The SIR model functions under several assumptions such as: the population under study is homogeneous in nature (all individuals behave the same), the mode of transmission of the disease from infectious to susceptible individuals is through direct contact between infectious and susceptible individuals, recovered individuals gain permanent immunity to the disease. The closed population is usually grouped into compartments (health states) denoted by, and. The following system of ODEs governs the dynamics of the SIR model

Where is the disease transmission rate, is the recovery rate, is the duration of infection and the basic reproductive number. is the proportion of individuals in the population that are susceptible to the disease and represents the proportion of individuals that are infectious. Susceptible individuals become infectious at a rate. At a rate , infectious individuals recover from the disease (gain permanent immunity to the disease) (LStone).

The population stays constant throughout the transmission dynamics over the set time period such that

Figure 3 illustrates the dynamics of a stochastic SIR model run in the R software over a time period of 75 days for a population of 1000 individuals. The blue curve indicates the Susceptible compartment, the red curve indicates the Infectious compartment and the green curve indicates the Recovered individuals. The susceptible compartment reduces to zero as the infectious compartment gradually picks up.

**Creating a raster**

A raster consists of a matrix of cells or pixels arranged into rows and columns to form a grid. Each cell contains a value which represents stored information. In order to compare the posterior densities of the two methods to the reference posterior density, we created a raster using the raster function from the raster library in the R software (R version 3.5.0 (2018-04-23)). The raster was created by considering the minimum and maximum values of beta and gamma accepted by both of the methods to be compared as well as the reference. This was done so that the same raster could be applied to both methods and the reference. The resulting parameter space was divided into equally sized bins with beta values on the x-axis and gamma values on the y-axis (see Figure *4*). This then formed a grid in which the posterior densities laid. We applied the grid to each posterior density in order to quantify the density of each cell or pixel.



Figure 4: 4x4 raster applied to a posterior density

**SIMULATION PROCEDURE**

1. **Obtaining targets**

A target is a data point from the observed data to be considered during the simulation procedure before a decision is finally taken, as to whether a certain parameter combination is to be accepted or discarded. As targets in this study, there were two scenarios. Scenario 1 considered two target features (prevalence at two time points, 50 and 75) and scenario 2 looked at three target features (considered the peak prevalence for each model run in addition to the two time points in scenario 1).

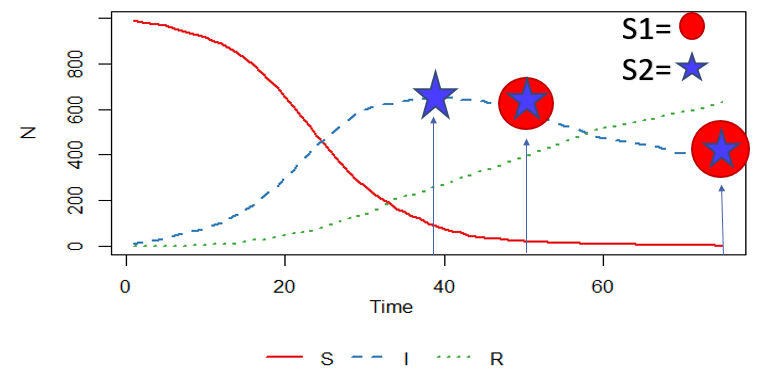


Figure 5: targets for scenarios 1 and 2. Scenario 1 considers only green points on the Infectious (I) curve while scenario 2 considers both red and green points on the (I) curve.

R version 3.6.2 (2018-04-23) was used to perform the statistical analyses and datasets were obtained from a stochastic SIR model using the SIR function in the SimInf library (siminfref). To obtain targets for scenario 1, the SIR model was run one hundred times and for each run, the prevalence at times 50 and 75 were saved in a matrix. Targets for scenario 1 were then computed as the means of these saved prevalence at the two time points. Similarly for scenario 2, the SIR model was run one hundred times and for each run, the prevalence at times 50 and 75 as well as the peak prevalence were saved in a matrix. Targets for scenario 2 were then computed as the means of these three target features.

1. **Running Simulations for methods at equal time**

In order to set equal times for the simulations to run, the following steps were followed in each case

1. Run 10000 simulations with both methods and recorded the time each method took to run. We found out that Sequential ABC took longer to run the 10000 simulations compared to Rejection ABC.
2. Estimate the number of simulations Rejection ABC could run in Sequential time as
3. At tolerance of 1, run these estimated number of simulations using Rejection ABC and record the computation time.
4. Estimate the number of simulations run by Rejection ABC at the amount of time used by Sequential ABC as

This step fixes the time for the two methods

1. Calculate the tolerance for Rejection ABC such that the number of accepted parameter combinations is equal to that of sequential ABC as follows;
2. **Obtaining a Reference (“true posterior”)**

At a sufficiently small tolerance, rejection ABC approximates the true posterior (ref: Sunnaker et al). For each scenario, we run a million simulations and saved all parameter combinations at tolerance = 1. We then chose the tolerance as low as possible in order to retain the same number of parameter combinations accepted by the methods to be compared.

1. **Applying a raster…**