**S1 Table. Description of calibration methods**

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| --- | --- | --- | --- |
| Calibration method | Brief description | Result | Reference |
| Rejection-Approximate Bayesian Computation (Rejection ABC) | ABC algorithms use simulation-based methods to approximate the posterior parameter distribution. ABC starts by sampling from prior distributions for the parameters under calibration. The rejection-ABC algorithm consists of running the simulation-model for each sampled parameter combination. Consequently, the model output is compared to the target statistics. The distance between the model-output and the target statistics is quantified using a GOF measure. The GOF measure for each parameter combination is then compared to a tolerance (ε), all parameter combinations with a GOF < ε are accepted. The accepted parameter combinations form the approximate posterior. Several extensions of rejection-ABC have been proposed to improve efficiency. | A sample from the approximate posterior distribution for parameter values | [1 - 4] |
| Bayesian calibration with Sampling Importance Resampling (BcSIR) | BcSIR is a method for sampling from the posterior. The first step (Sampling) is to draw a sample from the prior. The second step (Importance) involves calculating the measure of goodness-of-fit (e.g. the likelihood) for each of the parameter combinations drawn in step one. This measure of GOF is then used to compute an importance weight for each parameter combination. In the example of the likelihood, each parameter combination gets a weight proportional to the likelihood of the target statistics given the model output produced by running the model for this parameter combination. So, the parameter combination with the biggest likelihood gets the largest weight. In the third and final step, we draw a sample with replacement from the parameter combinations obtained in step one, using the weights obtained in step two. The result is a sample from the posterior. BcSIR was found to be inefficient in many practical applications. Therefore, more efficient methods such as *Bayesian calibration with* *Incremental Mixture Importance Sampling* (*BcIMIS*, see below) have been developed. | A sample from the approximate posterior distribution | [5] |
| Approximate Bayesian Computation with Sequential Monte Carlo (AbcSmc) | Approximate Bayesian Computation with Sequential Monte Carlo (AbcSmc), adapted from the ABC-SMC algorithms is an extension of Rejection ABC and aims at sequentially improving efficiency by sampling from intermediate distributions called predictive priors. These predictive priors are based on results of the algorithm in the previous step, which focuses the sampling on regions that have produced results that are close to observed data. | A sample from the approximate posterior distribution for parameter values | [6] |
| Sequential ABC Lenormand (Seq ABC) | Sequential ABC Lenormand (Seq ABC) is also an extension of Rejection-ABC. This algorithm adheres to the main principles of Sequential ABC by progressively approximating the posterior using sequential samples and a decreasing tolerance level. The first step of Seq ABC consists of the rejection ABC algorithm described above.  For the subsequent iterative steps, the prior depends on the previous retained sample. Seq ABC, like Rejection ABC quantifies the distance between the model-output and the target statistics using a GOF measure. The GOF measure for each parameter combination is then compared to a tolerance (ε). At the last step, all parameter combinations with a GOF < ε are accepted. The accepted parameter combinations form the approximate posterior. | A sample from the approximate posterior distribution for parameter values | [7] |
| Bayesian calibration with Incremental Mixture Importance Sampling (BcIMIS) | Like BcSIR, BcIMIS is a method for sampling from the posterior. The first step of BcIMIS consists of the BcSIR algorithm described above. In the second, iterative step, a multivariate normal distribution is constructed with the parameter combination with the maximum weight (i.e. maximum likelihood) from the first step as its centre. Then a new sample is drawn from the resulting multivariate normal distribution, and the process repeats itself until a convergence criterion is satisfied. After convergence, a resampling step similar to the resampling step used in BcSIR is used to obtain a sample from the posterior. | A sample from the approximate posterior distribution | [8] |

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