Bayesian analysis of non-linear differential equation models applied to a gut microbial system

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Biomathematics & Statistics Scotland



- ~ 35 members of staff
 (Statisticians, modellers, bioinformaticians, support staff)
- Funding from Scottish Government to support biological sciences, plus external funding
- Staff located at various biological research establishments in Scotland (Aberdeen, Dundee, Edinburgh, Ayr)
- Provision of
 - Consultancy, Research, Training

I am based at the Rowett Institute of Nutrition and Health

Digestion of food



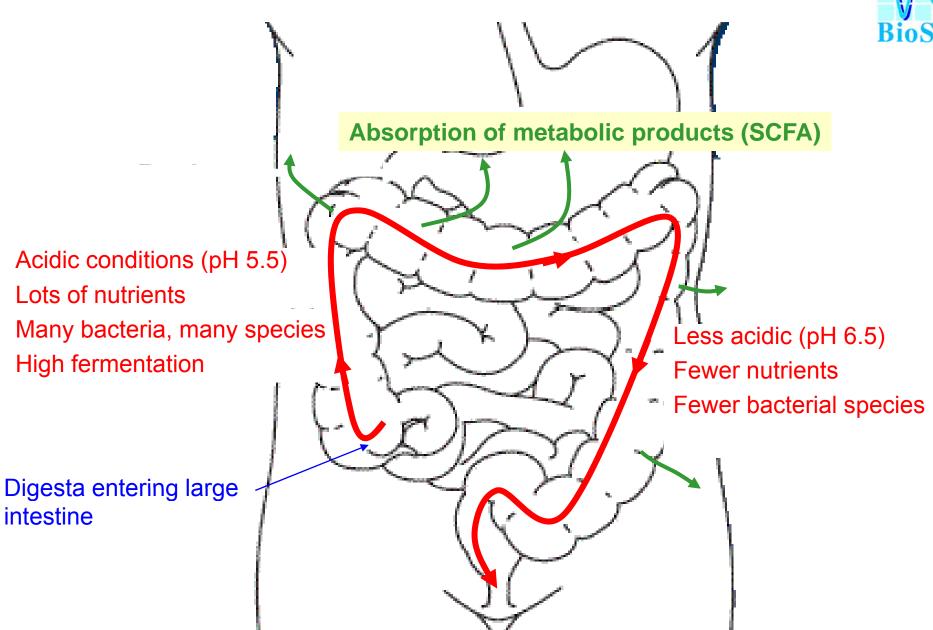
- Food is absorbed in the small intestine
- Undigested food (such as fibres) reach large intestine
 - Home to gut bacteria (10¹¹/g dry matter, several hundreds species)
 - Undigested food particles are fermented into metabolic products such as Short Chain Fatty Acids (SCFA)
 - These are then absorbed by the host to provide energy (up to 10% of total energy supply)
- Remainder leaves body as faeces

Digestion of food



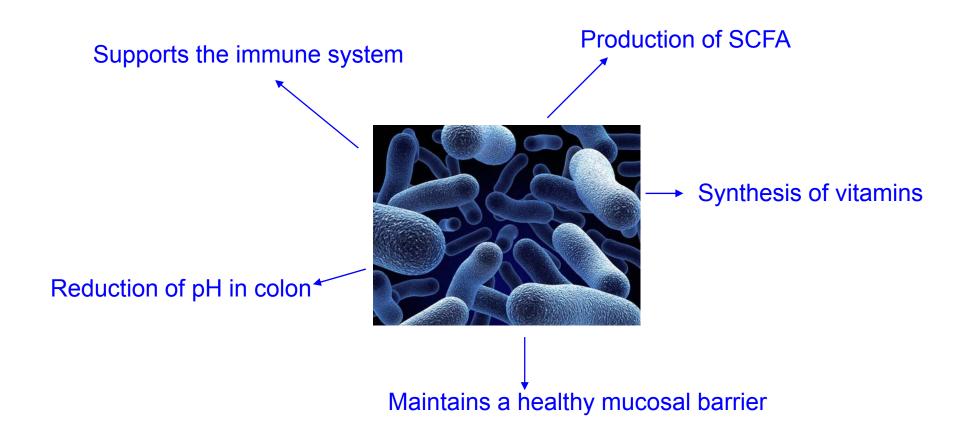
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- Health aspects:
 - Butyrate is thought to play protective role against colon cancer
 - Lactate associated with gut disorders such as Crohn's disease
 - Irritable bowel syndrome, inflammatory bowel disease





Healthy gut





Influencing gut health via nutrition



Can we create a 'healthy' environment for gut bacteria?

- Prebiotics such as cereals containing oats to stimulate growth of 'good' bacteria
- Probiotics such as yoghurts containing live biocultures to add 'good' bacteria to gut microbiota

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 For such approaches to be targeted and successful, knowledge is needed:

Preferred substrates

Environmental conditions (pH)

Competition between species, interactions

Experimental studies



 In vivo: feed volunteers a breakfast cereal and collect faecal samples

Experimental studies

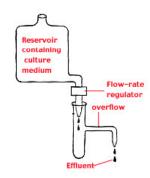


- In vivo: feed volunteers a breakfast cereal and collect faecal samples
- In vitro simple (batch cultures using 9 ml tubes)
 - tube with one known bacterial strain and a substrate of interest, monitor bacterial growth and production of metabolites
 - tube with several known bacterial strains and a substrate of interest, monitor bacterial growth and production of metabolites
 - tube with mixed bacterial population (from feacal sample) and a substrate of interest, monitor production of metabolites

Experimental studies

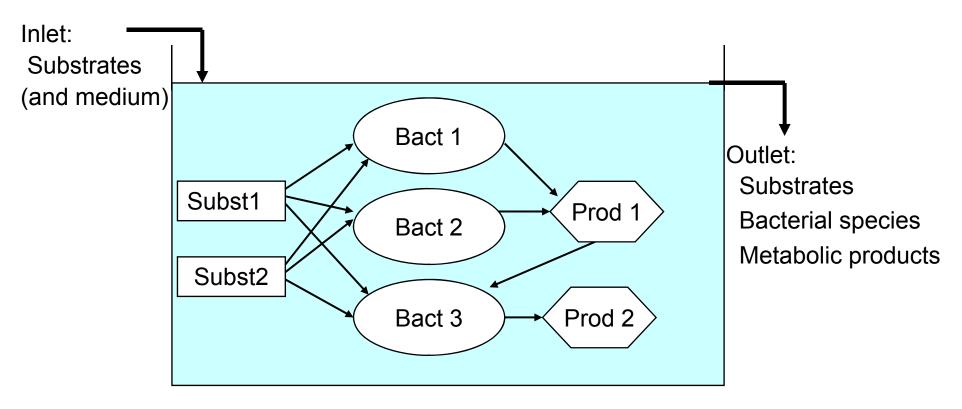


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- In vitro more realistic (continuous fermentor studies)
 - Representation of aspects of colon
 - Continuous supply of substrate



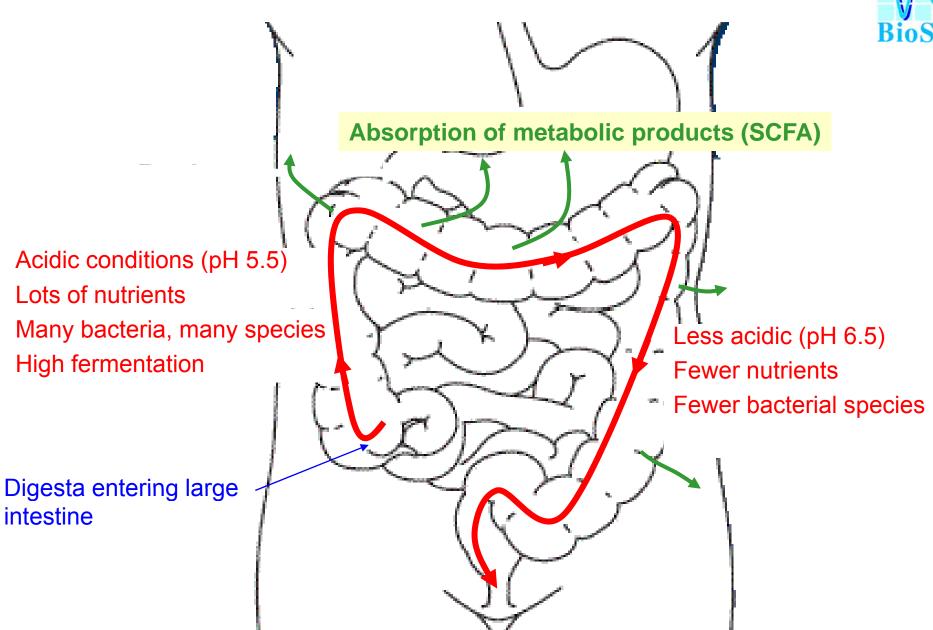
Fermentor



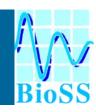


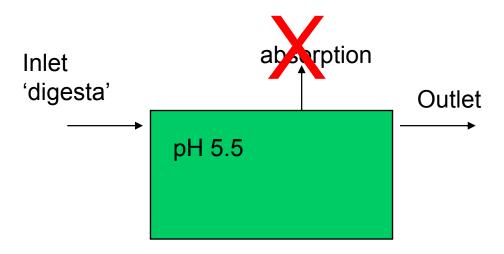
- Vessel with volume of 250 ml
- Faecal sample taken as a 'seed'
- Continuous supply of substrate
- Samples collected from outlet at regular time intervals
- Frequent gentle stirring to ensure mixing
- Controlled conditions (temperature, pH)



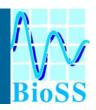


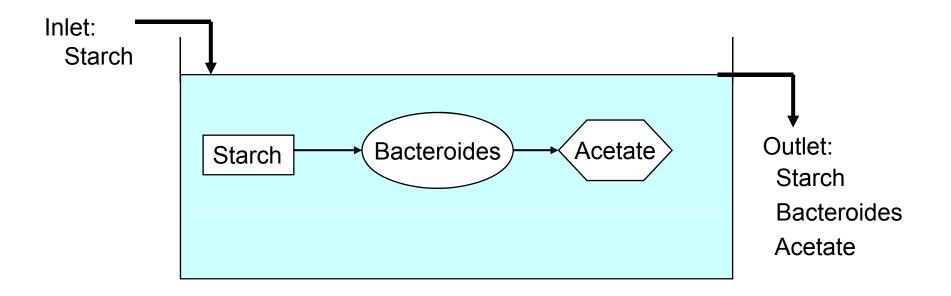
Colon simplified



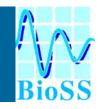


Illustration





Simple model



$$\begin{array}{ll} {\bf Bacteria} & \frac{d {\rm Bac}}{dt} \ = \ {\rm Bacterial\ growth-outflow\ bacteria} \\ \frac{d {\rm Bac}}{dt} \ = \ \frac{S\,G}{S+M}\,{\rm Bac} - k\,{\rm Bac} \end{array}$$

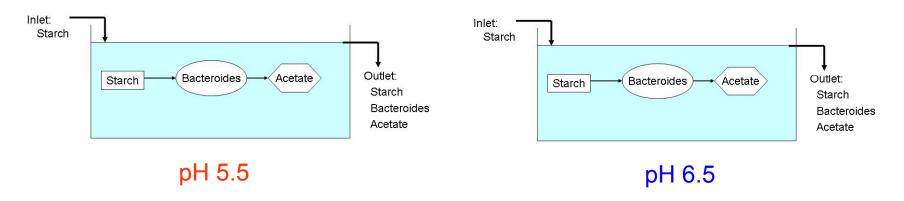
Substrate

Products

Simulation study



- Two experiments (pH 5.5 and pH 6.5)
- One bacterial strain, one substrate
- Assume maximum growth rate is different for the two pH levels
- All other parameters are assumed the same for both experiments

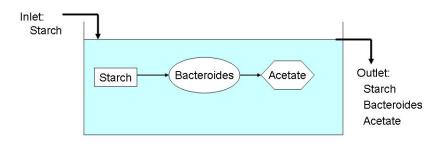


Bacteroides do not grow well

Bacteroides grow well

Simulation study





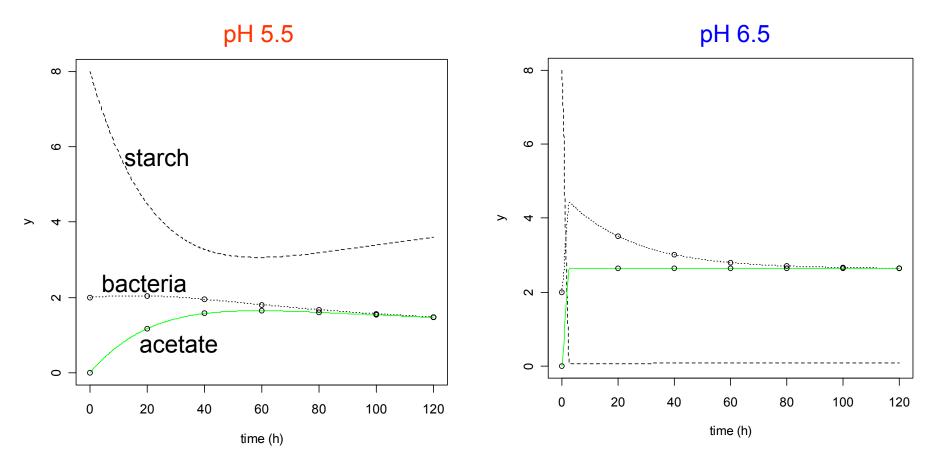
- To be inferred:
 - Max growth rate for pH 5.5
 - Max growth rate for pH 6.5
 - Michaelis-Menten factor
 - Inefficiency (use of substrate/g growth)
 - Acetate production (production/g growth)

The same for both experiments

Use simulated data to compare Bayesian approaches for inference

Simulated time series for fermentor





Parameter settings:

Starch input 5.6 g/d; turnover of 1/d;

Gmax=0.05/h for pH 5.5; Gmax=0.5/h for pH 6.5;

M=1; Starch use 3g/g bacterial growth; Acetate production 1g/g bacterial growth

Statistical model



System of differential equations

$$y_{abc}|\theta_a, t_{abc}, \sigma_{abc}^2 \sim N(f_a(\theta_a, t_{abc}), \sigma_{abc}^2)$$

 $\theta_a|\mu \sim N(X_a\mu, \Sigma)$
 $\mu \sim \text{Prior}$

Indices relate to study a, measurement b, time point c. X_a is a so-called design matrix for experiment a to allow for experiment-specific parameters. Variance components σ_{abc}^2 and Σ assumed known.

Priors chosen reasonably informative, based on biological knowledge. Metropolis-Hastings algorithm used to generate samples from posterior.

Time-consuming as for each parameter proposal the system of differential equations needs to be evaluated. R-code on Beowulf cluster.

Two scenarios for estimation



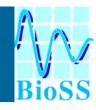
Scenario A:

 simultaneous inference using data from both pH 5.5 and pH 6.5 studies

Scenario B:

- analyse data from pH 6.5 first and summarise posterior density using mean and variance (ignoring correlations)
- Use this summary as prior for data analysis at pH 5.5 (for those parameters that are assumed identical across both studies)

Posterior densities for both scenarios



Scenario A: simultaneous

Scenario B: sequential

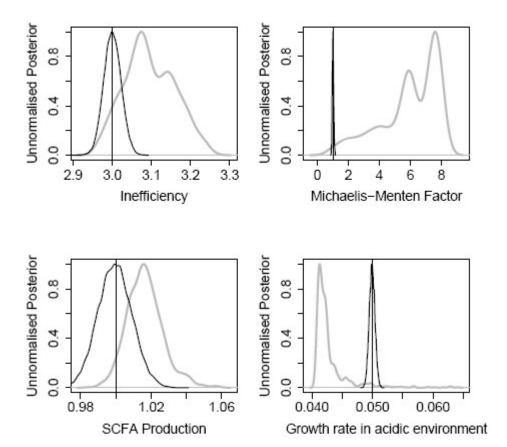


Fig. 3. Densities for the posterior probability of parameters using simulated data (Study 1, single bacterial strain) for (black line) Scenario A using simultaneous inference, and (grey line) Scenario B using summary information and separate inference. The true parameter values are indicated as a vertical line. Scenario A has a converged MCMC chain (> 200 effective samples per parameter) whereas no parameters have a large effective sample size in Scenario B.

Findings



Sequential inference doesn't work well

Poor mixing

Observed growth rate = Gmax Substrate / (Substrate + M)

- At pH 6.5 the bacteria grow well so that the substrate concentration low.
 The observed growth rate simplifies to (Gmax/M) Substrate, and Gmax and M cannot be separated from this data set alone.
- At pH 5.5 the bacteria don't grow well and substrate concentration is high.
 Hence the observed growth rate is (approximately) equal to Gmax. When at
 the second stage the pH 5.5 data are analysed we are working from the
 'wrong' prior for M and for some of the other parameters, and hence poor
 results.

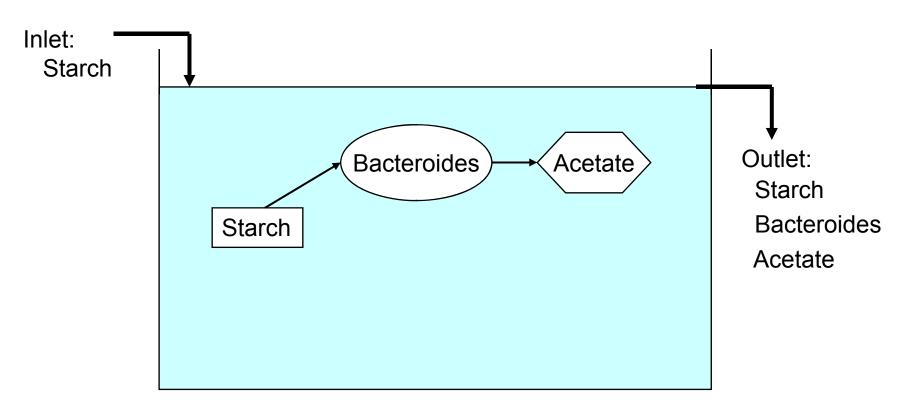
Findings



- Simple illustration that Bayesian approach of updating posterior distributions when data become available from new studies conducted under different experimental conditions, does not work here.
- Further investigations with two bacterial species.

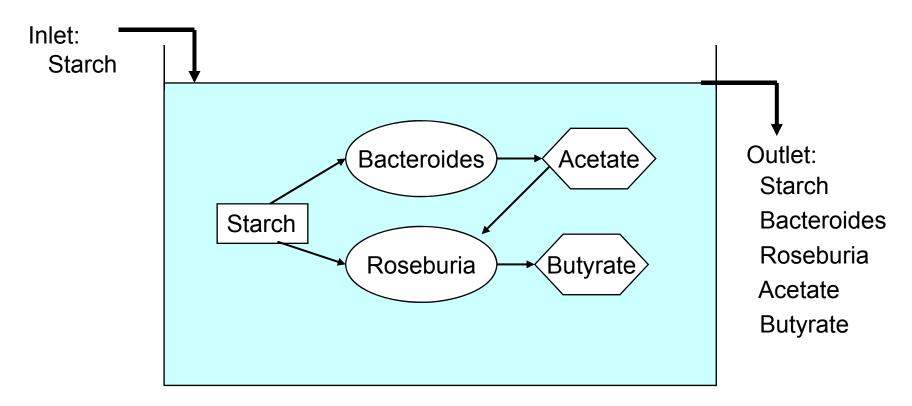
Two bacterial species





Two bacterial species





Simulation study to check performance of MCMC algorithm → OK (simultaneous inference of pH 5.5 and pH 6.5 'data')

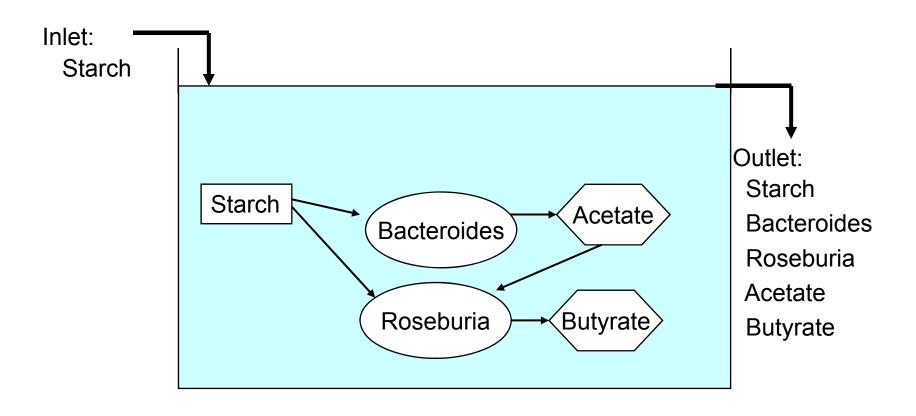
Data from fermentor study



- Mixed bacterial population (from faecal sample)
- Fermentor experiment at pH 5.5 and at pH 6.5
- Two types of substrates were fed to the fermentor
 - Starch: easily digestible, bacteria grow well
 - NSP (fibre): poorly digested, bacteria do not grow well
- Population is assumed to consist of 3 major functional groups

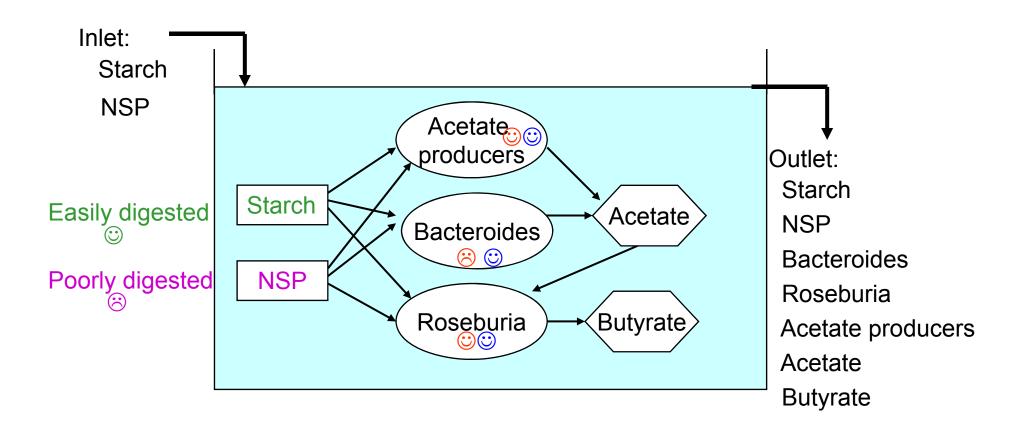
Data: 3 species-groups, 2 substrates





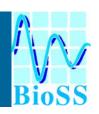
Data: 3 species-groups, 2 substrates





Data from fermentor study at pH 5.5 and from fermentor study at pH 6.5

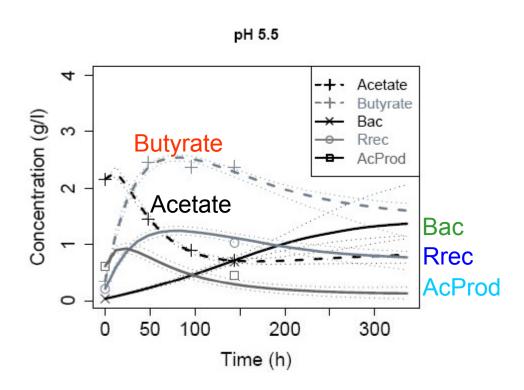
Estimation for data from fermentor study



- Data on bacteria (2 time points) and metabolic products (4 time points) for each fermentor
- 29 unknown parameters
- Prior distributions reasonably informative
- Variance components assumed known
- Highly structured model of differential equations, which acts as additional prior information

Data and posterior predictions





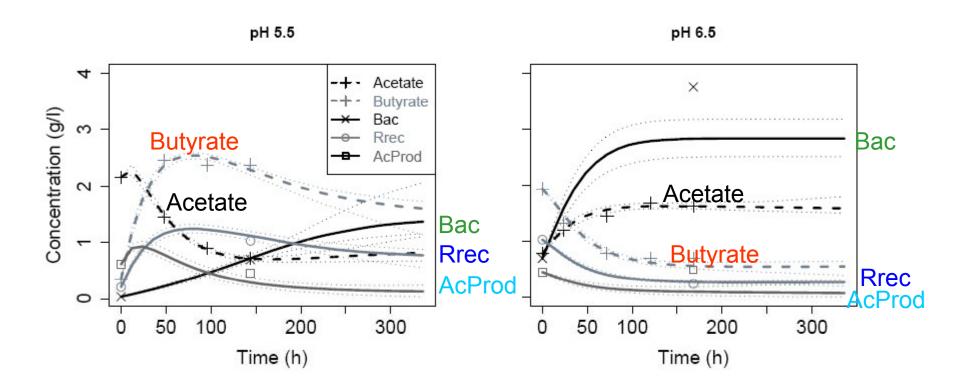
– – Metabolic products

Bacterial groups

Shown: median and 95% credible intervals

Data and posterior predictions





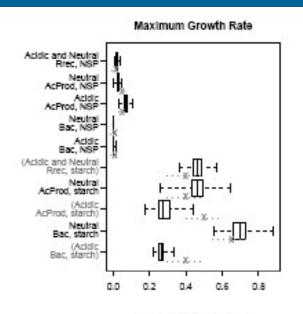
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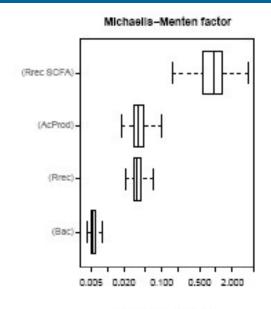
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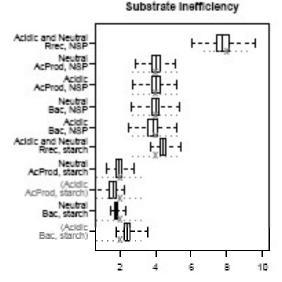
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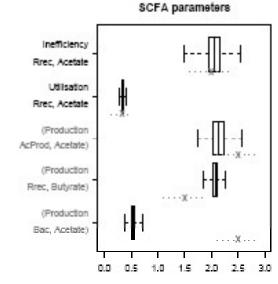
Posterior distributions









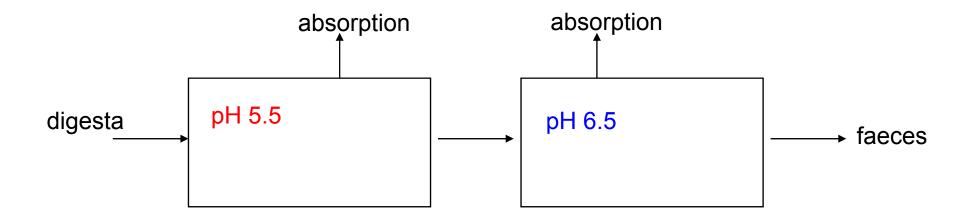


Predict behaviour in colon



Fermentor studies: no absorption

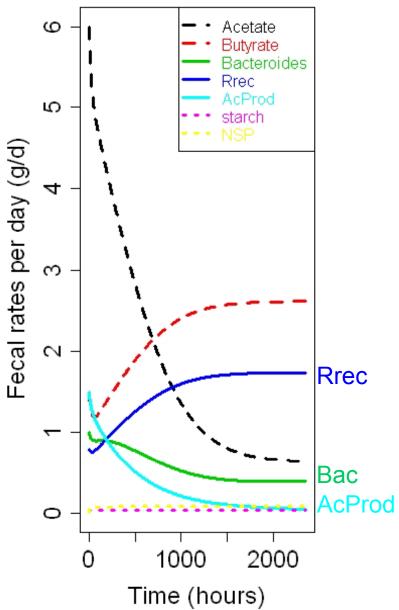
But this is major aspect of conditions in vivo!



Use model findings to simulate what would happen if absorption of metabolites is allowed for

No SCFA absorption: 0g/h



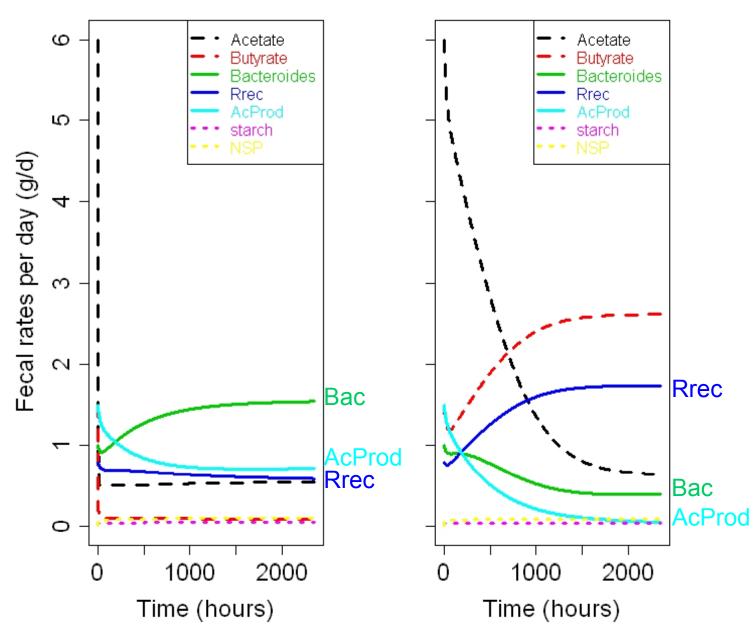


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SCFA absorption 0.375g/h

No SCFA absorption: 0g/h





Predict behaviour in colon



Results:

- Dominance of bacterial species has changed
- Metabolite concentrations reduced
- This helps to explain why observations from fermentor studies are different from those in vivo (faecal samples)

Conclusions



Systems with

- limited data
- Well-defined biological model structure (differential equations)
 - Non-linear
 - Non-steady state
 - No analytical solution
- Many unknown model parameters not measurable
- Often, observations only available from an easily accessible compartment (such as plasma, or faeces), with underlying compartments unobserved
- Usually, estimation of parameters for one data set at a time, which tends to be problematic: (non-)convergence, local? optima, only part of parameter space explored, no or limited information on dependencies between parameters.
- Here we have shown how Bayesian approaches may be useful
- Can take advantage of Bayesian approaches when combining studies (run under different conditions)
- Findings are preliminary!

Conclusions



Issues

- Issues with convergence, poor mixing, long chains needed, computational load
- How to select appropriate biological models (ODEs)
- Explore behaviour of ODEs for biological range of parameter values (insights into competition, exclusion, co-existence etc)
- So far only looked at simple bacterial systems

Future

- More complex bacterial behaviour
- 'Feedback' of products on bacterial growth (SCFA increase acidity)
- Use data from fermentor studies to infer systems parameters, then adapt models to simulate bacterial behaviour in the gut
 - Absorption
 - Movement of digesta and products down the colon
- Faecal samples representative of bacterial processes in colon?

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