

## **2.1 Linking Models and Reality: Reification Strategies for a Rainfall-Runoff Model.**

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\*work done in collaboration with Michael Goldstein, Allan Seheult, Leanna House, (Dept. Mathematical Sciences, Durham University), Prof Keith Beven (Lancaster University) Funding: MUCM and EPSRC.

# Overview

- Reification Strategies.
- The Rainfall-runoff model.
- Dynamic Reification.
- Modular Reification.

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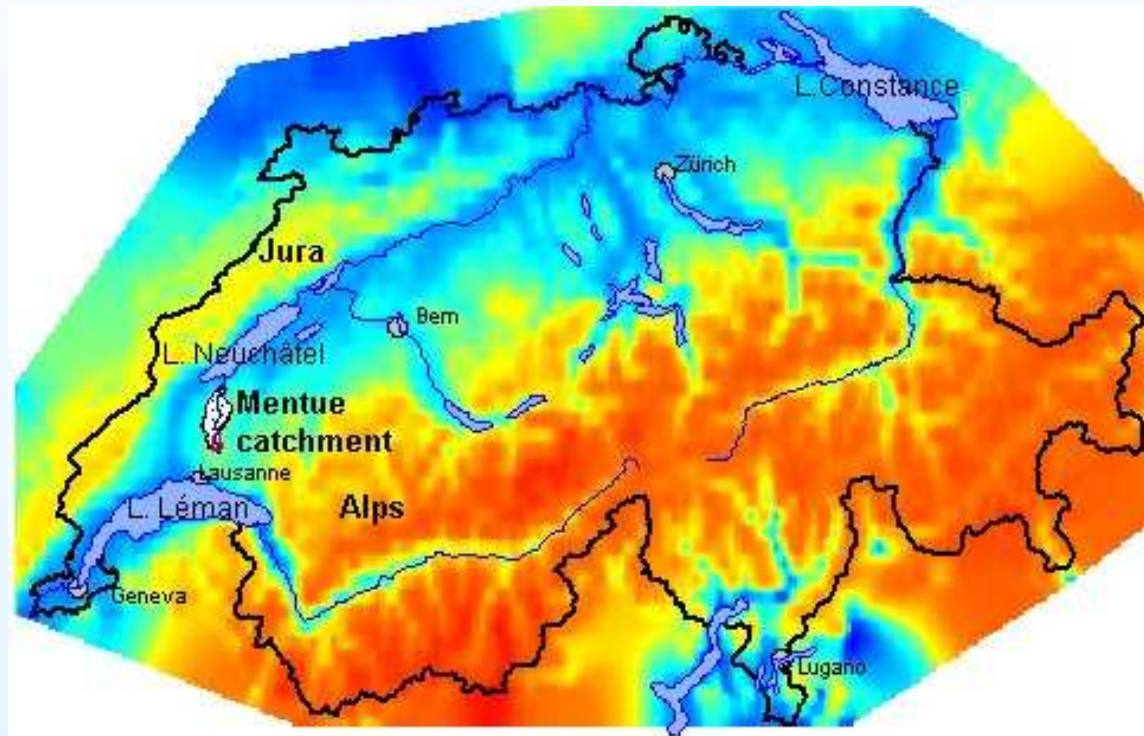
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  - Modular Emulation and Reification.
- The further down the list we go, the easier the Reification, but the harder the Emulation.

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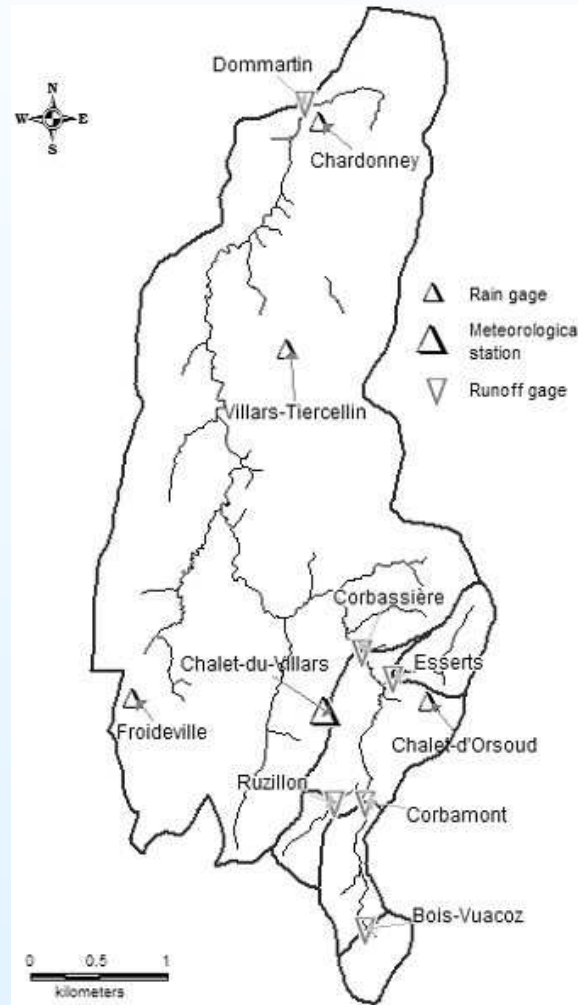
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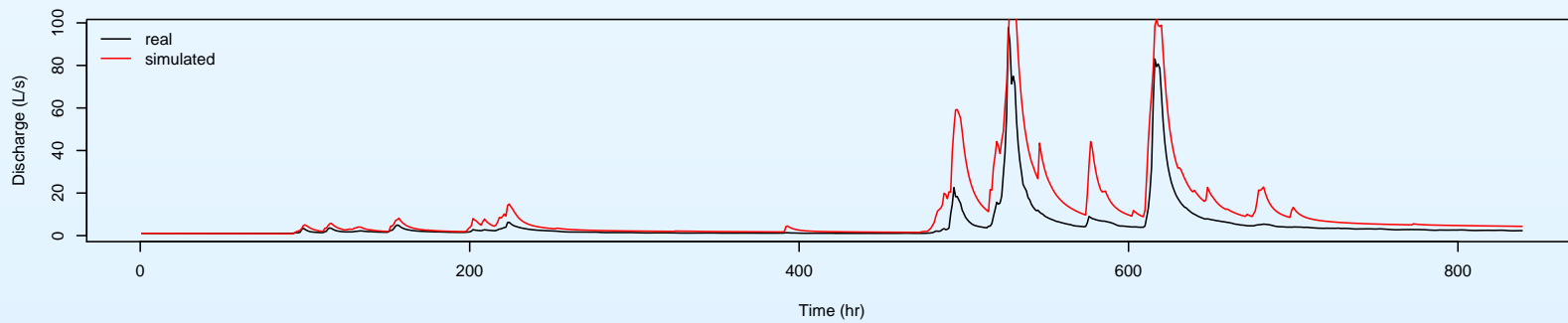
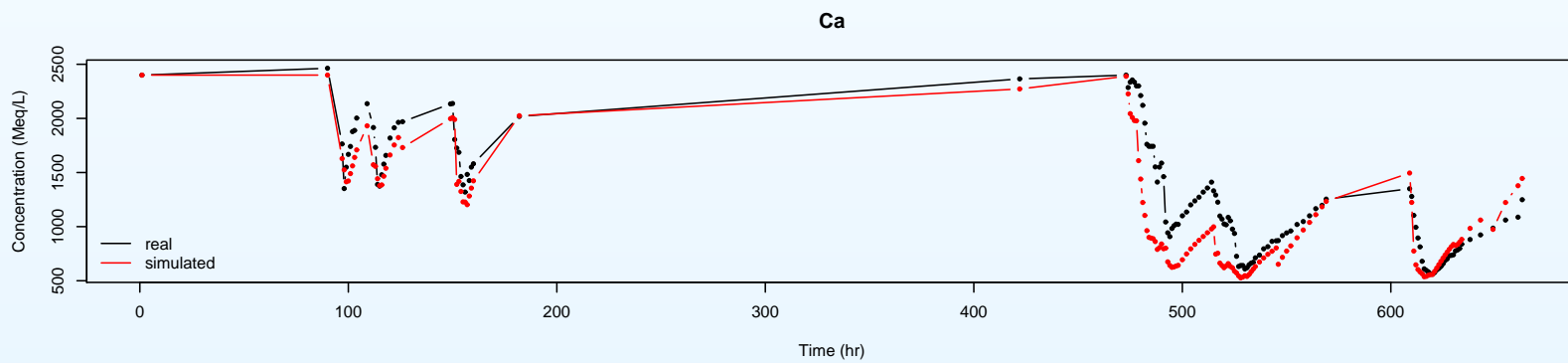
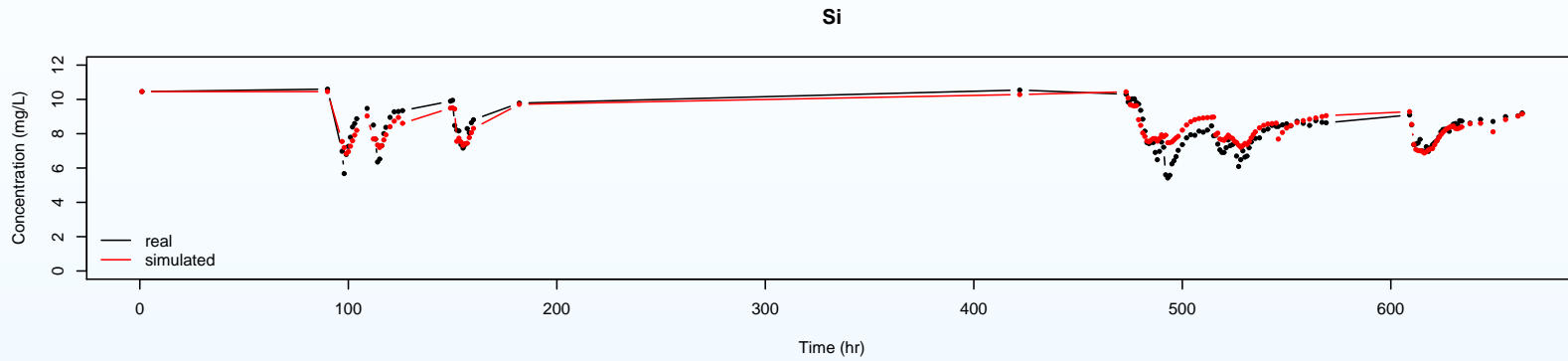
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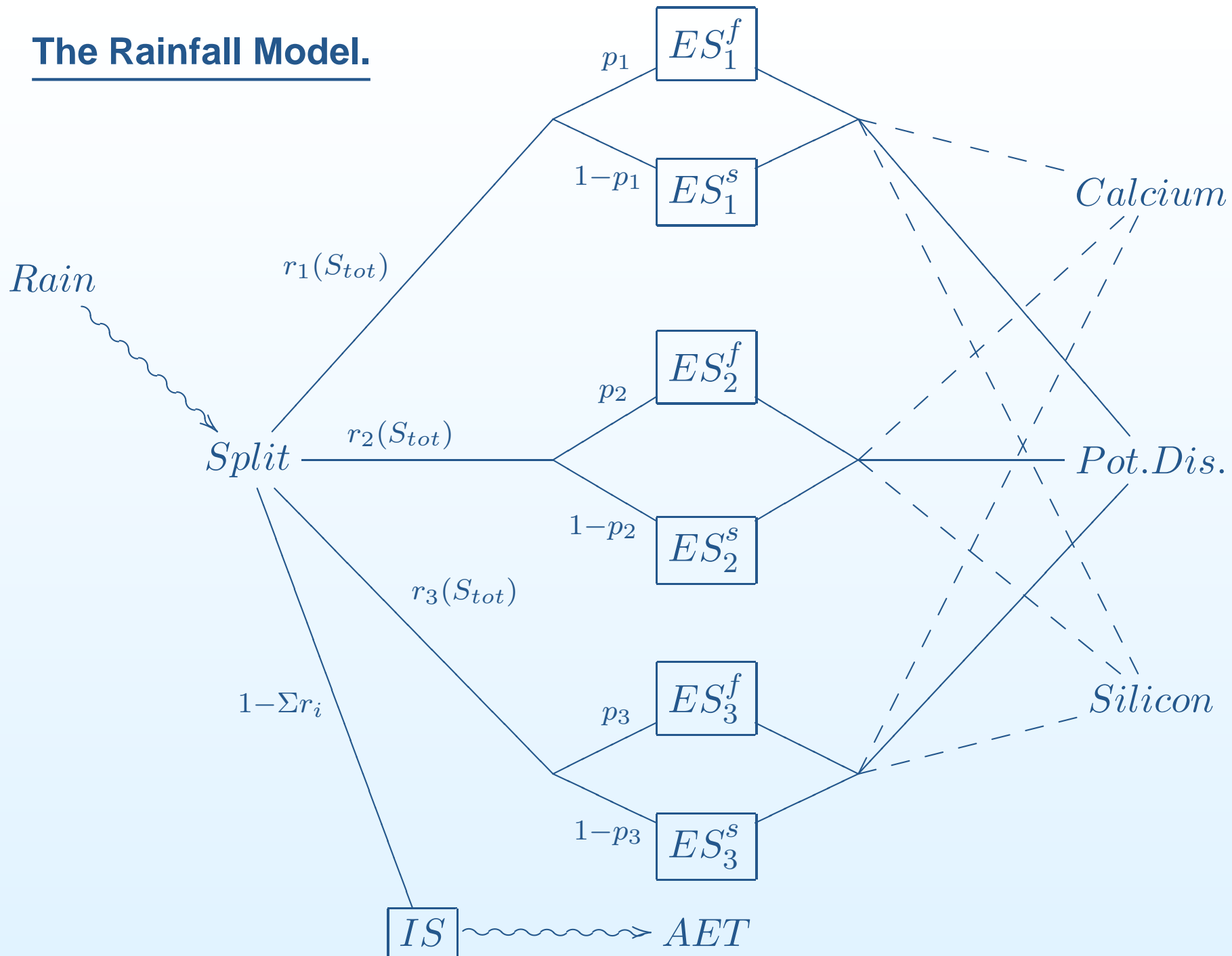
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- Model takes measured rainfall rates  $rain(t)$  and assumed evaporation rates  $AET(t)$  as forcing functions.

# Example of Model output





# The Rainfall Model.



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- $f^{(1)}$  is a function that has 26 inputs: the 17 usual inputs to the model  $x$ , the forcing functions at time  $t$  ( $rain(t), AET(t) = A(t)$ ) and the 7 State Variables at time  $t-1$ : ( $ES_i^{f/s}(t - 1), S_{tot}(t - 1) = S(t - 1)$ ).
- $f^{(1)}$  has 7 outputs that are the State Variables at time  $t$ : ( $ES_i^{f/s}(t), S_{tot}(t) = S(t)$ ).

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- Emulation techniques such as active variables can be misleading.
- Accounting for other sources of uncertainty, as required in the Reification process, can still be difficult at this level (although is far easier than Direct Reification).

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- Downside: it is difficult to link the modular emulators together (but we already have this problem in the Dynamic Case).

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- We identified active variables, and constructed fast emulators composed of linear models with 2nd order polynomials in the active variables.

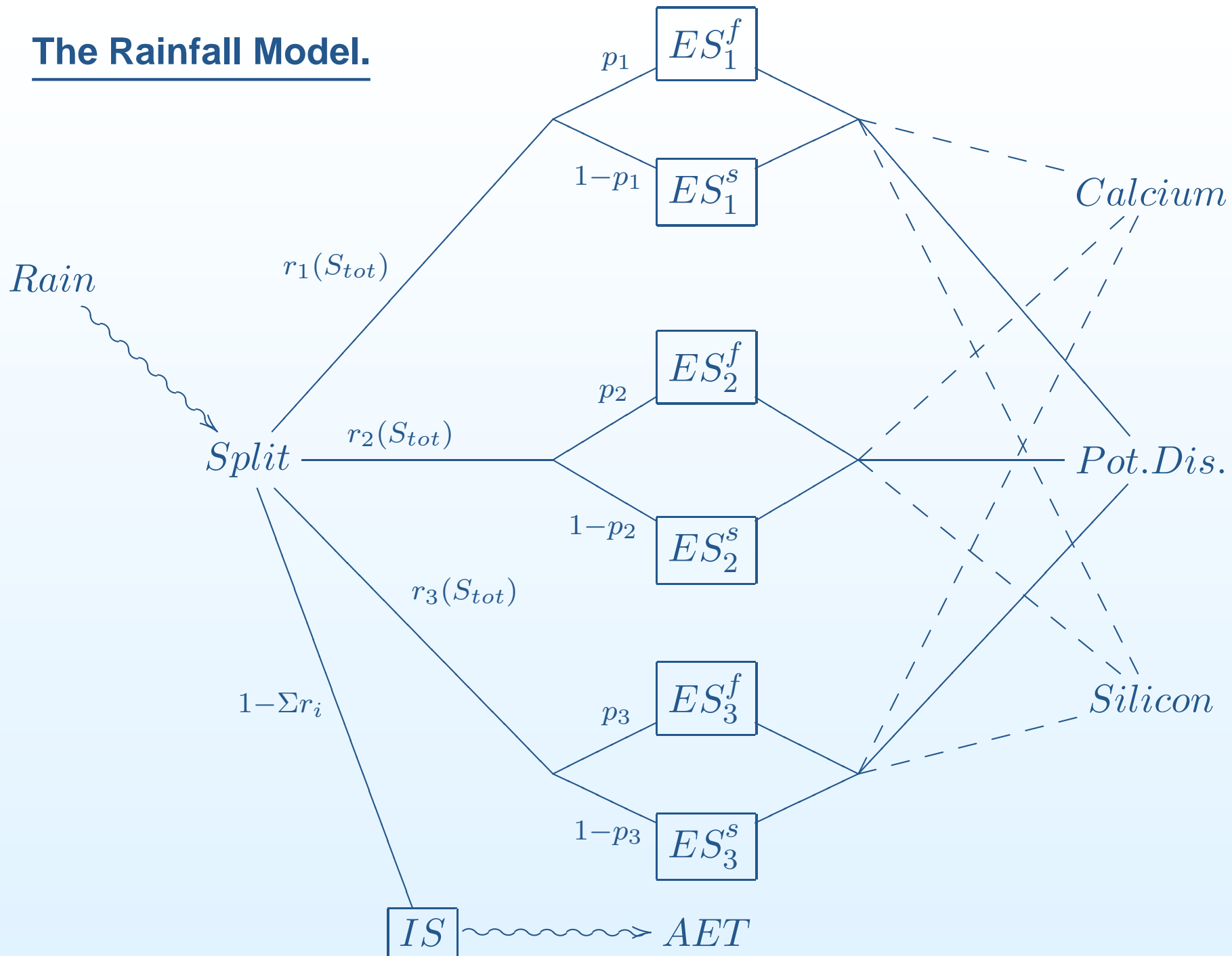
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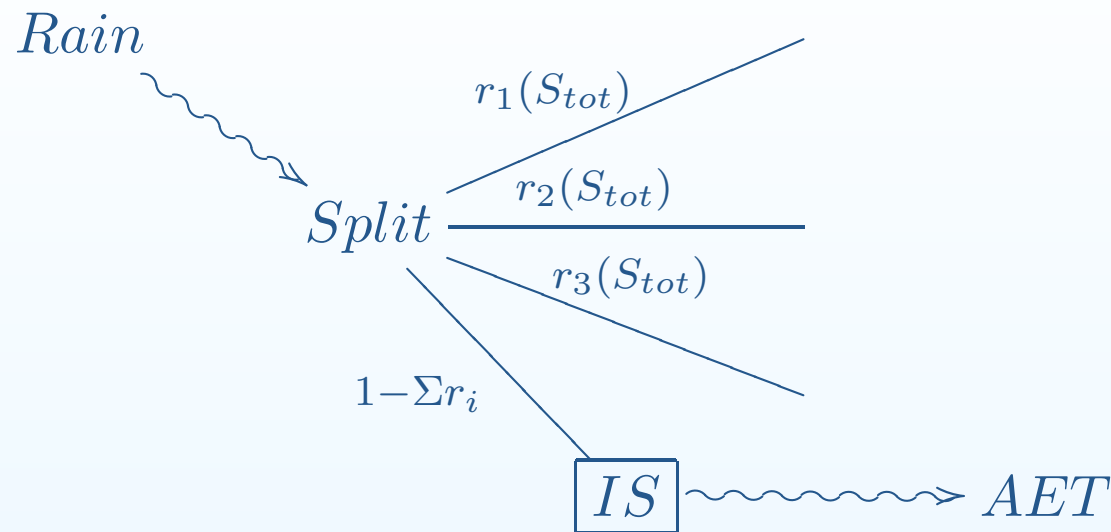
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- Intend to improve emulators at later stage.

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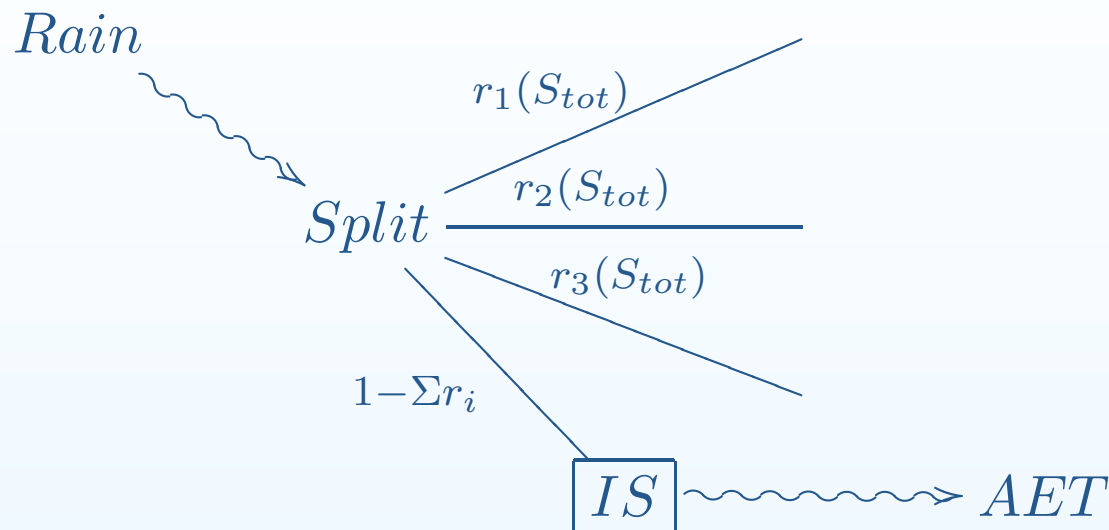


## Module 1



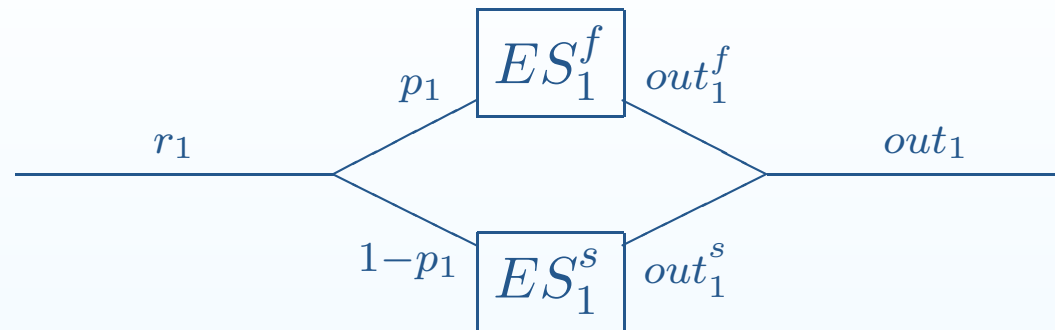
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- Find that the  $r_i$  depend on only  $k_i, a_i, b_i, S_{tot}, rain$ .
- Allowed incorporation of the uncertain forcing function rainfall.
- Will attempt to do internal reification on the  $r_i$  functions directly.

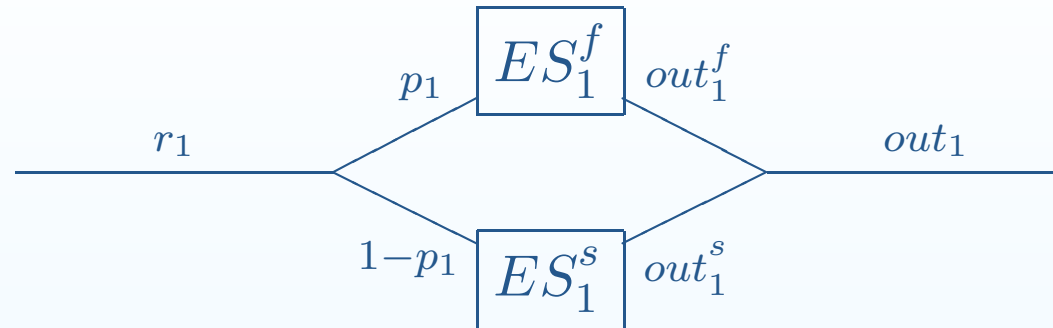
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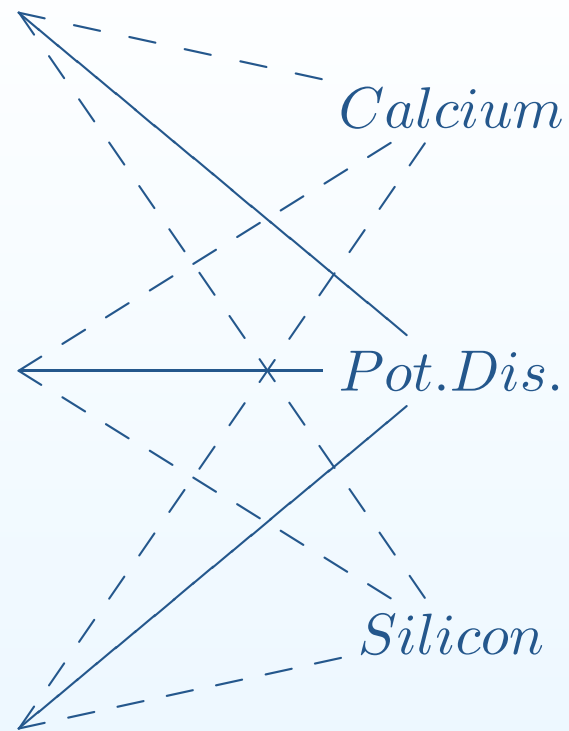


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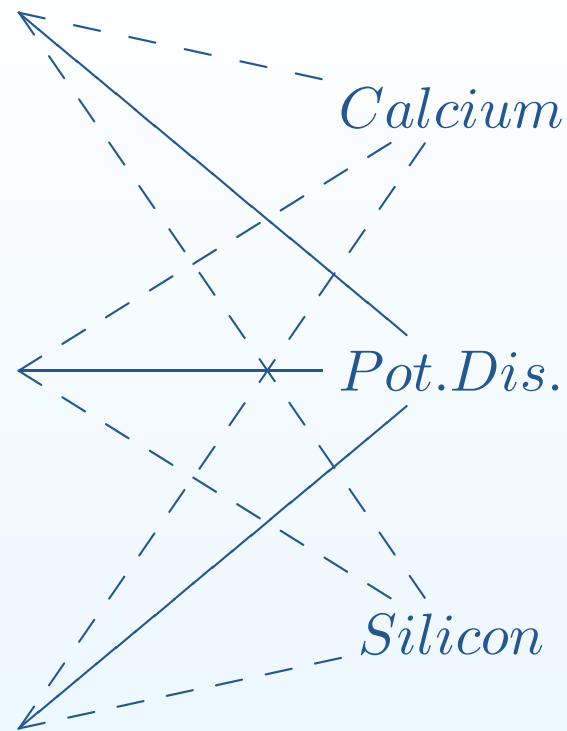
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- e.g. we find that  $out_1^f(t)$  is a function that only depends on two inputs:  $ES_1^f(t-1)$  and  $cf_1$ , and is trivial to emulate.
- Again can Reify this (or parts of this) compartment process.

## Module 3



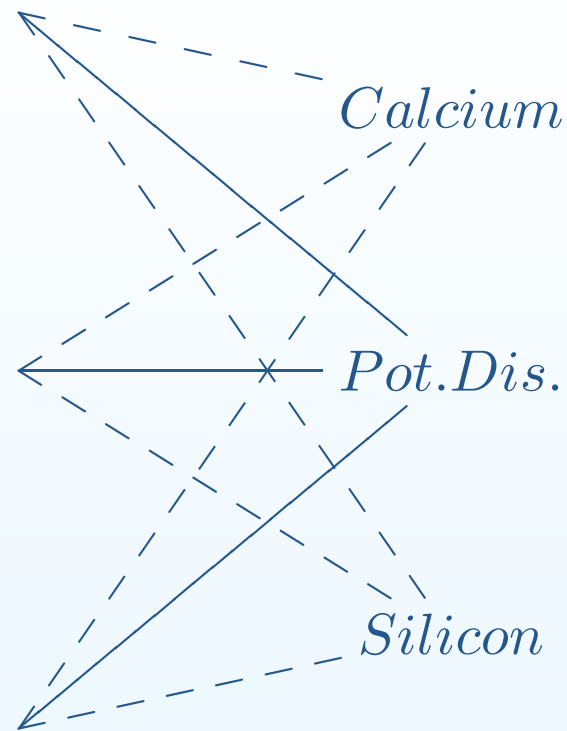
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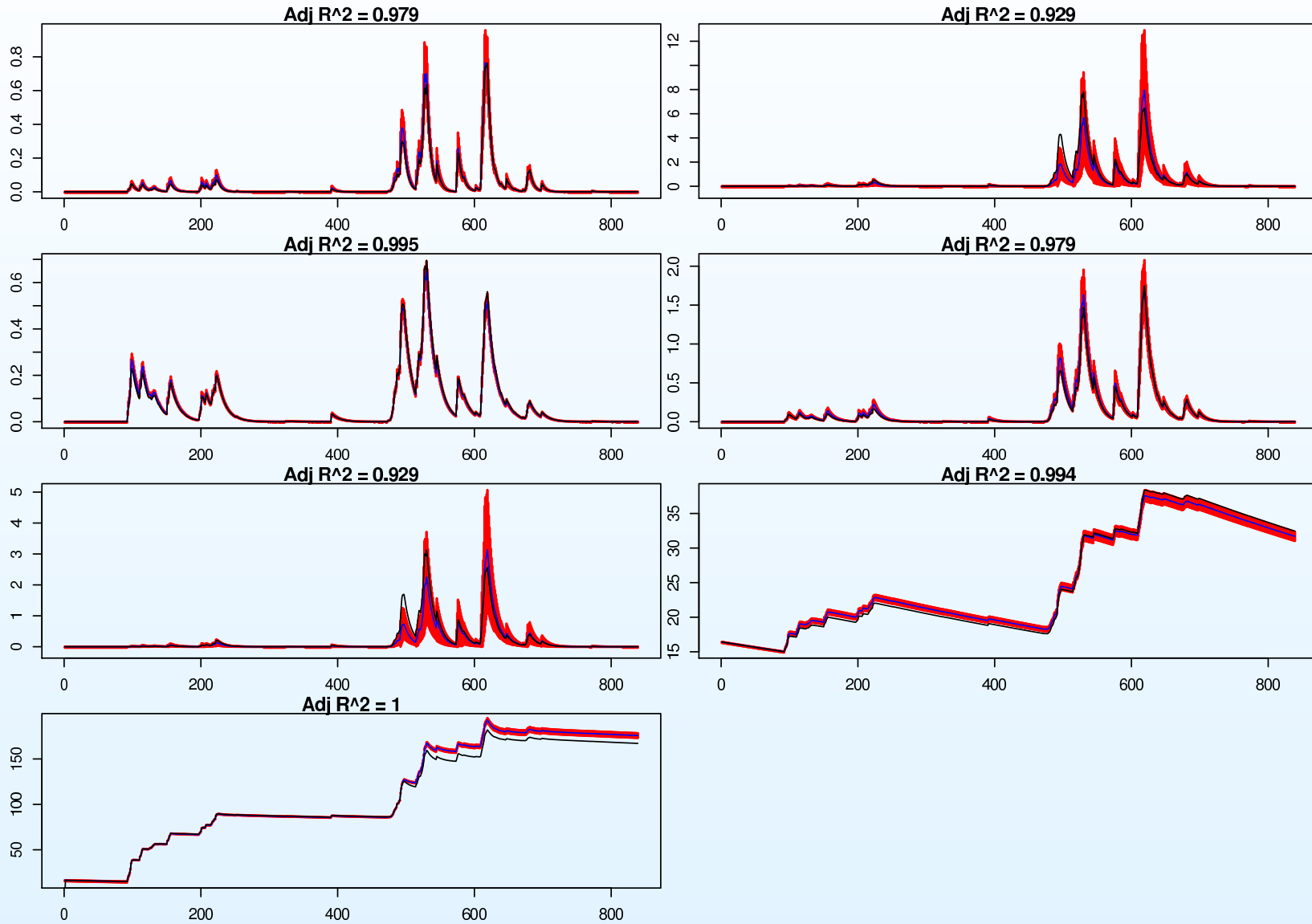
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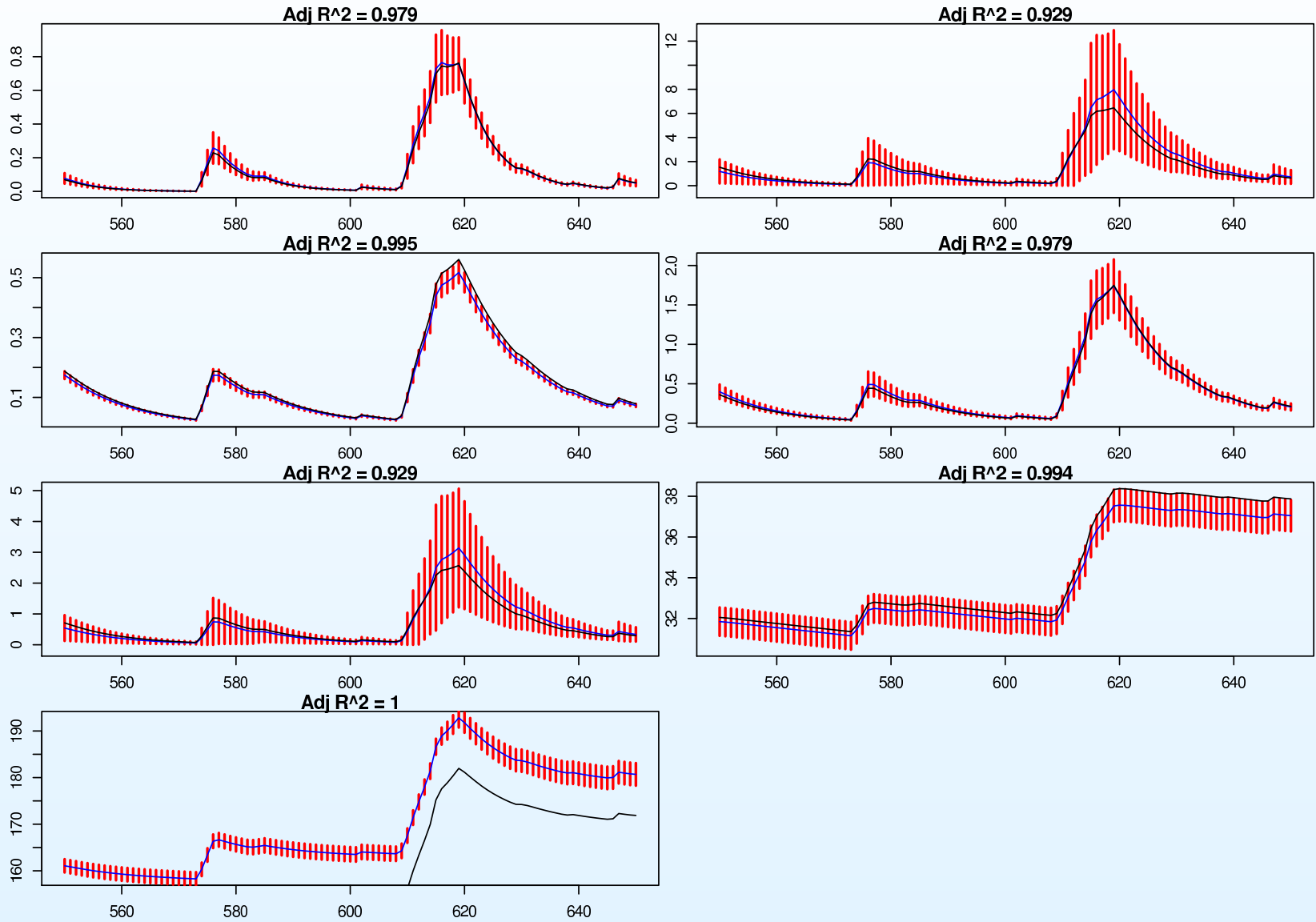


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- Contains assumption of fixed Tracers that lead to Ca and Si concentration in rivers.
- Modular Emulation has allowed incorporation of uncertainty due to Tracers: first step in a Reification of this function.

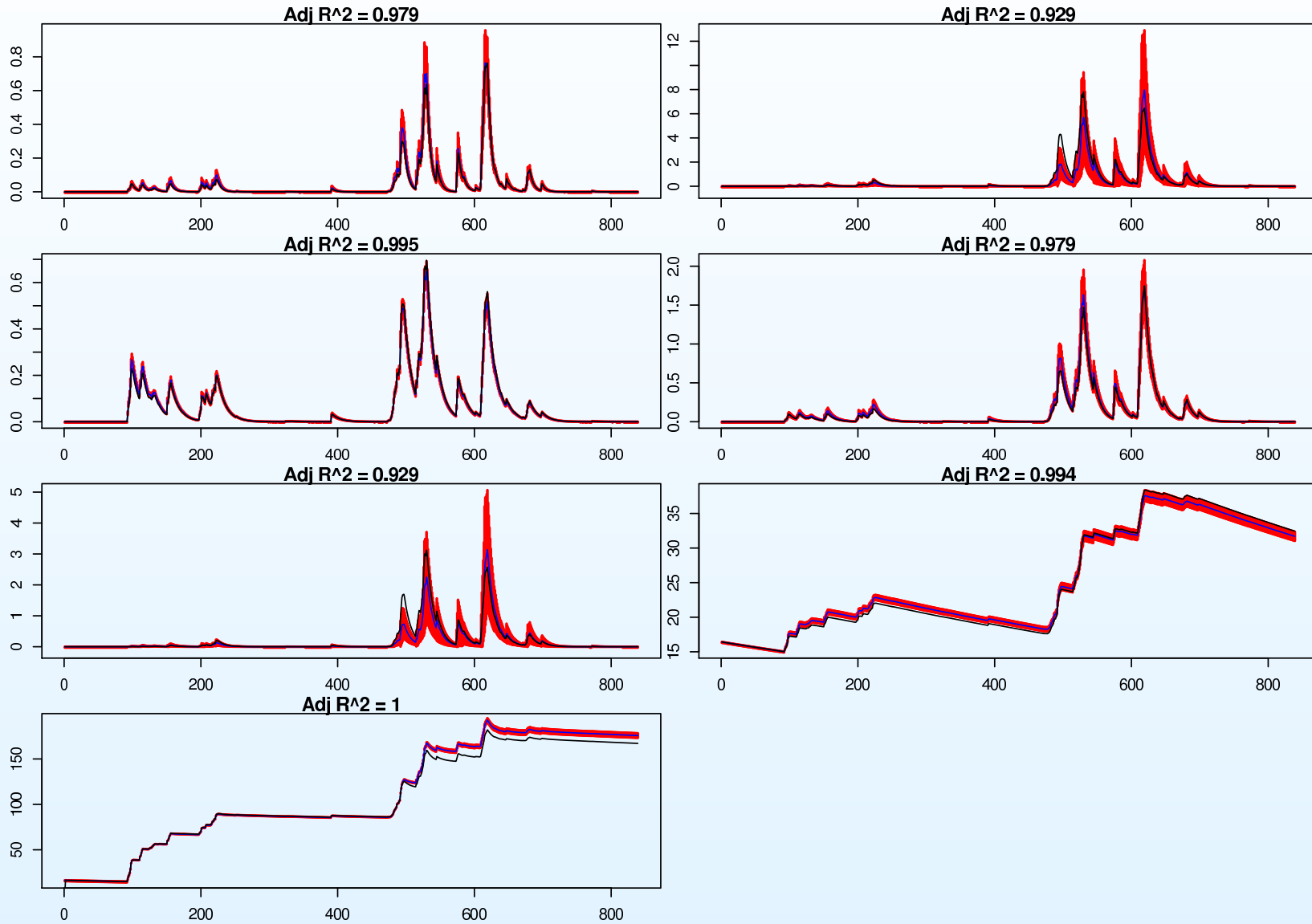
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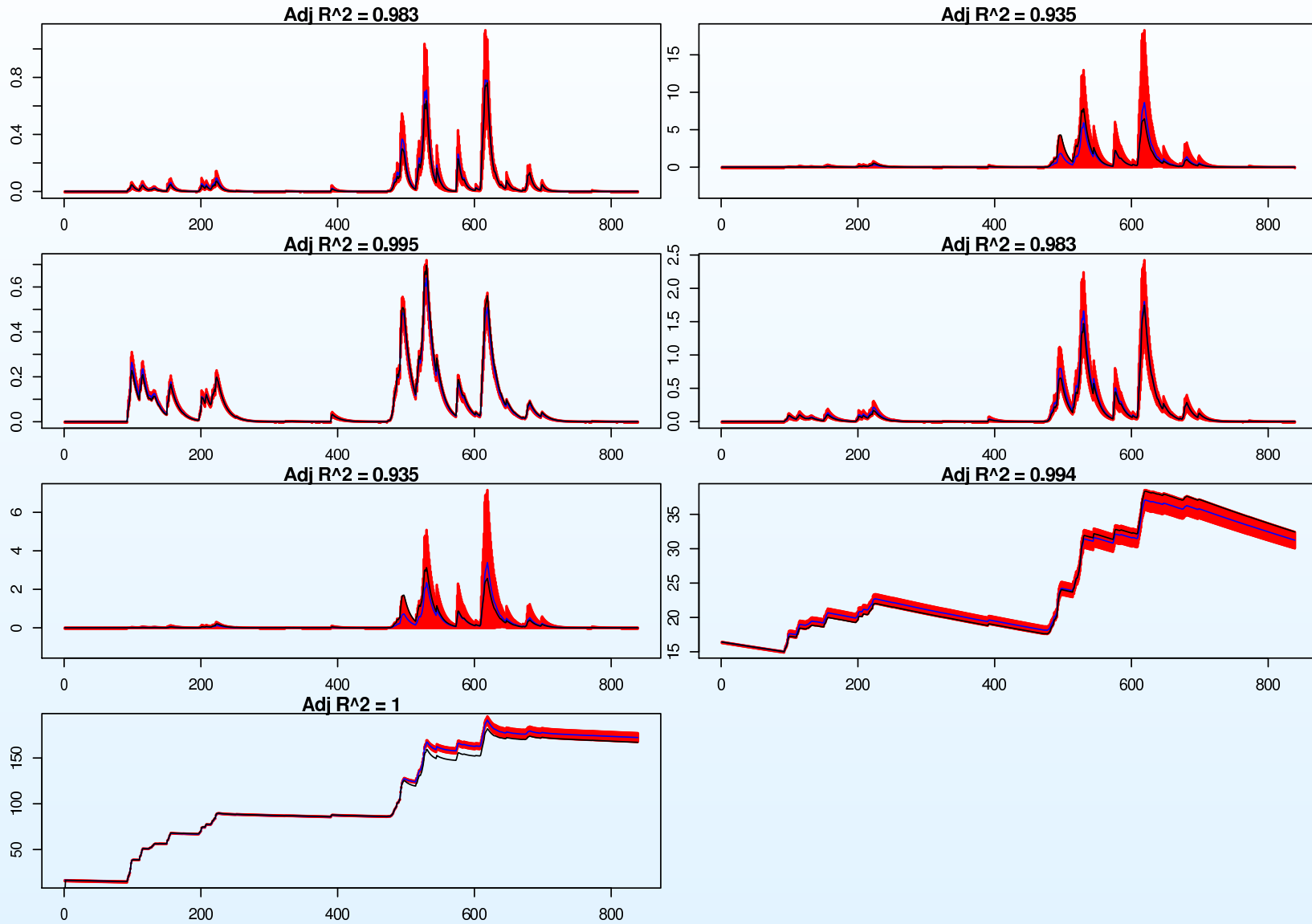
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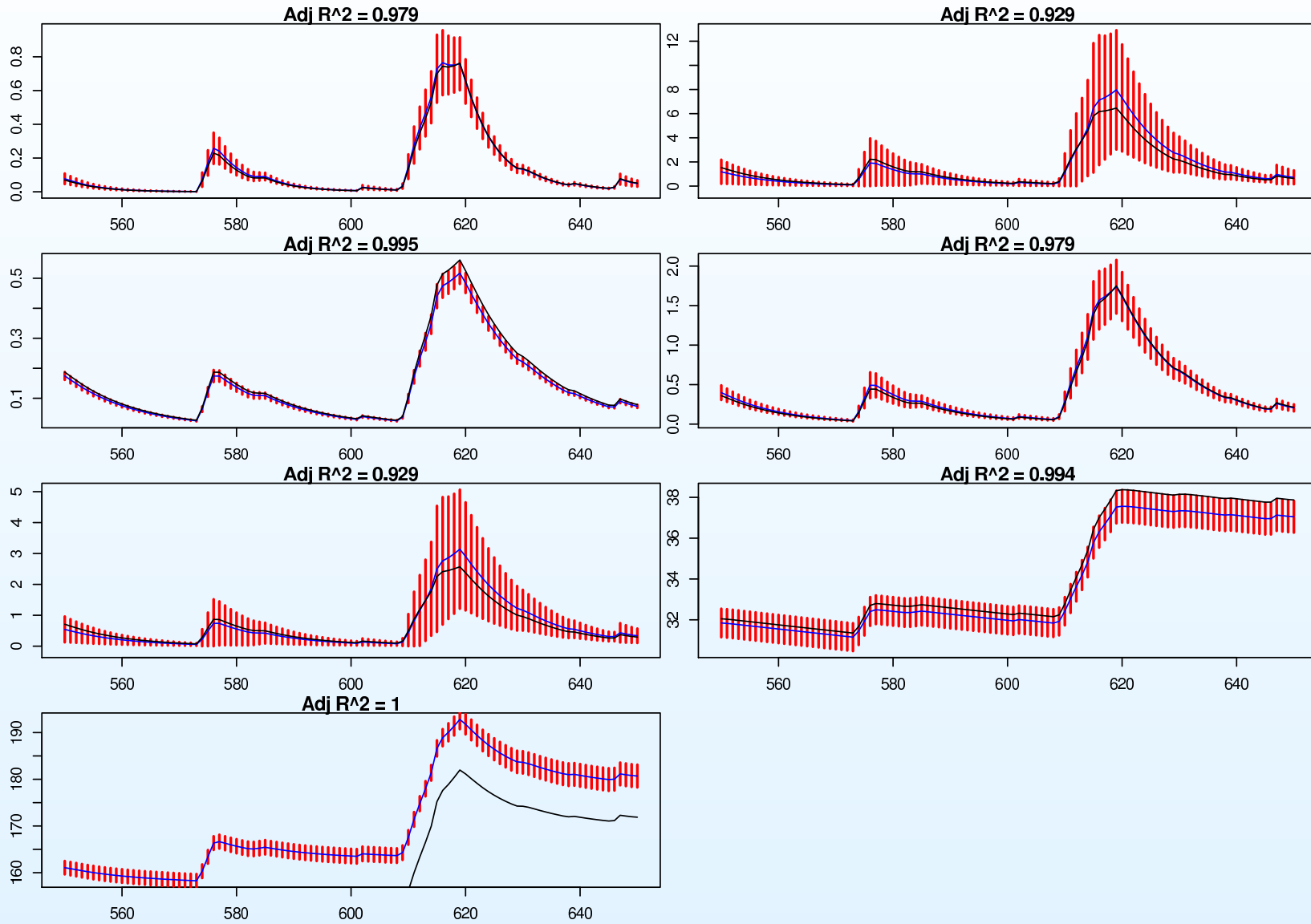


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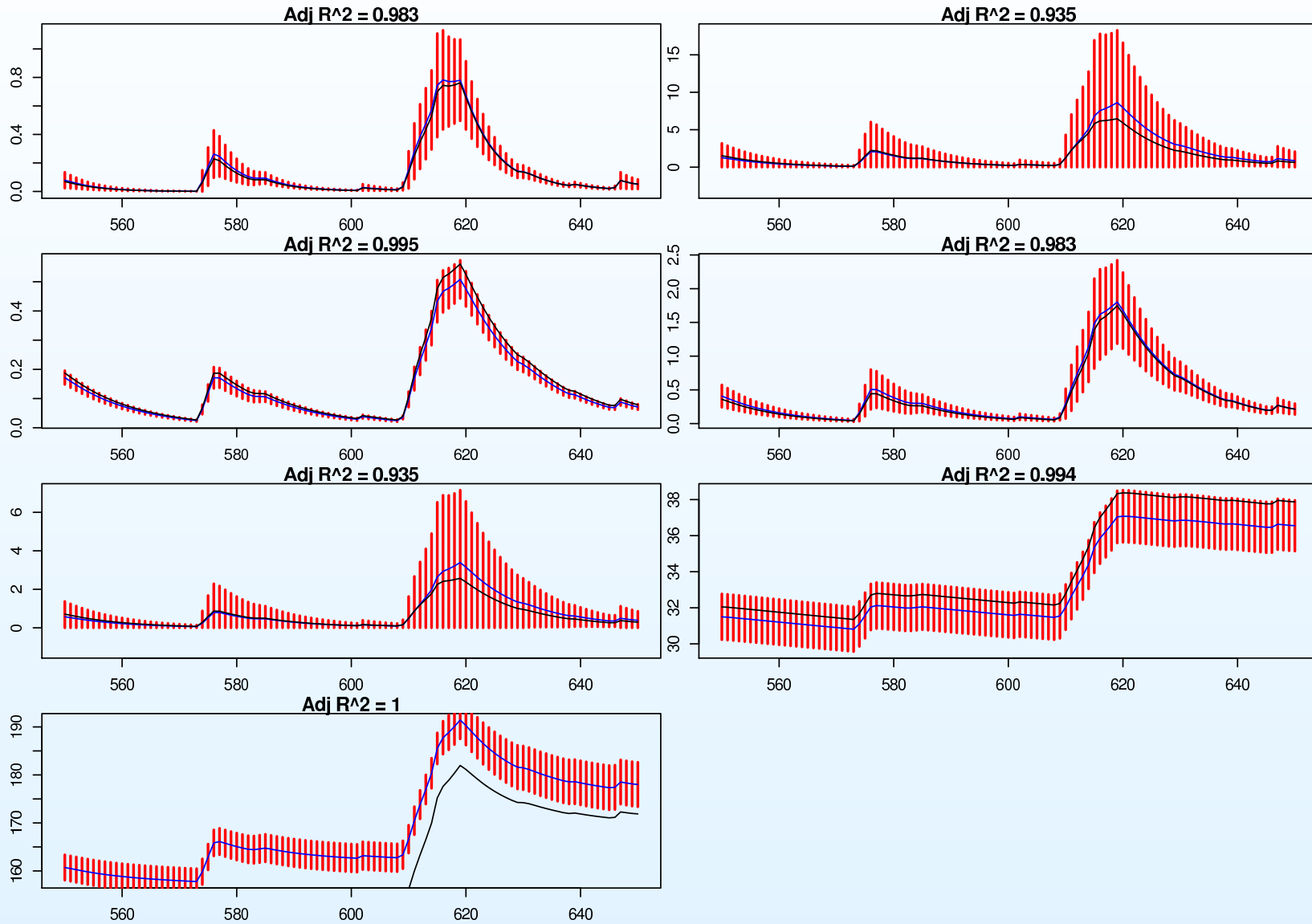




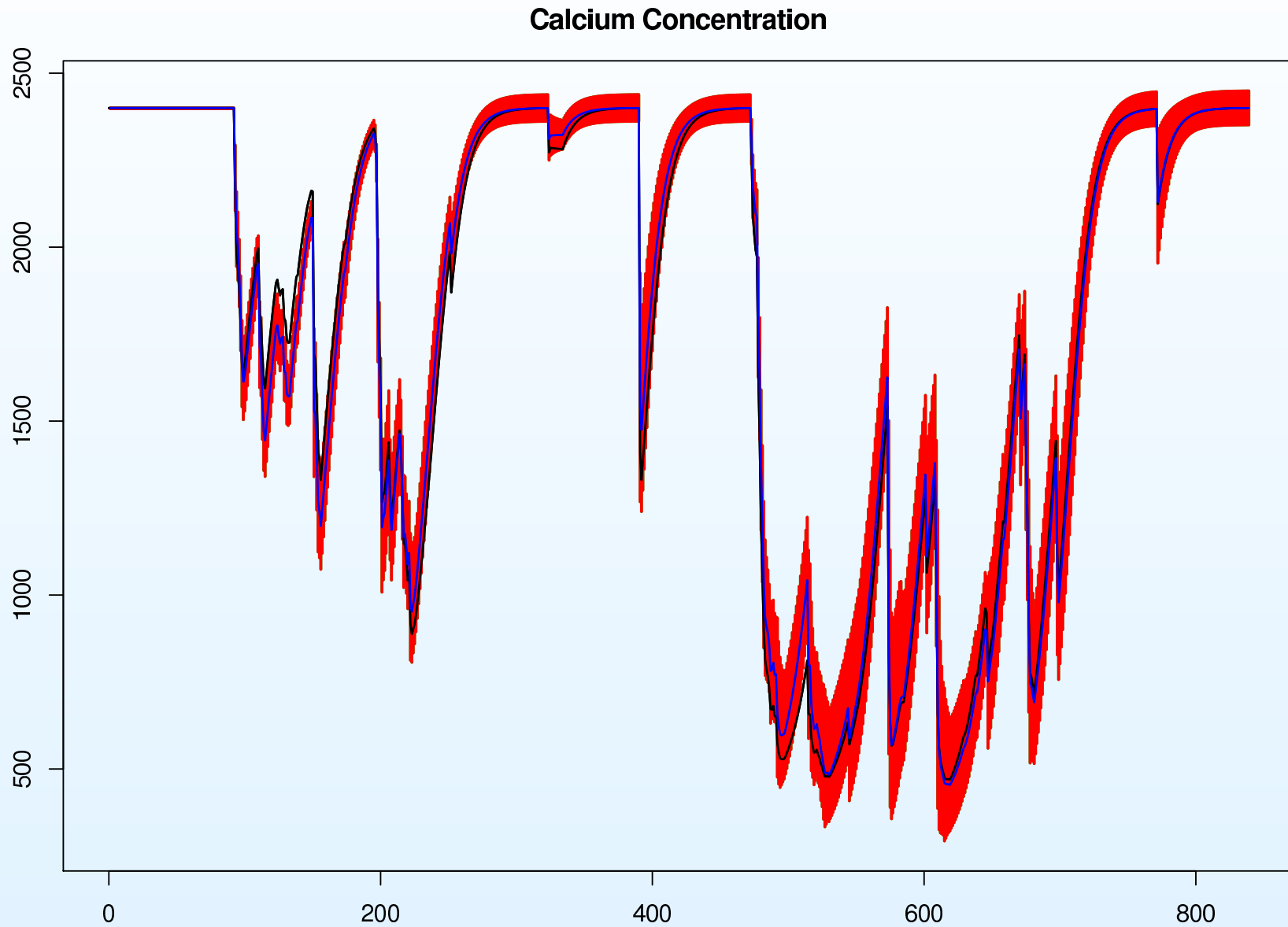
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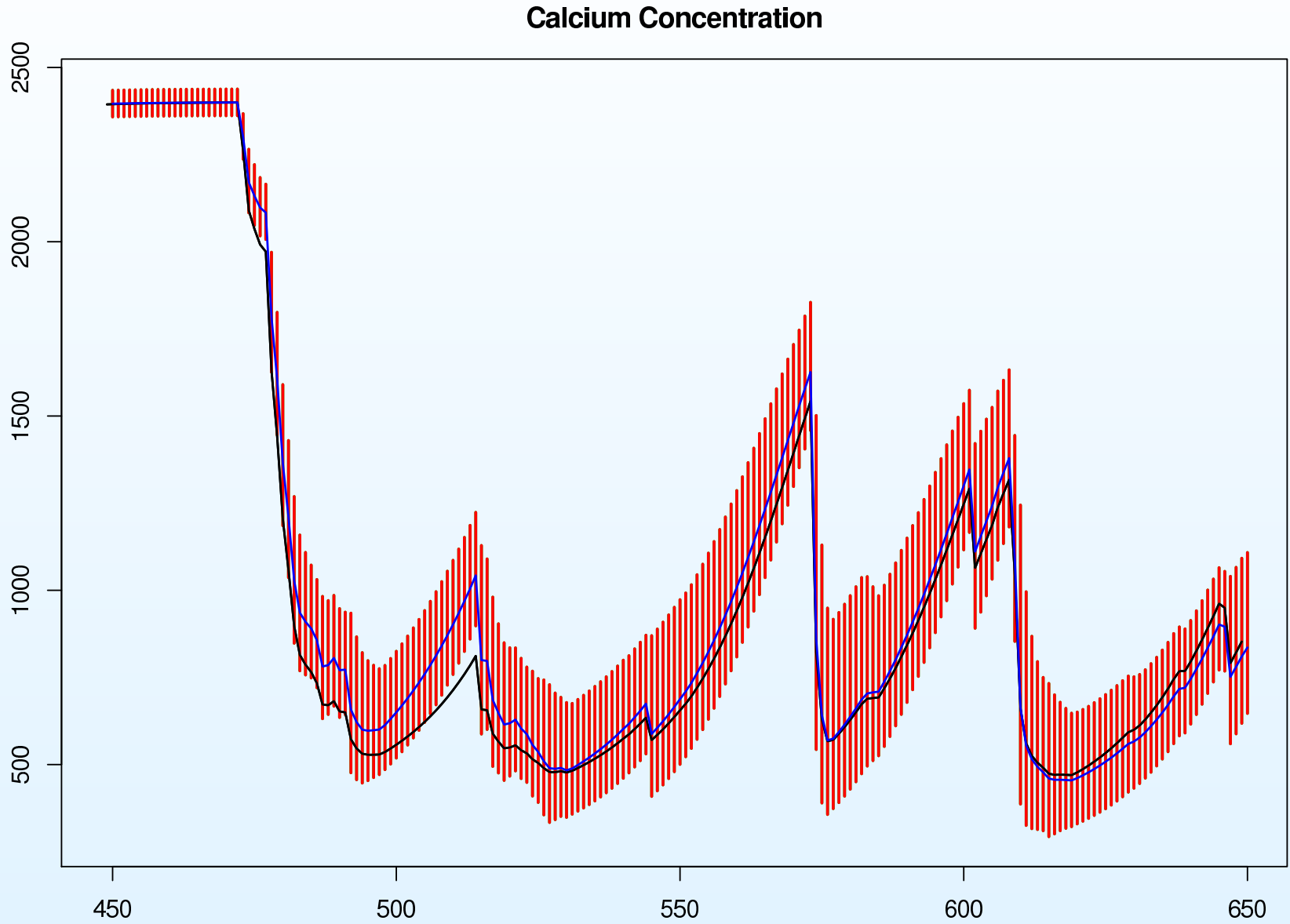
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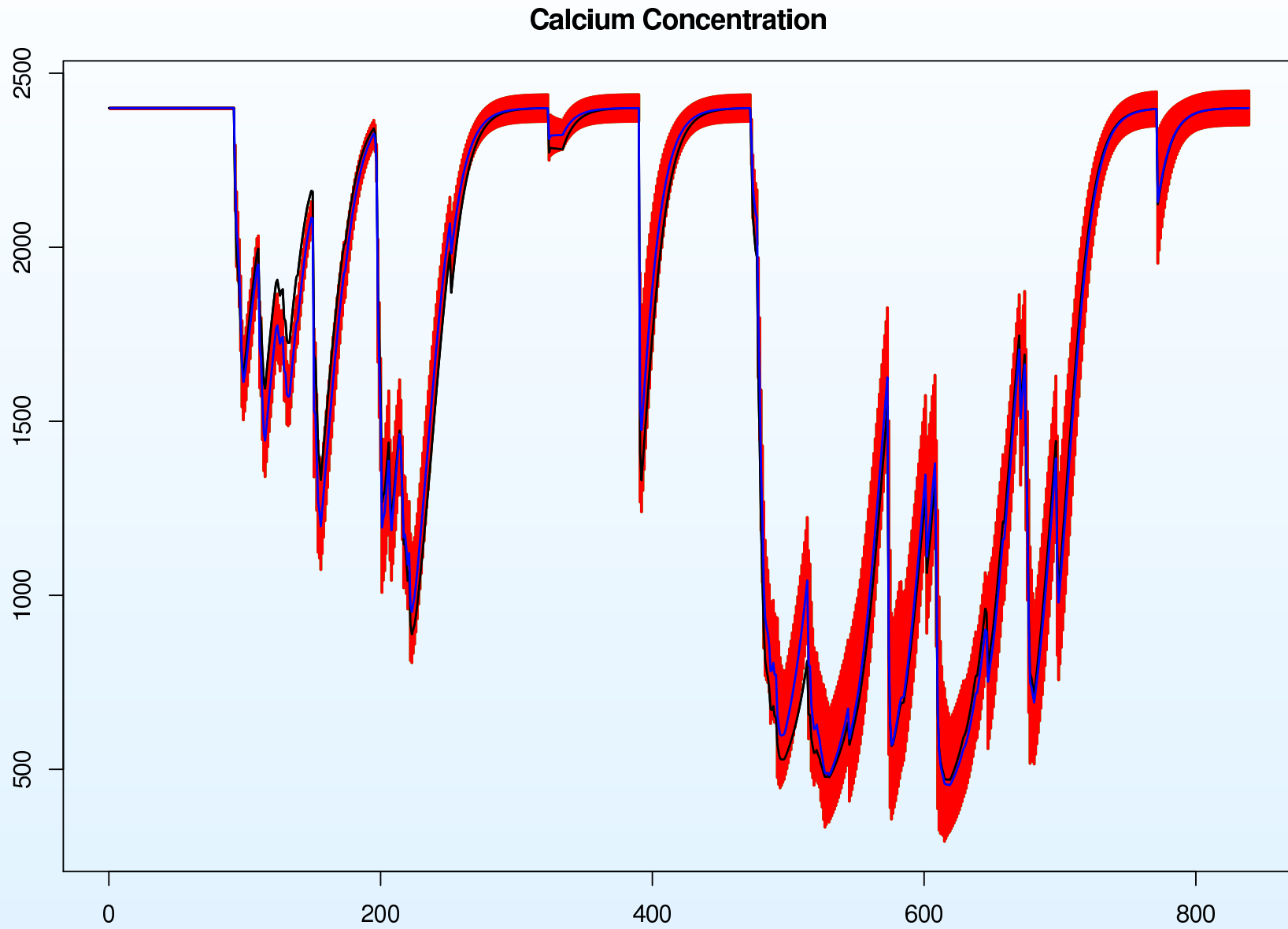
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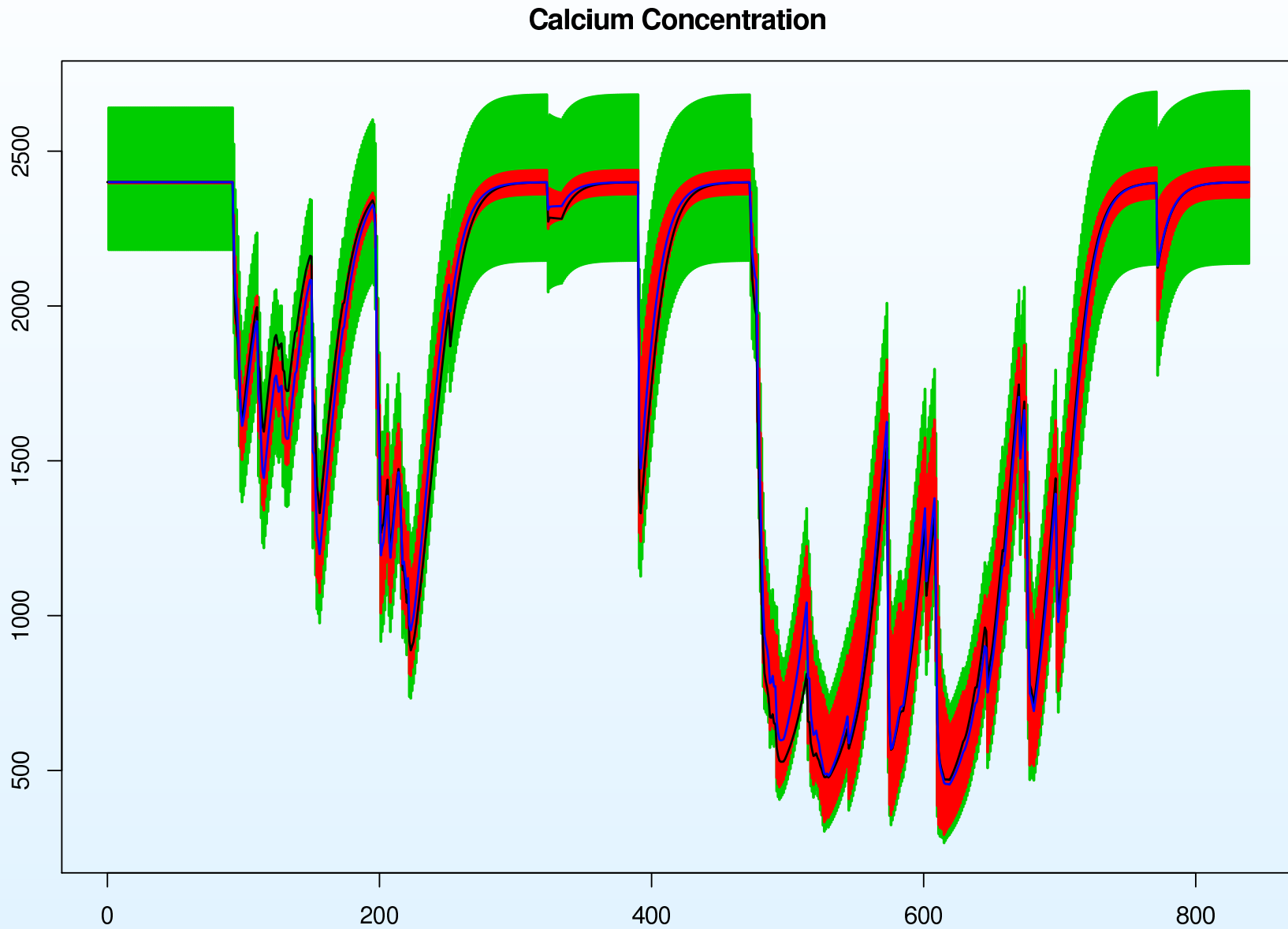
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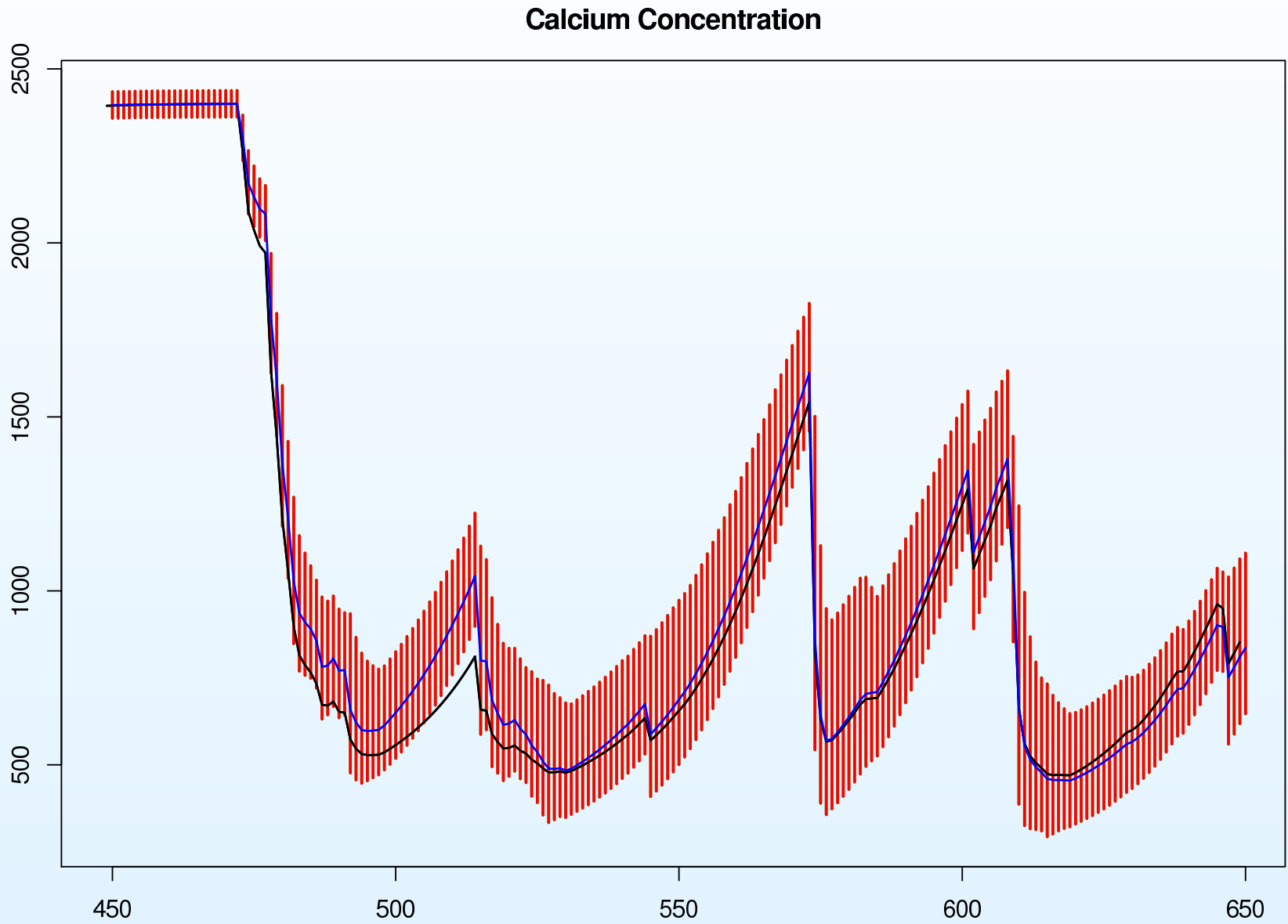
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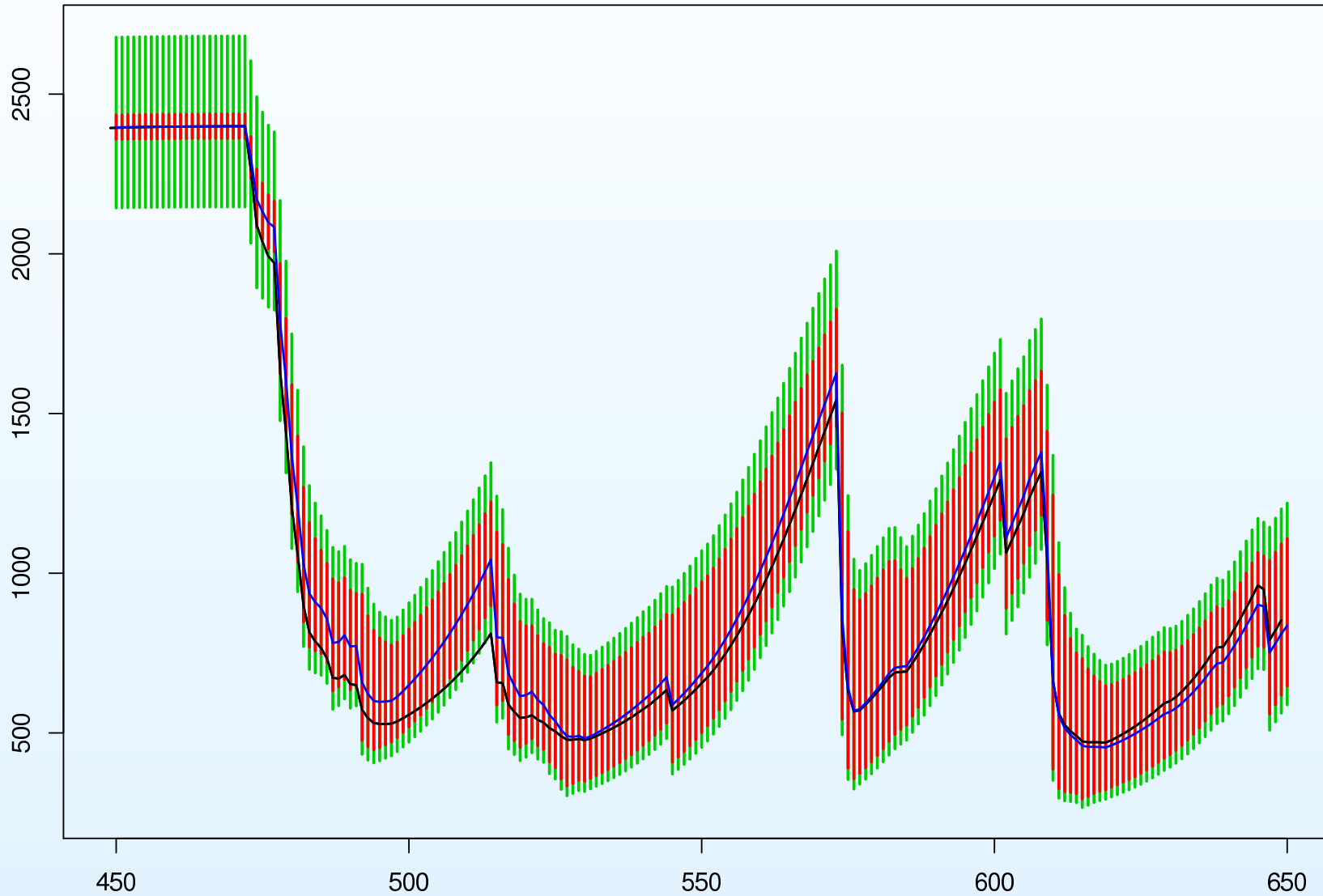


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- Lots more to say: Checking assumptions via simulation, comparisons of Direct Emulation with Dynamic and Modular Emulation, assessment of relative impact of different uncertainties, upgrading constant inputs to time dependent processes, External Reification...

## References

M. Goldstein and J.C.Rougier. Probabilistic formulations for transferring inferences from mathematical models to physical systems (2005) SIAM journal on scientific computing, 26, 467-487.

M. Goldstein and J.C.Rougier. Reified Bayesian modelling and inference for physical systems (2006) In revision for JSPI.