

# Improving the predictability of global CO<sub>2</sub> assimilation rates under climate change



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## INTRODUCTION

Predictions of the terrestrial carbon balance vary significantly due to differences between model formulations but also due to uncertainties in the process parameters of the terrestrial ecosystem models (TEMs), with parameters related to photosynthesis and leaf respiration being among the most sensitive ones. First attempts have been conducted to constrain the parameters of TEMs by inversion against eddy covariance measurements of CO<sub>2</sub> and energy fluxes at a site [1] and on a global scale by inversion against atmospheric CO<sub>2</sub> concentration measurements [2]. However, the huge amount of plant leaf level observations [3] have so far not been used to objectively constrain model parameter. Subsequently, parameter estimates in Earth system models used to simulate the strength of the climate-carbon cycle feedback are still mostly based on rather subjective “expert knowledge”. For that reason, we here apply a more objective method of parameter constraint based on model inversion against the leaf level observations, both for model parameter values and values assigned to model output.

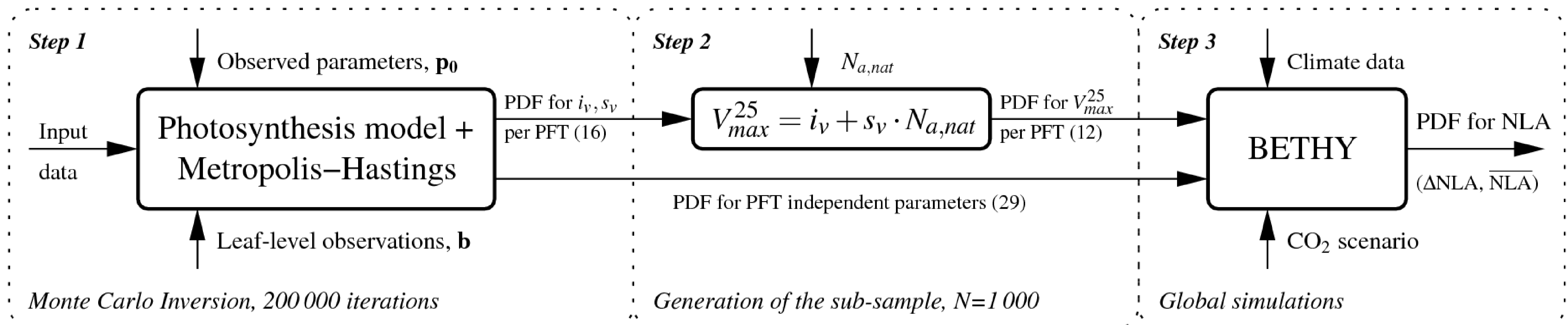


Figure 1: Flow chart of the assimilation scheme and the simulation of the sub-sample with BETHY based on the derived posterior parameter PDF. The number of estimated parameters is given in parentheses.

### MODEL (Step 1 in Figure 1)

- Extended version of Farquhar's photosynthesis model [4]
- 41 parameters
- All parameters of the model, apart from photosynthetic capacity which is dependent on plant functional type (PFT), have one value globally
- Acclimation of photosynthesis and respiration to plant growth temperature is taken into account [5]

### PARAMETRIZATION (Step 1 and 2 in Figure 1)

- Bayesian approach which combines the prior PDF of the parameters (derived from observed parameter values) with the PDF of the leaf-level observations
- Uncertainties in the observed parameters and the leaf-level observations are included via their error covariance matrix assuming a Gaussian distribution
- Posterior parameter PDF is calculated using the Metropolis-Hastings algorithm with 200000 iterations
- 1000 member sub-sample is generated from all iterations

### SIMULATION (Step 3 in Figure 1)

- Sub-sample is simulated with the Biosphere Energy Transfer Hydrology (BETHY) scheme [6] on a 2° x 2° grid
- Focus is on the net leaf assimilation (NLA), defined as gross photosynthesis minus leaf-level respiration, at the global scale
- BETHY is driven by present climate and a climate scenario (HadCM3) from 1979 to 2099
- Atmospheric CO<sub>2</sub> concentrations are based on the IPCC A2 scenario

## RESULTS

In this study, we focus on two characteristics of net leaf assimilation (NLA): The first one is mean NLA per year over the first 20 years of the simulation period, the second is the difference between mean NLA over the last 20 and mean NLA over the first 20 simulation years (ΔNLA).

Figure 2a shows the PDF of mean NLA for both cases. Both distributions can be approximated very well by a Gaussian as indicated by skewness and kurtosis. The mean value in the posterior case is slightly larger than in the prior case. However, the uncertainty is reduced by more than a factor of two, if using the posterior parameter values. We find similar results when analysing the PDF of ΔNLA (Figure 2b). Again, the distribution in both cases is approximately Gaussian and the mean values are nearly the same. The uncertainty, however, is reduced by nearly a factor of three between using the prior and the posterior parameter values.

A time series plot of NLA is presented in Figure 3 for both the prior and posterior cases, showing in each case and for each simulation year the 5th, 50th and 95th percentiles of NLA. The curve of the 95th percentile is nearly the same for both cases, indicating that the use of the prior and posterior parameter values results in the same upper constraint for NLA. A large reduction in the uncertainty is achieved almost entirely within the lower part of the distribution of NLA (less than the median).

## CONCLUSIONS

We have used leaf level plant trait data (e.g. observations of parameters and photosynthesis and respiration rates and stomatal conductance) to constrain the Farquhar photosynthesis model using a Bayesian approach. With this method we have derived a consistent parametrization of 29 PFT independent and 12 PFT dependent parameters. We were able to reduce posterior parameter uncertainties, which in turn led to a reduction in the uncertainty by more than a factor of two for two key diagnostics related to the climate-carbon cycle feedback: mean NLA and NLA change due to climate change. Given that data bases on plant traits are increasingly being made available to the modelling community [3], this method should be used extensively to parametrize Earth system models. A more comprehensive description of the study presented here can be found in [7].

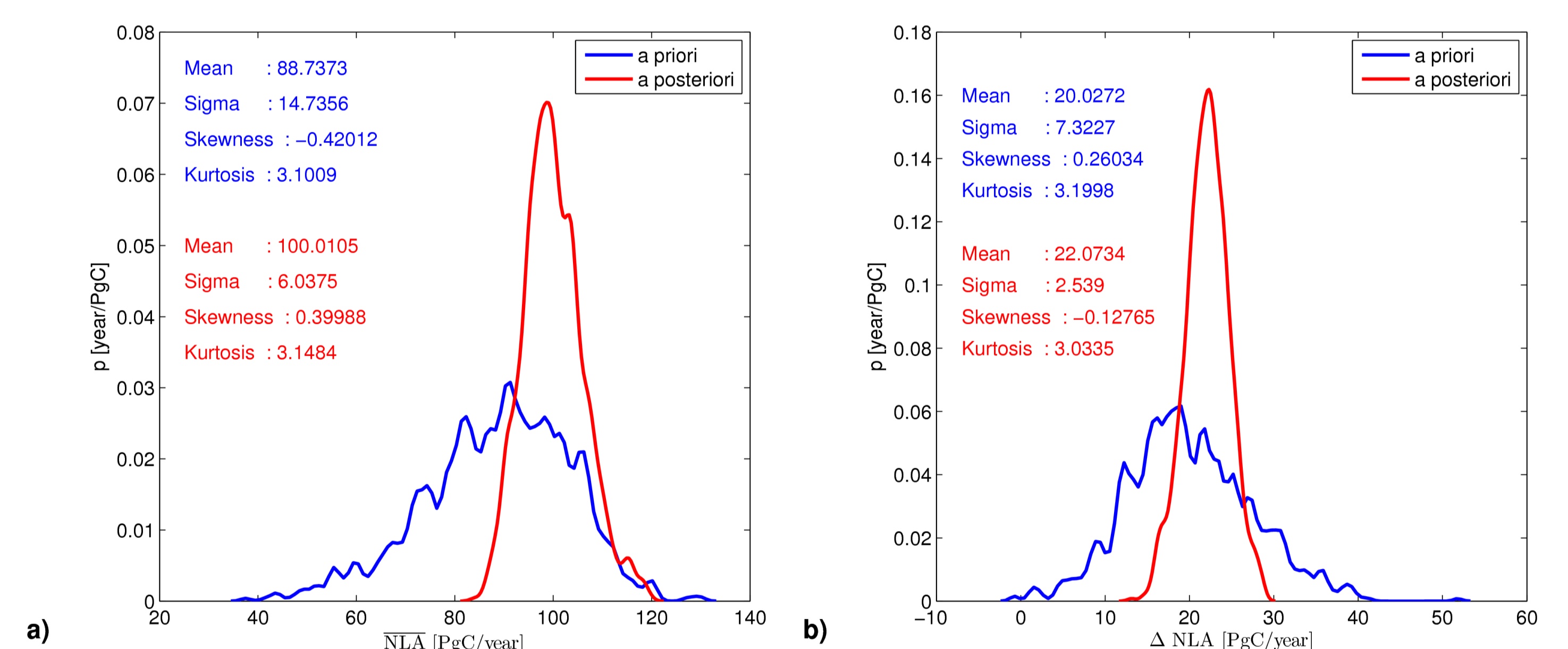


Figure 2: Probability function estimate of (a) mean NLA over the first 20 simulation years and (b) ΔNLA based on 1000 randomly sampled prior parameter values (expert knowledge) and 1000 posterior parameter values drawn from the Metropolis-Hastings sequence.

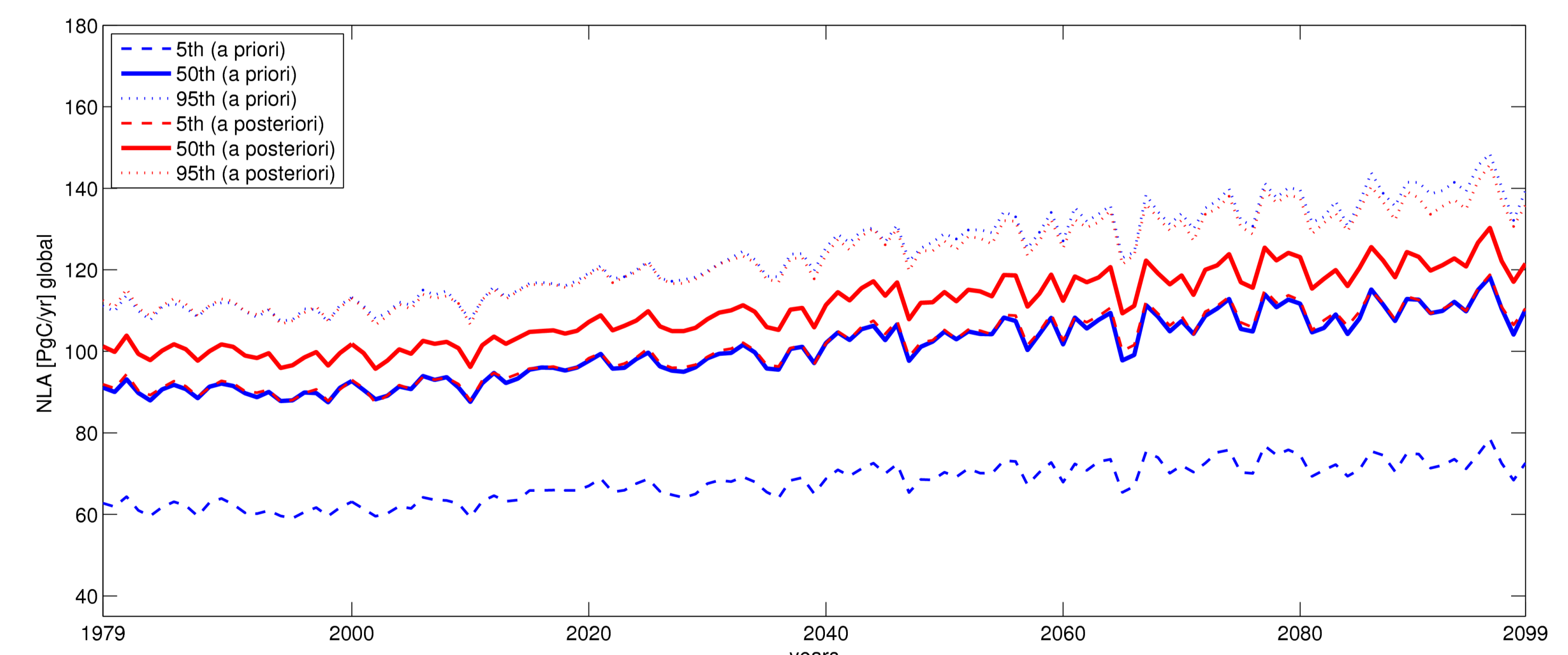


Figure 3: Percentiles of NLA for each year based on 1000 randomly sampled prior parameter values (expert knowledge) and 1000 posterior parameter values drawn from the Metropolis-Hastings sequence.

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