**Appendix I: Bayesian P-splines**

The relationship between leaf cover c and average flow velocity was investigated by first transforming the cover % by the logistic transformation y =logc/100-c. This opens up the bounded scale 0-100 of cover. A linear regression of transformed cover y against x and transforming the fitted values back to the percentage scale gave a bad fit. We thus needed a more flexible curve-fitting approach. We chose the penalized spline P-spline approach Eilers and Marx 1996. In this approach the flexibility is governed by the penalty parameter, with higher penalty giving curves that are smoother and closer to the straight line. We used a Bayesian method to estimate the penalty parameter and fitted a Bayesian P-spline Lang and Brezger 2004 by integrated nested Laplace approximation Rue et al. 2009 to the full Bayesian model as implemented in the INLA R package Rue et al. 2014 and a dedicated R-function available upon request. We used as prior distribution for the penalty parameter a type 2 Gumbel distribution with parameter λ=3 Martins et al. 2014. The result turned out to be very insensitive to choice of the prior distribution, which is as expected, because there are many data points. Bayesian P-splines average over the posterior distribution of the penalty instead of fitting these once by mixed models/marginal maximum likelihood MML or empirical Bayes. This Bayesian procedure better acknowledges the uncertainty in the smoothing parameters than MML and the uncertainty bands credible intervals around the curves incorporate this uncertainty. We estimated 95% credible intervals for the expected response and transformed fit and intervals back to the cover percentage scale.

Eilers PHC, Marx BD. 1996 Flexible smoothing with B-splines and penalties. *Statistical Science*, **11** : 89-121.

Lang, S. and Brezger A. 2004 Bayesian P-splines. *Journal of Computational and Graphical Statistics*, **13** : 183-212.

Martins TG, Simpson DP, Riebler A, Rue H. 2014 Penalising model component complexity: A principled, practical approach to constructing priors. arXiv 1403.4630v2.

Rue H, Martino S, Chopin N. 2009 Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B Statistical Methodology*, **71** : 319-392.

Rue H, Martino S, Lindgren F, Simpson D, Riebler ATK. 2014 INLA, functions which allow to perform full Bayesian analysis of latent Gaussian models using Integrated Nested Laplace Approximaxion. http://www.r-inla.org/:version 0.0-1396629476.