Assimilation of MERIS FAPAR into a terrestrial vegetation model and mission design

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Objectives

- Report on ESA-funded study “Remote Sensing Inputs for Regional to Global Data Assimilation” (http://RS.CCDAS.org)
- Demonstrate the assimilation of optical reflectance data from satellites into a new generic model of leaf phenology (Fig. 1)
- Assess the reduction in uncertainty of carbon fluxes after simultaneous assimilation of satellite-data at multiple sites
- Explore suitability for global-scale applications

Assimilation on Site Scale

- Extend the Carbon Cycle Data Assimilation System (CCDAS)[1] to include hydrology and leaf phenology. This includes update of adjoint and Hessian codes via the automatic differentiation tool TAF[4]
- Incorporate satellite data of the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) from ESA’s MERIS[2] instrument for 6 sites.
- Optimise process parameters of global vegetation model BETHY[3] for best agreement of model and satellite FAPAR.
- Use local information at the optimum to infer *a posteriori* uncertainties of parameters and compare to *a priori* uncertainties.
- Project *a priori* and *a posteriori* uncertainties from parameters to carbon fluxes.Efficient algorithm finds optimum for all 6 sites simultaneously after ~60 iterations, producing good fit to observed FAPAR (Fig. 1)
- For 6 sites, FAPAR data constrain most phenology parameters (Table 1).
- Limited constraint for parameters related to photosynthesis (≤7%).
- Only small constraint on carbon fluxes (Fig. 3).

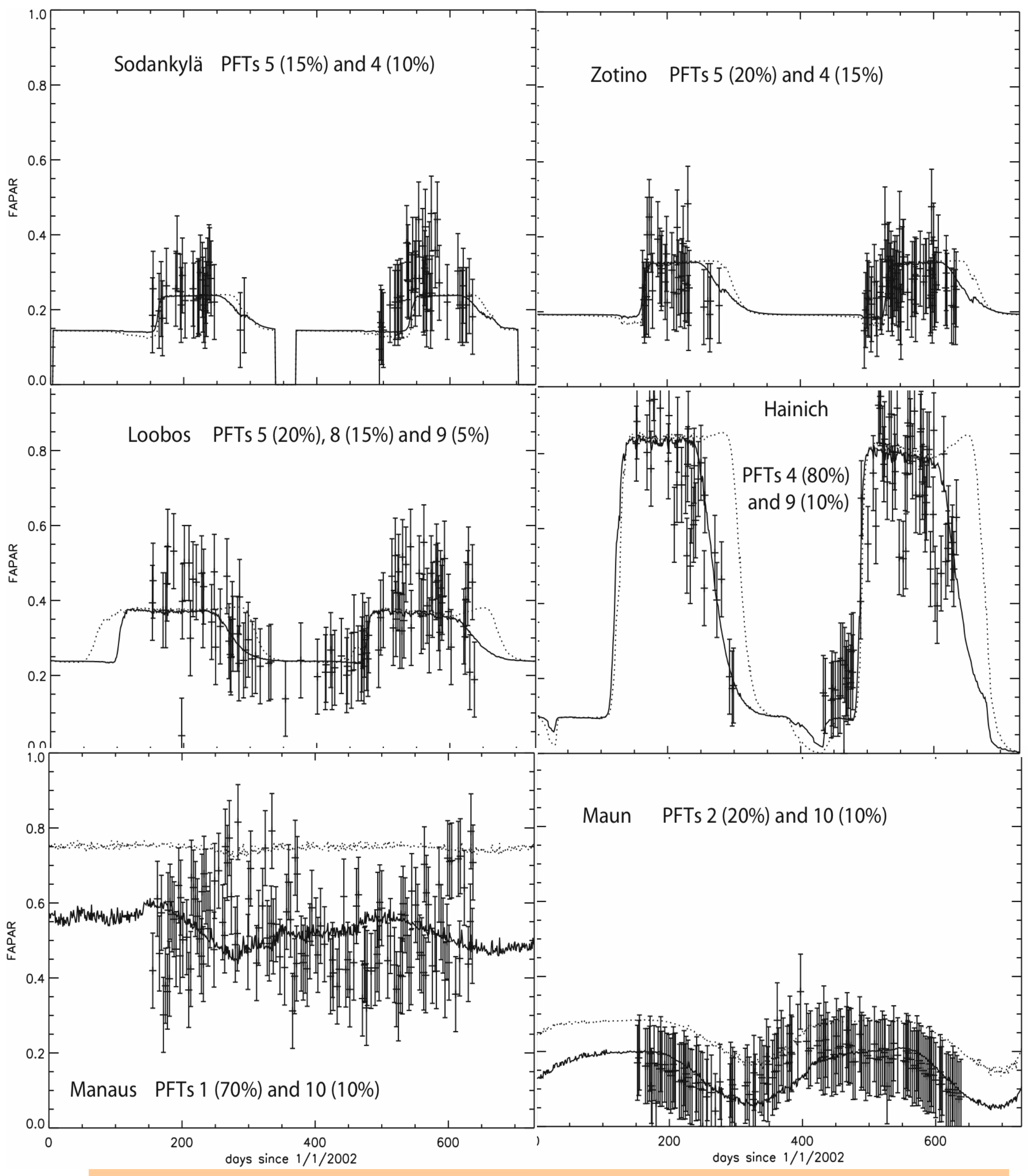


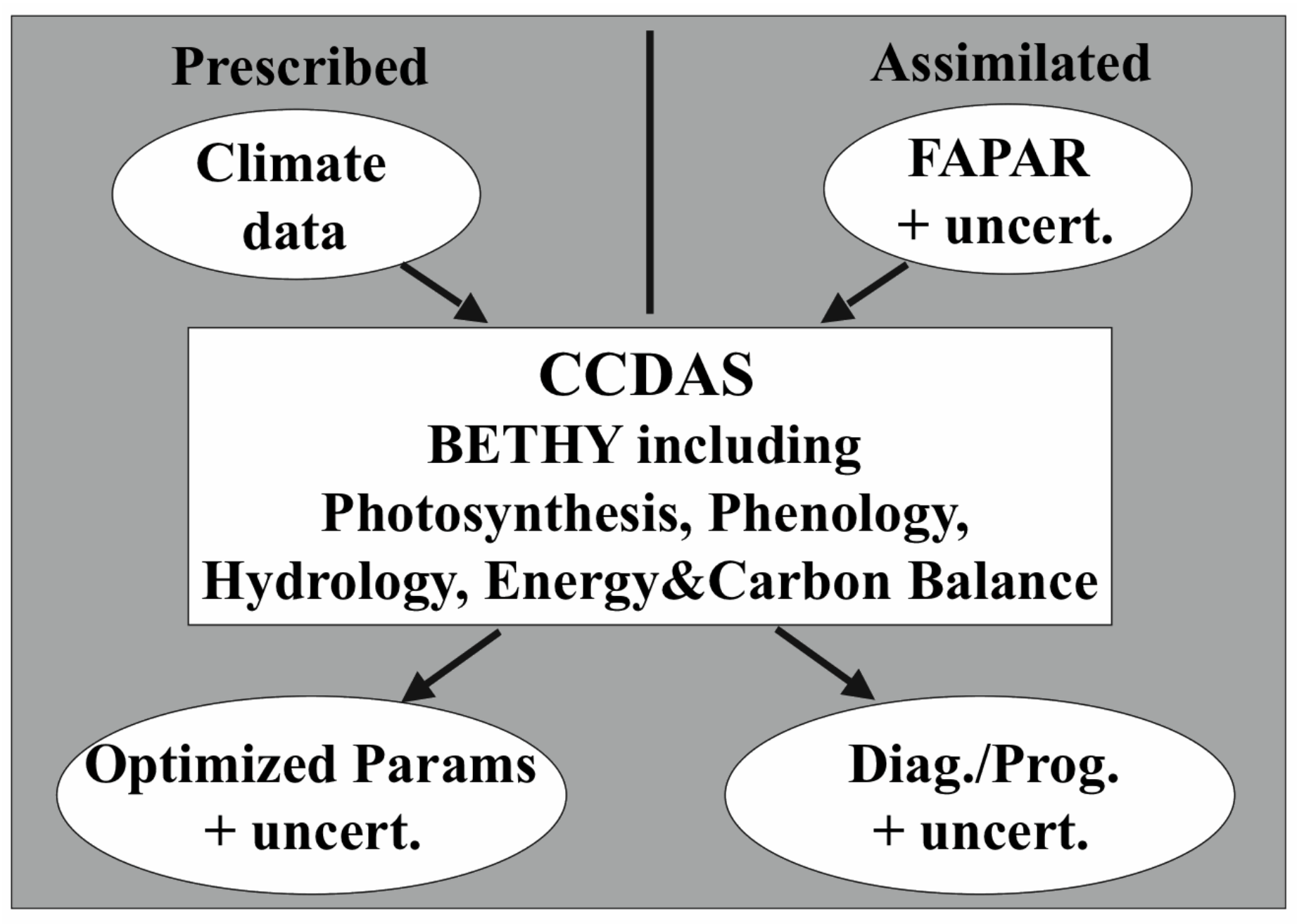
Figure 2: *a priori* (dotted) and *a posteriori* (solid) FAPAR simulated with BETHY at the 6 sites. Satellite data are shown with error bars.

References

1-Rayner, P. J., M. Scholze, W. Knorr, T. Kaminski, R. Giering and H. Widmann (2005), Two decades of terrestrial carbon fluxes from a Carbon Cycle Data Assimilation System (CCDAS), *Global Biogeochemical Cycles*, 19, doi:10.1029/2004GB002254.

2-Gobron, N., et al. (2008), Uncertainty estimates for the FAPAR operational products derived from MERIS - Impact of top-of-atmosphere radiance uncertainties and validation with field data, *Remote Sens. Eviron., 112*, 1871-1883.

3-Knorr, W. (2000), Annual and interannual CO_2 exchanges of the terrestrial biosphere: process-based simulations and uncertainties, *Global Ecology and Biogeography*, *9*, 225-252.



Prescribed

Assimilated

Climate data

FAPAR + uncert.

CCDAS
BETHY including
Photosynthesis, Phenology,
Hydrology, Energy&Carbon Balance

Optimized Params + uncert.

Diag./Prog. + uncert.

Figure 1: Revised CCDAS scheme.

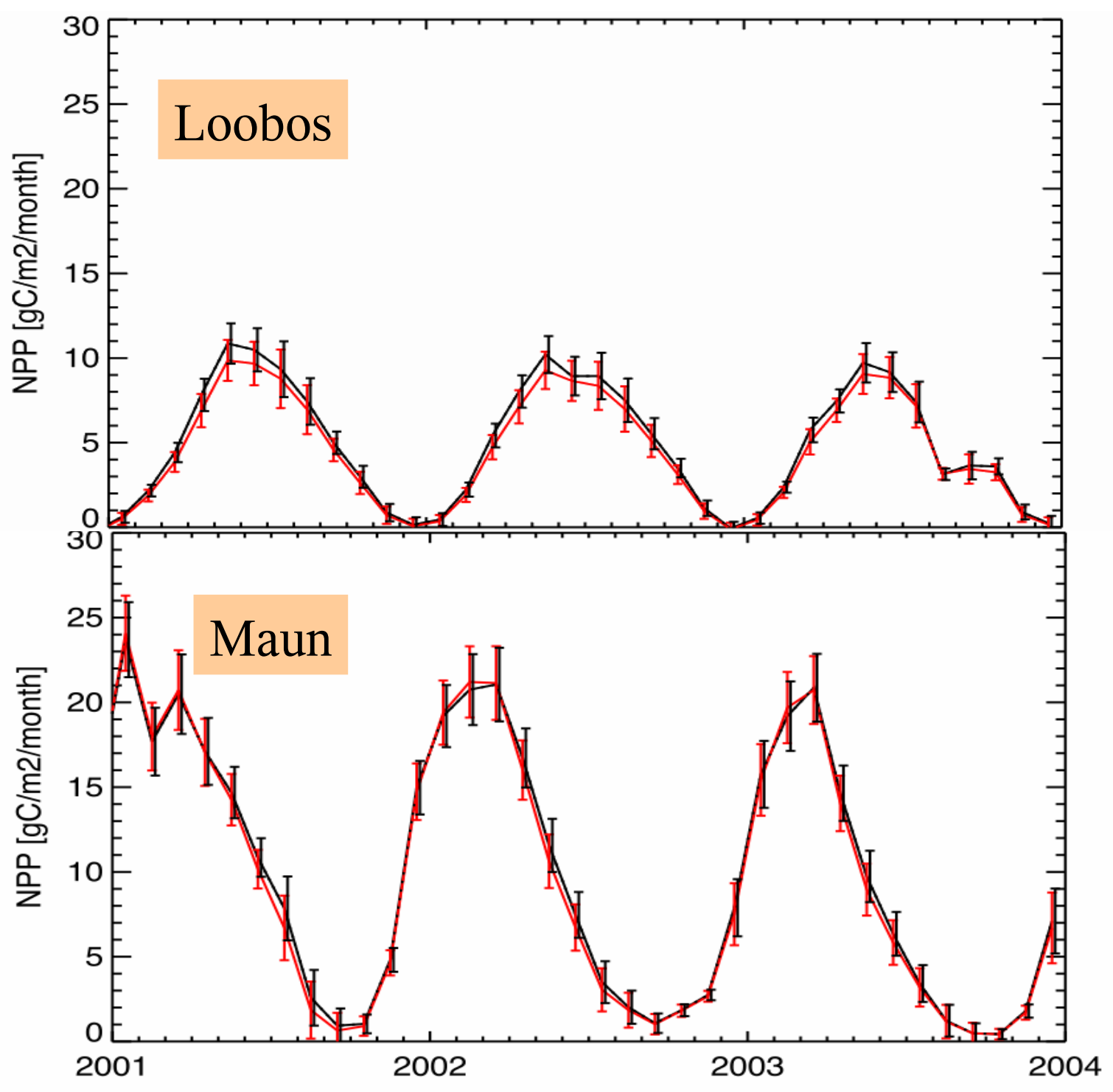


Figure 3: *a priori* (black) and *a posteriori* (red) NPP simulated with BETHY, with error bars.

First Results: Global Scale

- Simultaneous assimilation of level 2 MERIS FAPAR product on global grid and atmospheric CO_2 from 41 sites
- Cost function: $J(x) = J_{prior}(x) + J_{MERIS}(x) + J_{CO2}(x)$
- Optimised 72 process parameters
- Completed first run in test configuration: coarse resolution and only one year (2003)
- Optimisation takes about 200 iterations
- Cost function gradient reduced by almost 8 orders of magnitude
- Small deviation from prior parameter value improves fit by about 90%

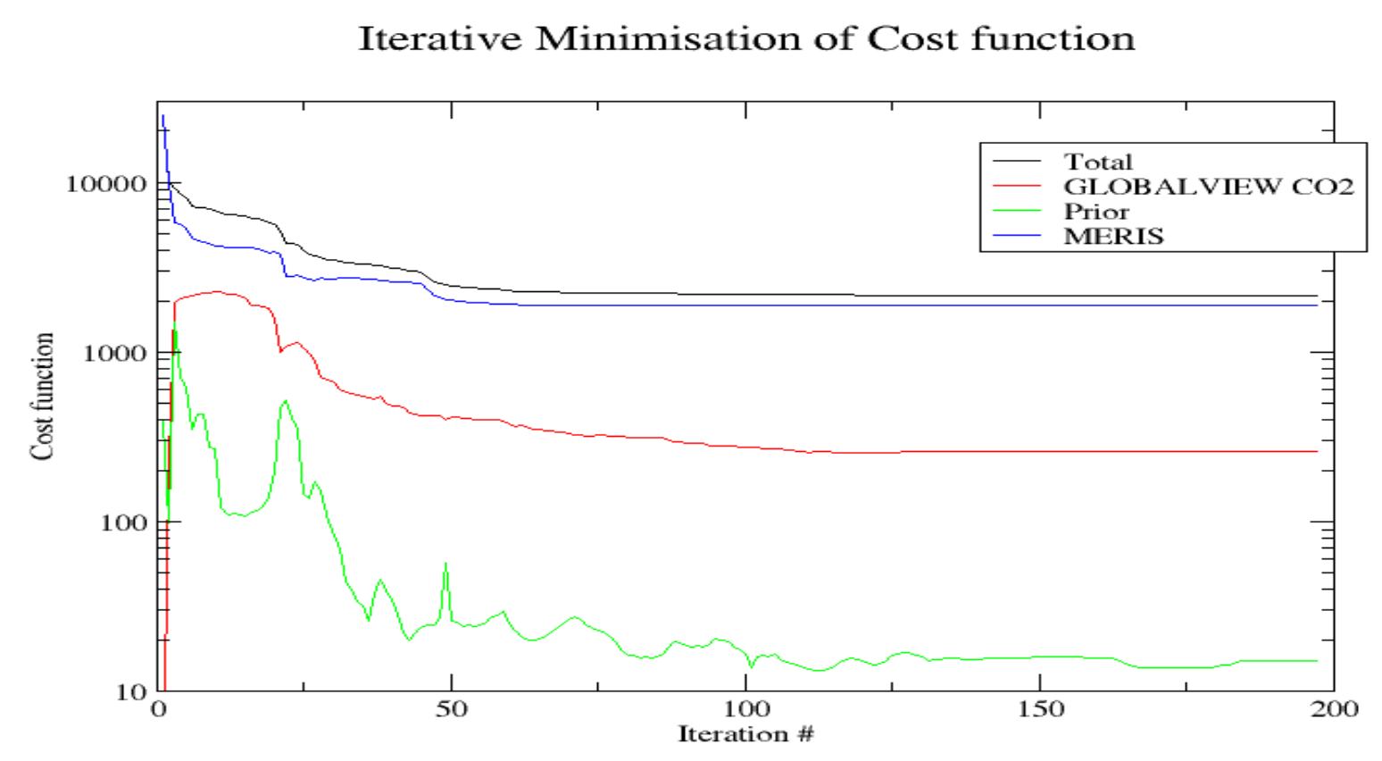


Figure 4: Iterative Minimisation of Total Cost function (black) and its components: prior (green), MERIS (blue), atmospheric CO2 (red)

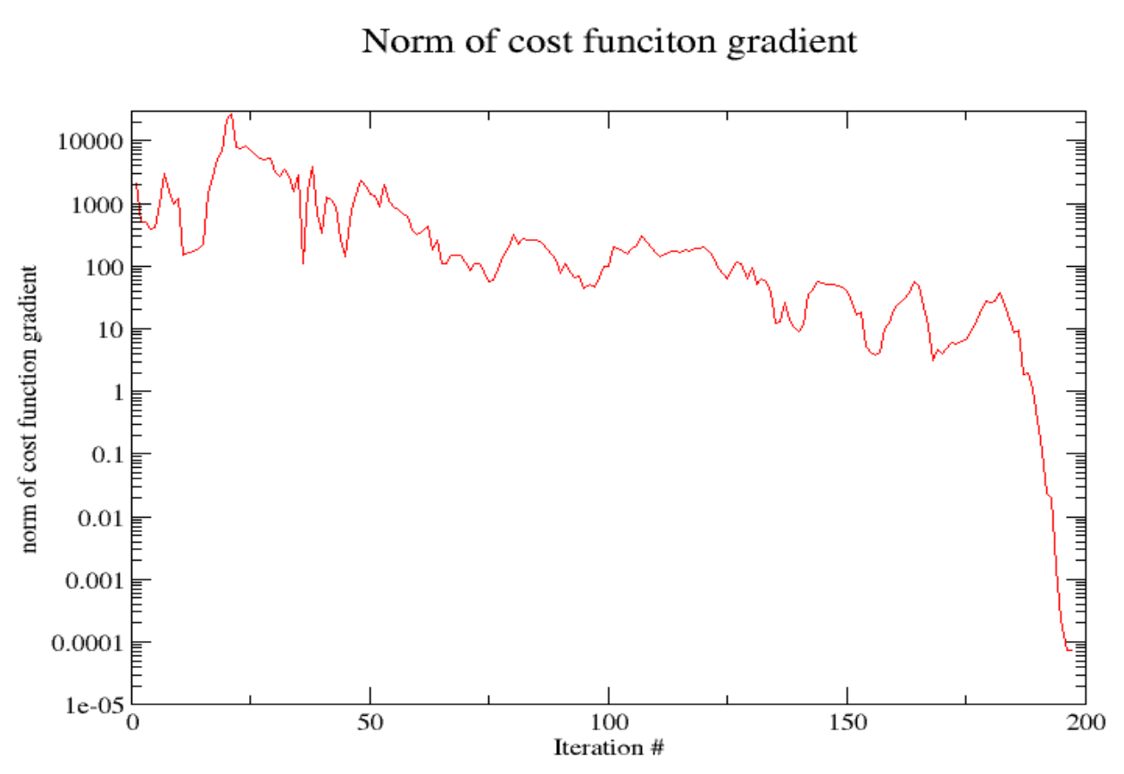


Figure 5: Iterative minimisation of norm of cost function gradien

Generic Phenology Model

$$\frac{dL(t)}{dt} = x[L_{\max} - L(t)]f - \frac{L(t)}{t_L}(1-f) \qquad \text{(Equ. 1)}$$

- Leaf aea index (LAI): Λ
- Leaf sprouting rate: ξ
- Leaf shedding time: τ_L
- Water-limited LAI: Λ_{max}
- Fraction of plants in growth phase: *f*

Table 1: The 14 parameters for the new phenology scheme as optimised in CCDAS. An additional 24 Parameters were optimised from the original CCDAS, with uncertainty reductions of up to 7%.

Parameter	PFTs[1]	Prior value	Posterior value	Uncert. reduction [%]
˜Λ maximum LAI	all	5.00±0.25	4.36±0.23	6
T_φ temperature threshold	4, 5	10.00±0.50	9.34±0.27	46
T_φ “	8	6.00±0.50	8.11±0.50	0
T_φ “	9, 10	2.00±0.50	1.53±0.41	18
T_r spatial variability of T_φ	1, 2, 4, 5, 8	2.00±0.10	2.04±0.10	1
T_r “	9, 10	0.50±0.10	0.52±0.10	0
t_c day length threshold	4, 5, 8	10.50±0.50	13.73±0.43	14
t_r spatial variability of t_c	4, 5, 8	0.50±0.10	0.46±0.10	0
ξ see Equ. (1)	all	0.50±0.10	0.52±0.10	0
$k_L=1/\tau_L$ see Equ. (1)	all exc. 5	0.100±0.050	0.058±0.012	76
$k_L=1/\tau_L$ see Equ. (1)	5	$3.0\pm1.5\times10^{-3}$	$3.3\pm8.9\times10^{-4}$	40
τ_W water-limited leaf longevity	1	360±180	1114±192	61
τ_W “	2	50±25	112±19	62
τ_W “	9, 10	50±25	28±12	9

[1] 1: tropical evergreen trees, 2: tropical drought-deciduous trees; 4: temperate cold-deciduous trees; 5: evergreen conifers; 8: deciduous understorey shrub; 9: C3 grass; 10: C4 grass. The PFTs exist at the following sites: Sodankylä (5, 4), Zotino (5, 4), Loobos (5, 8, 9), Hainich (4, 9), Manaus (1, 10) and Maun, Botswana (2, 10).

First Tests: Mission Design

- Can test the effect of hypothetical sensors on parameter uncertainties[5]
- Can carry parameter uncertainties forward along prognostic simulations[6].
- Have computed the constraint of the MERIS sensor and two hypothetical sensors, one with higher resolution and one that resolves PFT distributions on prognosed NEP (Fig 6)
- Method will be applied to global scale

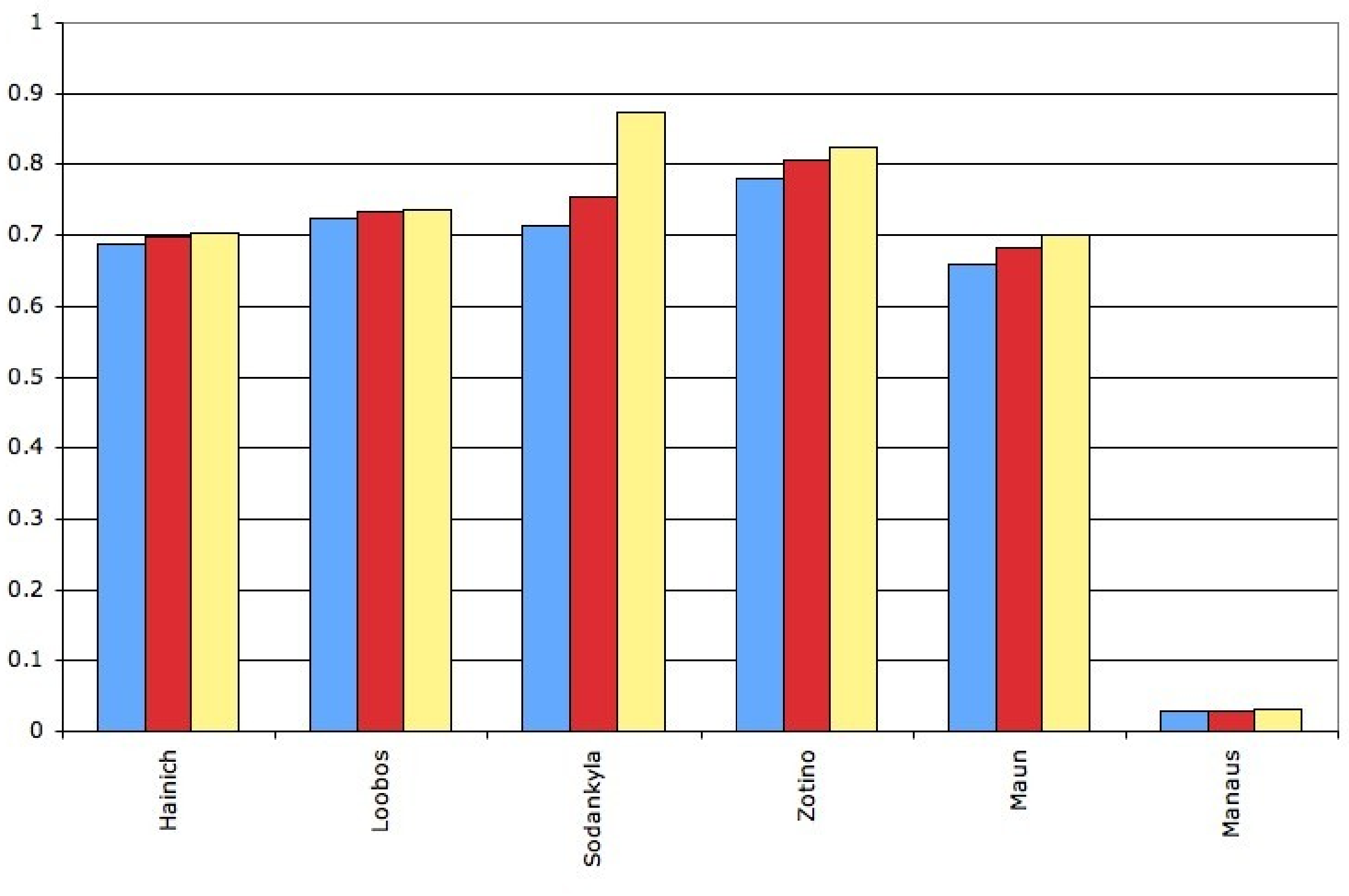


Figure 6. Reduction of uncertainty in prognostic NEP mean over the years 2030 to 2039 for the base case (blue), the higher resolution sensor (red) and the ideal resolution sensor (yellow).

More References

4-Giering, R. and T. Kaminski Knorr, W. (1998), Recipes for Adjoint Code Construction. ACM Trans. Math. Software, 24(4):437-474

5-Kaminski, T. and P. J. Rayner (2008). Assimilation and network design. In H. Dolman, A. Freibauer, and R. Valentini, editors, Observing the continental scale Greenhouse Gas Balance of Europe, Ecological Studies, chapter 3, pages 33-52. Springer-Verlag, New York.

6-Knorr, W., T. Kaminski, M. Scholze, N. Gobron, B. Pinty, and R. Giering (2008). Remote Sensing Input for regional to global CO2 flux modelling. In Proceedings of 2nd MERIS/(A)ATSR User Workshop, Frascati, Italy. European Space Agency.