REGIONALIZATION OF THE KEY CARBON STORAGE PARAMETER WITHIN THE CARBON CYCLE DATA ASSIMILATION SYSTEM (CCDAS)

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ABSTRACT
The aim of this study is to investigate the effects of incorporating the differences in the long-term carbon balance of various regions of the earth on predicted net CO_2 fluxes. Within the carbon cycle data assimilation system (CCDAS) the key carbon storage parameter is allowed to vary according to 11 predefined land regions. We find that this parameter is sensitive to the regionalization process and that the regionalization also leads to differences in the spatial distribution of predicted net CO_2 fluxes and its uncertainties.

INTRODUCTION
The carbon cycle data assimilation system (CCDAS) (Rayner et al., 2005) allows the current fluxes of CO_2 into the atmosphere to be mapped and the evolution of these fluxes into the future to be predicted (Scholze et al., 2007). Here, we concentrate on the calibration mode of CCDAS where an optimal parameter set is derived from 21 years of atmospheric CO_2 concentration observations using an adjoint approach. The terrestrial biosphere model BETHY (Knorr, 2000), which is combined in the assimilation system with the atmospheric transport model TM2 (Heimann, 1995), has 20 parameters for each plant functioning type (PFT) in a given grid cell. There is a total of 3462 grid cells within the model and each of the 20 parameters can be assigned to one global control parameter via a mapping routine (global description). It is also possible to assign each of the 20 parameters to one control parameter for each of the 13 PFTs or to one control parameter for each PFT occurring in each of the 11 Transcom land regions. In the base case, 17 of the 20 parameters are applied globally, mainly those concerning the soil model or general plant physiology. The key photosynthetic parameters (maximum electron transport and maximum carboxylation rate) and the key carbon storage parameter β vary with PFT, which gives a total of 57 control parameters. The focus of this work is on incorporating the differences in the long-term carbon balance in various regions of the earth by considering 11 land regions as defined in the Transcom 3 Level 2 Atmospheric Inversion Intercomparison Experiment (Gurney et al., 2005). Therefore, in a second configuration the key carbon storage parameter β is also allowed to vary by both land region and PFT, which results in an extended set of 155 control parameters.

MODEL
The process-based model of the terrestrial biosphere, BETHY, is the core of CCDAS. It simulates carbon assimilation and soil respiration embedded within a full energy and water balance and phenology scheme. BETHY is driven by observed climate data for the period 1979 to 1999 and is run on a $2°\times 2°$ grid resolution. Global vegetation is mapped onto 13 PFTs (see Table 1) and each grid cell can contain up to three different PFTs with their amount specified by their fractional cover. The net ecosystem productivity (NEP) in CCDAS is defined as:

$$\mathrm{NEP} = \mathrm{NPP} - R_{\mathrm{S}} = \mathrm{NPP} - (R_{\mathrm{S,s}} + R_{\mathrm{S,f}}) \tag{1}$$

where $R_{S,s}$ and $R_{S,f}$ are the respiration fluxes from the slowly and rapidly decomposing soil carbon pools, respectively, and NPP the net primary productivity. The size of the slow carbon pool is held constant through the simulation period and is determined for each grid cell and PFT by a long-term balance constraint:

$$\overline{\mathrm{NPP}} = b\,(\overline{R_{\mathrm{S,s}} + R_{\mathrm{S,f}}}) \tag{2}$$

where the overlaying bar denotes the average over the calibrations period. The PFT specific carbon storage parameter β determines whether the corresponding PFT acts as a long-term source ($\beta > 1$) or sink ($\beta < 1$). The balance constraint given in equation (2) circumvents various scientific problems concerning the limited knowledge we have about the history of the site and the impact it has on the long-term carbon balance.

RESULTS
The control parameters (N=57, base case and N=155, regionalization) are optimized by calculating the mismatch of the observations and prior knowledge of the parameters via a defined cost function. The minimization is controlled by a gradient algorithm, which searches the parameter space by iterative evaluation of the cost function and its gradient with respect to the parameters. The gradient information is provided efficiently by the

models adjoint. Table 1 presents the optimal β parameters for both cases. For the extended set of parameters (N=155) we present only the recalculated β values (using equation (1) and (2)) for each PFT for comparison. The fact that the values for β vary considerably between the two cases (only for PFT 3 and PFT 11 there is an agreement) indicates that the β parameter is sensitive to the regionalization process.

Table 1. Optimal β parameter for each PFT.

PFT[1]	1	2	3	4	5	6	7	8	9	10	11	12	13
Base case (N=57)	0.84	0.95	1.00	0.95	1.13	0.00	0.81	2.93	1.57	1.00	1.26	0.94	0.00
Regionalization (N=155)	0.55	1.21	1.02	0.80	0.97	0.68	0.58	1.03	1.12	0.91	1.26	1.12	0.88

[1]Definition of the PFTs: 1 tropical broadleaved evergreen tree, 2 tropical broadleaved deciduous tree, 3 temperate broadleaved evergreen tree, 4 temperate broadleaved deciduous tree, 5 evergreen coniferous tree, 6 deciduous coniferous tree, 7 evergreen shrub, 8 deciduous shrub, 9 C3 grass, 10 C4 grass, 11 tundra vegetation, 12 swamp vegetation, 13 crops.

Parameter uncertainties can also be inferred from uncertainties in observed CO_2 concentrations via the model's Hessian and then mapped forward on predicted quantities such as net CO_2 fluxes via the models Jacobian. The results for long-term mean NEP and its uncertainty resulting from the uncertainty in β alone are presented in Table 2. Uncertainties in the net flux are generally smaller for the base case. Here, the uncertainties in most of the β parameters could be reduced considerably from prior to posterior case, which also results in smaller uncertainties for NEP after propagation of parameter uncertainties. There is a disagreement in the direction of the net fluxes for region 6, 10 and 11. In the base case, region 6 and 10 were identified as CO_2 sources and region 6 as a carbon sink. The optimization considering the regionalization of the β parameter leads to the opposite results for those regions. However, taking the uncertainties for mean NEP into account region 6 for example could be a source or a sink in both cases.

Table 2. Long term mean NEP (TgC y^{-1}) and uncertainties (1 σ) in brackets for each Transcom land region.

Land region[2]	1	2	3	4	5	6
Base case (N=57)	-364 (62)	454 (101)	1100 (219)	-881 (131)	77 (76)	-106 (141)
Regionalization (N=155)	-121 (120)	340 (224)	2000 (333)	-1870 (271)	249 (222)	254 (233)
Land region	7	8	9	10	11	Total
Base case (N=57)	476 (196)	907 (150)	689 (72)	-232 (30)	96 (146)	2211
Regionalization (N=155)	1140 (309)	843 (273)	100 (184)	215 (131)	-939 (272)	2210

[2]Definition of the Transcom land regions: 1 North American boreal, 2 North American temperate, 3 South American tropical, 4 South American temperate, 5 Northern Africa, 6 Southern Africa, 7 Eurasian boreal, 8 Eurasian temperate, 9 Tropical Asia, 10 Australia, 11 Europe.

CONCLUSIONS

The extended set of control parameters (regionalization) leads to a smaller cost function value (c=5385) in comparison to the case where β was only allowed to vary with PFT (c=5921), which indicates a better fit to the observations. This is not surprising since we increase the degree of freedom for the optimization. Additionally, the rate of convergence is much higher for the extended set of parameters. In the base case twice the number of iterations are required in order to find the cost function minimum in comparison to the extended set of parameters. The results presented here demonstrate the possibility of combining process modeling and parameter regionalization in CCDAS.

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