Bayesian inference of a dynamic vegetation model for grassland

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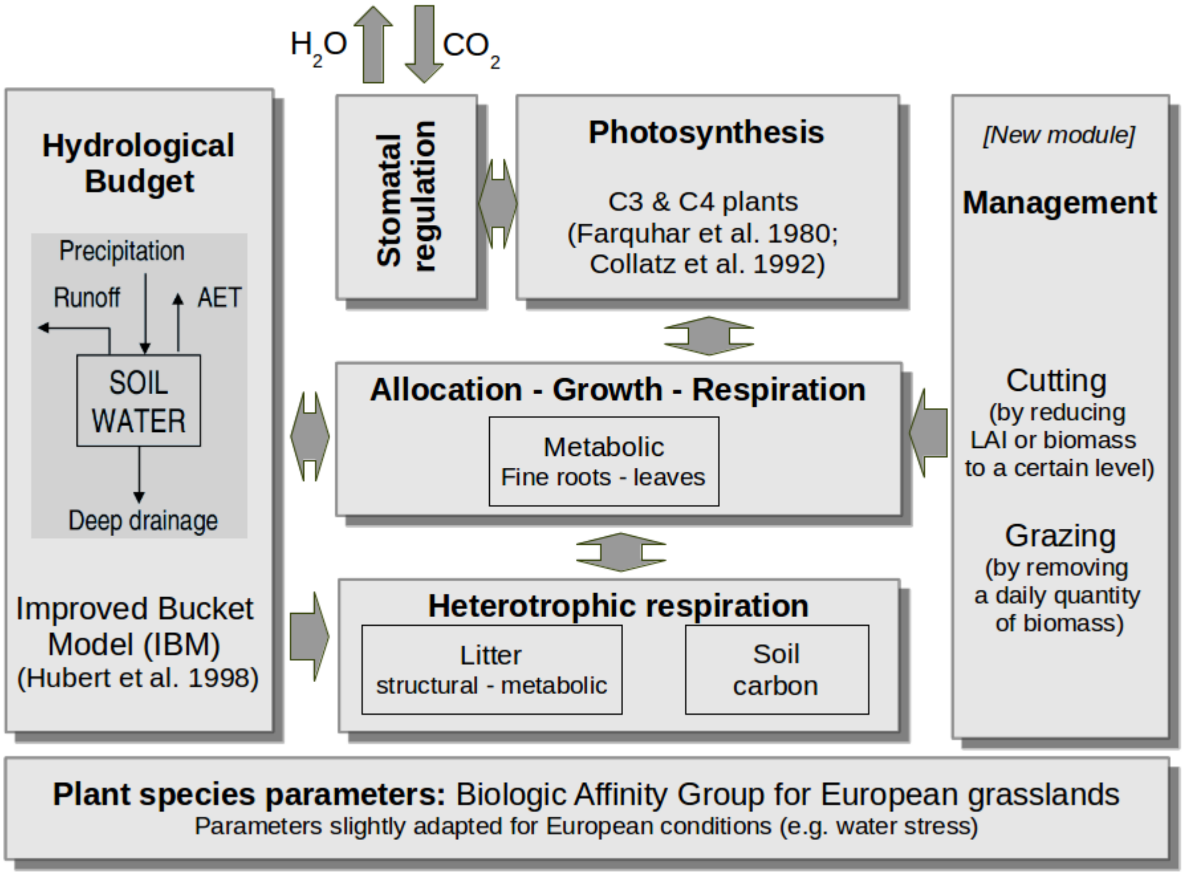
Framework

- MACSUR task L2.4 Grassland model intercomparison, G. Bellocchi.
- Phase 1 : Blind runs (end in January 2014)
- Phase 2 : Calibrated runs (on-going) : how to calibrate ?

→Calibration of a grassland model (CARAIB) by a Bayesian method

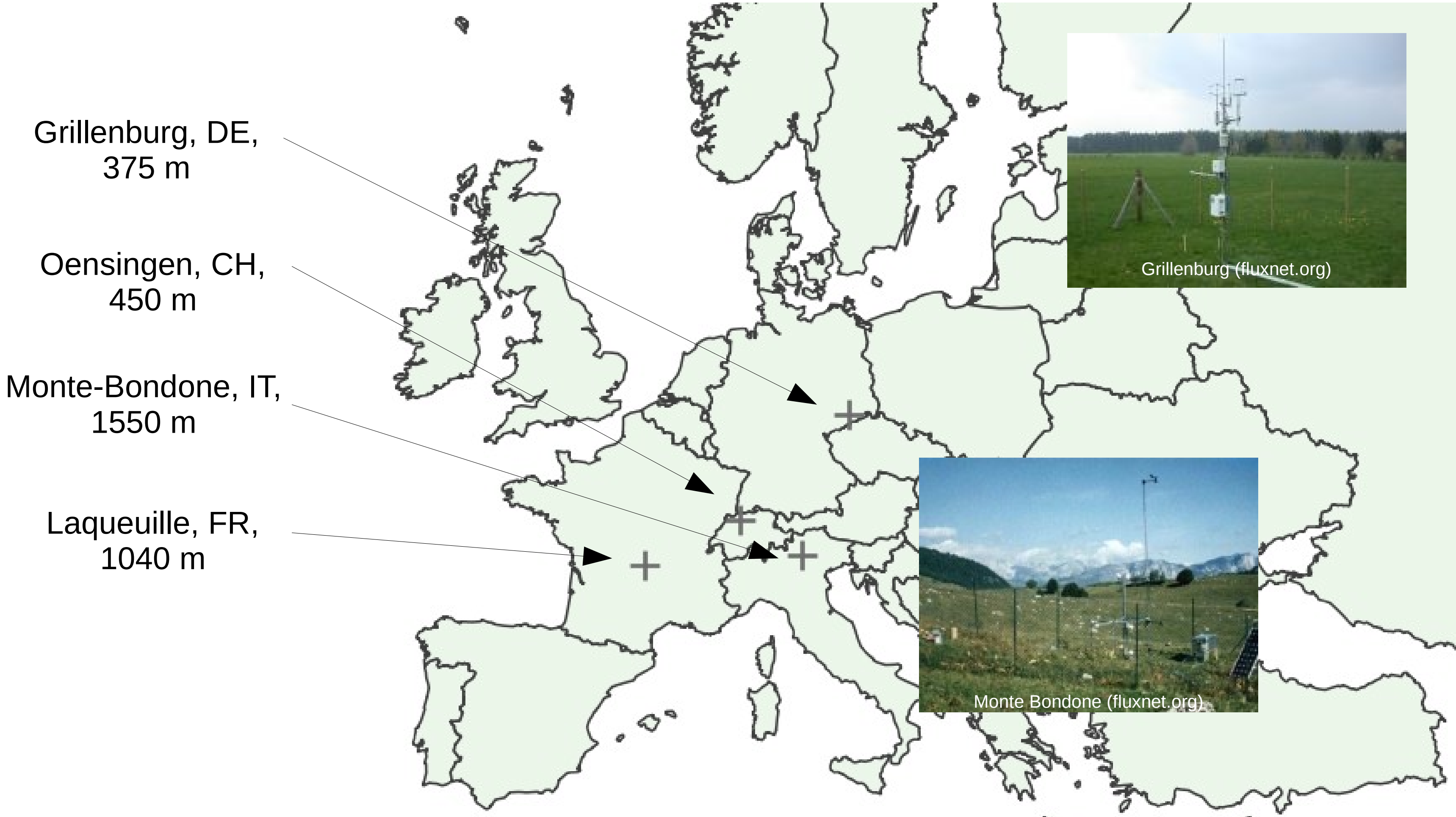
The grassland model : CARAIB



- See talk of Louis François on Wednesday 3rd April
- Focused on grassland
- New management functions for grassland: cut & grazing

Reference website: http://www.umccb.ulg.ac.be/Sci/m_car_e.html

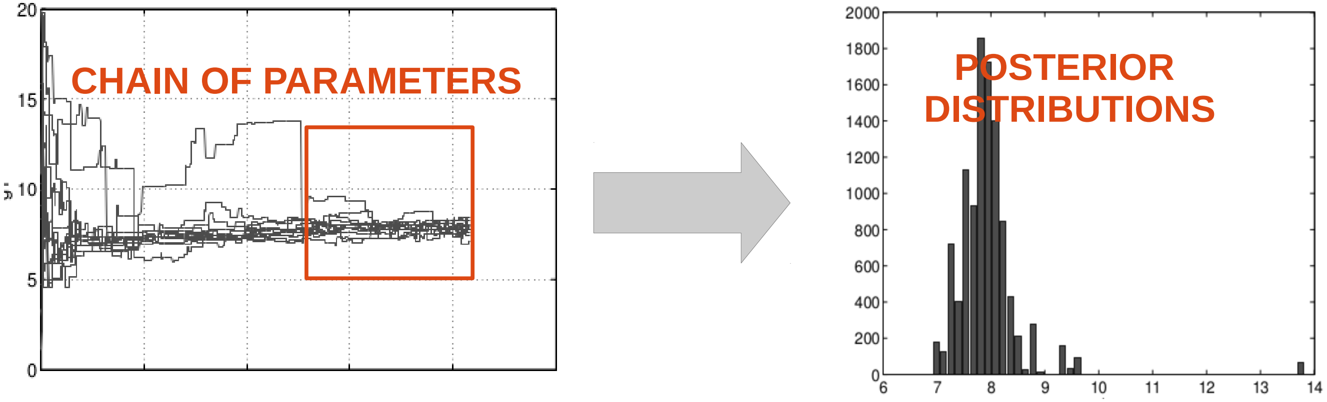
The sites



- Semi-natural grasslands : grazed (Laqueuille) or cut (other 3)
- Eddy-covariance sites : flux measurements available : GPP, RECO, ET, ...

The algorithm : DREAM_ZS

- Inverse problem: $Optimal\ parameters = argmin(Observations - Modeled(parameters))$
- DREAM_ZS: a Markov-Chain Monte-Carlo sampler
- Ideal for sampling a large number of parameters
- Multiple-chain : deal with local minima and correlation between parameters.



Laloy, E., and J.A. Vrugt, High-dimensional posterior exploration of hydrologic models using multiple-try DREAM_(ZS) and high-performance computing, Water Resources Research, 48, W01526, 2012

Vrugt, J.A., C.J.F. ter Braak, C.G.H. Diks, D. Higdon, B.A. Robinson, and J.M. Hyman, Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling, International Journal of Nonlinear Sciences and Numerical Simulation, 10(3), 273-290, 2009.

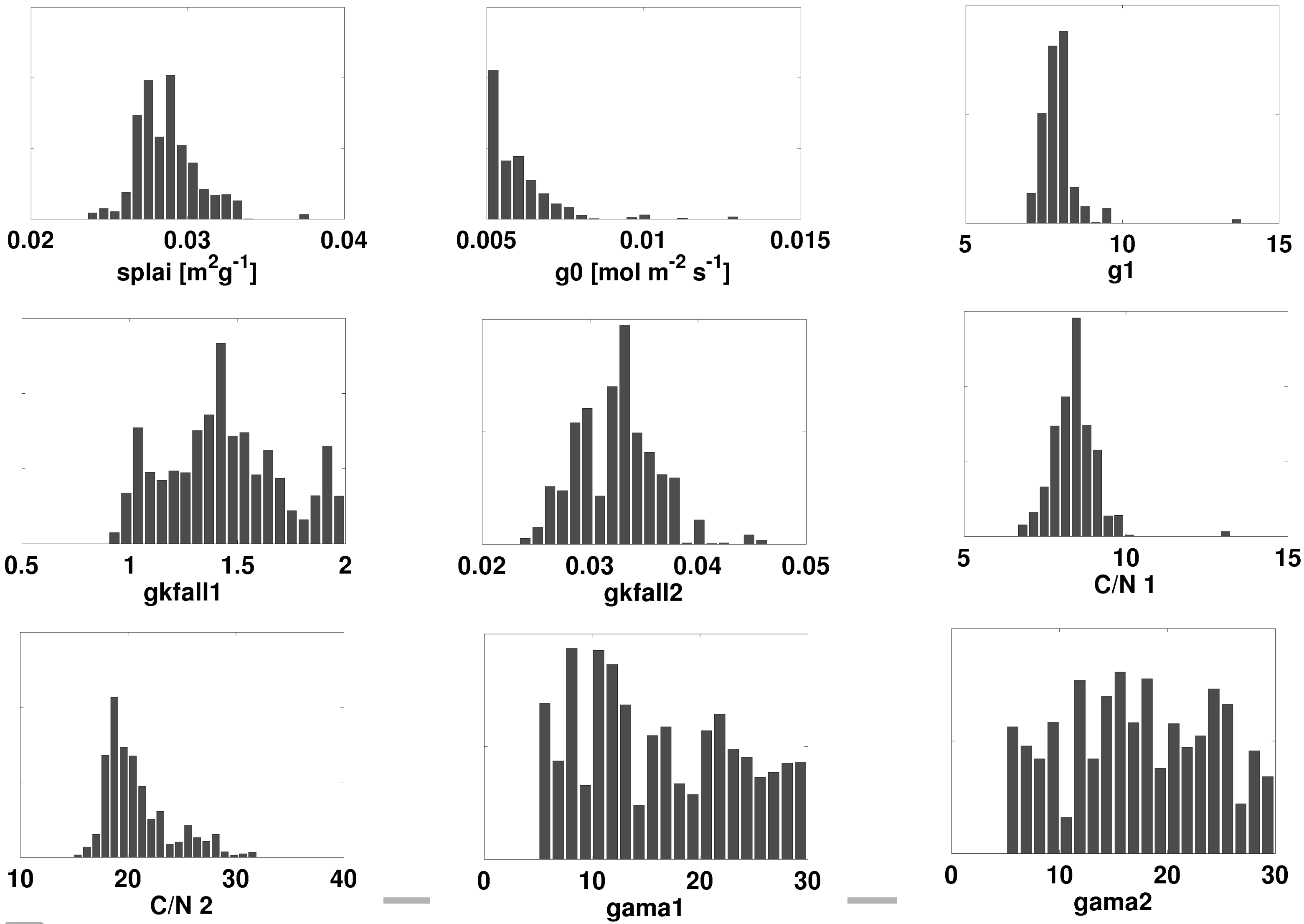
The algorithm : DREAM_ZS

- Inverse problem: $Optimal\ parameters = argmin(Observations - Modeled(parameters))$
- 12 parameters were sampled using 3 measurements variables from Eddy covariance: RECO, GPP, ET
- A multi-objective cost function (CF) was used : CF = f(RECO, U_{RECO}, GPP, U_{GPP}, ET, U_{ET})
- Uncertainties on measurement *U* were considered as follow (homoscedastic):

Meas. variables	U
RECO	1.5 gC m^{-2} day^{-1}
GPP	3 gC m^{-2} day^{-1}
ET	1 gC m^{-2} day^{-1}

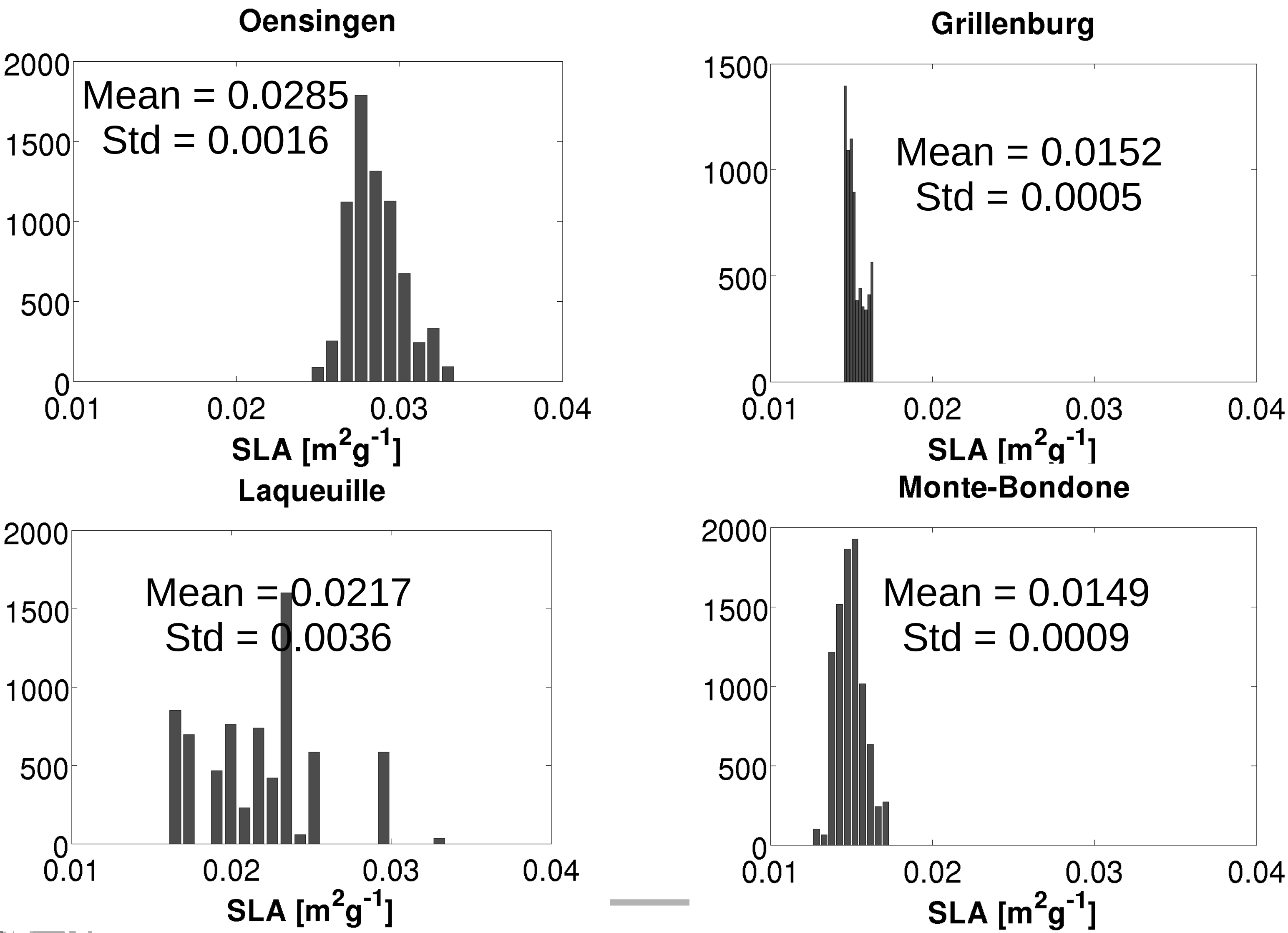
Results : parameter samplings

Posterior distributions of 9 parameters, Oensingen



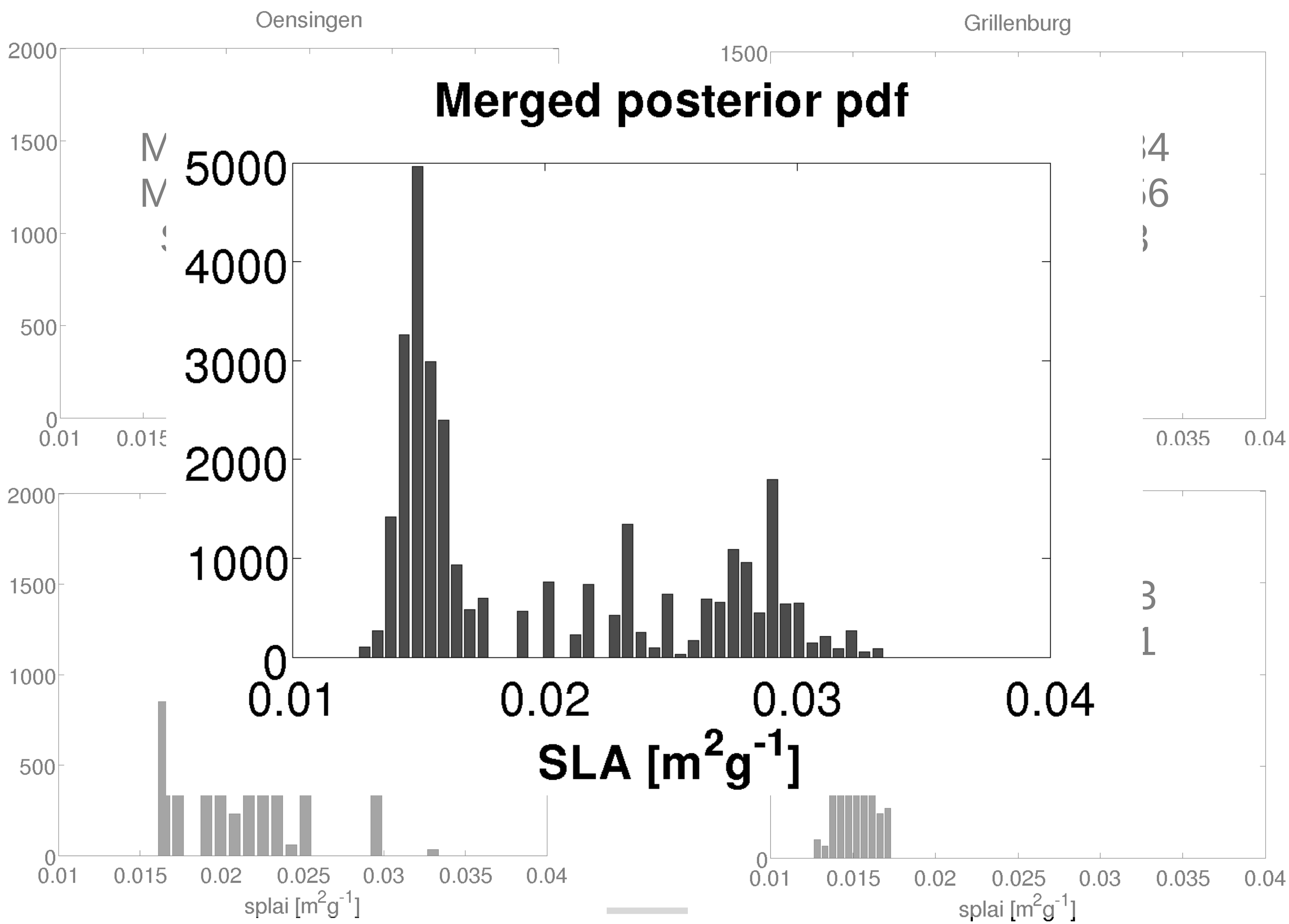
Results : parameter samplings

Specific leaf area (SLA) [m²/gC]



Results : parameter samplings

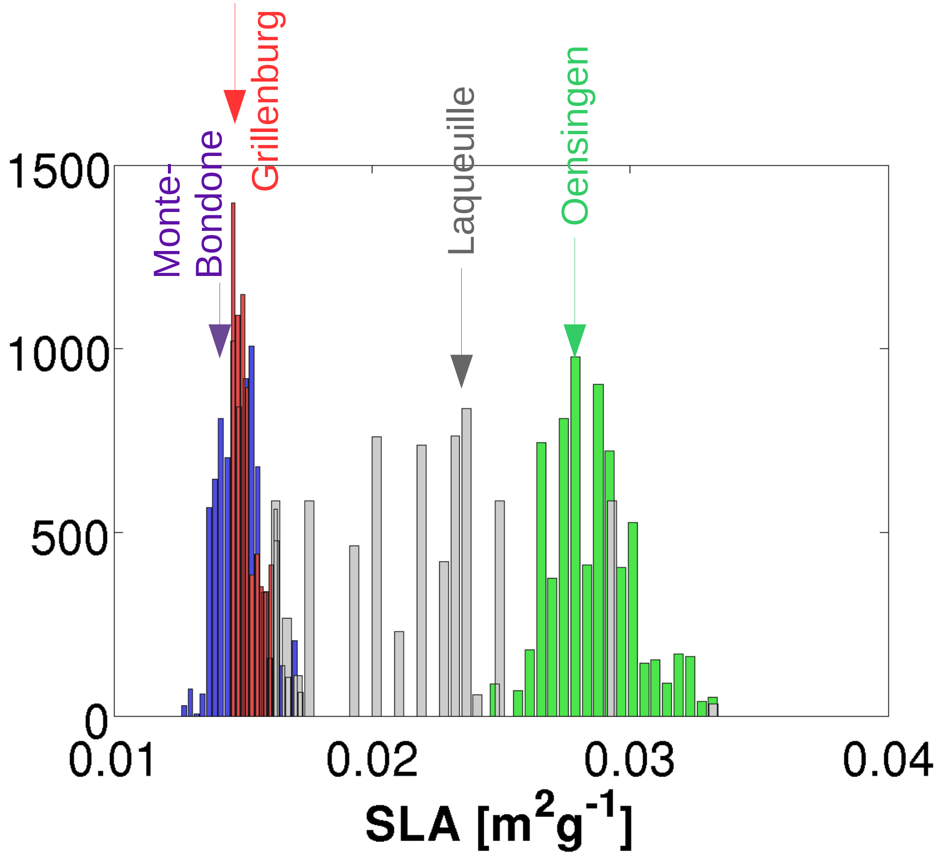
Specific leaf area [m²/gC]

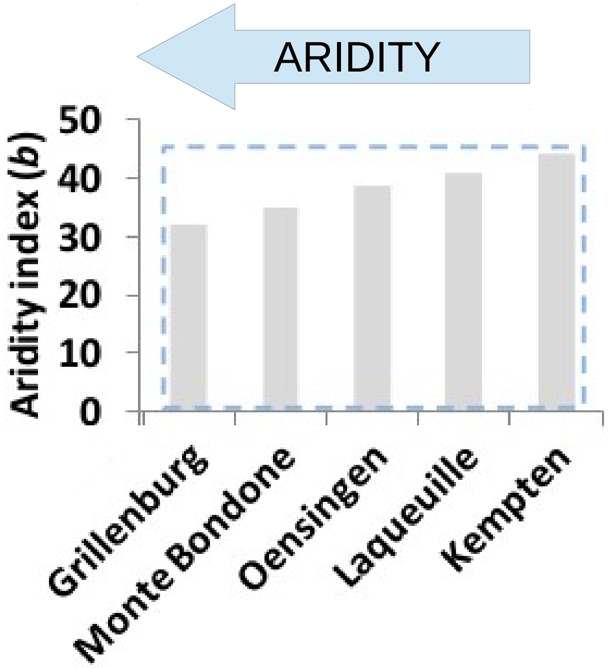


Results : parameter samplings

Specific leaf area (SLA) [m²/gC]

- SLA in CARAIB : *effective* SLA for a plant functional type !
- Actually, SLA is variable between leaves and along the season
- SLA is known to depend on aridity (-) and intensification (+)

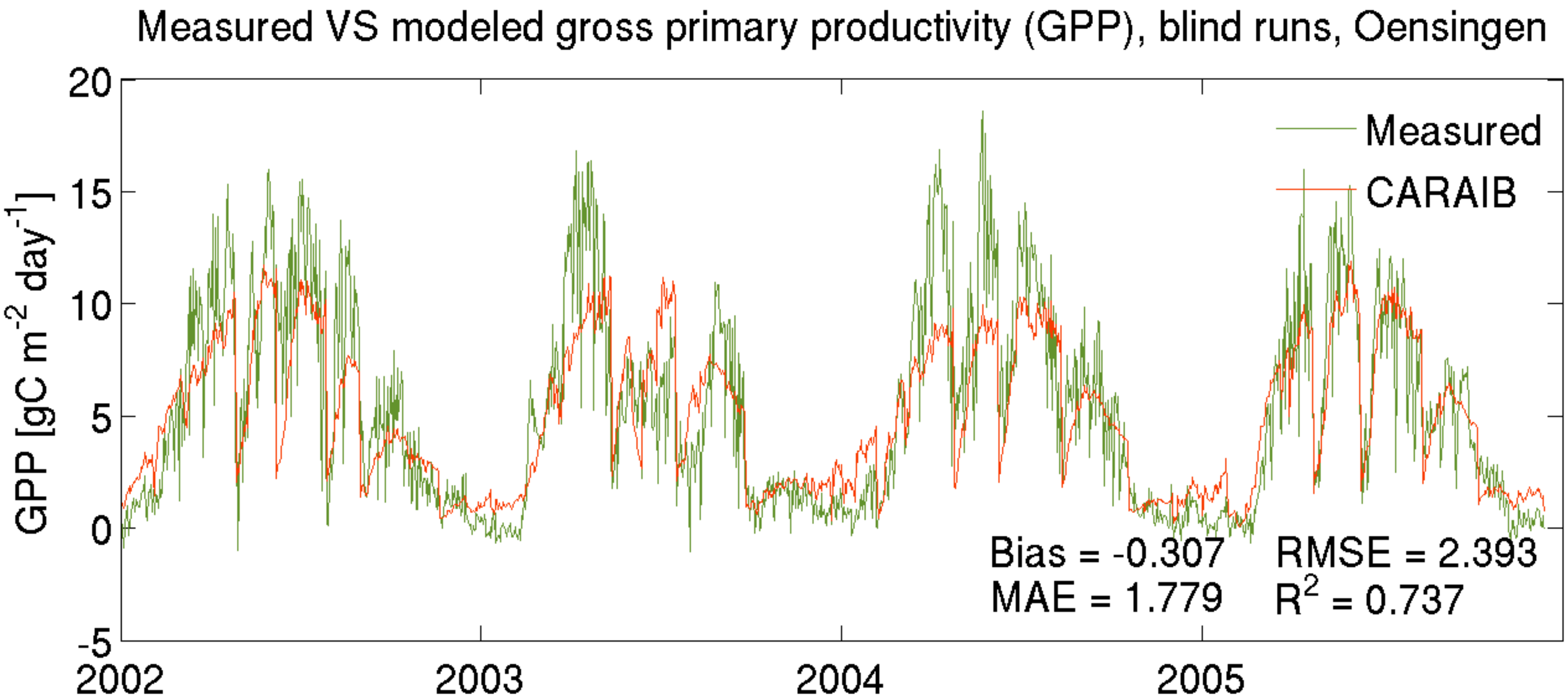




De Martonne-Gottmann aridity index
from Ma et al. iEMSs, 2014

Results : modeling improvement

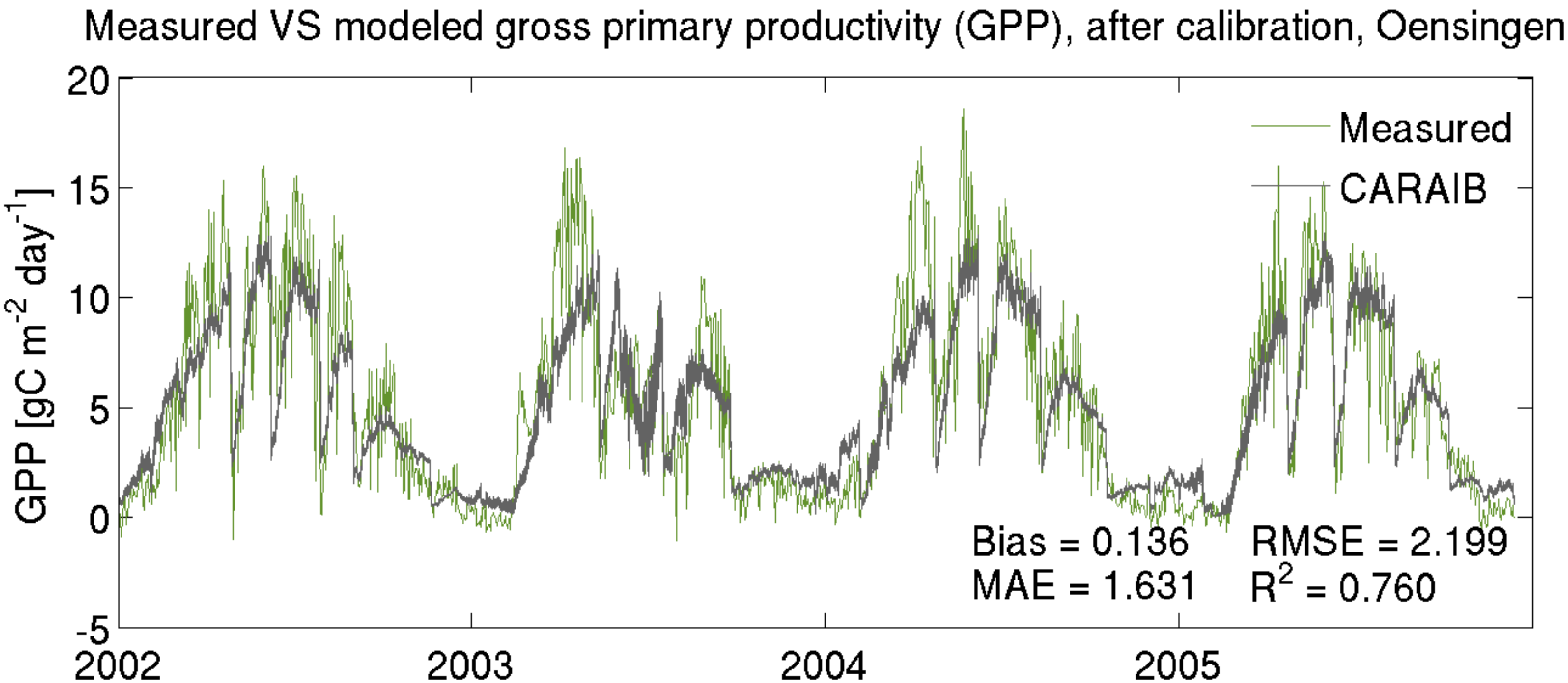
Oensingen, blind run



	Bias	RMSE	R^2
NEE [gC m^{-2} day^{-1}]	-0.513	2.034	0.487
GPP [gC m^{-2} day^{-1}]	-0.307	2.392	0.737
RECO [gC m^{-2} day^{-1}]	-0.820	1.615	0.805
ET [mm day^{-1}]	-0.107	0.910	0.549

Results : modeling improvement

Oensingen, after calibration (1000's of model outputs)



	Bias	RMSE	R^2
NEE [gC m^{-2} day^{-1}]	-0.013	1.991	0.477
GPP [gC m^{-2} day^{-1}]	0.136	2.199	0.760
RECO [gC m^{-2} day^{-1}]	0.123	1.260	0.808
ET [mm day^{-1}]	-0.020	0.675	0.751

Conclusion

Bayesian sampling with DREAM_ZS :

- Obtain a uncertainty assessment on model parameters
- Obtain an interval on model output due to parameters uncertainties
- Assess model sensitivity to its parameters

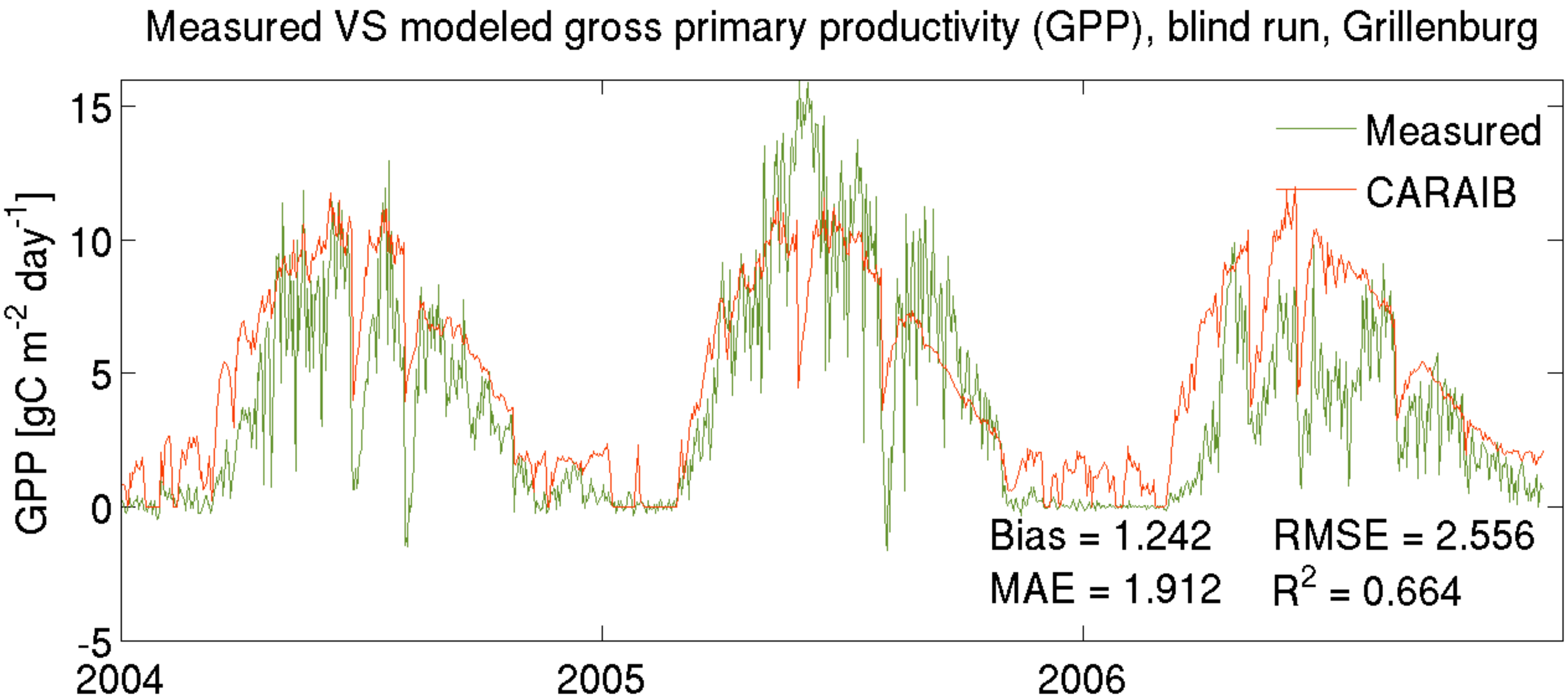
Future work :

- Interact with other modelers teams and intercompare...

Thanks for your attention

Results : modeling improvement

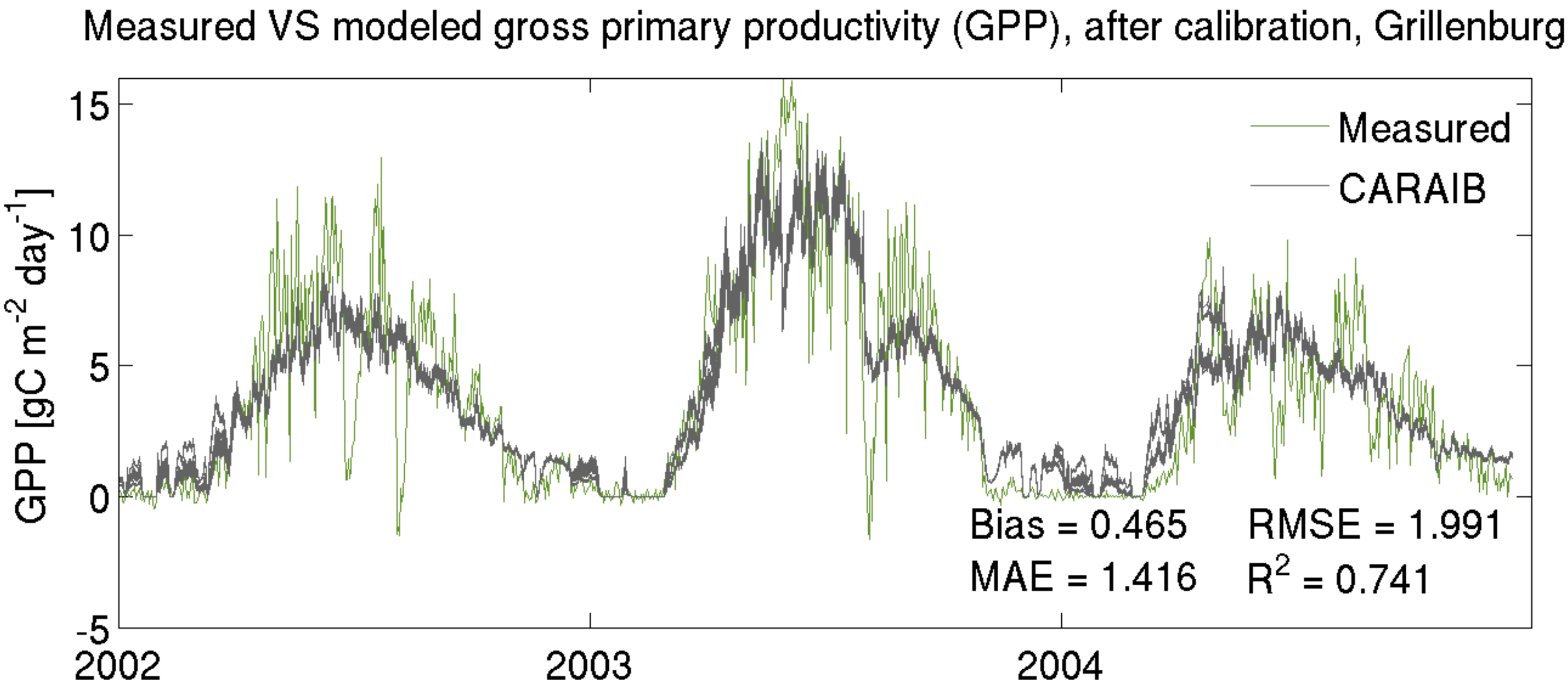
Grillenburg, blind run:



	Bias	RMSE	R^2
NEE [gC m^{-2} day^{-1}]	-0.715	1.901	0.343
GPP [gC m^{-2} day^{-1}]	1.242	2.556	0.664
RECO [gC m^{-2} day^{-1}]	0.238	0.728	0.498
ET [mm day^{-1}]	0.526	1.879	0.555

Results : modeling improvement

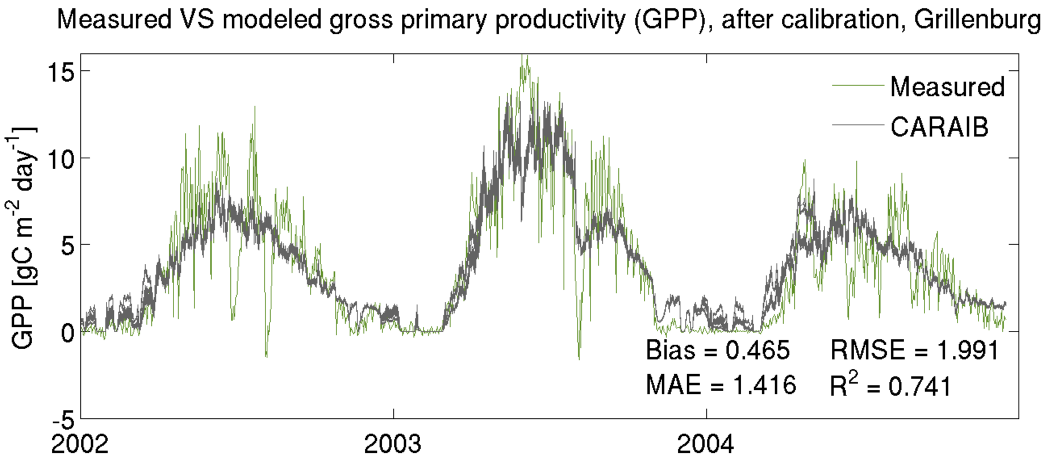
Grillenburg, after calibration (1000's of modeled GPP):



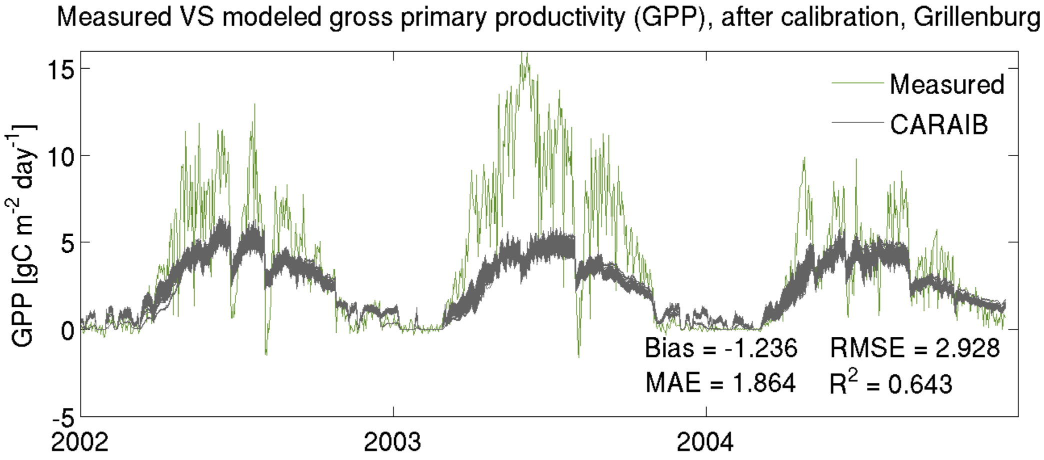
	Bias	RMSE	R²
NEE [gC m^{-2} day^{-1}]	-0.340	1.898	0.477
GPP [gC m^{-2} day^{-1}]	0.465	1.991	0.741
RECO [gC m^{-2} day^{-1}]	0.125	1.596	0.660
ET [mm day^{-1}]	0.100	0.616	0.584

Results : Error in measurements

Homoscedastic :



Heteroscedastic :



The algorithm : DREAM_ZS

- Inverse problem: $Optimal\ parameters = argmin\left(Observations - Modeled\left(parameters\right)\right)$
- 12 parameters were sampled using 3 measurements variables: RECO, GPP, ET
- A multi-objective cost function (CF) was used : CF = f(RECO, U_{RECO}, GPP, U_{GPP}, ET, U_{ET})
- Uncertainties on measurement *U* were considered as homoscedastic or heteroscedastic (i.e., constant or variable):

→ HOMOSCEDASTIC: $U = U_0$

→ HETEROSCEDASTIC: $U = \frac{U_0}{2} + \frac{U_0}{2\overline{X}} * X$

Where U_0 is a user-defined uncertainty for each variable *X*:

X	U_0
RECO	1.5 gC m^{-2} day^{-1}
GPP	3 gC m^{-2} day^{-1}
ET	1 gC m^{-2} day^{-1}