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Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

Constraints from atmospheric CO_2 and satellite-based vegetation activity observations on current land carbon cycle trends

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Abstract

Terrestrial ecosystem models used for Earth system modelling show a significant divergence in future patterns of ecosystem processes, in particular carbon exchanges, despite a seemingly common behaviour for the contemporary period. An in-depth evaluation of these models is hence of high importance to achieve a better understanding of the reasons for this disagreement.

Here, we develop an extension for existing benchmarking systems by making use of the complementary information contained in the observational records of atmospheric CO_2 and remotely-sensed vegetation activity to provide a firm set of diagnostics of ecosystem responses to climate variability in the last 30 yr at different temporal and spatial scales. The selection of observational characteristics (traits) specifically considers the robustness of information given the uncertainties in both data and evaluation analysis. In addition, we provide a baseline benchmark, a minimum test that the model under consideration has to pass, to provide a more objective, quantitative evaluation framework. The benchmarking strategy can be used for any land surface model, either driven by observed meteorology or coupled to a climate model.

We apply this framework to evaluate the offline version of the MPI-Earth system model's land surface scheme JSBACH. We demonstrate that the complementary use of atmospheric CO_2 and satellite based vegetation activity data allows to pinpoint specific model failures that would not be possible by the sole use of atmospheric CO_2 observations.

1 Introduction

The terrestrial and oceanic biospheres currently absorb almost half of the fossil fuel emissions, and thereby buffers the atmospheric CO_2 increase and reduces the rate of climate change (Cox et al., 2000; Raupach et al., 2008; Le Quéré et al., 2009). Because of the strong interactions between the biosphere net carbon (C) uptake and climate

(Cox et al., 2000; Friedlingstein et al., 2006), projections of future climate changes from Earth system models (ESMs) need to accurately simulate the processes that control the evolution of the terrestrial net C balance. However, despite a seemingly common behaviour of C cycle models for the contemporary period, estimates of the future C land balance by different terrestrial biosphere models (TBM) diverge significantly. This divergence contributes strongly to the overall uncertainty in the future evolution of the global carbon cycle (Friedlingstein et al., 2006; Sitch et al., 2008). The apparently contradictory behavior underlines the difficulty of constraining future projections of terrestrial models with current observations. It calls for an in-depth model evaluation that focusses on the model's capacity to simulate key features of C-cycle related processes rather than simply ensuring that the easily diagnosed simulated net land-atmosphere C exchange agrees with estimates inferred from observations.

Atmospheric CO_2 measurements and transport modelling that links surface fluxes to these measurements are a valuable approach to evaluate TBMs since the atmospheric CO_2 retains the signature of terrestrial ecosystem response to climate variability (Heimann et al., 1998; Randerson et al., 2009; Cadule et al., 2010). However, atmospheric CO_2 observations alone do not allow to infer the contribution of vegetation and soil components to the observed signal, such that a good fit might hide compensating model errors. Remote-sensing observations of vegetation activity may provide complementary information as they reflect the climate and disturbance related seasonal and interannual trends of vegetation greenness (Peñuelas et al., 2009; Richardson et al., 2009).

Recent model benchmarking initiatives (Randerson et al., 2009; Luo et al., 2012) have underlined the need for the development of a standard set of tests and metrics applicable to any land surface model at different spatial and temporal scales. This study adds a new component to this work by defining novel tests and quantitative model performance measures taking advantage of the complementary information contained in atmospheric CO_2 observations and remote sensing data of vegetation activity.

BGD
9, 16087–16138, 2012

A key challenge in evaluating global biosphere models comes from the, often unknown, uncertainties in observations and atmospheric transport modeling: the central question is how much relevant and robust information can be extracted from observations, which helps constraining model projections. The analyses performed here attempt to take account of this uncertainty by imposing a lower acceptable model performance measure (baseline benchmark) based on the assumption of a Null-model, i.e. a model that does not show any trend in the quantity under investigation.

Phasing and extent of the climate variability simulated by Earth System models (ESMs) often differs from observed climate because of unforced variability (Deser et al., 2010). To circumvent the resulting mismatch from a direct comparison of ESM simulations and modern observations and to make key characteristics of the observations useful for the evaluation of ESMs, priority was given to traits and metrics that describe the relationship between climate variables and carbon cycle processes rather than direct comparison of observed and modeled time-series. The analyses in this paper were performed on a seasonal and a deseasonalized signal to better identify C-cycle patterns and the relationship between C-cycle related processes and climate variability. As detailed in Sect. 2, we select several characteristics (traits) of the observational data that are of ecological relevance to inform about terrestrial C cycling patterns reflecting the biosphere response to climate variability in the last three decades, which is the period with the best data availability (Tables 2 and 3). For the selected tests, a list of comprehensive metrics was selected to quantify model performances according to the information content of identified traits and the potential sources of uncertainty in the observations. To provide a more informative and more intuitively interpretable evaluation of the model performance, we then compare this metric to a reference value of the metric obtained assuming a non-responsive and non-changing terrestrial biosphere baseline benchmark. In Sect. 3 we discuss the potential strengths and uncertainties of the evaluation framework at the example of the the JSBACH land surface model of the MPI-ESM (Raddatz et al., 2007; Giorgetta et al., 2012) driven by reconstructed meteorology.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

BGD

9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

2 Materials and methods

2.1 Observational datasets

2.1.1 Atmospheric CO_2

Atmospheric CO_2 concentration recorded at remote measuring stations were obtained from the flask data/continuous measurements provided by different institutions (e.g. flask data of NOAA/CMDL's sampling network, update of Conway et al., 1994; Japan Meteorological Agency (JMA), Meteorological Service of Canada (MSC), and many others, see Rödenbeck, 2005).

Simulated net land CO_2 fluxes for the period 1980 to 2009 were transported together with estimated net ocean CO_2 fluxes (Jacobson et al., 2007; Mikaloff Fletcher et al., 2006, 2007) and fossil fuel fluxes (EDGARv.4.0, Olivier et al., 2001, http://edgar.jrc.ec.europa.eu/faq.php) by means of an atmospheric transport model (TM) to estimate atmospheric CO_2 record at the measuring stations. For our analysis, we used the TM3 model, version 3.7.22 (Rödenbeck et al., 2003), with a spatial resolution of $4 \times 5^{\circ}$ and driven by interannually varying wind fields of the NCEP reanalysis (Kalnay et al.,1996).

The model-based time series of CO_2 at the measuring stations were based on sampling simulated CO_2 abundance at the same time where measurements were available in order to reduce the representation bias. Stations were selected in order to cover representatively a latitudinal gradient (Table 1). Latitudinal and vertical transport of CO_2 differs among TMs (Yang et al., 2007), but these differences are difficult to quantify and attribute to particular model features (Gurney et al., 2003; Peylin et al., 2005). In remote stations with simple topography, different TMs tend to agree better and are expected to have less error. The selection of monitoring station takes account of this by including mainly oceanic/islands stations, as these remote stations have a low uncertainty and are only marginally influenced by local C sources or sinks.

To assess the robustness of some of the CO_2 observation based traits (Sects. 2.3.1 and 2.3.5), two estimates of the net land-atmosphere CO_2 flux obtained from inverting

BGD
9, 16087–16138, 2012

the observed atmospheric concentrations using atmospheric transport modeling (hereafter referred to as "standard fluxes"), were also transported using the same protocol as for the simulated TBM fluxes. These fluxes were taken from the Jena Inversion system, which relies on the same TM3 transport model (Jena inversion version 3.7.22, available at http://www.bgc-jena.mpg.de/~christian.roedenbeck/download-CO2/, update of Rödenbeck et al., 2003; Rödenbeck, 2005, covering the periods 1996–2008 and 1981–2008, respectively). The standard fluxes were not used to derive an absolute benchmark sensu strictu, but as reference, as described in Sect. 2.3.

2.1.2 Vegetation activity datasets

To characterize seasonal and interannual changes in vegetation activity, we rely on two satellite-based products: the SeaWifs-fAPAR (Gobron et al., 2006a,b), the fraction of photosynthetically active radiation absorbed by vegetation, and the longer GIMMS-NDVI collection g, the normalized difference vegetation index, retrieved from the AVHRR sensor records (Tucker et al., 2005; Beck et al., 2011). Both FAPAR and NDVI provide a measure of greenness integrating canopy functioning. It has been previously shown that these quantities are nearly linearly related (Myneni and Williams, 1994). The selected fAPAR data were provided as 10-day aggregated time series from September 1997 until June 2006 at a nominal spatial resolution of 2 km and were used to analyze the seasonal cycle of vegetation activity (Table 2). The GIMMS dataset contains bi-weekly data at a spatial resolution of 8 km from 1981 until 2006 and was used to estimate long-term changes in vegetation activity (Table 3).

Satellite data were aggregated at the spatial resolution of the TBM, including grid cells that are partially covered by bare soils. With this approach, the aggregated signal indirectly accounts of changes in vegetation activity and density. A simple gap filling procedure based on polynomial interpolation in time (degree 2) was applied to replace bad-quality flag data. All data were aggregated at the monthly temporal resolution. In the case of GIMMS-NDVI, the maximum value composite (MVC) method was used (Holben, 1986). It is assumed that the process of temporal and spatial aggregation of

BGD
9, 16087–16138, 2012

satellite-based vegetation activity smoothens out noise in the data, and the uncertainty induced by the aggregation might be considered negligible for our purpose. Tropical areas were excluded from the analysis due to the high uncertainty in the interpretation of the satellite signal (Asner and Alencar, 2010) and high uncertainties in NDVI datasets in these regions (Huete et al., 2002; Brown et al., 2006).

2.2 The JSBACH model

JSBACH is the land surface model of the Max Planck Institute's Earth System Model (MPI-ESM) (Raddatz et al., 2006; Giorgetta et al., 2012). In this study we use the version as used for the CMIP5 activity (JSBACH version 2.0). JSBACH considers 11 plant functional types, which occupy annually varying fractions (tiles) of a model grid cell, prescribed from land-use data (see Sect. 2.3). Phenology and C cycling is simulated explicitly for each tile, while the half-hourly fluxes of energy and water are calculated for each grid cell, based on the relevant average properties of vegetation and soils across the tiles. JSBACH is applied here in offline mode, i.e. driven by reconstructed daily meteorology (see Sect. 2.4), at the same spatial resolution of the CMIP5 simulations of the MPI-ESM (T63, corresponding to a $1.875 \times 1.875^{\circ}$ resolution at the equator).

2.3 Climate and land-use forcing

Meteorological forcing data (air temperature and humidity, shortwave and longwave incident radiation, precipitation, and surface wind speed) for 1860 to 2010 were derived from CRU-NCEP (CRU-NCEPv4Viovy, N. 2011. Available from: http://dods.extra.cea.fr/data/p529viov/cruncep/), and were aggregated to the T63 resolution of the MPI-ESM grid at daily resolution. These data were used as model forcing and for the climate correspondence analysis. The standardized precipitation index SPI was computed from the precipitation record of the CRU observational dataset (Mckee et al., 1993; Lloyd-Hughes and Saunders, 2002). SPI is suitable as indicator of both dry and wet soil conditions. Irrespective of biomes or region, the six months cumulated precipitation was used to compute the SPI for each grid cell (see Appendix A for more details). Land cover and land-use change transition maps were derived from Hurt et al. (2006).

2.4 Evaluation methodology

The analyses in this study focus on seasonal and interannual time scales. To identify these components from the observed and simulated atmospheric CO_2, vegetation activity and climatic drivers, a seasonal component (up to annual time scale) and an interannual time scale component were isolated using a filter implemented in the Fourier space. We followed the method and the cut-off values presented in (Thoning et al., 1989), using Gaussian spectral weights (Rödenbeck et al., 2003). In terms of interannual variability this approach is more advantageous than consideration of monthly anomalies, since a deseasonalized signal provides a better measure of the strength and persistence of interannual variability related to climatic and natural events as El-Niño events and volcanic eruptions.

The analysis of seasonal patterns aims at the relative phasing of vegetation growth and ecosystem respiration and modeled phenology that affects the seasonal phasing of the net land-atmosphere C exchange (Prentice et al., 2000), but also biogeophysical effects such as the water and energy exchanges (Notaro et al., 2007; Peñuelas et al., 2009). Interannual variability and long-term trends of net land C exchanges and vegetation activity are an important and crucial aspect of the terrestrial ecosystem in a climate change context. Changes of vegetation activity might have implications to long term potential for retaining more C in the system, contributing hence to the biosphere-atmosphere feedbacks and internal plant-soil feedbacks (Bonan, 2008).

In the following sections we describe key features of the atmospheric CO_2 and vegetation activity obtained from the decomposed signals (Table 2: seasonal time scales; Table 3: interannual time scale). These traits are used to assess the capacity of the model to reproduce climate variability induced effects on terrestrial ecosystems. In addition, traits characterizing the co-variability of vegetation features/atmospheric CO_2 and land climatic patterns are defined. Some of the selected traits were analyzed

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |
BGD
9, 16087–16138, 2012
Atmospheric CO_2 and vegetation activity constraints
D. Dalmonech and S. Zaehle

separately in three time intervals according to two breakpoint events: the Mount Pinatubo eruption in 1991, and the El-Niño event in 1997, two of the most relevant natural events occurred in the last three decades, for simplicity referred to as the 80s, 90s and 2000s (Tables 2 and 3).

The systematic quantitative assessment of the correspondence of anomalies and trends in simulated vegetation activity and net C exchange is finalized by mean of normalized metrics (see Appendix B for the mathematical description). The proposed selected traits and metrics are suitable to be applied to land surface models run in either offline or fully coupled mode, because they are based on reproducing variability and/or statistical relationships with the driving climate, rather than focusing on the absolute correspondence of the variables. This strategy reduces potential biases in the assessment due to uncertainty in the predicted climatic variability (Deser et al., 2010).

Geographical regions at the continental scale consistent with the regions used for the Transcom3 project (Gurney et al., 2002; Fig. 1) were used to determine the influence of net land-atmosphere CO_2 fluxes from a particular region to the signal at the monitoring stations following the procedure reported in Cadule et al. (2010). The characterization of vegetation activity was performed at grid-cell level and at regional level according to the same Transcom3 Regions. The Transcom3 region maps were further intersected with the dominant vegetation map obtained from the Synmap vegetation classification of Jung et al. (2006). Grid cells with dominance of bare soil or ice, as well as grid cells with no valid observations were excluded from the analyses.

2.4.1 Seasonality of Atmospheric CO_2

The model's capacity to simulate phase and amplitude of the mean seasonal cycle of atmospheric CO_2 (MSC) was evaluated using the Taylor score (Taylor, 2001). The selected metric gives more weight to the correspondence in phase instead of amplitude (Taylor, 2001), which is the more reliable feature of transport models (Stephens et al., 2007). Additional information on the land net C exchange is contained in the latitudinal gradient of the amplitude of the mean seasonal cycle (MSClg), which increases from the South Pole northwards because of the relatively higher land masses fraction in the Northern Hemisphere (NH). A metric based on the variance of the amplitude data was used to assess the model performance (Table 2 and Appendix B).

The relative contribution of the land (and ocean) Transcom3 regions to the seasonal cycle amplitude (MSCc) was computed using the atmospheric CO_2 record obtained by transporting the standard fluxes constrained on the period 1996–2008 as reference. This choice was made so as to overlap with the time period for which the SeaWifs-fAPAR data are available (see Sect. 2.4.2). The relative contribution of each region to each single monitoring station in both standard and modeled fluxes was compared using the Pearson correlation coefficient. This trait identifies if large regional inconsistencies exist between modelled and reference fluxes, and hence identifies regions with fluxes that are potentially inconsistent with the atmospheric record.

Changes in the seasonal cycle over time, referred to as the monthly CO_2 trend (MT), are quantified as the year to year change in CO_2 concentration for each month. Previous works analyzed solely the change in amplitude of the seasonal cycle in Mauna Loa as response to land surface warming (Myneni et al., 1997; Angert et al., 2005; Buermann et al., 2007), while we focus on decadal trends in long-term Northern stations, which exhibit a clearer signal. This trait summarizes the seasonal change in the trend of land carbon sink/sources in response to climatic drivers and natural disturbances in the extra tropical latitudinal band. The model-data correspondence is analyzed using the Pearson correlation coefficient.

The trend in the seasonal onset of net land C uptake was computed as the annual downward zero-crossing date of the atmospheric CO_2 time serie (C-dd). This feature characterizes in particular the observed high-latitude ecosystem responses to recent land surface warming and it is indirectly linked to the beginning of the growing season (Keeling et al., 1996; Myneni et al., 1997).

Since the years 1991–1993 (the years following the Mount Pinatubo eruption) are an anomaly in this trend (e.g. Lucht et al., 2002), these three years were excluded from the analysis. The analysis for the MT and C-dd traits focuses on the stations in the

BGD
9, 16087–16138, 2012

extratropical areas with a clear signal from land and low contamination of the trends due to uncertainties in the fossil fuel emissions (Table 2).

2.4.2 Seasonality of vegetation activity

A direct comparison of absolute values of remote sensing data and their correspondent modelled variable is not a viable strategy, because of uncertainties in the retrieval process and differences in the way radiances are recorded by satellites and TBMs. However, the temporal evolution of the modelled signal should resemble the observations such that they can be evaluated by a metric that is independent from the absolute values of the time series.

As a first step, grid cells with only one observed growing season per year were selected by analyzing the autocorrelation of the seasonal record and its significance. The shape of the seasonality of vegetation activity was then characterized by two robustly identifiable and meaningful phases of the phenological cycle: the time of the beginning of the vegetative growing season, hereafter referred to as time of onset (t-onset), and the time of the maximum fAPAR signal (t-max) (Randerson et al., 2009). Data and model signals characterized by mean amplitude of the seasonal record within 1 % of total fAPAR range were excluded from the analyses. The definition of the beginning of the growing season is a subjective matter and a direct and precise link to ground level observation is difficult to identify (Lucht et al., 2002; Maignan et al., 2008; Verstraete et al., 2008). Analogously to the method to estimate the beginning of the net CO_2 uptake above, the time of onset was defined as the zero crossing points of the seasonal cycle curve. Linear differences of the most frequent month of time of onset or maximum of fAPAR were computed between model and observation. Consequently this metric ranges between one (no difference) to zero (6 months difference). The length of the growing season was not used as additional trait, because it is poorly defined from satellite data, as autumnal leaf-coloring and the simultaneous presence of living and dead leaves confounds the satellite signal, in particular in temperate regions (Estrella and Menzel, 2006; Menzel et al., 2006).

BGD
9, 16087–16138, 2012

2.4.3 Interhemispheric gradient and trend of atmospheric CO_2

The long-term trend in atmospheric CO_2 (C-LTT), given known fossil fuel, land use change emissions and ocean net emissions, is an indication of the long-term net C-balance of the terrestrial biosphere (Prentice et al., 2000). The trend was computed from the mean annual values of the deseasonalized signals and compared directly to the observations for stations covering the period 1982–2008 were used (Table 1). The interhemispheric gradient in atmospheric CO_2 abundance (IHG) measures the North-South differences in atmospheric CO_2, caused by changing balance of the increasing fossil fuel emissions in industrialized regions and the net ocean and land carbon up-take. For each year, this trait was computed by subtracting the observed and modelled annual CO_2 concentration at the South Pole station (SPO) from the respective station concentrations, as in Cadule et al. (2010). The metric was based on the comparison of the standard deviation of modelled and observed data.

2.4.4 Trend of vegetation activity

Analogously to atmospheric CO_2, vegetation activity trends were computed from modelled and observed data. Due to the uncertainties in absolute values of satellite-based vegetation data, this trait does not compare numerical trends. Instead, the selected metric determines the spatial patterns of positive, negative or no significant trend in vegetation signal from the GIMMS-NDVI dataset and compares this to the pattern in modeled fAPAR (Table 3). For each grid cell, the metric calculation was performed on annual values of the deseasonalized vegetation time series. The non-parametric Mann-Kendall test was used to determine whether a positive (greening), negative (browning) trend or no significant trend was detected (two-tailed statistic). The advantage of this approach is that it is robust against satellite-drift and high-model internal variability, for instance induced by high variability in the climate simulated by an Earth System model. At the grid-cell level, the metric is a binary score which measures whether the model

BGD
9, 16087–16138, 2012
Atmospheric CO_2 and vegetation activity constraints
D. Dalmonech and S. Zaehle

and data show a significant trend of the same sign. The global-scale metric is then a ranking of a percentage agreement for cells of a particular trend-class.

2.4.5 Quantification of interannual variability: atmospheric CO_2 and vegetation activity relationship with land climate pattern

The relationship between the seasonality of phenology and local climatic drivers at grid-cell level was explored using the annual variations of the time of beginning of the growing season (t-onset; Table 2). The time-series for the SeaWiFS fAPAR data is too short to allow for a trend analysis. Therefore the correlation of the t-onset with the annual temperature, given the annual SPI as conditional variable, was taken as a proxy. A ranking metric, analogous to the vegetation activity trend metric, was computed according to cell-by-cell agreement in terms of a significantly positive, negative or not existing correlation.

Interannual variability in vegetation activity was assessed using deseasonalized signals obtained from the GIMMS-NDVI/modelled-fAPAR aggregated to the Transcom3 land region. Cross-correlations between monthly records of vegetation activity and regional climatic variables, temperature and SPI, were computed with lags up to 24 months (Table 3). South American Tropical and Tropical Asia regions are excluded from the analysis (see Sect. 2.1.2).

The same approach was used to measure the relationship between atmospheric CO_2 growth rate and land surface climate (Table 3). The atmospheric CO_2 growth rate is well known to provide information on the interannual variability of the land response to climate variability at the ENSO time scale (Keeling et al., 1995; Le Quere et al., 2003). However, most of the land surface climate shows some coherence with this large-scale climatic feature (Buermann et al., 2003), such that the CO_2 signal in the atmosphere could be perfectly correlated, instantaneously or lagged, with climate over most of the land regions. To reduce this problem, an empirical orthogonal function (EOF) decomposition of the atmospheric CO_2 records, obtained by transporting the inverted fluxes from each land region, was computed. The three most contributing land

BGD
9, 16087–16138, 2012

regions (to at least the 80 % of the variability in the observed total signal) for selected monitoring stations were determined and only these were used in the analysis (see Appendix C).

The obtained statistically significant cross-correlations from data and model (vegetation and atmospheric CO_2 growth versus regional climate) were compared with a correlation metric, to test if the model is able to return the coupled patterns with time lags (see Appendix C). The use of inverted fluxes to determine the most contributing regions at interannual time scale and for the EOF decomposition does not affect significantly the results in terms of model behavior evaluation. However, it changes the degree to which the observations can effectively constrain the model, if in the model domain a region contributes less than inferred from the inverted fluxes.

The last selected feature of the carbon cycle uses the CO_2 growth rate to compute an apparent land C cycle sensitivity to global temperature anomalies, defined as the slope of the annual CO_2 growth rate versus the aggregated annual land surface temperature. The record at the station of Mauna Loa (MLO) was used as proxy of evolution of globally averaged atmospheric CO_2 concentration (Zeng et al., 2005).

2.5 The baseline benchmark

The reference minimum (baseline benchmark) concept applied in this study compares the skill of the model under investigation with the score of the metric obtained assuming a land biosphere that does not systematically contribute to any signal. For the C-cycle analyses, the baseline benchmark is set to be a biosphere without a terrestrial C-cycle ecosystem, implying that the signal or trend in the observations is driven by fossil fuel and net ocean fluxes only (no-land case). Since this lower benchmark is applied based on the same TM for all the simulations, this further reduces the potential errors introduced by transport modelling uncertainties. Only for the CO_2 drawdown test (C-dd; Table 2), the baseline benchmark is set as zero trend.

In terms of vegetation activity, the lower benchmark is provided by the case with constant vegetation (no-change case). Only in the case of t-onset and t-max vegetation trait (Table 2), the baseline benchmark is set as 6 months delay.

The final metrics for the model were obtaining by scaling the original computed metric M_{or} to the baseline benchmark according to:

$$M = \frac{M_{or} - M_{ref}}{1 - M_{ref}} \quad (1)$$

Where M_{ref} is the metric computed for the lower benchmark case.

3 Results and discussion

In the following, we discuss the results of the above framework at the example of the JSBACH model. The results for the individual traits are summarized by their global scores in Fig. 2. Table A1 reports the results of the baseline benchmarking for comparison. Table 4 reports results per latitudinal band.

3.1 Seasonality of atmospheric CO_2 and Vegetation activity (Table 2)

3.1.1 Seasonality of Atmospheric CO_2

The Taylor diagram (Fig. 3a) reports the data-model correspondence in terms of phase and amplitude of the mean seasonal cycle (MSC). JSBACH is in general capable of simulating the phase of the seasonal cycle of CO_2, with the exception of the stations south to the Equator that tend to be out of phase. At those stations, ocean fluxes dominate the signal, which can be seen in the large difference between the low original and the higher scaled metric (Table 4). The anticorrelation of the model seasonality might further indicate either (or both) a high contribution of the signal from the North hemisphere or reveal effective out of phase seasonal land C-fluxes. The in-depth analysis

BGD
9, 16087–16138, 2012

D. Dalmonech and S. Zaehle

of the regional contribution to the mean seasonal cycle (the MSCc trait) indicates that the Eurasia boreal and temperate regions slightly, but systematically, contribute more to the signal in the stations above the 50° N than inferred from observations (Fig. A1). At the southern stations, the model signal from the South American Temperate region clearly dominates the ocean signal (Fig. A2), suggesting that this region has a seasonal cycle of net land-atmosphere C fluxes inconsistent with the atmospheric record. This inconsistency leads to the low scores in the southern latitudinal band (Fig. 2, Table 4).

The model clearly overestimates the amplitude of the MSC across the global network of stations. This is particularly clear when plotting the latitudinal gradient of the seasonal cycle (Fig. 3b). Although uncertainties in the transport model could partially contribute to this, the steep drop of the CO_2 concentration during the summer months (data not shown) are an indication that an overestimation of spring C-uptake (i.e. too large global gross primary productivity) is responsible for the overestimation of the amplitude.

3.1.2 Seasonality of vegetation activity

Fig. 4 shows that JSBACH simulates the time of onset with a systematic lag of 1 to 2 months over large areas of the Northern Hemisphere (NH). A major exception is the North-East America temperate region, where the model tends to lead the observed growing season. Given the monthly temporal resolution of the analyses, these results in the NH are still in line with the good performance in terms of phase correspondence of the MSC of CO_2 at the northern stations (Fig. 3a).

In large parts of the tropical latitudinal band, most of the modelled signal is flat, in contrast to the observed seasonal cycle recorded in the SeaWifs-data (Fig. 4). Similarly, the model signal in the Australian scrubland does not show any clear seasonality in contrast of the observations. The flat tropical signal and the detected differences up to 3–4 months in some southern regions are responsible to the low aggregated global model performance (Fig. 2, Table 4). The vegetation classes contributing most to the lower performances are deciduous broadleaved forests and grassland, probably

BGD
9, 16087–16138, 2012

mostly due to their geographical distribution and presence in drought-prone areas (see Fig. A2).

The timing of the maximum analysis (t-max; data not shown) returns similar geographical pattern to the "time of onset" trait, but the differences are generally slightly higher. This aspect partly relates to the less well defined nature of the timing of the maximum in regions with several months of full foliar coverage. At the global scale, there are no discernible differences between the two scores (Fig. 2, Table 4). These results show that the seasonality in the model is slightly lagged in time but without strong distortions in the signal in the first period of the growing season in the Northern Hemisphere. However, an improvement in phenology parameterization for tropical rain forests and drought-prone shurblands is required.

3.2 Monthly CO_2 trend

As example for the monthly CO_2 trend (MT), Fig. 5a displays the trend computed for the station of Barrow (BRW). For the selected Northern stations, the observational analysis shows that, in particular in the summer months (June/July), the land is the most dominant contributor to the tendency towards a more pronounced seasonal cycle. That is to say, increased monthly land C uptake, rather than changes in ocean fluxes and fossil fuel emissions are responsible for this trend. This feature is particularly strong in the 1980s and consistent across the selected stations, although this trend is not always statistically significant for all the months (Fig. 5a). The monthly CO_2 trend in the 90s is less clear (data not shown), while the negative trend of the summer uptake occurs in the 2000s albeit weaker than in the 1980s. The latter pattern likely reflects the weakening of the positive land warming effect on phenology during the growing season, which was particularly apparent in the 1980s (Myneni et al., 1997).

Figure 5b exemplarily shows that JSBACH is able to qualitatively return the seasonal-like shape of the monthly CO_2 trend and the detected land-C uptake weakening, but it is not able to fully explain the observed signal (Fig. 2 and Table 4). Since the selected metric analyzes the correspondence of phase of the monthly trend, the non-perfect match could be attributable to asynchrony of photosynthesis and ecosystem respiration fluxes or differences in terms of magnitude of these fluxes.

Using an additional TM simulation, we verified that the observed weakening of the negative trend in summer is indeed mainly land induced and not induced by the interannual wind fields used in the transport model. The experimental results with constant wind (data not shown) confirmed that interannually varying transport can contribute but does not overwhelm the land-based trends in monthly CO_2 concentrations. Potential trends in the seasonality of fossil fuel emissions (Blasing et al., 2005) are unlikely to strongly affect this trend (data not shown).

3.3 Interhemispheric gradient and long term trend of atmospheric CO_2 (Table 3)

The IHG trait, which evaluates the interannual variability of the net land-atmosphere C exchange, agrees well between JSBACH and the observations (results not shown, but see Fig. 2). However, the analysis on the long-term C balance trend (C-LTT) shows that JSBACH substantially overestimates the long-term trend compared to observation (Fig. 6a), such that its score is actually lower than the baseline benchmark at all stations (Fig. 2, Table 4, Table A1). Since this detected data-model difference is unlikely to be due to uncertainties in fossil fuel or ocean fluxes, this result is due to a clear underestimation of net land C-uptake.

3.4 Vegetation activity trend (Table 3)

Fig. 6b displays the decadal patterns of the normalized annual vegetation activity time series (GIMMS-NDVI and JSBACH-fAPAR), excluding tropical area, iced and desert areas. There appears to be a good qualitative global agreement, suggesting that phenological limitations are not likely the cause for the aforementioned too low increase in land C. However, the good agreement is partly due to the compensation of errors (Fig. 7). The observed, spatially extensive positive trend in vegetation greenness in the 1980s is not fully captured by the model, because several areas have either no trend or

BGD
9, 16087–16138, 2012

even a negative trend (in parts of the South America, Australia and South East Asia). In the 1990s, no clear geographical pattern is detected (data not shown). For the 2000s, large areas with an observed positive trend in the 1980s, appear to have no or even negative trends. This phenomenon is only partly reproduced by JSBACH: in northern boreal and in the Southern Hemisphere, particularly in the South America temperate region, the negative trends are simulated.

The observed large-scale positive trends in vegetation activity during the 1980s is consistent with previous results (Myneni et al., 1997; Zhou et al., 2003). However, our analysis underlines that the observed positive warming effect on greening has not been persistent in time, but switched toward a neutral effect in the 90s and a localized negative trend in the 2000s. The observed negative pattern in the SH is generally consistent with the trends in evapotranspiration and in particular soil moisture reported in (Jung et al., 2010), even though our analyses ends in 2006, while theirs ends in 2008. Several factors might contribute to the observed overall behavior following the El Nino event in 1997. These include recurrent drought events, pest outbreaks and severe fire events over several regions responsible for the detected negative trends in boreal areas and the weakening of the summer C-uptake that we reported in Sect. 3.2 (van der Werf et al., 2004; Angert et al., 2005; Goetz et al., 2005).

The low final score of JSBACH in this metric (Fig. 2, Table 4) is in particular the result of the recurrent large-scale negative trends in several areas in the SH and in South-East Asia during the 80s and in the 2000s (Fig. 7). The non-quantitative nature of this comparison prohibits a too strict interpretation of the model-data differences. However, the disagreement in the sign of the trend can be attributed to model failure. It is unclear, whether this failure is caused by the phenological scheme of the model, or other factors such as the drought response, or fire processes.

Despite the spatial model-data disagreement, at global scale the errors in the model compensate. Assuming that vegetation activity is linked to plant productivity, and adding to this fact that the CO_2 response of photosynthesis in JSBACH agrees with

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

BGD

9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

previous studies (results not shown), the underestimation of the net land C uptake in JSBACH (Sect. 3.3) is likely the consequence of a too high soil C-turnover rate.

3.5 Terrestrial ecosystems and climate variability

3.5.1 Growing season response to local climate (Table 2)

The timing of the CO_2 drawdown point (C-dd) and the onset of vegetation greening (t-onset) represent two independent proxies to measure the effects of land warming on spring phenology (Badeck et al., 2004; Menzel et al., 2006). There is a tendency towards earlier CO_2 drawdown at the stations of STM, BRW and ALT (Fig. 8a, BRW as example), although this trend is statistically significant only for the latter two stations ($P < 0.10$). Such a negative trend in time is consistent with the advance of spring phenology induced by land surface warming (Fig. 8b): the correlation between climate variability and the timing of vegetation onset is significantly negative with annual temperature, implying earlier green-up in warmer years, mainly in the boreal areas as clearly shown in Fig. 8b.

JSBACH does not show any discernible trend in any of the three stations (Fig. 8a, example for BRW), despite the fact that it returns a similar correlation pattern the start of the growing season with local temperature (Fig. 8c), in particular in the extratropical northern areas. The final, global score for this trait is very low, despite the good visual matching, because of the low cell-by-cell correspondence (Fig. 2, Table 4). These two analyses underline that the model, although it realistically simulates the beginning of the growing season (Sect. 3.1), is likely to respond too weakly to land surface temperature anomalies.

3.5.2 Interannual variability of Vegetation activity and regional climate (Table 3)

The vegetation activity is analyzed separately for each climatic driver. It is not possible to clearly disentangle temperature and precipitation effects. Nonetheless, the analysis

BGD
9, 16087–16138, 2012

suggests that the NDV at high latitudes is mainly correlated with surface temperature, where plant growth is mainly limited by temperature. An exception to this pattern is boreal Eurasia (EAB), which shows a higher co-variation of vegetation activity with precipitation pattern. Regions with dominance of shrubs/grassland are mainly driven by precipitation anomalies, in agreement with previous studies (Groeneveld and Baugh, 2007).

Fig. 9a, b presents exemplary the computed cross-correlograms for Eurasia Temperate (EATe) and the North America Boreal (NAB). The pattern returned in NAB, which is common to NATe and EUR, reveals a strong co-variation of vegetation activity and temperature in both data and model. However, the model behavior suggests a strong correlation with temperature even in areas where the observations suggest a stronger covariation with precipitation (measures as SPI), as for instance in the EATe. One notable feature in these regions is that JSBACH shows a larger delay in the response of vegetation activity to SPI than observed, with differences of the order of 2–3 months (EAB, NA, SA). The final JSBACH score is in general good for this trait (Fig. 2, Table 4), when considering an average performance over all the regions, despite the low score in precipitation-driven areas mainly due to the different time-lag of the response.

An important aspect emerging from this simple trait is that the detected delay could hide an incorrect representation of the effects of soil drought on vegetation growth. The same regions, in which the model shows a delayed response to precipitation, also show a persistent negative trend in vegetation activity (Sect. 3.4, Fig. 7). This pattern is evident in particular in South-East Asia, South America Temperate, and Australia, which are mainly dominated by grasslands, shrub lands or crops. Even if at smaller spatial scales, other non-climatic effect (i.e. land degradation and management practices, and fire recurrence) might affect vegetation cover and activity (Foley et al., 2005), the longer lag in the co-variation of vegetation and precipitation might be caused by the same model fault responsible for the mismatch in the vegetation trends. From a biogeophysical point of view this model feature could also indicate a less reliable capability of the land surface model to return memory effects of the vegetation-precipitation pattern

BGD
9, 16087–16138, 2012

D. Dalmonech and S. Zaehle

emerging in the real Earth system (Alessandri and Navarra, 2008; Hirschi et al., 2010) in a coupled Earth system model setting.

3.5.3 Interannual variability of CO_2 growth rate and regional climate (Table 3)

The analysis of the CO_2 growth rate revealed distinctly different behavior in two latitudinal bands. In tropical latitudes, the correlation structure is similar between observations and model. Figure 9d, however, indicates that JSBACH performs less well in particular where the CO_2 growth rate is mainly correlated to temperature anomalies as for instance in boreal and temperate North America. It is noteworthy that this model failure occurs despite the good correspondence in terms of vegetation-temperature (Fig. 9b). One potential reason for this phenomenon might be modeled temperature sensitivities of ecosystem respiration parameterization, particularly soil C decomposition, inconsistent with the observations. However, it is also possible that the CO_2 signal at the monitoring station is influenced by net land-atmosphere C fluxes in other extratropical regions, obscuring the local relationship. In general, the observed weak correspondence for the station of BRW is also observed for the station of ALT, while for the stations between 60° N and 25° N, no statistically significant co-variations were found in observations (data not shown).

In all stations, where most of the contribution to the observed concentrations is from tropical regions (e.g. South American Tropical, North and South Africa), the results reveal a good correspondence of the pattern of the covariance. However, in contrast to the observations the modeled correlation is weaker and sometimes not significant (Fig. 9c). A comparison of the time-series of atmospheric CO_2 and land surface climate (data not shown), reveals that the modeled time-series exhibits more variability than observed and explained by for instance ENSO related events. One potential cause might be the omission of fire fluxes from the current version of the model, however, this is unlikely to be the only cause.

The apparent global land C sensitivity to land surface temperature anomalies (C-Clsens) computed for the model is not significant and very shallow (Fig. 10), in contrast

BGD
9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

to the observed sensitivity (4.2 $Pg\,C\,yr^{-1}\,K^{-1}$) ($P < 0.01$). It is not possible to determine to what extent the missing fire module or the use of a specific transport model contribute to this observed-modelled trait mismatch. However, the very low sensitivity returned by the model is comparable to the baseline benchmark (assuming a neutral biosphere, see Table 4), suggesting a fault in the model rather than a conceptual error in the methodology. As suggested by Rafelski et al. (2009), if there was a similarity in the climate sensitivity of the underlying C-processes at interannual and longer time scales, this would imply that the results obtained from the JSBACH model could have repercussions on C processes at longer temporal scales.

4 Concluding remarks

Pertinent information on current C-cycle related processes contained in the atmospheric CO_2 record and the satellite-based records of vegetation activity were compiled and synthesized into easily identifiable traits and a framework of comparable metrics. The results of the exploratory analysis of C-related processes and climate variability was presented with emphasis on the robustness of the information in light of the combined use of both atmospheric CO_2 concentration and vegetation activity at the appropriate time and spatial scale of a global land surface model. The results show that the simultaneous use of the atmospheric CO_2 record and satellite-based vegetation activity as two independent datasets help to identify the sources of data-model mismatch in terms of regional source of errors, or to detect potential compensation errors. In particular, the separate analysis of the atmospheric CO_2 and vegetation activity circumvent the problem that the atmospheric CO_2 retains the net effect of both vegetation activity (i.e. photosynthesis) and ecosystem C release response.

The use of a baseline benchmark with a clear ecological meaning, was shown to be a valuable approach to provide a more robust and objective quantification of data-model disagreement. In addition scaling the metric against a reference case, allows to

BGD
9, 16087–16138, 2012
Atmospheric CO_2 and vegetation activity constraints
D. Dalmonech and S. Zaehle

be more independent by the section of a specific metric and avoid misleading interpretation of the numerical score.

A key component of the evaluation framework developed here is that it is designed to be suitable and sensitive to evaluate global land surface models both offline mode, i.e. when driven by observed climate variability, and fully coupled to Earth system models with a different climate and climate variability. Therefore, in addition to providing metrics for key traits that describe climatological mean variables, we use a range of correlational metrics to analyze the climate sensitivity of key carbon cycle traits. We demonstrate that these metrics provide insight into the realism of the carbon cycle simulation that go beyond an evaluation of mean states and trends. In this paper, we described the framework and applied it to an example model. The next step will be the use of this framework to evaluate online and offline versions of JSBACH. Nonetheless, even application of the benchmarking framework for the evaluation of the JSBACH model in offline mode already allows some conclusion particular to the model:

- The traits at seasonal time scales showed that high-latitude terrestrial ecosystem patterns are a major strength of JSBACH, with good performances both in terms of mean vegetation activity and mean seasonal CO_2 cycle in the high latitudinal stations. Lower performance of mean pattern of phenology occurs in the Southern Hemisphere, in particular in shrubs dominated areas and in deciduous broadleaved forests in South Africa.

- The observed weakening of the positive warming effect to vegetation in the NH and the trend toward a neutral/negative effects in the SH pronounced in last decade are not fully captured by the model, both in CO_2 and vegetation activity traits. The analysis of vegetation-climate covariance revealed that the modelled ecosystem response is primarily driven by temperature anomalies, suggesting that this discrepancy might be associated with an incorrect sensitivity of vegetation to precipitation anomalies at interannual time scales.

BGD
9, 16087–16138, 2012

- While the analysis of CO_2 growth rate-climate drivers returned a weak covariation of the atmospheric signal with climate on selected regions on land, the model deviates strongly from the observations both in terms of the long-term trend of the atmospheric CO_2, and therefore the implied net land C uptake, and the apparent interannual land carbon sensitivity to temperature anomalies. The combined analysis of CO_2 with the vegetation trend analysis suggests that a too high soil C turnover rate might be responsible for the underestimation of net land C uptake.

Appendix A

A Computation of SPI index

The SPI is the transformation of the precipitation time series into a standardized normal distribution (z-distribution). First, a gamma distribution is fitted to the cumulative precipitation frequency distribution. The gamma distribution has been used to fit the empirical frequency of data. Since the gamma distribution is undefined for null values of the variables, the cumulative probability has been corrected according to Llouyd-yugher and Sanders (2002). Using an equiprobable transformation, the cumulative probability function of the gamma distribution is then transformed to the normal distribution function.

Appendix B

In addition to the classical statistics as the Pearson correlation coefficient (r), the squared correlation coefficient (r^2), cross-correlation and standard deviation statistics (σ), metrics were selected as combination of some of the previous statistics and built ad hoc for the specific trait analyzed.

BGD
9, 16087–16138, 2012

Taylor (2001):

$$\frac{4(1+r)}{(\hat{\sigma}_f + \frac{1}{\hat{\sigma}_f})^2(1+R_0)} \tag{B1}$$

Taylor (2001):

$$\frac{4(1+r)^4}{(\hat{\sigma}_f + \frac{1}{\hat{\sigma}_f})^2(1+R_0)^4} \tag{B2}$$

In the second metric, more weight is given to the capability of model to return the right phase of the trait rather than the amplitude. $\hat{\sigma}_f = \sigma_m/\sigma_0$ is the ratio between the modelled standard deviation and the observed standard deviation of the trait of interest. R_0 is the maximum correlation achievable and assumed to be 1.

Comparison of variability of the signal via standard deviation:

$$\frac{4}{(\hat{\sigma}_f + \frac{1}{\hat{\sigma}_f})^2} \tag{B3}$$

Linear differences metric:

$$\frac{|6 - |O - M||}{6} \tag{B4}$$

where O is the observed value and M is the modelled value. It is applied to the most frequent month of the variable observed. (0 when the maximum difference of the variables is six months, 1 when no differences occur).

Single value comparison metric:

$$\frac{1}{(1 + \left|(O-M)/O\right|)^2} \tag{B5}$$

BGD
9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

where O is the observed value and M is the modelled value.

At exception of the Taylor statistics, all the other metrics are symmetric.

Map cell-by-cell comparison metric:

The ranking metric specifies the number of agreement-cells against the total observed cell belonging to a specific class. The final score is the average over the selected classes. Three classes were used in our framework: no statistically significant relationship (i.e. no correlation, no trend detected); positive relationship (i.e. correlation/trend); negative relationships (i.e.correlation/trend) detected.

In terms of lower benchmark, the case of constant vegetation has been used. This is the equivalent to analyze the returned trend against a null hypothesis of a not changing vegetation. The average score obtained under this setting is equal to 0.3, considering the agreement cell-by-cell to each single class. The score of the model is thereinafter scaled to this lower benchmark.

Appendix C

Additional constraints for the computation of the final score

Negative correlations between model and data set the final score to 0, with the exception of the cross-correlation traits. When the signal has no standard deviation (i.e. constant vegetation activity), the score is automatically set to 0, if the model shows no variability in contrast to the observations, but to not determined if there is no observed variability. Only grid cells with a valid observed signal where considered in the model-data comparison analysis.

Correlations and cross-correlations, trend, number of growing seasons, were tested against random noise (t-two tailed statistics) at least $P < 0.1$ significance. For the scores based on cross-correlation statistics with climate drivers, the score is set to NA when observations do not show any statistically significant relationship. If the model does not return any significant relationship, the score is set to 0.

BGD
9, 16087–16138, 2012

When testing the degree and persistence of the association between temporal series using two tailed t-test, potential autocorrelations in the temporal series were considered by adjusting the degrees of freedom, hence the number of independent information (Trenberth and Caron, 2000). We assume a number $N/2$ of independent information, where N is the total number of months in the record (300 months).

For the atmospheric CO_2 traits, the final score is the average of the scores obtained each individual monitoring station. In terms of comparison to remote-sensing data, the, scores were first aggregated by vegetation class for each Transcom3 region, and then further aggregated using a weighted average and taking account of the number of grid cells belonging to the specific vegetation class.

Appendix D

The Synmap classification vegetation map

The following vegetation classes of the Synmap data set (Jung et al., 2006) were considered: shrubs, grass, crop, deciduous broad leaved forest (dbf), deciduous needle-leaved forest (dnf), evergreen broadleaved forest (ebf), evergreen needle-leaved forest (enf) along with unvegetated area (i.e. bared soil, ice lands) and water. This way to aggregate the information instead of using the model's vegetation classification helps to maintain flexibility and comparability across different model platforms and thereby creates less uncertainties in the performance evaluation analysis. The most dominant class is computed as the one covering at least the 80 % of the total area of each grid cell.

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BGD
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Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

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BGD

9, 16087–16138, 2012

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BGD

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D. Dalmonech and S. Zaehle

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BGD

9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

Table 1. List of selected atmospheric CO_2 monitoring stations and satellite-based vegetation activity datasets used in the analyses, as well as the time period used for elaborations.

Label	Name	Lat [degree]	Lon [degree]	Years of elaboration
ALT	Alert, Canada	82.45	−62.52	1982–2008
BRW	Point Barrow	71.32	156.6	1982–2008
STM	Station "M", Atlantic	66	2	1982–2008
CBA	Cold Bay, Alaska	55.2	162.72	1982–2008
SHM	Shemya Island, Alaska	52.72	174.1	1985–2008
MHD	Mace Head, Ireland	53.33	9.9	1991–2008
AZR	Azores	38.75	27.08	1995–2008
KEY	Key Biscayne, Florida	25.67	−80.2	1982–2008
MLO	Mauna Loa, Hawaii	19.53	−155.58	1982–2008
KUM	Kumakahi	19.52	−154.82	1982–2008
GMI	Guam, Mariana Island, Pacific	13.43	144.78	1996–2008
RPB	Ragged Point Barbados	13.17	−59.43	1987–2008
CHR	Christmas Island	1.7	−157.17	1982–2008
SEY	Mahe Island, Seychelles	−4.47	55.17	1996–2008
ASC	Ascension Island	−7.92	14.42	1982–2008
SMO	Tutuila, American Samoa, Pacific	−14.25	−170.57	1982–2008
PSA	Palmer station, Antarctica	−64.92	−64	1982–2008
HBA	Halley Bay, Antarctica	−75.67	−25.5	1996–2008
SPO	South Pole	−89.98	−24.8	1982–2008
GIMMS	GIMMS-NDVI collection g	/	/	1982–2006
SW	SeaWIFS-fAPAR	/	/	1998–2005

BGD
9, 16087–16138, 2012

Table 2. List of atmospheric CO_2 and vegetation activity traits used for the analyses at the seasonal time scale. A detailed explanation of metrics can be found in Sect. 2. and Appendices B and C.

Seasonal Time Scales					
CO_2 trait	Label	Test	Metric	Section Methods	Results
Mean seasonal cycle	MSC	centered pattern variability	Taylor (2001) Eq. (B2)	2.4.1	3.1.1
Regional contribution to mean seas. cycle	MSCc	relative contribution	Pearson correlation r	2.4.1	3.1.1
Latitudinal gradient of MSC amplitude	MSClg	latitudinal pattern of amplitude	standard deviation-based metric Eq. (B3)	2.4.1	3.1.1
Monthly CO_2 trend (1982–91/1992–97/1998–2008)	MT*	phase of the monthly pattern	Pearson correlation r	2.4.1	3.2
CO_2 drawdown points	C-dd*	direct comparison of numerical trend	single value comparison metric Eq. (B5)	2.4.1	3.5.1
Vegetation trait	Label	Test	Metric	Methods	Results
Time of onset	t-onset	most frequent month	absolute difference Eq. (B4)	2.4.2	3.1.2
Time of maximum activity	t-max	most frequent month	absolute difference Eq. (B4)	2.4.2	3.1.2
t-onset ~ drivers	Onset-CL	occurrence of positive/ negative/no correlations	spatial ranking	2.4.5	3.5.1

* Trait applied to the stations ALT, BRW and STM.

BGD
9, 16087–16138, 2012
Atmospheric CO_2 and vegetation activity constraints
D. Dalmonech and S. Zaehle

Table 3. List of atmospheric CO_2 and vegetation activity traits used for the analyses at the interannual time scale (higher than annual frequency). A detailed explanation of metrics can be found in Sect. 2. and Appendices B and C.

Interannual time scales					
CO_2 trait	Label	Test	Metric	Section Methods	Results
Long term trend	C-LTT	direct comparison of numerical trend	single value comparison metric Eq. (A5)	2.4.3	3.3
Interhemispheric gradient	IHG	variability in time	standard deviation based metric Eq. (A3)	2.4.3	3.3
CO_2 growth rate ~ regional drivers relationships	C-CL	covariance with time lag	Pearson correlation r	2.4.5	3.5.3
Apparent C-land sensitivity to surface temperature	C-Lsens	direct comparison of numerical trend	single value comparison metric Eq. (A5)	2.4.5	3.5.3
Vegetation trait	Label	Test	Metric	Methods	Results
Vegetation trend (1982–91/1992–97/1998–2006)	V-LTT	occurrence of positive/negative/no trends	spatial ranking	2.4.4	3.4
Veg. activity ~ regional drivers relationships	V-CL	covariance with time lag	Pearson correlation r	2.4.5	3.5.2

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

BGD

9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

Table 4. Final scores Atmospheric CO_2 scores are reported per latitudinal band. The numerical values prior of the scaling to the baseline benchmark are reported in brackets where they differ from the final scores. For the acronyms refer to Tables 2 and 3.

Atmospheric CO_2 trait:		Vegetation activity trait:	
MSC 90N60N	0.7 (/)	t-onset	0.65 (/)
MSC 60N30N	0.72 (/)	t-max	0.6 (/)
MSC 30N30S	0.5 (0.57)	Onset-CI	0.15 (0.4)
MSC 30S90S	0 (0.1)		
MSCc 90N60N	0.95	(0.96)	
MSCc 60N30N	0.95 (/)		
MSCc 30N30S	0.45(0.55)		
MSCc 30S90S	0 (/)		
MSCIg	0.77 (/)		
MT 80s	0.7 (0.75)		
MT 90s	0.4 (0.5)		
MT 2000s	0.4 (0.5)		
C-dd	0.1 (0.5)		
C-LTT 90N60N	0 (0.52)	V-LTT-80s	0.3 (0.5)
C-LTT 30N30S	0 (0.52)	V-LTT-90s	0.1 (0.35)
C-LTT 30S90S	0 (0.48)	V-LTT-2000s	0.1 (0.35)
IHG 90N60N	0.73 (0.97)	V-CI	0.6 (/)
IHG 30N30S	0.68 (0.8)		
IHG 30S90S	0.98 (0.99)		
C-CL 90N60N	0.1 (/)		
C-CL 30N30S	0.15 (/)		
C-CL 30S90S	0 (/)		
C-CLsens	0 (0.26)		

BGD

9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

Table A1. Global scores of atmospheric CO_2 and vegetation activity for the baseline benchmark. Correspondent data of the model, prior of the scaling, are reported for comparison.

Atmospheric CO_2 trait:		Vegetation activity trait:	
MSC 90N60N	0	t-onset	0
MSC 60N30N	0	t-max	0
MSC 30N30S	0.23	Onset-CI	0.3
MSC 30S90S	0.45		
MSCc 90N60N	0.1		
MSCc 60N30N	0.1		
MSCc 30N30S	0.18		
MSCc 30S90S	0.91		
MSClg	0		
MT 80s	0.2		
MT 90s	0.4		
MT 2000s	0.25		
C-dd	0.5		
C-LTT 90N60N	0.56	V-LTT-80s	0.3
C-LTT 30N30S	0.58	V-LTT-90s	0.3
C-LTT 30S90S	0.55	V-LTT-2000s	0.3
IHG 90N60N	0.54	V-CI	0
IHG 30N30S	0.39		
IHG 30S90S	0.18		
C-CL 90N60N	0		
C-CL 30N30S	0		
C-CL 30S90S	0		
C-CLsens	0.26		

BGD

9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

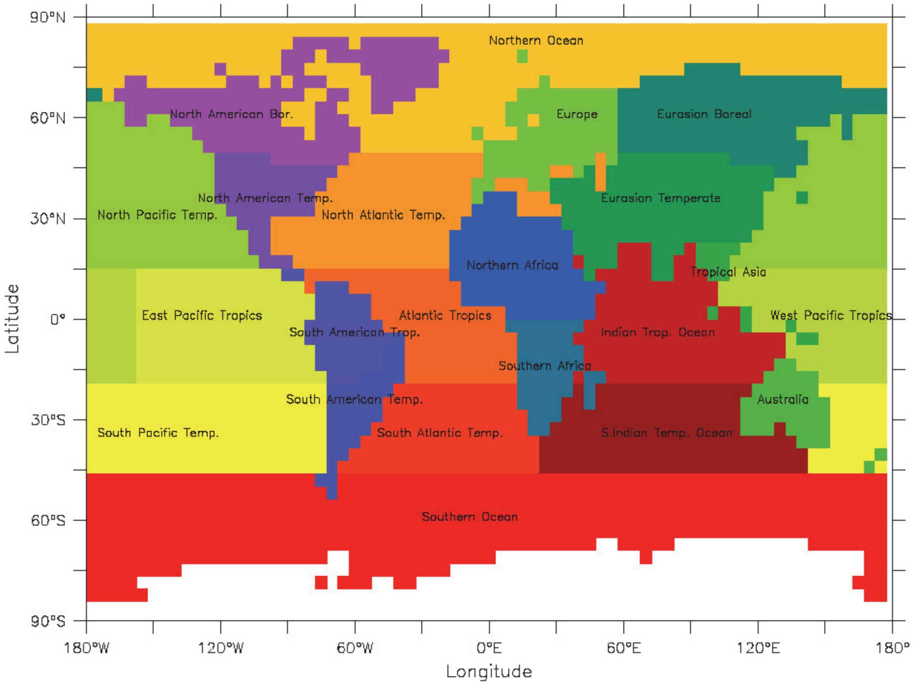

Fig. 1. Map of the land regions used for the regional benchmark of phenology and the analysis of the biosphere fluxes, as defined in the TransCom intercomparison studies (Gurney et al., 2002). The map shows the regions on the TM3 resolution. Code: North American Boreal (NAB), North American Temperate (NATe), South American Tropical (SATr), South American Temperate (SATe), Northern Africa (NA), Southern Africa (SA), Eurasian Boreal (EAB), Eurasian Temperate (EATe), Tropical Asia (TrA), Australia (AUS), Europe (EUR). The ocean was considered as a single region.

BGD

9, 16087–16138, 2012

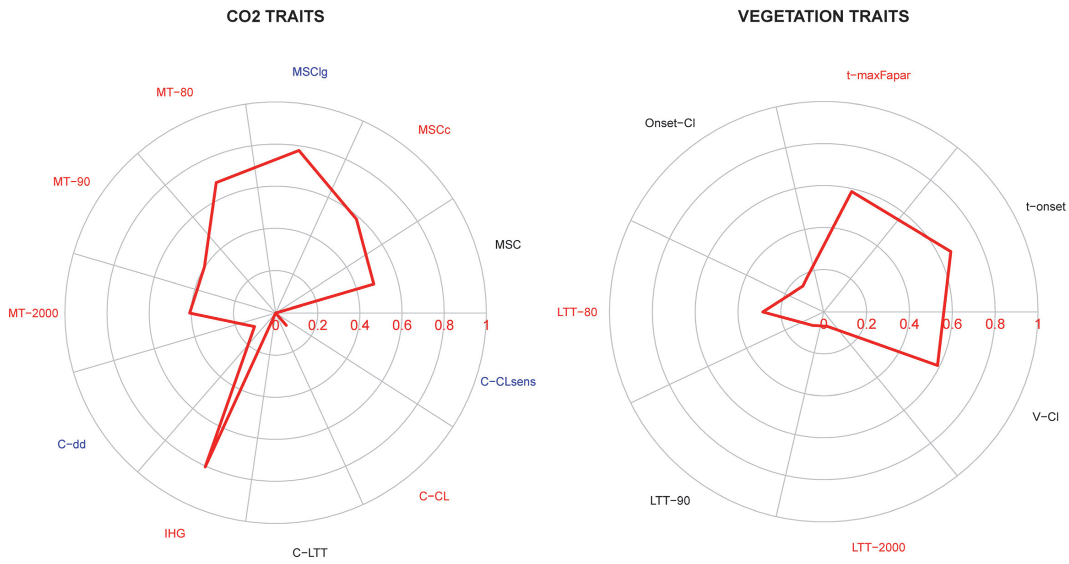

Fig. 2. Global atmospheric CO_2 scores performances and vegetation-activity score performances for the model JSBACH according to the list of traits in Tables 2 and 3.The polar plot goes radially from 0 (less skillful model), in the center, to 1 (skillful). Since we have only one model performance and the lower benchmark as limit, we refer to the threshold value of 0.5 to indicate the model good/high performances and less good/low performances.

BGD
9, 16087–16138, 2012

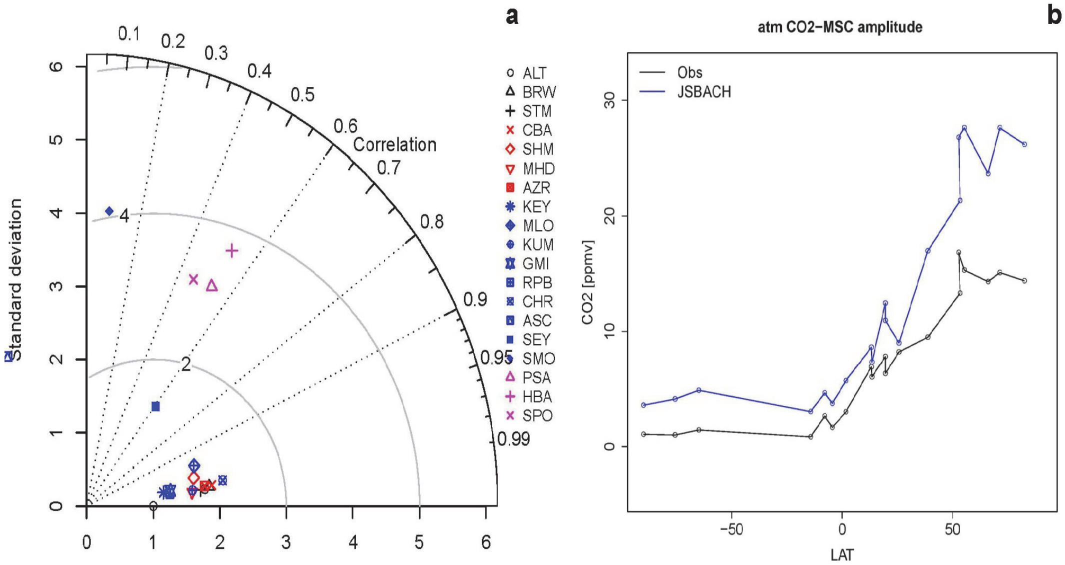

Fig. 3. **(a)** Taylor diagram of the mean seasonal cycle of JSBACH, **(b)** latitudinal gradient of the amplitude of the mean seasonal cycle. In the Taylor diagram, the x axes indicates mismatch in terms of amplitude and the radial direction provides information in term of phase correspondence. Stations in the list are sorted according to latitude.

BGD
9, 16087–16138, 2012

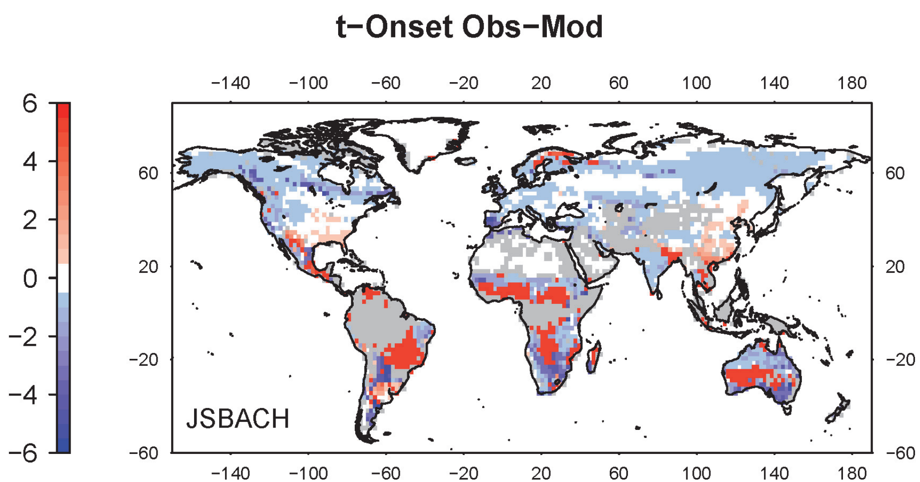

Fig. 4. Average 1998–2005 difference between the most frequent month of time of onset for SeaWifs fAPAR data and modelled fAPAR (expressed as months). Grey areas were masked out from the analysis and indicate missing observations, dominance of tropical rain, desert or ice, or areas with more than one growing season. Red cells indicate missing or not-valid data in the model.

BGD
9, 16087–16138, 2012

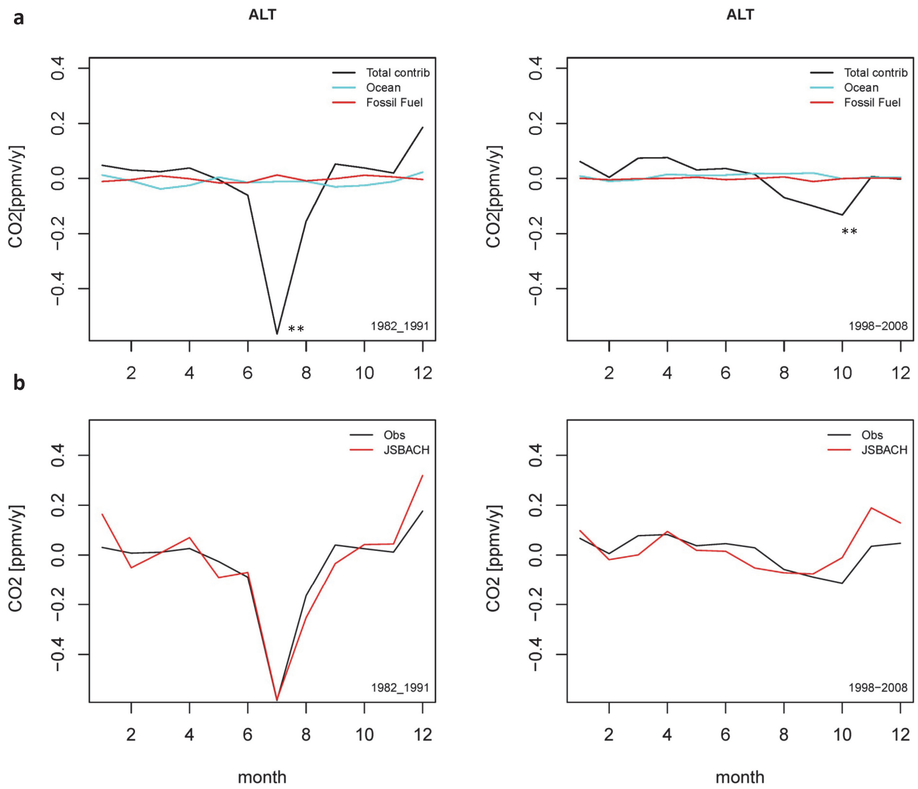

Fig. 5. Monthly CO_2 trend in the station of Alert (Canada, ALT) for the period 1982–1991 and 1998–2008. **(a)** Observations, as well as simulated contribution from fossil fuel emission and net Ocean fluxes ($^{**}P < 0.01$). **(b)** Monthly record for observations and modelled data. Negative values for a specific month indicate a decrease of seasonal atmospheric CO_2, indirectly linked to an increase of biosphere C uptake, and vice versa.

BGD
9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀I | ▶I
◀ | ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

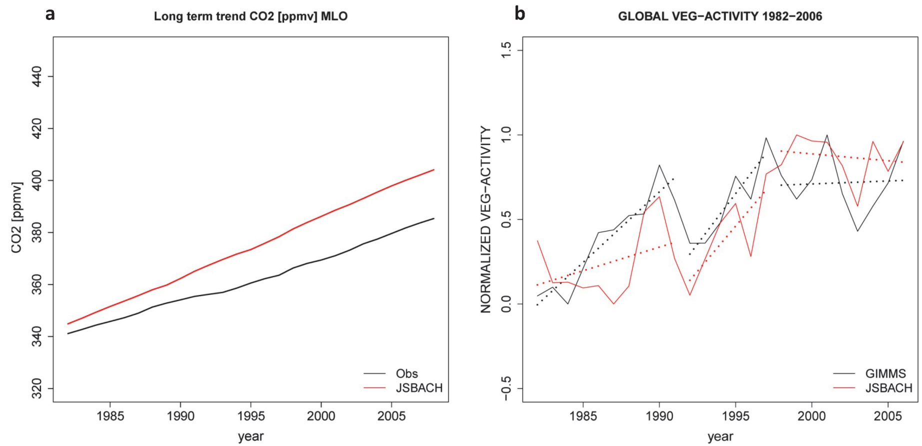

Fig. 6. (a) Long-term pattern of atmospheric CO_2 at the station of Mauna Loa (MLO); **(b)** normalized annual values of vegetation activity (excluding tropical areas, deserts and iced areas) for GIMMS-NDVI and modelled fAPAR. Period of reference 1982–2006. Dotted lines represent the linear trend computed on the normalized data (qualitative analysis).

BGD
9, 16087–16138, 2012

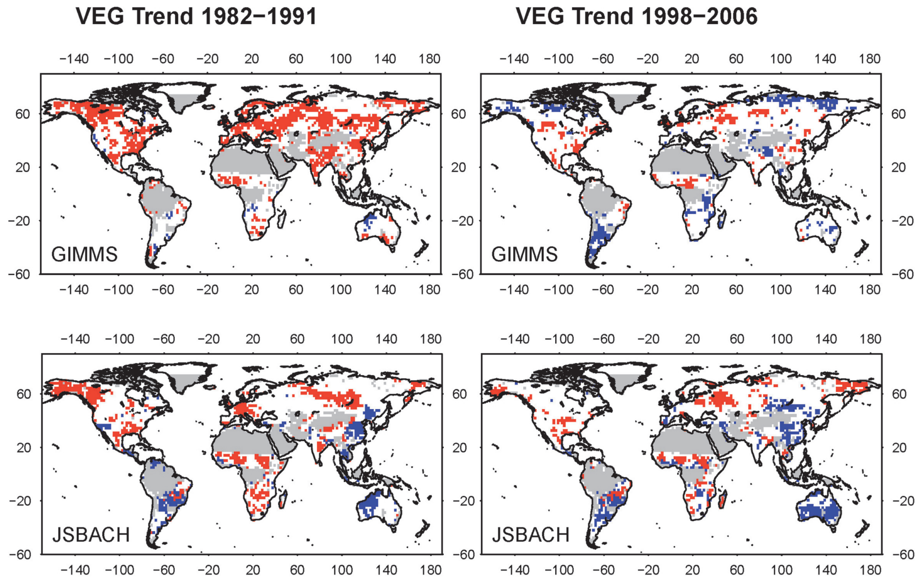

Fig. 7. Vegetation activity trend according to the Mann-Kendall statistics for the period of references is reported for GIMMS-NDVI and modelled fAPAR. Red: positive monotonic trend ($P < 0.10$); blue: negative monotonic trend ($P < 0.1$); white: no-significant trend; grey: areas masked out from the analysis (grid cells with dominance of tropical forests, dominance of desert and ice).

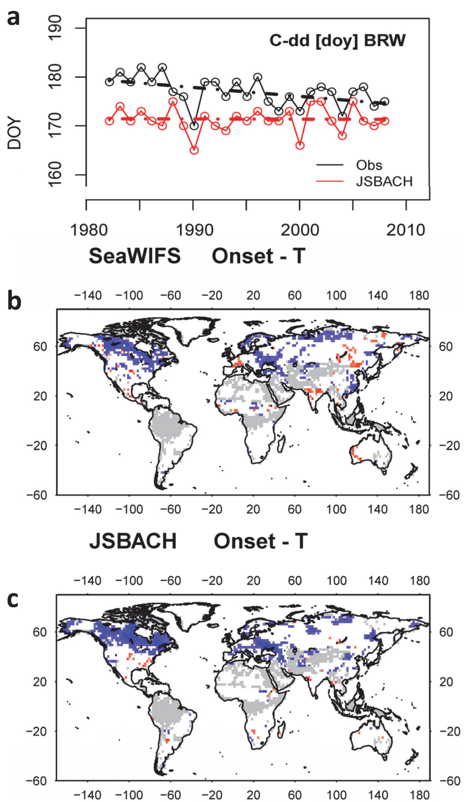

Fig. 8. **(a)** Atmospheric CO_2 drawdown points (C-dd) as computed at the station of Barrow (BRW) for observations and model. (**b** and **c**) Partial correlation between time of onset and mean annual temperature computed for observations and JSBACH, for the period 1998–2005. Red: positive correlations ($P < 0.1$); blue: negative correlations ($P < 0.1$); white: no significant correlations; grey: areas masked out from the analysis (grid cells with dominance of tropical forests, dominance of desert and ice,cells with more than one growing season).

BGD
9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle

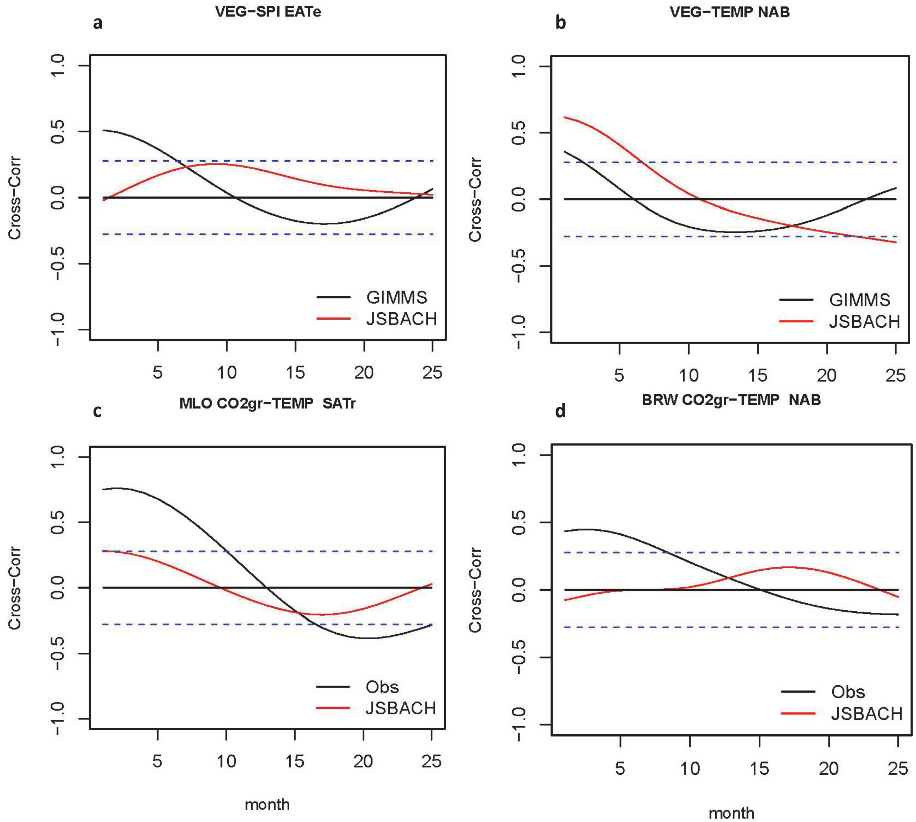

Fig. 9. (a) Cross-correlation between precipitation pattern (SPI) and vegetation activity in Eurasia Temperate (EATe); **(b)** cross-correlation between temperature and vegetation activity in North America Boreal (NAB); **(c)** atmospheric CO_2 growth rate in the station of Mauna Loa (MLO) and temperature pattern in the South America tropical (SATr); **(d)** atmospheric CO_2 growth rate in Barrow (BRW) and temperature patter in NAB. Dotted line are confidence internal at significant level of $P < 0.05$ (two tailed statistics).

BGD
9, 16087–16138, 2012

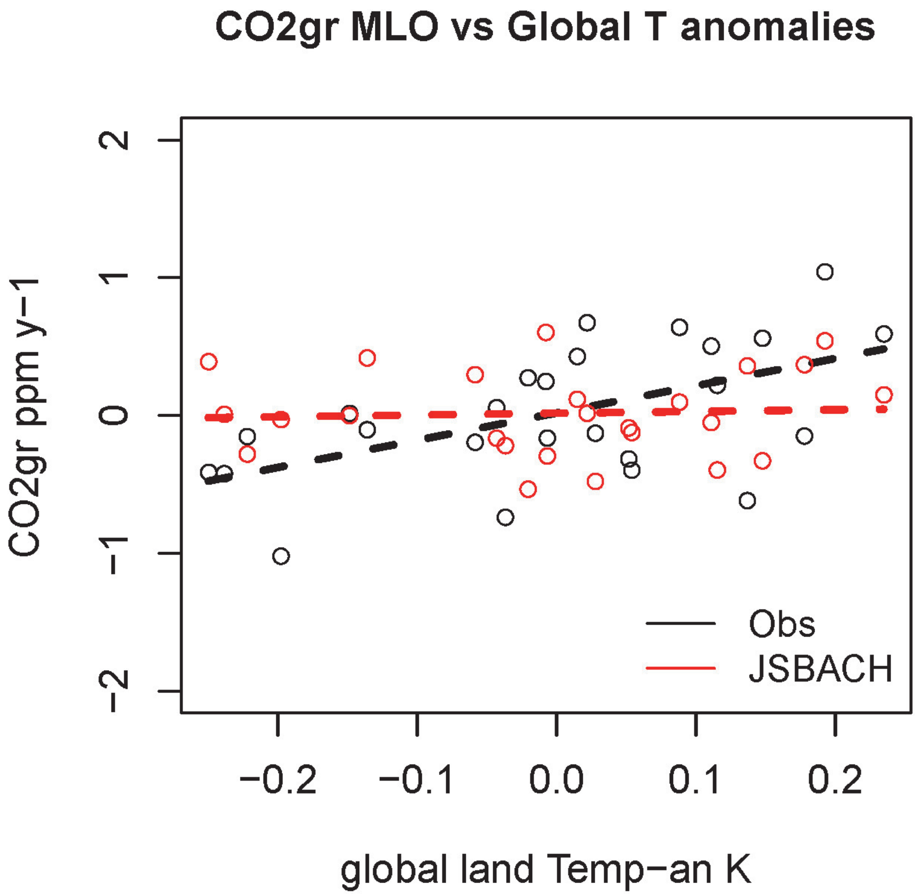

Fig. 10. Apparent Land C-sensitivity: CO_2 grow rate in Mauna Loa (MLO) versus global land surface temperature. Regression is significant at $P < 0.01$ for observations.

BGD
9, 16087–16138, 2012

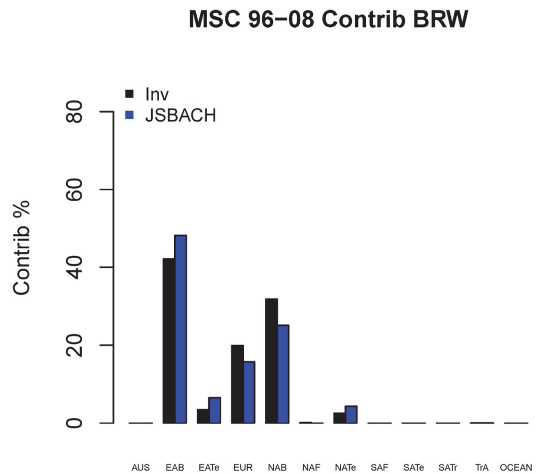

Fig. A1. Regional contribution (express as %) to the mean seasonal cycle in the station of Barrow (BRW) and South Pole (SPO). For the region labels refer to Fig. 1.

BGD
9, 16087–16138, 2012

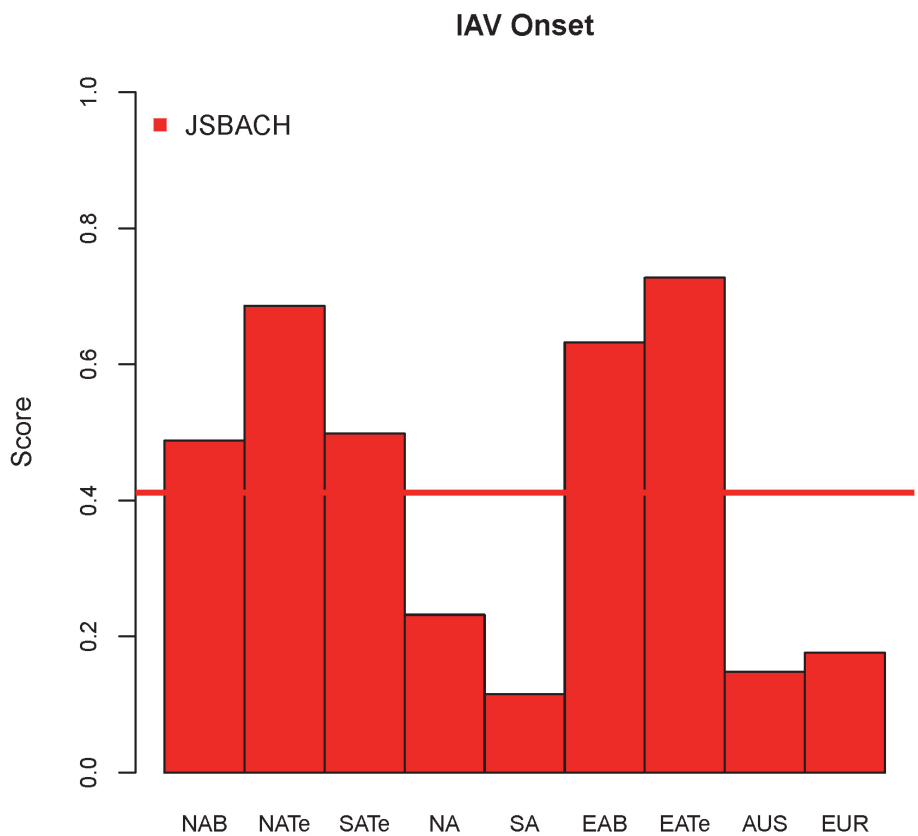

Fig. A2. Final score of the time of onset trait computed according to transcom3 land regions (Tropical Asia and South American tropical).

BGD
9, 16087–16138, 2012

Atmospheric CO_2 and vegetation activity constraints

D. Dalmonech and S. Zaehle