

Model-data fusion in the studies of terrestrial carbon sink

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Abstract: Current uncertainty in quantifying the global carbon budget remains a major contributing source of uncertainty in reliably projecting future climate change. Furthermore, quantifying the global carbon budget and characterizing uncertainties have emerged as critical to a successful implementation of United Nations Framework Convention on Climate Change and its Kyoto Protocol. Beyond fundamental quantification, attribution of the processes responsible for the so-called ‘residual terrestrial uptake’ is important to the carbon cycle communities’ ability to simulate the future response of the terrestrial biosphere to climate change and intentional sequestration activities. This paper’s objective is to describe the efforts of the workshop participants and their approaches to model-data fusion enabling continued advances in the solution of quantifying carbon cycling and the terrestrial mechanisms at work.

Keywords: Model-data fusion; Carbon cycle; Modelling

1. INTRODUCTION

Current uncertainty in estimating global carbon budget terms is not that profound that one can dispute their validity. Nevertheless, the estimates accuracy is critical for a successful implementation of UNFCCC and related international agreements. Of prime importance is the reduction of uncertainties in net terrestrial carbon uptake and the attribution of the so called 'residual terrestrial uptake' to well-established biophysical mechanisms.

Global residual terrestrial uptake is estimated to be the same order of magnitude as oceanic uptake; however it is not an independent estimate. It is obtained by adding the estimate of net terrestrial uptake to the estimate of emissions from land-use change. The estimate of net terrestrial uptake, in turn, is obtained by subtracting atmospheric and oceanic uptake from carbon emissions resulting from fossil fuel burning and cement production.

The resulting estimate of net terrestrial uptake ($0.7 \pm 1.0 \text{ Gt C yr}^{-1}$) is consistent with independent estimates derived from the trends in atmospheric O_2 concentration derived from analysis of air bubbles in glacier ice [Battle et al., 1996] and from high-precision atmospheric observations [Keeling et al., 1996].

One of the mechanisms hypothesized as responsible, in part, for sequestering excessive carbon dioxide from the atmosphere is carbon dioxide fertilization effect. Elevated carbon dioxide concentration enhances photosynthesis, and if turnover rate remains the same, leads to carbon accumulation in terrestrial ecosystems. The effect is quite small to be detected experimentally: the decadal rate of CO_2 elevation may cause about 1% increase in Net Primary Production, and 0.1% increase in total carbon stock in a given ecosystem. However, this locally weak effect is quite strong globally: depending on the turnover rate of sequestered carbon it may comprise to 2.5 Gt C/yr.

Another mechanism involved is the change in vegetation longevity. For example, large stocks of carbon may accumulate in managed forests due to the prolongation of the time period between cuts – a tendency currently observed in many developed countries. Similar effects may occur due to a reduction in forest fire occurrence. In natural ecosystems a change in vegetation longevity occurs when woody vegetation invades grassland. The magnitude of this change in vegetation longevity is difficult to quantify, but the effect itself may be globally strong enough to

compensate for the emissions from land use change.

National C budget of tree vegetation can be derived from National Forest Inventory data and harvest statistics with biomass equations. However, the changes of carbon stock in soil as related to land-use change, forestry and nitrogen deposition can be estimated mainly by modeling. They can be significant for the size of the pool is large: from 2011 to 2477 GtC, in total.

Climate-driven departures may include upto 20% of the terrestrial sink [Alexandrov and Yamagata, 2004]. However, the magnitude and even the sign of climate-driven departure for a given decade is difficult to quantify due to the uncertainty in relative strength of climate impact on productivity, respiration and emission from soil. Moreover, the estimates depend strongly on the input climate dataset [Ito and Sasai, in press].

Data and model validity are two facets of a problem that model-data fusion is expected to resolve.

2. MECHANISM AND MAGNITUDE OF CLIMATE IMPACT

The most obvious drivers affecting the magnitude of the terrestrial sink are climate factors which vary widely from year to year [Ito and Oikawa, 2000; Schaefer et al., 2002; Jones et al., 2003]. This variability, according to McGuire et al. [2001], accounts for a total land-atmosphere flux ranging from -0.2 to 0.9 GtC/yr in the 1980s. How large could be the difference between the sink magnitude expected for average climatic conditions and its value for actual climatic conditions of a given year or decade?

According to TsuBiMo [Alexandrov and Yamagata, 2004], the annual values of climate-driven departures vary from -1.7 to 1.2 GtC/yr. Climate conditions reduced the global terrestrial sink by 0.7 GtC/yr for the period 1978-82 and enhanced it by 0.4 GtC/yr for the period 1988-92. Hence, the use of a 5-year period to report on the results of a carbon sequestration project (for example for the first commitment period of the Kyoto Protocol) can reduce noise caused by climatic variations to some extent, excepting variability caused by ENSO [Jones et al 2001] and volcanic activities [Jones and Cox 2001, Lucht et al, 2002]

Moving averages of climate-driven departures calculated for 10-year periods, range between –

0.38 and 0.56 GtC/yr (standard deviation 0.27 GtC/yr). Hence, the relative effect of climate variations hardly exceeds 20% of the residual terrestrial sink strength estimated to be 2.3 GtC/yr.

The Osnabrück Biosphere model (OBM) suggests a more narrow range for climate-driven departures: e.g., from -0.17 GtC/yr in the period 1978-82 to 0.23 GtC/yr in the period 1973-77. Annual values range from -1 to 0.6 GtC/yr; moving averages (for 10-year periods) range between -0.16 and 0.12 GtC/yr (with a standard deviation of 0.07 GtC/yr), suggesting a negligible contribution to a global carbon budget spanning a 10-year period.

The two models applied in a study carried out by Alexandrov and Yamagata [2004] give a different sign for departures in the period 1973-77 (all regions), 1978-82 (high latitudes) and 1983-87 (low latitudes). Since the two models give contradicting departures for two out of five considered periods, it is likely that they disagree for the period 2008-2012 as well, e.g., the first commitment period for emission reduction under the Kyoto Protocol.

This discrepancy in model outcome leads to differences in the interpretation of the atmospheric CO₂ increase. For example, TsuBiMo leaves the assumption open that a reduction of the atmospheric CO₂ increase after 1988 is partly due to a climate-driven enhancement of the 'residual terrestrial uptake', whereas the Osnabrück Biosphere model abolishes this assumption.

The models considered are based on a similar conceptual and empirical basis. They agree together that P_n (Net Primary Production) and R_h (heterotrophic respiration) increase with temperature when water is not limiting. They also agree that in conditions where water is limiting both P_n and R_h are reduced. They only disagree on the relative strength of climate impact on these processes. This induces a discrepancy in the estimates of climate impact on the net of P_n and R_h .

3. THE USE OF FLUXNET DATA FOR PARAMETER ESTIMATION

The relative strength of climate impact on plant productivity and respiration can be characterized by using data from the FLUXNET network. This is a network where micrometeorological measurements are performed originally conceived by IGBP and the EUROFLUX project.

Temperature dependency of a chemical reaction is often parameterized by using the Arrhenius equation:

$$k = k_0 \text{Exp}[-E_a / RT]$$

where k is the rate coefficient, E_a the activation energy, R is gas constant (8.31 J K⁻¹mol⁻¹) and T the absolute temperature.

If $k=1$ when $T=T_0$ then

$$k_0 = \text{Exp}[E_a / RT_0]$$

and hence

$$\begin{aligned} k &= \text{Exp}[E_a / RT_0] \cdot \text{Exp}[-E_a / RT] = \\ &= \text{Exp}[E_a / RT_0 - E_a / RT] = \\ &= \text{Exp}\left[\frac{E_a(T - T_0)}{TRT_0}\right] \end{aligned}$$

Converting K to Celsius we obtain the normalized Arrhenius equation:

$$f_A[T] = \text{Exp}\left[\frac{E_a(T - T_0)}{(T + 273)R(T_0 + 273)}\right]$$

where E_a is activation energy (J mol⁻¹), R is the gas constant, T_0 is temperature at which the function is equal to 1 ($f_A[T_0]=1$). This equation is an alternative expression of the Arrhenius equation for $k=1$ when $T=T_0$.

Light-saturated photosynthesis is assumed to be a bell shaped function of temperature, to be considered as a modified Arrhenius equation when taking the effect of temperature on activation energy into account:

$$p_{\max}[T] = p_{\max}[T_{opt}] \frac{2f_A[T]}{1 + (f_A[T])^2};$$

where T_{opt} is the value of T where p_{\max} reaches its optimum, $T_0=T_{opt}$ [Alexandrov et al., 2005]

TsuBiMo relates GPP to day length and light intensity for given values of p_{\max} . Numerical inversion of the model relates p_{\max} to GPP estimates obtained from flux measurements -- that is, one may consider GPP data as an indirect measure of p_{\max} . When p_{\max} values derived from measured GPP are plotted against temperature, one finds activation energy.

Applying this scheme to data from the Takayama site of the AsiaFlux network (a subnetwork within FLUXNET), Alexandrov et al [2005] came to the conclusion that:

$$E_a = 92 \text{ kJ mol}^{-1}; T_{opt} = 26^\circ\text{C};$$

$$p_K[T_{opt}] = 17 (\mu\text{mol CO}_2) \text{ m}^{-2} \text{ s}^{-1};$$

It is worth mentioning that estimates of the activation energy of photosynthesis thus obtained are significantly higher than the activation energy of respiration, which is estimated for this site to be 49 kJ mol⁻¹.

There may be large uncertainties in the value of activation energies associated with both measurement errors and model restrictions. Some flux-changes do not result from changes in temperature or light intensity. Therefore, filtering out noise (resulted both from measurement errors and inadequacies in experimental design) is an essential part of parameter estimation.

Alexandrov et al [2005] applied one of the simplest linear filters – a 28-day moving average. This is a neutral method in the sense that it makes no assumptions on the process observed. However, neutrality is not a synonym for objectivity. When we consider the data as manifestation of a certain process, it is more objective to use some characteristic of the process to extract it as a signal from noise.

A characteristic of a process can be expressed, for example, as a linear model that relates the value of state variable (x) at time t to its value at time $t-1$ and to its control value (u):

$$x_t = Ax_{t-1} + Bu_{t-1}$$

In that case one may filter a signal out of noise by applying a so-called Kalman filter.

A Kalman filter is a set of equations providing a computational framework to estimate the values of state variables in the presence of a process related signal and measurement related noise. To apply a Kalman filter to smooth GPP (or NEP) values derived from FLUXNET data, one assumes that the true values of GPP (or NEP) ($P_g(t)$) change smoothly, that is

$$P_g(t) = P_g(t-1) + u(t-1) + w(t-1),$$

where

$$u(t-1) = \bar{P}_g(t) - \bar{P}_g(t-1),$$

$\bar{P}_g(t)$ is a GPP (NEP) value estimated with a model, $w(t)$ is process noise (something not explained by the model used). Assumptions about characteristics of the process and measurement noise ($v(t)$) have to be made as well, inducing deviations between observed and true values, e.g.:

$$\hat{P}_g(t) = P_g(t) + v(t).$$

The assumptions about the covariance of process noise are subjective, and therefore estimates of $P_g(t)$ obtained by applying a Kalman filter are closer to $\bar{P}_g(t)$ than to $\hat{P}_g(t)$, on the assumption that the covariance of measurement noise is larger than that of process noise.

The use of a Kalman filter can reveal seasonality in model parameters that would otherwise be set at a constant value. For example, the TsuBiMo estimates of GPP depend on the values of E_a and p_{opt} ($P_{opt} = P_{max}[T_{opt}]$) which are chosen to be constant because a better assumption lacks. If we assume that they are not constant but that they are changing smoothly with time, then

$$P_g(t) = P_g(t-1) + u(t-1) + w_1(t-1)$$

$$p_{opt}(t) = p_{opt}(t-1) + w_2(t-1)$$

$$E_a(t) = E_a(t-1) + w_3(t-1)$$

where

$$u(t-1) = \bar{P}_g(t; \tilde{p}_{opt}(t), \tilde{E}_a(t)) - \bar{P}_g(t-1; \tilde{p}_{opt}(t-1), \tilde{E}_a(t-1))$$

and

$$\tilde{p}_{opt}(t) = p_{opt}(t) + v_2(t)$$

$$\tilde{E}_a(t) = E_a(t) + v_3(t)$$

are ‘indirect measurements’ obtained through model inversion.

There are several versions of the Kalman filter. The original one is referred to as the linear Kalman filter, for it can be applied only to processes that are described by linear stochastic difference equations. If the process however is slightly non-linear, then one should apply the extended Kalman filter (EKF). When essentially non-linear processes are dealt with, one has to apply the ensemble Kalman filter (EnKF).

Chen et al [2005] developed a so-called smoothed ensemble Kalman filter (SEnKF) by combining Kernel smoothing [West, 1993] with the EnKF [Evensen, 2003]. They believe SEnKF is the most suitable filter to reduce noise in FLUXNET observations and to assimilate observed data into the following process-based carbon flux model:

$$P_e = P_g - R_e$$

$$P_g = LUE \cdot PAR \cdot NDVI \cdot f_1(T) \cdot f_2(VPD)$$

$$R_e = R_{ref} \exp\left(E_0 \left(\frac{1}{T_{ref} - T_0} - \frac{1}{T - T_0}\right)\right)$$

where R_e is ecosystem respiration, f_1 and f_2 are the factors describing the effect of temperature (T) and vapour pressure deficit (VPD).

Applying SenKF to the data from three AmeriFlux forest stations: e.g., Howland (Maine, USA), Boreas (Thompson, Manitoba, Canada) and Niwot Ridge Forest (Colorado, USA), they detected a pronounced seasonality in light use efficiency (LUE), and could reduce the uncertainty of LUE to a reasonable range.

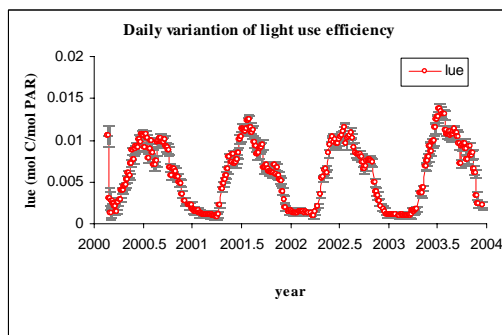


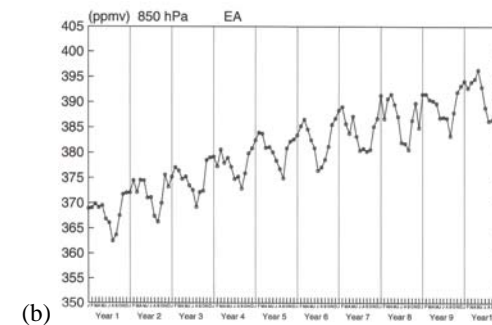
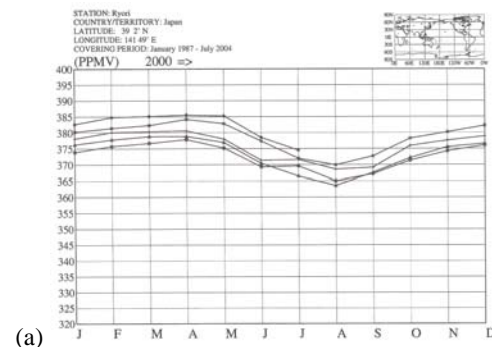
Figure 1. Seasonality of light use efficiency (red circle) and its uncertainty (gray).

The seasonality of LUE (Fig 1) detected as described implies that LUE may not simply be a function of temperature and VPD as is often assumed [Goetz et al, 1999]. It also provides support to the hypothesis that relates LUE to leaf age [Muraoka et al, 2002].

4 THE USE OF ATMOSPHERIC CO₂ CONCENTRATION MEASUREMENTS FOR THE EVALUATION OF MODEL CONSISTENCY

Flux measurements with chamber and eddy covariance measurements are local and therefore a dedicated measuring network is required to cover a sufficiently varied set of ecosystem types. However, the main purpose of network observations is to improve the understanding of biochemical and physical processes of carbon exchange for different ecosystem types. Subsequently, parameterization allows to scale up local flux estimates to the regional or continental scale. The validity of the scale up methodology can be evaluated in part using atmospheric CO₂ concentration measurements.

Mabuchi and Kida [2006] evaluated the validity of model calibrations by comparing simulated seasonal patterns of atmospheric CO₂ concentrations with observations at the stations of the WMO network. They recently developed the next version of the Biosphere-Atmosphere Interaction Model [Mabuchi et al, 1997; Mabuchi et al, 2000; Mabuchi et al, 2005], so-called BAIM2, which estimates not only the energy fluxes but also the carbon dioxide flux between terrestrial ecosystems and the atmosphere. They coupled the BAIM2 with a spectral general circulation model [Mabuchi and Kida 2006], set initial CO₂ concentration at 360 ppmv and anthropogenic emission fluxes at 6.2 GtC/year, assigned the values suggested by Obata and Kitamura [2003] to the fluxes related to air/sea exchange. Thus simulated amplitudes and characteristics of seasonal cycle of the carbon dioxide concentration for the areas around Hawaii and Japan were found to be consistent with the carbon dioxide concentrations measured at Mauna Loa (Hawaii) and Ryori (Japan) stations (Figure 2).



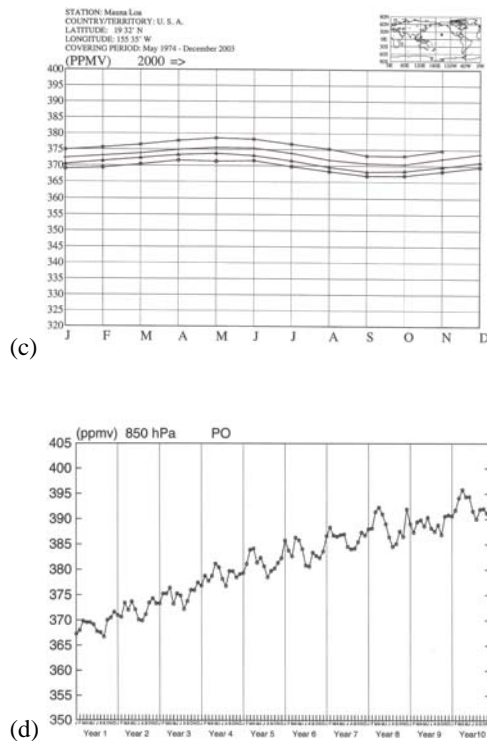


Figure 2 (a) The seasonal cycles of observed carbon dioxide concentration at Ryori, Japan. (b) The seasonal cycles of carbon dioxide concentration simulated by the model for the area around Japan (c) The seasonal cycles of observed carbon dioxide concentration at Mauna Loa. (d) The seasonal cycles of carbon dioxide concentration simulated by the model for the area around Hawaii.

Matross et al [2005] validated a bottom-up biospheric model by using tall tower CO₂ concentration data (new NOAA Global Monitoring Division Argyle tall tower in central Maine), indicative of regional scale carbon exchange. They develop a data-driven diagnostic tool to estimate terrestrial carbon flux on a regional continental scale by using so-called receptor-oriented modeling framework. The receptor-oriented framework can infer surface sources and sinks from atmospheric data in the PBL. It consists of a time-reversed Lagrangian adjoint model (STILT) [Gerbig et al. 2003a,b; Lin et al. 2003] coupled to a vegetation CO₂ flux model that calculates gross primary production and respiration, the Vegetation Photosynthesis and Respiration Model (VPRM) [Pathmathevan et al., 2006]. STILT simulates upstream influences on the observation location (receptor) proceeding from available data on wind fields (Colorado State Regional Atmospheric Modeling System (RAMS),

the Eta Data Assimilation System 40-km product (EDAS-40), the Weather Research and Forecasting (WRF) model). The parameters of VPRM related to surface spatial heterogeneity and variations in soil moisture, canopy density, solar input and phenology were derived from MODIS enhanced vegetation index (EVI) and land surface water index (LSWI), and radiation from the National Land Atmosphere Data Assimilation System (NLDAS). AmeriFlux data were used to initially calibrate the parameters characterizing functional dependence of CO₂ flux. This produced regional flux estimates for the greater Maine and southern Quebec region were found to be consistent with CO₂ concentrations observed in the summer of 2004. Atmospheric concentration data was then used to optimize scaling factors of gross ecosystem exchange and respiration calculated from the initial calibration of the VPRM. Thus deviations of Bayesian-optimized scaling factors from their *a priori* values encapsulate the deviation between local-scale carbon fluxes calibrated against eddy covariance measurements and regional-scale carbon fluxes constrained against atmospheric CO₂ observations. The receptor-oriented framework is able to link traditional “bottom-up” and “top-down” methodologies.

For any methodology applied to estimate net carbon fluxes, the fluxes must be consistent with estimates derived with other methods. At this date it becomes more common practice to invert an atmospheric transport model with atmospheric CO₂ measurements, thus deriving surface CO₂ fluxes. For this top-down approach to be useful for policy making, it is necessary to develop a regional inversion method with a monthly or weekly time step. This strategy is required when a convergence of flux estimate values from inversion calculations as opposed to bottom-up estimates with ecosystem models is strived for. Agreement of inversion flux estimates with processed-based ecosystem flux estimates would enforce the validity of the flux estimates, as well as confirm the validity of the biophysical processes involved.

The problem of dividing net carbon fluxes into respiration and soil emission could be evaluated at local scale and then extended to regional scale. The main problem is how to initialize soil carbon stock. Two approaches are in use now: the equilibrium approach [Alexandrov et al., 1999; Alexandrov and Yamagata, 2002; Liski et al., 2005] and successional approach [Chertov et al, 2002; Komarov et al., 2003]. Both approaches simplify the real situation, and thus produce

expedient estimates that need be validated by forest soil surveys.

5. THE USE OF REMOTE SENSING DATA IN PRODUCTION EFFICIENCY MODELS

A production efficiency model (PEM) employs conceptual scheme introduced by Monteith. Generally it is a multiplication of radiation absorption with a temperature function, a water limitation function, and vegetation specific radiation or light use efficiency. A PEM uses RS imagery to assess spatial and temporal estimates of the Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) and water limiting factors [Field et al, 1995; Goetz et al, 1999; Turner et al 2003; Veroustraete et al, 2002; Veroustraete et al, 2004]. The fAPAR is derived directly from a vegetation index [Myneni and Williams, 1994] or from radiation transfer modelling [Myneni, 1995; Veroustraete and Verstraeten, 2005]. Water limiting factors are estimated using evaporative fraction (EF) and soil moisture content (SMC) - or a similar soil water index - derived from optical & thermal [Verstraeten et al., 2005; Verstraeten et al., 2006] or microwave data [Wagner et al., 1999]. Light use efficiency or radiation use efficiency are stratified using land use data inferred from space observed data such as the GLC2000 land cover map [Bartholomé and Belward, 2005].

The raw RS imagery are essentially transformed to obtain fAPAR. Typical processing chains for polar orbiting visible and thermal satellite data are composed of procedures for image unpacking, calibration, geometric correction and atmospheric correction. The first step starts with unpacking raw image data thereby extracting digital imagery as well as ancillary data. Subsequently, calibration or the conversion of the digital numbers of the radiometer pixel values into physical units, e.g. reflectance and brightness temperature is executed. In this step sensor degradation as well as inter-platform differences are taken into account. The next step is image registration to establish the relationship between the geographical co-ordinate system of a reference image and the image co-ordinate system. During the geometric correction procedure imagery is re-sampled. The objective is to obtain a pixel location accuracy of 1 pixel or smaller. Next atmospheric correction significantly reduces atmospheric influences in the short wave bands (RED, NIR) and converts 'top of atmosphere' reflectances into surface or 'top of canopy' reflectances. Another important processing step, especially in view of cloud removal, is the compositing of vegetation indices. Vegetation indices can then be used to derive fAPAR.

The complexity of image processing induces some errors and uncertainty in the estimates of Gross Primary Production (GPP) that propagates to the estimates of Net Primary Production (NPP), and Net Ecosystem Production (NEP). Veroustraete and Verstraeten assessed the sensitivity of C-Fix projections of GPP at the EUROFLUX site of Brasschaat (BE2) for the year of 1998 [Veroustraete et al., 2004] to the errors in fAPAR. They found that the average errors of the average daily GPP of $3.9 \text{ gC m}^{-2} \text{ d}^{-1}$ elicit values from 0.62, to 1.24, to $2.48 \text{ gC m}^{-2} \text{ d}^{-1}$ if the errors in fAPAR are doubled from 5 to 10 to 20 % respectively. In other words, an error in fAPAR may cause three times larger error in GPP.

The surprising hypersensitivity of a PEM to the accuracy of remotely sensed inputs suggests that one need to develop a more robust scheme for using RS imagery in the studies of terrestrial carbon sink.

6. CONCLUDING REMARKS

In conclusion it is worth mentioning that this article does not provide a comprehensive review on model-data fusion related to global carbon cycle studies. This "position paper" was prepared by participants of the workshop as a part of the 'Summit on Environmental Modelling and Software'. The paper is intended to provide information for workshop participants on mutual efforts and approaches, to organize and outline our viewpoints on the issue, and in this process to provide the foundation for future cooperation. Cooperation is in fact what is strongly needed to resolve the long-standing problem of the "missing carbon sink"/"residual terrestrial uptake". Readers who are not well informed on model-data fusion might find it useful to read some seminal articles, which are related to the issues discussed above [Raupach et al., 2005; Williams et al., 2005; Knorr and Kattge, 2005; Denning et al., 2003; Gurney et al., 2002; Kaminski et al., 2002; Running et al., 1999].

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