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Optimization of the seasonal cycles of simulated CO₂ flux by fitting simulated atmospheric CO₂ to observed vertical profiles

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Received: 26 March 2009 – Accepted: 8 June 2009 – Published: 22 June 2009

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Published by Copernicus Publications on behalf of the European Geosciences Union.

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Abstract

An inverse of a combination of atmospheric transport and flux models was used to optimize model parameters of the Carnegie-Ames-Stanford Approach (CASA) terrestrial ecosystem model. The method employed in the present study is based on minimizing an appropriate cost function (i.e. the weighted differences between the simulated and observed seasonal cycles of CO₂ concentrations). We tried to reduce impacts that the inaccuracy of a vertical mixing in a transport model has on the simulated amplitudes of seasonal cycles of carbon flux by using airborne observations of CO₂ vertical profile aggregated to a partial column. Effect of the vertical mixing on optimized NEP was evaluated by carrying out 2 sets of inverse calculations: one with partial-column concentration data from 15 locations and another with near-surface CO₂ concentration data from the same 15 locations. We found that the values of simulated growing season net flux (GSNF) and net primary productivity (NPP) are affected by the rate of vertical mixing in a transport model used in the optimization. Optimized GSNF and NPP are higher when optimized with partial column data as compared to the case with near-surface data only due to the weak vertical mixing in the transport model used in this study.

1 Introduction

Accurate estimation of the global distribution of CO₂ flux is important not only for making a basis for imposing the emission restriction of CO₂ gases on each country under international agreement, but also for understanding both natural and anthropogenic processes controlling the CO₂ fluxes. One common approach for estimation of CO₂ flux is to use atmospheric transport inversions (Gurney et al., 2002; Rodenbeck et al., 2003). With increasing number of CO₂ observation data becoming available recently, the use of atmospheric transport inversion is producing more reliable results (Maksyutov et al., 2003). Equally important in increasing the reliability of the atmospheric trans-

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port inversions is to increase the reliability of the background CO₂ fluxes that are used to derive the a-priori values of CO₂ concentration fields for solving the inverse problems.

Fluxes of CO₂ due to net ecosystem production (NEP) of terrestrial ecosystem, fossil fuel combustions, biomass burning, and exchange with ocean are major contributors to the seasonal cycle of CO₂ in atmosphere. Among all of these CO₂ fluxes, NEP makes the largest contribution to variability in CO₂ in the atmosphere although it is very close to neutral over the course of a year (Tucker et al., 1986). To better understand the carbon cycle in the terrestrial ecosystem, several models have been developed to date. For example, Potsdam Model Intercomparison study compared a total of 17 global terrestrial biogeochemistry models, and analyzed these models from several aspects such as the simulated net primary productivities (NPP), using the common input data (Cramer et al., 1999).

Methods to optimize terrestrial ecosystem models vary quite dramatically from a model to model. One way is to adjust the model parameters one by one until a simulated physical quantity is close enough to the observed value. On the other hand, statistical approaches are commonly used to adjust model parameters. Fung et al. (1987) optimized temperature sensitivity of the ecosystem respiration globally to get a better fit of the simulated northern hemispheric CO₂ seasonality to the observations, and achieved quite reasonable results for the amplitude of seasonal cycle although with some problems in the phase. Later, Randerson et al. (2002) simultaneously optimized two parameters of the Carnegie-Ames-Stanford Approach (CASA) terrestrial ecosystem model by incrementally varying the values of two parameters and constructing a three-dimensional plot of a cost function describing the weighted difference between modeled and observed CO₂ concentrations. In their study, they used the Goddard Institute for Space Studies tracer transport model to simulate the atmospheric CO₂ concentrations from CASA fluxes with different values of parameters (Randerson et al., 2002). Kaminski et al. (2002) simultaneously optimized 24 parameters of the Simple Diagnostic Biosphere Model (SDBM) by assimilating seasonal cycles of CO₂ concentrations

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from 41 observing sites. Further, Rayner et al. (2005) elaborated on the carbon cycle data assimilation system developed by Kaminski et al. (2002) and simultaneously optimized 57 parameters of Biosphere Energy Transfer Hydrology Scheme (BETHY) using the observed data of CO₂ for 1979 to 1999.

To our knowledge, these studies which used the observed CO₂ concentrations to optimize parameters of terrestrial ecosystem model relied upon available CO₂ data which are dominated by surface level measurements. However, recent studies have revealed that the accuracies of vertical mixing scheme in transport models vary from a model to model. For example, Stephens et al. (2007) revealed that the significant number of transport models compared in the TransCom-3 study (Gurney et al., 2002) do not have sufficient vertical mixing. As a result, exclusive use of CO₂ concentration data in boundary layer in the atmospheric inversions can bias the estimated fluxes. Similarly, Yang et al. (2007) used ground-based FTS and aircraft measurements to reveal the weak vertical mixing in a number of the transport models of TransCom-3 both between PBL and free troposphere and within free troposphere, and implied that the use of CO₂ column data is more relevant for the reliable optimization of terrestrial ecosystem models.

In the present study, we optimized CASA with partial column data of CO₂ obtained by aircraft measurements, and separately, with near-surface data of CO₂. We applied the atmospheric transport inversion method, which is widely used to estimate regional fluxes of CO₂ (e.g. Gurney et al., 2004), to estimate 2 parameters of the CASA flux model independently for each of the 11 vegetation types. By analyzing the vertical profiles of simulated and observed CO₂, it was found that the transport model used in this study has a weak vertical mixing especially in the northern mid latitude during winter and this inaccuracy of the mixing led to the underestimation of NEP seasonality when near-surface data was used exclusively. The optimization with partial column data of CO₂, on the other hand, is less affected by mixing scheme of a transport model and expected to result in more accurate optimization of seasonal cycles of NEP field.

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2 Methods

In this section, we first present the overall description of the inversion method used for the CASA parameter optimization, followed by the detailed description of each part of the optimization process as well as the models used in this study.

5 2.1 Formalism of the parameter optimization

In this study, we optimized a set of the CASA parameters, \mathbf{p} , using the Bayesian inversion in which the weighted mismatches between the modeled and observed concentrations of atmospheric CO₂ concentrations are minimized. This is equivalent to minimizing the cost function J

$$10 \quad J = (\mathbf{x} - \mathbf{M}(\mathbf{p}))^T \mathbf{C}_x^{-1} (\mathbf{x} - \mathbf{M}(\mathbf{p})) + (\mathbf{p} - \mathbf{p}_0)^T \mathbf{C}_{p0}^{-1} (\mathbf{p} - \mathbf{p}_0) \quad (1)$$

where \mathbf{x} is a matrix consisting of the observed CO₂ concentrations, \mathbf{M} is a transport model which maps \mathbf{p} to concentrations of CO₂, \mathbf{p}_0 is the initial values of \mathbf{p} , and \mathbf{C}_x and \mathbf{C}_{p0} are the covariance matrices of \mathbf{x} and \mathbf{p}_0 , respectively. The operator \mathbf{M} consists of atmospheric transport model (\mathbf{A}) and CASA (\mathbf{B}), i.e. $\mathbf{M}(\mathbf{p}) = \mathbf{A}\mathbf{B}(\mathbf{p})$. As shown in the following section, \mathbf{B} is nonlinear while \mathbf{A} is linear, so in order to minimize Eq. (1) we expanded \mathbf{B} around \mathbf{p}_0 in Taylor series and approximated it up to the 1st-order term:

$$15 \quad \mathbf{M} = \mathbf{A} [\mathbf{B}(\mathbf{p}_0) + \mathbf{G}(\mathbf{p} - \mathbf{p}_0)] \quad (2)$$

where \mathbf{G} is the first derivative of $\mathbf{B}(\mathbf{p})$ with respect to \mathbf{p} at $\mathbf{p} = \mathbf{p}_0$. We evaluated $\mathbf{G}(\mathbf{p} - \mathbf{p}_0)$ numerically assuming a linear relationship between the first derivative and \mathbf{p} for a small change in \mathbf{p} . Furthermore, the solutions of \mathbf{p} which minimizes Eq. (1) is

$$20 \quad \mathbf{p} = \mathbf{p}_0 + [\mathbf{G}^T \mathbf{C}_x^{-1} \mathbf{G} + \mathbf{C}_{p0}^{-1}]^{-1} \mathbf{G}^T \mathbf{C}_x^{-1} [\mathbf{x} - \mathbf{G}\mathbf{p}_0] \quad (3)$$

and the associated covariance matrix of \mathbf{p} is

$$\mathbf{C}_p = [\mathbf{C}_{p0}^{-1} + \mathbf{G}^T \mathbf{C}_x^{-1} \mathbf{M}]^{-1}. \quad (4)$$

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The detailed derivations of Eqs. (3) and (4) were previously shown, for example, by Enting (2002) and Bousquet et al. (1999). In this study, the minimization of \mathbf{J} was done iteratively since we used the linear approximation in Eq. (2). Throughout the iterative process, the values of \mathbf{p}_0 and \mathbf{C}_{p0} were fixed at the values described in the following section. Note that, because Eq. (2) is not exact, neither \mathbf{p} nor \mathbf{C}_p obtained by Eqs. (3) and (4) are exact solutions to minimize \mathbf{J} . Thus, to assign the measure of the improvements in the simulation, we calculated χ^2 which is the mean-square mismatch between the observed and simulated concentrations:

$$\chi^2 = N_{\text{obs}}^{-1} \sum_n^{N_{\text{obs}}} (\mathbf{x}_{nn} - (\mathbf{M}(\mathbf{p}))_{nn})^T \mathbf{C}_x^{-1} (\mathbf{x}_{nn} - (\mathbf{M}(\mathbf{p}))_{nn}) \quad (5)$$

where N_{obs} is the number of observations (i.e. the size of \mathbf{x}), and $\mathbf{M}(\mathbf{p})$ is in its exact form.

2.2 Carbon cycle model

We used the Carnegie-Ames-Stanford Approach (CASA) model as \mathbf{B} in Eq. (2). Specifically, the CASA described by van der Werf et al. (2003) was used with following modifications. The fire activities in CASA were turned off by setting the burned fraction to zero at every grid cell of CASA for all times. This is because we are only interested in the seasonal cycle of NEP in the present study, and the inter-annual variability of the forest fire activities is too erratic to account for in the average seasonal cycle (van der Werf et al., 2006). As input data for CASA, we used the same dataset as described by van der Werf et al. (2003) except for monthly normalized difference vegetation index (NDVI). We used NDVI data from Pathfinder AVHRR Land dataset (Agbu and James, 1994) for 1981 to 2001, and derived the monthly climatology of NDVI following the method described by Randerson et al. (1997). Figure 1 shows the distributions of the vegetation types in CASA as well as the abbreviation for each vegetation type of CASA used throughout the rest of this paper. We used CASA with spatial resolution of 1°

latitude $\times 1^\circ$ longitude and monthly time steps. In the rest of this sub section, the algorithms of CASA used to derive NPP and flux of carbon due to heterotrophic respiration R_h are briefly introduced since the parameters that control these two quantities were optimized in this study.

5 The net ecosystem exchange (NEE) in CASA is obtained as a difference between the net primary productivity (NPP) and the sum of fluxes due to R_h , fuel wood burnings, and consumptions of plants by herbivores. In CASA, the NPP at a grid cell g and time t is given by

$$\text{NPP}(g, t) = \text{IPAR}(g, t)\varepsilon(g, t) \quad (6)$$

10 where IPAR is intercepted photosynthetically active radiation and ε is light use efficiency. The value of IPAR in Eq. 6 is a function of NDVI and proportional to photosynthetically active radiation PAR (Bishop and Rossow, 1991). On the other hand, ε is a production efficiency of an ecosystem for a given IPAR and is expressed as

$$\varepsilon(g, t) = T_s(g, t)W(g, t)E_{\max} \quad (7)$$

15 where functions T_s and W account for stresses induced by temperature and water availability, respectively, and E_{\max} is a maximum light use efficiency. To our knowledge, E_{\max} has been taken as a universal constant common to all ecosystem types in CASA (e.g. $0.5 \text{ g C (MJ PAR)}^{-1}$ was used by van der Werf et al., 2003).

Likewise, conditions of soil moisture and temperature dominate the control over R_h .
20 The effect of temperature on R_h is expressed as T_R which is an exponential function of a factor Q_{10} :

$$T_R(g, t) = Q_{10}^{\{T(g,t)-30\}/10} \quad (8)$$

where $T(g, t)$ is a surface temperature. In this study, we simultaneously optimized E_{\max} and Q_{10} of each vegetation type; that is, the size of \mathbf{p} is 1×22 (i.e. 2 parameters \times 11 vegetation types). Furthermore, we used $0.5 \text{ g C (MJ PAR)}^{-1}$ and 2.00 as the initial values of E_{\max} and Q_{10} , respectively, and $0.25 \text{ g C (MJ PAR)}^{-1}$ and 0.30 as the prior uncertainty of E_{\max} and Q_{10} , respectively.

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2.3 Atmospheric transport model

The NIES transport model (Maksyutov and Inoue, 2000) was used to simulate the global distributions of CO₂ resulting from a given surface CO₂ flux. It is an off-line model and uses National Centers for Environmental Prediction (NCEP) reanalysis meteorology (Kalnay et al., 1996). The model has a resolution of 2.5° latitude×2.5° longitude, 15 vertical levels (from ~0.15 to 20 km in altitude), and the time step of 15 min. The advection scheme is semi-Lagrangian with tracer mass adjustment for the conservation of tracer. The monthly mean climatological planetary boundary layer (PBL) height, derived from the GEOS-1 reanalysis (Schubert et al., 1995), was used to define the PBL height in the model. The detailed description of the model's scheme for vertical mixing can be found in Appendix A of Ishizawa et al. (2006). For this study, the NIES model was run for 3 model-years with the meteorology of 1997–1999 and appropriate background fluxes (described below), and the result from the 3rd year was used to represent the seasonal cycle of the CO₂ concentration for a given surface flux. Annual anthropogenic carbon fluxes for 1990 (Andres et al., 1996) and 1995 (Brenkert, 1998) and monthly oceanic flux (Takahashi et al., 2002) were used as the background fluxes. The linear trend of the simulated CO₂ concentration at each station was subtracted from each station data to prepare a detrended seasonal cycle at each station. The propagation of response function G (see Eq. 2) in the atmosphere was also simulated with the NIES transport model and used to evaluate Eqs. (3) and (4).

2.4 Observed data of CO₂

We used data of vertical profiles of CO₂ concentration from GLOBALVIEW-CO₂ (2007). The locations of the 15 vertical profiles used in this study are shown in Fig. 1, and the vertical coverage at each data point is listed in Table 1. The error of seasonal cycle was obtained using the method described by Kaminski et al. (2002). The discrete vertical profiles were converted to a partial column concentration, assuming that each data point represents a concentration of CO₂ in a column of atmosphere having a thickness

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of 1000 m centered at the altitude at which the data was taken (see Table 1). We used weighted mean of the uncertainty of each data point in the vertical profile to obtain the uncertainty of the partial column concentration. In addition to the dataset of partial column concentrations, the CO₂ concentrations at the lowest level of each vertical profile were collected to prepare the “near-surface” dataset of the CO₂ concentrations.

3 Results and discussions

In this section, we first describe the values of optimized parameters and the changes in their uncertainties. Then, the results of the seasonal cycles obtained from the partial column data and near surface data will be compared from several aspects.

3.1 Optimized parameters

The values of both Q_{10} and E_{\max} stabilized after five iterative calculations to minimize Eq. (1) with the observed seasonal cycles of partial column data. However, the values of Q_{10} and E_{\max} fluctuated quite significantly throughout the optimization with near-surface data. Thus, we chose to use the results which resulted in the smallest value of χ^2 since we derived χ^2 without any approximations. We found that the value of χ^2 decreased from 1.84 to 0.60 after optimization with the partial-column data, while it decreased from 2.60 to 1.67 after optimization with the near-surface data.

The optimization with partial-column data resulted in an average E_{\max} of 0.54 g C (MJ PAR)⁻¹ and Q_{10} of 1.81 for 11 vegetation types with standard deviations of ± 0.20 g C (MJ PAR)⁻¹ and 0.29, respectively; while the optimization with near-surface data resulted in average E_{\max} of 0.49 g C (MJ PAR)⁻¹ and Q_{10} of 1.81 with standard deviations of ± 0.27 g C (MJ PAR)⁻¹ and 0.27, respectively. The optimized values of E_{\max} and Q_{10} for each vegetation type are shown in Fig. 2. The value of E_{\max} optimized with partial-column CO₂ were greater than or approximately equal to the E_{\max} optimized with the near-surface CO₂ data for all vegetation types except for BNF. More-

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over, E_{\max} of BNF was more tightly constrained by the near-surface data than by the partial-column data (Fig. 3). On the other hand, near-surface and partial-column inversions resulted in the values of Q_{10} that are significantly different from each other for AGR and NEF, although these two vegetation types had the opposite trends in E_{\max} and Q_{10} (Fig. 2). Interestingly, near-surface data of CO₂ used in this study constrained E_{\max} more than partial-column CO₂ data while the trend was vice versa for Q_{10} of all vegetation types except for AGR (Fig. 3).

At the same time, it has to be emphasized that the optimizations of other parameters could have led to the comparable reduction in χ^2 and thus the physical meanings of the optimized parameters shown in Fig. 2 need to be carefully interpreted. Moreover, the available data on seasonal cycles of vertical profiles of CO₂ are quite limited at this point, and thus the results of this study are strongly biased toward the location of the available data as shown in Fig. 3 which shows that some of the vegetation types which have no nearby observation points have no significant reduction in the parameter's uncertainty. Therefore, increasing the number of the reliable vertical profile data is expected to improve the confidence level of the resulting parameters.

3.2 Growing season net flux and NPP

To analyze the amplitude of seasonality of NEP of CASA optimized in this study, we calculated growing season net flux (GSNF) which is defined as the sum of NEP for the months when NEP is greater than zero (Randerson et al., 1997). The use of GSNF is valuable in this study since CASA is designed to have no annual net flux (i.e. zero annual NEP) for each model grid, and so we can use GSNF as a measure of the productivity of ecosystem in CASA. The values of GSNF were higher when CASA was optimized with the partial-column CO₂ data than with the near-surface data at almost all latitudes except for around 40° to 45° (Fig. 4). We compared the values of GSNF and NPP for each vegetation type (Table 2), and found that GSNF decreased quite dramatically for BNF when we changed the CO₂ data for inversion from the near-surface to partial-column data which account for the low value of GSNF from partial-column

inversion between 40° and 45°. Except for BNF, GSNF and NPP of all vegetation types obtained by inversion with the partial column data were either approximately equal to or greater than those obtained with the near-surface data, accumulating to 15.8% and 17.0% increases in the total annual NPP and GSNF, respectively, upon changing the data choice from near-surface to partial column concentrations (Table 2). At the same time, Randerson et al. (1997) predicted that the global sums of NPP and GSNF for 1990 were 54.9 P g C y⁻¹ and 13.6 P g C y⁻¹, respectively, and both of these values are slightly larger than corresponding values obtained in this study (see Table 2). Correctly identifying the cause of this discrepancy is out of scope of the present study, since the datasets used for CASA in their study are different from those in the present study. Thus, directly comparing the results of these two studies is difficult, and so we limit our discussion to the comparison of our own results in this paper. Furthermore, using column concentrations of CO₂ observed by a ground-based FTS, Yang et al. (2007) found that the actual GSNF north of 30° is approximately 28% larger than the GSNF predicted by Randerson et al. (1997) using CASA. However, in their study, Yang et al. (2007) did not directly evaluate the effects of utilizing column or partial column concentrations of CO₂ instead of boundary concentration data, and so no conclusion was made on how much of this 28% is due to the weak vertical mixing in transport models. In the present study, we can directly compare these two cases. For example, our analysis indicates that the use of near-surface data of CO₂ resulted in GSNF that was 14% less than the case with partial-column data for north of 30° N. At the same time, we note here that this value (14%) can be expected to be slightly larger when total column concentrations (e.g. from ground-based FTS measurements) are used instead of partial columns used in this study.

3.3 Seasonal cycle and vertical profiles of CO₂ with optimized CASA NEP

Using two sets of optimized CO₂ flux field from CASA along with background fluxes, we simulated seasonal cycle of global CO₂ concentration field. Figure 5 shows that the optimized seasonal cycles of partial-column concentrations resulted in the better

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fits to observations of partial column concentrations than those simulated with prior values of E_{\max} and Q_{10} , for both cases of optimizations. Furthermore consistent with the trend of GSNF and NPP, the seasonal cycle of CO_2 partial-column concentrations simulated with CASA optimized with near-surface data had a smaller amplitude than those optimized with partial-column data (Fig. 5; results for only selected locations are shown). We also compared the vertical profiles of the observed and simulated CO_2 concentrations, by averaging vertical profiles for Northern Hemisphere summer (July, August, and September) and winter (January, February, and March) (Fig. 6). By comparing the vertical profiles simulated with 2 cases of optimized CASA, we found that the vertical gradients of their CO_2 concentrations are almost identical while the amplitude of seasonal cycle at a given altitude is greater for the CO_2 concentration simulated with CASA optimized with partial column data. On the other hand, for both of these simulated vertical profiles of many locations, the simulated vertical gradients are too strong compared with the observed vertical gradients especially in winter (Fig. 6). This indicates that the vertical mixings in the NIES transport model at these locations are not sufficient. Moreover, similarly to what was suggested by Yang et al. (2007) for the average of 12 transport models used in TransCom-3, NIES transport model has insufficient rates of vertical mixing both between the planetary boundary layer and upper troposphere and within the upper troposphere (Fig. 6). This weak vertical mixing in the transport model is attributed as a cause of the GSNF and NPP of CASA that was underestimated when CASA was optimized with the near-surface data. That is, low (in summer) and high (in winter) concentrations of CO_2 in boundary layer, caused by the net flux of CO_2 due to activities of terrestrial ecosystem (i.e. photosynthesis and respiration), are not effectively propagated to the higher altitudes due to the insufficient vertical mixing in the transport model, and this results in artificially high amplitudes of seasonal cycle of CO_2 concentration near surface even when the correct amount of CO_2 flux from CASA is given to a transport model. Thus, when only near-surface data of CO_2 concentrations are used to optimize CASA, the amplitudes of seasonal cycles of NEP in CASA are underestimated. On the other hand, when column concentrations

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of CO₂ are used, the optimization of CASA is affected less by the inaccuracy of vertical mixing in the transport model and more reliable results can be obtained although other deficiencies in the transport model as well as other parameters of CASA may bias the results. Furthermore, since the method described in this paper can correct the seasonality of CASA NEP without being much affected by a scheme of vertical mixing in a transport model, it can be used to prepare flux fields of CO₂ which can be used as a reference for tuning a scheme of vertical mixing in a transport model.

4 Summary

The seasonality of the CASA ecosystem model was optimized using the vertical profiles of the observed CO₂ concentrations and the inverse of transport model with CASA. We found that the method employed in this study can effectively optimize the seasonality of CASA NEP. Moreover, we found that the CASA NEP simulated with the partial column concentrations of CO₂ has larger amplitude of seasonality than that simulated with the near-surface data. Our analysis showed that annual GSNF predicted with the partial column data was 14% larger than that predicted with the near-surface data. Furthermore, the analysis of the vertical profiles showed that the low GSNF predicted with near-surface data is due to the weak vertical mixing in the transport model used in this study. In conclusion, optimization of an ecosystem model for CO₂ flux in conjunction with an atmospheric transport model can be more reliably achieved with CO₂ column concentrations than only with the near-surface data, especially when a vertical mixing scheme in a transport model is not accurate enough. As a result, we arrived at the CO₂ flux model which fits CO₂ column observations better and is less dependent on the mixing properties of the transport model used in the parameter optimization process. Better fit to the column average concentration can potentially improve a fit of the forward model simulations to the observations of the CO₂ by ground based and space based instruments.

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Acknowledgement. Authors wish to thank J. T. Randerson and G. van der Werf for generously providing us with the CASA code written in MATLAB and its input data. Additionally, data used by the authors in this study include data produced through funding from Earth Observing System Pathfinder Program of NASA's Mission to Planet Earth in cooperation with National Oceanic and Atmospheric Administration. The data were provided by the Earth Observing System Data and Information System, Distributed Active Archive Center at Goddard Space Flight Center which archives, manages, and distributes this data set. This work was partly supported by the Grants-in-Aid for Creative Scientific Research (2005/17GS0203) of the Ministry of Education, Science, Sports and Culture, Japan, and funding by Global Environment Research Fund of the Ministry of Environment, Japan.

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Table 1. Locations and amplitudes of the CO₂ vertical profile data used for this study. The data were obtained from GLOBALVIEW-CO₂ (2007).

| Code | Descriptive name | Latitude | Longitude | Altitudes (m) |
|------|-------------------------------------|----------|-----------|-----------------------------------------------|
| BNE | Beaver Crossing, Nebraska (USA) | 40.80° | 97.10° W | 500, 1500, 2500, 3500, 4500, 5500, 6500 |
| CAR | Carr, Colorado (USA) | 40.37° | 104.30° W | 3000, 4000, 5000, 6000, 7000, 8000 |
| DND | Dahlen, North Dakota | 48.38° | 97.77° W | 500, 1500, 2500, 3500, 5000 |
| ESP | Estevan Point, Canada | 49.58° | 126.37° W | 500, 1500, 2500, 3500, 4500, 5500 |
| HAA | Hawaii (USA) | 21.23° | 158.95° W | 500, 1500, 2500, 3500, 4500, 5500, 6500, 7500 |
| HFM | Harvard Forest, Massachusetts (USA) | 42.54° | 72.17° W | 1500, 2500, 3500, 4500, 5500, 3500, 7500 |
| EPT | Estevan Point, Canada | 49.38° | 126.55° W | 500, 1500, 2500, 3500, 4500, 5500 |
| HFM | Harvard Forest, Massachusetts (USA) | 42.54° | 72.17° W | 500, 1500, 2500, 3500, 4500, 5500, 3500, 7500 |
| HIL | Homer, Illinois (USA) | 40.07° | 87.91° W | 500, 1500, 2500, 2500, 3500, 4500, 5500 |
| LEF | Park Falls, Wisconsin (USA) | 45.93° | 90.27° W | 500, 1500, 2500, 2500, 3500, 4500, 5500 |
| NHA | Worcester, Massachusetts (USA) | 42.95° | 70.63° W | 500, 1500, 2500, 2500, 3500, 4500, 5500 |
| ORL | Orleans, France | 47.80° | 2.50° W | 500, 1500, 2500, 3500 |
| PFA | Poker Flat, Alaska (USA) | 65.07° | 147.29° W | 1500, 2500, 3500, 4500, 5500, 6500, 7500 |
| RIA | Rowley, Iowa (USA) | 42.40° | 91.84° W | 1000, 3000, 5000, 7000 |
| TGC | Sinton, Texas (USA) | 27.73° | 96.86° W | 50, 1500, 2500, 3500, 4500, 5500, 6500, 7500 |
| THD | Trinidad Head, California (USA) | 41.05° | 124.15° W | 500, 1500, 2500, 3500, 4500, 5500, 6500, 7500 |
| ZOT | Zotino, Russia | 60.00° | 89.00° E | 500, 1500, 2500, 3500 |

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Table 2. NPP and GSNF of each vegetation type after CASA optimizations with near-surface and partial columns of CO₂. The global totals are also shown (note the unit change).

| Vegetation type | NPP, g C m ⁻² y ⁻¹ | | GSNF, g C m ⁻² y ⁻¹ | |
|---------------------------------------|------------------------------------------|----------------|-------------------------------------------|----------------|
| | Near-surface | Partial-column | Near-surface | Partial-column |
| TRF | 434.4 (±14.7) | 492.4 (±14.6) | 82.1 (±1.6) | 92.2 (±1.6) |
| BDF | 295.9 (±14.7) | 332.1 (±14.9) | 80.9 (±2.7) | 90.7 (±2.7) |
| BNF | 919.9 (±5.9) | 728.9 (±8.1) | 328.1 (±2.7) | 229.6 (±2.24) |
| NEF | 238.2 (±1.9) | 378.2 (±2.2) | 66.2 (±0.6) | 147.6 (±1.0) |
| NDF | 183.8 (±3.5) | 278.5 (±4.2) | 55.2 (±1.2) | 78.1 (±1.4) |
| SVN | 698.5 (±6.7) | 802.2 (±7.3) | 185.8 (±1.1) | 223.3 (±1.2) |
| GSL | 49.3 (±4.9) | 126.5 (±5.2) | 18.2 (±1.1) | 45.9 (±1.1) |
| BSB | 55.4 (±1.5) | 54.2 (±1.5) | 19.6 (±0.4) | 19.2 (±0.4) |
| TUN | 112.3 (±1.5) | 103.5 (±1.6) | 29.9 (±0.6) | 26.8 (±0.6) |
| DST | 5.4 (±0.2) | 5.2 (±0.2) | 2.2 (±0.1) | 2.2 (±0.1) |
| AGR | 108.1 (±1.4) | 148.4 (±1.6) | 52.7 (±0.5) | 54.9 (±0.5) |
| Global total (P g C y ⁻¹) | 36.7 (±0.6) | 42.5 (±0.6) | 10.6 (±0.1) | 12.4 (±0.1) |

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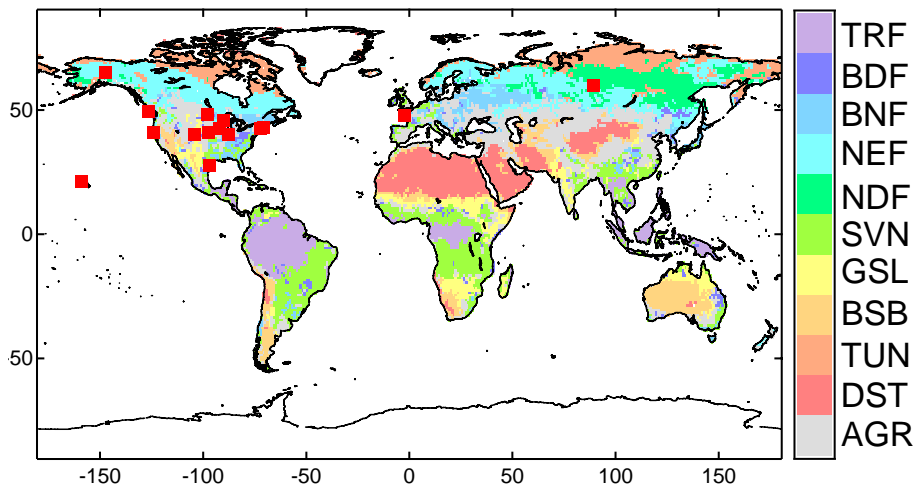


Fig. 1. Map of vegetation types in CASA. TRF: tropical rainforests, BDF: broadleaf deciduous forests; BNF: broadleaf and needleleaf forests; NEF: needleleaf evergreen forests; SVN: savannas, GSL: perennial grasslands, BSB: broadleaf shrubs with bare soil, TUN: tundra, DST: desert, AGR: agriculture. Red squares on the map indicate the locations of the vertical profile data used for this study (see Table 1).

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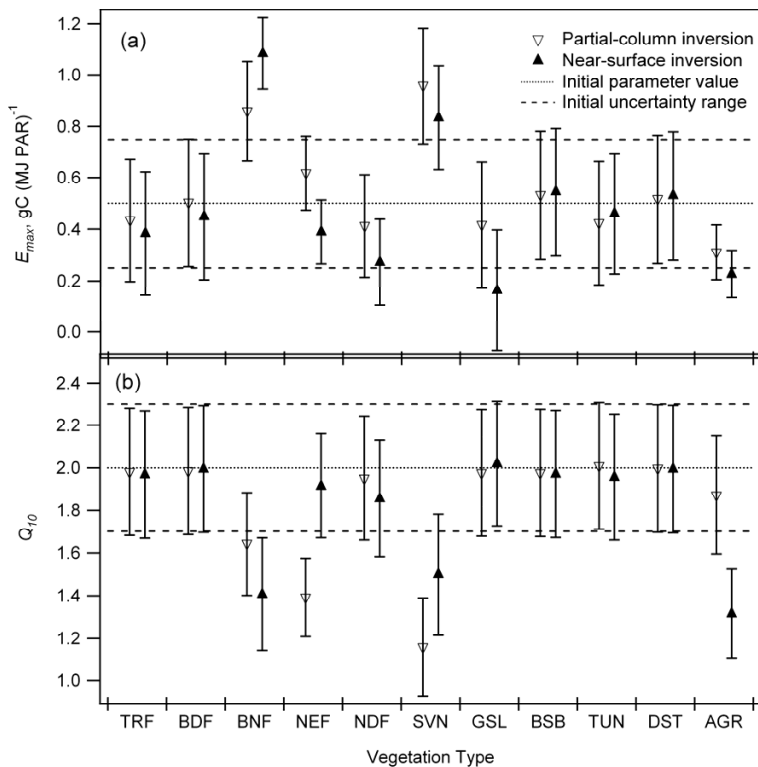


Fig. 2. (a) E_{max} (b) Q_{10} and of each vegetation type optimized with partial column concentrations of CO₂ and near-surface CO₂ concentration. The dotted and dashed lines represent the initial value and its uncertainty of respective parameter, respectively.

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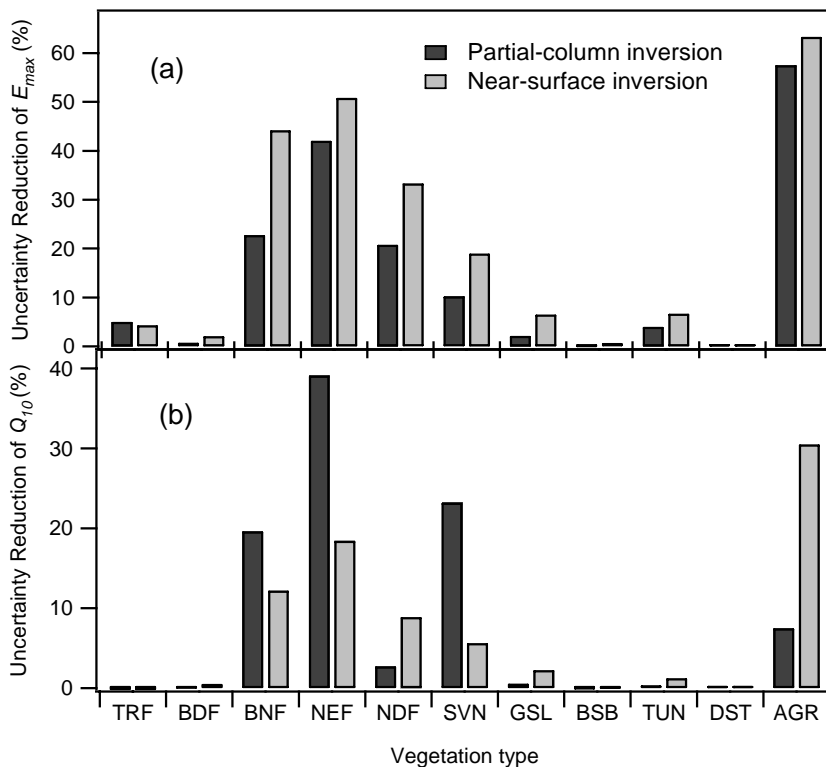


Fig. 3. Uncertainty reduction (%) of (a) E_{max} and (b) Q_{10} . Note that here, we defined the “uncertainty reduction” as $\{1 - C_p C_{p0}^{-1}\}$.

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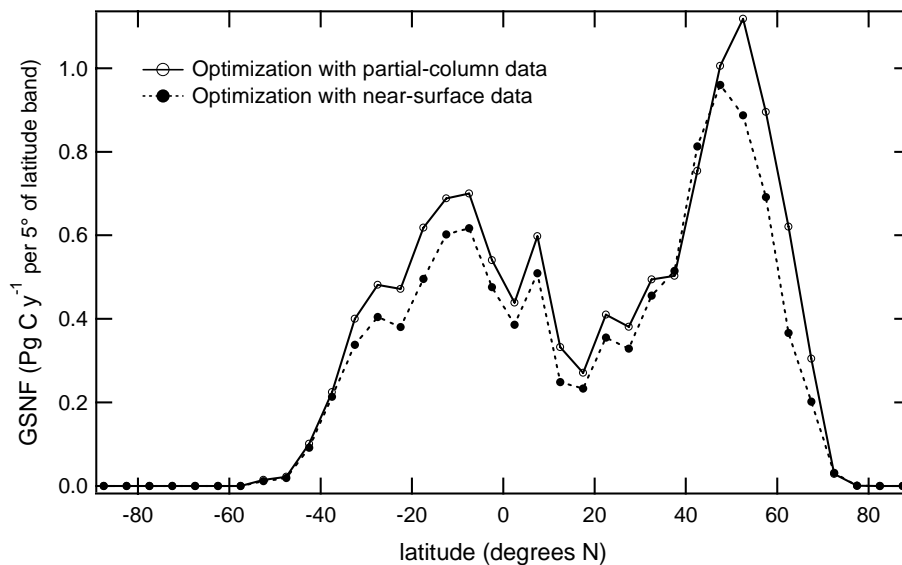


Fig. 4. Latitudinal distributions of GSNF obtained with partial-column CO₂ and near-surface CO₂.

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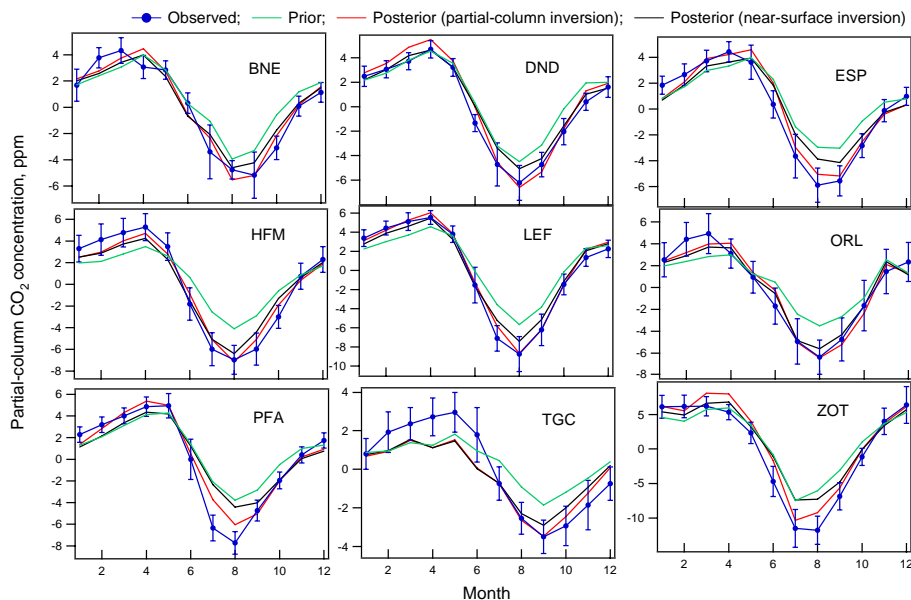


Fig. 5. Seasonal cycles of CO₂ partial column concentrations. Observed values are plotted with the results of 2 cases of CASA optimizations, as well as their prior values.

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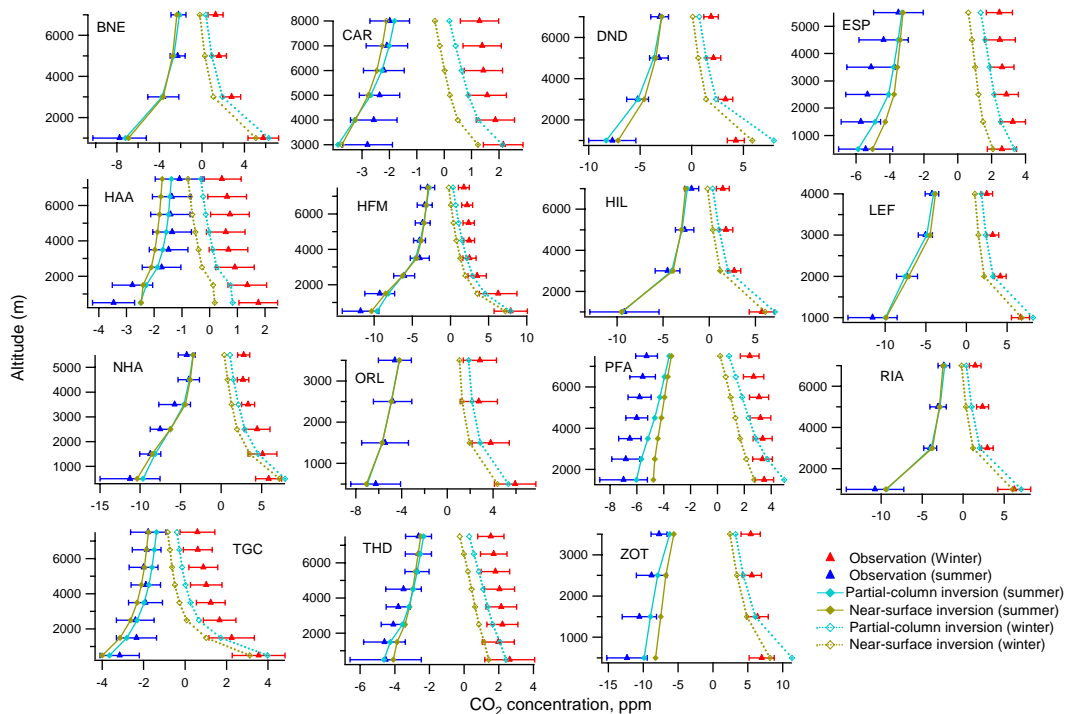


Fig. 6. Vertical profiles of the simulated and optimized CO₂ concentrations at each location. The simulated profiles were made using the CASA parameters obtained with partial column of CO₂ and near surface CO₂ data.

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