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Atmospheric Chemistry and Physics Discussions

Interactive comment on "Constraining terrestrial ecosystem CO2 fluxes by integrating models of biogeochemistry and atmospheric transport and data of surface carbon fluxes and atmospheric CO2 concentrations" *by* Q. Zhu et al.

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1. Estimating a state vector through sequentially applying (Bayesian) statistical methods is a promising approach to exploit the information content of observations with different constraint characteristics. The paper, here, combines direct flux measurements with atmospheric concentration measurements. However, it is not a 'clean' case since state vector of the first step are process parameters (from which surface fluxes are calculated), while the state vector of the second step are surface fluxes. Would

it be worthwhile to shortly discuss the theoretical, statistical background of sequential estimates? Response: The sequential Bayesian method (also known as recursive Bayesian estimation) is a widely used approach that updates probability density function of a target variable (in this case is global terrestrial net ecosystem production) by sequentially assimilating multiple datasets (in this case are AmeriFlux NEP and atmospheric CO2 concentration) (Figure 1). One of the most significant advantages of sequential Bayesian method is that as new data set emerges we simply apply the Bayesian method one more time to the latest estimate of the target variable, without starting over the entire data assimilation procedure. In our study, the first step is to use AmeriFlux NEP measurements to update global terrestrial NEP (NEP1) with TEM model. The second step uses both flask and satellite measurements of atmospheric CO2 concentration to update NEP1 to NEP2 using transport chemistry model GEOS-Chem. The TEM model plays a role in scaling up in situ level AmeriFlux NEP to the globe at a 0.5 by 0.5 degree resolution. Please note that, the global terrestrial NEP (NEP1) is constrained through constraining TEM model parameters in step 1.

2. One of the major advantages of sequential estimates is that the second step can identify its constraint matrix with the a posteriori covariance matrix derived from the first step. The paper, however, does not use the full covariance matrix but only the variances. Please comment on how your approach is actually different from just using a better a priori state vector for the top-down approach. Response: A better prior state vector is critically important for the success of top-down CO2 inversion. However, there does not exist large-scale measurements of such prior state (terrestrial ecosystem NEP). Thereby, it is a common practice to use ecosystem models to estimate the prior state vector. To date, most of top-down CO2 inversion studies relied on prescribed prior state vector that was estimated by an unconstrained model. For example, CO2 inversion of 16 transport models in The Atmospheric Tracer Transport Model Intercomparison Project (TransCom) used prior surface flux provided by CASA model, without any efforts on constraining the CASA model (Gurney et al., 2002). Similarly, CarbonTracker CO2 inversion used prior surface flux from a neutral biosphere run of CASA

model (Peter et al., 2007). One exception is the carbon cycle data assimilation system (CCDAS) (Rayner et al., 2005; Kaminski et al., 2013). They constrained a simple carbon model with remote sensing data of the fraction of Absorbed Photosynthetically Active Radition (fPAR). Then, they used the constrained model to generate the prior state vector for their top-down CO2 inverse modeling. We did not directly use prior state vectors from previous studies, because we believe they are not always reliable and safe to use (as is demonstrated in this study, the default CASA model derived prior state vector is not reliable). Following the efforts of CCDAS, we tried to obtain a better prior state estimate for our top-down inversion by using a more sophisticated ecosystem model (carbon-nitrogen fully coupled model rather than a simple carbon model) and high precision AmeriFlux surface flux measurements (more reliable than satellite derived fPAR). The major difference between our approach and using prior state in other studies is that the prior state from our approach is well constrained with high precision data. We agree that our estimation of the prior state vector does not contain covariance information. We argue that it has a minimum effect on our posterior estimation, since the surface flux spatial covariance are ignorable at the scale of 400∼500 km (Chevallier et al., 2012). Given that our CO2 inversion is conducted at 4 by 5 degree resolution (roughly 400 x 500 km), the bias from prior surface flux covariance ignorance is small.

3. The state vector of the top-down approach only includes terrestrial ecosystem fluxes (p. 22597, l.18; Figure 1). I would expect that atmospheric concentration measurements also exhibit some (albeit limited) sensitivity to ocean fluxes. Ocean fluxes are imposed. How sensitive are the estimated biosphere fluxes to ocean fluxes being potentially different from the imposed values? Response: Ocean acts as an important carbon sink, currently absorbing roughly 2 Pg C year-1 (Le Quere 2009). The reasons why we prescribed ocean fluxes rather than optimized them are two-fold. Firstly, CO2 concentration signal in the atmosphere is primarily regulated by terrestrial ecosystem carbon budget (controlling the seasonality) and anthropogenic CO2 emission (controlling the inter-annual variability) (Le Quere et al., 2013). Previous studies also showed

that changes of ocean CO2 fluxes only contributed to less than 4% of the variability of atmospheric CO2 concentration (Piao et al., 2008). Secondly, the oceanic carbon fluxes used in study is highly reliable, since they are derived upon about 3 million measurements of surface measurements (Takahashi et al., 2009). Other estimates based ocean general circulation model with parameterized biogeochemistry is consistent with Takahashi's estimate (Wanninkhof et al., 2013).

4. What is the assumed observation error for the atmospheric CO2 measurements? Does it include a representation error? Response: GLOBALVIEW-CO2 observation errors are from data product (GLOBALVIEW-CO2 2013). The errors are roughly 0.5 ppm including the instrumental error and errors from the GLOBALVIEW data fitting procedure. The representation error (inability of transport model to represent the observed site location) is not considered. A previous study implied that the representation error is about 0.3 ppm (Baker et al., 2006). AIRS CO2 errors are from AIRS CO2 level-2 dataset version 5 (Susskind et al., 2011). A two (two adjacent FOVs) by two (two adjacent scan lines) array of AIRS CO2 retrieval is used to determine the final retrieval of CO2 concentration. The error represents the spatial coherence over the 2 by 2 array. We only used the level 2 “standard product”, in which the errors are less than 2 ppm. The CO2 retrievals with errors larger than 2 ppm are placed in level 2 “support product”, which was not used. However, the representation error is not considered in the AIRS CO2 level 2 products.

5. The validation of the a posteriori concentration fields and the respective discussion should be refined. So far, it is mostly limited to comparing monthly averages at 6 surface sites plus the zonally averaged CONTRAIL data. How are the inland sites selected? Are they seasonally affected by small-scale meteorological variability or are they really representative of continental regions? Showing time series of model measurement comparisons and the assumed measurement errors might help. Response: The validation of our posterior estimates is based on: (1) independent CO2 inversions from multiple transport models inter-comparison studies; (2) GLOBALVIEW-CO2

inland sites; and (3) CONTRAIL CO2 data. Please note that our bottom-up NEP estimates are at a monthly step. Our CO2 inversion could at best capture the change of atmospheric CO2 signal at a monthly time scale (but not daily or diurnal variations). Therefore, we compared the simulated and observed monthly averaged CO2 concentrations. As is suggested by the reviewer, we modified the scatter plot to be showing the time series of GC-TEM, GC-CASA posterior CO2 concentrations against GLOBALVIEW-CO2 observations. Figure 2 implied that GC-TEM posterior is better than GC-CASA in terms of magnitude and seasonal variability. Six inland sites were selected for validation purposes. We agree with the reviewer that fine-scale meteorological variability will affect the observed CO2 concentrations. However, we argue that as we averaged the CO2 data to a monthly time scale, most of the fine-scale variability had been eliminated.

6. Table 4: I would prefer seeing a bar chart instead of a table Response: In order to clearly show the differences among different CO2 inversion setups, we added a new figure in the revised manuscript to show the difference between our two CO2 inversions (GC-TEM and GC-CASA) and CarboScope CO2 inversions (Figure 3).

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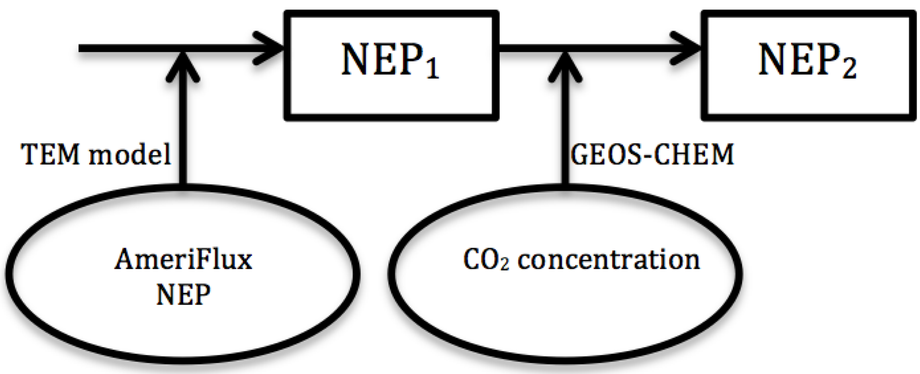

Fig. 1. Schematic representation of sequential Bayesian approach applied in this study. Rectangles are variables that are optimized. Ellipsoids are data

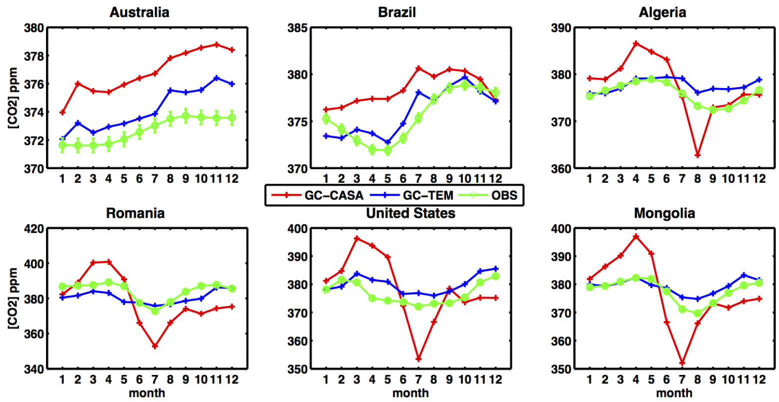

Fig. 2. Posterior monthly CO2 concentration in 2003 from GC-TEM (blue) and GC-CASA (red) inversions, evaluated at GLOBALVIEW-CO2 (green) inland sites from different continents.

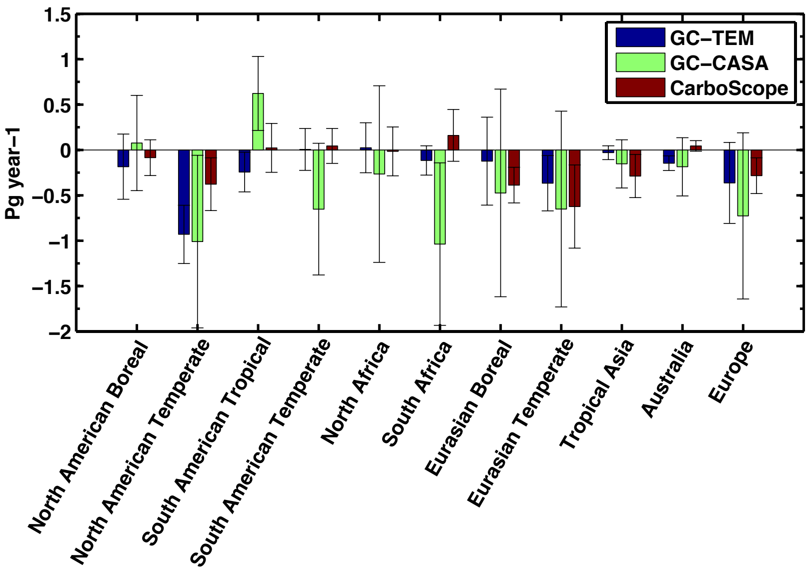

Fig. 3. Posterior NEP from GC-TEM, GC-CASA and CarboScope multi-model ensembles.