Evaluating atmospheric CO₂ inversions at multiple scales over a highly inventoried agricultural landscape

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Abstract

An intensive regional research campaign was conducted by the North American Carbon Program (NACP) in 2007 to study the carbon cycle of the highly productive agricultural regions of the Midwestern United States. Forty-five different associated projects were conducted across five US agencies over the course of nearly a decade involving hundreds of researchers. One of the primary objectives of the intensive campaign was to investigate the ability of atmospheric inversion techniques to use highly calibrated CO₂ mixing ratio data to estimate CO₂ flux over the major croplands of the United States by comparing the results to an inventory of CO₂ fluxes. Statistics from densely monitored crop production, consisting primarily of corn and soybeans, provided the backbone of a well studied bottom-up inventory flux estimate that was used to evaluate the atmospheric inversion results. Estimates were compared to the inventory from three different inversion systems, representing spatial scales varying from high resolution mesoscale (PSU), to continental (CSU) and global (CarbonTracker), coupled to different transport models and optimization techniques. The inversion-based mean CO₂-C sink estimates were generally slightly larger, 8–20% for PSU, 10–20% for CSU, and 21% for CarbonTracker, but statistically indistinguishable, from the inventory estimate of 135 TgC. While the comparisons show that the MCI region-wide C sink is robust across inversion system and spatial scale, only the continental and mesoscale inversions were able to reproduce the spatial patterns within the region. In general, the results demonstrate that inversions can recover CO₂ fluxes at sub-regional scales with a relatively high density of CO₂ observations and adequate information on atmospheric transport in the region.

Keywords: agriculture, atmospheric inversions, carbon cycle, CO₂ emissions, inventory, Mid-Continent Intensive

Received 6 November 2012; revised version received 6 November 2012 and accepted 10 December 2012

Introduction

For over half a century, the analysis of trace gases in the atmosphere has been a rich source of information about the contemporary global carbon cycle. Early studies of the secular trend and seasonal cycles of CO₂ mixing ratio revealed the accumulation of fossil carbon and the striking role of terrestrial ecosystems in planetary metabolism, and by the mid-1960s scientists had used spatial patterns in CO₂ and its isotopic composition to establish rates of atmospheric mixing (Bolin & Erickson, 1959; Bolin & Keeling, 1963), the penetration of anthropogenic CO₂ into the oceans, and the existence of a net sink in the terrestrial biosphere (Bolin & Keeling, 1963). Beginning in the 1980s, the global network of sampling stations from which accurate CO₂ measurements were available expanded rapidly with CO₂ measurements to support carbon cycle research. Denser data allowed formal estimation of the spatial patterns of sources and sinks at continental and ocean basin scale using inverse modeling, which also required quantitative accounting for atmospheric transport (Pearman & Hyson, 1981; Heimann & Keeling, 1986; Fung et al., 1987; Tans et al., 1990). A community of global CO₂ inverse modelers emerged during the 1990s and performed a series of atmospheric transport intercomparison (TransCom) experiments. TransCom
documented the sensitivity of estimated source/sink patterns to differences in advection, turbulence, and cloud transport among atmospheric models (Law & Simmonds, 1996; Denning et al., 1999; Gurney et al., 2002; Baker et al., 2006).

Despite decades of measurements, modeling, and field experiments, interactions between the carbon cycle, climate, and management now constitute a leading source of uncertainty in projections of 21st century climate change. Experiments with fully coupled carbon cycle-climate models show a range of over 250 ppm in CO₂ by 2100 given identical fossil fuel emissions (Friedlingstein et al., 2006; Solomon et al., 2007). Estimation of space/time variations of carbon sources and sinks by transport inversion provide an important constraint on coupled Earth system prediction. Tracking interannual variations in carbon source and sinks using transport inversion of atmospheric observation has become nearly routine in the 21st century (Peters et al., 2007, 2010). However, the relatively sparse data still require aggressive regularization through the use of Bayesian priors (Baker et al., 2006), geospatial smoothing (Michalak et al., 2004), or pre-aggregation of sources and sinks into coarse basis functions within which space/time patterns of flux are assumed to be known (Peters et al., 2007).

Formal evaluation of the accuracy of regional sources and sinks has remained elusive due to a lack of reliable independent measurements of regional CO₂ fluxes. CO₂ fluxes can be estimated locally by eddy covariance (Baldocchi et al., 2012), but the area represented by these estimates is generally a few square kilometers at maximum, far smaller than can be estimated from available concentration data. Field experiments during which greatly enhanced data collection is performed temporarily over a limited region and time period has provided opportunities to evaluate transport inversions (REACAB: Filippi et al., 2003; ChEAS: http://cheas.psu.edu/Chen et al., 2008; LBA: http://daac.ornl.gov/LBA/lba.shtml, COBRA: Gerbig et al., 2003; CERES: Dolman et al., 2006; ORCA: Goeckede et al., 2010a; ACME-07: Desai et al., 2011). Even for such limited regions, local bottom-up flux products (estimated from surface data, in contrast to models) must be interpolated across orders of magnitude of spatial scales to provide a quantitative constraint on top-down fluxes (estimated from atmosphere measurements).

As part of the North American Carbon Program (NACP) (Wofsy & Harriss, 2002; Denning, 2005), the Mid-Continent Intensive (MCI) field experiment was designed to evaluate innovative methods for CO₂ flux inversion and data assimilation by performing quantitative comparison of top-down and bottom-up inventory estimates of a regional carbon budget. The experiment was performed over a relatively flat, heavily managed landscape in the mid-continent region of North America and featured a high density of atmospheric CO₂ measurements (Ogle et al., 2006). A significant advantage of the study region was the fact that this area was relatively flat and devoid of complex topography, that would have made the meteorology more difficult to model for the inversions. Atmospheric CO₂ concentrations were measured using in situ analyzers installed on a ring of communication towers in the region (Miles et al., 2012), and vertical profiles of CO₂ were measured by a short dense aircraft sampling campaign (Martins et al., 2009). Another key advantage of this region for the inventory compilation was the detailed statistics available from US Department of Agriculture on commodity production in this economically important region. Consequently, the bottom-up inventory was developed at a high spatial resolution compared to previous studies and provided highly resolved maps of the annual uptake and release of CO₂ by agriculture, forests, fossil fuel combustion, and human respiration (West et al., 2011). In addition, surface fluxes over croplands were also estimated by eddy covariance (Meyers & Hollinger, 2004; Verma et al., 2005) and used to evaluate bottom-up inventory methods and as observational data for crop phenology models (Lokupitiya et al., 2009) used by the inversions.

Our primary objective in this study was to compare two sets of regional inversion estimates for the MCI region to a bottom-up inventory of fluxes. Estimates from a third inversion were also included, CarbonTracker (CT), which is a global scale inversion that does not use the finer scale network of observations in the MCI region. This inversion served as a standard for comparison to evaluate the influence of the higher density network on the inversion results, and we anticipated that the regional inversions would provide a more accurate estimation of CO₂ flux in the MCI study. Our secondary objectives were to explore reasons for differences between the inversion at both regional and sub-regional scales, with a primary focus on atmospheric transport, boundary inflow of CO₂, and a priori CO₂ flux estimates. This research extends work of Lauvaux et al. (2012a, b), incorporates CO₂ flux estimates from the operational CT system (Peters et al., 2007), and presents new results for the MCI following the methodology of Schuh et al. (2010). The three inverse analyses presented span a range of spatial domains from global to regional, and also a range of resolutions and different techniques for regularization. Comparing their results allows us to explore, for the first time, the strengths and weaknesses of many methodological choices in regional carbon analysis for an intensive campaign (MCI) in which we have uniquely detailed independent data from the bottom-up inventory.
Materials and methods

Observational data

The two regional inversions both used data from a ring of five towers (Miles et al., 2012; denoted from here on as the ‘Ring’). These five sites (Fig. 1) were located in the MCI region of the NACP (Ogle et al., 2006) and were outfitted with Picarro cavity ring down analyzers (Crosson, 2008). Hourly averages were computed from mixing ratios of CO2 recorded every 2 s, with daily calibrations. The analyzers had related measurement errors that were approximately 0.2–0.3 ppm for the hourly average mixing ratio data used in the two inversions (Richardson et al., 2012). The towers were instrumented beginning in May 2007. In addition to these data, both inversions used calibrated CO2 data from the 40 m Missouri Ozarks Ameriflux tower (Stephens et al., 2011) at the southern edge of the domain as well as NOAA-ESRL data from the WLEF tall tower in Wisconsin at the northern end of the domain and the WBI tall tower in the center of the domain.

Inversions

Most trace gas inversions use the same basic principles and structure that includes observations of trace gas concentrations, a priori estimates for trace gas fluxes, a mapping from fluxes to observations based upon an atmospheric transport model and an optimization of trace gas fluxes to minimize residuals between modeled trace gas concentrations and observed trace gas concentrations. There is a rich literature on the subject and several applications to CO2 fluxes (Tarantola, 1987; Enting et al., 1994; Evensen, 1994; Bishop et al., 2001; Whitaker & Hamill, 2002; Tippett et al., 2003; Zupanski, 2005; Peters et al., 2007; Lokupitiya et al., 2008). The goal of all three inversions in this article, labeled as the Penn State University (PSU) inversion, Colorado State University (CSU) inversion, and CT inversion, is to provide time-varying mean and covariance estimates for a set of spatial CO2 fluxes covering the MCI region that are consistent with observed CO2 concentrations.

A simplified flowchart of the atmospheric inversion technique is provided in Fig. 2 and the main differences among the three inversion frameworks are summarized in Table 1. After describing the domain for each inversion, a summary of differences among the three frameworks is given with respect to the following components (listed in Fig. 2): ‘Optimization’, ‘Atmospheric Transport’, ‘A priori CO2 fluxes’, ‘Boundary Inflow CO2’, and ‘Observed CO2’.

Spatial domain and resolution. The PSU inversion was run on a rectangular domain which overlapped portions of the non-rectangular MCI domain. Consequently, estimates for the PSU inversion were lacking for some areas in the MCI and were provided for some areas not in the MCI. As a result, we often present estimates for two areas, (i) the full MCI and (ii) the intersection of the PSU inversion domain and the MCI, which covers approximately 71% of the MCI domain. The CSU domain consisted of most of North America and extended out into the oceans to the east and west. Both domains are shown in Figure A1. The CT domain is global.

The CSU inversion domain consisted of a grid of 200 km by 200 km gridcells over most of North America with higher resolution grid of 40 km by 40 km grid cells over the MCI,
covering the entire underlying transport grid. The PSU inversion domain consisted of a grid of 20 km by 20 km gridcells over their transport grid. Both can be seen in Figure A1. The CSU and PSU inversion systems are grid based and allow flux adjustments to each individual grid cell of their inversion domain, relative to constraints imposed by a priori flux covariances. The CT inversion grid consists of ecoregions as seen in Figure A2. The CT system scales each individual ecoregion’s net ecosystem exchange (NEE) up or down each week and does not have the ability to provide any sub-ecoregion level flux adjustments (i.e. all cells are adjusted in the same manner within the region). The effect of the inversion resolution is tightly coupled to the a priori covariance assumptions which will be discussed later. It is important to note that due to the sparseness of available CO2 observations, the resolution of the inversion domain is coarser than that of the underlying transport and a priori fluxes.

**Optimization and temporal resolution.** The CSU inversion technique is a weekly sequential Bayesian batch inversion providing optimized total respiration (OPT_TRESP) and gross primary production (OPT_GPP) on a weekly time scale at 40 km by 40 km over the MCI and 200 km continentally. A priori total respiration (TRESP) and gross primary production (GPP) are independently ‘corrected’ via regression factors, \( \beta_{\text{TRESP}} \) and \( \beta_{\text{GPP}} \) applied to the a priori fluxes. The model and associated cost function, \( F(x) \), for a particular week, or ‘cycle’ are as follows:

\[
\text{OPT}_x TRESP(x, y, t) = \beta_{\text{TRESP}}(x, y)\text{TRESP}(x, y, t) \\
\text{OPT}_x GPP(x, y, t) = \beta_{\text{GPP}}(x, y)\text{GPP}(x, y, t) \\
\text{OPT}_x \text{NEE}(x, y, t) = \text{OPT}_x \text{RESP}(x, y, t) - \text{OPT}_x \text{GPP}(x, y, t)
\]

\[
F(\beta) = \frac{1}{2} \left( (\beta - \beta_0)^T B_{\text{flux pri}}^{-1} (\beta - \beta_0) + (H(\beta \cdot \text{flux prior}) - \text{obs})^T R^{-1}(H(\beta \cdot \text{flux prior}) - \text{obs}) \right)
\]

where \( B \) and \( R \) are the associated covariance matrices for the a priori flux corrective factor errors and the model/data mismatch, where \( \beta \) is the true but unknown correction factor on the fluxes and \( \beta_0 \) is the assumed correction factor, a priori. \( H \) is the observation operator providing the mapping from the flux space to concentration space and \( \text{obs} \) is the observed CO2 vector.

The PSU inversion technique is a weekly sequential Bayesian batch inversion providing optimized estimates of daytime NEE and nighttime NEE on a 7.5 day time scale at 20 km by 20 km spatial resolution. In contrast to optimizing ‘correction factors’ as the CSU inversion does, the PSU inversion directly optimizes the fluxes. The associated cost function is as follows:

\[
\text{OPT}_x TRESP(x, y, t) = \beta_{\text{TRESP}}(x, y)\text{TRESP}(x, y, t) \\
\text{OPT}_x GPP(x, y, t) = \beta_{\text{GPP}}(x, y)\text{GPP}(x, y, t) \\
\text{OPT}_x \text{NEE}(x, y, t) = \text{OPT}_x \text{RESP}(x, y, t) - \text{OPT}_x \text{GPP}(x, y, t)
\]

\[
F(\beta) = \frac{1}{2} \left( (\beta - \beta_0)^T B_{\text{flux pri}}^{-1} (\beta - \beta_0) + (H(\beta \cdot \text{flux prior}) - \text{obs})^T R^{-1}(H(\beta \cdot \text{flux prior}) - \text{obs}) \right)
\]

Fig. 2 Flowchart of atmospheric inversion process.

<table>
<thead>
<tr>
<th><strong>Table 1</strong> Comparison of inversion model components</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CarbonTracker</strong></td>
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<tr>
<td><strong>Inversion method</strong></td>
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<tr>
<td><strong>Transport</strong></td>
</tr>
<tr>
<td><strong>Land surface model†</strong></td>
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<tr>
<td><strong>A priori CO2 fluxes/photosynthesis model type</strong></td>
</tr>
<tr>
<td><strong>Domain</strong></td>
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<tr>
<td><strong>Transport resolution</strong></td>
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<tr>
<td><strong>Inversion resolution</strong></td>
</tr>
<tr>
<td><strong>Boundary CO2</strong></td>
</tr>
</tbody>
</table>

*BRAMS 3.2 was used as the basis for the transport model but the code has undergone numerous changes, fixes, and improvements over the last decade at Colorado State University.

†The LSM used to drive the meteorology in the inversion, not necessary consistent with the LSM used to generate the a priori CO2 fluxes.

‡CarbonTracker posterior CO2 fluxes were also used in Lauvaux et al. (2012a,b) but not shown here.

§See notes in Inversions section.
\[ F = \frac{1}{2} \begin{bmatrix} (\text{flux} - \text{flux}_{\text{prior}})^T R^{-1} (\text{flux} - \text{flux}_{\text{prior}}) \\
+ (H(\text{flux}) - \text{obs})^T R^{-1} (H(\text{flux}) - \text{obs}) \end{bmatrix} \]  

(5)

where \(B\) and \(R\) are the associated covariance matrices for the a priori flux errors and the model/data mismatch. \(H\) is the observation operator providing the mapping from the flux space to concentration space and \(\text{obs}\) is the observed \(\text{CO}_2\) vector. We note that the PSU inversion was run from June through December of 2007 due to its domain and dependency on the Ring data which began in June 2007. Where annual totals were required, a priori \(\text{CO}_2\) distributions were used. This is not likely to be a critical limitation to the comparison, however, because the dominant fluxes are occurring between June and August. In addition, the PSU inversion uses an a priori annual flux consistent with the removal of harvested crops and thus one would not expect large differences in the optimization during January through May, when respiration is the primary \(\text{CO}_2\) flux.

The NOAA CT system is based on a sequential ensemble Kalman filter (EnKF) framework and provides optimization of NEE from 2000 through 2009 on a weekly time scale at the resolution of ‘ecoregions’. The correction to NEE is performed multiplicatively similar to the CSU inversion although the complete procedure is more complicated (Supporting Information, Appendix A2). Although the statistical procedure is applied to ecoregions, the results are often presented as the ecoregion correction applied to the higher resolution underlying a priori flux field, which gives an artificial sense of precision. We present mean results from CT in this fashion but use fractional ecoregion-wide uncertainty for the variability estimates.

Atmospheric transport. The WRF-Chem (Skamarock et al., 2005) was used for transport by the PSU inversion system at a resolution of 10 km by 10 km. A CSU version of the Brazilian Regional Atmospheric Modeling System (BRAMS) was used for transport in the CSU model at a resolution of 40 km by 40 km (Pieke et al., 1992; Denning et al., 2003; Nicholls et al., 2004; Wang et al., 2006; Corbin et al., 2010; Schuh et al., 2010). Transport fields are provided for CT by the TM5 model (Krol et al., 2005), and those winds are derived from the ECMWF operational forecast model. Model resolution is 6° by 4° globally with nests down to 1° by 1° over the United States. The main difference here is that the regional models will be more accurate at resolving synoptic scale transport, i.e. storms, and vertical transport near the surface due to more highly resolved vertical grids.

The Lagrangian particle model LPDM (Uliasz & Pieke, 1991; Uliasz, 1993, 1994, 1996) is used by both PSU and CSU. It effectively acts as a transport adjoint (i.e. ‘inverse’) by diagnosing turbulent motions in the atmosphere as a function of high time resolution fields of zonal and meridional winds, potential temperature, and turbulent kinetic energy output from a parent mesoscale model. This allows for the creation of a Jacobian matrix representing the partial derivatives of \(\text{CO}_2\) concentration (at a fixed location) with respect to the surrounding fluxes of \(\text{CO}_2\). The details of the Lagrangian model that produces the particle movements from the parent mesoscale model can be found in Uliasz (1994) and there are many applications in the literature (Zupanski et al., 2007; Lauvaux et al., 2008, 2012b; Schuh et al., 2009, 2010). Further details on this technique can be seen in the Supporting Information, Appendix D1.

A priori \(\text{CO}_2\) fluxes. The inversions use a priori \(\text{CO}_2\) flux distributions that are Gaussian in nature and are thus composed of mean and covariance information.

Means: The a priori flux assumptions for the CSU and PSU regional models are based on the Simple Biosphere model (SiB), a land surface parameterization scheme originally used to compute biophysical exchanges in climate models (Sellers et al., 1986), but later adapted to include ecosystem metabolism (Denning et al., 1996; Sellers et al., 1996). The photosynthesis in SiB follows the Farquhar approach (Farquhar et al., 1980). A phenology-based crop module was then added to SiB and is detailed in Lokupitiya et al. (2009). This model was used in two ways. First, hourly \(\text{CO}_2\) fluxes were calculated from offline runs of the model driven by North American Regional Reanalysis meteorological data, at 40 km by 40 km resolution and 10 km by 10 km resolution, respectively, with three sub-gridscale landcover patches for each configuration. Secondly, the CSU model also ran test cases in which the SiB-CROP model was run in coupled-mode inside of BRAMS in an effort to provide consistency between the modeled \(\text{CO}_2\) fluxes and the meteorological data.

For CT, the a priori NEE estimates are recreated from CASA-GFEDv2 model runs of the Carnegie-Ames Stanford Approach (CASA) biogeochemical model, which employs a light use efficiency (LUE) photosynthesis model based upon AVHRR NDVI and year-specific weather. Global 0.5° by 0.5° resolution monthly output from the CASA-GFEDv2 model (van der Werf et al., 2006) for GPP and TRESP is scaled down to 3 hourly fluxes using a simple \(Q_{10}\) relationship and a linear scaling for photosynthesis based upon ECMWF analyzed meteorology. These are then differenced to provide diurnally varying NEE, while conserving monthly mean NEE in a manner similar to that of Olsen & Randerson (2004). The most significant differences between the CT inversion and regional inversions is the lack of an explicit crop model and the lack of explicit sub-daily predictions of C exchange in CASA-GFEDv2.

Covariances: For the CSU inversion, a priori covariance matrices for the multiplicative biases on GPP and TRESP (\(b\) factor in Eqn 4) were formed by constructing isotropic exponential spatial covariance structures over North America with decorrelation length scales of 500 and 1000 km (more information available in the Supporting Information, Appendix A4) and scaling them to 0.2, which amounts to standard deviations of 20% on GPP and TRESP. A priori covariance assumptions for the PSU inversion, i.e. \(B_{\text{flux}} - \text{flux}_{\text{prior}}\) (see Eqn 5), included smaller decorrelation length scales (exponential covariance) of approximately 300 km, compared to the CSU inversion which generally employed 500 and 1000 km for results shown in this article. The smaller decorrelation length scales of the PSU inversion were further decreased by modeling the covariance length scale as a function of ecosystem type, resulting in
equivalent isotropic decorrelation length scales of approximately 100 km. The temporal correlations were calculated consistent with Lauvaux et al. (2009). More information on a priori covariance of flux fields in the PSU inversion is available in the Supporting Information, Appendix A4 and Lauvaux et al. (2012b). There are no explicit spatial correlation assumptions in CT due to the use of larger ecoregions in its optimization but the a priori standard deviations are 0.85 on each ecoregion, amounting to a standard deviation of 85% of a priori NEE.

The main difference in covariance structures between the inversions is directly related to the ability of the inversions to assign, or adjust the prior based on the observed CO₂ concentrations, on a finer scale within the MCI region. The PSU inversion has the most freedom to make fine scale adjustments due to smaller spatial correlations followed by the CSU inversion with a moderate ability to correct subregional fluxes. The CT inversion has the most freedom to make fine scale adjustments, on a finer scale within the MCI region. The PSU inversion also utilizes optimized CT CO₂ flux estimates while the PSU inversion also utilizes optimized CT CO₂ and thus is the most restricted.

**Boundary inflow CO₂.** While global inversion systems like CT inherently have no boundaries, regional inversion results can be very sensitive to boundary conditions, i.e. the inflow of CO₂ from the boundaries of the model domain (Goecckede et al., 2010b; Gourdji et al., 2012). The CT inversion utilizes much lower variability in boundary inflow due to its eastern and western boundaries being over the ocean. This will make boundary bias corrections easier than correcting for boundary inflow over locations with more variability in CO₂ fluxes occurring in the middle of the continent (PSU).

However, the distance between the boundaries of the domain and the boundaries of the MCI make the PSU inversion dependent upon optimized fluxes over the continent with much weaker observational constraints. In particular, the PSU inversion utilizes inflow estimates (optimized CO₂) from the global CT inversion system with a bias correction based on interpolated global CO₂ from NOAAs GlobalView (GV) product while the PSU inversion also utilizes optimized CT CO₂ bias corrected with routine NOAA aircraft flights near their domain boundaries (Lauvaux et al., 2012b). We provide results with both bias-corrected and uncorrected CT inflow for the PSU inversion and detail the bias correction procedure in the Supporting Information, Appendix A3.

**Observed CO₂.** The PSU and CSU inversions both used the Ring data while using slightly different data streams from NOAA tall towers at WLEF in Wisconsin and WBI in Iowa. The PSU inversion used data from 122 m at WLEF and 99 m at WBI meters to be consistent with the other tower heights while the CSU inversion used the highest levels for WLEF and WBI which are 396 and 379 m, respectively. The full observational constraints for the PSU and CSU inversions are summarized in Table 2. As mentioned earlier, the PSU inversion only ran from June through December. The PSU and CT inversions used data from the NOAA WLEF and WBI tall towers from January to May and otherwise were constrained by the sparser continental network. The effect of the data gap on the PSU inversion is probably minimal in this study because of the a priori knowledge that a large percentage of the Net Primary Production is removed from the study region and not available for decomposition, however, we emphasize that, in general, this should not be the case.

The CT inversion is nearly real-time operational and uses global in situ as well as flask-collected data in its flux optimization (Peters et al., 2007). An important note is that it does not use the Ring data situated in the heart of the MCI region (Miles et al., 2012). Modified runs were performed with the data from the Ring for 2008. However, the inclusion of the data did not significantly alter the cropland flux estimates, instead increasing uptake in upwind grassland/shrub areas to the west and no additional diagnosis was performed to determine the exact cause of the insensitivity of local fluxes to the Ring data. Therefore, the original and publicly available flux estimates (CarbonTracker, 2009) were used in this study. The lack of any sensitivity of CT to the Ring data, and inability to optimize subregional fluxes, were two particular reasons that mesoscale inversions were employed in this study.

Specified model-data mismatch errors (the R matrix in Eqns 4 and 5) correspond to posterior model fits of the observations and thus, theoretically, are generally not available before the inversion step is run. The errors in the CSU inversion are thus formed by running the inversion initially using differences between the a priori modeled CO₂ concentrations and the observations and then reducing this a priori error by a somewhat arbitrary 40%. To create the model-data mismatch in the PSU inversion, R, the framework used a combination of projections of boundary layer depth errors and forward-adjoint consistency to create the errors. The CT system uses subjective choices for the errors which depend upon the location of the observing tower and how well the authors felt that the transport model, TM5, could reproduce local atmospheric motions there (see Supplementary Material, Peters et al., 2007). All three inversions calculate the chi-square innovation statistic and use this value to scale the a priori model-data mismatch to guarantee that they do not overestimate or underestimate the model-data mismatch a priori, which reduces some of the apparent dependency on the initial setting of R described above.

**Inventory methods.** A bottom-up CO₂ flux inventory was compiled for the MCI region for evaluating against the atmospheric inversion results. This inventory utilizes data on forest biomass, harvested woody products, and agricultural soil C from the US Greenhouse Gas Inventory (EPA, 2010; Ogle et al., 2010), in addition to fine resolution data on fossil and biofuel CO₂ emissions (Gurney et al., 2009), CO₂ uptake by agricultural crops and grain harvest (West et al., 2011), and CO₂ losses through livestock and human respiration associated with agricultural products (West et al., 2011). Uncertainties were derived from a Monte Carlo analysis in which probability distribution functions were developed for the flux estimates from each of the sources and random draws were made to produce 100 realizations of the total flux in the region. The carbon inventory was constructed on an annual time frame, due to temporal limitations in the FIA and harvest statistics, and was derived from
spatial data with a US county level resolution. For example, US counties in Iowa are very homogenous in size and shape and have a resolution of approximately 40 km by 40 km and thus the county sizes are comparable to the 0.5° by 0.5° resolution grid cells used to display the inventory.

Results

Bottom-up annual inventory of CO2 fluxes

Based on the bottom-up inventory analysis, sources of CO2 in the MCI domain are dominated by fossil fuel combustion (262 TgC source), in particular the city of Chicago (Gurney et al., 2009). Inversions usually consider fossil fuel fluxes as ‘known’ and without error and optimize the nonfossil fuel CO2 fluxes due to better knowledge of fossil fuel combustion when compared to natural biospheric fluxes and difficulties optimizing very localized point sources of CO2. The nonfossil fuel inventory data show a net CO2 uptake of 135 TgC for 2007 and are shown in Fig. 3. The flux is dominated by the harvest and export of grain from the region (West et al., 2011). Smaller sources and sinks associated with feedlots, forests, other natural vegetation, and human respiration also contribute to the total. Uncertainty for the nonfossil inventory is largely dominated by the harvest product while relative uncertainties, i.e. standard deviation in NEE as function of mean NEE, is largest for the FIA forest product. The spatial correlations in the inventory impact the region-wide uncertainty and can be better understood by an investigation of Fig. 3 of Cooley et al. (2012). Using a Monte Carlo analysis based on uncertainties in each component flux, we constructed 95% confidence limits on the CO2-C balance (net fossil fuels) of the MCI domain which resulted in a sink of \( -104 \) to \(-204 \) TgC for 2007 (mean: \(-135 \) TgC).

Annual CO2 fluxes from inversions

The results for all three inversions are statistically indistinguishable from the inventory results for the annual

<table>
<thead>
<tr>
<th>Site</th>
<th>Contact</th>
<th>PSU inversion</th>
<th>CSU inversion</th>
<th>CarbonTracker inversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argyle, ME</td>
<td>A. Andrews, NOAA-ESRL</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
<tr>
<td>Centerville, IA</td>
<td>N. Miles/S. Richardson, Penn State U</td>
<td>All hours</td>
<td>12:00–18:00 LST</td>
<td>Not used</td>
</tr>
<tr>
<td>Candle Lake, BC</td>
<td>D. Worthy, EnviroCanada</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
<tr>
<td>Fraserville, ON</td>
<td>D. Worthy, EnviroCanada</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
<tr>
<td>Galesville, WI</td>
<td>N. Miles/S. Richardson, Penn State U</td>
<td>All hours</td>
<td>12:00–18:00 LST</td>
<td>Not used</td>
</tr>
<tr>
<td>Kewanee, IL</td>
<td>N. Miles/S. Richardson, Penn State U</td>
<td>All hours</td>
<td>12:00–18:00 LST</td>
<td>Not used</td>
</tr>
<tr>
<td>Park Falls, WI</td>
<td>A. Andrews, NOAA-ESRL</td>
<td>All hours (122 m)</td>
<td>12:00–18:00 LST (396 m)</td>
<td>12:00–16:00 LST (396 m)</td>
</tr>
<tr>
<td>Lac Labiche, AB</td>
<td>D. Worthy, EnviroCanada</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
<tr>
<td>Metolius, OR</td>
<td>M. Goeckede/Beverly Law, Oregon State University</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
<tr>
<td>Mead, NE</td>
<td>N. Miles/S. Richardson, Penn State U</td>
<td>All hours</td>
<td>12:00–18:00 LST</td>
<td>Not used</td>
</tr>
<tr>
<td>Missouri Ozarks, MO</td>
<td>N. Miles/S. Richardson, Penn State U</td>
<td>All hours</td>
<td>12:00–18:00 LST</td>
<td>Not used</td>
</tr>
<tr>
<td>Round Lake, MN</td>
<td>N. Miles/S. Richardson, Penn State U</td>
<td>All hours</td>
<td>12:00–18:00 LST</td>
<td>Not used</td>
</tr>
<tr>
<td>Sable Island, NS</td>
<td>D. Worthy, EnviroCanada</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
<tr>
<td>West Branch, IA</td>
<td>A. Andrews, NOAA-ESRL</td>
<td>All hours (99 m)</td>
<td>12:00–18:00 LST (379 m)</td>
<td>12:00–16:00 LST (379 m)</td>
</tr>
<tr>
<td>Moody, TX</td>
<td>A. Andrews, NOAA-ESRL</td>
<td>Outside domain</td>
<td>12:00–18:00 LST</td>
<td>12:00–16:00 LST</td>
</tr>
</tbody>
</table>

Observations used by inversions. All towers used by PSU inversion were used by CSU inversion. Additional towers were used by CSU due to larger domain size. CarbonTracker use of data, common to PSU and CSU inversions, is shown as ancillary information. CarbonTracker is a global inversion framework and thus makes use of large amounts of data outside of North America which are not detailed here. Although custom filtering of observations is inversion dependent as well as dependent upon quality flags/operability of the towers, the times for considered data in each inversion are given in the table. PSU inversion uses all hours but with different weightings for different times of day and therefore nocturnally collected data is usually weighted more weakly, see Lauvaux et al. (2012b).
net CO₂ budget of the region (Fig. 4). After correcting the regional inversions for boundary inflow, all three inversion estimates show a slightly stronger sink than the inventory (CT = −155 ± 173 TgC, PSU = −140 ± 26 TgC for reduced ‘PSU domain’, CSU = −145 ± 29 TgC). The difference in the inversion system results was primarily influenced by the a priori flux uncertainty estimates, i.e. the initial range for the ‘best guess’ NEE. The CSU inversion used independent ±20% standard deviations for GPP and TRESP fluxes which is equivalent to an enormous range of possible flux results. The particular choice of 20% comes from the desire to keep correction factors positive, ensuring positive optimized GPP and TRESP. These conservative choices introduce flux scenarios that could be well outside the range of reasonableness, for example a 20% increase in annual TRESP and 20% reduction in annual GPP, relative to a balanced biosphere would cause a C source on the order of 300 TgC. It is important to note that the variability around the CT estimate is unrealistically large. This is well known and documented (CarbonTracker, 2011). However, the predictions generally appear more accurate than would be inferred from the formal flux uncertainty.

The three inversions produce similar spatial patterns in annual NEE compared to the inventory, with an important sink in the center of the domain corresponding roughly to the highest density of agricultural area (Fig. 5). However, at finer scales, the location of the maximum of uptake and the shape of the sink area varies substantially among the inversions. To evaluate this pattern, the inversion results were compared to the inventory data from the individual grid cells. Scatterplots of annual NEE values for the inversions vs. the inventory are shown in Fig. 6. Correlations with the inventory are higher for the CSU (r = 0.76) and PSU (r = 0.55) inversion results. The weaker correlation of the CT results with the inventory (r = 0.36) can be seen along with a bimodal feature in the figure.

Much of the spatial structure in the estimated maps of net annual flux is driven by the structure of the Bayesian a priori mean and the optimization method in each inversion model, i.e. the degree to which the inversion framework allows for independent adjustments to the a priori fluxes given the observed CO₂ data. The CSU inversion shows a strong correlation with the a priori June/July/August uptake in the region, but with a weaker C sink in Illinois and a stronger C sink in western Iowa. The spatial resemblance to the inventory is likely due to the strong 500–1000 km a priori decorrelation lengths used in the inversion and the strong summer time CO₂ deficit. Using a 500-km decorrelation length as an example, and noting that the width of Iowa is about 500 km, the inversion would assume that a weekly multiplicative error in GPP on one end of Iowa is correlated with an error in GPP on the other end of Iowa at a level of 0.37, a priori. Posterior correlations were reduced by about half although the reduction was different for GPP and TRESP and not isotropic, instead following the sampling gradient. There were no significant differences between using 500 and 1000 km on the regional NEE (Table 3).

The smaller a priori decorrelation length scales used in the PSU inversion, approximately five times less that those used in the CSU inversion, lead to much finer spatial adjustments in the a priori fluxes within the region. The PSU inversion shows a very large sink in the eastern part of the domain (northern Illinois), 20–30% larger than the inventory estimate in the area, as well as a stronger more diffuse sink to the northeast of the domain, an area of larger uncertainty in the inventory.

In contrast, the strongest sink for the CT inversion is located in the extreme northwest portion of the MCI
although the overall sink appears more diffuse. This is likely due to a strong flux in the prior for this particular area of the MCI and may be a result of inadequate crop modeling in CASA, which does not explicitly account for agricultural crops. Northern portions of the MCI have strong influences from soybeans and spring wheat, but these crops do not assimilate as much carbon during the peak of summer according to the inventory and eddy covariance studies (Lokupitiya et al., 2009), suggesting that a mix of wheat and soybeans contributes a weaker NEE signal than a mix of soybeans and corn. Overestimating the flux in the northwest portion of the MCI led to the bimodal distribution in flux mismatch between the CT inversion and inventory that was apparent in Fig. 6.

Although not included in Fig. 4, we also assessed the variability in CO2 inflow and its effect on the PSU and CSU inversions. For the CSU inversion, this sensitivity can be viewed in Table 3 while a general discussion of the inflow uncertainty for both regional inversions is provided later.

Transport and boundary inflow considerations

The transport and inflow boundary conditions could also influence the pattern and strength of fluxes within the region. However, the transport fields produced from the mesoscale models displayed a surprising amount of similarity. Despite different mesoscale models, PBL schemes, land surface models, and external forcing scales in time and space, differences in time-space integrated afternoon observation footprints for the towers in the 'aaa'ring' remained on the order of 20% of the absolute signal or less, varying as a function of distance from the tower (Supporting Information, Appendix D). Among the differences between the transport fields that could not be immediately explained, was the sensitivity to surface fluxes as a function of distance from tower. The RAMS model (CSU) appeared to show weaker sensitivity in the local vicinity of the tower and a stronger long-distance sensitivity than the corresponding WRF model (PSU).

In addition, regional inversion results can be sensitive to boundary conditions, i.e. the inflow of CO2 at the boundaries (Goeckede et al., 2010b; Gourdji et al., 2012). We evaluated the influence of inflow boundary conditions on the CSU inversion by using the CT-optimized CO2 as inflow with and without corrections for a known Northern Hemispheric seasonal bias. Bias correction to the CT optimized CO2 inflow reduced the CSU sink in the MCI by approximately 33%, from 174 TgC to 117 TgC in the ‘online’ case, while reducing the continental sink (data not shown) by 62% (1.6–0.6 PgC) providing better agreement with independent CO2 inventory estimates for North America (King et al., 2007). This inflow sensitivity is consistent with the findings of others who used similar methodologies (Gourdji et al., 2012). Furthermore, this adjustment to boundary inflow in the CSU inversion appeared, to first order, to simply shift the posterior annual NEE up or down. Similar results are summarized for the PSU inversion in the Supporting Information (Appendix A3) and Lauvaux et al. (2012b).
We conducted an additional test by evaluating the CSU inversion results outside of the MCI for consistency with the bias-corrected inflow used by the PSU inversion. Inflow estimates for the Kewanee tower were calculated from the CSU inversion by subtracting out the effect of the PSU inversion region from the CSU modeled Kewanee CO2. In this fashion, we were able to compare the expected inflow at the Kewanee tower from the boundaries of the PSU inversion region, for both the CSU and PSU inversion systems. Posterior inflow estimates for the CSU inversion at the boundary had a correlation of 0.82 compared to 0.41 for the...
priori inflow estimates and the mean difference between the CSU inflow estimate and the PSU bias-corrected inflow estimate dropped from 2.8 to 1.8 ppm. Thus, despite limited towers outside of the MCI, the CSU inversion appeared to provide inflow estimates at the MCI boundary which were more consistent with the bias-corrected CT inflow. However, a positive annual difference exists in the inflows, 1.8 ppm. If this difference is allocated to the PBL, roughly 1/7 of the atmospheric column, and spread evenly over the MCI region, it appears to provide an explanation for the fact that the CSU CO$_2$ sinks are often 10–15% stronger than the PSU CO$_2$ sinks (Table 3).

**Discussion**

Continental and meso-scale inversions were developed for 2007 using a relatively high density of observations in the MCI region. These data were compared to a bottom-up inventory and a global inversion framework, CT, which did not assimilate the higher density of CO$_2$ observations in the region. NEE flux estimates are similar among inversions, even from the CT system, and are reasonable for 2007 in the sense that they are statistically consistent with the inventory. The results are promising because they show that CO$_2$ inversion methods can be robust, in the sense that they deliver similar inverse flux solutions which are consistent with C inventory results, despite being constructed across very different frameworks, e.g. global to continental to regional, with very different assumptions. Nevertheless, comparisons to the inventory at spatial scales finer than 100–200 km and finer temporal scales on the order of weeks (data not shown), demonstrate the value of higher resolution inversion systems that can benefit from finer scale observations in terms of recovering finer CO$_2$ flux patterns within a region.

The agreement of large-scale posterior CT CO$_2$ fluxes to the inventory, despite major differences in fine scale flux signals may be fortuitous. The minimum scale of the gradients of CO$_2$ resolved by the CT transport model TM5 at 1° by 1° resolution is likely in the 200–300 km range. However, the region was chosen to avoid complex meteorology induced by land-sea contrasts or complicated topography. Hence, if the observations used by CT constrain the MCI domain reasonably well, it is certainly reasonable to recover large-scale agreement in flux estimates. Nevertheless, the very nature of the coarse inversion region used by CT (Supporting Information, Appendix A1) prohibits the CT system from recovering fluxes on most scales less than the MCI region and forces strong coherence to a priori CASA flux patterns at higher resolutions. Furthermore, the lack of higher resolution attribution of flux errors might limit this type of inversion from being used to further future prognostic carbon cycle modeling efforts.

The PSU inversion framework uses the most highly constrained area, i.e. an area slightly larger than the Ring of towers. The advantages of this are that they use a wealth of eddy covariance tower data to help constrain the a priori fluxes as well as provide more flexibility spatially to adjust fluxes. This was shown in Lauvaux et al. (2012b) to allow some degree of robustness of the posterior flux result to distinct underlying a priori flux fields. Therefore, given dense enough observational coverage of CO$_2$, one would expect to be able to proceed toward improvements in prognostic carbon cycle modeling where this is not possible with the CT inversion system. The disadvantage of this particular inversion is that the corrections to inflow on the sides of the domain will likely be larger and more variable than those made over marine boundary layer conditions and require the use of aircraft to obtain vertical profiles.
Table 3  MCI source/sink results (due to model variations)

<table>
<thead>
<tr>
<th>Inversion method</th>
<th>Inflow</th>
<th>Prior description</th>
<th>Post NEE</th>
<th>Prior NEE</th>
<th>Post NEE</th>
<th>Prior NEE</th>
<th>Post NEE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>(MCI)</td>
<td>(PSU Dom.)</td>
<td>(June–December)</td>
<td>(MCI)</td>
<td>(PSU Dom.)</td>
</tr>
<tr>
<td>CarbonTracker</td>
<td>N/A</td>
<td>CASA-GFED</td>
<td>−40 TgC</td>
<td>−155 TgC</td>
<td>−125 TgC</td>
<td>−124 TgC</td>
<td>−196 TgC</td>
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<tr>
<td>PSU</td>
<td>Aircraft-corrected CT</td>
<td>SiB3-offline</td>
<td>N/A</td>
<td>N/A</td>
<td>−65 TgC</td>
<td>−140 TgC</td>
<td>−109 TgC</td>
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<tr>
<td>PSU</td>
<td>Aircraft-corrected CT</td>
<td>CarbonTracker optimized</td>
<td>N/A</td>
<td>N/A</td>
<td>−154 TgC</td>
<td>−127 TgC</td>
<td></td>
</tr>
<tr>
<td>CSU</td>
<td>CarbonTracker opt.</td>
<td>SiB3-offline</td>
<td>−82 TgC</td>
<td>−235 TgC</td>
<td>−75 TgC</td>
<td>−200 TgC</td>
<td>−126 TgC</td>
</tr>
<tr>
<td>CSU</td>
<td>GV-corrected CT opt.</td>
<td>SiB3-offline (forced annual balance)</td>
<td>0 TgC</td>
<td>−145 TgC</td>
<td>−75 TgC</td>
<td>−127 TgC</td>
<td>−66 TgC</td>
</tr>
<tr>
<td>CSU</td>
<td>GV-corrected CT opt.</td>
<td>SiB3-offline (dec length: 1000 km)</td>
<td>−82 TgC</td>
<td>−160 TgC</td>
<td>−75 TgC</td>
<td>−143 TgC</td>
<td>−127 TgC</td>
</tr>
<tr>
<td>CSU</td>
<td>GV-corrected CT opt.</td>
<td>SiB3-offline (dec length: 500 km)</td>
<td>−82 TgC</td>
<td>−160 TgC</td>
<td>−75 TgC</td>
<td>−143 TgC</td>
<td>−127 TgC</td>
</tr>
<tr>
<td>CSU</td>
<td>CarbonTracker opt.</td>
<td>SiB3-RAMS coupled</td>
<td>0 TgC</td>
<td>−174 TgC</td>
<td>0 TgC</td>
<td>−154 TgC</td>
<td>−62 TgC</td>
</tr>
<tr>
<td>CSU</td>
<td>GV-corrected CT opt.</td>
<td>SiB3-RAMS coupled</td>
<td>0 TgC</td>
<td>−117 TgC</td>
<td>0 TgC</td>
<td>−107 TgC</td>
<td>−62 TgC</td>
</tr>
</tbody>
</table>

Negative NEE indicates carbon moving from atmosphere to the biosphere. These SiB3-offline fluxes were driven from offline run of the model driven by NARR data, which were used as the driving external forcing necessary for both WRF and RAMS. Inversion results for PSU inversion are put on a full annual 2007 basis by adding a priori fluxes from SiB3-CROP for January–May 2007 (before MCI towers were instrumented) to both a priori and a posterior flux estimates for June 2007 through December 2007. PSU inversion results for the ‘optimized CarbonTracker flux’ case are on the native PSU grid which is slightly larger than the ‘PSU grid’ which is used throughout this article which represents the intersection of the native PSU grid and the MCI domain. A priori fluxes from SiB3-offline are characterized by a ‘realistic’ annual harvest sink while the ‘forced annual balance’ case forces NEE to zero over all gridcells by balancing total respiration with gross primary production. Typically, the a priori fluxes and transport are derived in a decoupled environment. However, the ‘SiB3-RAMS’ a priori fluxes are those produced as a result of the parent SiB3-RAMS simulation, which produced the transport used in the CSU inversion, i.e. coupled. ‘Dec length’ indicates the a priori decorrelation length scale, or e-folding length, used for the exponential spatial correlation in the a priori fluxes. This value is generally less than 300 km for PSU inversions and 1000 km for CSU, unless otherwise noted.
The CSU inversion is largely a compromise between the CT and PSU systems. Boundary inflow corrections are still necessary because of the regional nature of the inversion but are made over marine boundary sites that are generally less variable in time and space and observed with the operational NOAA flask network. This tends to preserve the a priori flux gradients around the perimeter of the MCI because rapid flux adjustments are not needed to force agreement between tower observations and model observations close to the model domain boundary. The disadvantage is the need for a unified framework to simultaneously model the more densely observed MCI region and the rest of the continent. This topic was studied recently (Wu et al., 2011), but the heterogeneous nature of the evolving CO2 observing network probably demands continued investigation especially as satellite observations of CO2 become available. Furthermore, the impact of estimating (i) NEE, (ii) day/night NEE, or (iii) total respiration and GPP upon the inversions is still uncertain and remains an active research question.

With respect to our secondary objectives, differences between the inversions and inventory were influenced by boundary inflow estimates of CO2, a priori flux signals and differences in transport. As can be clearly seen from Table 3, the domain wide flux is most strongly influenced by the inflow estimates. Finer spatial scale flux variations then result from differences in transport and a priori flux patterns. Increased observations in the inversion domain should lessen the impact of the a priori flux assumptions, but the inflow estimate errors generally remain a systematic error, which must be corrected in an independent manner. Inflow corrections were performed using the GV NOAA product and the NOAA weekly aircraft samples as the basis of the bias correction scheme to the optimized global CT CO2 product and significantly improved the accuracy of the inversion results we showed. This demonstrates the importance of maintaining well calibrated global CO2 networks and in particular aircraft profile programs with respect to estimating regional carbon budgets with CO2 data. Differences in the bias-corrected inflow estimates between the two regional inversion appeared to be the primary cause of the differences in the annual CO2 flux estimates from the MCI region as a whole.

Posterior variance estimates of CO2 exchange continue to be one of the most difficult estimates to make for inversion modelers. Variance estimates from these CO2 inversion systems are sensitive to both inversion method and a priori covariance specifications. For example, posterior covariance from EnKF methods such as used for CT are strongly dependent upon the particular EnKF algorithm (Tippett et al., 2003). The a priori flux variances are generally very conservative on annual scales. Standard deviations of 85% on ecoregion-wide NEE for CT and standard deviations (independent) of 20% for TRESP and GPP for the CSU inversion led to a large range of possible net fluxes; far stronger annual sources and sinks than could be possible given global constraints and thus sufficiently conservative. Shortages of ancillary information on NEE, such as spatially dense eddy covariance observations or temporally and spatially rich biomass accumulation statistics often necessitate ‘broad’ a priori covariance structures be used in inversion systems attempting to estimate fluxes over continental or larger regions. While inversion modelers can attempt to control for portions of this uncertainty, i.e. model methodology, other portions such as ancillary data to constrain the fluxes a priori are generally outside of their control. Nevertheless, results from this study showed that quite good agreement can result from two inversions (CSU and PSU) where different a priori flux uncertainties, as well as system and method, were used.

In summary, regional flux estimates from each of the three frameworks agreed well with the estimates provided by the inventory data, but the continental and meso-scale inversions were better able to recover the spatial pattern of fluxes in the region. We consider this a first step toward ascertaining feasibility of the CO2 inversion method to produce regional carbon flux estimates as would be done under a monitoring program. Moreover, this study shows that atmospheric inversions are capable of capturing regional CO2 flux estimates at sub-national scales, scales which will be useful for future carbon-cycle research and regional greenhouse gas initiatives. The most critical next steps are to further refine the inversion frameworks to better quantify boundary inflow uncertainty, sensitivity to a prior flux estimates, and to provide explicit characterizations of transport variability as well as leverage the most recent and comprehensive sources of data on CO2.

Author Contributions and Acknowledgements

Andrew Schuh and Thomas Lauvaux performed the biospheric model runs, atmospheric transport runs, and new atmospheric inversions included in this manuscript. Tristram West and Stephen Ogle provided most of the inventory data used for the ‘bottom up’ portion of the comparison with the exception of fossil fuel inventory data for the MCI region, which was provided by Kevin Gurney (Arizona State) and FIA data provided by Linda Heath and James Smith (US Forest Service). Natasha Miles and Scott Richardson instrumented, maintained and analyzed the PSU ‘Ring of towers’ CO2 data for the MCI campaign (and the Missouri Ozarks tower) while Arlyn Andrews did the same for the WBI and WLEF towers within the MCI domain, in addition to the remainder of NOAA’s tall tower sites.
across the US. Marek Uliaasz provided assistance with the LPDM model used by both the PSU and CSU inversions. Dan Cooley provided advice and discussion on inversions and state-space modeling. Scott Denning provided the majority of the introduction including the historical context. Ken Davis and Stephen Ogle helped initiate the original campaign, provided many useful comments on manuscript and provided overall guidance to the project. The authors would like to thank a great many people who were involved with this project as well as generous support from the National Aeronautics and Space Administration (NASA #NNX08AK08G), National Oceanic and Atmospheric Administration (NOAA #NA080AR4320893) and the Department of Energy (DOE #DE-FG02-06ER45437). Thanks to NOAA-ESRL and Andy Jacobson in particular, for many useful discussions on these inversions as well as the CarbonTracker results which were used in this paper. Tower data were graciously provided, and commented on, by Beverly Law and Matthias Goeckede (Oregon State University), NOAA-ESRL (Arlyn Andrews), and Environment Canada (Doug Worthy).

This research used the Evergreen computing cluster at the Pacific Northwest National Laboratory. Evergreen is supported by the Office of Science of the US Department of Energy under Contract No. (DE-AC05-76RL01830).

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Appendices.
Figure A1. Inversion domains shown in native polar stereographic projections. Left panel (A) shows nested inversion grid with coarser grid at 200 km by 200 km and fine grid over MCI at 40 km by 40 km. Right panel (B) shows high resolution 20 km by 20 km grid for PSU inversion system.
Figure A2. CarbonTracker ecoregion-based inversion domain. Figure courtesy of NOAA-ESRL.
Figure C1. Time series of net ecosystem exchange (NEE) estimates from a variety of inversion models for 2007. PSU inversion is based on SiB3-CROP offline prior. CSU inversion is also based on SiB3-CROP offline prior with GV-bias corrected-CT inflow. Results from PSU inversion are from the intersection of PSU inversion domain and MCI domain while the results for the Carbon-Tracker and CSU inversions are on the MCI domain.
Figure D1. Sensitivity of daytime observations of passive surface flux to daytime passive flux releases during June, July, and August. Left panel shows results for PSU transport with WRF and LPDM and middle panel shows results for CSU transport with RAMS and LPDM. Right panel shows the difference. Releases were constant 1 μmol C m⁻² s⁻¹ over the PSU inversion domain (subset of MCI) and passive signal was integrated over this same area for both models.
Figure D2. Sensitivity of daytime observations of passive surface flux to nighttime passive flux releases during June, July, and August. Left panel shows results for PSU transport with WRF and LPDM and middle panel shows results for CSU transport with RAMS and LPDM. Right panel shows the difference. Releases were constant 1 μmol C m⁻² s⁻¹ over the PSU inversion domain (subset of MCI) and passive signal was integrated over this same area for both models.