



**Michigan
Technological
University**

Michigan Technological University
Digital Commons @ Michigan Tech

Michigan Tech Research Institute Publications

Michigan Tech Research Institute

3-10-2015

An approach for verifying biogenic greenhouse gas emissions inventories with atmospheric CO₂ concentration data

Stephen M. Ogle

Colorado State University - Fort Collins

Kenneth Davis

Pennsylvania State University - University Park

Thomas Lauvaux

Pennsylvania State University - University Park

Andrew Schuh

Colorado State University - Fort Collins

Dan Cooley

Colorado State University - Fort Collins

See next page for additional authors

Follow this and additional works at: https://digitalcommons.mtu.edu/mtri_p



Part of the [Environmental Indicators and Impact Assessment Commons](#)

Recommended Citation

Ogle, S. M., Davis, K., Lauvaux, T., Schuh, A., Cooley, D., West, T. O., Heath, L. S., Miles, N. L., Richardson, S., Breidt, F. J., Smith, J. E., McCarty, J. L., Gurney, K. R., Tans, P., & Denning, A. S. (2015). An approach for verifying biogenic greenhouse gas emissions inventories with atmospheric CO₂ concentration data. *Environmental Research Letters*, 10(3). <http://dx.doi.org/10.1088/1748-9326/10/3/034012>
Retrieved from: https://digitalcommons.mtu.edu/mtri_p/36

Follow this and additional works at: https://digitalcommons.mtu.edu/mtri_p



Part of the [Environmental Indicators and Impact Assessment Commons](#)

Authors

Stephen M. Ogle, Kenneth Davis, Thomas Lauvaux, Andrew Schuh, Dan Cooley, Tristram O. West, Linda S. Heath, Natasha L. Miles, Scott Richardson, F. Jay Breidt, James E. Smith, Jessica L. McCarty, Kevin R. Gurney, Pieter Tans, and A. Scott Denning

Environmental Research Letters



LETTER

OPEN ACCESS

RECEIVED

1 November 2014

REVISED

2 February 2015

ACCEPTED FOR PUBLICATION

13 February 2015

PUBLISHED

10 March 2015

Content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](#).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.



An approach for verifying biogenic greenhouse gas emissions inventories with atmospheric CO₂ concentration data

Stephen M Ogle¹, Kenneth Davis², Thomas Lauvaux², Andrew Schuh³, Dan Cooley⁴, Tristram O West⁵, Linda S Heath⁶, Natasha L Miles², Scott Richardson², F Jay Breidt⁴, James E Smith⁶, Jessica L McCarty⁷, Kevin R Gurney⁸, Pieter Tans⁹ and A Scott Denning¹⁰

¹ Natural Resource Ecology Laboratory and Department of Ecosystem Science and Sustainability, Campus Delivery 1499, Colorado State University, Fort Collins, CO 80523, USA

² Department of Meteorology, Walker Building, The Pennsylvania State University, University Park, PA 16802, USA

³ Cooperative Institute for Research in the Atmosphere and Natural Resource Ecology Laboratory, Campus Delivery 1375, Colorado State University, Fort Collins, CO 80523, USA

⁴ Department of Statistics, Campus Delivery 1877, Colorado State University, Fort Collins, CO 80523, USA

⁵ Joint Global Change Research Institute, 5825 University Research Court, Pacific Northwest National Laboratory, College Park, MD 20740, USA

⁶ USDA Forest Service, Northern Research Station, Forest Sciences Laboratory, 271 Mast Road, Durham, NH 03824, USA

⁷ Michigan Tech Research Institute, 3600 Green Court, Ann Arbor, MI 48105, USA

⁸ School of Life Sciences, PO Box 874501, Arizona State University, Tempe, AZ 85287, USA

⁹ National Oceanic & Atmospheric Administration, Earth Systems Research Laboratory, Global Monitoring Division, 325 Broadway, Boulder, CO 80305, USA

¹⁰ Department of Atmospheric Science, Campus Delivery 1371, Colorado State University, Fort Collins, CO 80523, USA

E-mail: stephen.ogle@colostate.edu

Keywords: greenhouse gas emissions inventory, atmospheric inversion modeling, emissions verification, carbon cycle

Abstract

Verifying national greenhouse gas (GHG) emissions inventories is a critical step to ensure that reported emissions data to the United Nations Framework Convention on Climate Change (UNFCCC) are accurate and representative of a country's contribution to GHG concentrations in the atmosphere. Furthermore, verifying biogenic fluxes provides a check on estimated emissions associated with managing lands for carbon sequestration and other activities, which often have large uncertainties. We report here on the challenges and results associated with a case study using atmospheric measurements of CO₂ concentrations and inverse modeling to verify nationally-reported biogenic CO₂ emissions. The biogenic CO₂ emissions inventory was compiled for the Mid-Continent region of United States based on methods and data used by the US government for reporting to the UNFCCC, along with additional sources and sinks to produce a full carbon balance. The biogenic emissions inventory produced an estimated flux of -408 ± 136 Tg CO₂ for the entire study region, which was not statistically different from the biogenic flux of -478 ± 146 Tg CO₂ that was estimated using the atmospheric CO₂ concentration data. At sub-regional scales, the spatial density of atmospheric observations did not appear sufficient to verify emissions in general. However, a difference between the inventory and inversion results was found in one isolated area of West-central Wisconsin. This part of the region is dominated by forestlands, suggesting that further investigation may be warranted into the forest C stock or harvested wood product data from this portion of the study area. The results suggest that observations of atmospheric CO₂ concentration data and inverse modeling could be used to verify biogenic emissions, and provide more confidence in biogenic GHG emissions reporting to the UNFCCC.

Introduction

As evidence for anthropogenic impacts on climate change continue to grow (IPCC 2013), the need to reduce emissions looms as a key issue of global debate.

Greenhouse gas (GHG) emission reductions continue to be at the center of negotiations about future agreements (Tollefson 2013). A key opportunity to establish a new agreement is occurring at a meeting of the United Nations Framework Convention on

Climate Change (UNFCCC) during late 2015 in Paris, France. Along with the scope and magnitude of emission reductions, methods to verify reductions has emerged as a key challenge for negotiators (NRC 2010).

Signatory countries to the UNFCCC are required to conduct an inventory and report GHG emissions to the UNFCCC. Reporting is based on GHG inventory guidelines developed by the Intergovernmental Panel on Climate Change (IPCC 2006). The guidelines include estimation of anthropogenic-driven emissions of CO₂ and other GHGs from energy use, industrial processes, waste management, agriculture, as well as biogenic carbon (C) sinks and sources from managed land, such as C stock changes in soils and biomass.

Estimating biogenic emissions is complicated because of UNFCCC reporting requirements. First, emissions are not reported for all activities, such as lateral transport of C in products that lead to CO₂ emissions elsewhere (Ciais *et al* 2007, West *et al* 2011). Consequently, inventories do not provide a full C balance for a region. Second, GHG emissions are only reported for managed land, which is a proxy to isolate emissions directly influenced by anthropogenic activity (IPCC 2010). However, emissions on managed land will also be driven by natural processes and indirect effects of anthropogenic activity, such as CO₂ fertilization or atmospheric N deposition. Third, emissions accounting may allow for exclusions, such as factoring-out of emissions due to natural disturbances (e.g., wildfires) that are not directly under the control of managers (Canadell *et al* 2007, Kurz *et al* 2013).

Biogenic emissions will likely be a part of an agreement to reduce GHG emissions, particularly if offsets are allowed through management of biogenic sources and sinks (Smith *et al* 2007a, 2007b). In addition, biogenic emissions may increase if bioenergy is used to reduce fossil fuel combustion in order to meet reduction targets (e.g., see US Energy Independence and Security Act of 2007). Bioenergy feedstock production contributes to GHG emissions, such as C stock changes in soils and biomass due to land use change (Fargione *et al* 2008). Verifying biogenic emissions will be challenging given the complexities in reporting, and due to the large uncertainties in estimation of biogenic emissions arising from the complex interactions among driving variables, including weather patterns, topographic variation, soil characteristics, disturbances and a variety of land use and management activities.

Verification of biogenic emissions could incorporate several levels of evaluation. First, inventory methods can be evaluated for consistency with UNFCCC reporting guidelines. Appropriate application of methods provides assurance that the emission estimates are credible. This type of evaluation is currently conducted by the UNFCCC on a periodic basis for developed countries through an expert review process.

Second, an independent verification program could confirm adoption of land use and management practices that are reported to enhance biogenic sinks or reduce biogenic sources. Verifying practices provides confidence that managers have taken the necessary steps to reduce GHG emissions. Third, verification could incorporate further evaluation using direct measurements of C sources and sinks that are independent of the inventory compilation (IPCC 2006). For example, soil monitoring networks are in various stages of implementation in several countries that could serve as an independent check (van Wesemael *et al* 2011). Another option would be to measure fluxes using eddy-covariance flux towers that are deployed throughout a region. When combined with modeling, an independent estimate of the regional flux can be produced and compared to an inventory (Xiao *et al* 2010, Raczka *et al* 2013, Hilton *et al* 2014).

Fourth, methods have been under development for more than a decade that utilize observations of CO₂ concentrations in the atmosphere to estimate the biogenic CO₂ flux with inverse modeling (Tarrantola 2004). CO₂ fluxes are estimated based on knowledge of wind speeds and directions in conjunction with CO₂ concentration changes in the atmosphere. This technique has been widely used, including applications at the global scale (Tans *et al* 1990, Bousquet *et al* 2000, Gurney *et al* 2002), continental scales (Peters *et al* 2007, Gourdji *et al* 2012), and more recently at regional scales (Göckede *et al* 2010, Lauvaux *et al* 2012a, Schuh *et al* 2013). Using these data to evaluate a biogenic emissions inventory is likely to offer a strong inference for verification by demonstrating that reported biogenic emissions are consistent with changes in atmospheric CO₂ concentrations.

Both the IPCC (2006) and US National Research Council (NRC 2010) have raised the possibility of using atmospheric measurements of GHGs to verify emission inventories. We report here on an approach evaluating how this type of verification could be accomplished for biogenic sources and sinks using national GHG emissions data. Our case study focuses on emissions reporting for 2007 in the Mid-Continent region of the United States, which is dominated by agricultural production (figure 1). Several challenges must be addressed in order to verify biogenic emissions data compiled by governments for UNFCCC reporting using this approach. First, a complete C budget is needed in order to make relevant comparisons with fluxes derived from atmospheric CO₂ concentration data (Hayes and Turner 2012). A full biogenic carbon budget is not compiled by governments for reporting to the UNFCCC, requiring estimation of additional sources and sinks. Second, inventory data from individual emission categories, such as cropland and forestland, must be combined on a common grid from a variety of data sources with different spatial and temporal resolutions. Third, an

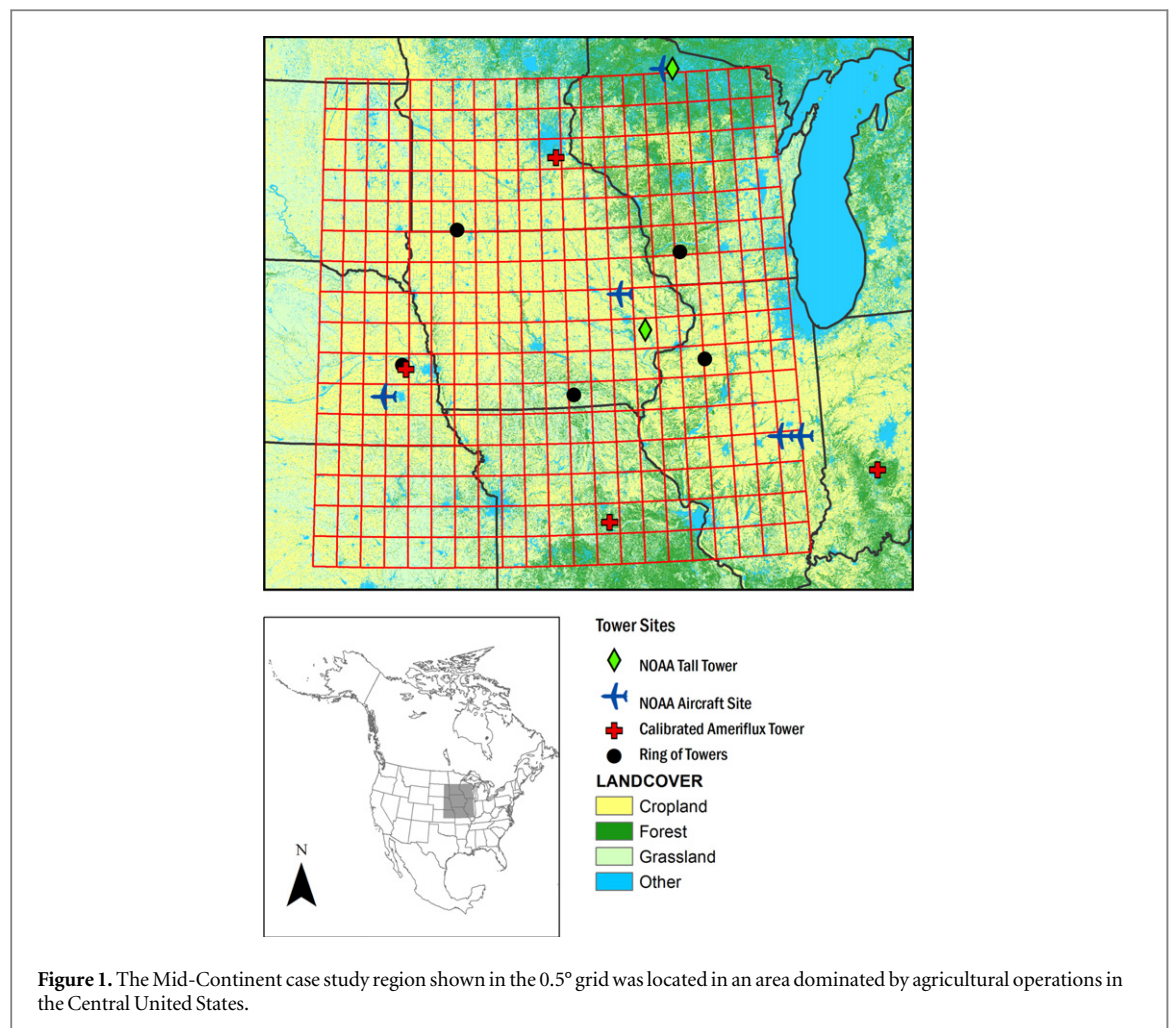


Figure 1. The Mid-Continent case study region shown in the 0.5° grid was located in an area dominated by agricultural operations in the Central United States.

approach was needed to statistically verify if CO_2 fluxes from the emissions inventory are consistent with fluxes estimated with atmospheric CO_2 concentration data based on the associated probability distributions for each set of fluxes.

Methods

Biogenic CO_2 emissions inventory

The biogenic CO_2 emissions inventory for this case study included emission categories associated with forest biomass, incorporation of C in wood products, and agricultural cropland and grassland soil C as reported in the United States GHG Inventory (USEPA 2010, 2013) (table 1). Additional emission categories were needed to obtain the full C balance for comparison to CO_2 fluxes derived from atmospheric concentration data (Hayes and Turner 2012). Therefore, the inventory also included CO_2 emissions from decomposition of waste in landfills and agricultural residue burning (McCarty 2011), CO_2 uptake by agricultural crops and C in harvested grains, and CO_2 returned to the atmosphere from livestock and human respiration (West *et al* 2011). The emission categories can have a net positive or negative annual emission

rate; net negative emissions result from CO_2 that is removed from the atmosphere and sequestered in biomass, soils or commodity products (e.g., harvested wood used in housing construction).

Agriculture dominates the study region requiring tracking C through crop and livestock production system. Cropland biomass was estimated based on county-scale crop yield data compiled in the USDA National Agricultural Statistics (USDA-NASS 2010), and crop-specific parameters for harvest indices, root: shoot ratio, moisture and C contents to convert the harvested grain data into units of C (West *et al* 2010, 2011). Grassland biomass stock changes were not estimated given the limited amount of data, and is likely a minor contributor to net C stock change in this region.

The residues remaining after harvest were burned or incorporated into soil C pools. CO_2 emissions from agricultural residue burning were estimated based on the area burned using 500 m MODIS 8-day Surface Reflectance Product (MOD09A1) and 1 km MODIS Active Fire Products (MOD14/MYD14) (McCarty *et al* 2009), fuel load (i.e., amount of crop residue biomass), combustion efficiency and CO_2 emission factors for residue burning (McCarty 2011). Soil C stock changes for agricultural cropland and grassland were

Table 1. Summary of commodity, census and remote sensing products that were used to estimate C stock changes and emissions, in addition to the spatial and temporal resolution of the original emission category data. References provide more information about the methods for deriving the estimates and uncertainties for each emission category. The asterisks (*) identifies CO₂ sources or sinks that are reported to the UNFCCC.

Biogenic emission category	Main data source	Spatial scale of data	Temporal scale of data	Inventory method references
Agricultural cropland and grassland C				
Harvested crop yield C	USDA-NASS agricultural statistics	County	Annual	West <i>et al</i> 2010
Cropland residue burning*	MODIS products (MOD09A1, MOD14/MYD14)	Sub-county (500 m)	8-day cycle	McCarty 2011
Soil C stock changes*	USDA-NRI land survey data	Sub-county (survey sample)	Daily	Ogle <i>et al</i> 2010, US-EPA 2013
Livestock respiration	USDA-NASS agricultural statistics	County	Annual	West <i>et al</i> 2011
Human respiration	United States population census	County	Annual	West <i>et al</i> 2011
Forestland C				
Biomass C stock changes*	USFS-FIA forest plot data	Sub-county (survey sample)	5 year intervals	Smith <i>et al</i> 2007a, 2007b, Heath <i>et al</i> 2011, Smith <i>et al</i> 2013, US-EPA 2010
Coarse woody debris/soil C Stock changes*	USFS-FIA forest plot data, STATSGO soil database	Sub-county (survey sample)	Annual average over 5–7 years	US-EPA 2010, Smith <i>et al</i> 2013
Harvested wood products*	US Department of Commerce statistics compiled/augmented by USFS	National, scaled to county	Annual	Skog 2008, Smith <i>et al</i> 2013, US-EPA 2010
Landfill decomposition	US-EPA landfill methane outreach program	County	Annual	This publication ^a

^a Uncertainty in the landfill estimates was derived using a Monte Carlo approach by sampling probability distribution functions for the amount and fraction of degradable organic carbon that is decomposable, methane correction factor for aerobic decomposition, fraction of methane generated as landfill gas, and a reaction constant.

estimated by simulating the balance between C input from residues and C loss from decomposition using the land use and cropping histories from the USDA National Resources Inventory (USDA-NRCS 2009) using the DAYCENT ecosystem model (Ogle et al 2010, US-EPA 2013).

Harvested C from croplands is returned to the atmosphere within the region through livestock and human respiration. The remaining harvested C is transported and emitted in other regions of the United States or exported to foreign countries (West et al 2011). The exported C effectively represents a sink for CO₂ in the study region, but is ultimately returned to atmosphere through heterotrophic respiration in other regions. CO₂ emissions from human respiration were estimated from population data provided in the United States Population Census and total food intake by gender and age class (West et al 2009). CO₂ emissions from livestock respiration were derived from livestock population data compiled in the USDA National Agricultural Statistics (USDA-NASS 2010). The amount of C emitted as CO₂ was based on the difference between C intake from harvested grain and grazing pastures relative to C released as waste, milk, and methane, or incorporated into livestock growth (West et al 2011). C in manure was included as an input to the soil in the DAYCENT model simulations for soil C stock changes.

In addition to agricultural systems, carbon flows were monitored into forestland biomass, litter and soil C pools using the USDA Forest Service, Forest Inventory and Analysis data (FIA) (USFS 2009), and standard inventory-to-C conversion methods (Smith et al 2007a, 2007b, US-EPA 2010, Heath et al 2011, Smith et al 2013). Live biomass, standing and down coarse woody debris, and soil C are periodically surveyed by the FIA program. A portion of field plots are visited annually, but data were compiled across all plots for this analysis to increase precision. Average stock changes were estimated over five to seven year time blocks, which varied based on the frequency of individual plot resampling. A portion of the biomass C is harvested, removed from sites, and incorporated into wood products rather than returned to the atmosphere as CO₂ (Skog 2008, Heath et al 2011). Decay rates are applied to harvested wood products to estimate how much carbon remains in this pool over time.

Emissions from decomposition of waste in landfills were estimated at a county scale from information on waste disposal compiled in the US-EPA Landfill Methane Outreach Program from 2399 landfills (US-EPA 2012). CH₄ emissions were estimated according to IPCC methods (Pippatti and Svardal 2006), and were used to approximate the amount of CO₂ emissions based on guidelines developed by the US-EPA (US-EPA 2001), which assume equal amounts of CO₂ and CH₄ emissions for landfills.

Estimates and uncertainties for the biogenic emission categories were derived based on probability distribution functions for model parameters, structure and inputs as described elsewhere (see references in table 1). Some emission categories were estimated at sub-county spatial resolution or sub-annual time scales, but were aggregated to county and annual time scales for this analysis. The one exception was forest C, which was estimated on five to seven year time intervals, and were down-scaled based on annual averages. The result was a sample of 100 Monte Carlo draws of net annual emissions for all categories at a county scale. The county-scale data were interpolated to a 0.5° grid based on area weighting of the county data associated with each grid cell (figure 1). Total CO₂ emissions were estimated for each replicate draw by summing the emissions for all categories in a respective draw. The final estimate for each grid cell was the average of the 100 replicates. Uncertainty was quantified based on the standard deviation of total emissions at each location using the sample covariance matrix, capturing spatial correlation in the estimates across the entire grid. A standard shrinkage estimate was used to derive the uncertainty because the number of cells (i.e., 336) is greater than the number of Monte Carlo replicates (i.e., 100) (e.g., Schäfer and Strimmer 2005). To estimate fluxes at larger scales, we aggregated each replicate draw on the 0.5° grid to 1°, 2° and 4° grid resolutions, and the entire region.

Atmospheric measurements and inversion

The atmospheric CO₂ concentration measurement network consisted of a combination of flux towers with infrared gas analyzers (Stephens et al 2011), NOAA-ESRL tall radio towers with gas analyzers (Bakwin et al 1998), and cavity ring-down spectrometers deployed on cellular communications towers (Richardson et al 2012). Aircraft measurements from the NOAA-ESRL continental profiling network (Crevoisier et al 2010) and the Carbon Tracker global inversion system (Peters et al 2007) were used to provide CO₂ boundary conditions.

Inverse modeling was used to estimate the net flux of CO₂ between atmosphere and land surface based on variation in atmospheric CO₂ concentrations over space and time with knowledge of atmospheric transport (Lauvaux et al 2012a, 2012b, Schuh et al 2013). The regional inversion utilized the Weather Research and Forecast model for atmospheric transport (Skamarock et al 2005), Lagrangian particle dispersion model to associate surface fluxes and boundary conditions with atmospheric measurement data (Uliasz 1994), and a Bayesian style least squares solution technique to solve for the surface fluxes (Lauvaux et al 2012a). Prior flux estimates were obtained from the SiB-CROP model (Lokupitiya et al 2009). In order to focus on biogenic emissions, the atmospheric signal associated with fossil fuel emissions was subtracted

from the simulated CO₂ concentrations within the inverse modeling framework, using fine resolution fossil fuel emissions data (Gurney et al 2009).

Uncertainties were approximated for the *a priori* biogenic fluxes, the transport model, and the boundary conditions by performing sensitivity experiments across a range of plausible error estimates (Lauvaux et al 2012b). While the inversion utilized in the regional inverse modeling system provided a formal estimate of the uncertainty for the posterior fluxes, the uncertainty estimate was limited by assumptions inherent to the inverse model. To improve the estimation of uncertainty, Lauvaux et al (2012a) experimented with a number of the assumptions required by the regional inverse model including prior fluxes, CO₂ inflow at the domain boundaries, atmospheric CO₂ uncertainties (which encompasses transport, model-data mismatch, and observational uncertainties), and spatial coherence of corrections to prior fluxes. These experiments provided a range of posterior flux distributions and differences in the mean estimates, which were used in an ad hoc way to inflate the variance of a single inverse model simulation accounting for biases. Additional analysis of the degree of freedom in the signals showed that the inverse solution is primarily constrained by the atmospheric data rather than *a priori* information (Lauvaux et al 2012b). In the analysis presented here, the prior fluxes from SibCROP were not included because the annual C flux for the MCI region was imposed rather than simulated (Schuh et al 2013).

The inversion results and uncertainties, initially produced at a weekly time step with a 20 km resolution, were interpolated to a 0.5° grid covering the Mid-Continent study region (figure 1). This 0.5° grid did not correspond exactly to the domain on which the inversion was modeled and so the outer grid cells were removed that were only partially covered by the inversion (i.e., we did not extrapolate the results to cover the entire grid). This resulted in a slightly smaller study region and estimated CO₂ flux compared to previous publications (Lauvaux et al 2012a, Schuh et al 2013). Similar to the inventory, the data on the 0.5° grid were aggregated to the larger grid resolutions of 1°, 2° and 4°, as well as the entire region.

Verification analysis

Statistical hypothesis tests were used to formally verify the agreement between the emissions inventory and the CO₂ fluxes estimated from the atmospheric measurement network and the inverse model system. The tests are similar to two-sample t-tests for equality of means. However, a difference arises because rather than having repeated samples, this comparison is based on point estimates and covariance matrices. The information used in the hypothesis tests are the annual emissions totals on the 0.5° grid and the covariance matrices associated with the inverse modeling and

inventory methods that describe both uncertainty at the location and spatial correlation between estimates on the grid. Temporal correlation was not relevant for this test because there was only one time step in the analysis.

To formalize, let $t_i^{(A)}$ denote the vector of fluxes estimated from the atmospheric CO₂ concentration data and inverse model system for each location in the study region. Likewise, let $t_i^{(E)}$ be the vector of fluxes from the emissions inventory. Let $\Sigma^{(A)}$ and $\Sigma^{(E)}$ represent the covariance matrices associated with the inversion and inventory respectively. All of the tests were performed to evaluate if $a^T t_i^{(A)}$ is significantly different from $a^T t_i^{(E)}$, where a is a vector which corresponds to the test performed. Underlying each test is the assumption that $t_i^{(A)}$ is normally distributed with mean μ and covariance matrix $\Sigma_i^{(A)}$, and likewise for $t_i^{(E)}$. Here, μ denotes the vector of true fluxes at each location in the study region. Our test statistic for each test is $a^T (t_i^{(A)} - t_i^{(E)})$ under the assumptions that the statistic has a normal distribution with mean zero and variance $a^T (\Sigma_i^{(A)} + \Sigma_i^{(E)}) a$, and that $t_i^{(A)}$ is uncorrelated with $t_i^{(E)}$. Our tests account for the uncertainty associated with each estimate given the information comprising $\Sigma^{(A)}$ and $\Sigma^{(E)}$.

Verification of the emissions inventory using atmospheric CO₂ concentration data were evaluated at 0.5°, 1°, 2° and 4° grid resolutions, as well as the entire region. Differences were considered significant at an alpha level of 0.05. This analysis does not address multiple testing issues. However, the main purpose is to explore differences, and then further evaluate the inventory, to the extent that differences are found, and determine if an error exists. Consequently there are minimal consequences for identifying a statistically significant difference when there are no differences in reality (i.e., type I error).

Results

The Mid-Continent region was a net sink for biogenic CO₂ fluxes in 2007 according to the emissions inventory (table 2, figure 2). The flux was dominated by C uptake driven by crop production and export of grain from the region. Other emission categories contributing to the biogenic sink include forest growth, and incorporation of C into wood products, and C sequestration in agricultural soils (table 2, figure 2). Livestock respiration produced the largest net positive biogenic emissions to the atmosphere. Other biogenic emission categories such as CO₂ emissions from human respiration, crop residue burning or decomposition of waste in landfills were smaller contributors to the regional flux.

Measurements of CO₂ concentrations also indicated a strong biogenic CO₂ sink over the study region during the 2007 summer growing season, June

Table 2. CO₂ emissions (Tg CO₂ eq.) associated with individual sources of biogenic emissions in the Mid-Continent study region. Forestland C stock change includes biomass, coarse woody debris, soil and harvested wood products.

Biogenic emission categories	Estimate (Tg CO ₂ eq)	95% Confidence interval
Cropland harvested yield C	−367.97	−497, −239
Forestland C stock changes	−85.08	−107.7, −62.4
Agricultural soil C stock changes	−33.56	−58.3, −8.7
Agricultural residue burning	0.79	0.78, 0.80
Landfill decomposition	2.16	1.29, 3.03
Human respiration	18.85	18.84, 18.86
Livestock respiration	56.73	30.48, 82.98
Total emissions inventory	−408.1	−544, −272
Total atmospheric inversion	−478.0	−624, −332

through August, consistent with the period of highest crop growth (Miles *et al* 2012, Lauvaux *et al* 2012a). Midday atmospheric boundary layer CO₂ concentrations had a very strong seasonal cycle over the middle of region from Southwest Minnesota to Northern Illinois (>35 ppm), which is dominated by corn and soybean production (figure 2). There was also a reduced but substantial seasonal cycle in Northern and Southern portions of the region (>25 ppm) (Corbin *et al* 2010, Miles *et al* 2012).

According to the biogenic emissions inventory, there was a net flux of −408 Tg CO₂ from the atmosphere into the study region during 2007, with a 95% confidence interval of ±136 Tg CO₂. The estimated biogenic flux was -478 ± 146 Tg CO₂ based on the atmospheric CO₂ concentration data and inversion. Consequently, the CO₂ flux according to the biogenic emissions inventory was not statistically different from the inversion. A non-significant result means that the emissions inventory is consistent and verifiable with the changes in atmospheric CO₂ concentrations, given their associated uncertainties.

Comparisons were also made between the inventory and inversion results across incrementally larger resolutions within the Mid-Continent study region, including 0.5°, 1°, 2°, and 4° resolution grid scales (see figure 2 for 0.5° gridded data). No significant differences were found at any of the scales, except at the 0.5° scale in one isolated area of West-central Wisconsin, near the border with Minnesota. The isolated area was largely dominated by forestland, suggesting further investigation may be needed into small scale forest inventory data in this region and harvested wood product estimates.

The relative uncertainty associated with the inventory and inversion results changed with the spatial scale from the entire region to the finest resolution of a 0.5° (figure 3). However, the change in uncertainty across the scales was much greater for the inversion results. The inversion analysis was well constrained at the scale of the entire region with a coefficient of variation of 0.16, which was similar to the coefficient of variation of 0.17 for the CO₂ flux from the emissions inventory. The relative uncertainty increased dramatically in the atmospheric inversion with an average

coefficient of variation of 0.91 at the 0.5° resolution, compared to a value of 0.43 for the flux estimates from the inventory.

Discussion

The results of the Mid-Continent case study show promise for using atmospheric CO₂ concentration data and inverse modeling systems to verify biogenic GHG emission inventories. North American continental scale comparisons have also been made in previous studies and demonstrated that emissions inventories are consistent with inversions of atmospheric CO₂ measurements, even though the estimates could vary by more than 1000 Tg CO₂ (Pacala *et al* 2001, Gourdji *et al* 2012, Hayes *et al* 2012, King *et al* 2012). The large differences may be caused by biases in the transport models (Baker *et al* 2006), or unrealistic constraints imposed on the inverse modeling system resulting from limited atmospheric CO₂ measurement data. The Mid-Continent study attempted to overcome limitations in CO₂ observations with a network of measurements that was denser than typically available for deriving an atmospheric-based C budget (figure 1).

Errors in the emissions inventory may have also contributed to the large differences in past comparisons with inverse modeling results due to limited, inconsistent or no data collection for certain land surface processes that influence CO₂ fluxes, such as woody encroachment in the Southwestern United States (Hayes *et al* 2012), or urban trees in regions with a large proportion of metropolitan areas (Nowak *et al* 2013). However, the Mid-Continent case study utilized extensive land-based surveys, remote sensing products, census data and commodity statistics that are collected to support trade in this important economic region for agriculture. One notable gap in the inventory, however, was the lateral transport of C from terrestrial systems into rivers and lakes (Butman and Raymond 2011). While it is less likely that limited or missing data is an issue in this region, there are still uncertainties associated with gaps that will require further study.

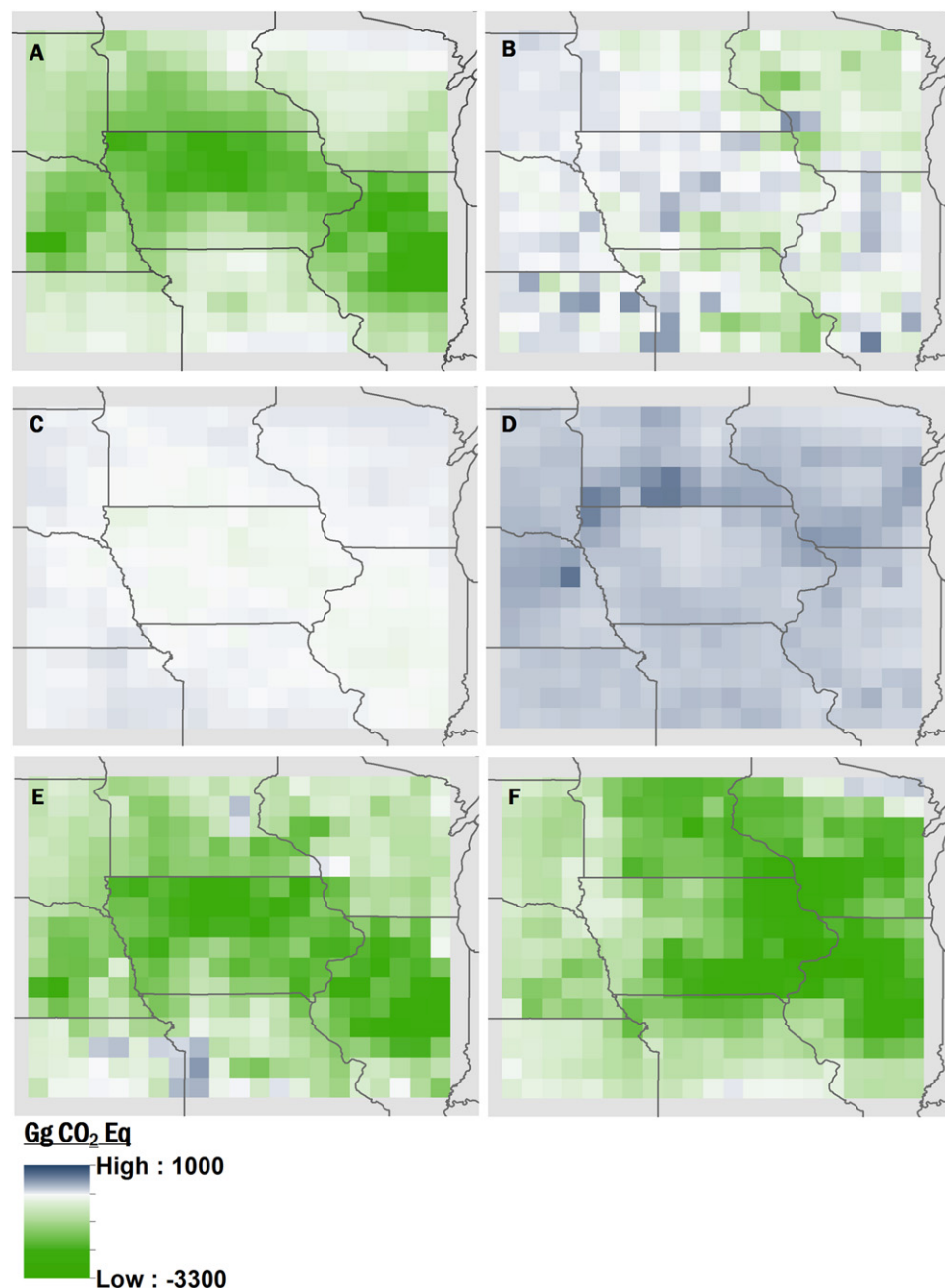


Figure 2. Net annual CO₂ emissions (Gg CO₂) in 2007 at a 0.5° spatial resolution from dominant emission categories in the Mid-Continent study region, including (A) cropland harvested crop biomass, (B) forest C stock changes and harvested wood products, (C) agricultural soil C stock changes, (D) livestock respiration emissions, (E) total biogenic emissions inventory, and (F) atmospheric CO₂ inversion. Negative emissions represent a net annual CO₂ uptake from the atmosphere to the land surface, and positive emissions represent a net annual release of CO₂ to the atmosphere from the land surface. CO₂ emissions from landfills, human respiration and agricultural residue burning have smaller net annual fluxes.

The uncertainty in the inventory and inversion results both increased from the largest scale of the entire region to the finer resolutions of 4°, 2°, 1°, and 0.5° gridded CO₂ fluxes (figure 3). However, the uncertainty increased more with the inversion estimates than the inventory. The higher precision in the inventory estimates at smaller scales is likely due to finer resolution data that were used to estimate the emissions, such as county-scale agricultural statistics and forest plot data. In contrast, the inversion relied on the atmospheric

concentration data dispersed in a ring near the boundary of the region (figure 1). To obtain more precise estimates, the atmospheric inversion would likely require more towers dispersed within the region, providing more spatially-detailed data on atmospheric CO₂ concentrations. Regardless, the relatively high precision in the inversion results for the entire region suggests that the design of the network as a ring surrounding the region can provide a reasonable constraint on the total regional flux (Lauvaux *et al* 2012a).

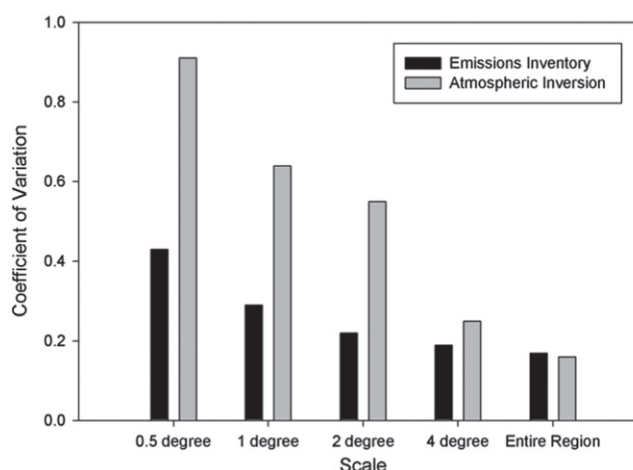


Figure 3. Coefficient of variation (i.e., standard deviation divided by the median, which is a measure of the relative uncertainty) averaged across the grid cells for biogenic CO₂ emissions inventory and atmospheric inversion at several scales, including 0.5°, 1°, 2°, and 4° grids, in addition to the entire region.

If biogenic emissions inventories are to be verified by an operational atmospheric CO₂ measurement and inverse modeling system, additional information will be needed beyond current requirements for national GHG inventory reporting to the UNFCCC. First, non-anthropogenic sources of biogenic emissions must be estimated to be comparable to CO₂ fluxes estimated from atmospheric concentration data because both anthropogenic and non-anthropogenic activities are integrated in the atmosphere. UNFCCC reporting of biogenic emissions currently only requires estimation of activity on managed land, while biogenic emissions from other areas are considered non-anthropogenic and hence, not included in an inventory (IPCC 2006, IPCC 2010).

Second, some components of the C budget that are influenced by anthropogenic activity are largely ignored in a national GHG inventory. In these cases, the impact on atmospheric CO₂ concentrations is considered transient with limited effect outside of an annual cycle. One example is the production and use of agricultural commodities that remove and return about the same amount of C to the atmosphere on annual time scales (Ciais *et al* 2007, West *et al* 2011). However, documenting the location of biogenic C uptake and release in commodities will be necessary in a national GHG inventory to make valid comparisons with fluxes estimated from atmospheric CO₂ concentration data.

The Mid-Continent region is a nearly optimal location for this case study due to the strong influence of biogenic emission categories on the CO₂ flux (e.g., agricultural crop production); relatively simple terrain and abundant meteorological data for the inverse modeling; and extensive land surveys and commodity data to support the inventory compilation (figure 1). Further testing in other regions is warranted. Moreover, new satellite-based CO₂ data are emerging that

can be incorporated into inverse modeling (Crisp *et al* 2004, Houweling *et al* 2004, Kadygrov *et al* 2009), and studies are suggesting that inversion results can be further optimized by combining in situ atmospheric CO₂ concentration data from a ground-based network and aircraft campaigns, with the emerging satellite-based CO₂ data (Nassar *et al* 2011, Keppel-Aleks *et al* 2011, Basu *et al* 2013, Lauvaux and Davis 2014).

The goals of a verification system for biogenic emissions will need to be clarified before mobilizing an operational CO₂ measurement and inverse modeling system to support emissions reporting. The levels of accuracy and precision, and the spatial and temporal resolution required will dictate the investment to create a functional system. In addition, an operational system could be used to verify total biogenic emissions from a region, as we have presented here, or it could be used in combination with the inventory data to produce emission estimates. For example, Cooley *et al* (2013) found that the uncertainty in the total CO₂ flux for the Mid-Continent region is reduced by 21% if the results from the emissions inventory and inverse modeling system are combined into a single CO₂ emissions estimate.

Conclusions

Our study demonstrates how atmospheric CO₂ concentration data combined with inverse modeling technology could provide a robust check on biogenic emissions inventories using statistical methods applied in the Mid-Continent case study. This level of evaluation would complement other forms of verification, such as evaluation of inventory methods for consistency with UNFCCC reporting guidelines, confirmation that management practices have been adopted to enhance biogenic sinks, or evaluation of C stock changes and fluxes at specific locations in a

region. Over time, incorporating verification based on the atmospheric CO₂ concentration data is likely to produce more accurate and credible estimates for reporting biogenic emissions to the UNFCCC, as errors are discovered and corrected. In turn, more credible estimates will lead to less uncertainty for developing and monitoring the outcomes of climate change policies associated with biogenic sources and sinks.

Acknowledgments

This synthesis and analysis was supported by a grant from the National Aeronautics and Space Administration (NASA), Terrestrial Ecology Program (NNX08AK08G to Colorado State University and NNH12AU35I to Department of Energy). The Mid-Continent study was supported by multiple agencies in the US government through the North American Carbon Program, particularly NASA, US Department of Energy, National Oceanic and Atmospheric Administration and US Department of Agriculture. Inventory and inversion results are archived in the NASA Distributed Active Archive Center at Oak Ridge National Laboratory.

References

- Baker D F *et al* 2006 TransCom 3 inversion intercomparison: impact of transport model errors on the interannual variability of regional CO₂ fluxes, 1988–2003 *Glob. Biogeochemical Cycles* **20** GB1002
- Bakwin P S, Tans P P, Hurst D F and Zhao C 1998 Measurements of carbon dioxide on very tall towers: results of the NOAA/CMDL program *Tellus B* **50** 401–15
- Basu S *et al* 2013 Global CO₂ fluxes estimated from GOSAT retrievals of total column CO₂ *Atmos. Chem. Phys.* **13** 8695–717
- Bousquet P *et al* 2000 Regional changes in carbon dioxide fluxes of land and oceans since 1980 *Science* **290** 1342–6
- Butman D and Raymond P A 2011 Significant efflux of carbon dioxide from streams and rivers in the United States *Nat. Geosci.* **4** 839–42
- Canadell J G, Kirschbaum M U F, Sanz M-J, Schlamadinger B and Yamagata Y 2007 Factoring out natural and indirect human effects on terrestrial carbon sources and sinks *Environ. Sci. Policy* **10** 370–84
- Ciais P, Bousquet P, Freibauer A and Naegler T 2007 Horizontal displacement of carbon associated with agriculture and its impacts on atmospheric CO₂ *Glob. Biogeochemical Cycles* **21** 2011–2
- Cooley D, Breidt F J, Ogle S M, Schuh A and Lauvaux T 2013 A constrained least-squares approach to combine bottom-up and top-down CO₂ flux estimates *Environ. Ecological Stat.* **20** 129–46
- Corbin K D *et al* 2010 Assessing the impact of crops on regional CO₂ fluxes and atmospheric concentrations *Tellus B* **62** 521–32
- Crevoisier C, Sweeney C, Gloor M, Sarmiento J and Tans P 2010 Regional US carbon sinks from three-dimensional atmospheric CO₂ sampling *Proc. Natl Acad. Sci. USA* **107** 18348–53
- Crisp D *et al* 2004 The orbiting carbon observatory (OCO) mission *Adv. Space Res.* **34** 700–9
- Fargione J, Hill J, Tilman D, Polasky S and Hawthorne P 2008 Land clearing and the biofuel carbon debt *Science* **319** 1235–8
- Göckede M, Michalak A M, Vickers D, Turner D P and Law B E 2010 Atmospheric inverse modeling to constrain regional-scale CO₂ budgets at high spatial and temporal resolution *J. Geophys. Res.* **115** D15113
- Gourdji S M *et al* 2012 North American CO₂ exchange: inter-comparison of modeled estimates with results from a fine-scale atmospheric inversion *Biogeosciences* **9** 457–75
- Gurney K R *et al* 2002 Towards robust regional estimates of CO₂ sources and sinks using atmospheric transport models *Nature* **415** 626–30
- Gurney K R, Mendoza D L, Zhou Y, Fischer M L, Miller C C, Geethakumar S and de la Rue du Can S 2009 High resolution fossil fuel combustion CO₂ emissions fluxes for the United States *Environ. Sci. Technol.* **43** 5535–41
- Hayes D J *et al* 2012 Reconciling estimates of the contemporary North American carbon balance among terrestrial biosphere models, atmospheric inversions, and a new approach for estimating net ecosystem exchange from inventory-based data *Glob. Change Biol.* **18** 1282–99
- Hayes D and Turner D 2012 The need for ‘apples to apples’ comparisons of carbon dioxide source and sink estimates *EOS* **93** 404–5
- Heath L S, Smith J E, Skog K, Nowak D and Woodall C 2011 Managed forest carbon estimates for the US greenhouse gas inventory, 1990–2008 *J. Forestry* **109** 167–73
- Hilton T W, Davis K J and Keller K 2014 Evaluating terrestrial CO₂ flux diagnoses and uncertainties from a simple land surface model and its residuals *Biogeosciences* **11** 217–35
- Houweling S, Breon F-M, Aben I, Rodenbeck C, Gloor M, Heimann M and Ciais P 2004 Inverse modeling of CO₂ sources and sinks using satellite data: a synthetic inter-comparison of measurement techniques and their performance as a function of space and time *Atmos. Chem. Phys.* **4** 523–38
- IPCC 2006 *Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories* ed S Eggleston, L Buendia, K Miwa, T Ngara and K Tanabe (Eds) Institute for Global Environmental Strategies Hayama, Japan
- IPCC 2010 *Revisiting the use of Managed Land as a Proxy for Estimating National Anthropogenic Emissions and Removals* ed Eggleston, H S, Srivastava, N, Tanabe, K, Baasansuren Institute for Global Environmental Strategies, Hayama, Japan pp 1–23
- IPCC 2013 *Climate Change 2013: The Physical Science Basis Contribution of Working Group I to the 5th Assessment Report of the Intergovernmental Panel on Climate Change* ed T F Stock, D Qin, T-F Plattner, T Tignor, S K Allen, J Boschung, A Nauels, Y Xia, V Bex and P M Midgley (Cambridge, UK: Cambridge University Press) pp 1–1535
- Kadyrov N, Maksyutov S, Eguchi N, Aoki T, Nakazawa T, Yokota T and Inoue G 2009 Role of simulated GOSAT total column CO₂ observations in surface CO₂ flux uncertainty reduction *J. Geophys. Res.* **114** D21208
- Keppel-Aleks G, Wennberg P O and Schneider T 2011 Sources of variations in total column carbon dioxide *Atmos. Chem. Phys.* **11** 3581–93
- King A W, Hayes D J, Huntzinger D N, West T O and Post W M 2012 North American carbon dioxide sources and sinks: magnitude, attribution, and uncertainty *Front. Ecol. Environ.* **10** 512–9
- Kurz W *et al* 2013 Methods for estimation, measurement, monitoring and reporting of LULUCF activities under articles 3.3 and 3.4 *Revised Supplementary Methods and Good Practice Guidance Arising from the Kyoto Protocol* ed T Hiraishi, T Krug, K Tanabe, N Srivastava, J Baasansuren, M Fukuda and T G Troxler (Eds) Institute for Global Environmental Strategies, Hayama, Japan pp 1–2
- Lauvaux T *et al* 2012a Constraining the CO₂ budget of the corn belt: exploring uncertainties from the assumptions in a mesoscale inverse system *Atmos. Chem. Phys.* **12** 337–54
- Lauvaux T, Schuh A, Bocquet M, Wu L, Richardson S, Miles N and Davis K J 2012b Network design for mesoscale inversions of CO₂ sources and sinks *Tellus B* **64** 17980

- Lauvaux T and Davis K J 2014 Planetary boundary layer errors in mesoscale inversions of column-integrated CO₂ measurements *J. Geophys. Res.* **119** 490–508
- Lokupitiya E et al 2009 Incorporation of crop phenology in simple biosphere model (sibcrop) to improve land-atmosphere carbon exchanges from croplands *Biogeosciences* **6** 969–86
- McCarty J L, Korontzi S, Justice C O and Loboda T 2009 The spatial and temporal distribution of crop residue burning in the contiguous United States *Sci. Total Environ.* **407** 5701–12
- McCarty J 2011 Remote-sensing-based estimates of annual and seasonal emissions from crop residue burning in the contiguous United States *J. Air Waste Manage. Assoc.* **61** 22–34
- Miles N L et al 2012 Large amplitude spatial and temporal gradients in atmospheric boundary layer CO₂ mole fractions detected with a tower-based network in the US upper Midwest *J. Geophys. Res.* **117** G01019
- Nassar R et al 2011 Inverse modeling of CO₂ sources and sinks using satellite observations of CO₂ from TES and surface flask measurements *Atmos. Chem. Phys.* **11** 6029–47
- Nowak D J et al 2013 Carbon storage and sequestration by trees in urban and community areas of the United States *Environ. Pollut.* **178** 229–36
- NRC 2010 *Verifying Greenhouse Gas Emissions: Methods to Support International Climate Agreements* National Research Council (Washington, DC: The National Academies Press) p 110
- Ogle S M, Breidt F J, Easter M, Williams S, Killian K and Paustian K 2010 Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model *Glob. Change Biol.* **16** 810–20
- Pacala S W et al 2001 Consistent land- and atmosphere-based US carbon sink estimates *Science* **292** 2316–20
- Peters W et al 2007 An atmospheric perspective on North American carbon dioxide exchange: CarbonTracker. *Proc. Natl Acad. Sci. USA* **104** 18925–30
- Pipatti R and Svardal P 2006 Solid waste disposal 2006 *IPCC Guidelines for National Greenhouse Gas Inventories* vol 5 ed S Eggleston, L Buendia, K Miwa, T Ngara and K Tanabe (Hayama, Japan: Institute for Global Environmental Strategies) ch 3 pp 3.1–3.44
- Raczka B M et al 2013 Evaluation of continental carbon cycle simulations with North American flux tower observations *Ecological Monographs* **83** 531–56
- Richardson S J, Miles N L, Davis K J, Crosson E R, Rella C W and Andrews A E 2012 Field testing of cavity ring-down spectroscopy analyzers measuring carbon dioxide and water vapor *J. Atmos. Ocean. Technol.* **29** 397–406
- Schäfer J and Strimmer K 2005 A shrinkage approach to large-scale covariance matrix estimation and implications for functional genomics *Stat. Appl. Genetics Mol. Biol.* **4** 1541–6115
- Schuh A et al 2013 Evaluating atmospheric CO₂ inversions at multiple scales over a highly-inventoried agricultural landscape *Glob. Change Biol.* **19** 1424–39
- Skamarock W C, Klemp J B, Dudhia J, Gill D O, Barker D M, Wang W and Powers J G 2005 *A Description of the Advanced Research WRF Version 2* (Boulder, USA: National Center of Atmospheric Research) p 100
- Skog K E 2008 Sequestration of carbon in harvested wood products for the United States *Forest Prod. J.* **58** 56–72
- Smith J E, Heath L S and Nichols M C 2007a US forest carbon calculation tool: forest-land carbon stocks and net annual stock change (revised for use with FIADB 4.0) *Gen. Tech. Report NRS-13* United States Forest Service, Durham, New Hampshire
- Smith J E, Heath L S and Hoover C M 2013 Carbon factors and models for carbon pool estimates for the forest national greenhouse gas inventories of the United States for the submission years 2005–2011 *Forest Ecol. Manage.* **307** 7–19
- Smith P et al 2007b Greenhouse gas mitigation in agriculture *Phil. Trans. R. Soc. B* **363** 789–813
- Stephens B B, Miles N L, Richardson S J, Watt A S and Davis K J 2011 Atmospheric CO₂ monitoring with single-cell NDIR-based analyzers *Atmos. Meas. Tech.* **4** 2737–48
- Tans P P, Fung I U and Takahashi T 1990 Observational constraints on the global atmospheric CO₂ budget *Science* **247** 1431–8
- Tarantola A 2004 *Inverse Problem Theory and Methods for Model Parameter Estimation* (Philadelphia, PA: SIAM) p 342
- Tollefson J 2013 Warsaw talks to thrash out UN climate roadmap *Nature* **503** 174–5
- Uliasz M 1994 Lagrangian particle modeling in mesoscale applications *Environmental Modeling II* ed P Zannetti (Southampton, UK: Computational Mechanics Publications) pp 71–102
- USDA-NASS 2010 *Data and Statistics* United States Department of Agriculture, National Agriculture Statistics Service, Washington, DC
- USDA-NRCS 2009 *Summary Report: 2007 National Resources Inventory* Natural Resources Conservation Service, Washington, DC and Center for Survey Statistics and Methodology, Iowa State University, Ames, Iowa
- US-EPA 2001 *Solid Waste Management and Greenhouse Gases—A Life-Cycle Assessment of Emissions and Sinks* EPA530-R-02-006 United States Environmental Protection Agency
- US-EPA 2010 *Inventory of US Greenhouse Gas Emissions and Sinks: 1990–2008* EPA 430-R-10-006 US Environmental Protection Agency, Washington, DC p 407
- US-EPA 2012 *Landfill Methane Outreach Program—Landfill and Project Database* United States Environmental Protection Agency, Washington DC
- US-EPA 2013 *Inventory of US Greenhouse Gas Emissions and Sinks: 1990–2011* EPA 430-R-13-001 US Environmental Protection Agency, Washington, DC p 505
- USFS 2009 *Forest Inventory and Analysis National Program: Data and Tools* United States Department of Agriculture, Forest Service, Washington, DC
- van Wesemael B et al 2011 How can soil monitoring networks be used to improve predictions of organic carbon pool dynamics and CO₂ fluxes in agricultural soils? *Plant Soil* **338** 247–59
- West T O, Marland G, Singh N, Bhaduri B L and Roddy A B 2009 The human carbon budget: an estimate of the spatial distribution of metabolic carbon consumption and release in the United States *Biogeochemistry* **94** 29–41
- West T O et al 2010 Cropland carbon fluxes in the United States: increasing geospatial resolution of inventory-based carbon accounting *Ecological Appl.* **20** 1074–86
- West T O, Bandaru V, Brandt C C, Schuh A E and Ogle S M 2011 Regional uptake and release of crop carbon in the United States *Biogeosciences* **8** 2037–46
- Xiao J et al 2010 A continuous measure of gross primary production for the conterminous United States derived from MODIS and AmeriFlux data *Remote Sens. Environ.* **114** 576–91